Multiunit Water Resource Systems Management by Decomposition, Optimization and Emulated Evolution

A Case Study of Seven Water Supply Reservoirs in Tunisia

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MULTIUNIT WATER RESOURCE SYSTEMS MANAGEMENT BY DECOMPOSITION, OPTIMIZATION AND EMULATED EVOLUTION

A Case Study of Seven Water Supply Reservoirs in Tunisia

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PROPOSITIONS

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Multiunit Water Resource Systems Management by Decomposition, Optimization and Emulated Evolution: A Case Study of Seven Water Supply Reservoirs in Tunisia.

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◊ Work expands so as to fill the time available for its completion.

Parkinson, C.N., *Parkinson's Law or The Pursuit of Progress*, John Murray, London, 1958 (p. 9).

◊ Man can act only on external and visible characters: Nature cares nothing for appearances, except in so far as they may be useful to any being. ...Man selects only for his own good; Nature only for that of the being which she tends.

Darwin, C., *On the Origin of Species*, A Facsimile of the First Edition (1859), Harvard University Press, 1979 (p. 83).

◊ Natural selection will not produce absolute perfection,...

idem, (p. 202).

◊ ...the imagination that things are real does not represent true *reality*.

Feynman, R.P., *"Surely You're Joking Mr Feynman!"*, edited by E. Hutchings, first published by W.W. Norton & Company (1985), Vintage, London, 1992, (p. 335).

◊ If you've made up your mind to test a theory, or you want to explain some idea, you should always decide to publish it whichever way it comes out. If we only publish results of a certain kind, we can make the argument look good. We must publish *both* kinds of results.

idem, (p. 343).

◊ Anyone who switches on the electric light, turns on the television, makes a phone call, watches a film, plays a record, takes a photograph, uses a personal computer, drives a car or travels by aeroplane has the lone eccentric to thank, not institutional science.

Milton, R., *Forbidden Science,* Fourth Estate, London, 1994, (p. 92).

◊ ...the space race, however costly, is to be welcomed between superpowers obsessed with anxieties about their relative rank order. Some day we must find a way of curing them of the obsession, but until that day comes we must count it as a step forward that while H-bomb was an agonic signal, the moon landing was a hedonic one. Nation-states still behave far more irrationally than most of their individual members, but we may cherish a small hope that one day they may catch up with the chimpanzee.

Morgan, E., *The Descent of Woman,* Souvenir Press Ltd., London, 1972 (p. 216).

◊ ...performance indicators like reliability of meeting the targeted demand, resilience with regard to the system escaping from failure mode, vulnerability as a measure of the most severe failure and the likes play an essential role in comprehensive assessment of the operation of a complex reservoir system.

This thesis.

◊ ...it is essential that decision makers are offered a number of alternative plans to be able to assess how well the individual options meet their preferences. Eventually, they could make a decision to choose either a single, the most preferable plan, or a group of alternatives that are to be further analyzed in more detail, or they might even change their preferences towards the future plans on the basis of the knowledge gained from the given set of options.

idem.

◊ ...systems analysts ought to concentrate on the creation of such models and analytical algorithms that would be sufficiently understandable to decision makers and potential users.

idem.

◊ *Cassius:* ...Tell me, good Brutus, can you see your face?
Brutus: No, Cassius; for the eye sees not itself. But by reflection, by some other things.

Shakespeare, W., *Julius Caesar,* Act I, Scene II, ll51-53.

◊ Wherever I may be going, whether I'm feasting or fasting,
One thing I cannot forget: I shall never forgive you for the children.

Bora Čorba, (a translation of) the first verse of the song "Decu ti neću oprostiti" (I shall never forgive you for the children), *Njihovi dani,* SIM Radio Bijeljina, 1996.

SUMMARY

Milutin, D. 1998. *Multiunit Water Resource Systems Management by Decomposition, Optimization and Emulated Evolution: A Case Study of Seven Water Supply Reservoirs in Tunisia*. Doctoral Dissertation, Wageningen Agricultural University, The Netherlands. (xx)+183pp., 26 figures, 31 tables.

Being one of the essential elements of almost any water resource system, reservoirs are indispensable in our struggle to harness, utilize and manage natural water resources. Consequently, the derivation of appropriate reservoir operating strategies draws significant attention in water resources planning and management. These operational issues become even more important with the ever increasing scale and complexity of water resource systems.

In this respect, the primary obstacle in the analysis of a multiple-reservoir-multiple-user water supply system operation is the dimensionality of the problem. Namely, being a sequential decision making process, the operation of a complex reservoir system over a certain period of time can adequately be described only if all the relevant variables and parameters related to possible system state and decision realizations are taken into account. Clearly, this requirement tends to grow rapidly with the size of the system considered. The computational burden expands even more drastically if the processes involved bear unavoidable stochastic characteristics which are, in this study, assumed to be attributed only to reservoir inflows.

With regard to the problem in hand, the methods proposed and analyzed in the study can be divided into three major groups. The first group of methods falls into the family of system decomposition approaches within the optimization and/or simulation of the operation of complex systems. The second one involves the assessment of the impact various simulation alternatives may have on the performance of the adopted iterative decomposition algorithms. Finally, the third part includes the application of genetic algorithms for the derivation of the best water allocation patterns within a multiple-reservoir-multiple-user water supply system.

The decomposition models proposed and analyzed in this study are known as sequential decomposition methods. Essentially, to reduce the dimensionality of an optimization problem, they split up a complex system into its elementary units (i.e. reservoirs). Subsequently, the operating strategy of the system is derived in an iterative fashion by applying successive optimization, simulation and release allocation analyses to individual system elements.

The optimization method employed within all the decomposition models is stochastic dynamic programming (SDP). Due to the inherent discrete nature of SDP operating policies, the iterative, decomposition-based optimization models have a certain "inaccuracy threshold" which directly affects the performance of the system. Therefore, three different simulation alternatives have been employed to assess the possibility of reducing this negative impact of discretization. It is shown that, by allowing limited policy violations within simulation, the system performance can improve significantly relative to the case when the operating policies are strictly followed.

Ultimately, a method based on the theory of genetic algorithms (GA) has been employed to derive the most favourable water allocation patterns within a multiple-reservoir-multiple-user water supply system. Since GAs make use of simulation to guide their search for promising solutions, two distinct GA models have been tested: i) the first one assumes that individual reservoirs are to be operated according to the standard reservoir operating rule; and ii) the second model simulates the operation of the system according to the policies derived by a prior application of an iterative decomposition/SDP-based optimization of the system's operation.

Throughout this study, particular emphasis is given to the appraisal of the system performance derived by different methods. Since all of the employed optimization and search models are essentially single-objective optimization techniques, and given the fact that the operation of a reservoir system cannot adequately be appraised on the basis of a single criterion, this study makes use of simulation to evaluate the performance of the system over a number of criteria, and thereby broaden the basis for the comparison of different models. Ultimately, it is believed that the presented results clearly exemplify the fact that performance indicators like reliability of meeting the targeted demand, resilience with regard to the system escaping from failure mode, vulnerability as a measure of the most severe failure and the likes play an essential role in comprehensive assessment of the operation of a complex reservoir system.

The analyses performed in this study showed that a complex water resource system decomposition, combined with the appropriate choice of optimization and simulation approaches could provide a sound basis for a transparent, yet efficient and effective operational analysis of very large reservoir systems. In addition, the application of genetic algorithms to solve a rather large resource allocation problem of a multiple-reservoir-multiple-user water supply system proved to be both relatively uncomplicated and remarkably efficient. Furthermore, it is believed that the coupling of a genetic algorithm resource allocation model with a decomposition-based optimization model represents a potentially powerful approach for solving highly complex operational problems related to multiple-reservoir water resource systems.

SAMENVATTING

Milutin, D. 1998. *Multiunit Water Resource Systems Management by Decomposition, Optimization and Emulated Evolution: A Case Study of Seven Water Supply Reservoirs in Tunisia.* Proefschrift, Landbouwuniversiteit Wageningen, Nederland. (xx)+183pp., 26 figuren, 31 tabellen.

Reservoirs vormen een wezenlijk onderdeel van vrijwel ieder watervoorzieningssysteem, en zijn onmisbaar bij het beheersen, het gebruik en het beheer van natuurlijke watervoorraden. Bij de planning en het management van de watervoorziening krijgt hierdoor het opstellen van juiste beheersstrategieën voor deze reservoirs veel aandacht. Het belang hiervan wordt steeds evidenter met de aldoor optredende schaalvergroting en mate van complexiteit van watervoorzieningsystemen.

De dimensie van het probleem vormt een belangrijk knelpunt in de analyse van een multi-reservoir watervoorzieningssysteem met vele eindgebruikers. Het beslissingsproces bestaat uit een aantal opeenvolgende stappen. Hierdoor kan het beheer van een complex netwerk van reservoirs alleen voldoende adequaat beschreven worden indien alle relevante variabelen en parameters die verband houden met de mogelijke toestanden waarin het systeem zich kan bevinden en met eerder genomen beslissingen, in beschouwing worden genomen. Het is duidelijk dat dit probleem snel groeit met de omvang van het systeem. De hoeveelheid rekenkundig werk groeit nog drastischer indien één of meerdere processen inherente stochastische eigenschappen heeft. In dit proefschrift is aangenomen dat dit alleen de aanvoer van water naar de reservoirs betreft.

Afhankelijk van de aard van het probleem kunnen de in deze studie voorgestelde en geanalyseerde methoden onderverdeeld worden in drie groepen: de eerste groep methoden kenmerkt zich door de zogenaamde systeem-decompositie benadering bij optimalisering en/of simulatie van het exploiteren van complexe systemen; de tweede groep betreft het inschatten van

de gevolgen die verschillende simulatie alternatieven kunnen hebben op de prestatie van de gebruikte iteratieve decompositie algoritmen; de derde groep tenslotte omvat de toepassing van genetische algoritmen voor het afleiden van de optimale patronen voor de bestemming van water in een multi-reservoir systeem met vele eindgebruikers.

De decompositiemodellen die in deze studie geanalyseerd zijn, staan bekend als de stapsgewijze decompositiemodellen. Om de omvang van een optimaliseringsprobleem te reduceren wordt een complex systeem opgesplitst in elementaire eenheden (in dit geval reservoirs). Vervolgens wordt een beheersstrategie voor het systeem op iteratieve wijze afgeleid door achtereenvolgens optimalisering, simulatie en analyse van de bestemming van waterstromen naar individuele systeemelementen toe te passen.

De optimaliseringsmethode die in alle decompositiemodellen wordt toegepast staat bekend als stochastisch-dynamisch programmeren (SDP). Door het inherent discrete karakter van toepassingen van SDP hebben iteratieve optimaliseringsmodellen die gebaseerd zijn op decompositie een bepaald onnauwkeurigheidsniveau, dat het functioneren van een systeem direct kan beïnvloeden. Om de mogelijkheden te onderzoeken de negatieve effecten van deze discretisering te reduceren, zijn drie alternatieven voor de simulatie onderzocht. Er is aangetoond dat wanneer in de simulatie beperkte overtredingen van de regels worden toegestaan, het functioneren van het systeem significant verbeterd kan worden ten opzichte van een situatie waar deze exploitatieregels strikt in acht worden genomen.

Tenslotte is een methode gebaseerd op de theorie van genetische algoritmen (GA) toegepast om het meest gunstige patronen voor waterbestemming in een multi-reservoir systeem met meerdere eindgebruikers af te leiden. Daar een GA gebruik maakt van simulatie om de zoektocht naar veelbelovende oplossingen te leiden, zijn twee verschillende GA modellen getest: i) de eerste gebruikt de aanname dat individuele reservoirs beheerd worden op een wijze die in overeenstemming is met de standaardregels voor het beheer van reservoirs, en ii) het tweede model simuleert het beheer van het systeem volgens de regels die afgeleid zijn bij eerdere toepassing van een iteratieve decompositie en een op SDP gebaseerde optimalisering van de exploitatie van het systeem.

In deze studie wordt voortdurend speciale nadruk gelegd op de beoordeling van het functioneren van het systeem zoals dat is afgeleid met behulp van de verschillende methoden. Alle toegepaste optimaliserings- en zoekmodellen zijn essentieël optimaliseringstechnieken met een enkelvoudig criterium. Gegeven het feit dat het functioneren van een systeem onvoldoende op basis van een enkel criterium beoordeeld kan worden, wordt in deze studie gebruik gemaakt van simulatie om het functioneren van een systeem te evalueren met betrekking tot meerdere criteria. Hierdoor wordt de basis voor het vergelijken van de verschillende methoden breder gemaakt. Uiteindelijk wordt gesteld dat de gepresenteerde resultaten duidelijk aantonen dat indicatoren voor het functioneren, zoals de betrouwbaarheid dat het systeem aan een doelstelling voldoet, de weerstand die een systeem ondervindt om uit een faaltoestand te ontsnappen, de

kwetsbaarheid van het systeem gemeten naar de ergst mogelijke faaltoestand en dergelijke, een wezenlijke rol spelen voor het op brede wijze vaststellen van de exploitatie van een complex reservoirsysteem.

De analyses die in dit onderzoek zijn uitgevoerd hebben aangetoond dat de decompositie van complexe watervoorzieningssystemen, gecombineerd met een juiste keuze van toegepaste optimalisering- en simulatietechnieken, een goede basis kunnen vormen voor een doorzichtige, maar efficiënte en effectieve analyse van de exploitatie van zeer grote reservoirsystemen. Daarnaast bleek de toepassing van genetische algoritmen voor het oplossen van het probleem van de bestemming van water in een watervoorzieningssysteem bestaande uit meerdere reservoirs en met vele eindgebruikers relatief eenvoudig te zijn en toch opmerkelijk efficiënt. Daarnaast lijkt het koppelen van een model voor waterbestemming op basis van genetische algoritmen met een optimalisatiemodel op basis van decompositie een potentiëel sterke benadering voor het oplossen van zeer complexe operationele problemen met multi-reservoir watervoorzieningssystemen.

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LIST OF ABBREVIATIONS

A-GA-D	approximate genetic algorithm/decomposition model
CDDP	constrained differential dynamic programming
C-GA-D	complete genetic algorithm/decomposition model
DBTS	deterministic binary tournament selection
DDDP	discrete differential dynamic programming
DMG	decision making group
DP	dynamic programming
ESDD	extended sequential downstream-moving decomposition
ESEMOPS	evolutionary sequential multiobjective problem solving
GA	genetic algorithm
GDP	gradient dynamic programming
IDD	iterative downstream-moving decomposition
IDP	incremental dynamic programming
LP	linear programming
MIDP	multilevel incremental dynamic programming
MSIS	multi single start search
NN	neural network
NLP	non-linear programming
PCA	principal component analysis
PI	performance indicator

PI_1	expected annual supply deficit
PI_2	time-based reliability
PI_3	average recovery time
PI_4	average recurrence time
PI_5	average monthly deficit
PI_6	maximum vulnerability
PI_7	maximum duration of failure
SDD	sequential downstream-moving decomposition
SDD-A	sequential downstream-moving decomposition utilizing the average demand concept of policy violation in simulation
SDD-M	sequential downstream-moving decomposition utilizing the monitored demand concept of policy violation in simulation
SDP	stochastic dynamic programming
SOR	standard reservoir operating rule
SSDP	sampling stochastic dynamic programming
UDD	iterative up-and-downstream-moving decomposition
VEGA	vector evaluated genetic algorithm

1 INTRODUCTION

The crucial role reservoirs play in the management of the ever-increasing demand for water is an indisputable fact. By "demand for water" one should not only consider water consumption as the essential aspect of human life sustenance (i.e. drinking, irrigation and food industry related water demands) but also other areas of water use (i.e. industrial, navigation, energy production, recreation). Furthermore, reservoirs and reservoir systems also provide the means to alleviate mounting problems related to the maintenance and improvement of water quality, aquatic life preservation and environmental protection, the conditions of which have been degrading due to the decades of irresponsible human actions mainly based on the notion that water, although indispensable, is still a renewable resource which is never going to be depleted. Ultimately, by providing a partial control over the temporal distribution of available water, reservoirs enable us to act upon mitigation of the negative effects of droughts and, with regard to the other side of the nature's coin of water related disasters, they play - on a different time scale - an equally essential role in flood protection.

According to Takeuchi (1996), there are presently nearly 40000 large reservoirs in the world impounding approximately 6000 km^3 of water and inundating an area of 400000 km^2. Recent surveys show that this number increases at a rate of approximately 250 new reservoirs each year. These figures clearly reflect the fact that reservoirs have a firmly established position in our striving to harness and manage the available water resources. Consequently, the increasing number of reservoirs make the existing water resource systems ever more complex and, therefore, more difficult to operate in an optimal way. However, despite the recent boom of computer technology and, consequently, the increasing ability to apply more complex mathematical methods to the analysis of the operation of reservoir systems it is still very seldom, even in the developed countries, that novel and more efficient optimization and/or simulation systems analysis methods find their place in planning and day-to-day operation of water resource systems (Schumann 1997). This is partially due to the lack of constructive and fruitful communication between those who carry out the research and development of the models, and the practitioners who are directly responsible for the operation of reservoir systems (cf. Loucks and Sigvaldason 1980). On the other hand, many researchers in the field of water resource management (e.g. Rogers and Fiering 1986, Loucks 1992, Parker et al. 1995) have stressed the need for making the models less intricate and more transparent to enable their end users to understand them better and, consequently, to use them in a more efficient and beneficial way.

The need for a comprehensive analysis of the operational aspects of water resource systems has long become an integral part of any water resource management study. However, the increasing complexity of the systems considered brings about the inevitable requirement to build more complex models in order to be able to address the respective intricate operational problems. Consequently, the models used become ever more complicated, often employing highly sophisticated mathematical theories and complicated algorithms, thus frequently making them hardly understandable to their potential users. It is, therefore, not surprising that, as mentioned in the previous paragraph, decision makers and water resource system operators seldom find the proposed methods and models attractive and suitable for their intended practical purposes.

The crucial question thus arises as to whether it is possible to reconcile the inevitable requirement for the analysis of ever more complex water resource systems and the opposing desire for the developed models to be as simple, transparent and easy to use as possible. Having this in mind, the primary objective of this study is to identify, develop, combine and appraise a number of alternative systems analysis approaches which could enable a more transparent, yet efficient and effective analysis of long-term operation of multiple-reservoir water supply systems.

In this respect, it is believed that, by combining various systems analysis approaches, it is still possible to create effective and suitable models without risking that they would be rejected because of their complexity and lack of transparency. However, the primary intention is far from proposing a universal model for such a water management problem. It is rather to identify a number of relevant aspects of the strategic operation of multiple-reservoir water supply systems and to propose alternative approaches to deal with the respective problems. These include the dimensionality of such an operational problem with regard to the number of reservoirs and users in a system, the consideration of stochasticity of the underlying hydrological processes, the resolution of the optimal allocation of resources within a multiple-reservoir-multiple-user water supply system and the identification of the most relevant aspects of a complex system performance which should be considered within the process of the analysis of the alternative operating strategies derived for the system. To summarize, this study argues for the case of a sensible use of the advanced systems analysis and artificial intelligence methods to develop models which would draw positive response from potential users, help them understand a problem they are facing and, ultimately, assist them in finding and appraising the alternative development, planning and operational options.

The applicability and appraisal of the methods used in this study is tested on a seven-reservoir water supply system in Tunisia. All the necessary data, which include reservoir characteristics, time series of monthly incremental inflow volumes into the reservoirs and the estimates of monthly water demands of the 18 demand centres considered in the study, originate from the project EAU 2000 (Agrar-und Hydrotechnik 1992, 1993). However, it should be stressed here that the study executed within this dissertation is an independent academic research and is not a part of this particular project, thus bearing no particular relation, explicit or implied, to the results, conclusions and recommendations provided by the original project.

With regard to the objectives set, several systems analysis approaches and one specific method from the realm of artificial intelligence methods or, to be more specific, from the family of evolutionary algorithms, are considered in this study. The selection of approaches is made upon the requirements to address different aspects of a multiple-reservoir water supply system strategic operation.

Firstly, it is asserted that the dimensionality of a complex system operational problem can adequately be tackled by means of system modelling based on decomposition of the system into its elementary units (i.e. reservoirs). In this respect, three alternative system decomposition approaches are analyzed: i) sequential downstream-moving decomposition; ii) iterative dow stream-moving decomposition; and iii) iterative up-and-downstream-moving decomposition. Suffice it to say at this point that the principal difference among the three approaches is reflected in the way they model the interaction among serially connected reservoirs.

Within each of the three system decomposition approaches, the long-term operation of a complex system is optimized by means of an iterative, six-step algorithm. Namely, upon decomposing a system into individual reservoirs, the operating policies of each of the reservoirs are derived iteratively by performing: i) estimation of the total inflow into a reservoir; ii) evaluation of the demand imposed upon a reservoir; iii) stochastic dynamic programming optimization of its operation; iv) simulation of its operation according to the derived operating policy; v) allocation of simulated release to the associated demand centres; and vi) estimation of the expected unmet demands and supply deficits associated with the reservoir in question. Depending on the adopted decomposition approach, the within-iteration and iteration-to-iteration data flow includes different consideration of the estimated time series of non-utilized reservoir releases and expected supply deficits of individual reservoir units.

To assess the impact of the discrete nature of stochastic dynamic programming operating policies on the performance of a complex reservoir system, this study further compares three alternative simulation options within the proposed decomposition-based optimization models: simulation strictly following the derived operating policies and two simulation alternatives which allow limited policy violations. Namely, if the release which corresponds to the original policy recommendation exceeds the selected demand estimate, both policy violation-based simulation models reduce the recommended release volume to the level of the imposed demand.

Furthermore, a novel search strategy based on the theory of genetic algorithms is applied to identify the set of most favourable water allocation patterns within a multiple-reservoir-multiple-user water supply system. In fact, two distinct genetic algorithm search models are developed. The first utilizes system simulation based on the assumption that individual reservoirs are operated according to the standard reservoir operating rule. The second model, however, assumes that the genetic algorithm search parameters can be obtained by the simulated appraisal of the system's performance based on the respective set of operating policies which are derived by a prior optimization of its operation employing one of the earlier mentioned decomposition algorithms.

Ultimately, the appraisal of the system performance obtained by different models developed in this study is carried out over a number of performance-related indicators. Namely, it is fully recognized that a single value of a certain objective criterion cannot adequately describe, let alone comprehensively evaluate, all the relevant aspects of the operation of any water resource system. Therefore, the comparison of the models developed in this study is based on the respective simulated estimates of seven system performance indicators: i) the expected annual supply deficit; ii) the time-based reliability; iii) the average recovery time; iv) the average recurrence time; v) the average monthly supply deficit; vi) the maximum vulnerability; and vii) the maximum duration of failure.

2 OPERATIONS RESEARCH IN RESERVOIR MANAGEMENT

Reservoir operation and management problems draw significant attention in water resources planning. Being practically the only means available to enforce significant changes to the temporal distribution of natural streamflow conditions, reservoirs play a crucial role in almost all areas of water consumption, use and management: water supply (domestic, irrigation and industrial), hydropower production, flood control, water quality improvement, aquatic life enhancement, navigation, recreation and aquifer recharge. Without diminishing the importance of other aspects of water management, this dissertation concentrates only on quantitative analysis of long-term operation of multiple-reservoir water supply systems.

The actual process of derivation and appraisal of alternative reservoir operating strategies falls into the realm of a mathematical science branch named *operations research*. The applicability and the role of operations research in water resource systems planning and management in general has been extensively researched in the past decades. Incidentally, a number of terms has emerged, each essentially referring to the same discipline. For instance, Hall and Dracup (1970:39) referred to it as *systems engineering*, whereas in Loucks et al. (1981:14) the authors recognized that the terms *systems analysis* and *management science* had frequently appeared as the synonyms to the former two.

In a broad sense of abstraction, operations research methods can be classified into two basic groups. On the one hand, various optimization algorithms are employed to identify the subsets of most promising alternatives out of a broader set of feasible operating strategies. On the other hand, simulation techniques can be used to evaluate the performance of a reservoir system operated under a particular operating strategy. Although both optimization and simulation can be, and at times are, used independently to analyze an operational problem, they are essentially two complementary methods. In fact, and this is the case in analyzing water resources systems in general as well as single- and multiple-reservoir systems, optimization and simulation are used conjunctively to derive and to assess alternative operating strategies of the system in question (e.g. Jacoby and Loucks 1972; Mawer and Thorn 1974; Gal 1979; Karamouz and Houck 1982, 1987; Stedinger et al. 1984; Tejada-Guibert et al. 1993; Harboe et al. 1995; Liang et al. 1996).

This chapter presents a review of a selection of optimization and simulation applications to reservoir operation problems relevant to the work reported in this dissertation. Although the operation of multiple-reservoir water supply systems is the primary topic addressed in this study, the following review includes the works involving both water supply and hydropower reservoir systems. This extension to the area of hydropower systems operation was necessary because many novel ideas and approaches to the analysis of multiple-reservoir systems operation were introduced in this field. The first section includes a review of reservoir operating strategies most frequently used in practice, the methods to derive them and the argumentation for the choice of dynamic programming as the optimization method used in this dissertation. The second part presents a selection of dynamic programming based optimization models for multiple-reservoir systems operation analysis. The following section reviews the advances in the theory of genetic algorithms and the discussion on the reasons for selecting genetic algorithms to address the water allocation problem while deriving the operating strategy of a complex reservoir system. The chapter is concluded by a section on the argumentation for the use of various reliability and performance indicators in the assessment of the operation of water resources systems.

2.1 Methods to Derive Reservoir Operating Rules

2.1.1 Reservoir Operating Rules

The majority of operating rules for a single reservoir presently in use fall into the category known as *rule curves*. The formulation of rule curves assumes the reservoir is to be operated under stationary conditions, thus implying that the derived operating strategy is going to remain unchanged from one annual cycle to another. The devised rule curves generally identify the ideal storage volumes (or pool levels) of the reservoir or target releases to be maintained during different periods of a year. Most frequently, the recommendations on what action should be taken is derived on the basis of the time of the year and one or more of the following three factors: the known reservoir storage volume, the imposed demand for water and the expected inflow into the reservoir. The process of derivation of rule curves is generally based on the previous operating experience, often complemented by additional simulation analyses. The main disadvantage of rule curves which identify the ideal storage or release targets lies in the fact that they do not provide any guidelines for making operating decisions under non-ideal conditions.

Loucks and Sigvaldason (1980) reviewed the existing reservoir operating rules used for multiple-reservoir systems operation in North America. The authors identified two main classes of operating principles: those applied to single-purpose multiple-reservoir systems and operating rules for multiple-purpose multiple-reservoir systems. They concluded that single-purpose water supply reservoir systems were usually operated according to one of the following principles:

1. *Reservoirs in series* are operated in such a way that the downstream reservoir capacity is depleted before the upstream reservoir's resources are mobilized to supply the common demand. This approach ensures maximum utilization of the available storage and no unnecessary spilling from lower reservoirs.

2. *Reservoirs in parallel* are frequently operated by giving the release priority to reservoirs with larger drainage area to storage capacity ratios. This principle ensures reasonably high levels of water conservation. However, it is based on the assumption that the runoff per unit drainage area is the same for each of the reservoirs. A more precise way to operate a parallel reservoir system is to draw the reservoirs down simultaneously, thus minimizing release surplus. However, this operating principle requires continuous monitoring of reservoir storage volumes and availability of inflow forecasts.

As to multiple-purpose systems, the authors pointed out the advantages and disadvantages of reservoir operating strategies which included one of the following four components:

1. *Target storage volumes or water levels.* The operator is expected to maintain the recommended storage targets as close as possible while, at the same time, trying to meet the imposed release requirements. As their main shortcoming, the earlier mentioned remark on operation under non-ideal conditions is particularly applicable to this type of rule curves.

2. *Multiple storage zoning.* This type of rule curves is apparently more adaptable to changing hydrological and reservoir storage conditions than the former one. They generally identify different reservoir storage or release targets for a number of storage allocation zones (e.g. spill zone, flood control zone, conservation zone, buffer zone, inactive zone), thus providing the operator with the guidelines on what to do under different water availability conditions.

3. *Downstream flow ranging.* The inclusion of downstream channel flow ranging for each storage allocation zone enables the operator to maintain "smoother" changes in release rates as the storage volume of the reservoir falls or rises from one allocation zone to another.

4. *Conditional rule curves.* This type of rule curves defines the storage volume or release decisions at different time periods of a year as a function of two parameters: the existing storage volume and the expected inflow over some predefined time period in the future.

Recent developments in computer technology have attracted numerous researchers to investigate the applicability of advanced mathematical optimization and search techniques to reservoir operation and management problems. More sophisticated analytical tools have allowed the formulation of more complex operating rules, like those which define functional relationships between the desired storage or release decisions and all possible combinations of the independent variables involved (e.g. time of the year, existing storage and inflow). Additional advances have also been made with regard to the consideration of uncertainty which is an inherent phenomenon in the operation of any water resource system. The uncertainty of hydrological processes and the imposed water demands or energy requirements, economic and societal uncertainties are just a few of stochastic factors that have major impact on the operation of water resources systems. The consideration of uncertainty is particularly important in strategic water resources planning where the estimation of the expected future benefits associated with alternative development plans plays a crucial role in the selection of the preferred option. Therefore, due to their inability to address the issue of uncertainty, purely deterministic optimization methods are not the best choice for strategic water resources planning studies. However, stochastic optimization methods themselves generally cannot accommodate all aspects of uncertainty inherent in the operation of real-world systems. This is partially due to the inability to quantify the stochasticity of each and every process involved (e.g. uncertainty of the structural integrity of the engineering object, economic development, population migration and the resulting changes in the quantity and distribution of water demands). Furthermore, the inclusion of several aspects of uncertainty into the analysis would inevitably result in more complex and costly modelling. Therefore, the formulation of stochastic models is in most cases concentrated on the explicit consideration of uncertainty of a single, the one assumed most relevant, stochastic process while addressing other possible random processes through sensitivity analyses. In reservoir operation studies the uncertainty is most frequently associated with the stochastic nature of river flows. With respect to the way streamflow uncertainty is addressed in a model, the developed stochastic optimization approaches can be divided into two groups:

1. *Implicit stochastic optimization* models combine synthetic time series generation models, deterministic optimization and multiple regression analysis. Namely, based on the available historical record of streamflow observations, a time series generation model is used to create a number of synthetic inflow scenarios. Subsequently, pursuing the predetermined common objective, a deterministic optimization model is applied to derive the optimal operating strategy for each of the hypothetical streamflow records. The ultimate operating rule for the reservoir is then formulated by multiple regression over the family of strategies obtained for the set of synthetic inflow time series. Implicit stochastic optimization models can easily be implemented to single reservoir operation analysis. However, they exhibit a number of disadvantages if applied to multiple-reservoir systems. The major problem arises when river flows to different reservoirs show strong dependency which requires the development of complex and expensive time series generation models. Another difficulty associated with implicit stochastic optimization models is that they are generally extremely time consuming due to the need for repeated optimization runs over all synthetic streamflow records.

2. *Explicit stochastic optimization* models rely on the probability distribution of reservoir inflows instead of using a specific, thus assumed known, streamflow sequence. The stochastic

inflow process is either represented by a Markov chain using inflow transition probabilities or, if river flows in subsequent time intervals prove to be uncorrelated, by their respective independent probability distribution functions. The optimization itself is therefore pursuing the minimum or maximum of the expectation of the selected objective function. The resulting operating strategy provides separate guidelines for each time step within an annual cycle on storage or release decisions for all possible combinations of reservoir initial storage and inflow variables.

2.1.2 Optimization and Simulation Methods in Reservoir Operation Analysis

A comprehensive review of mathematical models developed for reservoir operation analyses was prepared by Yeh (1985). The review concentrated on both optimization and simulation models, as well as on operations analyses under deterministic and stochastic conditions. Optimization techniques included linear programming (LP), dynamic programming (DP) and non-linear programming (NLP). The author concluded that both LP and DP optimization models, as well as simulation and combined optimization-simulation models have been extensively used in reservoir operation analyses. On the other hand, relative unpopularity of NLP techniques was put down to three basic reasons:

1. The formulation of NLP optimization models involves much more complex mathematics than in the case of LP and DP.
2. The computer storage and processing time requirements are rather large for NLP models.
3. In general, NLP optimization models cannot easily accommodate the stochasticity of reservoir inflows as DP-based models do.

The remainder of this section concentrates on LP and DP applications in reservoir management. It should, however, be noted here that these two are not the only methods used in this field. Namely, the fast expanding capabilities of computer facilities have allowed analysts to explore the applicability of various novel optimization and search methods to reservoir operation problems. For instance, Saad et al. (1994, 1996) and Bouchart (1996) applied neural networks, genetic algorithms were used by Esat and Hall (1994) and Oliveira and Loucks (1997), whereas Shrestha et al. (1996) used fuzzy rule-based modelling to derive operating rules for a reservoir.

Linear programming has established itself as a valuable tool in reservoir operation analysis. The basic requirement of LP is that the problem to be solved must be linear both in the objective function and the related constraints. Although the linearity condition may seem too restrictive, it is frequently possible to apply linear approximation methods to make problems containing non-linear functions solvable by LP (Loucks et al. 1981:57). Roefs and Bodin (1970), for instance, used piecewise linearization to approximate the adopted non-linear benefit function.

The principal advantage of LP models is that they do locate the global optimum with comparative ease, even if the optimization problem is relatively large. Another argument in favour of LPs is that the standard computer software is readily available. However, applications of LP to multiple-time step and/or multiple-reservoir operation problems can require thousands of decision variables and constraints making it too costly to opt for a straightforward LP optimization. Furthermore, if the consideration of uncertainty is deemed an essential factor in the optimization problem to be solved by an LP model, the number of decisions and constraints can easily explode beyond any manageable limits. Consequently, the computation time required to solve such large problems becomes too high to be acceptable. Gablinger and Loucks (1970), for instance, reported that their stochastic LP formulation for the operational problem of a single reservoir required approximately 2000 equations and 15000 variables. In their comparison of stochastic LP, DP and policy iteration methods for reservoir operation, Loucks and Falkson (1970) further concluded that the application of LP models to large multiple-time step problems was computationally too expensive and that their practical purpose was limited to the analyses of single-reservoir operation problems which involved relatively small number of possible discrete storage volumes, inflows and time intervals. Similar conclusion was drawn by Roefs and Guitron (1975) who also compared the same three types of optimization techniques. They reasserted that stochastic, multiperiod LP models were much more time consuming than the equivalent DP models. In general, the authors argued in favour of DP as the preferred candidate for stochastic reservoir optimization models over the other two methods.

To reduce the immense computational load associated with pure LP models, the solution to such large problems is frequently sought through the development of auxiliary decomposition techniques (Yeh 1985). Roefs and Bodin (1970) proposed an approach based on LP to optimize the operation of a three-reservoir hydropower facility over a period of 36 months. However, their attempt to reduce the dimensionality of the problem by applying both spatial and temporal decomposition still did not make it sufficiently small for an LP formulation.

Pereira and Pinto (1985) presented an algorithm devised for optimal real-time scheduling of weekly or monthly energy generation of multiunit hydropower systems. The method applied an extended Benders decomposition, which is an iterative solution seeking procedure directly applicable to two-stage linear optimization problems. Thus, a standard LP was used to derive the suboptimal solutions at each temporal stage. The extension of Benders decomposition was required in order to incorporate the stochastic nature of river flows into the optimization model. The stochasticity of inflows was represented by multiple sets of synthetic inflow scenarios at each stage. The initial assumption was that the realization of a certain inflow scenario at a stage could be followed by one of the two generated scenarios at the subsequent stage. Consequently, with the increase of the number of stages, the number of possible inflow sequences would also increase by branching out along two new "inflow paths" for each inflow realisation at the preceding stage. The algorithm was illustrated on a four-reservoir case study. The results of the application of the method to a 37-reservoir hydropower system were also presented in the paper.

It can also frequently be found that a combined LP-DP (both deterministic and stochastic) optimization method is used to alleviate the dimensionality difficulties posed by a pure LP model development. For instance, Hall et al. (1968) proposed a deterministic LP-DP model to derive the optimum operating policy of a multiple-reservoir-multiple-purpose system. The objective was to derive the best possible utilization of a multiple-reservoir system for firm water supply, firm energy generation, dump water supply and dump energy production with respect to the maximization of the system's economic return. The system was decomposed into individual reservoir subsystems and, for the given set of prices for different water uses, the sequences of individual optimal release decisions for each reservoir were obtained independently using DP. These policies were subsequently used by an LP model to derive the optimal combination of reservoirs' individual allocations for each of the purposes. The derived shadow prices of the LP dual problem were in turn used in the repeated DP optimization to obtain the improved individual reservoir policies. The iterative LP-DP cycles were repeated until no improvement in the system return could be induced by the use of new shadow prices, or until a new shadow price set did not differ from the one derived in the preceding step.

Becker and Yeh (1974) combined LP with deterministic DP to derive the optimum real-time operating trajectory of the complex hydroelectric facility of the California Central Valley Project. Based on the inflow forecasts provided for each reservoir in the system, the DP model was used to identify the optimum operating strategy of the system over a period of 12 months. At each time step, an LP model minimized the accumulated loss in potential energy of the stored water in the reservoirs resulting from a particular release policy. To generate multiple alternative release policies at a time step, the authors assumed a number of different levels of peak energy production for the system. The LP model was run once for each of the peak energy thresholds resulting in a number of energy production strategies and their respective expected energy loss function values. Thus, a single-stage LP procedure embedded in a multiple-time step DP model was used to generate alternative policy paths for the DP's enumeration search.

On the other hand, Takeuchi and Moreau (1974) combined LP with stochastic DP to optimize the operation of a five-reservoir water supply system providing water for eight distinctive users. The LP model was nested in the stochastic DP optimization model to minimize the expected value of the accumulated future losses associated with the respective storage volumes in the reservoirs at the end of a time step. The non-linearity of expected accumulated cost function was addressed through piecewise linearization.

Vedula and Kumar (1996) proposed an approach which combined LP and stochastic DP to optimize the operation of a single irrigation water supply reservoir. The objective pursued in optimization was to maximize the expectation of the relative annual multiple-crop yield. The method was a modification of the earlier developed model which employed deterministic and stochastic DP techniques to solve the same type of problem (Vedula and Mujumdar 1992). The 1992-model was defined over 10-day time intervals within a year and consisted of two phases. In the first phase, deterministic DP was used to optimize the allocation of reservoir releases among multiple crops in each of the within-year periods. Based on the allocation patterns obtained in the first phase, the second step employed stochastic DP to derive the optimal steady state operating policy of the reservoir. The principal modification introduced by Vedula and Kumar (1996) was that the temporal discretization for the stochastic model was set to two seasons within a year (i.e. monsoon and non-monsoon seasons) instead of thirty-six 10-day-long time steps. In addition to the present season inflow forecast, the new stochastic DP optimization model also utilized the present season rainfall forecast as a stochastic state variable. Furthermore, the deterministic DP release allocation phase was substituted by an LP intraseasonal allocation model which optimized the distribution of the seasonal releases among multiple crops over 10-day-long within-season periods. The authors concluded that the new LP-DP model provided a better modelling of the crop growth process, resulting in further improvements of the expected yields relative to those obtained by the formerly devised method.

Each of the four presented approaches reflect the principal rationale behind most of the LP-DP coupling methods. Namely, a DP model is used to drive the optimization process through successive temporal stages, thus avoiding the major cause of dimensionality problems in LP applications. On the other hand, an LP model, embedded in the outer DP procedure, takes over the task of solving a multiple-source-multiple-user resource allocation problem which is an extremely "DP-hard" problem. Despite obvious advantages, the coupling of LP with DP still requires rather complicated and time consuming mechanisms to resolve serious non-linearity problems and to accommodate stochasticity considerations in applications where uncertainty plays a crucial role in the operation of the system.

Dynamic programming, however, exhibits a number of features that make it particularly suitable for solving reservoir operation problems. It is a stagewise optimization technique based on the Bellman's principle of optimality (Bellman 1957:83): *An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision.* Bellman (1957) stressed the value of DP as a tool for deriving the structure of optimal policies by decomposition. In essence, DP is a solution seeking strategy which decomposes a sequential decision problem into a series of subproblem stages consisting of only one decision each. The optimal solution is then sought recursively over the stages by adding the immediate objective function achievement at the present stage to the objective function value accumulated over the stages passed so far. In other words, the applicability of DP depends on whether a multiple-stage decision formulation can be transformed into a sequence of single-stage decisions each of which depends only on the decision taken at the preceding stage (i.e. the underlying process affected by the set of decisions has Markov-1 property). Nemhauser (1966:76-79) demonstrated the advantages of DP over direct enumeration methods both with regard to the size of the required data space and the number of computational steps necessary to arrive at the solution to a problem.

The Markov-1 property requirement posed by DP can easily be recognised in operation of reservoirs. Namely, the decision on reservoir target storage or release is taken at each time step of a predefined sequence of temporal stages. In addition, the conditions upon which a decision is to be made at a certain stage can be generally summarized in the state of reservoir storage at the beginning of that time step and the inflow into the reservoir regardless of how this particular state has been reached. Another favourable feature of DP is that it poses no restrictions on the type of the objective function and the type and number of constraints. The objective function can be linear or non-linear, continuous or discrete, and can even include different functions defined over different intervals of the decision variable domain. Furthermore, unlike LP, DP can handle almost unrestricted number of constraints regardless of their respective types. Maybe the most significant advantage of DP over other optimization methods is that it can easily accommodate the uncertainty of the processes inherent in the addressed operational problem. The stochastic dynamic programming (SDP) formulation can include both the implicit and explicit stochastic approaches. With regard to the earlier definition of implicit stochastic models and their use in reservoir operation studies, the core of an implicit SDP procedure becomes, in fact, the classical deterministic DP which is applied over a number of synthetic streamflow scenarios. On the other hand, the explicit SDP utilizes either a Markov chain representation or an independent probability distribution of river flows to describe the stochasticity of the hydrological process.

Dynamic programming is not, however, without flaws. Being essentially a discrete mathematical enumeration procedure, DP requires that the intrinsic state and decision variables be represented by their respective limited discrete domains. Furthermore, at each stage the actual DP optimization involves the computation of the accumulated objective function value for each and every possible combination of system states and decisions at that stage. The optimal decision for the stage is then selected with regard to the derived set of objective achievements. Obviously, the increase of the number of state and decision variables and the refinement of their respective discrete domains can result in the explosion of possible state transitions rendering a potential DP application too costly to run. Bellman (1957) himself recognized this problem and named it *curse of dimensionality*. He also proposed an approach to alleviate it by using an iterative concept, known as *successive approximations*, which breaks down the original multiple-state problem into a series of problems having only one state variable each. The single-state problems are then optimized one at a time by means of DP, each time having the remaining state variables fixed at the values obtained in the previous iterations. Bellman (1957) and Bellman and Dreyfus (1962) showed that DP with successive approximations achieves monotonic convergence with no guarantee, however, that the solution would converge to the global optimum.

As a potential tool to cope with the curse of dimensionality, Larson (1968) introduced the state incremental dynamic programming (IDP). Being an iterative procedure, IDP starts the search from an arbitrary, however feasible, solution trajectory. Instead of examining the whole feasible state space, IDP confines the search only to the close neighbourhood of the trial trajectory. In other words, the DP recursion is applied to a limited number of system transitions, thus reducing the dimensionality of the problem. Consequently, if any of the neighbouring trajectories is found to bring improvement to the objective function value, then this new trajectory is used as the initial one for the next iteration step. The procedure continues until no improvement in the objective function value is obtained. However, Turgeon (1982) showed that IDP may end up at a local optimum and, to avoid this, he proposed a gradual reduction of the state increment size. Basically, the procedure should use a fixed state increment until the stability of objective function is achieved. This is in turn followed by the increment size reduction and repeated iterations. Another way to avoid reaching a local optimum is to repeat the IDP procedure with different initial trajectories. Finally, both methods, i.e. varying state increments and starting with different trial trajectories, can be coupled.

As it has been mentioned earlier, the incorporation of stochasticity within a DP optimization model can be achieved with relative ease. The numerous reported works on SDP-based applications to reservoir operation problems include both the implicit and explicit consideration of uncertainty. The following selection of studies concentrates only on single-reservoir SDP models. A broader review, focusing on SDP-based methodologies devised to analyze multiple-reservoir operation problems, is given in the succeeding section.

Young (1967) proposed an implicit stochastic approach to optimize the operation of a single reservoir. He combined Monte Carlo simulation for synthetic streamflow generation, deterministic DP optimization and regression analysis to derive the operating strategy which was expressed in terms of release as a function of the initial storage volume in the reservoir and the inflow during the time step.

Harboe et al. (1970) used deterministic DP to derive the optimal operating policy of a single reservoir serving multiple purposes: water supply, energy generation, flood and water quality control downstream of the reservoir. The last two purposes were considered as a maximum storage and minimum downstream release constraints, respectively, whereas the target water supply was incorporated as a parameter into the optimization procedure. By varying the level of the water supply target, successive DP optimizations were applied to obtain a family of the optimal operating trajectories with respect to the maximization of the firm energy production. The authors stressed the efficiency of the developed algorithm and suggested that it could easily be implemented as an optimization core of an implicit stochastic DP methodology.

An implicit SDP-based algorithm for optimal long-term control of a single multipurpose reservoir with both direct and indirect users was presented by Opricović and Djordjević (1976). The approach takes into account the fact that water already used for one purpose (direct user) can be utilized by another user located further downstream (indirect user). The developed optimization method maximized the total benefit earned from the delivered water by applying DP at each of the three levels of the adopted hierarchical decomposition of the problem. At the first level, the temporal distribution of reservoir releases is optimized. This is followed by the optimization of the allocation of available releases to direct users in each time interval. At the third level, the release volumes already used by direct users are distributed to indirect users.

Karamouz and Houck (1982) proposed an iterative approach which combined deterministic DP, multiple regression and simulation to derive a general operating rule of a single water supply reservoir. Although not entirely conforming to the general definition, the method was essentially an implicit stochastic optimization approach. One iterative cycle consisted of deterministic DP optimization over the available historical inflow record, the subsequent derivation of the general linear release rule by means of multiple regression and the final step which included the simulation of the reservoir operation according to the defined operating rule over a long synthetic sequence of reservoir inflows. The principal idea behind the developed method was to start iterations without any further limitations on the feasible release decision space except those determined by the capacities of the reservoir's outlets and spillways. However, the decision space was narrowed down in DP optimization as the iterations proceeded by using the general release rule defined in the previous cycle. The width of the reduced feasible decision space was corrected by a lower/upper bound factor, the value of which was adjusted at the end of each iteration with respect to the objective function achievement obtained by simulation. The authors reported the results of the application of the approach to 48 test cases involving both annual and monthly temporal discretization. In all of the cases, the average annual objective function achievement obtained by simulation over a synthetic inflow record showed improvement over iterations, clearly outperforming the initial iteration outcomes obtained without restricting the release domain.

In their later work, Karamouz and Houck (1987) used their iterative DP model (Karamouz and Houck 1982) and the explicit SDP optimization model to derive monthly operating rules for a set of 12 different single-reservoir test cases. The explicit SDP model used lag one Markov chain representation of river flows and the derived optimal operating policy was given in terms of the storage volume at the beginning of the following month as a function of the initial storage and inflow at the present time step. The two models were compared on the basis of the objective function achievement derived by simulation over a long synthetic set of river flows. For the 12 test cases, the authors concluded that the explicit SDP model resulted in better operating policies for smaller reservoirs whereas the iterative DP proved to be more effective for medium to very large reservoirs. Relatively poorer performance of SDP on large reservoirs was attributed to the inability to use finer state discretization as the size of the storage state space was increasing which would , in turn, impose the well-known dimensionality difficulties associated with SDP. On the other hand, the iterative DP did not suffer from such restrictions because of the embedded mechanism for the iterative reduction of the feasible release decision space.

As a way to overcome dimensionality problems in stochastic optimization a variation of an implicit SDP, named sampling stochastic dynamic programming (SSDP), was introduced by Kelman et al. (1990). What differentiates SSDP from other implicit stochastic approaches is that the whole set of synthetic 12-month long streamflow scenarios was simultaneously considered in the optimization process. The approach is said to be very efficient in describing river flow processes and in coupling such a streamflow representation with DP optimization principles. It should be noted that if the number of inflow scenarios is reduced to only one, SSDP transforms itself into deterministic DP deriving the set of optimal decisions for the given inflow sequence.

Butcher (1971) used explicit SDP to derive an optimal long-term operating strategy of a single multipurpose reservoir. The optimization model was developed for a monthly temporal discretization assuming that monthly flows were serially correlated. The objective pursued was to maximize the expectation of the annual monetary return gained from irrigation water supply, energy production and potential benefit from recreational use of the reservoir. The optimal release policy was expressed as a function of the reservoir state given as the storage volume of the reservoir at the beginning of the month and the inflow during the preceding month.

Loucks et al. (1981:324-332) elaborated the explicit SDP approach for the optimization of a single reservoir operation. Stochasticity of inflows represented by the first order Markov chain was explicitly incorporated into the optimization procedure by considering inflows to the reservoir as an additional state variable. Thus, the procedure assumed a two-state (i.e. reservoir storage at the beginning of and inflow to the reservoir during a time step) SDP optimization problem with the decision to be taken being the reservoir storage at the end of a stage. The objective was to minimize the total expected sum of the squared deficit of the release from the respective demand and the squared deviation of the storage from the constant storage target. For each time step, the resulting steady state operating policy was derived in the form of the final reservoir storage volume as a function of the initial storage and the present inflow. The technique was demonstrated on a simple hypothetical example considering two within-year time periods and a discrete two-class representation for both inflow and reservoir storage variables.

Maidment and Chow (1981) developed two SDP optimization models for a single reservoir operation problem. The temporal discretization was set to monthly time steps and the authors distinguished between two different representations of inflow stochasticity. One model assumed that the monthly river flows were serially correlated and the stochasticity of subsequent monthly flow processes were described by inflow transition probabilities (i.e. Markov chain) whereas the second approach considered monthly flows as independently distributed. The objective for both models was to maximize the expectation of the annual net benefit gained from the releases allocated for energy generation and irrigation water supply. The resulting steady state release strategies were given as a function of the storage volume of the reservoir at the beginning of a month and the inflow during the preceding month.

Stedinger et al. (1984) compared the simulation results based on different operating policies derived for the High Aswan Dam on the River Nile by five SDP-based optimization models. Apart from models that used the previous period inflow as the hydrological state variable, the authors proposed approaches that utilized the best forecast of the current period inflow instead. They concluded that the use of the best inflow forecast instead of the inflow during the preceding time period resulted in significant improvements in the operation of the reservoir.

Somewhat contrary results were reported by Huang et al. (1991) who compared four explicit SDP optimization models using the Feitsui reservoir in Taiwan. The four models were devised upon the assumption that a streamflow process could be modelled as being either serially correlated or independent, and that the consideration of reservoir inflow as an additional state variable could use either the forecast of the present period streamflow or the known observation of the past period flow. Each model was formulated for a 36-period annual cycle and utilized the same objective function, which was to maximize the expectation of the annual energy generation. The authors found that the best performance of the reservoir resulted from the use of the model which assumed serial correlation of river flows, and the previous time step inflow as an additional state variable. However, they recognized that their findings were applicable to the particular case they used, and stressed that the model which used the present time step inflow forecast as a serially correlated hydrological state variable did outperform the other three models when a perfect forecast was assumed available. An additional advantage of SDP models based on the present inflow forecast is that they derive operating policies which specify the optimum achievement of the objective criterion expectation for the given inflow forecast state. Thus, any failure to maintain the optimal operating strategy is due only to the imperfect inflow forecast.

A number of studies have dealt with the choice of the hydrological state variable in SDP. For instance, Karamouz and Vasiliadis (1992) used the present time step inflow forecast as an additional state variable in one of their SDP models. In another model, as Vasiliadis and Karamouz (1994) did too, they adopted both the present period inflow and the next period inflow forecast as hydrological state variables. The latter also applied the Bayes theory to account for the uncertainty of inflow forecasts while updating the inflow transition probabilities during the SDP optimization process. The Bayes-SDP model was found to bring improvement in the operation of the test case as compared to the classical SDP model which utilized only the present period inflow as a hydrological state variable. In another study, Tejada-Guibert et al. (1995) found that, as compared to deterministic DP or no-hydrological-state-variable SDP models, the operation of the case study system improved if the operating policies were derived by SDP models which used either the present period inflow or the past period inflow in combination with the best forecast of the forthcoming snowmelt runoff as hydrological state variables. On the other hand, the earlier mentioned SDP model developed by Vedula and Kumar (1996) utilized both the present period inflow and rainfall forecasts as stochastic state variables.

2.2 Dynamic Programming in the Optimization of Multiple-Reservoir Systems Operation

Regardless of the adopted mathematical programming approach, straightforward optimization of a multiple-reservoir system operation is impossible to achieve in most of the cases. In general, the analysis of a multiple-reservoir system operation imposes significant dimensionality problems due to the inevitable introduction of three inherent computational difficulties:

1. The increasing dimensionality of the problem is reflected in the number of state and decision variables necessary to describe a multiple-reservoir system and its operation.

2. Operation of complex reservoir systems involves multiple, and often non-commensurate objectives and it is not often the case that these can be approximated by a single, clearly defined surrogate objective or criterion.

3. Additional difficulties in modelling are brought about by the necessity to consider stochasticity, which is an inherent feature in the operation of reservoir systems. Although it is common to reduce this scope to river flow uncertainty only, the problem itself does not seem to be significantly alleviated due to the fact that multiple reservoirs imply consideration of multiple, independent or cross-correlated, stochastic inflow processes.

Although regarded as the most promising stochastic optimization technique, SDP is still hampered by well-known dimensionality restrictions and the resulting huge computational requirements imposed when applied to multiple-state-multiple-decision problems. In general, and this was also reported by Yeh (1985), systems analysts have opted for one of the following three remedies, or combinations thereof, to overcome these difficulties:

1. By decomposing the system into smaller and simpler subsystems the complex problem can be reduced to a set of tractable tasks (e.g., decomposition based on physical or functional structure of the system, multilevel hierarchical decomposition, etc.).

2. Aggregation of the system, or parts thereof, into a composite system may allow a straightforward application of the optimization procedure and the subsequent disaggregation of the derived composite operating strategy into control policies of individual system elements.

3. Attempts have also been made to replace discrete state, decision and objective function domains by their continuous approximations and subsequently to apply complex mathematical methods to derive the optimal solutions to the problems.

This section reviews DP-based applications in operational analyses of complex reservoir systems. Although the necessity for consideration of uncertainty in long-term optimization has been stressed many times, both deterministic and stochastic approaches are presented here due to the fact that deterministic optimization models present an integral part of implicit stochastic optimization techniques.

2.2.1 Decomposition-Based Methodologies

Various decomposition approaches seem to be the most frequent means used to alleviate dimensionality problems in operational analysis of large-scale systems. Yeh (1985), for instance, observed that the majority of methods devised for dimensionality reduction involved some type of decomposition of the system into smaller and simpler subsystems, and the subsequent use of iterative procedures to find a solution to the complex problem. The advantage of decomposition is that it allows a large, for a straightforward approach unsolvable, problem to be reduced to a series of small tractable tasks. Furthermore, unlike continuous function approximation techniques, decomposition methods usually employ less complicated mathematical theories and, which is perhaps their most important characteristic, their computational complexity increases at a lower rate with the number of decomposed system elements. The other side of the decomposition coin, however, shows that, in general, decomposition-based optimization approaches do reach a local rather than the global optimum. Nevertheless, numerous studies have shown that near-optimal solutions derived by decomposition techniques could provide significant improvements in the operation of the systems in question.

Yakowitz (1982) reviewed DP applications in water resources analyses. The review included both deterministic and stochastic based DP algorithms developed to obtain solutions to a variety of water resources related problems, such as: water resources project development, water quality control, irrigation, reservoir operation, etc. The curse of dimensionality, as the paramount obstacle in DP modelling, was indicated as one of the features that brought about the development of numerous DP-based optimization formulations. The dimensionality problem inhibits the applicability of DP especially if the analysis confronts stochastic operational problems of complex systems. This is due to the significant increase in the number of state variables required to describe such a system while, at the same time, the number of system's state transitions grows exponentially with respect to the discretization of state variables. The discrete differential dynamic programming and incremental dynamic programming were described as possible ways to overcome the curse of dimensionality.

Heidari et al. (1971) introduced discrete differential dynamic programming (DDDP) to solve a deterministic optimization problem of a four-reservoir system. In essence, DDDP could be understood as an extension of IDP (Larson 1968) to a multidimensional problem. Chow et al. (1975) analyzed the computer time and memory requirements for a classical DP and DDDP and proposed the methodologies to estimate them. With regard to the necessary computer storage, they concluded that DDDP required substantially less data space than DP. Although a significant reduction in state and decision space size was evident, DDDP still retained exponential growth in the number of system transitions with respect to the number of state variables. Aware of the fact, Nopmongcol and Askew (1976) proposed a decomposition approach named multilevel incremental dynamic programming (MIDP) to solve the same problem. The search for the optimal operational strategy of a multiple-reservoir system was carried out through several stages denoted as "one-at-a-time", "two-at-a-time", "three-at-a-time", etc. The core of the approach was that, at each stage, a set of individual IDP problems was solved, each of them having one, two, and three reservoirs taken into consideration, respectively. The search at each stage included all possible combinations of reservoirs (i.e. all single units, all pairs of reservoirs, all triplets, etc.). The procedure was terminated when no improvement of the objective function has been observed at two consecutive levels. The convergence to the same result obtained by Heidari et al. (1971) was observed already after the second MIDP level (i.e. "two-at-a-time").

Trott and Yeh (1973) proposed a method to resolve the dimensionality problems inherent in operational analyses of multiunit reservoir systems with both serial and parallel connections. The sample system consisted of six water supply reservoirs with a single demand point located immediately below the lowest reservoir. The objective was to maximize the firm water supply at the demand location. They applied Bellman's method of successive approximations (Bellman 1957; Bellman and Dreyfus 1962) and used IDP (Larson 1968) to solve the decomposed, one-dimensional problems. In essence, the deterministic problem having six state variables was broken down into six problems having only one state variable and five equality constraints each. Thus, while optimizing the operation of a chosen reservoir, the operating policies of the remaining five reservoirs were kept constant as had been derived beforehand. Iterative cycles comprising six IDP runs were repeated until a stable benefit is observed in consecutive iterations. The necessary prerequisite for starting the iterative procedure was to first select six independent, yet feasible, operating strategies, one for each reservoir. The method was tested with three different sets of initial operating strategies. All trials converged towards the respective benefits falling within the 0.05% range of each other. Nevertheless, the authors stressed the possibility of the procedure's convergence to a local optimum rather that the global one. To avoid this, it was proposed to repeat computations with different initial policies to test whether the stable convergence threshold could be reached.

Turgeon (1980) applied two iterative decomposition techniques to optimize the long-term operation of a multiple-reservoir hydropower system consisting of a number of independent rivers, each with one or more serially connected reservoirs. Both approaches assumed that river flows were uncorrelated random processes. The first one, named "one-at-a-time" decomposition technique, broke down a system into a set of single-reservoir subsystems whose operations were optimized by SDP (n.b. Arunkumar and Yeh (1973) suggested essentially the same heuristic decomposition to maximize the firm energy output of a multiple-reservoir hydropower system). The second, "aggregation/decomposition" method split up an n-reservoir system into n subsystems having two elements each. One of the elements corresponded to a selected single reservoir while the second described the hypothetical reservoir created by aggregating the remaining n-1 reservoirs into a single unit. Thus, the SDP optimization was in this case applied to a two-reservoir operation problem. The application of the former approach resulted in a local optimal operating strategy for each power plant, whereas the latter derived the global suboptimal operating policies for n individual reservoirs. The two models were compared on a pilot six-reservoir system and the "aggregation/decomposition" model derived better system returns in terms of the operating costs accumulated over the simulation period.

As a supplement to the previous work, Turgeon (1981) proposed an algorithm to derive monthly operating strategies of a hydropower system consisting of multiple, serially linked, reservoirs. The optimization itself was again based on SDP considering monthly inflows to reservoirs as independent random processes. Basically, the approach decomposed an n-reservoir system into n-1 subsystems having two elements each. The elements of an ith subproblem were reservoir i and the respective hypothetical reservoir generated from all the remaining reservoirs situated downstream of i (i.e. reservoirs i+1, i+2, ..., n). The suboptimal operating strategy of reservoir i for a particular month defined the release policy as a function of its storage and the total amount of energy available in all downstream reservoirs. The main advantages of the algorithm were said to be the fact that it was not an iterative procedure, and that the computational requirements increased only linearly with the number of reservoirs.

Similar decomposition/aggregation idea was exploited by Archibald et al. (1997) to optimize the operation of a multiple-reservoir hydropower system. The method was devised to be applicable to any connected and acyclic reservoir network provided that the water released from any reservoir in the system directly and instantaneously enters at most one other reservoir. Consequently, the operating strategy for a reservoir could be determined by an SDP-based model formulated for that reservoir and a two-dimensional representation of the rest of the system. Namely, given a particular reservoir, the remaining part of the system could be divided into a subset of reservoirs whose releases can reach the selected one, and a subset of the remainder of the system. To reduce the dimensionality of the optimization problem, aggregation was used to represent each of the subsets by a single hypothetical reservoir. The authors tested their approach on several reservoir systems, the largest containing 17 reservoirs. To evaluate their method, the authors derived the true optima for smaller test cases (i.e. having three and four reservoirs) by applying the equivalent full optimization models, whereas the larger systems' optima were obtained by LP. In addition to substantial savings in processing time, the proposed decomposition/aggregation method was found to provide solutions close to the real optima.

Tai and Goulter (1987) developed an iterative algorithm for the optimization of a "Y" shaped three-reservoir hydropower system operation (i.e. two parallel upstream reservoirs were serially connected to the third reservoir situated further downstream). It should be noted that only the downstream reservoir had hydroelectric generation facilities, whereas the two upstream reservoirs served as storage regulation structures for the downstream one. The core of the method was a single reservoir SDP-based optimization model given in Loucks et al. (1981). The adopted temporal discretization was set to a monthly scale. The monthly inflows were assumed to be serially correlated and the first order Markov chain was used to describe transition probabilities between different inflow classes in consecutive months. Prior to starting the iterative procedure, the operation of the downstream reservoir was optimized using the historical inflow record to derive inflow transition probabilities. This step provided the initial release targets for the two upstream reservoirs. The operating strategies of each of the two upstream reservoirs were optimized separately for the previously derived release targets. Subsequently, the estimated releases from the upstream reservoirs were used as additional inflows to the downstream reservoir in a repeated optimization of its operation. For this purpose, a new set of transition probabilities was calculated, considering the changes in the inflow record. These iterative cycles were repeated until the stability of the overall system return was registered. The results obtained in the application of the methodology on the case study system showed close similarity to the observed historical system return. Slightly lower system benefits derived from the model are said to be the consequence of the limited precision of the SDP procedure, which was mainly due to the computational limitations on storage and inflow discretization.

Hall and Buras (1961) applied a three-level, DP-based approach to solve a planning problem of capacity allocation among a number of reservoir sites. To reduce the dimensionality, they decomposed the original problem into three deterministic, hierarchically arranged, subproblems. At the first level, the objective was to identify a group of reservoir sites and their respective capacities by maximizing the overall system return. The second level optimization derived the optimal allocation of available releases among different uses for each of the selected reservoirs. Ultimately, using the former results, the water available for a particular use was optimally distributed among individual users. The solution to the overall problem was sought in a stepwise hierarchical manner starting from the first level. The results derived at a higher computational level were used as constraints at the immediate lower optimization level.

Major contribution to hierarchical multilevel decomposition approaches comes from Haimes (1977, 1982). The methodology is based on the decomposition of a complex system into smaller subsystems categorised into different levels of hierarchy. The principal idea behind the approach is to allow separate modelling and analysis at different decomposition levels. The information obtained at a certain decomposition level can then be further transmitted and used while analyzing the subsystems at the higher level of hierarchy. In general, hierarchical multilevel decomposition allows conceptual simplification of a complex system modelling which can result in the reduction of dimensionality. In addition, the analyst generally has to develop simpler computational and programming procedures and can even sometimes use the existing models. The author proposed four different angles for a complex system definition: temporal, physical-hydrological, political-geographical and goal-functional description. Obviously, overlapping among the four was concluded to be inevitable. The author further distinguished between three general hierarchical multilevel structures:

1. Multistrata hierarchy employs different levels of model resolution with the principle assumption that subsystems at lower levels have more detailed and specialised description.

2. Multilayer hierarchy is used to solve complex decision making problems by assuming layers to be different levels of decision making complexity within the scope of the same system.

3. Multiechelon hierarchy is applied if the system can be clearly defined as a composition of many interacting subsystems.

2.2.2 Approaches Based on Aggregation/Disaggregation Principles

To solve highly dimensional optimization problems aggregation/disaggregation aims towards developing auxiliary models which are reduced in their complexity and which, at the same time, provide good approximations of the original problem. In most of the reported applications a multiple-reservoir system was aggregated into a hypothetical single reservoir and the subsequent optimization was carried out for this simplified composite representation of the system. It is also quite frequent that aggregation/disaggregation methods were used in combination with some decomposition principles to alleviate computational difficulties in optimization of a complex reservoir system operation (cf. Turgeon 1980, 1981 and Archibald et al. 1997 in Section 2.2.1).

Rogers et al. (1991) presented the general concepts of aggregation/disaggregation methods and reviewed the respective applications in operations research. The authors emphasized several reasons in favour of using an aggregation/disaggregation modelling approach:

1. It provides quick insight into the overall system's structure and performance.
2. Possible lack of reliable microlevel data may prohibit the development of a detailed model but, if the corresponding macrolevel data are available, it can also motivate the formulation of an aggregate model to analyze the problem on a larger scale.
3. It enables analysts to obtain results at different levels of detail.
4. The inherent computational burden can be significantly reduced.

Regardless of the mathematical programming and modelling techniques used in a particular application, a general formulation of an aggregation/disaggregation methodology comprises four principal steps. The first step involves the identification of pertinent data for aggregation and the subsequent process of combining them. This is followed by the creation of a composite model which provides the reduction in complexity relative to the original model. Subsequently the analysis is carried out on the composite model and, at the final stage, the results derived for the hypothetical composite model are disaggregated into the respective components of the original problem. Although aggregation/disaggregation methods prove to be powerful tools for the dimensionality reduction of large-scale problems, they do require particular effort to be put into careful selection of principles which are to be employed at each of the modelling stages in order to minimize the error induced by the simplification of the problem representation.

Although originally devised to optimize a single reservoir operation, the approach presented by Mawer and Thorn (1974) is mentioned here due to their suggestion that the same procedure could be used in multiple-reservoir studies by applying some aggregation technique to represent a complex system by a hypothetical single reservoir. By assuming that reservoir inflows were not serially correlated, they combined SDP-based optimization and simulation to iteratively derive a near optimal long-term operating strategy for a reservoir. The pursued objective was to minimize the expected costs incurred by potential supply shortages. The procedure started by optimizing the operation of a reservoir for an assumed value of the marginal penalty cost. Subsequently, the derived SDP policy was appraised by simulation and, if the desired reliability of the reservoir's performance was not met, the marginal penalty cost was re-evaluated accordingly. The optimization was then repeated with the new estimate of the penalty and the resulting policy was in turn evaluated by simulation. The iterative procedure terminated when the policy which met the desired reliability of the reservoir's performance was found.

Saad and Turgeon (1988) proposed the principal component analysis (PCA) technique to reduce the number of state variables in the analysis of long-term multiple-reservoir operation problems. The PCA method was said to be applicable to problems where strong correlation between inflows to two or more reservoirs (or between reservoir storage states) could be detected. The procedure started by generating a set of synthetic streamflow sequences. Implicit SDP optimization followed to derive optimal operating strategies upon each generated inflow record. Subsequently, the PCA method was used to analyze the resulting policies and the achieved state variable values to find out whether the problem could have been modelled with fewer state variables. If so, the optimal operating policy for the reduced problem was derived by explicit SDP. The authors tested the applicability of the algorithm on a five-reservoir hydropower system on the La Grande river in Canada. In this particular case, the authors managed to reduce the original stochastic optimization problem of 10 state variables to a four-state variable problem which was then solvable by DP.

Further improvements of the PCA method were reported in Saad et al. (1992) where the authors used the censored-data statistical analysis to identify the parameters needed for the PCA. Censored-data method provides the means to analyze a sample of observations for which is known that the existing lower and/or upper bounds, if recorded a substantial number of times, can result in a biased estimate of the sample's probability distribution. With regard to the PCA method applied to a reservoir operation problem, these lower and upper bounds are the minimum and maximum storage volumes in the reservoirs observed from the sequence of deterministic optimizations performed over the set of synthetic streamflow sequences.

Using the same hydropower system as a case study, Saad et al. (1994) proposed a disaggregation approach based on the theory of neural networks. Initially, a five-reservoir system was aggregated into a single hypothetical reservoir whose operation was optimized by means of SDP. The composite operating strategy was subsequently disaggregated into individual reservoir policies using a feed-forward back-propagation neural network. The training of the neural network was previously carried out over a large set of equally probable operating scenarios. To provide the training set, the authors generated a series of synthetic flow scenarios which were further used to optimize the operation of the system assuming deterministic flow conditions. The application of the approach to the La Grande river hydropower system proved more efficient than the PCA method reported by Saad and Turgeon (1988).

Kularathna (1992) used aggregation/disaggregation methodology coupled with SDP-based optimization to derive the operating strategy of the Mahaweli water resources system in Sri Lanka. The case study system consisted of three subsystems having three interlinked reservoirs each. First, each subsystem was represented by a single hypothetical composite reservoir. In the subsequent step the optimal operating policies were derived for the simplified system of three hypothetical reservoirs. Ultimately, the resulting operating policies of the composite reservoirs were decomposed into control rules of their respective individual reservoirs. The author found that the devised SDP-based aggregation/disaggregation optimization approach produced a set of reservoir operating strategies which resulted in the system's performance very close to the deterministic optimum obtained by IDP. This work also included the applications of two different decomposition techniques, i.e. the sequential and iterative decomposition algorithms, in optimization of multiple-reservoir systems operation. In addition, the comparison of explicit and implicit SDP optimization approaches was carried out on a reduced, three-reservoir subsystem. The conclusion drawn was that the explicit SDP model outperformed the implicit one. Such an outcome was put down to the inaccuracies incurred by the adopted streamflow generation model and the selection of the independent variables in the regression analysis phase.

2.2.3 Approaches Based on Continuous Approximations of Discrete Functions

The basic idea behind this group of approaches is to tackle the DP's curse of dimensionality by using a continuous rather than discrete representation of the objective function in order to allow a coarser discretization of the state space. This in turn enables the analyst to opt for a straightforward application of the chosen DP optimization approach, thus simultaneously considering all state variables of a multiple-state problem. Most of the reported studies have shown significant reductions in the number of discrete state values necessary to achieve acceptably low error levels of the objective function approximation. However, due to the fact that all state variables are considered simultaneously, the computational load imposed by these methodologies still increases exponentially with the number of state variables.

Murray and Yakowitz (1979) introduced constrained differential dynamic programming (CDDP) to operational analyses of multiunit reservoir systems under deterministic hydrological conditions. The proposed approach was actually a variation of IDP applied to all reservoirs of the system simultaneously. In order to avoid discretization of state and decision variables, the authors assumed that the objective function could be described by its continuous quadratic approximation. Therefore, the major task was to solve a quadratic programming problem at each stage, i.e. to minimize the quadratic function of multiple variables, subject to a set of imposed constraints. As a comparison to other approaches and to present the advantages of the method, CDDP was used to derive optimal policies for three characteristic multiple-reservoir system configurations: a four-reservoir system introduced by Larson (1968) and also used by Heidari et al. (1971) and Nopmongcol and Askew (1976); a four-reservoir system used by Chow and Cortes-Rivera (1974), and a hypothetical 10-reservoir system. Finally, as the main features of the algorithm, the authors emphasized fast convergence of CDDP, no need for discretization of state and decision space, and low computer storage, memory and processing time requirements.

Similar idea was utilized by Foufoula-Georgiou and Kitanidis (1988) who introduced gradient dynamic programming (GDP) as a tool to solve optimal control problems of multiple-reservoir systems. In essence, GDP is a backward moving DP carried out through temporal stages. The GDP approach allows simultaneous consideration of all system state variables by using cubic Hermite polynomial approximation of the objective function over the state and decision space. The requirement of this approach is that the first derivatives of the interpolation polynomials must be continuous and known at each grid node. The method was tested on both deterministic and stochastic optimization problems of a four-reservoir system. In addition GDP algorithm was compared with the standard discrete DP procedure on a single-reservoir optimization problem. The results showed that the highly sophisticated mathematical procedure employed in GDP contributed to a significant reduction of the required state discretization level needed to achieve the acceptable accuracy of the results. In their earlier paper, Kitanidis and Foufoula-Georgiou (1987) compared the convergence rates of the classical discrete DP and GDP and showed that, with the decrease of the state discretization interval, the GDP procedure converged more rapidly than the conventional DP. The authors further expressed their belief that solutions to multiple-reservoir optimization problems should be sought in appropriate, case-dependent, interpolation-based numerical techniques rather than in discrete decomposition approaches. It is, however, arguable whether such an approach could be generally applicable since the computational load associated with GDP still increases exponentially with the number of state variables involved. Thus, and the obvious advantages GDP offers notwithstanding, the respective application of the method to very large reservoir systems would inevitably lead to the prohibitive increase of dimensionality, the well-known drawback of DP.

Johnson et al. (1993) proposed a high-order piecewise polynomial approximation of the objective function to allow a coarse discretization of the state space in multidimensional DP optimization problems. They used a piecewise cubic spline approximation of the objective function over the intervals created by state discretization. The coefficients of the cubic polynomials were derived upon the condition that they had to interpolate the objective function at each grid point of the state space. In addition, the first and second derivatives of the splines defined over the neighbouring discretization intervals were required to be equal at the interval boundaries, thus providing the second degree continuity of the approximation functions. The latter condition allowed the use of quasi-Newton optimization algorithm to locate the extreme of the objective function approximation. The authors tested their approach on the same four-reservoir system used by Foufoula-Georgiou and Kitanidis (1988). They also carried out a comparison of the computation error and processing time requirements between their model, a piecewise linear approximation based model and GDP by Foufoula-Georgiou and Kitanidis (1988). A general conclusion was drawn that both the cubic spline model and GDP provided substantial processing time savings and error reduction as compared to the piecewise linear approximation model. The cubic spline based DP model was also found to achieve only slightly smaller error for the same processing time than GDP. In Tejada-Guibert et al. (1993) the authors compared the same cubic spline DP and piecewise linear DP approaches on the two-reservoir Shasta/Trinity system in California and arrived at similar conclusions. Additional experiments showed that the proposed approach was successful in reducing the execution time for systems containing up to five reservoirs. However, further increase in the number of reservoirs would make the analysis susceptible to the curse of dimensionality for the number of state transitions still increased exponentially with the number of reservoirs in the system.

2.2.4 Decomposition Revisited

The presented applications of DP to long-term operational assessment of multiple-reservoir systems reflect one major general conclusion. That is, no universal solution to a stochastic optimization problem of a large-scale reservoir system can be recommended. It is rather the case that the choice of the methodology largely depends on a multitude of factors. The most demanding problems stem from the size of the system (i.e. the number of reservoirs), combined with the decision on whether the desired approach is to employ implicit or explicit consideration of stochasticity. These two factors directly influence the state space dimensions, the number of which is seriously limiting a straightforward application of DP. In addition, the choice of the approach may depend on the number and the type of different purposes a system is expected to serve (i.e. water supply, energy generation, etc.). Namely, the complexity of the optimization problem is significantly simplified if the system serves a single purpose. Thus, if the anticipated utilization of water can be approximated by a single user point targeted by the entire system, the dimensionality of the problem can be further reduced. With respect to the presented applications of DP to multiple-reservoir optimization problems, a number of general remarks can be made:

1. In cases of deterministic optimization of the operation of systems consisting of only few reservoirs IDP seems to be the most frequently used method. However, even IDP becomes susceptible to dimensionality limitations if applied to very large reservoir systems.

2. As for stochastic approaches it can be said that implicit SDP is generally a favourable choice. The approach comprised of a separate streamflow generation process, followed by deterministic optimization and the subsequent regression analysis to derive the expected optimal operating strategy allows more detailed modelling at each of the major computational steps. However, the dimensionality problems of large-scale systems still require considerable level of simplification to be adopted. This may include the application of a continuous approximation of the objective function along with a coarse discretization of the state space, decomposition or aggregation/disaggregation of the system. In addition, if applied to a multireservoir system the

implicit stochastic approaches require highly complex inflow generation algorithms to be employed to account for the interdependence of the streamflow processes (Kularathna 1992).

3. Although explicit consideration of inflow stochasticity can easily be incorporated into a DP algorithm the inherent dimensionality limitations restrict the use of explicit SDP in optimization of a multiple-reservoir system operation. Namely, Bogardi and Nandalal (1988) showed that the conventional explicit SDP procedure could handle only a two-reservoir system operation without exceeding the practical limitations of computer memory and time requirements. Nevertheless, even such a model could violate those restrictions by refining the discrete state representations.

4. Several methods have been developed to overcome the inherent shortcoming of dynamic programming that state and decision space have to be discretized. In general, they all rely on a multivariate, piecewise polynomial approximation of the objective function over a coarsely discretized state space. Subsequently, complex mathematical methods are employed to derive the extreme values of such objective function representations. Although these approaches have proved to be efficient in the reduction of the required number of discrete state representations their applicability to very large systems is still hampered by the exponential increase of the number of state transitions with respect to the number of state variables.

5. Most of the successful applications have been developed in long-term operational analyses of complex hydropower systems. This is mainly due to the possibility to represent the overall objective of the system's operation by a single goal of maximizing the total energy production regardless of the way how this output is distributed among the potential energy consumers.

6. However, considering mainly water supply reservoirs, another obstacle in operational analyses of large-scale systems lies in the inevitably complex demand structure. Highly complex water allocation patterns are due to the fact that a single reservoir may have multiple demands to cover, while water supply to a single demand centre may be provided by several reservoirs. Diversity in water demands is also reflected in different, often competing and non-commensurable objectives. It is obvious that such complex water allocation and optimization problems become too difficult, if not prohibitive, to model. To overcome this, the objective pursued in optimization is usually modified so as to be expressed as a maximization of water supply (or minimization of supply deficit) of the system with respect to the aggregated, single-component demand. Thus, no competing demands are assigned to a single reservoir and no conflict among reservoirs is attempted to be reconciled during the optimization phase.

A comprehensive and effective water resources planning and management involves close cooperation among engineers, systems analysts, decision makers and water resources systems operators. The interrelationship among them is reflected in a continuous exchange of their respective knowledge, experience, preferences, authority and potential limitations that they encounter within their own domains of expertise and influence. Loucks (1992) stressed that the continuous communication between water resources planners and managers on one side and modellers on the other constitutes the most important factor for a successful application of contemporary system analysis methods and models in the field. In addition, he asserted that the use of models in planning should be recognized as an aid to, and not a replacement for water resources planners' and managers' decision making processes. Furthermore, he emphasized that *"...the test of analysts is to provide planners and managers with meaningful (understandable), useful, accurate, and timely information to help them better understand their problems and how to solve them, and to help them better manage their financial, human, and water resources."*

Consequently, it is essential that decision makers are offered a number of alternative plans to be able to assess how well the individual options meet their preferences. Eventually, they could make a decision to choose either a single, the most preferable plan, or a group of alternatives that are to be further analyzed in more detail, or they might even change their preferences towards the future plans on the basis of the knowledge gained from the given set of options.

However, Rogers and Fiering (1986) pointed out to the existence of factors that discourage the use of effective systems analysis approaches in planning and design of water resource systems, and large-scale systems in particular. Large-scale systems are especially important for substantial improvements could be gained if some optimization technique were used in their planning and design. They referred to the reported experience both in developed (i.e. the USA) and developing countries. In developing countries, the reasons not to use recent developments in systems analysis are: i) institutional (political); ii) economic; iii) insufficient data availability and reliability; iv) insufficient manpower and equipment availability; v) high research costs in terms of time and money; and vi) ineffective communication between decision makers and analysts. As for the developed countries, these reasons could be narrowed down to institutional factors and substantial research costs. The authors also proposed that *"...systems analysis be used to identify the negotiation frontier, as part of larger activity which looks carefully at models, particularly the very large ones..."* and to introduce some effort that *"...would make the models more humane and would ultimately reduce their scale, so that they become less of a computational burden and provide more insight into the decision-making process."*

Therefore, it is essential to direct efforts towards sensible inclusion of powerful systems analysis methodologies into water resources management and planning. Concurrently, systems analysts ought to concentrate on the creation of such models and analytical algorithms that would be sufficiently understandable to decision makers and potential users. In that respect, Parker et al. (1995) reflected on the main dangers hidden behind the use of large and complex models. They emphasized the importance and the role of model calibration and verification, the estimation of confidence limits of the derived results, and the need for a comprehensive assessment of the input data quality. However, they reasserted that *"the more variables in the model, the more difficult it becomes to use as a practical management tool"* and that *"...we should not be surprised by poor decisions when personnel inexperienced in the use of models apply them with the expectation that models are straightforward arbiters of truth."* Therefore, attention should carefully be paid to creating credible, but still flexible, simple, and easy to use optimization and/or simulation models that would be able to justify the agreed investments. At the same time, those methodologies should provide significant adaptability to incorporation of new development plans and options. Schumann (1995), for instance, stressed the importance of the changing socio-economic conditions along with the resulting changes of water demands and their impact on the operation of water supply reservoirs. He suggested that reservoir operating rules should be subject to continuous monitoring and adaptation to new demand conditions. In that respect, he presented a methodology for adaptation of a single reservoir management to changing water demand conditions. The model consisted of three modules. The first module was an SDP-based optimization routine with a possibility to change the objective function through a set of weight parameters. The second part was a simulation module which was used to assess the derived steady state operating policy. Ultimately, a risk handling system based on fuzzy sets was devised in the third module to tackle extreme drought situations.

Decomposition techniques seem to be quite promising with respect to the need for a comprehensive, yet simple and "easy-to-understand" modelling of large systems. Not only is the modelling simplified by using decomposition but meeting the necessary requirements with regard to model transparency, monitoring of its performance, and its adaptability to changes in the system configuration is equally facilitated too. Djordjević (1993:136-139), for instance, perceived the use of decomposition in analyzing a complex operational problem as a means for more accurate modelling rather than a mere simplification of the problem. The author further asserted that solutions to operational problems of large and complex water resources systems could only be obtained by applying one or more of the four basic decomposition principles:

1. *Functional decomposition* partitions a system according to its purposes and/or goals.
2. *Spatial decomposition* breaks down a large system into a number of smaller subsystems.
3. *Temporal decomposition* employs a sequence of analyses along with a gradual reduction of the time scale considered.
4. *Numerical decomposition* utilizes various recursive and/or iterative mathematical methods to arrive at the solution to a complex problem.

The decomposition approach adopted in this dissertation is based on a physical partition of a multiple-reservoir system into a set of individual reservoirs. The subsequent optimization of the system's operation is an iterative procedure comprising a coupling of optimization, simulation and release allocation analyses performed for individual reservoirs. The main advantages that the proposed decomposition algorithm offers can be summarized in the following:

1. Simple and straightforward representation of a complex system makes the model more transparent and easier to handle by potential users.
2. It offers a considerable dimensionality reduction of the original problem. Consequently, the inclusion of new reservoirs and/or other elements like water transfer or conveyance structures to the system results in a relatively small increase of the computational load.

3. Due to the fact that the basic optimization problem is reduced to a single reservoir operation, the proposed decomposition model allows full utilization of the advantages of the explicit SDP optimization approach having almost no limitations associated with the well-known curse of dimensionality phenomenon.

4. Although not tested in this dissertation, the adopted decomposition method also allows the use of different optimization, simulation, and/or release allocation methods to derive and to assess the operating strategies of different reservoirs in the system. Namely, the application presented in this dissertation uses SDP to derive reservoir operating strategies whereas Horvath (1994) and Klaas and Van den Oever (1996) applied the same decomposition methodology in combination with the standard reservoir operating rule as the control strategy for individual reservoirs. Similarly, distinct objectives can be pursued in optimization of the operation of different individual reservoirs or groups thereof. For instance, Ampitiya (1995) used both water supply and energy generation related objective functions within the SDP optimization to analyze the operation of the Mahaweli water resources system in Sri Lanka (n.b. the same system used by Kularathna 1992). In addition, Ghany (1994) and Milutin et al. (1996) combined this decomposition methodology with different system representations to analyze the operation of a two-reservoir system on the Blue Nile.

5. The proposed decomposition technique requires relatively little further modelling effort to accommodate new alternative plans (i.e. different reservoir systems, water allocation patterns, etc.), thus reducing the necessary work load while assessing a range of planning options.

2.3 Applications of Genetic Algorithms in Water Resources Management

Genetic algorithms (GA) are solution seeking strategies based on the principles of natural evolution and genetics. Together with *evolutionary programming* (Fogel et al. 1966) and *evolution strategies* (Schwefel 1981), genetic algorithms form a group known as *evolutionary algorithms*. The basic theoretical aspects of these three main streams of evolutionary algorithms, including a broader reference list on the respective literature sources, is given in Bäck and Schwefel (1993). As to the genetic algorithms, the foundations of the theory were put down by Holland (1975) who proposed that the mechanisms recognized to drive the processes of evolution and adaptation of living organisms in their natural environments could be used to facilitate the search for solutions to problems involving complex artificial systems.

With regard to the views expressed by the founder of the modern evolutionary theory, it can be said that a GA-based search for better solutions to a problem is guided by the principles of *Natural Selection* and *survival of the fittest* (Darwin 1859:80): "*...can we doubt (remembering that many more individuals are born than can possibly survive) that individuals having any advantage, however slight, over others, would have the best chance of surviving and of procreating their kind? On the other hand, we may feel sure that any variation in the least* *degree injurious would be rigidly destroyed. This preservation of favourable variations and the rejection of injurious variations, I call Natural Selection. Variations neither useful nor injurious would not be affected by natural selection, and would be left a fluctuating element,...* " In order to emulate the evolution process, GAs recognize the three basic principles understood to drive the evolution and adaptation of living organisms:

1. The principle of *heredity* states that the offspring bear close similarity to their parents. Or, in the words of Charles Darwin (1859:127): *"But if variations useful to any organic being do occur, assuredly individuals thus characterised will have the best chance of being preserved in the struggle for life; and from the strong principle of inheritance they will tend to produce offspring similarly characterised."*

2. The *variability* principle ensures that the offspring are not identical copies of either of their parents, thus bringing about new qualities to new generations (Darwin 1859:170): *"Whatever the cause may be of each slight difference in the offspring from their parents - and a cause for each must exist - it is the steady accumulation, through natural selection, of such differences, when beneficial to the individual, that gives rise to all the more important modifications of structure, by which the innumerable beings on the face of this earth are enabled to struggle with each other, and the best adapted to survive."*

3. The principle of *fecundity* describes how different individuals leave different number of offspring, resulting in an uneven progression of the traits born by the variants of the same species. Darwin (1859:186) touched this issue through his discussion on the *struggle for existence*: *"He who believes in the struggle for existence and in the principle of natural selection, will acknowledge that every organic being is constantly endeavouring to increase in numbers; and that if any one being vary ever so little, either in habits or structure, and thus gain an advantage over some other inhabitant of the country, it will seize on the place of that inhabitant, however different it may be from its own place."*

In addition to the recognition of these three evolutionary principles, GAs utilize the advantage of the fact that while the survival and successful procreation of a species depends solely on the ability of the individual organisms to adapt to the changing environmental conditions, the progression of their specific traits to their progeny is maintained through the information stored in their genetic pool. Shortly, GAs combine the Darwinian concept of *Natural Selection* with the contemporary perception of the relationship between the genetic imprint of a living organism (i.e. genotype) and its traits (i.e. phenotype) exposed to the environment it lives in.

The above brief departure along the parallels between the GA theory and the basics of evolutionary adaptation may have brought very little insight into the workings of genetic algorithms. Significantly clearer picture could, however, be drawn through a description of the basic steps of a GA-based solution seeking process. Namely, a potential solution to a problem is in a GA replaced by its specific encoded representation, which can be viewed as a complete genetic material of an artificial being. To locate the desired solution, a GA model maintains a population of such artificial organisms through an emulated evolution of the "species": by means of selection, crossover and mutation individuals from a population undergo reproduction to create new potential solutions which form the succeeding generation. The criterion used to select an individual for reproduction is based on its "fitness", which is the measure of the objective achievement the respective potential solution has reached with regard to the problem in hand. Once a pair of individuals is selected for reproduction a crossover operator is applied to create the offspring of the selected parents. Obviously, the rationale behind crossover is information exchange between different potential solutions. Ultimately, each newly created individual may undergo mutation. However, as it happens in the nature, the rate of change due to mutation is kept very low. The principal role of mutation is, logically, the introduction of variability into newly created generations. Consequently, a typical GA search is characterized by repeated creation of new generations of individuals with the expectation that the individual members of succeeding populations would converge towards encoded representations of better (in terms of the objective criterion) solutions to the problem. The term "expectation" in the above statement is used deliberately to indicate that the convergence of the individuals in a population towards the desired solution cannot be achieved with certainty in a GA search. It is rather the case that a careful selection of the representation coding, definition of GA operators, formulation of the fitness function and calibration of model parameters, combined with successive executions of a GA serach constitute a necessary set of preconditions that must be met to be able to evaluate objectively the success or failure of a series of GA searches.

However, although they cannot guarantee the identification of a global optimum to a problem, GAs compare favourably to conventional optimization and search methods due to the fact that they can handle otherwise intractable complex problems with relative ease and can locate good solutions within reasonably low computational times. Consequently, the main advantage that GAs hold against traditional optimization and search methods is their robustness. In this regard, the area particularly amenable to application of GAs includes optimization problems involving multidimensional solution spaces with multimodal objective functions. The robustness and effectiveness of a GA search are primarily due to the four basic features that characterize GAs (Goldberg 1989:7):

1. Genetic algorithms work with a coding of potential solutions, not the solutions themselves. Namely, GAs require that a potential solution to the problem be represented by a specific coding which is analogous to chromosomes in biological systems. From this point onwards, the terms string, chromosome and individual are used interchangeably in this dissertation to refer to the encoded representation of a potential solution to a problem. The encoded solution representation is further regarded as a complete genetic material (genotype) of an artificial being whose characteristics (phenotype) are depicted by the potential solution it represents. The encoding itself is performed over some small finite alphabet, which is usually the binary alphabet: {0, 1}. The choice of binary coding to represent a chromosome in a GA environment stems directly from the *minimal alphabet principle* which states that (Goldberg 1989:80) *"The user should*

select the smallest alphabet that permits a natural expression of the problem". The binary transformation is fairly straightforward if the solution itself is a pseudo-Boolean or an integer variable, whereas the cases involving variables which take real values within a known range require that the solution interval be mapped over the interval of its binary representation. In the end, it should be noted here that attempts have also been made to develop GA models which utilize integer or real-valued (decimal) rather than binary solution representation (e.g. Janikow and Michalewicz 1991, Michalewicz and Janikow 1991, Michalewicz 1992, Groen and Zaadnoordijk 1994, Cieniawski et al. 1995, Oliveira and Loucks 1997).

2. Genetic algorithms search the solution space from a population of points, and not a single point. Namely, a GA search starts by generating the initial population of potential solutions at random. The subsequent actions emulate the evolution of the initial population through creation of new populations by applying three principal GA operators: selection, crossover and mutation. Thus, in each generation GAs maintain a simultaneous inspection of a larger area of the solution space rather than being concentrated on a single intermediate solution point.

3. Genetic algorithms work directly with the objective function requiring no additional knowledge about its derivatives or any other auxiliary information. This feature brings about a significant advantage in favour of GAs for it allows their application to a wide variety of problems without imposing almost any restrictions on the type of the objective criterion used.

4. Finally, genetic algorithms direct their search by probabilistic, not deterministic, rules. However, this does not make GAs just another type of random search methods. It can rather be said that GAs use random choice to guide their search towards the regions of the solution space which offer improvement in the selected objective criterion. In fact, by applying probabilistic operators (selection, crossover and mutation) to a population of potential solutions, GAs maintain a balanced sweep of the solution space: i) they not only promote the procreation of individuals representing better solutions but also acknowledge the potential contribution of less favourable solutions; ii) randomly driven crossover creates new alternative solutions; and iii) occasional mutation introduces new regions of the search space to be explored.

Despite the fact that the definition of GAs states such attributes as random generation of the initial population and probabilistic nature of GA operators, it should be noted here that GAs also allow problem-specific knowledge to be used while devising the framework of a GA model. This may include user-defined constraining of the solution space, formulation of non-standard GA operators, selection of the initial population members, etc.

As already mentioned earlier, GAs employ three basic operators to emulate the evolution of the population of potential solutions: selection, crossover and mutation. To clarify the principles behind the workings of each of them, the following paragraphs provide a brief description of the originally proposed, and most frequently used within binary-coded GAs, GA operators. It should be noted here that the choice of the operators is both problem-dependent and closely related to the employed chromosome representation. A detailed discussion on the operators adopted in the GA models developed in this study is provided in Sections 4.5.1 and 5.5.1.

Selection identifies individuals from the present population that are going to reproduce into the subsequent generation. In essence, selection is based on the individuals' fitness, thus reflecting directly the principle of *survival of the fittest*. The most frequently used selection mechanism is *proportional selection*. It states that the likelihood that an individual be selected for reproduction is proportional to its fitness relative to the fitness of all the individuals in the generation. In addition to the classical proportional selection procedure, a number of other selection principles has been proposed in the literature. To mention just a few, they include the *elitist selection* which states that the fittest individual in a generation must always survive, *crowding selection* which performs the replacement of individuals on the basis of fitness comparison among a predetermined subset of randomly selected chromosomes, and *tournament selection* which selects the reproduction candidate as the fittest individual from a randomly chosen subset of strings.

Once a pair of strings is selected for reproduction a crossover operator is applied to create two children out of the selected parents. The simplest crossover operator for a binary chromosome representation is the classical, *one-point crossover*. Given a pair of chromosomes selected for reproduction, the crossover operator is applied by randomly selecting a crossover site along a string length, cutting both strings at this site, and exchanging the created sub-strings. In addition to the classical one-point binary crossover, a number of other crossover operators have also been reported: *multiple-point crossover* cuts the parent strings at several locations, whereas *uniform crossover* traverses over the parent strings and randomly selects which bit in a child string is going to be taken from which of the parents.

Selection and crossover are the major engines of GAs. In principle, by selecting and crossing over more fit individuals they deserve the credit for a successful search within the problem space and fast convergence towards the optimum solution(s). On the other hand, mutation is somewhat a secondary GA operator. Nevertheless, its importance should not be gauged by its secondary role. Mutation is important because it is the only operator that is able to insert a new quality into an individual, and thereby into a population. It provides the means to maintain diversity within a population, thus preventing it from "degenerating" towards a stable, but very likely non-optimal solution (n.b. this phenomenon is known as *premature convergence*). The most frequently used mutation operator within binary-coded GAs is a *single-bit mutation* (or *bitwise complement mutation*) which, at a rather low rate, occasionally changes the value at a randomly selected bit position (i.e. changing the original bit value from 0 to 1 and vice versa).

In addition to the GA operators, the resolutions of three other issues are equally important for a good GA model development. These include the problems related to solution feasibility and population variability, and the adoption of the GA run termination criterion.

Solution feasibility is particularly obstructive to GA models which deal with highly constrained optimization models, and especially if subsets of solution coordinates are interdependent. This obstacle stems from the fact that GAs, by "working" on a representation of pumps each. The pumping stations were assumed to be operating within the limits of the known maximum discharge and minimum and maximum suction pressure constraints. Given the known pump characteristics, the desired flow rate and the initial upstream supply pressure, the objective was to find the operating schedule for the 40 pumps which would result in the minimum total power of the entire 40-unit pump system. The adopted chromosome representation included a 40-bit binary string with four-bit sub-strings depicting one pumping station, and each bit representing a decision on whether the respective pump is to be switched on (bit value 1) or off (bit value 0). They used a simple, classical GA with proportional selection, one-point crossover and bitwise complement mutation, along with a penalty function for identification of infeasible pumping schedule representations. The optimal solution to the problem was derived by mixed integer programming and the best solutions provided by three independent GA runs, each starting with a different initial random population and running for 100 generations, fell short of the optimum between 0.18% and 1.34%. An interesting observation was also that each of the GA runs reached near-optimal solutions already after only 50 generations.

Davidson and Goulter (1995) proposed a GA-like model to determine the optimum layout geometry of a branched rectilinear pipe network for a rural gas (or water) distribution system. The model was developed to minimize the length of a no-loop pipe network consisting of a primary set of basic nodes describing the single source and multiple recipients, and a secondary set containing dummy nodes which represented the necessary elbows, tees and intersections in the network layout. In essence, their model was a type of an evolution program (Michalewicz 1992) devised as a combination of a GA-based binary coding of a potential solution and a set of problem-specific evolutionary operators. A single potential network design was initially depicted by a matrix representation of all network nodes and their respective links. The subsequent step included a partition of the network into a set of links between the basic node closest to the upper-left corner of the network matrix and one of the remaining basic nodes. Ultimately, a chromosome representation of the whole network was created by concatenating the binary sub-strings representing each of the two-node links. Given the adopted binary chromosome representation, the authors recognized that the use of classical crossover and mutation operators would result in a high proportion of infeasible individuals and therefore developed two alternative operators: *recombination* and *perturbation*. The basic principle of the recombination operator was to combine sub-strings representing different two-node links in two selected individuals. In addition, to minimize the number of duplicate links, the recombination operator was extended by a mechanism which removed duplicate links from every other sub-string of the newly created individual. On the other hand, the perturbation operator was conceived as an equivalent of mutation by substituting an existing single link between two neighbouring nodes with one of the alternative three-link paths. The creation of new populations in the adopted model was carried out according to the evolution strategy proposed by Schwefel (1981). Namely, unlike in standard GA models, a single iteration consisted of random selection of a pair of chromosomes, creation of a single new individual, and inclusion of that individual into the population by replacing the worst-fit member of the population. Using a number of small problems consisting of no more than 10 basic nodes, the authors compared their evolution program with their earlier developed model which employed a heuristic procedure coupled with a rule-based algorithm derived from the practical experience (Davidson and Goulter 1991a, 1991b). In general, they found that the shortest-length network designs derived by the evolution program were consistently matching or outperforming those provided by the heuristic model. In addition, the authors emphasized that while the heuristic model was able to identify only a single solution, the evolution program was always offering a number of potentially desirable network designs. However, the authors concluded that the main disadvantage of the evolution program was its applicability to relatively small problems due to the exponential increase of the time required to generate the initial population.

Another application of GAs to pipe network optimization problems was presented by Dandy et al. (1996). The developed model was conceived as an optimization tool for the design of gravity scheme water distribution networks. Based on the given layout of pipes and the specified demands at control nodes, the model was expected to find the optimal combination of pipe diameters with respect to the minimum construction and maintenance cost, subject to the standard flow continuity and head loss constraints, and the minimum and maximum pressure limitations at certain nodes. Using the primary water distribution system of New York City, the authors developed two different GA models and compared their performance against the alternative solutions for the extension of the original system proposed by a number of previous studies. Both GA models employed a potential solution encoding consisting of an 84-bit-string representation for the 21-pipe primary distribution network of the city, thus mapping each pipe's diameter over a four-bit sub-string. Therefore, each pipe in the system could have a diameter from a set of 16 possible values, each of which was represented by a distinct four-bit binary sub-string. In addition, both models used the same fitness function which was to minimize the total construction, maintenance and operation cost, increased by a penalty cost due to the violation of the minimum pressure requirements at control nodes. The latter component of the fitness was estimated upon the steady state hydraulic analysis of the flow in the respective network design. The first model was a classical GA with binary coding, proportional selection based on raw fitness, one-point crossover and a bitwise complement mutation. The second model, however, utilized Gray coding, variable power scaling of fitness, proportional selection, the standard bitwise complement and an additional *adjacency mutation* operators. Similar to binary coding, the Gray coding also uses only the two letters of the binary alphabet (i.e. 0 and 1) to depict an integer number. However, unlike binary ones, Gray code representations of adjacent integer values differ by only one bit. This enabled the representation of nearby pipe diameters by similar 4-bit sub-strings. Consequently, the application of the classical bitwise complement mutation was more likely to create a sub-string representing a pipe diameter not far from the one subjected to mutation. In addition, the authors introduced another mutation operator which was particularly suitable for Gray-coded bit strings. Namely, the adjacency mutation acted upon a 4-bit sub-string representing the diameter of a particular pipe and changed it to the adjacent diameter Gray code up or down the list of the possible diameter values. Another novelty within the second GA model was fitness scaling. To ensure sufficient variability of the fitness at later stages of the GA run, the model employed a variable power fitness scaling. Namely, the scaled individual fitness was a simple power function of the raw fitness. The scaling function exponent was set to unity at the beginning of the GA run allowing the selection procedure to utilize the variability of fitness due to random generation of the initial population. As the GA iterations proceeded and the raw fitness values began to show less variability, the exponent was gradually increased to promote highly fit individuals. The application of both models to the case study showed that the Gray-code GA consistently produced better results than the classical model. In addition, the Gray-code GA identified three different pipe network designs with lower costs than any of the feasible solutions obtained by any other approach reported in the literature. Finally, the authors also recognized that a GA-based search was the only approach which could offer a number of low-cost feasible solutions, thus providing a potential decision maker with a set of alternative plans to choose from.

The work of Wang (1991) exemplifies an application of GAs to another potential area of water related problems: model calibration. The presented GA model was a variant of a classical GA with binary coding, retaining only the bitwise complement mutation from the standard GA operator set. The departures from the standard GA were introduced into the selection and crossover operators. The employed selection procedure, known as the *proportional ranking selection*, is briefly described in the sequel. The individuals from a generation were initially ranked according to their respective fitness values. Assuming that the average probability of chromosome selection was the inverse of the number of individuals in the population, the top-ranking string was assigned a probability of selection of twice the average and the last on the list was given the selection probability of zero. Subsequently, the selection probabilities of the remaining ranks were computed by linear interpolation. Thereafter, the selection process was carried out as a classical proportional selection. Another departure of the developed model from the classical GA formulation was the use of the *two-point crossover*, which differed from its one-point ancestor in that that it cut each of the parent strings at two randomly selected bit locations. The two new chromosomes were subsequently created by shuffling the resulting six sub-strings. The developed GA model was applied to a problem of a conceptual rainfall-runoff model calibration. The objective was to identify the optimal set of seven model parameters with respect to the minimization of the sum of squared differences between the computed and the observed discharges. The adopted GA formulation used a 10-bit binary representation of a single unknown parameter (thus resulting in a 70-bit-long chromosome) with 100 individuals in a generation and the maximum of 50 generations, and crossover and mutation probabilities set to

1.0 and 0.01, respectively. Finally, the model was run 10 times with different initial random populations. As the author reported, in eight of the runs the best solution found fell in the vicinity of the optimum, whereas the two remaining searches ended up at local optima.

Similarly successful results of GA applications to model calibration problems were reported by Babović (1993) and Babović et al. (1994). The former presented a simple, classical GA developed for a flood routing model calibration. The author first generated a synthetic input flood hydrograph and selected the values for the four model parameters. Subsequently, the flood routing model was used to compute the output hydrograph. Thereafter, the GA search was initiated to try to identify the four model parameters by minimizing the sum of the squared deviation of the computed flood wave output from the previously obtained synthetic output hydrograph. The author pointed out to the success of the GA search by graphically presenting the almost perfect match between the two output hydrographs and by reporting that the respective standard deviation was of the order of magnitude of 10^{-2}. The latter work (Babović et al. 1994) was however dealing with a substantially more complicated problem. Namely, a GA model was applied to calibrate a set of 117 Manning coefficients of a pipe flow hydrodynamic model tested on an existing urban drainage network. Again, a classical GA with binary coding, linear fitness scaling, proportional selection, one-point crossover and bitwise complement mutation was used. The objective was to minimize the total distance between the simulated and observed water level points at all control nodes. The best match obtained after only 10 generation runs of 50 individuals each resulted in the deviations between the simulated and observed levels at control nodes not higher than 10 cm.

Groundwater management problems have also been addressed by some researchers interested in analyzing the potentials of genetic algorithms. McKinney and Lin (1994) presented the application of GAs to solve three typical groundwater-related problems. They used a classical binary chromosome representation with one-point crossover and bitwise complement mutation operators. The violation of constraints was tackled by an external penalty function and the selection mechanism was based on a variation of *tournament selection*. The tournament selection procedure generally consists of two distinct phases. In the first step an intermediate mating pool is created by randomly selecting two chromosomes from the present population and placing the fitter one into the mating pool. Once it is filled, the mating pool is used to select pairs of chromosomes at random and to cross them over to create new individuals for the succeeding generation. The authors applied the developed GA models to solve the following three problems: i) deriving the maximum pumping scheme from an aquifer; ii) finding the minimum cost of a groundwater supply development; and iii) identification of the minimum cost design of an aquifer remediation system to remove a contaminant plume. The performance of each of the three models was tested on a hypothetical case and was appraised against the optimal, or approximate if the former could not have been obtained, solution derived by some other optimization method. As to the first problem, formulated as a purely linear one, the GA model with a population of sixty-four 30-bit-long chromosomes was applied to find the maximum pumping rates of the hypothetical system of 10 wells. After only 10 generations, the solution obtained by the GA deviated by only 2% from the optimum solution provided by an LP model. The second GA application involved also a system of 10 wells, this time searching for the minimum cost of installing and operating the wells with respect to the given total water abstraction target. Within only 14 generations, the GA model managed to identify the solution which fell short by only 0.4% from the optimum derived by an NLP technique. However, the pumping rates of individual wells did not show such an agreement, indicating that this particular problem might have had a number of equally good solutions. The third example included a five-unit system of abstraction/injection wells for the remediation of a groundwater contaminant plume. Since the global optimum to the problem could not have been obtained, the best GA-based solution was compared with the approximate solution obtained by an NLP model. The developed GA had a population of 128 individuals, each being 30 bits long. After only 19 generations the GA search located an abstraction/injection design with the minimum capital and operating cost, which was by 1.4% lower than the approximate solution provided by an NLP model. However, this outcome should not be viewed as if the GA has managed to locate the true optimum. It is rather that it only shows that there exists at least one other solution better than the NLP-based approximate solution.

Ritzel et al. (1994) presented an application of GAs to a multiobjective groundwater management problem. The hypothetical problem involved the optimization of pumping rates of a 16-well abstraction/injection system for the containment of the contaminant groundwater plume. The objective was to identify the trade-off curve between the maximization of the reliability of capturing a plume and the minimization of the costs incurred by the installation and operation of the system of wells. The reliability of capturing a contaminant plume by a well system was approximated by the ratio between the number of detected plumes and the total number of Monte Carlo simulated plume realizations (n.b. the simulated set consisted of 100 plume realizations). With the exception of the adopted selection mechanism and the multiobjective fitness representation, the developed GA models were entirely based on the classical GA formulation principles. The employed selection operator was a *deterministic binary tournament selection* (DBTS). The only difference between the DBTS and the classical tournament selection (cf. McKinney and Lin 1994) is that in DBTS each individual is permitted to compete in exactly two tournaments. The authors also tested two different multiobjective fitness representation approaches within the employed tournament selection mechanism. The first model utilized the *vector evaluated genetic algorithm* (VEGA) developed by Schaffer (1985). According to VEGA, the fitness of an individual was described by a vector whose coordinates were the respective individual objective function achievements. During the tournament selection, a fraction of the mating pool was selected upon comparisons on one objective function values and the remaining part of the pool was filled by comparing the second objective achievements of the selected chromosome pair. The decision which objective to use for the comparison of a particular pair of parent candidates depended on a random choice guided by a prespecified probability threshold. The second model was based on the method named *Pareto ranking GA* (Goldberg 1989:199-201). Namely, all nondominated individuals in a population were flagged, given the highest rank and were temporarily removed from the population. The remainder of the chromosomes was thereafter scanned for the next set of nondominated individuals. Those found were given the next lower rank and they too were temporarily extracted out of the population. This procedure was repeated until all of the chromosomes were given a rank. The established ranking was subsequently used as the criterion in the tournament selection procedure. As it might have been expected, the analyses showed that the Pareto ranking GA performed significantly better than the VEGA-based model. While the trade-off curve derived by VEGA covered only the top half of the "plume-capturing reliability" range (i.e. the number of captured plumes varied between 50 and 100), the Pareto ranking GA managed to identify the nondominated solutions across the whole range of possible "plume-capturing reliabilities". In addition, the trade-off curve obtained by the Pareto ranking GA was much closer to, and nearly matched, the nondominated solution set derived by the mixed integer chance constrained programming. The authors also emphasized the ability of genetic algorithms to handle complex, highly non-linear problems and to locate multiple solutions in a single run, which is a significant advantage in dealing with multiobjective decision making problems.

A similar multiobjective analysis was carried out by Cieniawski et al. (1995). They investigated the application of different GA formulations to find the optimal location of a set of groundwater monitoring wells for the detection of contaminant plumes. The location of the potential contaminant source was assumed to be known whereas Monte Carlo simulation was used to generate several hundred plume realizations from a random sample of aquifer parameters and leakage events. The objective put before the developed GAs was to identify a nondominated set of well networks with respect to the maximization of the reliability of plume detection and minimization of the contaminated area at the time of the first plume detection. The authors tested three different GA models on a hypothetical case study consisting of five monitoring wells and 135 potential well locations. The developed models used an integer instead of a binary chromosome representation. That is, a chromosome consisted of a number of integer fields depicting the respective locations of the monitoring wells. Consequently, the standard crossover and mutation operators had to be adapted for the chosen mapping scheme. The crossover operator was therefore allowed to cut a string only at a boundary between two well location integer codes. Similarly, if an integer field was subjected to mutation, the resulting mutated value was determined by a random draw from the set of possible well location indices (i.e. between 1 and 135). The three models differed in the employed multiobjective consideration of chromosome fitness. The first two models utilized the earlier described VEGA (Schaffer 1985) and Pareto ranking (Goldberg 1989) approaches, respectively. The third model was, in fact, the combination of the former two: the VEGA would run for a certain number of generations, at which point the Pareto ranking GA would take over. Previous runs showed that the optimum switch point was around population No. 70. The general conclusion from the performed analyses was that all of the three models did manage to find large portions of the "true" trade-off curve, which was previously derived by a simulated annealing algorithm. However, the combined VEGA-Pareto ranking GA outperformed the other two models in that it was the only one which was able to reproduce almost the entire curve. The authors finally emphasized that the ability of GAs to handle multiple objectives and to derive a family of solutions in a single run made them a valuable means for solving multiobjective decision making problems.

Genetic algorithms have also found their way to the field of reservoir operation problems. Esat and Hall (1994), for instance, developed a GA model to optimize the operation of a multiple-reservoir system. The system in question was a well-known four-reservoir system introduced by Larson (1968), and later also used in the studies of Heidari et al. (1971), Nopmongcol and Askew (1976) and Murray and Yakowitz (1979). The choice of this particular system allowed the authors to test the performance of their GA model because the optimal solution had already been obtained by both LP and DP optimization methods. The objective was to determine the optimal set of release decisions for the reservoirs over 12 two-hour time steps. The inflows to the reservoirs during the 12 time periods were known and the releases were used to generate power. In addition, the release from the lowest reservoir was also diverted to an irrigation project after passing through the turbines. The objective pursued in optimization was to maximize the overall benefit from generated energy and irrigation water supply, taking into account the penalty for not reaching the specified storage volumes in the reservoirs at the end of the 12th operating period. The developed model was a classical GA with binary coding, proportional selection, one-point crossover and bitwise complement mutation. To ensure feasibility of the newly created individuals, the authors opted for an external penalty function. The sensitivity analyses produced the following set of GA parameters: i) 40 individuals in a generation with the maximum number of generations being between 30 and 40; ii) the three crossover probabilities of 0.8, 0.9 and 1.0; and iii) the mutation probability of 0.005. Starting with different initial random populations, the GA search was initiated 20 times for each of the three crossover probabilities. The objective function achievements for the solutions obtained in all three cases were very close to the optimum of 401.3 units, with the standard deviation of the objective function value being less than 0.75 of a unit. The authors further presented the estimates of the computation time and memory requirements versus the number of reservoirs for both the DDDP (Heidari et al. 1971) and the GA. They showed that while the DDDP exhibited an exponential dependence, the GA's computational complexity was increasing only linearly with the number of reservoirs in a system.

Oliveira and Loucks (1997) developed a GA-based model to obtain the operating strategy of a multiple-reservoir system. The operating rules to be derived consisted of a set of system release and reservoir balancing functions formulated for each of the defined within-year time periods.

The system release rule was conceived as a piecewise linear relationship between the total system release and the total amount of water (i.e. storage plus inflow) available in the system during a time step. The reservoir balancing rules were also assumed to be piecewise linear functions. They defined the end-of-period reservoir storage targets as a function of the total system storage at the end of the time step. The task put before the GA was therefore to identify the inflection points that define these functions (i.e. the points which define the linear segments of a function) with respect to the minimization of the average water supply or energy deficit in a within-year time period, and subject to the standard set of reservoir balance constraints. The model employed real-valued chromosomes with each gene representing a pair of coordinates of an inflection point of either of the functions. Thus, a subset of adjacent genes fully defined one piecewise linear function. Similar subsets were further created for each of the functions and each of the time periods within a year. The fitness of an individual was estimated by simulating the operation of the reservoir system according to the respective rules. The adopted proportional selection procedure was based on the ranking of population individuals according to their fitness. In addition, the elitist selection principle was introduced to ensure that the fittest individual from the present population survives into the succeeding one. The authors tested a number of crossover operators and concluded that two of them were yielding the best results. The first one was a variation of the bitwise *uniform crossover* (Syswerda 1989). In essence, two parent chromosomes were crossed over by exchanging their sub-strings representing entire functions. For each of the function sub-strings, the choice which child is going to receive the respective sub-string from which of the parents was determined by a random fair coin toss. The second crossover operator created only a single child as a randomly driven weighted combination of the respective sub-string functions defined by the two selected parents. Unlike crossover, the mutation operator was defined to change the coordinates of a single point of a function, rather than the entire sub-string function. Namely, if a point was a candidate for mutation, it was displaced from its original position by a distance which was normally distributed in both x and y directions about the original coordinates. If the newly created point proved to be infeasible, its coordinates were adjusted to the nearest feasible point. The authors presented the results of the GA application to two hypothetical case study systems, both having two reservoirs in parallel. The temporal discretization was set to only two within-year seasons and the same sequence of synthetic reservoir inflows was used in both applications. The best operating rules derived from 10 independent GA runs were further compared to the ones obtained by some other methods by simulation over 10 additional synthetic flow sequences. In the case of the first, water supply, system the best GA-based policy was found to yield only a slightly worse average seasonal supply deficit than those derived by the space rule (Bower et al. 1962) and SDP. For the second system, which had the purpose of energy generation, the simulation results showed that the GA policy resulted in a better system performance than its equivalent derived by a heuristic greedy hill-climbing approach.

The applications reviewed in this section show that the robustness of the GA-based search can efficiently and effectively be used to solve a variety of water management problems. Similar conclusion can be drawn from the application of the GA model developed and presented in this dissertation. As it will be shown later, the use of a GA to solve the problem of water allocation within a multiple-reservoir-multiple-user water supply system proved to be less complex and computationally less expensive than the alternative LP-based method. Furthermore, the GA was also able to identify a number of alternative water allocation strategies which would result in comparatively good performance of the reservoir system. This is a significant advantage of the method because one of the aims in water resources management and planning is, in fact, to identify various alternative options which could then serve as a basis for the selection of the most preferred one in the subsequent decision making process. Namely, the alternative water allocation strategies derived by the GA were appraised over an array of system performance indicators, thus enabling a comprehensive assessment of the identified set of promising solutions. Consequently, such an approach offers a possibility of analyzing the operation of the system from a multiobjective decision making point of view which, although not explicitly explored and exemplified in this work, is an inherent part of any water resource planning and management study.

2.4 Reliability Criteria Assessment in Evaluation of Reservoir Performance

As shown in Sections 2.1 and 2.2, various optimization techniques have been extensively used to derive operating strategies of reservoir systems. Most frequently, the devised optimization models have relied on maximization or minimization of the selected objective criterion to arrive at the best achievable operating policy of the system in question. Similarly, within a multiobjective framework, the proposed approaches have usually utilized repeated optimization analyses concentrated on alternative single criteria while considering the remaining objectives as constraints. In this way, the analysts have been able to construct the trade-off relationships among the estimated achievements of the objectives imposed upon the analyzed system.

Within stochastic optimization concepts the most frequently used objective criteria include either the maximization of the expected system output or benefit function, or the minimization of the expectation of some form of loss function. Utilization of this type of criteria provides the estimate of the expected performance of the system on the long run. However, they cannot shed any light on the frequency of the system's failing to provide the required service, the duration and severity of potential failures, nor the ability of the system to return to satisfactory operating state once a failure has occurred. These important facets of a system's performance are widely known as reliability indicators. Consequently, substantial effort has been put into the explicit consideration of reliability into the optimization of the operation of reservoir systems. It could be said that the most significant advancements in the field started with the work on chance-constrained programming by ReVelle et al. (1969), which was further extended by, to name just a few, ReVelle and Kirby (1970), Eastman and ReVelle (1973), ReVelle and Gundelach (1975), Gundelach and ReVelle (1975), Loucks and Dorfman (1975), Houck (1979), Houck and Datta (1981) and many others, including the works on reliability programming by Simonović and Mariño (1980, 1981, 1982).

Another way of considering reliability related aspects of reservoir performance is to combine optimization with the subsequent simulation-based appraisal of the reservoir's operation. In essence, the optimization is carried out with respect to the selected objective criterion and the simulation of the reservoir's operation according to the derived optimal policy is used to provide a basis for the evaluation of the respective set of reliability criteria. This approach enables the analyst to screen the operation of the reservoir over any number of relevant criteria, i.e. the performance measures which will further be referred to as performance indicators (PIs). The choice of PIs relevant for the analyzed problem, as it can clearly be seen from the works reviewed in this section, is primarily problem-dependent and can be made from a variety of reliability, risk and other performance related indicators. Consequently, in order to reflect better the most relevant aspects of a particular operating problem, the definition of the adopted performance indicators often varies from one application to another. It is therefore important to point out that no universal definition exists for almost any one of the most frequently used performance indicators. This is the main reason why the reviews given further in this section include also the definitions of the PIs used in each of the selected studies. Despite the fact that often the same names appear for certain PI measures, their definitions frequently differ from each other and, in order to avoid the misinterpretation of the respective results and conclusions, each of the presented studies should therefore be viewed independently from the others.

The advantage of the simulation-based performance assessment is particularly pronounced in the operational analysis of multiple-reservoir systems where the complexity prohibits the explicit consideration of performance criteria in the optimization process. By adopting this simulation-based reliability appraisal approach, analysts can opt for simpler optimization methods enabling at the same time the application of complex simulation models to obtain detailed information about various operating aspects of the system's performance. Therefore, the evaluation of different operating strategies derived for the case study system in this dissertation is based on this approach.

Recognizing that the simulated estimates of the mean and the variance of a selected performance measure (e.g. output, operating cost) could not provide accurate information about the frequency and magnitude of operational failures, Hashimoto et al. (1982) used three additional performance indicators to compare a number of different operating policies of a single irrigation water supply reservoir. They introduced *reliability* to describe how often the system failed to meet the target; *resiliency* to assess how quickly the system managed to return to a satisfactory state once a failure had occurred; and *vulnerability* to estimate how significant the likely consequences of a failure might be. Based on simulation of the reservoir's operation over a long synthetic inflow time series, a set of operating strategies was evaluated by deriving trade-offs among the expected loss, reliability, resiliency and vulnerability. For instance, one conclusion that could be drawn from the analyses was that, for the given case study, high system reliability was always accompanied by high vulnerability (i.e. the fewer failures the reservoir had, the higher deficits were encountered in the failure periods). The authors also pointed out that each problem bears its own unique features and, therefore, the selection of appropriate performance indicators should always reflect upon those unique characteristics of the problem.

Similar conclusions were also drawn by Moy et al. (1986) in their study of the operation of a single water supply reservoir. They used mixed-integer linear programming to derive trade-off curves among the virtually same three performance indicators presented by Hashimoto et al. (1982). Namely, they defined *reliability* as the probability of failing to meet the desired target; *resilience* as the maximum number of consecutive failures prior to the reservoir's return to the full supply state of operation; and *vulnerability* as the maximum supply deficit observed during simulation. The major finding described the relationship between vulnerability and the other two PIs. In general, the results showed that a reservoir would likely exhibit higher vulnerability (i.e. larger magnitudes of failure) if it were more reliable (i.e. had fewer operating failures), or if it were more resilient (i.e. had shorter sequences of repeated failures).

Duckstein et al. (1987) emphasized the necessity to analyze and to compare alternative water resource system operating plans from a multiobjective point of view. In that respect, they proposed a framework for embedding a number of criteria related to operating failures into the analysis of water resources systems operation. The selected performance indicators included:

1. *The grade of service* described the frequency of the system providing at least a fraction of the desired service.
2. *The quality of service* was defined as the percentage of the requirement satisfied.
3. *The speed of response* depicted the time lapse between the occurrence of a demand and the delivery of the requested service.
4. *The reliability performance index* was defined as a frequency that the system would not experience an operating failure.
5. *The incident period* described the average duration of periods between two failure events.
6. *The mission reliability* was defined as the probability that the system would fall into failure mode between the time of demand announcement and the corresponding system response.
7. *The availability* was defined as the probability that the system would not be in failure mode at the time of demand announcement.
8. *The repairability* described the average length of time the system stayed in failure mode.
9. *The vulnerability* measured the average severity of a failure event.

In addition to these nine PIs, the authors suggested that some type of economic PI measure could also be used to describe, for instance, the expected costs, losses and benefits, etc. To illustrate the use of the proposed PIs, the authors used an example of a single reservoir with the main purposes of water supply and flood protection.

Bogardi et al. (1991) presented a summary of the results of an extensive study on the sensitivity of the operation of a multiple-reservoir system to the objective criterion and constraint set, as well as various inflow transition probability representations used in the SDP-based optimization of the system's operating strategy. The case study system in question was a three-reservoir system of the Mahaweli river development scheme in Sri Lanka (n.b. a part of the system used by Kularathna 1992 and Ampitiya 1995). The two main services the system was assumed to provide were energy generation and irrigation water supply. In general, the study showed that, for the four alternative inflow transition probability representations, the derived SDP operating strategies were virtually insensitive to the adopted characterization of river flow stochasticity. However, the authors emphasized that the simulated value of the objective function alone did not provide an adequate measure of the system's performance for the appraisal of different alternatives that had been analyzed. They used 18 different objective criteria to derive an array of the system's long-term operating strategies, each of which was subsequently appraised by simulation over the historical inflow record. The selected objective functions were generally based on either the maximization of the expected annual energy output or the minimization of the expected penalty for not meeting one or both of the given targets (i.e. energy and irrigation). The resulting simulated value of the average annual energy generation exhibited very little variability across all the analyzed alternatives. On the other hand, the average annual irrigation shortage did show some sensitivity to the changes of the objective criterion used. However, the authors introduced an additional performance indicator which proved extremely valuable for the evaluation of the derived operating strategies. Namely, they appraised the system's performance *reliability* by counting the total number of time steps when simulation resulted in the system's failure to meet the given energy and irrigation water supply targets, respectively. Consequently, the combined use of the introduced performance reliability indices, together with the expected annual energy generation and irrigation water supply estimates, did show that the simulated performance of the system was sensitive to the objective criterion used in optimization. However, the authors also noted that the ability to evaluate the sensitivity of the system's performance to different objective criteria depended on the right selection of the appropriate indices to measure those impacts.

The extensive study of Bogardi and Verhoef (1995) presented a more detailed analysis of the sensitivity of the operation of the same three-reservoir Mahaweli river development scheme in Sri Lanka. Using a wide range of different objective criteria, they optimized the operation of the system by means of SDP and subsequently appraised the derived operating strategies by simulation. In addition to the simulated objective criterion estimates, the comparisons were carried out on the basis of an array of both energy and irrigation related PIs. The set of PIs included (n.b. for each PI, separate estimates were derived for energy and irrigation):

1. *The number of failure months* was defined as the total number of time steps with the recorded failure to meet the desired target (i.e. failure mode).

2. *The number of failures* indicated the number of time intervals consisting of one or more consecutive failure months.

3. *The annual occurrence-based reliability* depicted the fraction of years without any failure months detected.

4. *The time based reliability* was defined as the fraction of the total time period when the system's operation was not exhibiting a failure.

5. The *quantity-based reliability* was defined as the ratio between the total system output and the total targeted output over the entire simulation period.

6. *The period of incident* depicted the mean duration of periods between two failure months.

7. *The repairability* described the average duration the system stayed in a failure mode.

8. *The mean vulnerability* was defined as the average magnitude of failure.

9. *The maximum vulnerability* equalled the largest magnitude of failure.

The adopted set of both energy and irrigation water supply PIs allowed a significantly more detailed assessment of the system's operation than the simulated objective criterion values could provide. Namely, the consideration of an array of performance measures provided a sound multiobjective framework for a comprehensive comparison of the proposed operating alternatives. However, the authors also emphasized that the appropriate selection of PIs should always be paid due attention because the choice of relevant PIs is highly problem-dependent and, in addition to the particular aspects of the system's purpose, their selection should always reflect the decision maker's attitude towards various aspects of risk and/or other performance attributes.

Burn and Simonovic (1996) analyzed the sensitivity of the operation of a single reservoir to changes in the hydrological regime considered to be caused by altered climatic conditions. They assumed two different climatic scenarios reflecting the anticipated conditions of potential "cool" (i.e. increased runoff in hydrological sense) and "warm" (i.e. reduced runoff) climatic regimes. The respective hydrological conditions were represented by two sets of one hundred 50-year-long synthetic river flow scenarios. The reservoir in question was serving three primary purposes: flood control, recreation and water supply. The sensitivity of the reservoir's operation was evaluated by simulation and the subsequent estimation of the basic statistics (i.e. the minimum, maximum, mean and standard deviation) of the three, reservoir purpose related, reliability indicators: *the flood control reliability* was defined as the frequency of downstream flow being less than the capacity of the downstream river reach; *the recreation reliability* depicted the frequency of the end-of-month reservoir storage being above the desired level; and *the water supply reliability* was defined as the frequency of the full supply attainment. The analyses resulted in an apparent sensitivity of the reservoir's operation to the anticipated climatic changes. Namely, upon the comparison of the respective reliability PIs it could be concluded that, by "switching" from a "cool" to a "warm" climatic scenario, the performance of the reservoir is likely to exhibit a reduction in the recreation and water supply reliabilities while showing an increase in the flood control reliability.

Nandalal and Bogardi (1996) used an array of quantity related PIs to evaluate the performance of a single water supply reservoir whose operating strategies were derived by optimization considering both the quantity and quality of reservoir releases. Specifically, they adopted seven PIs to investigate the impacts of different salinity reduction measures of reservoir releases on the quantitative aspects of the reservoir's performance:

1. *The quantity-based reliability* depicted the total amount of delivered water relative to the total targeted release.
2. *The time-based reliability* was defined as the probability that the reservoir would be able to meet the full demand.
3. *The average interarrival time* described the average duration the system was continuously failing to provide the desired service.
4. *The average interevent time* depicted the average duration the system was managing to maintain full supply (i.e. the average time between two failure events).
5. *The mean monthly deficit* measured the average magnitude of failures.
6. *The resilience* was defined as the longest duration of consecutive failure events.
7. *The maximum vulnerability* measured the magnitude of the most severe failure event.

The use of the above set of PIs provided a broad basis for the comparison among a number of proposed operating strategies and allowed the authors to evaluate the trade-offs between the quantitative and qualitative aspects of the reservoir's performance. The authors also emphasized the important role of performance reliability measures in building a multiobjective framework within reservoir management and planning analyses.

Bouchart (1996) combined the SDP backwards recursion with the neural network (NN) based comparison procedure to optimize the operation of a single irrigation water supply reservoir. The objective criterion used in optimization was to achieve the most preferred probability distribution of the expected cumulative supply deficit. To depict the desired objective criterion the author used risk curves defined as stepwise cumulative distribution functions of the probability that the future accumulated supply deficits will be greater than or equal to the prespecified threshold levels. Given that the risk curves were presented in a graphical form, it was not possible to use a conventional SDP enumeration search at a stage. Therefore, a neural network pattern recognition model was employed at each temporal stage of the SDP recursion to compare and to select the most preferred decision according to the respective rule curves. To compare the devised NN-SDP model with the conventional SDP optimization which pursued the minimum of the expected cumulative squared supply deficit, the author relied upon the simulated estimates of the reservoir's performance reliability, resilience and vulnerability (as defined by Moy et al. 1986). The results showed that the NN-SDP policies exhibited hedging and generally maintained higher storage volumes than the conventional SDP strategies. In addition, the NN-SDP policies resulted in higher reliability (i.e. had fewer periods with observed supply deficit) and higher resilience (i.e. had shorter sequences of repeated failures), although at the expense of the increased performance vulnerability (i.e. the maximum observed failure) and the expected annual supply deficit. Nevertheless, the author suggested that the NN-SDP coupling provided a good basis for the explicit incorporation of risk into the optimization process. Thus, through the process of training the neural network, the analyst could allow a direct consideration of the potential decision maker's attitude towards risk.

The presented applications of the use of different reliability, risk and other problem-specific performance indicators to evaluate the operation of reservoir systems clearly show their usefulness in reservoir operation and management studies. Furthermore, there are also four common points which emerge from all of the presented works:

1. They all emphasize the crucial role of simulation in reservoir operation analysis.

2. They all agree that the simulated objective function value only is not sufficient for a comprehensive assessment of a particular reservoir operating alternative.

3. Consequently, the use of multiple PIs allows the analyst to formulate a type of multiobjective framework for the analysis of reservoir operation problems, thus meeting the inevitable requirement of any real-world water resources management application.

4. There is no unique definition of a set of PIs to be used for any type of problem. It is rather the case that the analyst has to define the specific, problem-dependent PIs based on the relevant aspects of the system's performance.

A number of PIs is selected to compare different operating strategies of the case study system in this dissertation. The defined PIs do not depict the operating details of individual reservoirs. They rather describe the performance of the entire multiple-reservoir system with respect to the quantitative fulfilment of the water demand imposed upon the system (n.b. similar approach has also been adopted in Milutin and Bogardi 1995, 1996a and 1996b). The set of PIs used in this study includes a number of criteria defined to evaluate various facets of reliability, resilience and vulnerability of the system's operation. A detailed definition of the adopted PIs is given in Section 5.6.

3 THE CASE STUDY SYSTEM

The case study used as a basis for the analyses is a real-world seven-reservoir system located in the northern part of Tunisia (Figure 3.1). The seven reservoirs represent the backbone of the complex reservoir system envisaged within the project EAU 2000 (Agrar-und Hydrotechnik 1992). It should also be noted here that all the data used in this dissertation originate from the EAU 2000 project. The project defined a water master plan on the national level proposing strategic water development measures to be implemented in phases and completed by the year 2010. According to the project, the completion of the development of the complex reservoir system would ultimately include 14 large reservoirs and two major diversion weirs located over eight large river basins and interconnected into an intricate water supply reservoir network.

In addition to water supply as their primary purpose, all of the seven reservoirs selected for this study serve for flood protection whereas some of them also have hydropower generation facilities. However, this study concentrates only on the long-term operational aspects of water supply, thus taking no account of flood protection and energy generation purposes. As Figure 3.2 reveals, the reservoirs interact by means of both serial and parallel interconnections. The available release from a reservoir may be distributed both to the local water users within its own basin, as well as towards remote users situated in other basins. The complexity of feasible water allocation patterns is reflected in the fact that one reservoir may provide water for a number of demand centres while, at the same time, a single demand may be supplied by more than one reservoir. The envisaged reservoir/demand links, together with the active storage capacities of the seven reservoirs are given in Table 3.1.

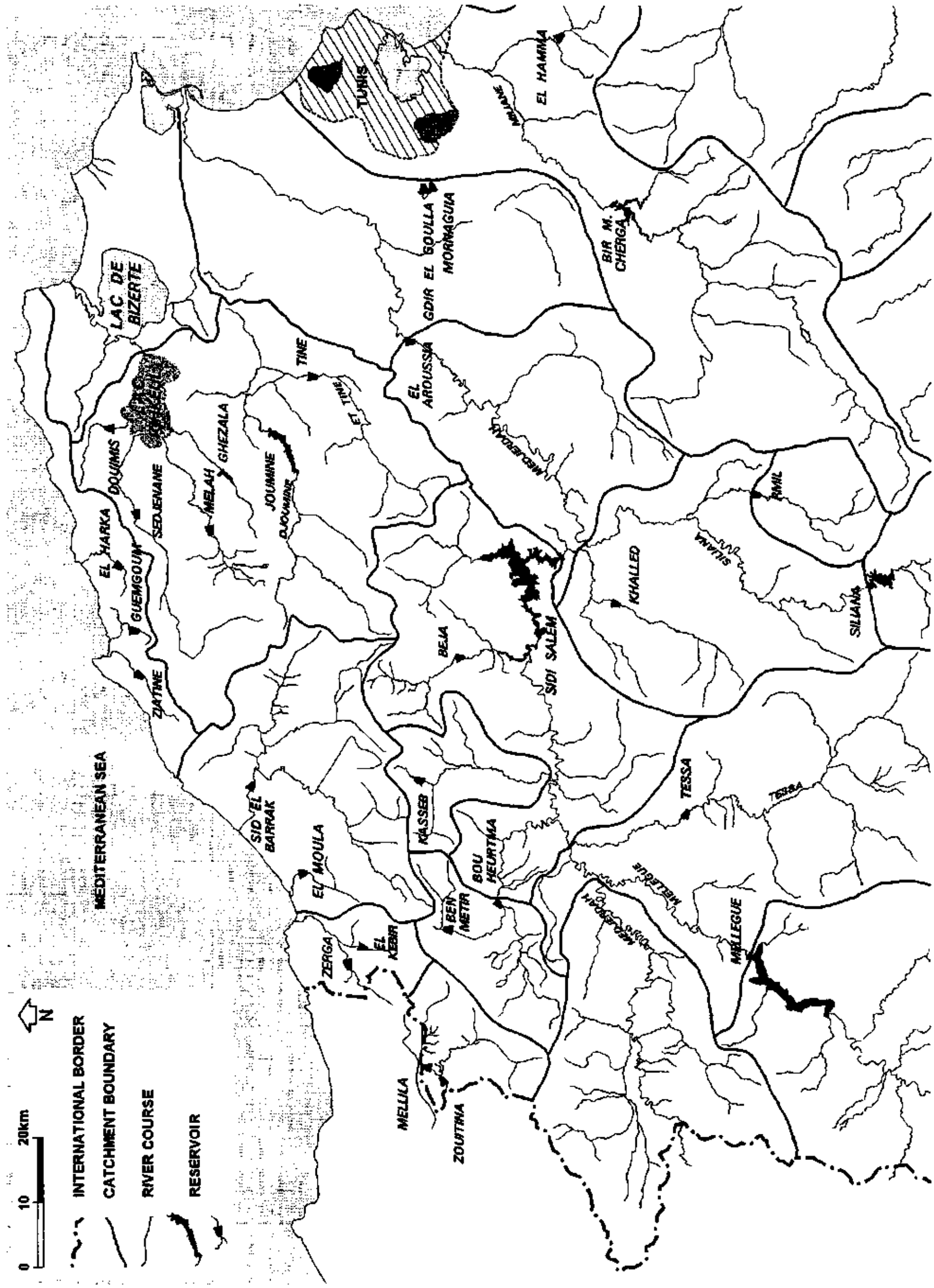

Figure 3.1 The map of the northern part of Tunisia

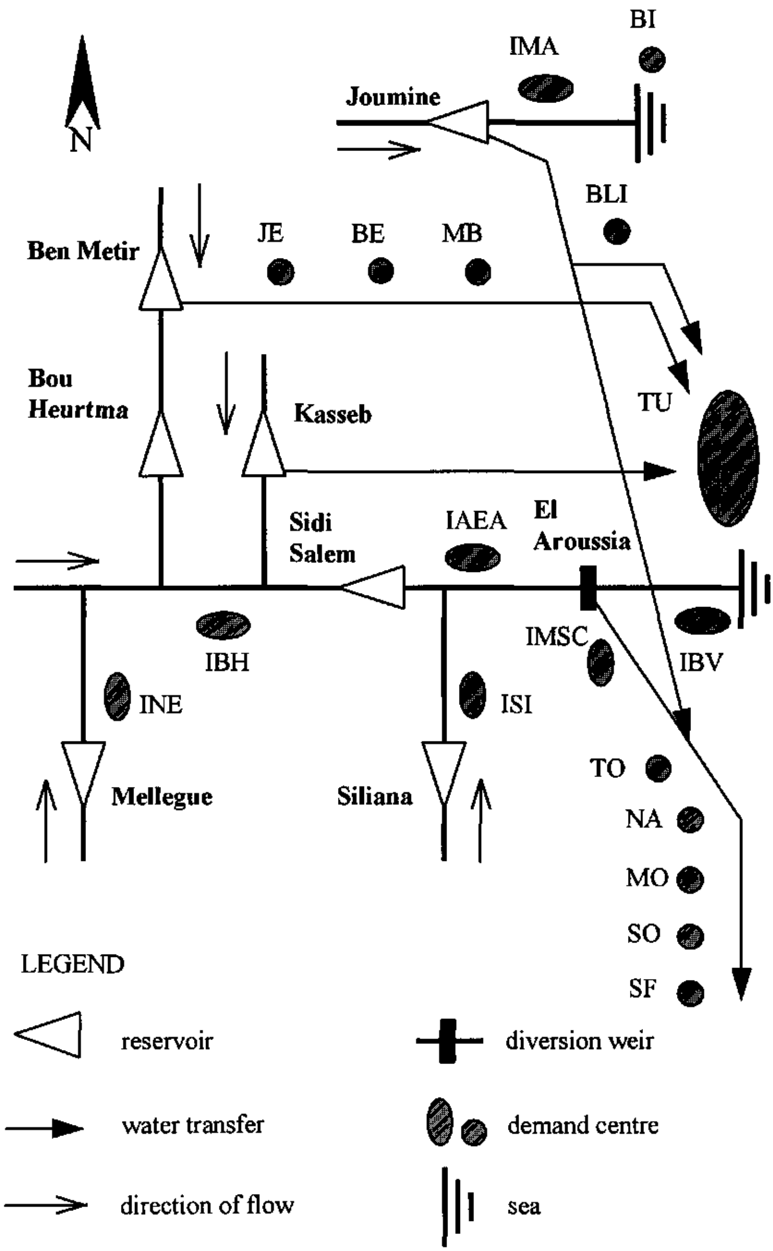

Figure 3.2 The seven-reservoir case study system

Table 3.1 Reservoir capacities and the associated demand targets

Reservoir	*In operation since*	*Capacity* $[10^6 m^3]$	*Targeted demand centres*
Joumine	1983	121.3	BI, IMA, BLI, TU, TO, NA, MO, SO, SF
Ben Metir	1954	44.2	BE, JE, MB, TU
Kasseb	1968	72.2	TU
Bou Heurtma	1976	102.5	IBH
Mellegue	1954	89.0	INE, IBH
Sidi Salem	1981	510.0	IAEA, TU, TO, NA, MO, SO, SF, IBV, IMSC
Siliana	1988	61.5	ISI, IAEA, TU, TO, NA, MO, SO, SF, IBV, IMSC

Time series of monthly inflow volumes for the seven reservoirs, as provided by the EAU 2000 project, cover a period of 44 years (i.e. 1946-89). The average annual inflow to the entire system is estimated at 963.834 ($10^6 m^3$/year) and the total active storage of the seven reservoirs amounts to 1000.7 ($10^6 m^3$). However, the great variability of inflows under the prevailing semi-arid climatic conditions tends to constrain the utilization of the available resources. The magnitude of river flow variability can be observed from the figures derived from the available inflow data and presented in Tables 3.2 and 3.3. The two tables compile the historical mean incremental inflow data on monthly and annual scales for individual reservoirs as well as the respective total flow availability for the entire system. Namely, the coefficient of variation of mean incremental annual inflows for the seven reservoirs varies between 0.481 for Kasseb and 0.968 for Siliana. On the system level, this statistic is estimated at 0.465. As to the seasonal flow variability, the major portion of the system inflow (i.e. 84.6%) arrives in the period October-April whereas the remaining 15.4% of the total are distributed over the period May-September. The three driest months on the record are June, July and August, jointly contributing only 6.3% of the total mean annual system inflow.

Table 3.2 The reservoirs' mean monthly incremental inflows (period 1946-89) $[10^6 m^3/\text{month}]$

Reservoir	*Sept.*	*Oct.*	*Nov.*	*Dec.*	*Jan.*	*Feb.*	*March*	*Apr.*	*May*	*June*	*July*	*Aug.*
Joumine	0.967	4.799	12.295	24.033	30.715	28.052	20.357	8.145	2.852	0.543	0.110	0.093
Ben Metir	0.287	0.864	2.925	6.825	8.974	9.445	7.224	4.189	0.920	0.303	0.181	0.187
Kasseb	0.682	1.551	3.699	7.956	11.104	8.136	6.935	4.897	1.643	0.687	0.587	0.512
Bou Heurtma	0.792	2.023	5.955	14.513	18.830	19.477	15.344	9.734	2.977	0.995	0.680	0.694
Mellegue	24.965	34.384	12.574	10.395	9.351	9.490	12.170	16.396	15.302	13.975	5.262	11.594
Sidi Salem	10.587	21.818	25.553	53.054	88.203	76.697	68.194	45.242	19.533	7.563	4.567	8.176
Siliana	3.456	5.610	3.431	3.690	5.164	5.157	5.548	4.484	2.496	1.282	1.049	1.732
System	41.736	71.049	66.432	120.466	172.341	156.454	135.772	93.087	45.723	25.348	12.436	22.988

Table 3.3 Basic statistics of the annual inflows for the seven reservoirs (period 1946-89)

Reservoir	*Range* [10^6m^3/year]	*Mean* [10^6m^3/year]	σ [10^6m^3/year]	C_v [-]
Joumine	20.100 - 300.720	132.959	79.494	0.598
Ben Metir	3.740 - 111.480	42.325	22.537	0.532
Kasseb	7.840 - 141.580	48.389	23.264	0.481
Bou Heurtma	9.360 - 245.320	92.015	48.494	0.527
Mellegue	53.640 - 804.850	175.859	125.335	0.713
Sidi Salem	152.778 - 1300.359	429.188	234.077	0.545
Siliana	7.520 - 201.960	43.099	41.715	0.968
System	335.261 - 2504.679	963.834	448.020	0.465

In addition to inflow variability, the efficient exploitation of the available water is further limited by water losses, mainly due to evaporation. For instance, the mean monthly elevation losses due to evaporation estimated for the entire system vary between 24 mm/month in January and 172 mm/month in July (Table 3.4).

Table 3.4 The estimated mean monthly elevation losses due to evaporation [mm/month]

Reservoir	*Sept.*	*Oct.*	*Nov.*	*Dec.*	*Jan.*	*Feb.*	*March*	*Apr.*	*May*	*June*	*July*	*Aug.*
Joumine	132	66	34	27	25	22	36	47	105	159	227	204
Ben Metir	111	72	44	33	31	31	53	64	99	130	162	152
Kasseb	111	55	29	22	21	18	30	40	89	135	191	172
Bou Heurtma	79	51	25	22	20	20	32	33	61	99	131	125
Mellegue	99	57	32	21	21	25	46	61	99	132	166	155
Sidi Salem	120	77	48	36	33	34	57	69	107	141	176	164
Siliana	88	59	34	25	20	22	33	42	75	114	148	129
Average	106	62	35	27	24	25	41	51	91	130	172	157

The total estimated demand imposed upon the system is 469.504 (10^6m^3/year). This amounts to 48.7% of the mean annual inflow to the system. However, the unfavourable temporal and spatial distribution of demands and available inflows still poses a considerable obstacle for successful operation of the system. For instance (cf. Table 3.5), the driest three-month period from June to August is characterized by the total system demand of 210.155 (10^6m^3), which is 44.7% of the total annual demand. On the other hand, the mean available inflow volume in the same period reaches only 60.772 (10^6m^3), which amounts to 6.3% of the mean annual inflow into the system (Table 3.2).

According to the EAU 2000 project, water demand imposed upon the system is partitioned among 18 individual demand centres (Table 3.5). There are four distinctive water uses considered: drinking water demands of various municipal areas, a specific drinking water demand of large tourist centres along the Mediterranean coast, irrigation demands and a recharge of one natural lake (Lac Ichkeul) located in the north of the country. The major water users in the system are the drinking water demand TU, the tourist centres' water demand TO, the requirement for the natural lake recharge BLI and the IAEA, IBV, IMSC, IBH and ISI irrigation demands. These eight demand centres constitute 94.1% of the total demand imposed upon the system.

As Table 3.1 reveals, a considerable number of the demand centres gets water from more than one reservoir. Namely, in four cases there are two reservoirs supplying a demand centre (i.e. irrigation water demands IBH, IAEA, IBV and IMSC), whereas five demand centres (i.e. drinking water demands NA, MO, SO, SF and the tourist centres' water requirement TO) receive water from three reservoirs, and only one user (i.e. drinking water demand TU) gets water from five reservoirs. These 10 demands amount to 86.5% of the total annual demand. The remaining eight demand centres depict reservoirs' local users (n.b. 13.5% of the total demand imposed upon the system): irrigation schemes IMA, INE and ISI; drinking water demands BI, JE, BE and MB; and water requirements for the recharge of the Lac Ichkeul lake (BLI).

Table 3.5 Monthly water demands for the 18 demand centres [$10^6 m^3$/month]

Demand	*Sept.*	*Oct.*	*Nov.*	*Dec.*	*Jan.*	*Feb.*	*March*	*Apr.*	*May*	*June*	*July*	*Aug.*
TU	4.634	4.538	4.305	4.181	4.529	4.048	4.515	4.691	4.977	5.234	5.734	5.738
MO	0.101	0.090	0.082	0.079	0.069	0.065	0.084	0.094	0.100	0.110	0.129	0.128
NA	0.116	0.099	0.086	0.081	0.080	0.073	0.090	0.098	0.108	0.119	0.145	0.150
SO	0.290	0.275	0.252	0.229	0.205	0.190	0.250	0.264	0.274	0.296	0.355	0.372
SF	0.762	0.654	0.626	0.567	0.544	0.484	0.615	0.675	0.715	0.739	0.766	0.801
BI	0.245	0.233	0.217	0.215	0.231	0.197	0.220	0.239	0.250	0.250	0.278	0.289
JE	0.108	0.103	0.092	0.090	0.096	0.084	0.096	0.099	0.104	0.106	0.105	0.130
BE	0.136	0.125	0.120	0.119	0.105	0.108	0.128	0.128	0.137	0.147	0.166	0.162
MB	0.039	0.036	0.034	0.034	0.030	0.031	0.037	0.037	0.039	0.042	0.047	0.046
IMA	0.172	0.188	0.228	0.000	0.000	0.138	0.644	0.489	0.934	1.132	0.771	0.714
BLI	0.122	0.609	1.913	3.874	4.741	4.147	2.943	1.211	0.352	0.063	0.015	0.011
TO	1.624	1.459	0.914	0.777	0.716	0.765	1.138	1.211	1.388	1.531	1.892	2.077
IAEA	2.881	2.131	1.391	0.000	0.000	0.235	2.287	4.820	7.488	9.350	10.001	7.519
IBV	1.250	0.627	0.305	0.002	0.002	0.003	0.154	0.768	1.813	2.736	3.089	2.715
IMSC	12.784	5.420	2.258	0.606	0.505	2.020	6.586	7.675	13.132	21.709	26.502	25.250
INE	0.204	0.079	0.060	0.000	0.000	0.000	0.070	0.119	0.224	0.487	0.654	0.585
IBH	20.154	10.369	6.283	0.000	4.363	6.611	7.790	16.018	10.660	16.661	21.693	13.170
ISI	2.360	1.308	0.676	0.000	0.042	0.975	0.862	1.770	4.286	5.619	6.227	5.380
Total	47.982	28.343	19.842	10.854	16.258	20.174	28.509	40.406	46.981	66.340	78.578	65.237

The largest reservoir in the system, Sidi Salem, is situated on the Medjerdah river and represents the backbone of the seven-reservoir system. Its capacity amounts to 51.0% of the total system active storage while, on an average annual scale, its incremental inflow reaches 44.5% of the total inflow to the system. Sidi Salem also regulates and utilizes any excess release that may originate from the three reservoirs situated directly upstream: Kasseb, Bou Heurtma and Mellegue. The users associated with this reservoir include almost all of the major demand centres in the system. Some of the associated demand centres are located immediately downstream of the reservoir (i.e. IAEA, TU and IBV), whereas the rest of them (i.e. TO, NA, MO, SO, SF and IMSC) get water via a man-made Medjerdah-Cap Bon canal which departs from the diversion weir El Aroussia situated on the Medjerdah river downstream of Sidi Salem (cf. Figure 3.2).

Siliana is a small reservoir located on the river Siliana in the Medjerdah basin. Although the inflow to this reservoir is quite poor (i.e. 4.5% of the total annual inflow into the system), the list of potential Siliana users is perhaps surprisingly long: ISI, IAEA, TU, TO, NA, MO, SO, SF, IBV and IMSC. Nevertheless, the main purpose of Siliana is to provide water for the local irrigation scheme ISI. To a certain extent, and besides its main purpose, Siliana is expected to try to compensate for potential supply shortage that may occur in the operation of other reservoirs supplying the common demands on the list of Siliana's users. Thus, a part of Siliana release may also be conveyed through the Medjerdah-Cap Bon canal.

Unlike Siliana, the Joumine reservoir can contribute significantly towards the supply of all the associated demand centres. It is located on the Joumine river in the far north of the country. This is the only reservoir in the system which is not located in the immediate Medjerdah river basin. Its mean annual inflow amounts to 13.8% of the total system water resource. In addition to the three local users (BI, IMA and BLI), Joumine plays an important role in providing water for the remaining remote demand centres (TU, TO, NA, MO, SO and SF) whom it supplies jointly with other reservoirs from the system. The remote users get water allocated from Joumine via a pipeline which, at its end, discharges into the Medjerdah-Cap Bon canal.

The Bou Heurtma reservoir serves primarily for irrigation water supply of its local demand IBH. It is located on the Bou Heurtma river, a tributary of the Medjerdah, with the mean unregulated inflow to the reservoir of 9.5% of the total annual inflow into the system. Furthermore, Bou Heurtma can accommodate and regulate any excess release that may be produced by its upstream counterpart Ben Metir. In addition to its consumptive demand IBH, Bou Heurtma may contribute to the increase of the inflow to Sidi Salem.

The Mellegue reservoir is located on the Mellegue tributary of the Medjerdah river. The mean unregulated inflow to Mellegue amounts to 18.2% of the total system inflow. However, this is the reservoir with the far lowest reservoir volume factor among all the reservoirs in the system. Namely, its capacity hardly reaches 50.6% of the respective mean annual inflow. As a comparison, the next higher volume factor is that of Joumine (0.912) whereas the highest one is related to Kasseb: 1.492. As to the associated water users, Mellegue provides water for the local irrigation scheme INE and, jointly with Bou Heurtma, covers the IBH irrigation demand. Like Bou Heurtma, Mellegue can also contribute to the increase of Sidi Salem's inflow.

The Kasseb reservoir is situated on the Kasseb river in the Medjerdah basin. Its mean annual incremental inflow is at the level of only 5.0% of the total system inflow. The sole purpose of this reservoir to provide, via a pipeline connection, drinking water for the TU demand centre. Any excess release from Kasseb may be used to cover the supply shortage of Sidi Salem.

Ultimately, Ben Metir is the smallest reservoir in the system with the equally small incremental inflows (i.e. only 4.4% of the total system inflow). It is located on the El Lil river in the immediate basin of the Bou Heurtma river. Ben Metir contributes primarily towards drinking water supply of its local users JE, BE and MB and, via a pipeline, provides water for the TU demand. Since it is located upstream of Bou Heurtma, if any surplus of water is available, Ben Metir is expected to compensate for potential shortage of Bou Heurtma's water deliveries.

The above description of the system also indicates the existence of a number of water conveyance structures. Although each of those is associated with its respective discharge capacity (Table 3.6), this aspect of the system operation is not taken into account in this study. This assumption has been made because the existing capacities of the conveyance structures mentioned in this study were generally well over the maximum discharges expected to be flowing via those structures. In addition, the primary objective of this study was to devise and to appraise a number of mathematical models for the long-term operational analyses of multiple-reservoir systems in general, and the case study system in particular, thus taking no account of those aspects of the case study system performance which are related to the real-time operation of the system under present operating conditions.

Table 3.6 The capacities of the existing water conveyance structures

Water conveyance structure	*Capacity*	
	[m^3/s]	[$10^6 m^3$/month]*
Medjerdah-Cap Bon canal (MCB)	16.0	42.163
Joumine-MCB pipeline	4.0	10.541
Kasseb-Tunis pipeline	1.1	2.899
Ben Metir-Tunis pipeline	1.0	2.635

* estimated assuming the average number of days in a month to be 30.5

4 PROBLEM FORMULATION

The main objective of this study is to appraise the applicability of a type of decomposition approach to the planning and management of complex water resource systems. In this particular case, the focus of the work is limited to the optimization of the long-term operating strategy of a multiple-reservoir water supply system. The study identifies a series of relevant aspects of, and the inherent difficulties posed by such a type of optimization problem and, with regard to the chosen optimization approach, proposes alternative means to tackle them. In addition, it presents the development and application of a novel method in the field of reservoir operation. Namely, a genetic algorithm (GA) model has been devised to address the problem of water allocation within a multiple-reservoir-multiple-user water supply system.

In the most general sense, the problem under consideration involves a multiple-reservoir system which provides water for a number of users. The reservoirs may be situated in a number of neighbouring and/or distant river basins. The interaction among the reservoirs may include both serial and parallel interconnections allowing water to flow along a natural water course downstream of a reservoir or to be transferred from one basin to another, both towards demand centres and other reservoirs. In addition, any one reservoir may provide water for a number of users while, at the same time, a single demand may be covered by more than one reservoir. Given such a system configuration, the main task is to derive the best achievable long-term operating strategy of the system towards meeting the imposed water demands. The fact that long-term operating policies are pursued brings about the inevitable requirement for the consideration of uncertainty inherent in the operation of any water resource system. With no intention to diminish the relevance of the impact the stochasticity of other factors has on the operation of a water supply system (i.e. to name just a few, those include the economic and technological development and, largely dependent on the former two, the development of water demands), the optimization approach proposed in this study takes into consideration only the stochasticity of reservoir inflows. With regard to the temporal discretization, the analyses are limited to monthly time steps assuming the stationarity of the stochastic properties of monthly river flows (i.e. the probability distribution of a stochastic process is not changing over time). Monthly water demands, on the other hand, are assumed to be deterministic and considered to be recurring in annual cycles. Since the chosen monthly time base is long enough the required time for the released water to travel between any two serially linked reservoirs and any reservoir and the respective demand centres can safely be neglected.

The kernel of the adopted operations research methodology for the analysis of the operation of a complex reservoir system falls into the group of decomposition methods. In essence, decomposition approaches break down a complex optimization problem into a series of simpler tasks and, subsequently, employ an iterative derivation procedure to arrive at the respective solution. One common characteristic of almost all the approaches of this kind is, however, that the global optimality of the obtained solution cannot be guaranteed. It is, therefore, necessary to emphasize that the starting point of this study was not to pursue a methodology which would guarantee the derivation of the global optimum operating strategy at any cost, but rather to try and identify a relatively simple and transparent, however yet efficient and effective approach for the analysis of the operation of complex reservoir systems. Consequently, any method which meets the latter requirements and, at the same time, offers the improvement in the operation of a reservoir system relative to other methods or the existing operating rules, holds higher chance of becoming a candidate for entering the world of reservoir management practice (cf. Rogers and Fiering 1986, Loucks 1992 and Parker et al. 1995).

The adopted methodology for the optimization of the long-term operation of a multiple-reservoir system combines a physical decomposition of the system into individual reservoir subsystems, stochastic dynamic programming (SDP) optimization of a single reservoir operation, simulation and hierarchical release allocation among each reservoir's water users. In addition, the above approach is coupled with a GA-based model, which is applied prior to the decomposition model to derive the best achievable allocation of water resources within the system. The following sections introduce each of the employed techniques, together with the respective problems they deal with and the reasoning for the particular choice of method.

4.1 Dimensionality of the Optimization Problem

The case study system presented in Chapter 3 exhibits a number of features which are common to many multiple-reservoir water supply systems. These characteristics are also among the most frequent factors which prohibit a direct application of almost any stochastic optimization technique to the analysis of the operation of such a system. Given the particular choice of stochastic dynamic programming as the optimization method used in this study (n.b. the reasons for selecting SDP are given in the following section), the most profound computational and modelling difficulties for a straightforward optimization of the operation of such a system arise from the dimensionality of the problem. Namely, the number of dimensions of the state space in the direct optimization of the entire system's operation is twice the number of reservoirs in the system (i.e. storage volume and inflow state variables must be specified for each of the reservoirs). Recalling that SDP is essentially a discrete enumeration technique, this results in the number of possible discrete system states at a single stage (i.e. time period) being:

$$NS_t(N_r) = \prod_{i=1}^{N_r} n_{s,i,t} \cdot n_{q,i,t}, \quad \forall t \tag{4.1}$$

where

N_r	the number of reservoirs in the system;
$n_{s,i,t}$	the number of representative storage volume classes for reservoir i at stage t;
$n_{q,i,t}$	the number of representative inflow classes for reservoir i at stage t.

Furthermore, and without any loss of generality, if the decision variable in such an SDP formulation is a vector of storage volumes in the reservoirs at the beginning of the succeeding stage, the number of possible system state transitions to be examined at each stage t becomes:

$$NST_t(N_r) = \prod_{i=1}^{N_r} n_{s,i,t} \cdot n_{q,i,t} \cdot \prod_{i=1}^{N_r} n_{s,i,t+1}, \quad \forall t \tag{4.2}$$

Even assuming that $n_{s,i,t}$ and $n_{q,i,t}$ both equal a fairly low constant value n for all reservoirs i along all the stages t, the numbers of discrete state representations and the corresponding possible state transitions at each stage still remain prohibitively high, i.e.

$$NS_t(N_r) = n^{2N_r}, \quad \forall t \tag{4.3}$$

$$NST_t(N_r) = n^{3N_r}, \quad \forall t \tag{4.4}$$

For instance, if the number of representative discrete values for the storage and inflow state variables is set to only n=3 and the number of reservoirs is N_r=7 as in the case of the case study system used in this work, the number of discrete state representations becomes $NS_t(7)$=4,782,969 while the number of possible state transitions equals $NST_t(7)$=10,460,353,203 at each stage t. Obviously, resorting to such a coarse discretization of storage and inflow state spaces of individual reservoirs would be both too imprecise to reflect the intricacy of the reservoirs' operation and computationally untenable. With regard to storage discretization, Klemeš (1977) substantiated theoretically and provided a numerical demonstration that a too coarse storage representation could severely impede the accuracy of the analyses. The author did point out, however, that the minimum number of discrete storage classes of a reservoir in a dynamic programming formulation was three, although with a reservation that such a coarse discretization was not sufficient to guarantee significant accuracy of the results. Similar conclusions were drawn by Goulter and Tai (1985) who, using a test case of a single hydropower reservoir, showed the impact of storage discretization in SDP on the probability distribution of the resulting reservoir storage volume. The authors found out that, for the chosen test case, the storage discretizations containing less than nine discrete classes resulted in probability distributions of the reservoir storage volume which exhibited an unrealistic positive skewness (i.e. the distribution tail extended towards high storage volume classes). This feature, completely contradictory to the existing reservoir operating objectives and experience gained from practice, was attributed to the storage state being "trapped" in the region of lower storage classes due to very large storage class intervals.

The existence of multiple users further increases the complexity of the optimization problem. As it can be seen from the description of the case study system (Chapter 3), each reservoir may supply a number of demand centres while, at the same time, a single demand may be associated with more than one reservoir. This feature may be seen as an indicator that the whole problem falls within the realm of multiobjective analysis. However, since all the demands considered in this study represent consumptive water uses and can therefore be described by commensurate quantities the problem in hand can be perceived as a single-objective optimization task. Nevertheless, the existence of multiple demands further complicates the problem by making the optimum operating strategy of the system strongly dependent on the distribution of the demand load a group of reservoirs shares towards supplying each of their common demand targets. In other words, not only the total release volumes of individual reservoirs are to be optimized but the optimum distribution of those releases among the associated demands has to be determined for each of the reservoirs in the system. Consequently, the solution to the problem in hand could be sought by a two-level optimization directed towards the derivation of the optimum distribution of demand loads among the reservoirs in the system and the identification of the corresponding optimum operating policies of the individual reservoirs.

The necessity to consider the stochasticity of river flows brings about an additional strain to the formulation of the optimization methodology. On the one hand, SDP can easily meet this requirement but, as mentioned earlier, a potential SDP formulation faces severe limitations due to the dimensionality of the problem (e.g. Bogardi and Nandalal 1988). On the other hand, as shown in Section 2.1.2, it can be said that linear programming is somewhat less restricted by dimensionality. However, while the linearity requirement posed by LP can be relatively easily met by using piecewise linearization to approximate non-linear functions, the issues regarding simultaneous consideration of multiple reservoirs and time steps, as well as the stochasticity pose a much more complex problem. Namely, an LP formulation of multiple-reservoir-multiple-time step stochastic optimization problems requires thousands of decision variables and constraints making its application unacceptably expensive (e.g. Gablinger and Loucks 1970; Loucks and Falkson 1970; Roefs and Guitron 1975). There is, however, an LP-based approach which can, albeit only partially, eliminate this problem. Namely, Kuczera (1989) and Karim (1997) used similar formulations of the network linear programming approach for a straightforward optimization of an entire multiple-reservoir system operation. However, in both cases, the problems had to be viewed as deterministic due to the limitations imposed by the method used. Consequently, if compared to the equivalent stochastic solution, the resulting deterministic performance of the system is an optimistic estimate of the future operation of the system. This is entirely due to the fact that purely deterministic solutions, if used to appraise the long-term operation of a system, tend to overestimate the benefits and, at the same time, to underestimate the losses associated with the anticipated future performance of the system. The only way to partially overcome this setback would be to tackle the issue of stochasticity in an implicit fashion. That is, a deterministic optimization problem could be solved for a number of equally likely synthetic inflow scenarios and the long-term operating strategy could thereafter be derived by applying regression analysis to the derived set of deterministic policies. However, besides being a deterministic method, the network linear programming still suffers from "dimensionality ailments". That is, the number of variables and constraints required to describe a multiple-time step operation problem of a multiple-reservoir system is *still* exceptionally high. As an illustration, the network linear program of Karim (1997) had almost 7000 nodes and little over 17000 arcs representing the operation of a six-reservoir system over 240 time periods.

All of the above impediments, or at least some of them, have frequently been stated as the principal reasons which force the analysts to resort to some type of decomposition within a formulation of an optimization methodology for the operation analysis of multiple-reservoir systems (e.g. Chapter 2: Nopmongcol and Askew 1976; Haimes 1977, 1982; Turgeon 1980, 1981; Yeh 1985; Djordjević 1993; Archibald et al. 1997). The decomposition approach tested in this study is known as sequential decomposition. While a detailed description of the adopted decomposition method, and the variations thereof, is given in Section 5.1, the following passage includes a formulation of the basic principles of the approach.

The selected sequential decomposition approach is an iterative procedure which, within the computational process, describes a complex system as a set of individual reservoirs. The iterative optimization process repeats the principal computational cycles until the stabilization and no further significant improvement of the system return are detected. Within one iterative cycle, each reservoir's operating strategy is optimized independently from the remaining part of the system. The order upon which the reservoirs enter the computational cycle is largely dependent on their physical position in the system. Two basic ordering schemes are used in this study. The first one starts with the uppermost reservoir in the system, with each subsequent selection being made by moving to the next downstream reservoir. The other scheme assumes the reverse order:

it starts from the most downstream site and proceeds in an upstream direction. The optimization and evaluation of each reservoir's operation is executed through a six-step procedure:

1. *Inflow estimation*: The time series of the total inflow into a reservoir is estimated by accumulating all the flows entering the reservoir. These include the reservoir's own incremental inflows and the non-utilized releases from the reservoirs situated directly upstream of it.

2. *Demand estimation*: All the individual demand components associated with the particular reservoir are aggregated into a single composite demand.

3. *Optimization*: The operating strategy of the reservoir is optimized towards meeting the imposed composite demand.

4. *Simulation*: The derived operating strategy is evaluated by simulation resulting in the time series of total releases (i.e. consumptive and spilled) from the reservoir.

5. *Release allocation*: The releases resulted from simulation are allocated to individual users.

6. *Supply deficit estimation*: Upon allocating the available release, the remaining uncovered demands of its individual water users and the total supply deficit of the reservoir are estimated.

The reason why such a complex analysis has to be applied to each reservoir's operation problem is entirely due to the decomposition of the system. Namely, by decomposing a system into individual reservoirs the intricate operating interactions among the reservoirs cannot be modelled accurately and must be approximated in some way. In fact, these interactions are the main cause of the increase of the problem dimensionality and thus are the reason for the adoption of system decomposition. Therefore, the choice of decomposition brings about the need for solving or, better to say, approximating the solution of the two major problems:

1. In reality, reservoirs in series may interact in such a way that upstream reservoirs contribute to the increase of the downstream reservoir's inflow in those periods when the downstream reservoir experiences shortage in the available water for meeting its demands. This type of interaction can precisely be modelled when the applied optimization method considers all the reservoirs simultaneously. However, it cannot be maintained if the system is decomposed into individual reservoir units. Therefore, as it will be shown in detail in Chapter 5, the adopted decomposition methodology makes use of a specific formulation of the above described inflow aggregation, optimization, simulation and supply deficit estimation steps to approximate this process. In this respect, one basic principle needs to be explained here. That is, the average monthly supply deficits of a reservoir estimated upon the derived simulated total releases are, in turn, used as an additional demand component associated with all the reservoirs situated immediately upstream, i.e. those reservoirs which can contribute to the increase of the inflow of the reservoir in question. Consequently, the subsequent optimization of the operation of each of the immediate upstream reservoirs is expected to result in such operating policies which would provide additional release volumes to augment the inflow into the downstream reservoir in those months when the supply deficit has occurred.

2. Similarly, the simultaneous optimization of the entire system's operation can be formulated in such a fashion so as to be able to derive the optimum distribution of releases

among groups of reservoirs towards their common demand targets. However, by decomposing the system into individual reservoirs, this aspect of the reservoirs' joint operation cannot be explicitly considered. To a certain degree, this is the major shortcoming of the adopted decomposition approach. To provide an alternative approximation of the solution to this problem, the devised decomposition method makes use of a rule which is often used in reservoir management practice. Namely, the employed principle combines the sequence of reservoir selection in a computational cycle and the hierarchical arrangement of demands associated with a reservoir to approximate the solution to this problem (cf. Section 4.4). This approach, however, has its own limitations and a separate method is proposed to derive the best release distribution for a multiple-reservoir water supply system (Section 4.5).

An apparent feature of this decomposition approach is that, after completing the optimization and the assessment of each reservoir's operation, the demand records for the remaining part of the system must be regularly updated. This represents the essential part of data interchange within one iteration. In addition to the necessity to maintain the demand records "up-to-date", the information interchange within a single iteration and that between two consecutive iterative cycles also include the individual reservoir's supply shortage and non-consumptive release records. Which of these two estimates is to be used within an iteration and which needs to be considered as an "iteration-to-iteration" data flow depends on the chosen decomposition approach (n.b. a detailed discussion about data interchange is given in Section 5.1).

Ultimately, it is fully recognized that the proposed decomposition approach cannot guarantee the derivation of the global optimum operating strategy of a reservoir system. However, despite the fact that the solutions derived by the method are generally local optima, it is believed that the presented concept of system decomposition, in conjunction with the proposed release distribution algorithm, offers a valuable alternative approach for the planning and management of multiple-reservoir water supply systems. The major advantages of the method are the transparency and flexibility of its description of a multiple-reservoir system. Namely, a system is decomposed into its elementary building blocks (i.e. reservoirs) whose individual operating strategies are subsequently expressed in their most basic form, i.e. being independent of the states and operating policies of other reservoirs in the system. In addition, the determination of reservoir ordering within one computational cycle is not governed by any strict rules. It is rather left to the analyst's discretion and expertise to choose and to test any of the possible orderings he/she may find relevant and suitable for the problem in question.

4.2 Optimization

As it has repeatedly been pointed out in the previous section and in Chapter 2, SDP compares favourably to other methods if the optimization problem includes variables whose stochasticity cannot be neglected. However, the application of SDP is severely limited by the dimensionality of the multiple-reservoir operation problem considered in this study. The proposed coupling of decomposition and SDP offers a simple and efficient means to eliminate the dimensionality restrictions a straightforward application of SDP would bring about (cf. Equations 4.1 and 4.2 in Section 4.1) and, at the same time, enables full utilization of the advantages SDP exhibits over linear and non-linear methods with regard to reservoir operation problems (cf. Section 2.1.2). Namely, by decomposing a system into individual reservoirs the SDP-based optimization is applied to a single-reservoir operation problem, which poses no computational difficulties with respect to the storage, memory and execution time requirements. The main characteristics which make SDP particularly suitable for the optimization of a single-reservoir operation are (n.b. a broader discussion on this issue is given in Section 2.1.2):

1. The solution to a problem of a single-reservoir operation optimization is composed of a sequence of decisions (in a deterministic case) or decision functions (in a stochastic case) which identify the reservoir's storage or release to be made over a number of consecutive time steps (i.e. stages). In this respect, DP qualifies as a strong candidate because it is essentially a solution seeking strategy perfectly suitable for sequential decision problems. Namely, DP breaks down a complex sequential decision problem into a set of single-decision subproblems. Following the Bellman's principle of optimality (Bellman 1957:83) the optimum decision sequence is derived by a recursive estimation of the objective function value over the stages. Equation 4.5 represents the Bellman's backward DP recursion for a deterministic case (n.b. without any loss of generality, the presented equation assumes that the objective is to minimize the aggregate of a certain cost incurred by the set of decisions made over the stages):

$$f_n^*(s_n) = \min_{x_n}\{C(s_n, x_n) + f_{n-1}^*(s_{n-1})\}, \quad \forall s_n; \quad x_n \ feasible \tag{4.5}$$

where

s_n, x_n — the state of the system and the unknown optimal decision at stage n, respectively; the relationship between the state of the system and the decision to be made is described by the *state transformation equation*:

$$s_{n-1} = t(s_n, x_n) \tag{4.6}$$

$C(s_n, x_n)$ — the immediate cost resulting from making the decision x_n at stage n;

$f_n^*(s_n)$ — the suboptimal aggregate of the objective function accumulated over all the stages starting from the first one and up to and including the stage n.

Thus, the DP recursive relationship requires that only the present state of the system and the accumulated objective function value associated with that state need to be known to be able to estimate the overall aggregate of the objective function value resulting from the decision made at the present stage. In other words, it is not important how the system may have reached the present state. It is only necessary to know the accumulated objective function value associated with the optimum subset of decisions which have led to the present state of the system.

2. In addition to being monotonically non-decreasing over stages (i.e. temporal or spatial decomposition of the problem), the objective function used in both deterministic and stochastic DPs must meet only one specific requirement, which stems directly from the recursive nature of the DP formulation. It states that the objective function must be separable with respect to the optimization stages. In other words, a function of n variables $f(x_1, x_2, \ldots, x_n)$ is separable if it can be written as a sum of n individual functions, each having only one independent variable:

$$f(x_1, x_2, \ldots, x_n) = f_1(x_1) + f_2(x_2) + \ldots + f_n(x_n) \tag{4.7}$$

In the light of the reservoir operation problem, this means that the objective function has to be formulated in such a way that its incremental value at a certain stage can be estimated on the basis of the knowledge of the reservoir's state and decision at that stage only. In general, this hardly makes any problem due to the fact that the objective functions used in reservoir operation are usually defined as the accumulated benefit or cost, or the expectations thereof, resulting from the decisions made at each time step of the time period under consideration. In addition to the separability condition, no further requirements on the type of the objective function and constraints used to describe the optimization problem are imposed by DP (e.g. linearity, differentiability, etc.). This feature is particularly important because it allows the application of DP to problems involving non-linear functional relationships (e.g. use of non-linear objective functions, consideration of evaporation losses from a reservoir, hydropower generation, etc.).

3. The requirement for the consideration of inflow stochasticity can easily be met within a DP formulation. In short, inflow to a reservoir is represented by different inflow classes with their respective transition or independent probabilities and is further considered as an additional state variable in the SDP optimization procedure. Examples of the Bellman's backward recursive relationships for these two cases are depicted by Equations 4.8 and 4.9, respectively (n.b. again assuming a minimization problem):

$$f_n^{(t)}(k,i) = \min_l \left\{ C_{k,i,l}^{(t)} + \sum_{j=1}^{N_{t+1}} p_{i,j}^{(t)} \cdot f_{n-1}^{(t+1)}(l,j) \right\}, \quad \forall k,i; \quad l \textit{ feasible} \tag{4.8}$$

$$f_n^{(t)}(k,i) = \min_l \left\{ C_{k,i,l}^{(t)} + \sum_{j=1}^{N_{t+1}} p_j^{(t+1)} \cdot f_{n-1}^{(t+1)}(l,j) \right\}, \quad \forall k,i; \quad l \textit{ feasible} \tag{4.9}$$

where

k, l the discrete storage states of the reservoir at the beginning of the time steps t (stage n) and $t+1$ (stage n-1), respectively; in this case, l also depicts the decision $l = l(k, i, t)$ to be taken at stage n;

i, j the discrete reservoir inflow states during the time steps t and $t+1$, respectively;

N_{t+1} the number of discrete inflow classes in time step $t+1$;

$p_{i,j}^{(t)}$ the transition probability which states the likelihood that the inflow in time step $t+1$ will fall into class j given that the inflow in time step t is in class i;

$p_j^{(t+1)}$ the probability of occurrence of inflow of class j in time step $t+1$;

$C_{k,i,l}^{(t)}$ the immediate contribution towards the value of the objective function induced by the decision $l = l(k, i, t)$;

$f_n^{(t)}(k,i)$ the suboptimal aggregate of the objective function expectation accumulated over all the stages starting from the first one (i.e. time step $t = 0$) and up to and including the present stage n (i.e. time step t).

Without presenting the actual mathematical relationships, the remaining part of this section describes briefly the employed SDP optimization algorithm. The detailed formulation of the entire SDP model, including all the related functional relations, is given in Section 5.2.

The SDP optimization algorithm used in this study is formulated to derive the long-term operating strategy of a single water supply reservoir. The adopted temporal discretization is set to monthly time steps within an annual cycle. Thus, the decision stages within the employed SDP problem decomposition are defined over time assuming that the stochastic properties of the 12 monthly flow processes fulfil the stationarity condition (i.e. they are not changing over time). Thereafter, the monthly flows are viewed as a Markov chain and represented by their respective transition probability matrices. Contrary to the inflows, the monthly water demands imposed upon the reservoir are assumed deterministic. Thus, the same sequence of 12 monthly demand values is recurring in each annual cycle within a single SDP optimization run.

At each stage (i.e. monthly time step) the state of the reservoir is described by two state variables: the storage volume of the reservoir at the beginning of the stage and the inflow into the reservoir during that time step. The decision to be taken at each stage is the target storage volume of the reservoir at the end of the stage. Thus, the decision variable for a certain month automatically becomes a storage state variable for the subsequent month.

In the reservoir balance, the model also takes into account the evaporation water losses. To calculate this loss, the model assumes that the total volume which evaporates from the reservoir's surface during a single monthly time step is proportional to the average surface area of the reservoir in that month and the average evaporation loss per unit of the surface area estimated for that particular month. Given the initial and final storage volumes, the inflow and the estimate of the evaporation loss, the model can compute the resulting total reservoir release from the basic continuity equation written for a single time step.

Consequently, having compiled all the information related to a particular reservoir state and the alternative final storage decision for the given operating stage, the model can compute the resulting incremental objective function value. The objective function adopted in this study is to minimize the expectation of the accumulated annual squared deviation of the release from the demand. It should be noted here that, due to the fact that the inflow state variable is regarded as a stochastic process, the accumulated objective function value obtained in the SDP recursion represents the estimate of the function's expectation, rather than its exact value. Apparently, the chosen objective function penalizes both the shortage and surplus which may result from a particular release decision. This choice is made because the primary goal was to try and find the operating strategy which would provide the maximum level of demand satisfaction and, at the same time, maintain the reservoir's storage volume at the maximum possible level, thus minimizing spilling. If only the shortage were penalized, the respective operating policy might result in an excessive unnecessary spilling. Furthermore, the use of the squared deviation provides an incentive for the optimization procedure to opt for, whenever possible, the sequences of decisions which would result in multiple failure events of a smaller magnitude instead of a single, possibly catastrophic failure.

The SDP optimization process starts from the first month of an arbitrary year in future by setting the initial objective function values for all possible combinations of the reservoir's initial storage and inflow states to some, also arbitrary, value (n.b. without any loss of generality, this arbitrary value is chosen to be zero for all state combinations). Thereafter, the enumeration recursion proceeds backward in time across the temporal stages. At each subsequent stage, and for each combination of the reservoir's initial storage volume and inflow states, the SDP model assumes that the reservoir may undergo a transition to any of the feasible final storage volumes. After estimating the respective expectations of the accumulated objective function values for each of the feasible state transitions, the transition with the minimum objective expectation is identified as the suboptimal decision associated with the given combination of the initial storage volume and inflow states.

After repeating the recursion process for a number of annual cycles, all of the derived operating decisions will become stable (i.e. for a particular stage and a particular combination of the system states, the resulting decision remains the same in each of the subsequent annual cycles). Furthermore, if the annual increment of the objective function value becomes constant for each stage and each combination of the system states, it can be concluded that the derived monthly operating strategies have reached the steady state and the SDP recursion can be terminated (Loucks et al. 1981:325). Ultimately, the derived operating strategy for a reservoir consists of 12 monthly policy tables. Each table provides the recommendations on the target final storage volume in a month for each and every possible combination of the reservoir's storage volume at the beginning of the month and inflow during the month (n.b. obviously, the knowledge about the reservoir's inflow refers to the respective flow forecast). The derived policy ensures that, if the reservoir is operated according to this policy over a long period of time, the resulting expected annual objective function achievement would approach the respective value obtained during the SDP optimization process.

4.3 The Role of Simulation

Simulation of a reservoir's operation is an irreplaceable part of the proposed decomposition/SDP methodology. Namely, once a long-term operating strategy is obtained for a reservoir, the only way to assess the impact it may have on the operation of the entire system is to simulate the reservoir's operation according to the derived policy. The simulation itself is carried out over the same inflow record which has previously been used in the SDP optimization to derive the stochastic properties of the inflows. The use of the same inflow time series in both optimization and simulation is justified by the fact that the interaction among two serially linked reservoirs is partially described by the time series of non-utilized release from the upstream reservoir in such a cascade. Thus, the time series of incremental inflows into the downstream reservoir must coincide in time and length with the time series of excess outflows from the upstream reservoir.

As the initial condition required by simulation, it is only necessary to specify the storage volume in the reservoir at the beginning of the first month of the simulation period (n.b. in this study, it is assumed that each reservoir's simulation starts with the reservoir's storage being at its full capacity). Similarly to the SDP-based optimization procedure, the simulation follows the same principles of evaporation loss estimation and complies with the same continuity equation and reservoir volume and release constraints (n.b. the detailed mathematical formulation of the simulation algorithm is given in Section 5.3). As the final result of simulation, the time series of the total reservoir's release is obtained. The total release is compound of the utilizable reservoir outflow through the service and bottom outlets, and the overflow of the reservoir over the spillways. This record is subsequently used within the release allocation procedure to estimate the amounts of water delivered to individual water users associated with this reservoir and, consequently, to update those demand records for the following computational steps. In addition, any excess non-utilized release in a certain month is added to the respective own incremental inflow of the reservoir situated immediately downstream of the reservoir in question.

Due to the discrete nature of the SDP operating policies, the simulation has been assigned an additional role in the devised decomposition algorithm. Namely, by strictly following an SDP policy, simulation may sometimes result in decisions whose outcomes are release volumes that exceed the corresponding demands for water. It is clear that such a decision may sometimes cause a substantial loss of water which might otherwise be stored in the reservoir for the later use. Dealing with a system whose only purpose is water supply and having no consideration of floods it would be quite logical to store this, otherwise non-utilizable excess release volume so that it could be utilized at a later stage. Bearing also in mind the objective pursued in optimization (see Section 4.2) it is fully justified to violate those policy decisions in the simulation phase as described above. By doing so the modified decision remains concurrent with the policy expressed by the objective function used in the optimization.

Additionally, given the fact that water demands are considered deterministic in the optimization (i.e. the same total and distribution of demands are recurring in annual cycles over the time period considered) it has initially been assumed that, for the simulation purposes within one iterative cycle, any reservoir's contribution towards a particular demand could be sufficiently represented by its expected (average) value. However, such a representation inevitably results in two drawbacks that emerge by viewing the reservoir's simulated operation over the entire simulation period:

1. The expected unmet demand which remains after the allocation of the release from one reservoir overestimates the actual demand in those months when the supply exceeds the respective estimated average supply. This, in turn, will result in unnecessary withdrawals from other reservoirs towards this demand centre in this particular month.

A hypothetical example is perhaps the best way to illustrate this feature. Let two reservoirs, R_1 and R_2, provide water for a common demand represented by a sequence of 12 monthly values d_i, $i \in \{1, 2, ..., 12\}$. Furthermore, monthly demands are assumed to be recurring in annual cycles over the entire period of n years of the available inflow data. Let the operation of reservoir R_1 be optimized and simulated first. Let us further on concentrate only on the simulation results pertaining to a single month indicated by the subscript i. The resulting simulated releases in month i are $r_{i,j}$, $j \in \{1, 2, ..., n\}$. Clearly, the release volumes vary from year to year and, in general, it could be said that a release from reservoir R_1 in month i could fall short of, be equal to, or exceed the value of the respective demand d_i. By assuming that reservoir R_1 alone cannot fully satisfy the given demand in month i, the average contribution of R_1 to the supply of this demand will be:

$$\bar{r}_i < d_i \tag{4.10}$$

where

$$\bar{r}_i = \frac{1}{n}\sum_{j=1}^{n}\hat{r}_{i,j} \quad , \quad \hat{r}_{i,j} = \min(r_{i,j}, d_i) \tag{4.11}$$

Consequently, the average supply shortage of reservoir R_1 towards the common demand in month i (i.e. the value to be used to optimize and subsequently simulate the operation of reservoir R_2) is $d_i - \bar{r}_i$. Let further the asterisk superscript label those years $j = j^*$ in which the release from reservoir R_1 was higher than the respective average monthly supply. Ultimately, while simulating the operation of reservoir R_2 with respect to the average remainder of the demand $d_i - \bar{r}_i$ it is realistic to assume that reservoir R_2 would attempt, and sometimes do manage to release water up to the required volume $d_i - \bar{r}_i$. This means that there is a great possibility that in some of the years $j = j^*$ the aggregate of releases from both the reservoirs towards the common demand in month i exceeds the targeted value d_i.

2. Quite opposite, the information on extreme monthly supply shortages associated with a particular demand is lost by relying on the average supply value. By underestimating these

extreme events the reservoirs that might contribute to cover these shortage peaks would not do that due to the lack of relevant data.

The clarification for this statement could also be found in the former example. Namely, let $j = j^*$ now indicate the years in which the ith monthly release from reservoir R_1 fell short of the respective average monthly supply. As the operating policy of reservoir R_2 targets the remainder of the demand $d_i - \bar{r}_i$ it is unlikely that the supply shortage encountered by reservoir R_1 in month i in years $j = j^*$ would be fully compensated for by the releases from reservoir R_2.

The major factors which are responsible for these two drawbacks are the inevitable state and decision space discretization requirement as well as the expectation and not extreme event-oriented nature of SDP. Thus, the discrete nature of SDP policies and the use of the average monthly demand estimates would, if the policies are strictly followed, affect the overall simulated performance of the system in two ways. On the one hand, the system's operation is likely to exhibit a tendency towards releasing substantial amounts of non-utilizable water. Consequently, it can be expected that some, otherwise avoidable, unnecessary supply shortage will occur. On the other hand, in some months, due to the overestimation brought about by the averaging of demand updates, the amount of water allocated to some users may easily exceed the actual water requirements. To illustrate this, and to propose an alternative means to eliminate these drawbacks, three different simulation models are devised and tested within the complex system evaluation algorithm:

1. *Strict policy compliance* simulation model adheres closely to the derived SDP policies.

2. *Average demand threshold* simulation violates the SDP policy only to prevent decisions that result in oversupply towards the estimated average demand. That is, if a policy-based decision is to release a volume that is greater than the respective expected demand the decision is overruled by setting the release to the level of the demand. Thereby the excess release volume is stored in the reservoir with a prospect to be utilized at a later stage.

3. *Monitored demand* simulation concept circumvents the drawbacks of altering a policy with respect to the average demand estimates. Namely, the information on how much water has been allocated towards each individual demand centre in each time step (month) over the entire simulation period is repeatedly updated in every simulation run. Thus, instead of comparing a policy-based release with the respective average monthly demand the model is provided with the estimate of the actual demand to decide whether to violate the policy or not in the month in question. Consequently, decisions on policy violation are no longer prone to factors like overestimated and underestimated (average) demand values, nor is the system allocating any surplus water to each of the demand targets.

It should be noted here that these modifications apply to simulation only. Due to the assumed deterministic nature of water demands, the SDP optimization is still based on the expectation of the demand which is assumed to be recurring in annual cycles. Namely, to ensure that the SDP recursion ultimately reaches the steady state operating policy, the objective function formulation must meet the condition that, for each month and each respective combination of the reservoir's initial storage and inflow states, the immediate contribution of a potential decision towards the objective function value must be constant and time invariant (n.b. a precise mathematical interpretation of this condition is given in Section 5.2). However, despite the fact that only the simulation outcome is affected by the proposed overruling the beneficial effects of those measures are substantial, which is supported by the results presented in Section 6.3.

4.4 Release Allocation

Along with the description of the basics of the employed methodology, this section provides the rationale for the need for a separate release allocation analysis within the proposed decomposition algorithm. Full mathematical formulation of all of the principles and relationships mentioned in this section can be found in Section 5.4.

As already mentioned earlier in this chapter, multiple demands associated with a reservoir are aggregated into a single composite demand for the optimization and simulation of that reservoir's operation. Consequently, the resulting simulated release record does not provide any information as to how much water has been allocated for the individual demand centres. To estimate these quantities, the proposed model makes use of a simple rule which arranges the respective demands of each of the reservoirs into a hierarchical sequence. The demand hierarchy essentially assigns different priorities to different users and the release allocation process follows closely the established priority ordering. In short, the total estimated reservoir release in a particular month is distributed among the associated demands on the "first-come-first-serve" basis. Namely, the total available release volume is first used to cover the demand placed on the top of the demand hierarchy. The remaining unused portion of the total release, if any, is then used to allocate water for the next demand centre down the priority list. This hierarchical allocation process stops when the entire release volume becomes exhausted.

Obviously, this allocation principle is likely to result in greater supply shortage towards those water users which are assigned lower priority. In general, the determination of the demand hierarchy for each of the reservoirs in a system is left to the analyst's discretion. In this study, partly due to the features of the adopted decomposition method and partly based on the characteristics of the given water supply test case system, the formulation of the demand hierarchy for a reservoir adheres to the following set of rules:

1. All demands associated with a reservoir are separated into two groups: the direct water users which are usually located in the immediate vicinity of the reservoir, and the remote users to whom water has to be delivered through an interbasin water conveyance system. In the allocation process, the direct users are generally given higher priority over the remote ones.

2. With regard to specific water uses, the allocation process generally recognizes the following hierarchical sequence: drinking water, irrigation, industrial water use and water demands of tourist centres.

3. As to the estimated average supply deficits of the immediate downstream reservoir and the respective consideration of those as an additional hypothetical demand of the reservoir in question (cf. Section 4.1), this demand component is always given the lowest priority on the demand list. This effectively means that any of the immediate upstream reservoirs would provide an additional release to augment the respective downstream reservoir's inflow only if the total release volume were sufficient to cover all of its consumptive demands.

In essence, the release allocation process is an integral part of simulation. It is the only way to determine how much water a reservoir has provided for each of the demands over the time period considered in simulation. In that respect, it is necessary to formulate a separate release allocation procedure for each of the three different simulation alternatives (cf. Section 4.3). In fact, there are only two release allocation approaches needed to cover all of the simulation options. The first one is coupled with both the *strict policy compliance* and the *average demand threshold* simulation models. Therefore, to derive the actual water allocations for individual demand centres, this approach utilizes the information on the average monthly estimates of the respective demands. On the other hand, the allocation of the total reservoir releases obtained by the *monitored demand* simulation concept is carried out on the basis of the updated time series of unmet demands of each of the water users in the system.

Regardless of the type of release allocation approach, the final result of this process consists of three different blocks. Each block holds information of a particular importance for the optimization and simulation of the operation of other reservoirs in the system:

1. After allocating water to a demand centre, the resulting time series of monthly supply volumes is used as a basis for the estimation of the respective average monthly supplies, and the corresponding average monthly demands that could not have been covered so far. The new average demand estimates are to be used as the targets in the optimization of the operation of the remaining reservoirs associated with this demand. That is, those reservoirs whose operation has not yet been analyzed in the current iterative cycle.

2. Subsequently, the aggregate of the average monthly estimates of all of the unmet demands associated with a reservoir forms the so-called *reservoir supply deficit*. Being based on the simulation over the entire time period under consideration, this deficit represents the expectation of the reservoir's failure to meet the imposed demands for water. This estimate is further going to be used as an additional demand in the analysis of the operation of all the reservoirs situated immediately upstream of the reservoir in question.

3. Ultimately, a time series of any non-consumptive release left after allocating water to all of the reservoir's water users becomes an additional inflow to the reservoir located immediately downstream.

It should be stressed here that the resulting release allocation obtained following the principles presented in this section strongly reflects both the employed reservoir decomposition sequence and the adopted hierarchical demand arrangement. In that respect, it is likely to expect that any changes in either of the two orderings would bring about tangible changes in reservoir operating policies, their respective release allocation patterns and, consequently, the performance of the entire system. Thus, the obtained results could exhibit a bias with regard to the chosen decomposition ordering. Therefore, to mitigate the expected negative effects of those factors, an independent release allocation analysis based on genetic algorithms is proposed and presented in the following section.

4.5 Water Allocation and Genetic Algorithms

So far, this chapter has introduced the adopted decomposition methodology for the analysis of the operation of multiple-reservoir water supply systems. In addition, one of the most pronounced shortcomings of the proposed decomposition approach has been discussed in the preceding section. That is, due to the apparent limitations imposed by decomposing a system into individual reservoirs and the necessity to adopt some type of demand precedence when allocating the derived reservoir releases, the method cannot guarantee that the resulting demand sharing among the reservoirs and the corresponding performance of the system are truly the best ones. Therefore, a genetic algorithm (GA) based model has been devised to identify the most favourable water allocation patterns (i.e. sharing of the common demand loads) among the reservoirs in the system. The following two sections provide a general introduction to the theory of genetic algorithms and the particulars related to the application of this methodology to the problem of water allocation within a multiple-reservoir water supply system, respectively.

4.5.1 Introduction to Genetic Algorithms

Since Section 2.3 contains a rather descriptive introduction to the origin and the foundations of the GAs, together with a discussion about the pros and cons of the method, this section will concentrate on the definition and formulation of a typical binary-coded GA model, its basic parameters and operators, fitness evaluation and fitness scaling, feasibility issues and the termination conditions for a GA run. As already mentioned in Section 2.3, GAs are robust search algorithms which apply the principles of natural genetics and evolution to solve maximization problems related to artificial systems. Their search of a solution space is guided by the Darwinian concept of *survival of the fittest*. In other words, GAs emulate the natural principle of *survival of the fittest* on a population of artificial creatures. Each individual in such a population represents a very specific coding of a potential solution to the problem being solved. It can therefore be said that a typical GA search strives to locate the solution to a problem by letting a population of potential solutions "evolve" towards it. The "evolution" of such an artificial species in its equally artificial environment is guided by the equivalent of the three basic principles of the natural evolution process (cf. Section 2.3): heredity, variability and fecundity.

Representation. Genetic algorithms require that a potential solution to the problem be represented by a specific code, which is analogous to chromosomes in biological systems. The encoded representation of a value the unknown variable may take is regarded as a complete genetic material (i.e. genotype) of an artificial being whose traits (i.e. phenotype) are reflected in the variable's value itself. Note that, in this dissertation, the terms string, chromosome and individual all refer to the same thing - the encoded representation of a potential solution.

The encoding itself is usually performed over some small finite alphabet, which is usually the binary alphabet: $\{0, 1\}$. For instance, if a solution to the problem is a real-numbered variable α, any potential value of α that is to be used within a GA search is represented by a continuous sequence of zeroes and ones. The length of such a binary string depends on the precision required for the estimation of the variable's value. That is, a binary number represented by a bit-string of a certain length is mapped over the entire range of possible values the related variable α can take. In general, a binary string of length L can be defined as an ordered set of L elements each of which can take a value of either 0 or 1:

$$B^{(L)}:\{b_i \mid b_i \in \{0,1\}, i \in \{1,2,\ldots,L\}\} \tag{4.12}$$

Naturally, a bit-string $B^{(L)}$ is essentially a binary number which can be translated into its decimal representation $\beta^{(L)}$ using the following relationship:

$$\beta^{(L)} = \sum_{i=1}^{L} b_i \cdot 2^{i-1} \tag{4.13}$$

As a direct consequence of the selected bit-string length, the minimum and the maximum values a binary number $B^{(L)}$ can represent are:

$$\begin{aligned} \beta_{\min}^{(L)} &= 0 \quad \Leftrightarrow \quad b_i = 0, \forall i \\ \beta_{\max}^{(L)} &= \sum_{i=1}^{L} 2^{i-1} = 2^L - 1 \quad \Leftrightarrow \quad b_i = 1, \forall i \end{aligned} \tag{4.14}$$

Thus, if the variable α can take values from the interval $(\alpha_{\min}, \alpha_{\max})$, the representative L-bit-long binary string $B^{(L)}$ with the associated value $\beta^{(L)}$ can be (linearly) mapped to the real value of α through the following transformation:

$$\alpha = \alpha_{\min} + \frac{\alpha_{\max} - \alpha_{\min}}{2^L - 1} \cdot \sum_{i=1}^{L} b_i \cdot 2^{i-1} \tag{4.15}$$

Consequently, the mapping of the unknown variable α over an L-bit-long binary string achieves a precision of:

$$\delta^{(L)}(\alpha) = \frac{\alpha_{\max} - \alpha_{\min}}{2^L - 1} \tag{4.16}$$

The above description was based on the assumption that the solution to a problem tackled by a GA was a single, real-valued variable. However, a bit-string representation does not necessarily have to be a mapping of a single variable, nor do the variables have to be real-valued ones. For instance, the unknown variable α may take only integer values within a certain interval. In fact, it may also happen that $\beta^{(L)}$ itself is the unknown variable, thus making it unnecessary to perform the mapping transformation given by Equation 4.15. Furthermore, it is also possible that a binary string be viewed as a sequence of "on/off" decisions of some sequential control process. In this case, each bit would directly represent a single decision (i.e. 0≡"off" and 1≡"on") associated with a particular stage of the entire process. To summarize, if a solution to a problem tackled by a GA consists of a number of variables, i.e. the solution is a vector $\vec{\alpha} = (\alpha_i \mid i \in \{1,2,\ldots,n\})$, the representation problem is resolved by first deciding upon the individual lengths L_i of binary sub-strings representing each coordinate α_i. The binary representation of the entire vector is subsequently created by simply attaching one binary sub-string to the next, thus forming a continuous sequence of zeroes and ones:

$$B^{(L)}:(B_1^{(L_1)}B_2^{(L_2)}\ldots B_i^{(L_i)}\ldots B_n^{(L_n)}) \tag{4.17}$$

where $L = \sum_{i=1}^{n} L_i$ depicts the total length of string $B^{(L)}$ and

$$B_i^{(L_i)}:\{b_{ij} \mid b_{ij} \in \{0,1\}, j \in \{1,2,\ldots,L_i\}\}, \quad \forall i \in \{1,2,\ldots,n\} \tag{4.18}$$

Table 4.1 may serve as an illustration of the above description. It shows that a sample binary string which is 16 bits long may be interpreted in several different ways. For instance, the entire range of 16 bits may be used to represent a single variable. It may also be assumed that the four leftmost bits represent one variable, the central eight bits map over another variable and the rightmost four bits describe the third unknown parameter. Similarly, the entire string may also represent four different parameters, each being mapped over a four-bit-long binary sub-string. Obviously, one may come up with a great many alternative interpretations of such a binary map. It should be noted here that this example refers only to the way of building up a binary string configuration and not to the types (e.g. integer, real, etc.) and possible values of variables represented by those binary maps.

Table 4.1 An example of binary string mapping

$B^{(16)}$		0	0	1	0	0	0	1	1	1	1	1	1	1	0	0	1
$B_i^{(L_i)}$	map 1	←							$B_1^{(16)}$								→
	map 2	←	$B_1^{(4)}$		→	←			$B_2^{(8)}$				→	←	$B_3^{(4)}$		→
	map 3	←	$B_1^{(4)}$		→	←	$B_2^{(4)}$		→	←	$B_3^{(4)}$		→	←	$B_4^{(4)}$		→

With regard to the above description, it can be concluded that GAs work with the encoded representation of a solution they are seeking and not with the solution itself. It can therefore be said that GAs do not need to know and "do not really care" what kind of quantities are represented by the encoded strings. In fact, the only link between a GA search and the actual problem whose solution is sought lies in the *fitness* of the individual chromosomes (i.e. potential solutions to the problem).

Fitness. In addition to the solution encoding requirement, another favourable feature of GAs is the fact that they perform their search from a population of potential solution points rather than from a single, most promising point. By doing this, they manage to scan large areas of the solution space, thus increasing the likelihood of locating the solution to the problem. In principle, a GA search starts by randomly generating a number of potential solutions (i.e. individuals). As it will be explained later in this section, the search process consists of the creation of new batches of potential solutions by applying a number of GA-specific operators. However, it should be stressed here that GAs do not constitute yet another random search procedure. It is rather the case that a GA search combines the knowledge gained from the search performed so far (i.e. the goodness of the individuals created during the creation of the preceding populations) with the random, yet structured, process of the creation of new individuals to direct the search towards more promising areas of the solution space. Namely, the search itself is guided by probabilistic rules based on the goodness (i.e. fitness) of the potential solutions represented by the individuals of the currently available population.

What fitness really is within a GA formulation can best be explained on a simple example. Consider an optimization problem where the objective function $f(\alpha)$ is a univariate function whose maximum $f_{max} = f(\alpha_0)$ is to be found by a GA. In this case, the solution to the problem is α_0, the value of the unknown independent variable for which the function achieves its maximum. Let it be assumed that the binary representation and mapping of the solution have already been defined. Thus, the relationship between a binary string within the GA search and the respective value of the unknown variable are described by Equations 4.12 through 4.16. Consequently, given a certain binary string $B^{(L)}$ (i.e. individual) created during a GA search it is possible to derive the corresponding value of the function argument α. The fitness of that particular individual is nothing else but the estimate of the objective function for the derived value of the argument α: $f(\alpha)$. Obviously, the closer the derived argument value is to the solution α_0, the higher the value of the objective function will be. This, consequently, results in the higher fitness of the respective individual $B^{(L)}$. To summarize, given an optimization problem to be solved by means of a GA, the fitness of an individual in a GA search is the estimate of the objective function value for the potential solution point represented by that particular individual.

This example deliberately refers to a maximization problem because GAs are essentially maximization search procedures. Therefore, if a problem to be solved is of a minimization type, the fitness function definition within a GA must be transformed into the objective function of the equivalent maximization problem. Furthermore, GAs can accommodate only positive fitness values. Both of the conditions are implicitly imposed by the way the fitness is used in the GA selection procedure, which is described later in this section.

GA operators. As already mentioned earlier, a GA search starts from a population consisting of a predetermined number of randomly generated individuals, i.e. potential solutions. The subsequent actions constitute the emulated evolution of the initial population through creation of new populations by applying three principal GA operators: selection, crossover, and mutation.

Selection establishes a subset of individuals from the present population that is to be used for reproduction into the subsequent generation. In essence, the selection process is based on the individuals' fitness, thus reflecting directly the principle of the *survival of the fittest*. Among a great variety of selection mechanisms reported in GA literature the most frequently used one is *proportional selection*, also known as *biased roulette wheel selection* (Goldberg 1989). It states that the likelihood p_s that an individual i be selected for reproduction among N individuals in a generation is proportional to its fitness f_i relative to the aggregate fitness of all individuals in the generation:

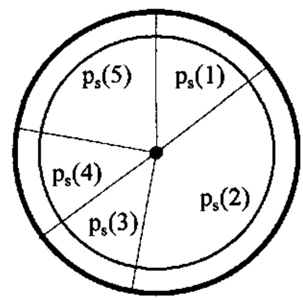

Figure 4.1 Biased roulette wheel selection

$$p_s(i) = \frac{f_i}{\sum_{i=1}^{N} f_i} \tag{4.19}$$

As Goldberg (1989) pointed out, this selection mechanism imitates a biased roulette wheel. The number of slots on the wheel equals the number of individuals in a population. Unlike the equally sized slots on a real gambling one, the slots on a GA biased roulette wheel are sized in proportion to the respective individual's relative fitness. Consequently, a roulette spin has higher chance of yielding a slot assigned to fitter individuals. An example of a *biased roulette wheel selection* is graphically presented in Figure 4.1. The imaginary population in this example consists of five individuals whose fitness values are f_1, f_2, f_3, f_4, and f_5, respectively, and the individual slot sizes are estimated according to the relation given by Equation 4.19. The selection itself is performed by first generating a uniformly distributed random number $p \in [0, 1]$ which emulates a roulette spin and thereafter assuming that the roulette ball is going to rest in the slot K indicated by the following relationship ($p_s(i)$ is defined by Equation 4.19, where $p_s(0) = 0$):

$$\sum_{i=0}^{K-1} p_s(i) < p \le \sum_{i=0}^{K} p_s(i), \quad K \in \{1,2,\ldots,N\} \tag{4.20}$$

A pair of strings (parents) is selected for reproduction by spinning the biased roulette wheel twice. Subsequently, the selected parents undergo crossover to create two new individuals (children). It should be noted here that the choice of the crossover operator depends on the selected solution representation method and it can also frequently be problem-dependent. Consequently, a number of different crossover types can be found in the reported GA literature (cf. Section 2.3 for some examples on crossover types). The simplest crossover operator used within a binary string representation is the classical, *one-point crossover*: given a pair of chromosomes selected for reproduction, the crossover operator is applied by randomly selecting a crossover site along a string length, cutting both strings at this site, and exchanging the created sub-strings (Figure 4.2).

parent 1	:	0	0	1	0	0	0	1	1	1	1	1	1	1	0	0	1
parent 2	:	1	0	1	1	1	1	0	1	1	0	0	0	1	0	1	0
crossover site	:						|										
child 1	:	0	0	1	0	0	0	0	1	1	0	0	0	1	0	1	0
child 2	:	1	0	1	1	1	1	1	1	1	1	1	1	1	0	0	1

Figure 4.2 One-point crossover

It should be noted here that not all of the selected parents undergo crossover. Namely, crossover is applied with a certain probability thus resulting in a fraction of a new generation being created by simply copying the selected parents. The crossover probability is usually kept rather high. In most of the reported applications the range of crossover probability varies between 0.6 and 1. To summarize, the one-point crossover operator can be defined as:

$$\begin{gathered} B_1^{(L)}:\{b_{1,i}\,|\,b_{1,i}\in\{0,1\}, i\in\{1,2,\ldots,L\}\} \\ B_2^{(L)}:\{b_{2,i}\,|\,b_{2,i}\in\{0,1\}, i\in\{1,2,\ldots,L\}\} \\ \xi(B_1^{(L)},B_2^{(L)},p_\xi,p_c,l_c):\{(B_1^{(L)},B_2^{(L)})\rightarrow(C_1^{(L)},C_2^{(L)})\} \end{gathered} \tag{4.21}$$

where

$B_j^{(L)}$ the two parent strings selected for reproduction ($j\in\{1,2\}$);

$C_j^{(L)}$ the two resulting child strings ($j\in\{1,2\}$);

p_ξ a GA parameter representing the crossover probability ($0\le p_\xi\le 1$);

p_c a uniformly distributed random number ($0\le p_c\le 1$);

l_c a crossover site defined as a uniformly distributed random number ($0\le l_c\le L$).

The way two new individuals are created depends upon the relation between the crossover probability p_ξ and the randomly drawn number p_c:

$$
\begin{aligned}
&C_1^{(L)}:\left\{c_{1,i}\middle| c_{1,i}=\begin{cases} b_{1,i} & i\le l_c \\ b_{2,i} & i>l_c \end{cases}, i\in\{1,2,\dots,L\}\right\} \\
&C_2^{(L)}:\left\{c_{2,i}\middle| c_{2,i}=\begin{cases} b_{2,i} & i\le l_c \\ b_{1,i} & i>l_c \end{cases}, i\in\{1,2,\dots,L\}\right\}
\end{aligned}
\quad , \quad p_c \le p_\xi \tag{4.22}
$$

or, if the above condition is not met:

$$
\begin{aligned}
&C_1^{(L)}:\{c_{1,i}| c_{1,i}=b_{1,i}, i\in\{1,2,\dots,L\}\} \\
&C_2^{(L)}:\{c_{2,i}| c_{2,i}=b_{2,i}, i\in\{1,2,\dots,L\}\}
\end{aligned}
\quad , \quad p_c > p_\xi \tag{4.23}
$$

Selection and crossover are the principal GA operators. Mutation, however, has a somewhat secondary role in a GA search. Nevertheless, mutation is important because it provides the means to maintain the diversity within a population, thus preventing it from "degenerating" towards a stable, but likely non-optimal solution (i.e. *premature convergence*). Similarly to crossover, the definition of mutation depends on the choice of the solution representation method. Within the binary string representation, the most frequently used mutation operator is a *bitwise complement mutation* (Figure 4.3). In short, while traversing across a binary string, the bitwise complement mutation selects one or more bit positions at random and changes their values from 0 to 1 and vice versa. The rate of mutation is highly problem-dependent but it is generally kept rather low (i.e. a few mutations per one thousand bit positions).

before mutation	:	0	0	1	0	0	0	1	1	1	1	1	1	1	0	0	1
mutation site	:										|						
after mutation	:	0	0	1	0	0	0	1	1	1	0	1	1	1	0	0	1

Figure 4.3 Bitwise complement mutation

Thus, given a binary string:

$$
B^{(L)}:\{b_i| b_i\in\{0,1\}, i\in\{1,2,\dots,L\}\} \tag{4.24}
$$

the bitwise complement mutation operator is defined as:

$$
\begin{aligned}
&\mu(B^{(L)}, p_\mu, p_m(1), p_m(2),\dots,p_m(L)):\{B^{(L)}\to C^{(L)}\} \\
&C^{(L)}:\{c_i| c_i\in\{0,1\}, i\in\{1,2,\dots,L\}\} \\
&c_i=\begin{cases} 1-b_i\ , & p_m(i)\le p_\mu \\ b_i\ , & p_m(i)>p_\mu \end{cases} \quad , \quad i\in\{1,2,\dots,L\}
\end{aligned}
\tag{4.25}
$$

where

$B^{(L)}$	the string which undergoes mutation;
$C^{(L)}$	the resulting mutated string;
p_μ	a GA parameter representing the mutation probability ($0 \le p_\mu \le 1$);
$p_m(i)$	a unique uniformly distributed random number drawn for each bit position i ($0 \le p_m(i) \le 1$);

GA parameters. There are four basic parameters of a simple binary-coded GA model described in this section. The values of all four of them are highly problem-dependent, thus requiring to be calibrated for each individual GA application. The four parameters include:

1. *The population size* is the number of individuals in a population. This parameter is highly problem-specific, but it can be said that good performance of GAs in function optimization problems could be expected already with populations consisting of as little as 20 individuals. In general, the population size is rarely greater than 100.

2. *The maximum number of generations* is the upper limit on the number of newly created populations. It can easily be understood from the definition of GAs that the evolution process could go on endlessly. Therefore, this parameter needs to be decided upon to enable the ultimate termination of a GA search. Similarly to the population size, the limit on the number of generations depends on the problem being solved. The most frequently used thresholds vary between 100 and 200 generations.

3. *The crossover probability* is the expected frequency of chromosome crossovers in the entire GA run. As already mentioned earlier, the crossover probability is usually kept between 0.6 and 1 in binary-coded GAs.

4. *The mutation probability* is the expected rate of mutation in a GA run. The reported applications suggest that a simple binary-coded GA usually achieves a good performance with the rates of about a few mutations per one thousand bit positions.

In addition to these four, a GA parameter list may also include a number of problem-specific parameters or some supplementary termination (convergence) criteria chosen to control the execution of a GA search. These are not presented here because this section concentrates only on the basic features of a genetic algorithm. However, a separate passage is reserved later in this section to introduce some of the most frequently used criteria for the termination of a GA run.

Solution feasibility. Because GAs work on a specific coding of potential solutions it sometimes may happen that the application of crossover and/or mutation results in an individual which represents an infeasible value of the unknown variable. This is particularly likely to occur if the problem solved by a GA is a highly constrained one, and especially if the solution to the problem is a vector and some of the subsets of solution coordinates are interdependent. In general, there are two methods which are most frequently applied within a binary representation scheme. One involves the use of a *penalty function* which assigns an inferior fitness value to the infeasible individuals. The other method employs a problem-specific *repair algorithm* which usually utilizes some random-based modification procedure to transform the infeasible individuals into feasible ones.

Fitness scaling. Premature convergence of a GA search can be prevented by maintaining sufficient population diversity throughout the entire run. This phenomenon is obviously closely related to the fitness variability of the individuals in a population. In general, the impact of fitness variability on a GA search is greatest during the initial and final phases of a run. Namely, the variability of fitness is generally high in the initial population due to random generation of chromosomes. If the initial generation contains a few chromosomes with outstanding fitness values it can then be expected that the adopted selection procedure which is based on the original fitness (n.b. also known as the *raw fitness*) would inevitably favour those individuals over the rest of the population. Consequently, a majority of strings created into the succeeding generation would be the offspring of the fit ones and the diversity of future populations would quickly be lost resulting in a premature convergence of the search. On the other hand, the principle of the survival of the fittest ensures that the fitness variability be reduced to moderate levels during the later stages of a GA run. In other words, the evolution process has managed to single out the individuals which are fitter and thus better adapted to their environment. It can therefore be expected that the members of later populations have similar fitness values. Consequently, all the chromosomes would have similar chance to be selected for reproduction. However, this means that strings with highest fitness would not have any advantage in the selection process. Ultimately, the search would be reduced to a mere random walk.

The maintenance of fitness variability can efficiently be resolved by applying *fitness scaling* (Goldberg 1989). It allows a GA to base its search on a modified fitness value system which provides a consistent diversity of populations by enforcing the fitness variability levels to the values specified by the user. In other words, fitness scaling enables the selection mechanism to distinguish between "better" and "worse" fit individuals at all times. Furthermore, it also keeps the difference between fitness values of "the best" and "the worst" chromosomes within certain limits thus allowing "the weaker" ones to stand some realistic, albeit small, chance for reproduction.

The simplest and most frequently used fitness scaling method is *linear fitness scaling* (Goldberg 1989). It prevents premature convergence caused by the high fitness variability of the initial random population and promotes more fit individuals in later generations when fitness variability is generally rather low. As the name itself reveals, the fitness transformation is linear (f_i and f_i^* are the raw and scaled fitness values of individual i, respectively):

$$f_i^* = a_1 \cdot f_i + a_0 \tag{4.26}$$

Taking into account the basic scaling relation given by Equation 4.26, the slope a_1 and the intercept a_0 are derived by simultaneously solving the following set of equations:

$$\begin{aligned} \bar{f}^* &= \bar{f} \\ f^*_{\max} &= C_{\max} \cdot \bar{f} \end{aligned} \tag{4.27}$$

The first condition states that the raw and the rescaled average population fitness values must be equal. The second one limits the expected number of offspring the individual with the highest rescaled fitness is going to get. This number equals the factor C_{max}, which is a scaling parameter whose value should usually be kept in the range [1.2, 2] to achieve a good GA performance for relatively small populations (i.e. having up to 100 individuals). In some cases, however, if the parameters a_1 and a_0 are estimated according to Equations 4.27, the rescaled fitness may violate the non-negativity condition put forward by the definition of a GA. This generally happens when the average and the maximum raw fitness in a population are fairly close to each other but the minimum fitness is rather far below. The rescaled minimum fitness may then easily fall below zero. This means that the selected value of the factor C_{max} is too high. Therefore, the estimate of this parameter should be adjusted so as to ensure that the non-negativity of rescaled fitness is fulfilled. Thus, C_{max} becomes the third unknown variable in the problem presented by the Equations 4.26 and 4.27 and, therefore, one more equation is needed to solve the problem. Logically, the additional relation should state that the minimum rescaled fitness equals zero:

$$f^*_{\min} = 0 \tag{4.28}$$

The additional equation (4.28) ensures that, while preserving the non-negativity of the rescaled fitness, the maximum possible value of the factor C_{max} is going to be used in the scaling process.

Termination conditions. A number of criteria may be used to determine when to terminate a GA search. One of the reasons why there may be several termination criteria is the fact that GAs provide a multitude of alternative solution points in each generation. The simplest way to end a GA run would be to limit the number of newly created generations, or to set the maximum number of fitness function evaluations in the search. Thereafter, the individual which is found to have the highest fitness in the whole run could be singled out as the solution provided by the GA. However, it may also be interesting to analyze and to compare a number of alternative, highly fit solutions located in the run. Having this in mind, an additional termination criterion could be set up. Namely, a GA search could also end when the convergence rate of the maximum (and/or the average) population fitness reaches a certain predetermined level. Another possibility for a termination criterion could also be to limit the time available for a single GA run. And, finally, it should be noted that it is not infrequent to find that two or more of the above criteria are used simultaneously to control the process of a GA search.

A simple GA flow chart. A typical GA search consists of three basic phases. Figure 4.4 depicts these fundamental stages for a simple genetic algorithm (n.b. note that, without any loss of generality, this chart does not include the feasibility testing and fitness scaling issues).

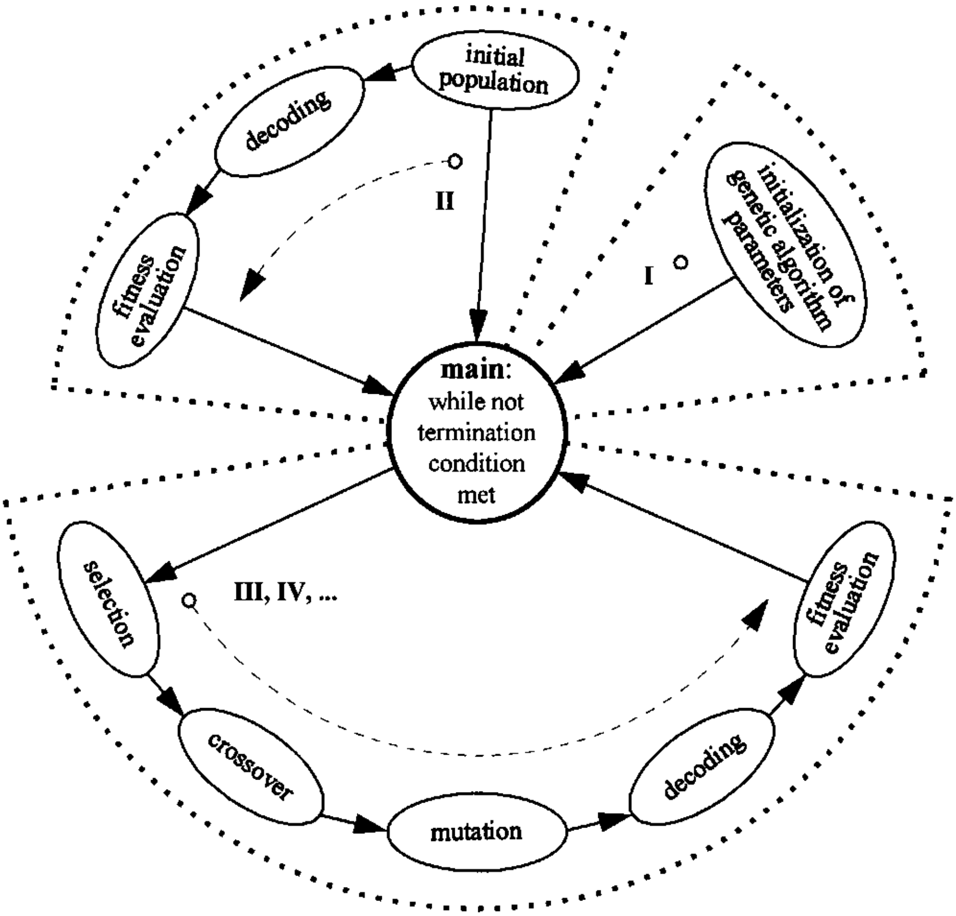

Figure 4.4 Genetic algorithm flow chart

The first step involves the initialization of the GA parameters (n.b. those should previously be calibrated to ensure a good performance of a GA search of the problem solution space): the population size, the maximum number of generations and the crossover and mutation probabilities. Obviously, this list should be extended by including the selected problem-specific parameters, if any.

The second phase is solely related to the creation of the initial population - the basis for the subsequent search. It consists of the random generation of the members of the starting population, their decoding into the potential solutions they represent and the evaluation of their respective fitness values.

The final stage includes a repeated process of creation of new generations of individuals. In the case of a simple GA presented in Figure 4.4 this phase involves the following basic steps: chromosome creation by applying the selection, crossover and mutation operators, and the evaluation of the fitness of the newly created potential solutions (n.b. in a more general case, the feasibility testing and fitness scaling would be a part of the "decoding-fitness evaluation" step).

All of the three phases, and the third one in particular, are overseen by the core of the "GA engine". This is the part of the model which controls the whole search process and checks whether the predefined termination conditions have been met or not.

4.5.2 Deriving the Best Water Allocation Pattern by Means of a Genetic Algorithm

Obviously, the distribution of the common demand load derived by the proposed decomposition methodology is highly dependent on the sequence upon which the reservoirs are entering the analysis. For instance, let three reservoirs (e.g. R_1, R_2 and R_3) supply a common demand and let the sequence of the reservoirs' entering the computational cycle comply with their respective indices. Assuming that neither of the reservoirs has sufficient resources to cover the common demand alone, the derivation of the sharing of the common demand load among the reservoirs would be based on the following:

1. Being the first in the computational sequence, the optimization of the reservoir's R_1 operation would target the entire common demand.

2. Subsequently, the operation of the reservoir R_2 would be optimized towards meeting only the portion of the common demand which could not have been covered by the reservoir R_1.

3. Similarly, only the part of the common demand which could not have been met by the reservoirs R_1 and R_2 is going to be used to optimize the operation of the reservoir R_3.

Consequently, the only way to obtain and to analyze any other alternative distribution of the common demand load would be to try and apply different decomposition orderings of the reservoirs. However, and despite the fact that the proposed decomposition principles do allow the use of alternative reservoir orderings, there is no guarantee that the structure of the system in question and the respective reservoir-demand links would make it possible to analyze all of the reservoir orderings which may be relevant for the given release distribution problem. For instance, if the three reservoirs from the above example are serially connected (e.g. R_3 is located downstream of R_2 which is, in turn, downstream of R_1), the orderings R_1-R_2-R_3 and R_3-R_2-R_1 can be analyzed by the proposed decomposition method. However, any of the other four possible combinations of reservoir sequencing (i.e. R_1-R_3-R_2, R_3-R_1-R_2, R_2-R_1-R_3 and R_2-R_3-R_1) do not comply with the adopted decomposition principles.

On the other hand, the hierarchical arrangement of demands assumed in the release allocation process causes that the demands with lower priority generally suffer higher supply shortages than those on the top of the hierarchy list. This, however, is not an unexpected problem. In fact, the introduction of demand ordering directly implies the anticipation of such consequences. The really unforeseeable impact of demand hierarchy is related to the resulting distribution of common demand loads among the reservoirs. Similarly to the reservoir ordering problem, this limitation can only be overcome if the alternative demand hierarchies are analyzed and, subsequently, the obtained results compared. Obviously, such an extensive undertaking would frequently prove too costly to opt for.

Consequently, a question must arise as to whether the proposed decomposition methodology can be modified in order to achieve the improvement of its performance in this respect. However, if the apparent simplicity and transparency of the method are to be preserved and, even more, if one wants to avoid the dimensionality problems which characterize the SDP, the likely answers should be sought in extending the decomposition algorithm by adding new external analytical tools, rather than in changing the original approach from within. In this respect, this study suggests that, based on the simulation of the entire multiple-reservoir system operation over a long historical record of reservoir inflows, it may be possible to arrive at an approximate estimate of the optimum distribution of demand loads within the system. In other words, the task would be to estimate the portions of the individual demands to be targeted by each of the reservoirs. Once these estimates are obtained, the originally proposed decomposition algorithm could be applied to the "new" system configuration, which is characterized by the modified demand structure. The advantage gained is reflected in the fact that, regardless of the adopted decomposition approach, the demands imposed upon individual reservoirs remain virtually unchanged during the iterative optimization process. In fact, according to the proposed combined approach, they do change from one iteration to another by only small amounts. That is, although each of the reservoirs has a fixed share of their common demand to supply, if any of the reservoirs could not supply its demand share in full, the reservoirs that follow in the decomposition sequence would take over that unmet demand and would try to cover it.

Unfortunately, however short this description of the desired goal may be, the problem itself is exceptionally large. Consequently, given the problem presented below, the task is to try and find the efficient and effective analytical tool to solve it.

Consider a hypothetical multiple-reservoir water supply system which provides water for a number of users. The reservoirs' interconnections include both serial and parallel links. Each reservoir may supply multiple demands and, at the same time, each demand centre may receive water from more than one reservoir. Based on the reservoirs' characteristics, the available historical inflow records of the reservoirs and the estimates of water demands in the system, the objective is to derive the optimum distribution of the demand load of each of the users among all the respective reservoirs, subject to the minimization of some function of the total supply deficit (n.b. without any loss of generality, the evaporation loss component is neglected in the following discussion; however, the final formulation of the GA model presented in Section 5.5 does take into account the inevitable evaporation losses from the surface of a reservoir;):

$$\text{minimize} \sum_{t=1}^{N_t} f(A,B,D) \tag{4.29}$$

subject to

$$s_{i,t} + q_{i,t} + \sum_{k=1}^{N_r} \rho_{i,k} \cdot w_{k,t} - \sum_{j=1}^{N_d} (\alpha_{i,j} - \beta_{i,j,t}) \cdot d_{j,t} - w_{i,t} = s_{i,t+1}, \quad \forall i,t \tag{4.30}$$

$$\sum_{i=1}^{N_r} \alpha_{i,j} = 1.0, \quad \forall j \tag{4.31}$$

$$\alpha_{i,j} \geq 0, \quad \forall i,j \tag{4.32}$$

$$\beta_{i,j,t} \geq 0, \quad \forall i,j,t \tag{4.33}$$

$$\beta_{i,j,t} \leq \alpha_{i,j}, \quad \forall i,j,t \tag{4.34}$$

$$s_{i,t,\min} \leq s_{i,t} \leq s_{i,t,\max}, \quad \forall i,t \tag{4.35}$$

$$w_{i,t} \geq 0, \quad \forall i,t \tag{4.36}$$

where

N_r	the number of reservoirs in the system (reservoirs are depicted by the index i);
N_d	the number of demands in the system (the demand index is j);
N_t	the length of the time period analyzed (i.e. the number of time steps t);
$s_{i,t}$	the storage volume of reservoir i at the beginning of month t;
$q_{i,t}$	the inflow to reservoir i in month t;
$d_{j,t}$	the volume of demand j in month t;
D	the $N_d \times N_t$ matrix of all $d_{j,t}$'s (n.b. note that $d_{j,t} = d_{j,t+12k}$ $\forall k \in \mathbf{N}$);
$\alpha_{i,j}$	the relative contribution of reservoir i to supplying demand j (n.b. $\alpha_{i,j}$ is assumed constant over the entire time span);
A	the $N_r \times N_d$ matrix of all $\alpha_{i,j}$'s;
$\beta_{i,j,t}$	the relative supply deficiency of reservoir i towards the demand j in month t (n.b. expressed relative to the total of the demand);
B	the $N_r \times N_d \times N_t$ matrix of all $\beta_{i,j,t}$'s;
$w_{i,t}$	the excess, non-consumptive release from reservoir i in month t;
$\rho_{i,k}$	the factor which indicates whether reservoirs i and k are serially linked and, if so, whether reservoir k is situated upstream of reservoir i:

$$\rho_{i,k} = \begin{cases} 1, & i \text{ and } k \text{ are serially linked and } k \text{ is upstream} \\ 0, & \text{otherwise} \end{cases}, \quad \forall i,k \tag{4.37}$$

$(\alpha_{i,j} - \beta_{i,j,t})\cdot d_{j,t}$ is the consumptive release from reservoir i to demand j in month t.

Table 4.2 The number of unknown variables

	$\alpha_{i,j}$	$\beta_{i,j,t}$	$s_{i,t}$, $w_{i,t}$	*Total*
extended	$(N_\alpha = N_r \cdot N_d)$	$(N_\beta = N_r \cdot N_d \cdot N_t)$	$(N_{s,w} = 2 \cdot N_r \cdot N_t)$	$(N_\alpha + N_\beta + N_{s,w})$
	$7 \cdot 18 = 126$	$7 \cdot 18 \cdot 528 = 66528$	$2 \cdot 7 \cdot 528 = 7392$	74046
actual	28	$36 \cdot 528 = 19008$	$2 \cdot 7 \cdot 528 = 7392$	26428

Table 4.3 The number of constraints

	The number of constraints given by...			
	Equation 4.30	*Equation* 4.31	*Equation* 4.34	*Total*
extended	$(N_1 = N_r \cdot N_t)$	$(N_2 = N_d)$	$(N_3 = N_r \cdot N_d \cdot N_t)$	$(N_1 + N_2 + N_3)$
	$7 \cdot 528 = 3706$	18	$7 \cdot 18 \cdot 528 = 66528$	70252
actual	$7 \cdot 528 = 3706$	10	$36 \cdot 528 = 19008$	22724

The structure of the problem depicted by Equations 4.29 through 4.37 immediately suggests that, provided the objective function is linear, the solution could be obtained by linear programming. However, both the number of unknown variables and the number of constraints involved grow rapidly with the increase of the number of reservoirs, demands and time periods considered. For instance, Tables 4.2 and 4.3 represent those estimates for the seven-reservoir case study system (n.b. the rows labelled "extended" give the estimates for the extreme case where each reservoir is assumed to supply each of the demands). The length of the time period is 44 years, i.e. 528 monthly time steps. Although the total number of demand centres is 18, only 10 of those are supplied by more than one reservoir (cf. Table 3.1). Consequently, the number of unknown variables $\alpha_{i,j}$ becomes only 28 (i.e. $5+3+3+3+3+3+2+2+2+2$ for the demands TU, TO, NA, MO, SO, SF, IBH, IAEA, IBV and IMSC, respectively). Note that, for the remaining eight demands which are supplied by only one reservoir (i.e. BI, IMA, BLI, BE, JE, MB, INE and ISI), $\alpha_{i,j} = 1$ for the reservoir i which supplies the demand j and $\alpha_{i,j} = 0$ for those reservoirs i which do not cover this particular demand. Similarly, the number of relative monthly supply deficits $\beta_{i,j,t}$ is reduced to $(28 + 8) \cdot 528 = 19008$ (i.e. 28 for each of the $\alpha_{i,j}$

variables and the additional eight for the demands BI, IMA, BLI, BE, JE, MB, INE and ISI, times the number of time periods).

It should be noted here that the constraints given by the Equations 4.32, 4.33, 4.35 and 4.36 do not contribute to the size of the constraint set because they represent the non-negativity, upper and lower bounds of the unknown variables and thus can be avoided in the linear programming formulation. Nevertheless, the problem still remains exceptionally complex: for the given case study system, a potential application of linear programming would have to find the values of 26428 unknown variables bounded by 22724 constraints. The computational frustration grows even bigger upon realizing that only the 28 $\alpha_{i,j}$ parameters (Table 4.2) are relevant for the further analyses.

This study proposes an alternative way of solving the problem described by Equations 4.29 through 4.37. Namely, a search strategy based on genetic algorithms is developed and tested on the seven-reservoir case study system. The rationale behind the selection of GAs is threefold:

1. Firstly, the problem itself is exceptionally large. Even if the objective function given by Equation 4.29 were linear, the above example shows that an LP formulation would be confronted with almost prohibitive sizes of the variable and constraint sets. This is even more true if the system to be analyzed is larger and more complex than the seven-reservoir test case used in this study. However, as it will be shown in this section and in Section 5.5, GAs exhibit much less sensitivity to the size of the problem.

2. Secondly, if the objective function used in the described water allocation analysis were to be at least partially compatible with its counterpart adopted in the SDP optimization within the proposed decomposition algorithm (cf. Section 4.2) the choice of linear programming would not be a viable one. On the other hand, GAs put no specific restrictions as to the type of objective function used in the search (cf. Section 2.3).

3. Finally, as the results presented in Chapter 6 clearly show, the water allocation problem addressed here does not have a unique optimum solution. Namely, for a particular objective function, there exist a number of equally good water allocation patterns within the system. In other words, for a group of reservoirs supplying a common demand target, there are multiple distributions of the demand load among the reservoirs which result in the identical, or at least very close, objective function values. With regard to the objective function itself, this means that the surface of the chosen multivariate function contains multiple peaks of the same, or very close, magnitude (n.b. in the actual minimization problem, this statement refers to the inverse of the objective function). This last characteristic of the problem poses yet another question: Is it, perhaps, possible to identify all those peaks, or at least some of them? The results in Chapter 6 show that the GA-based approach might be able to provide an affirmative answer to this question.

The remaining part of this section introduces the genetic algorithm model devised to solve the water allocation problem within a multiple-reservoir system. In addition to this description, Section 5.5 provides a detailed mathematical formulation of the complete GA model.

The developed GA model searches the solution space of a multivariate objective function trying to locate the points associated with the minimum objective function value. The objective function adopted for the GA is the aggregate of the squared monthly deficits of each of the demands over the entire time period under consideration. Thus, after rewriting the Equation 4.29, the GA fitness function becomes:

$$\text{minimize} \sum_{t=1}^{N_t} \sum_{j=1}^{N_d} \left(\sum_{i=1}^{N_r} \beta_{i,j,t} \cdot d_{j,t} \right)^2 \tag{4.38}$$

Within the model, the coordinates of a potential solution point represent the values of the $\alpha_{i,j}$ elements of the $N_r \times N_d$ matrix A (i.e. the decision variables of the problem depicted by the Equations 4.29 through 4.37). The respective $\beta_{i,j,t}$ factors and the corresponding fitness (i.e. objective) function value from Equation 4.38 are estimated by simulating the performance of the reservoir system over the entire time period under consideration. The underlying encoding mechanism in the devised GA model utilizes the most frequently used binary representation of individual potential solutions. The GA search starts from a population of potential solution points generated at random. The emulated evolution of a population of solutions is guided by the scaled fitness of the individuals and is executed with the help of proportional selection, one-point crossover and bitwise complement mutation operators. In addition, to ensure the feasibility of the newly created solution strings, the devised GA model utilizes a type of random-driven repair mechanism.

Two different GA formulations are devised in this study (n.b. the detailed descriptions of both of the models are given in Section 5.5). The main distinction between the two is in the way they are to be linked with the decomposition-based SDP optimization model.

One GA model is assumed to utilize the decomposition algorithm as a means to estimate the fitness of individual alternative solutions during its run. In essence, this means that the iterative decomposition-based optimization procedure has to be executed each time a new individual is created in the GA. Namely, each individual in a GA population represents a specific set of demand sharing parameters $\alpha_{i,j}$. In other words, different individuals depict different demand patterns and, consequently, each of them is associated with a different optimal operating strategy of the system. Subsequently, the derived operating strategy has to be appraised by simulation to obtain the estimate of the respective fitness function value (Equation 4.38). This approach, however, can be very time consuming. Namely, assuming a conservative estimate of 3000 fitness function evaluations in a single GA run (e.g. 100 generations containing 30 individuals each) and a no less conservative estimate of 60 seconds of processing time on a standard Pentium 120 for a two-iteration optimization of a seven-reservoir system operation by means of the decomposition-based model, the expected execution time for function evaluations in one GA search amounts to 180000 seconds (i.e. 50 hours). Although fairly insignificant in comparison to the fitness function evaluation time, the duration of the additional operations like encoding, selection, crossover, mutation, fitness scaling, feasibility testing and repairing steps in a GA run have to be added to the former estimate.

To reduce the computation time requirements, an alternative approach is proposed. In this case, the GA model and the decomposition-based optimization algorithm are separated and executed in sequence. The GA allocation model is first used to determine the most likely optimum distribution of demand loads among the reservoirs. Subsequently, upon deriving the values of the unknown variables $\alpha_{i,j}$, the decomposition-based optimization is carried out using the demand distribution generated according to the values of parameters $\alpha_{i,j}$.

Essentially, the alternative GA model differs from the former one only in the fitness evaluation module. Namely, the new model utilizes a very fast simulation procedure to appraise the fitness of an individual. The computation time spent for fitness evaluation of a single individual is significantly reduced by assuming that each reservoir is to be operated according to the standard operating rule (cf. Section 5.5). It is worth mentioning that, for the test case system used in this study, a single system simulation run within the alternative GA model (i.e. a single individual fitness evaluation) takes approximately 0.14 seconds resulting in about 420 seconds (i.e. 7 minutes) needed for an average GA run involving 3000 fitness evaluations (n.b. the time estimates are given for the Pentium 120). This is by all means a substantial gain as compared with 50 hours required by the decomposition-based fitness evaluation.

This execution time reduction is achieved solely by separating the GA and decomposition models. In fact, such a large time saving is entirely due to the elimination of the need to optimize the operation of the system within each fitness evaluation. Consequently, the decision to opt for the fitness evaluation based on the simulation according to the standard operating rule should be discussed a bit further.

The standard reservoir operating rule (SOR) is a well known operating principle which can almost be summarized in a single sentence: *Subject to the physical limitations of the reservoir's storage and release volumes, release as much water as possible to meet the targeted demand.* With regard to SDP, Hashimoto et al. (1982) analyzed different SDP policies derived upon using a family of objective functions defined as:

$$\text{minimize}\, E[l_\gamma(R)] \tag{4.39}$$

where

T	target release;
R	release;
E	expectation operator;
$l_\gamma(R)$	penalty function defined as follows:

$$l_\gamma(R) = \left[\max\left(0, \frac{T-R}{T}\right)\right]^\gamma, \quad 0 \le \gamma \le 7 \tag{4.40}$$

They showed that the SDP optimization of a single reservoir operation would result in the policy identical to the standard operating rule for the objective function with the exponent $\gamma = 1$. The authors also pointed out that the SDP policies derived using the penalty functions where $\gamma > 1$ were exhibiting hedging, i.e. occasionally releasing less water than the targeted demand was, despite the fact that the available volume of water was sufficient to meet the demand in full.

The conclusions drawn by Hashimoto et al. (1982) were based on the use of the objective functions which penalized only the shortage of supply (Equations 4.39 and 4.40). This type of penalty is further referred to as a single-sided deviation. Similar conclusions could also be drawn for the objective functions which penalize both the shortage and the surplus of the respective supply (i.e. double-sided deviation). Namely, the operation of the Joumine reservoir (cf. Chapter 3) has been optimized by means of SDP four times using the objective function given by Equation 4.39 where the penalty function $l_\gamma(R)$ was defined as:

1. The single-sided linear deviation of the release from the respective demand:

$$l_\gamma(R) = \max(0, T - R) \tag{4.41}$$

2. The single-sided squared deviation of the release from the respective demand:

$$l_\gamma(R) = [\max(0, T - R)]^2 \tag{4.42}$$

3. The double-sided linear deviation of the release from the respective demand:

$$l_\gamma(R) = |T - R| \tag{4.43}$$

4. The double-sided squared deviation of the release from the respective demand:

$$l_\gamma(R) = (T - R)^2 \tag{4.44}$$

The following discussion about the obtained results concentrates only on SDP policies for summer months, when water availability is very low as compared to the respective demand. The dry period policies are particularly important because they can illustrate better the difference between the chosen objective functions. That is, the effects of using the double-sided instead of the single-sided deviation are much more pronounced in dry summer months. This is because the operating policies for hydrologically wet periods are frequently forced to recommend releases higher than the respective demand due to the reservoir getting filled up. In addition, such excess releases may also be opted for to avoid even higher spilling in the following time periods.

The SDP policies obtained by using the objective functions depicted by Equations 4.41 and 4.43 (i.e. single-sided and double-sided linear deviations, respectively) showed very close similarity to the standard reservoir operating rule. Apart from a few minor differences which were believed to be entirely due to the necessary storage and inflow discretization in SDP, the two policies were almost identical. On the other hand, the two policies derived upon the single-sided and double-sided squared deviations (Equations 4.42 and 4.44, respectively) did exhibit hedging. If compared to its single-sided counterpart, the double-sided squared deviation policy was further characterized by higher releases when the available volume of water in a month was higher than the half of the reservoir's capacity. This was entirely due to the used objective function which penalized both the deficit and the surplus incurred by the decisions made. However, this difference is not so relevant because it is less likely that the water availability in a reservoir would reach such high levels in dry summer months of a semi-arid climate, which characterizes the region where the reservoir is located.

Thus, the implementation of the decomposition-based SDP optimization model with the double-sided squared deviation objective function (Equation 4.44) for fitness evaluation within a GA would result in reservoir operating policies which are characterized by hedging. On the other hand, the standard reservoir operating rule lacks this intrinsic SDP policy feature. This means that the SOR-based simulation would result in higher releases than the corresponding SDP-based simulation when water availability during a time period is rather low. Consequently, this may cause the SOR simulation to exhibit more severe water shortages during extended drought periods which is less likely to be the case with the SDP. Therefore, the fitness function used within the developed GA models is defined as the aggregate of the squared deviation of the total monthly system releases from the respective individual demands (cf. Section 5.5). The chosen fitness function is thus expected to drive a GA search away from those demand distribution patterns which cause more extreme shortages if the reservoirs are operated according to the standard reservoir operating rule. It should, however, be pointed out here that the proposed coupling of the SOR simulation and the chosen fitness function is not changing any of the basic principles of SOR, i.e. it is not introducing hedging into SOR. It is rather acting as an additional incentive for the GA to search for such demand distribution patterns which would make the system's (SOR-based) operation less susceptible to long and/or extreme drought events.

The above discussed similarities between the SDP policies obtained for the objective functions based on the single-sided and double-sided, both linear and quadratic, deviations and the standard reservoir operating rule show that the alternative GA-SOR model may provide a good approximation of the complete model based on the coupling of the GA and the decomposition algorithm. This is further supported by the presentation of the major differences and similarities between the results obtained by the two GA models which are given in Sections 6.4 through 6.6.

5 MODELLING FRAMEWORK

This chapter describes all the mathematical models used in this study. Similarly to the outline of Chapter 4, this part is divided into separate units with respect to the specifics of the problems addressed by particular models:

1. The description of the adopted system decomposition approaches (Section 5.1);
2. Stochastic dynamic programming as the choice for optimization (Section 5.2);
3. The formulation of alternative simulation options (Section 5.3);
4. The adopted demand and inflow estimation methods and the description of the release allocation model within the proposed decomposition algorithm (Section 5.4);
5. The genetic algorithm model developed to derive the best achievable water allocation pattern within a multiple-reservoir water supply system (Section 5.5); and
6. The formulation of the system performance evaluation criteria used in this study (Section 5.6).

5.1 System Decomposition

All of the three decomposition methods presented in this dissertation are based on essentially the same principle - breaking down a multiple-reservoir system into individual reservoir units and a subsequent iterative determination of the individual reservoir operating policies. To derive the operating policies of individual reservoirs, each of the methods employs the same iterative six-step optimization/simulation procedure which involves:

1. Estimation of the inflow into a reservoir;
2. Evaluation of the demand imposed upon a reservoir;
3. Stochastic dynamic programming based optimization of the operation of a reservoir;
4. Simulation of the reservoir's operation according to the derived SDP policy;
5. The total releases obtained by simulation are allocated to individual users; and
6. Estimation of the expected unmet demands and the expected total supply deficits associated with the operation of the reservoir in question.

With regard to the relative flexibility of the basic decomposition principles (cf. Section 4.1), there generally exist a number of possible reservoir orderings which comply with the imposed decomposition rules. However, the operational analysis of the case study system presented in Chapter 3 has been limited to only three alternative reservoir sequences, each exemplifying a distinct decomposition approach. What distinguishes these three decomposition approaches from one another is the way they address the problem of modelling the interaction among serially linked reservoirs. The remaining part of this section introduces the three employed decomposition approaches and presents their respective applications to the case study system used in this dissertation.

5.1.1 Sequential Downstream-Moving Decomposition

The ordering of individual reservoirs according to this decomposition approach generally follows the direction of river flows in the river basin(s). Namely, within each iteration, the analysis starts from the uppermost reservoir in the system. Thereafter, the selection of reservoirs proceeds in the downstream direction until all the reservoirs have been taken into consideration, which completes one iterative cycle. Such cycles are then repeated until a satisfactory stabilization of the total system return has been achieved.

Figure 5.1 presents the general flow chart of the applied *sequential downstream-moving decomposition* (SDD) and Figure 5.2 depicts the symbolic representation of the decomposed case study system according to this approach (n.b. both figures utilize the same notation, which is described along the introduction of the main SDD decomposition features). The definition of reservoir ordering is based on two principles:

1. Reservoirs are initially clustered into *cascade levels* (K) to distinguish between subsets of reservoirs with respect to the sequence upon which those subsets will be entering the principal iterative cycles (I). According to the SDD approach, the cascade level ordering is guided by the descending arrangement of their respective indices K. The total number of cascade levels is represented by the parameter M in the flow chart (Figure 5.1).

2. Reservoir selection order (L) within a cascade level can be defined upon any rules imposed by the analyst. These may include firm water allocation schemes, water quality requirements or some empirical rules based, for instance, on some operating or environmental issues.

The reservoir ordering for the case study system in the SDD decomposition approach is (Figure 5.2): Joumine, Ben Metir, Kasseb, Bou Heurtma, Mellegue, Sidi Salem and Siliana. The choice of the Joumine-Ben Metir-Kasseb ordering in cascade $K = 3$ is generally an arbitrary one. On the other hand, the Bou Heurtma-Mellegue ordering in cascade $K = 2$ is determined upon the priority Bou Heurtma has towards supplying their joint irrigation demand IBH (cf. Table 3.1 in Chapter 3). The Sidi Salem-Siliana sequence in cascade $K = 1$ is solely based on the superior size, water availability and principal role Sidi Salem exhibits in the system.

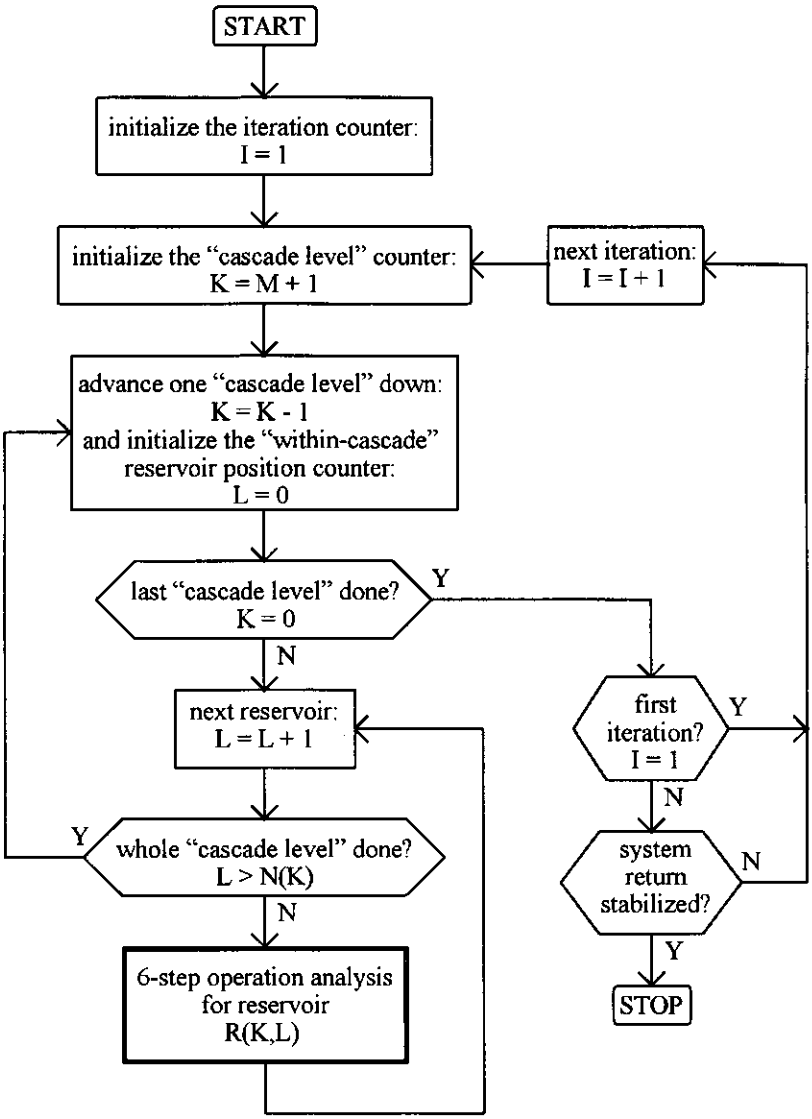

Figure 5.1 Sequential downstream-moving decomposition flow chart

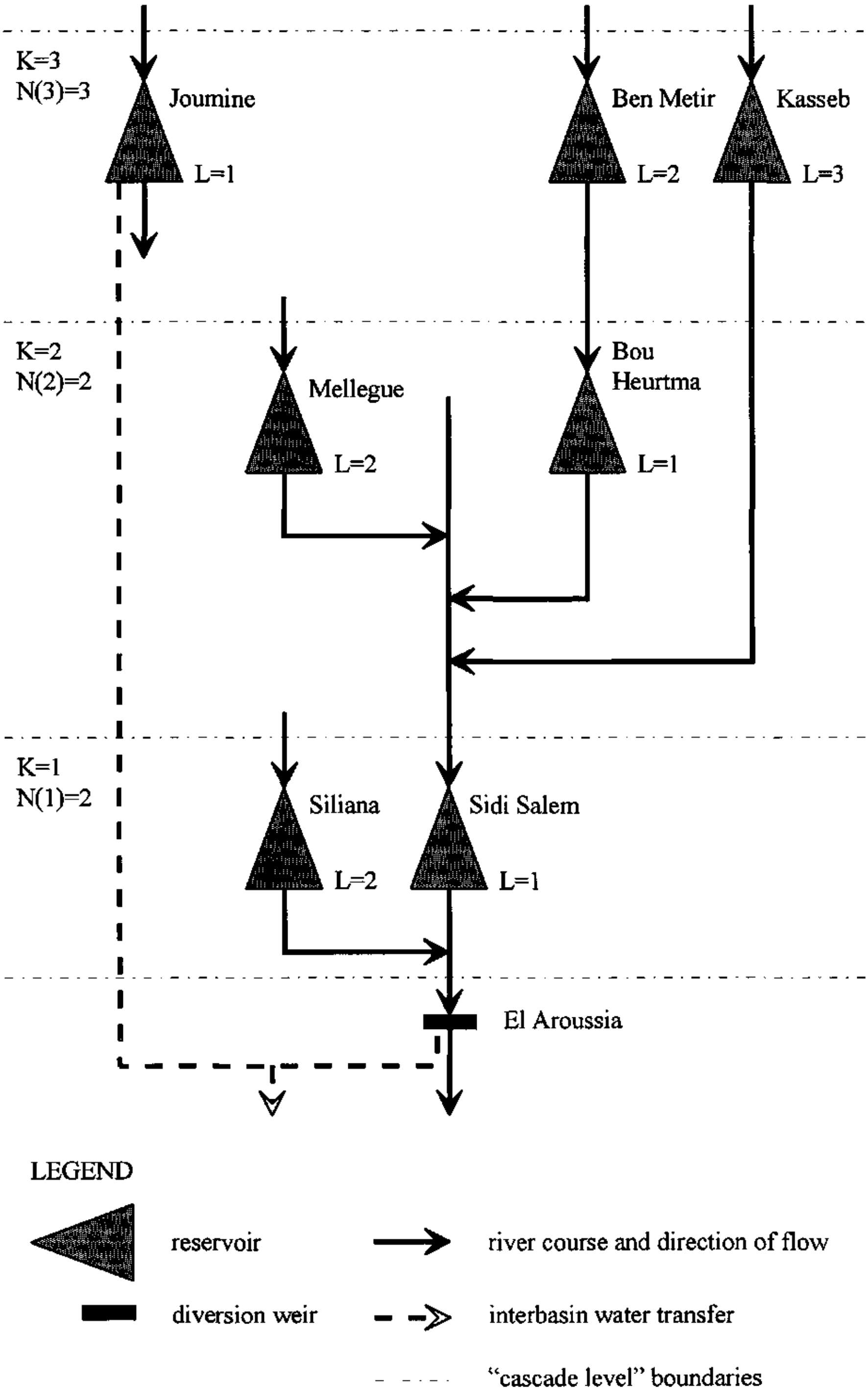

Figure 5.2 Sequential downstream-moving decomposition of the case study system

The adopted decomposition methodology relies on the iterative analyses of individual reservoir operations to arrive at the operating strategy of the entire system. Therefore, the approach must provide the means to maintain, or at least approximate, the interactions among reservoirs within its iterative process. The SDD decomposition utilizes three principles to this end. Namely, upon completing the analysis of the operation of a reservoir, three distinctive pieces of information are made available for further analyses:

1. Within one iterative cycle, the estimated expectations of monthly demands which have not been covered so far are regularly updated after each reservoir's operating strategy has been derived by optimization and appraised by simulation. That is, the operation of the next reservoir in the sequence is going to be analyzed with respect to the updated expectation of the system's demand records. For instance (cf. Table 3.1 and Figure 5.2), being the first in the optimization sequence Joumine faces the entire TO demand. Upon estimating the expected monthly allocation of Joumine resources to this demand, any of the expected unmet monthly TO requirements are to be associated with Sidi Salem, the next reservoir in sequence to supply this demand. Ultimately, the operation of Siliana is optimized taking into account the expected remaining part of the TO demand which could not have been covered by Joumine and Sidi Salem.

2. The aggregate of the expected monthly estimates of all the unmet demands associated with a particular reservoir are regarded as the total expected supply deficit of that reservoir. In the subsequent iteration cycle, the monthly estimates of a reservoir's supply deficits are used as an additional, hypothetical demand imposed upon the reservoirs situated directly upstream of the reservoir in question. Consequently, the upstream reservoirs' operating strategies derived in the succeeding iteration would be altered so as to try to release additional water to increase the inflow into the downstream reservoir in those periods when the operation of the downstream reservoir exhibits supply shortage. With regard to the case study system (Figure 5.2), for example, the total consumptive demand imposed upon Ben Metir is increased by the expected supply deficit of Bou Heurtma estimated in the preceding iteration. Similarly, the previous iteration supply deficit of Sidi Salem is associated with Kasseb, Bou Heurtma and Mellegue (n.b. being covered by more than one reservoir, the expected supply deficit of Sidi Salem is also subject to demand updating as described in the previous point).

3. Upon allocating water to all the associated users, the remaining part of the total reservoir release, if any, is considered as a supplementary inflow to the reservoir located immediately downstream. For instance, Bou Heurtma's incremental inflows are increased by the non-utilized releases from Ben Metir estimated in the same iterative cycle and, similarly, Sidi Salem makes use of the additional inflow originated from excess releases from Kasseb, Bou Heurtma and Mellegue, all obtained in the same iteration (Figure 5.2).

5.1.2 Iterative Downstream-Moving Decomposition

Iterative downstream-moving decomposition (IDD) is essentially a variation of the SDD approach. Consequently, reservoir ordering in IDD is also determined on the basis of the two principles related to the cascade level definitions and within-cascade reservoir sequences (cf. Section 5.1.1). In addition, the interactions among the serially connected reservoirs and demand updating are defined in the same way as within the SDD approach. The flow chart of the IDD decomposition is given in Figure 5.3 and the case study system decomposition according to this approach is presented in Figure 5.4. The notation used to describe the IDD decomposition is identical to the one introduced in Section 5.1.1, with the only addition to the already presented set being the cascade attribute D whose role is clarified in the following passage.

The formulation of the IDD approach brings about an improvement to the way the SDD decomposition deals with the cases where several reservoirs in parallel are serially linked to one reservoir situated downstream of them (Bogardi and Milutin 1995). Namely, in SDD the analyses of the operation of all the reservoirs on one cascade level are completed before proceeding to the next downstream cascade level. Thus, if the upper cascade level contains a number of reservoirs which can contribute to the increase of the inflow to one of the reservoirs on the lower cascade level, the optimization of the operation of the downstream reservoir is carried out only after the analyses of all of its direct upstream counterparts have been completed. Since the interactions among serially connected reservoirs are approximated by the exchange of the information about the expected supply deficits of the downstream reservoir obtained in the preceding iteration and the time series of non-utilized flows from the upstream reservoirs derived in the present iterative cycle, it is obvious that the estimation of the expected supply deficit of the downstream reservoir can repeatedly be updated after completing the analysis of the operation of each of the upstream reservoirs. In other words, the time series of the excess flows from the first analyzed upstream reservoir can be used to make the initial update of the downstream reservoir's operating policy and, in turn, to re-evaluate its expected supply deficits. Thereafter, the updated expected supply deficits are to be used as additional hypothetical demand imposed upon the next upstream reservoir. This process is repeated for each of the upstream reservoirs which are serially connected to the downstream one.

According to the IDD decomposition, the sequence upon which the reservoirs enter the computational process within one iterative cycle is (Figure 5.4): Joumine, Ben Metir, Kasseb, Sidi Salem, Bou Heurtma, Sidi Salem, Mellegue, Sidi Salem, Siliana. Clearly, the operation of Sidi Salem is derived in three consecutive steps following the optimization of Kasseb, Bou Heurtma and Mellegue, respectively. This process is controlled by the introduction of the cascade level attribute D identifying the reservoir from the immediate downstream cascade level whose operation is to be repeatedly optimized following the analysis of each of the reservoirs from the present cascade level (e.g. the value of D for cascade level $K = 2$ is $D(2) = 1$ which points to Sidi Salem whose index in the immediate downstream cascade is $L = 1$).

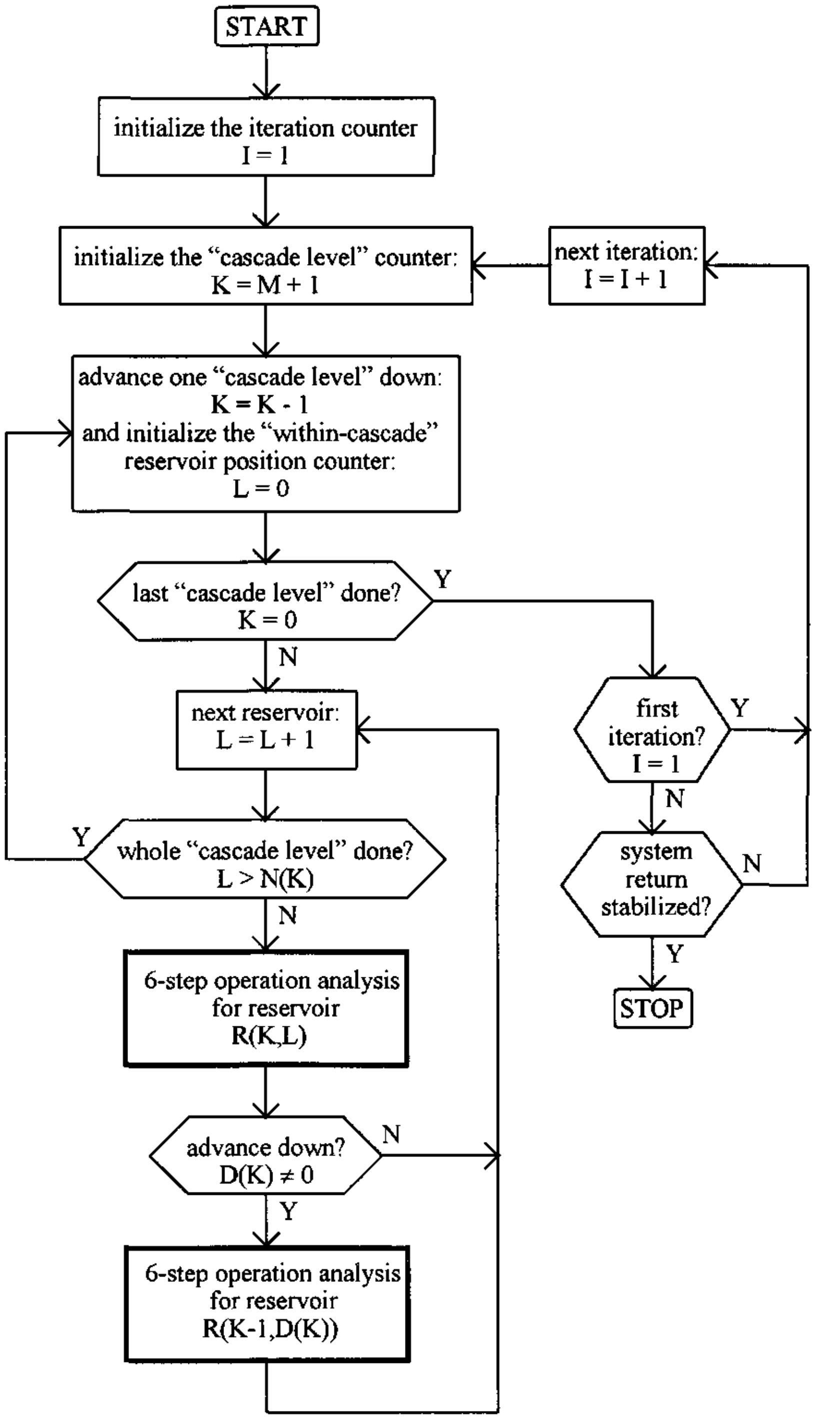

Figure 5.3 Iterative downstream-moving decomposition flow chart

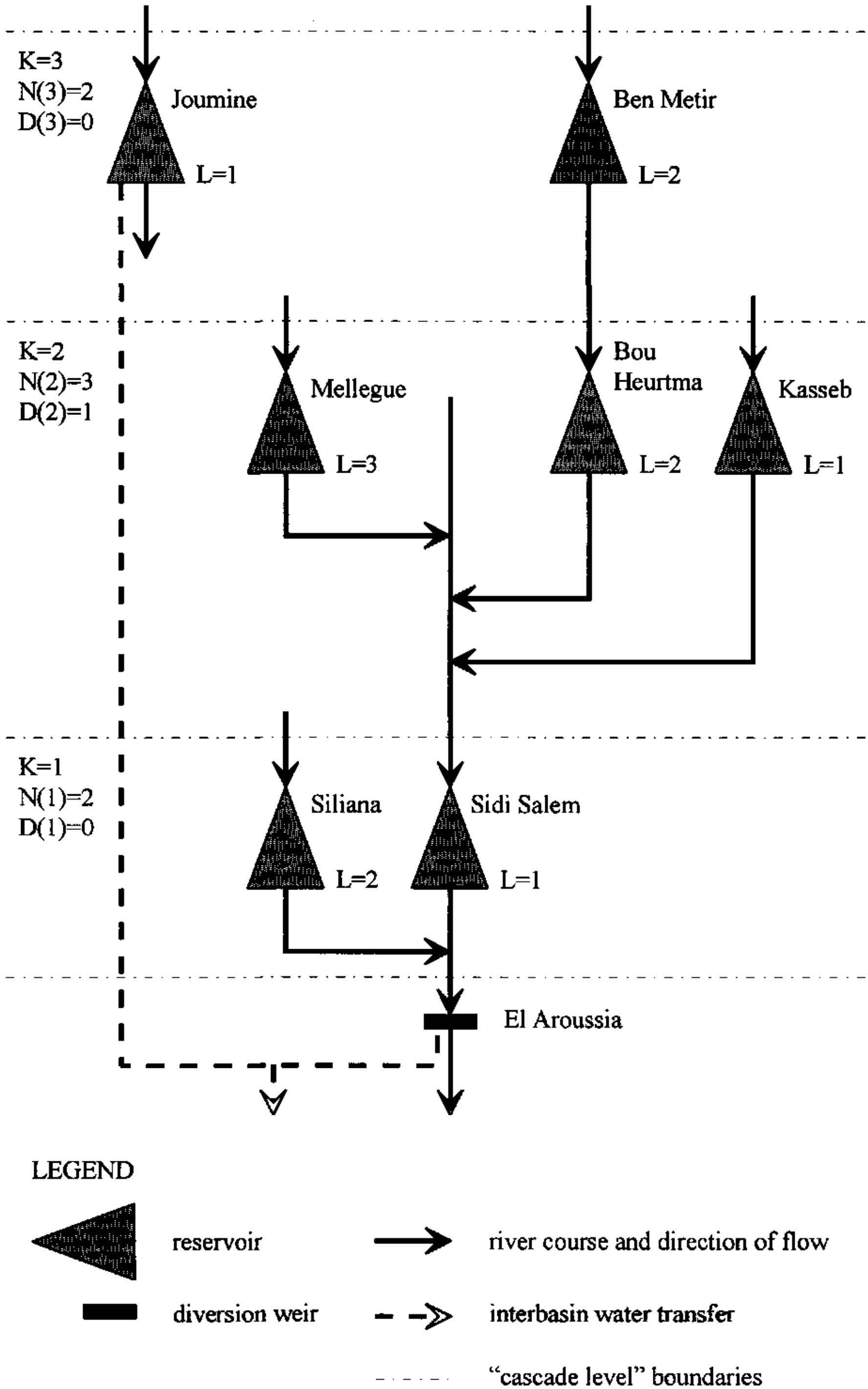

Figure 5.4 Iterative downstream-moving decomposition of the case study system

5.1.3 Iterative Up-and-Downstream-Moving Decomposition

Iterative up-and-downstream-moving decomposition (UDD) departs from the former two decomposition methods in a sense that the adopted reservoir sequence generally follows the direction opposite to the direction of river flows. On the other hand, the common feature among the three is the principle of breaking down a complex system into individual reservoirs by identifying reservoir subsets at different cascade levels with the subsequent determination of within-cascade reservoir analysis orders. However, unlike the SDD and IDD methods, the UDD decomposition analyzes the individual reservoir operations by starting from the lowest cascade level and thereafter proceeding upstream along the cascade levels. In addition, any of the existing serial reservoir links are modelled by an iterative up-and-down progression within the respective subset of reservoirs. The flow chart of the UDD decomposition is depicted in Figures 5.5 and 5.6. The case study system decomposition according to this method is presented in Figure 5.7. The general cascade level and reservoir position notation used in the UDD decomposition is identical to the one given for the former two methods (cf. Section 5.1.1). Some additional system decomposition attributes, i.e. the parameter U identifying the number of upstream reservoirs serially linked to a particular reservoir and the vector of indices V of the respective upstream reservoirs, are described in the following passages.

The individual reservoir operation analysis within one iteration of the UDD decomposition starts from the lowest cascade level in the system. The information interchange between two subsequent iterations is, unlike in SDD and IDD approaches, the set of time series of non-utilized flows from the reservoirs. These records are used as additional inflows into the respective downstream reservoirs in serially linked reservoir clusters, if any. If the reservoir whose operating analysis has just been completed is serially linked to any number of reservoirs from the upstream cascade level (i.e. the attribute U for the reservoir is not zero), the process continues by advancing to the upstream cascade level to analyze the operation of those reservoirs V which are linked to the reservoir in question. The operations of those reservoirs are then optimized and simulated taking into account the expected monthly supply deficits of their downstream counterpart. Upon completing the upstream cascade analyses, the process returns to the downstream reservoir where it has made the advance in the upstream direction. At this point, the optimization and simulation of the operation of this reservoir is carried out once again. This is done to update its operating strategy by taking into account the additional inflow time series obtained in the analyses of the reservoirs from the upstream cascade level. Once such an iterative up-and-down analysis is completed for a serially linked cluster, the process continues with the next reservoir in the presently lowest cascade whose analysis has not been completed yet. Similarly to the other two decomposition methods, the UDD decomposition also observes the demand updating principle in addition to the exchange of information about the non-utilized releases and the expected monthly supply deficits.

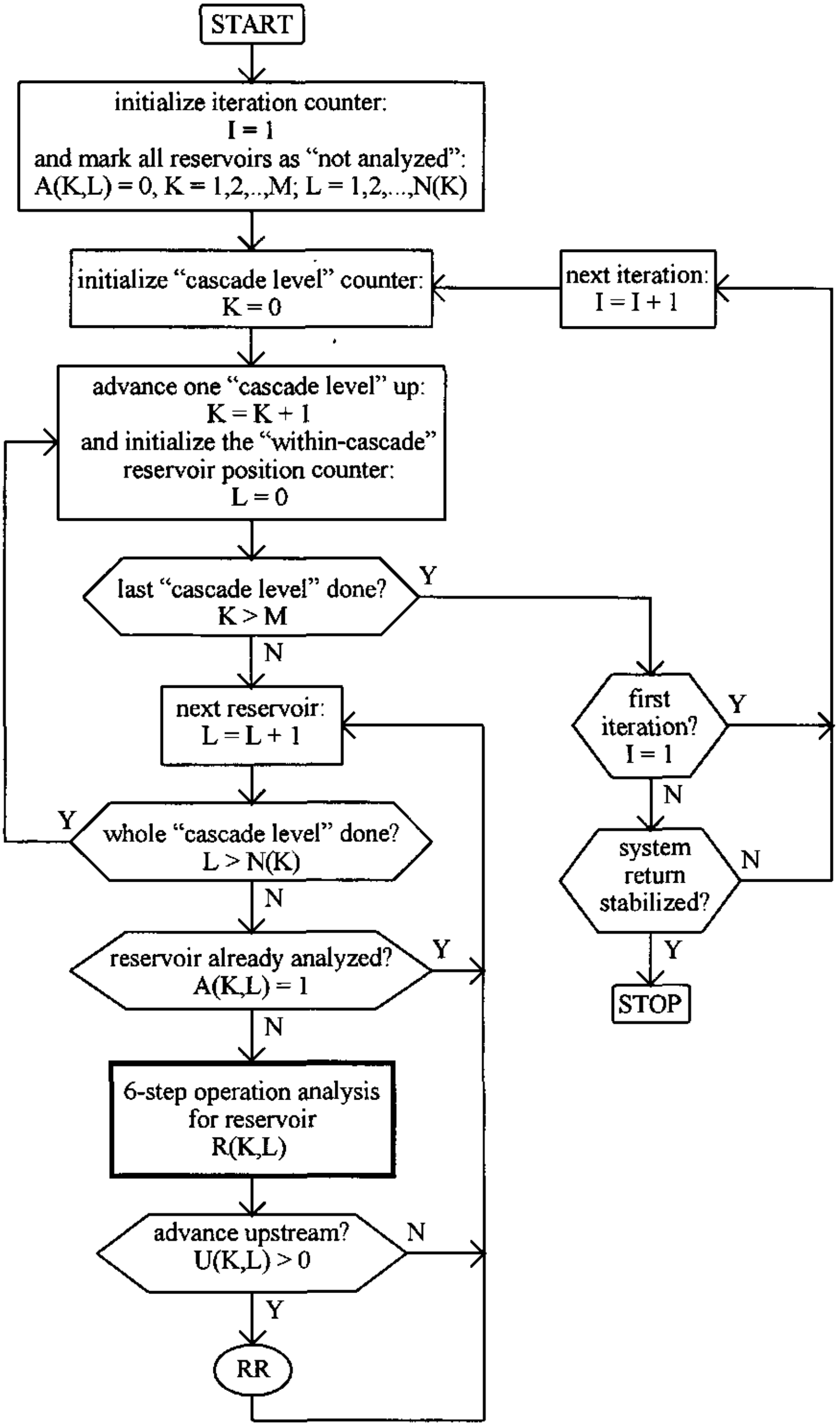

Figure 5.5 Iterative up-and-downstream-moving decomposition flow chart (1)

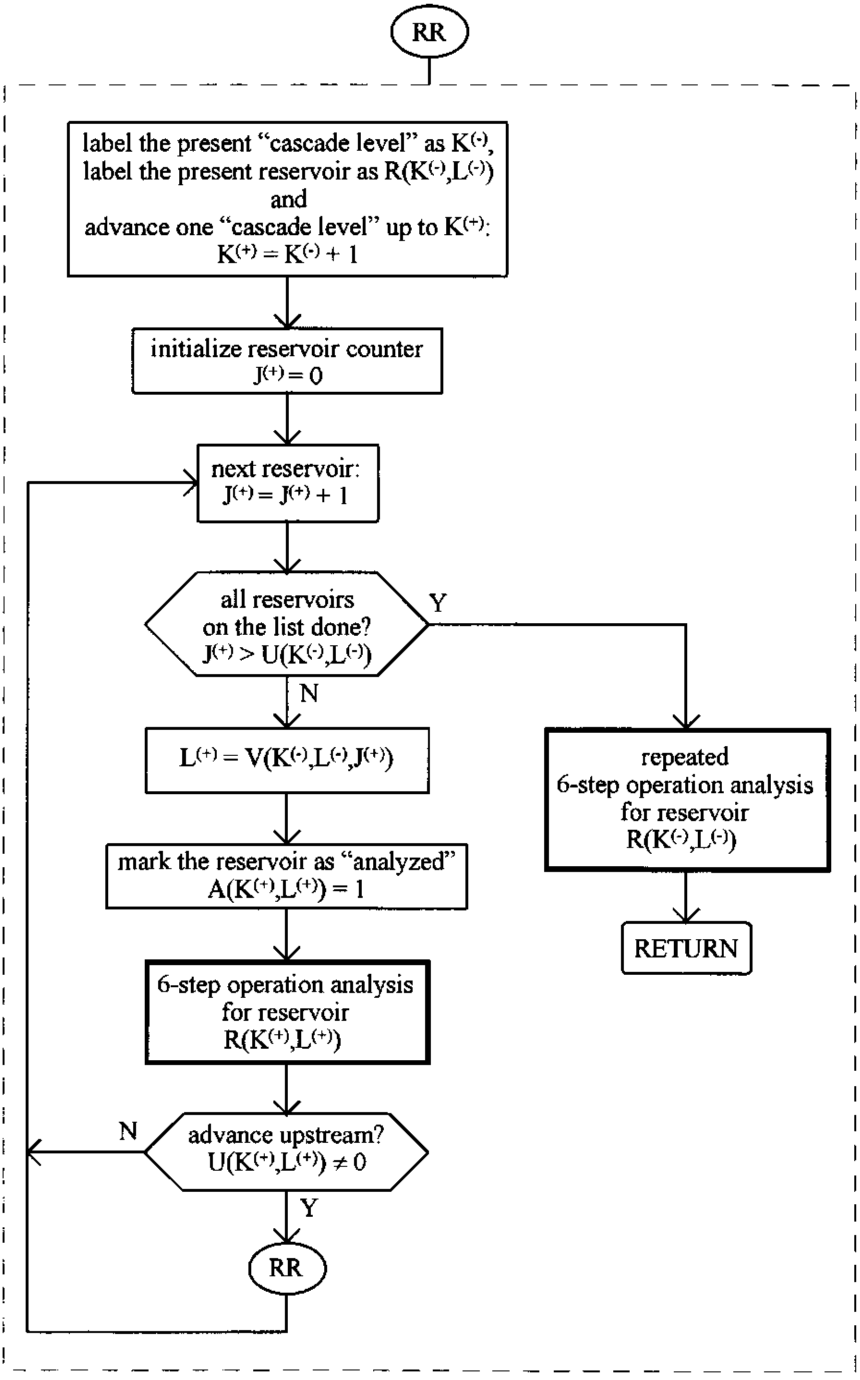

Figure 5.6 Iterative up-and-downstream-moving decomposition flow chart (2)

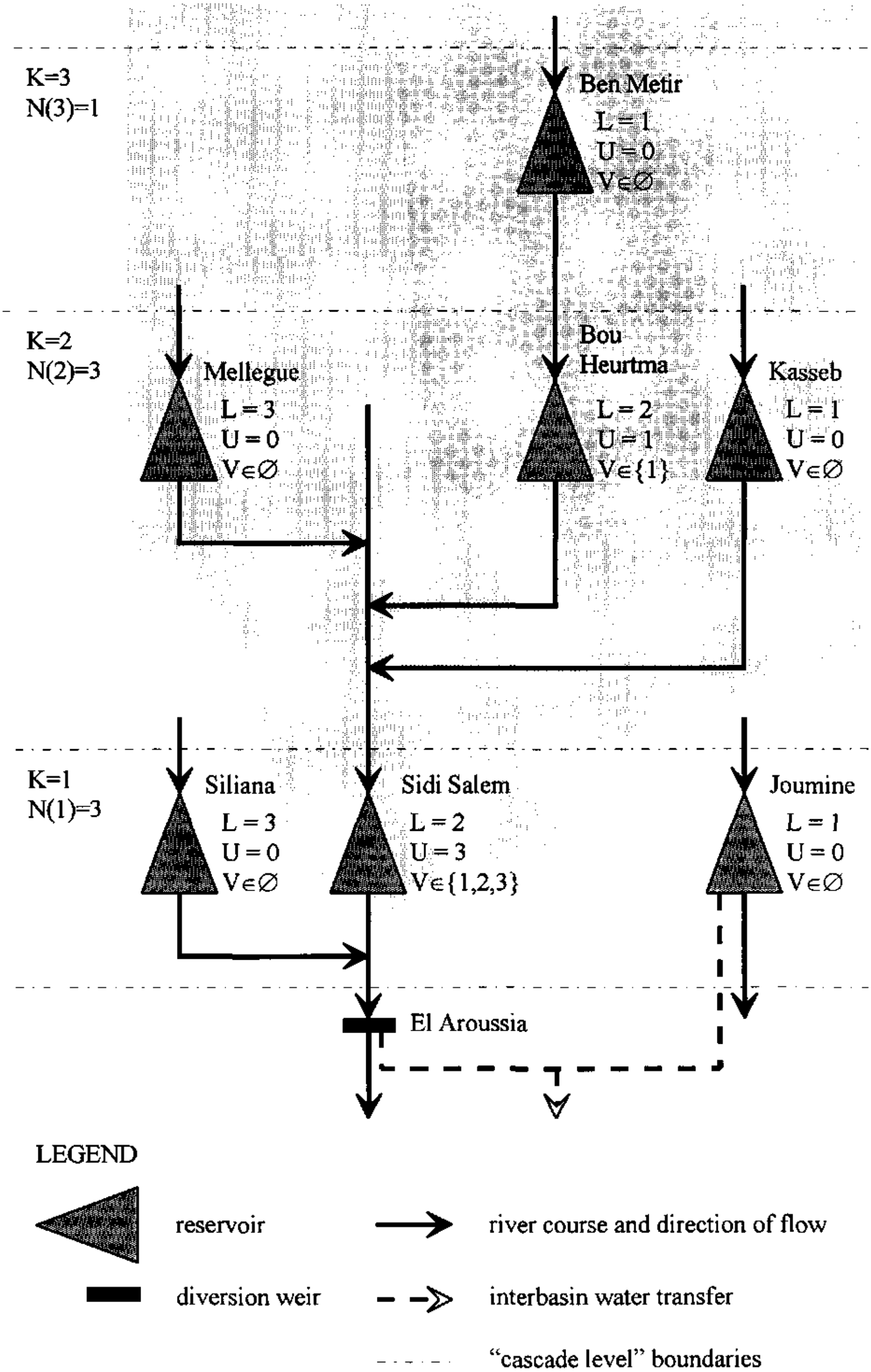

Figure 5.7 Iterative up-and-downstream-moving decomposition of the case study system

Perhaps the best way to clarify this description is to apply the UDD principles to the case study system (Figure 5.7). Thus, the reservoir sequence in an iteration of the UDD decomposition is: Joumine, Sidi Salem, Kasseb, Bou Heurtma, Ben Metir, Bou Heurtma, Mellegue, Sidi Salem and Siliana. It can be clearly seen that the iterative process of the analysis of serially linked reservoirs is recursive. Namely, the outer cluster with the Sidi Salem reservoir as the downstream one contains two serially linked reservoirs: Bou Heurtma and Ben Metir. Therefore, upon reaching Bou Heurtma in the process of analyzing the Sidi Salem's upstream counterparts, the analysis is held up until the Bou Heurtma-Ben Metir serial link is completed. This is indicated by different shading patterns used to identify the respective reservoir clusters (Figure 5.7) and by the flow chart of the recursive part of the algorithm given in Figure 5.6.

5.2 Stochastic Dynamic Programming Optimization

Apart from the necessary problem-specific modifications, the implemented SDP formulation follows the definition given by Loucks et al. (1981:321-332). The optimization process derives the optimal, expectation-oriented, long-term operating strategy for a single reservoir. Temporal discretization along the optimization stages is set to monthly time intervals. The state of the system (i.e. reservoir) is the volume of water stored in the reservoir at the beginning of a stage. The consideration of uncertainty is restricted to the stochasticity of river flows only. Namely, monthly inflows to a reservoir represented by different classes with their respective transition probabilities are considered as an additional state variable in the SDP-based optimization procedure. Thus, the state of the reservoir at a certain stage is described by two state variables: reservoir storage at the beginning of the month and the inflow to the reservoir during the month.

The decision to be taken at each stage is the targeted storage volume of the reservoir at the end of the month. Thus, the resulting SDP operating policy consists of 12 distinct monthly control rules expressed in terms of the optimal decision (i.e. the final storage volume in a month) to be taken as a function of the system states (i.e. the initial storage volume in the month and the expected inflow during the month). Having these three quantities defined and assuming that reservoir losses can be derived thereupon, the total release from the reservoir could be estimated from the continuity equation which describes the balance of water in the reservoir during the given time interval:

$$r_t = \max[r_{t,\min}, \min(r_{t,\max}, s_t + q_t - e_t - s_{t+1})], \quad \forall t \tag{5.1}$$

where

s_t, s_{t+1} the storage volume of the reservoir at the beginning and at the end of time step t, respectively; both variables are constrained by the minimum and maximum storage thresholds:

$$s_{t,\min} \le s_t \le s_{t,\max}, \quad \forall t \tag{5.2}$$

$s_{t,min}$ the minimum allowable storage volume of the reservoir during a time step is set in the model to the respective dead storage volume for all time periods t;

$s_{t,max}$ the maximum allowable storage volume of the reservoir during a time step is set in the model to the respective capacity of the reservoir for all time periods t;

q_t the expected inflow volume to the reservoir during time step t;

e_t the estimated loss of water from the reservoir during time step t;

r_t the total release from the reservoir during time step t;

$r_{t,min}$ the minimum allowable release from the reservoir during a time step is set in the model to zero for all time periods t;

$r_{t,max}$ the maximum allowable release from the reservoir during a time step is assumed to be unlimited for all time periods t (n.b. this includes both the utilizable and non-utilizable releases and spilling).

Within all the optimization and simulation models developed in this study, water losses from a reservoir are assumed to be originating only from evaporation from its surface. The total volume of water lost to evaporation during a single time step is estimated according to:

$$e_t = \frac{1}{2} \cdot e_{t,0} \cdot [a(s_t) + a(s_{t+1})], \quad \forall t \tag{5.3}$$

where

$e_{t,0}$ the expected evaporation loss per unit of the reservoir's surface area in period t;

$a(s_t)$ the surface area of the reservoir corresponding to storage volume s_t.

Having defined all the necessary quantities relevant for the description of the operation of a reservoir during a single stage, the SDP optimization process derives the optimum operating strategy of a reservoir from the Bellman's backward recursive relationship:

$$f_n^{(t)}(k,i) = \min_l \left\{ C_{k,i,l}^{(t)} + \sum_{j=1}^{N_{t+1}} p_{i,j}^{(t)} \cdot f_{n-1}^{(t+1)}(l,j) \right\}, \quad \forall k,i; \quad l \textit{ feasible} \tag{5.4}$$

where

k the index depicting one of a number of possible discrete values the storage state variable s_t can take at the beginning of time step t;

i the index of a discrete inflow volume class which is one of a number of possible realizations of the inflow state variable q_t during time step t;

l depicts the decision $l = l(k, i, t)$ to be taken at stage n (time step t) or, in other words, it is the index of one of a number of possible discrete decision realizations, i.e. the storage volume of the reservoir at the end of time step t;

Note that this variable also identifies the storage volume of the reservoir at the beginning of time interval t+1, thus being at the same time the storage state variable for time step $t+1$. Therefore, using the notation from Equation 5.1, the relationship between the decision and state variables can be written as:

$$s_{t+1} = s_{t+1}(s_t, q_t)\,, \quad \forall t \tag{5.5}$$

j the index of a discrete inflow volume class, which is one of a number of possible realizations of the inflow state variable q_{t+1} during time step $t+1$;

N_{t+1} the number of the representative discrete inflow classes at time step $t+1$;

$p_{i,j}^{(t)}$ the transition probability which states the likelihood that the inflow in time step $t+1$ will fall into class j given that the inflow in time step t is in class i;

$C_{k,i,l}^{(t)}$ the immediate contribution towards the value of the objective function induced by the decision $l = l(k, i, t)$;

$f_n^{(t)}(k,i)$ the suboptimal aggregate of the objective function expectation accumulated over all the stages starting from time step $t = 0$ and up to and including time step t.

The foregoing description of the SDP recursion clearly illustrates the dynamic programming requirement for the discretization of the state and decision variables present in the problem. Therefore, the formulation given in Equation 5.4 uses the respective indices (i.e. k, i, l and j) rather than the variables those indices represent (i.e. s_t, q_t, s_{t+1} and q_{t+1}, respectively). The description of storage and inflow discretization schemes adopted in the developed SDP optimization model is given in the sequel.

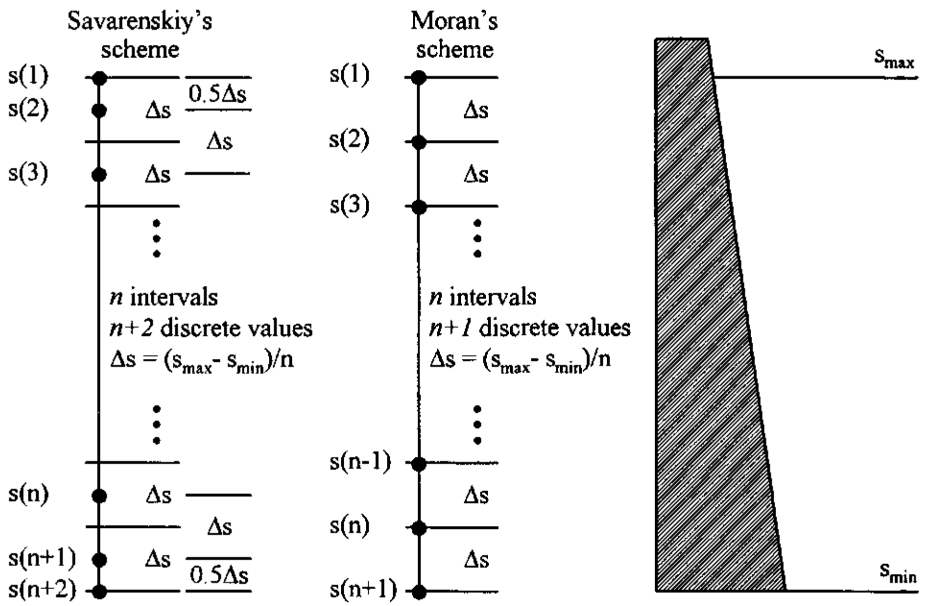

Figure 5.8 Savarenskiy's and Moran's storage discretization schemes

The devised SDP optimization model employs the Savarenskiy's scheme (Savarenskiy 1940) to discretize the storage state and decision variables (i.e. s_t and s_{t+1}, respectively). This scheme is frequently used in SDP applications to reservoir operation problems. A number of studies (e.g. Doran 1975, Klemeš 1977, Karamouz and Vasiliadis 1992) have been carried out to compare the Savarenskiy's scheme to the Moran's scheme (Moran 1954), the other well-known storage discretization approach. Each of the three aforementioned studies drew the conclusion that the SDP algorithms using Savarenskiy's scheme required fewer discrete storage states to achieve the same precision than the Moran's scheme did and, for the same number of discrete storage classes, the former ensured faster convergence to the steady state solution than the latter did.

As Figure 5.8 shows the Moran's scheme defines the representative discrete storage values as the boundaries between the equidistant storage classes whereas, in addition to the two extreme points identified by the maximum and minimum storage volumes, the Savarenskiy's scheme chooses the centre points of the classes as the respective discrete storage representations. With respect to the above definitions, Table 5.1 presents the functional relationships for the estimation of the discrete storage representation sets for both methods given the same number of classes.

Table 5.1 Savarenskiy's and Moran's storage discretization schemes

Discretization scheme	*Number of classes*	*Number of discrete states*	*Representative discrete storage definition*
Savarenskiy	n	n+2	$s(1) = s_{\max}$ $s(n+2) = s_{\min}$ $s(k) = s_{\max} - \frac{2k-3}{2} \cdot \Delta s, \quad k \in \{2,3,\dots,n+1\}$
Moran	n	n+1	$s(k) = s_{\max} - (k-1) \cdot \Delta s, \quad k \in \{1,2,\dots,n+1\}$

As to the inflow state variable, the discretization scheme used to derive the respective characteristic discrete representations is described in the following:

1. The entire range of the observed historical flows for a particular month is initially divided into a predefined number of equidistant intervals. The historical flow observations in that month are subsequently classified with regard to the inflow intervals they fall into. A flow observation which falls into a certain class (i.e. interval) is hereafter referred to as a *class member*.

2. The adopted inflow discretization scheme does not allow the existence of an inflow class with no class members (i.e. *empty inflow class*). If an empty inflow class exists, it is merged with the neighbouring class in the direction of the increase of the flow. This process is repeated until all the classes have at least one class member. The number of inflow classes is thus ensured to be greater than or equal to two.

3. The representative discrete flow value for a class is estimated as the average of all of its class members.

4. The stochastic properties of the monthly river flows (i.e. the transition probabilities $p_{i,j}^{(t)}$) represented by the discrete class averages are derived from the historical inflow records available for the reservoir in question.

The objective pursued in optimization is to minimize the expected annual sum of a penalty induced by failing to match the desired release. The penalty function itself is defined as the squared deviation of a monthly release from the corresponding demand for water. Since a reservoir may supply a number of demand centres, the individual demands associated with the reservoir are aggregated into a single composite demand and the penalty function value is estimated with respect to this single compound demand:

$$C_{k,i,l}^{(t)} = (r_t - D_t)^2\,, \quad \forall k,i,t \wedge l = l(k,i,t) \tag{5.6}$$

where

r_t	the total release from the reservoir during time step t;
D_t	the sum of all individual demands imposed upon the reservoir at time step t.

Since any DP enumeration involves the consideration of all possible combinations of the discrete system states and decisions it is obvious that this includes both feasible and infeasible system state transitions. With regard to the problem in hand, the developed SDP model distinguishes between feasible and infeasible decisions by assigning a high penalty to decisions which would result in the violation of either of the release constraints embedded in the reservoir balance given by Equation 5.1. Note that the storage state and decision constraints given by Equation 5.2 are implicitly fulfilled by setting the sets of possible representative discrete storage volumes to be within the limits imposed by those constraints.

The SDP optimization procedure starts by initiating the value of the objective function to zero, or any other arbitrary value, for each and every combination of the discrete values of the two state variables at some time step in the future. Thereafter, the process continues by traversing backwards along the temporal stages (i.e. months). The optimization consists of a number of iterations, each having $T = 12$ monthly stages representing one annual cycle. The aggregate of the objective function's expectation grows up by setting its value at the beginning of each iteration (i.e. year) to the respective accumulated value of the objective function at the end of the last stage of the previous iteration.

After a number of iterations (Y_0) the optimal decision associated with a particular month and a particular combination of the two state variables remains unchanged for each successive annual cycle:

$$l(k,i,t) = l(k,i,t+T)\,, \quad \forall k,i \wedge \forall t > Y_0 \cdot T \tag{5.7}$$

If, in addition to the condition given by Equation 5.7, the increase of the objective function's value over a period of one annual cycle becomes constant and independent from time and state:

$$f_n^{(t+T)}(k,i) - f_{n-T}^{(t)}(k,i) = const\ , \quad \forall k,i \wedge \forall t > Y_0 \cdot T \tag{5.8}$$

it can be said that the operating policy has reached steady state conditions and the iterative SDP cycles could be terminated. To summarize, the two conditions given by Equations 5.7 and 5.8 constitute the necessary convergence criteria for the SDP based optimization procedure (Loucks et al. 1981:325). It should be noted here that the convergence of the SDP recursion can be achieved only if the values for each $C_{k,l,t}^{(t)}$ and $p_{i,j}^{(t)}$ are not changing from one annual cycle to another. This also implies that the demand imposed upon the reservoir in a certain month should not change from one year to another. Therefore, monthly demand expectations are used to represent the requirements for water imposed upon a reservoir in each of the annual cycles.

Since it is unlikely that the condition given by Equation 5.8 will be exactly met in any problem with real-numbered state, decision and the objective function values, this criterion is replaced by the condition describing the relative acceptable deviation from the desired outcome:

$$\frac{\max\limits_{k,i,t}[\Delta f_n^{(t)}(k,i)] - \min\limits_{k,i,t}[\Delta f_n^{(t)}(k,i)]}{\min\limits_{k,i,t}[\Delta f_n^{(t)}(k,i)]} \le \varepsilon\ , \quad \forall k,i \wedge \forall t > Y_0 \cdot T \tag{5.9}$$

where

$\Delta f_n^{(t)}(k,i)$ the annual increment of the cumulative objective function expectation for the month depicted by the time step index t and the state combination (k,i) defined as:

$$\Delta f_n^{(t)}(k,i) = f_n^{(t+T)}(k,i) - f_{n-T}^{(t)}(k,i) \tag{5.10}$$

Equation 5.9 states that if, for each month and each combination of the two system states, the annual increments of the objective function are deviating within the ε-neighbourhood of the respective minimum observed objective function increment for that annual cycle, the SDP optimization procedure is to be assumed to have reached the steady state annual objective function increment as given by Equation 5.8. In this study, the parameter ε is set to 0.01. If, however, either of the two criteria (Equations 5.7 and 5.9) is not met after $Y_0 = 30$ iterative cycles, the optimization process is terminated with a convergence failure condition. This iteration number threshold is necessary to prevent the recursive process from entering an infinite loop. If the iterations are terminated due to this condition, the optimization model offers the latest derived SDP policy and reports which of the two convergence criteria was not met. It is then up to the user to decide whether to accept or reject the obtained results. It should be mentioned here that the analyses carried out in this study did not reveal a single case where the SDP optimization process had to be terminated due to reaching the maximum allowable number of iterations.

5.3 Simulation

The SDP operating strategy obtained by optimization is appraised by simulation to estimate the expected effects of the reservoir's operation on the performance of the whole system. The simulation is carried out over the same historical inflow record used in optimization to derive the stochastic properties of the river flows. The developed model offers three distinct simulation alternatives, two of which are devised to mitigate the negative effects related to unnecessary oversupply caused by the discrete nature of the SDP operating policies (cf. Section 4.3).

At a particular time step t, all of the three simulation models assume that the initial decision recommended by the SDP policy is to be strictly followed. The decision to be made depends on two reservoir state variables: the volume of water stored in the reservoir at the beginning of a time step and the expected inflow into the reservoir during this time period. Since, in simulation, the two state variables can take upon any value within their respective continuous ranges and the SDP policies are defined only over their respective discrete domains, it is likely that the values of these two independent variables will seldom match any of the predefined discrete points exactly. Therefore, the recommended SDP decision for a particular combination of the reservoir states is determined by linear interpolation among the four decisions identified by the respective neighbouring lower and upper characteristic discrete representations of the two state variables. Thus, given the values of the two state variables at a time step t:

$$\begin{aligned} s(k+1) &\le s_t < s(k) \\ q_t(i) &\le q_t < q_t(i+1) \end{aligned} \tag{5.11}$$

the final decision on the storage volume s_{t+1} is estimated by linear interpolation among the following four discrete decisions:

$$\begin{aligned} s_{t+1}^{(1)} &= s(l_1)\,, \quad l_1 = l_1(k,i,t) \\ s_{t+1}^{(2)} &= s(l_2)\,, \quad l_2 = l_2(k,i+1,t) \\ s_{t+1}^{(3)} &= s(l_3)\,, \quad l_3 = l_3(k+1,i,t) \\ s_{t+1}^{(4)} &= s(l_4)\,, \quad l_4 = l_4(k+1,i+1,t) \end{aligned} \tag{5.12}$$

where

s_t	the storage volume of the reservoir at the beginning of time step t;
$s(k)$	the class k representative storage volume of the reservoir;
q_t	the expected inflow into the reservoir during time step t;
$q_t(i)$	the class i representative expected inflow into the reservoir during time step t;
$s_{t+1}^{(l)}$	the targeted discrete storage volume of the reservoir at the end of time step t is one of a class $l \in \{l_1, l_2, l_3, l_4\}$ defined by the SDP policy for the respective combination of the reservoir states.

Consequently, the release from the reservoir resulting from the interpolated decision s_{t+1}, which is the function of the given reservoir states s_t and q_t is obtained by solving the continuity equation written for time step t (n.b. note that the related storage and release constraints are implicitly incorporated into the policies $l = l(k, i, t)$ during the optimization):

$$r_t = s_t + q_t - e_t - s_{t+1} \tag{5.13}$$

where

r_t the total release from the reservoir in time step t.

e_t the loss of water from the reservoir during time step t estimated on the basis of the respective initial and final storage volumes s_t and s_{t+1} (cf. Equation 5.3);

Upon estimating the total reservoir release which would result from the policy-based decision, the simulation proceeds to determine the final decision to be made at this stage with respect to the chosen type of simulation (cf. Section 4.3):

1. *Strict policy compliance.* If this simulation approach is opted for, the model accepts and carries out the SDP policy recommendation on the final storage volume s_{t+1} and the release r_t.

2. *Average demand threshold.* If the policy-based decision results in the release r_t which is greater than the expectation of the total demand for water imposed upon the reservoir for month τ which is indicated by the time step index t, this simulation alternative reduces the recommended release to the level of the demand expectation (Equation 5.14). Since the amount of water by which the release is decreased is stored in the reservoir for possible use at a later stage, the resulting final storage must not violate the constraint on the maximum allowable storage volume in the reservoir. The release constraint is not required here because of the adopted lower and upper bounds on reservoir releases (cf. Equation 5.1 in Section 5.2).

$$\hat{r}_t = \max[s_t + q_t - e_t(s_t, s_{t,\max}) - s_{t,\max}, \min(r_t, \overline{D}^{(\tau)})], \quad \forall t \tag{5.14}$$

where

τ the index depicting the month indicated by the time step index t:

$$\tau \equiv \begin{cases} t & t \le 12 \\ t \bmod 12 & t > 12 \end{cases}, \quad 0 < \tau \le 12\,, \quad t > 0 \tag{5.15}$$

$\overline{D}^{(\tau)}$ the expectation of the total demand imposed upon the reservoir in month τ;

$\hat{r}_t$ the final decision on the release in time step t.

3. *Monitored demand.* Similarly to the former one, this simulation alternative also allows the reduction of the total reservoir release. However, this time the benchmark release volume is the actual total demand imposed upon the reservoir in time step t, rather than the expected demand for month τ indicated by time step t:

$$\hat{r}_t = \max[s_t + q_t - e_t(s_t, s_{t,\max}) - s_{t,\max}, \min(r_t, D_t)], \quad \forall t \tag{5.16}$$

where

D_t the total demand imposed upon the reservoir in time step t.

As already described in Section 4.3, this approach requires that the time series of the actual monthly allocations from the part of the system analyzed so far to each of the demand centres be updated upon completing the analysis of each of the reservoirs in the system.

5.4 Model Supplements Within the Devised Decomposition Methodology

The decomposition into individual reservoirs and the existence of multiple water users within a system, along with the employed demand hierarchy, make it necessary to introduce a few additional computational steps into the model. These supplementary modules provide the essential information updating and exchange between the optimization and simulation phases, as well as the data flow between the subsequent iterative cycles in any of the decomposition methods used (cf. Sections 4.1 and 5.1). The additional computational facilities involve the estimation of the total demand imposed upon a single reservoir, the aggregation of the total inflow into a reservoir, the allocation of reservoir releases towards the individual demand centres and the estimation of the expected monthly supply deficits of a reservoir:

1. *Demand estimation.* The total expected demand imposed upon a single reservoir in a certain month is estimated by simply adding up the individual demand expectations for that month of all the demand centres associated with the reservoir in question. The updating of monthly demand expectations following the allocation of a reservoir's resources to this demand centre is described further in this section.

2. *Inflow estimation.* The total inflow into a reservoir in a certain month is computed by increasing its own unregulated inflow by the respective non-utilized releases from all the reservoirs situated immediately upstream of the reservoir in question (n.b. the description on how to estimate the non-utilized reservoir releases is given at the end of the following item).

3. *Release allocation.* Since simulation results in a time series of total monthly releases from a reservoir, the information that is still missing is how much water has actually been provided for each of the associated demand centres. The adopted release allocation principles are based on the hierarchical arrangement of demands associated with a reservoir (cf. Section 4.4). Given a certain reservoir and its respective demand hierarchy, the allocation of the reservoir's total release in a certain time step t is carried out according to the following equations:

3.1 *Strict policy compliance simulation*

$$x_{u,t} = \max\left[0, \min\left(\bar{d}_u^{(\tau)}, r_t - \sum_{v=0}^{u-1} x_{v,t}\right)\right], \quad \forall t \wedge \forall u \in \{1,2,\ldots,N_d\} \tag{5.17}$$

3.2 *Average demand threshold simulation*

$$x_{u,t} = \max\left[0, \min\left(\bar{d}_u^{(\tau)}, \hat{r}_t - \sum_{v=0}^{u-1} x_{v,t}\right)\right], \quad \forall t \wedge \forall u \in \{1,2,\ldots,N_d\} \tag{5.18}$$

3.3 *Monitored demand simulation*

$$x_{u,t} = \max\left[0, \min\left(d_{u,t}, \hat{r}_t - \sum_{v=0}^{u-1} x_{v,t}\right)\right], \quad \forall t \wedge \forall u \in \{1,2,\ldots,N_d\} \tag{5.19}$$

where

r_t the total release from a reservoir in time step t;

$\hat{r}_t$ the reduced total release from a reservoir in time step t ($\hat{r}_t$'s in Equations 5.18 and 5.19 are estimated by Equations 5.14 and 5.16, respectively);

N_d the number of demands associated with a reservoir;

u the rank of a demand in a reservoir's demand hierarchy;

$\bar{d}_u^{(\tau)}$ the expected water demand of demand centre u in month τ (n.b. τ is related to the time step index t through Equation 5.15);

$d_{u,t}$ the actual water demand of demand centre u in time step t;

$x_{u,t}$ the allocation from a reservoir to its uth demand in time step t ($x_{0,t} = 0$, $\forall t$).

Any release volume which may remain after allocation of water to all of the demand centres in time step t constitutes the non-utilized component of the reservoir's total release. This part of the release is subsequently considered as an additional inflow to the reservoir situated immediately downstream of the reservoir in question.

4. *Expected monthly supply deficits of a reservoir* are estimated as the aggregate of the expected remainder of the individual monthly demands associated with the reservoir. These individual demand estimates are represented by the average monthly demand volumes which have remained uncovered upon allocating the reservoir's releases in all the time periods covered by simulation. The uncovered monthly expectation of a single demand centre is subsequently going to be assigned to the next reservoir in the computational sequence which is associated with this particular demand. The expected monthly allocation of a reservoir to one of its demands is estimated according to the following:

$$\bar{x}_u^{(\tau)} = \frac{1}{Y}\sum_{y=1}^{Y} x_{u,\tau+(y-1)\cdot T}, \quad \forall u \in \{1,2,\ldots,N_d\} \wedge \forall \tau \in \{1,2,\ldots,T\} \tag{5.20}$$

where

Y the total number of years in the simulation record;

T the number of months in a year ($T = 12$).

Subsequently, the expected uncovered volume of demand u in month τ is computed by subtracting the average allocation of the reservoir to this demand centre $\bar{x}_u^{(\tau)}$ from the respective expected demand $\bar{d}_u^{(\tau)}$ imposed upon the reservoir in the optimization and simulation processes.

5.5 Genetic Algorithm Model

As already described in Section 4.5.2, the problem of finding the best release allocation pattern for a multiple-reservoir water supply system is addressed through a genetic algorithm (GA) based search strategy. To be more precise, two GA models have been conceived. The two models are identical with regard to their purely GA-related characteristics. The only difference between the two is reflected in the way the models carry out fitness evaluation of individual chromosomes. Namely, one of the models (i.e. *the complete GA-decomposition model*, abbreviated as C-GA-D) uses the decomposition-based optimization/simulation algorithm for fitness evaluation while the other relies on a simple simulation of the system's operation wherein each of the reservoirs is operated according to the standard reservoir operating rule. The latter GA release allocation model is coupled with the decomposition-based optimization/simulation algorithm to form *the approximate GA-decomposition model* (A-GA-D): once the best release allocation pattern is identified by the GA, the decomposition algorithm is applied to the system configuration with the modified demand structure to derive the SDP operating policies of individual reservoirs. Since the decomposition methodology has already been described in detail (Sections 4.1 through 4.4 and 5.1 through 5.4), this section concentrates mainly on the introduction of the latter GA model. Furthermore, to draw a clear distinction between the C-GA-D and A-GA-D models, the following description is given in two parts:

1. The specifics of the GA-related features of both models are given first. These include the formulation of the release allocation problem and the respective potential solution representation, GA parameters and operators, repair and fitness scaling principles, and the adopted termination conditions.

2. The former is followed by the introduction of the adopted fitness evaluation algorithm. This includes the description of the simulation model used within the GA which assumes that individual reservoirs are operated according to the standard reservoir operating rule.

5.5.1 Problem Definition and the Adopted Genetic Algorithm Formulation

The problem put before the developed GA models is formulated with regard to the following initial assumptions:

1. The system consists of a number of reservoirs which are interacting through both serial and parallel interconnections.

2. The reservoir system provides water for multiple users.

3. A reservoir may cover multiple demands while, at the same time, a demand centre may be associated with more than one reservoir.

4. The hierarchical arrangement of demands associated with a reservoir is maintained and complied with as defined within the earlier described decomposition approches (cf. Section 4.4).

5. Any supply deficit of a reservoir is considered as an additional hypothetical demand associated with all the reservoirs which are serially connected to, and situated immediately upstream of the reservoir in question. Consequently, this hypothetical demand is also subject to the same principles of demand sharing as the consumptive water demands are. In addition, this demand is always assigned the lowest rank in a reservoir's demand hierarchy.

6. The temporal base is set to one month and the relative contribution a reservoir is expected to provide towards the supply of a certain demand is not changing from one month to another. This restriction is obviously an approximation of what one may expect to be a realistic situation. However, by assuming them constant over a year, the number of unknown variables is kept at the lowest possible level. In this particular case, there are already 20 unknown variables whose values are to be identified (cf. Sections 6.4 and 6.5). To assume that reservoirs may have different relative demand loads in different seasons or even months would make the total count of unknowns be a multiple of the initial 20 and the chosen number of seasons (or months). Furthermore, since the demand-related subsets of the unknown variables are bound by a constraint that the aggregate of relative contributions of all the reservoirs associated with a particular demand must add to unity, the assumption of their seasonal or monthly variability would drastically increase the number of constraints, thus making it more likely too hard a problem for a GA search. Ultimately, and likely due to the fact that the case study system has relatively high inflows and ample storage capabilities, the adopted approximation seems to be justified by the resulting system performance (cf. Sections 6.4 and 6.5).

Problem formulation. Given a number of reservoirs N_r and a demand centre j with the respective monthly water requirements $d_{j,t}$, the developed GA model is expected to find the best distribution of the relative contributions of each of the reservoirs towards meeting the imposed demand. The solution to the problem is to be sought with respect to the minimization of the selected penalty function value. Leaving the objective criterion aside for the time being, the solution to the above release allocation problem can be formulated as a vector:

$$\vec{\alpha} = (\alpha_{i,j} \mid i \in \{1,2,\ldots,N_r\}, j \in \{1,2,\ldots,N_d\}) \tag{5.21}$$

subject to

$$\alpha_{i,j} \geq 0, \quad \forall i,j \tag{5.22}$$

$$\sum_{i=1}^{N_r} \alpha_{i,j} \cdot d_{j,t} = d_{j,t} \quad \Leftrightarrow \quad \sum_{i=1}^{N_r} \alpha_{i,j} = 1.0, \quad \forall j,t \tag{5.23}$$

where

i, j, t	the indices depicting reservoirs, demands and time steps, respectively;
N_r	the number of reservoirs in the system;
N_d	the number of demand centres in the system;
$\alpha_{i,j}$	the relative contribution of reservoir i towards supplying demand j (n.b. by definition, $\alpha_{i,j} = 0$ for those (i,j) pairs where reservoir i does not cover demand j);
$d_{j,t}$	the amount of water requested by demand centre j in time step t; note that monthly demands are assumed to be recurring in annual cycles:

$$d_{j,t} = d_{j,t+12k}\ , \quad \forall j,t \wedge \forall k \in \mathrm{N} \tag{5.24}$$

Within the formulated GA model, the coordinates of vector $\vec{\alpha}$ are represented by a single binary string where different sub-strings correspond to different coordinates $\alpha_{i,j}$. Thus, given a particular chromosome, i.e. a solution vector represented by that chromosome, the total monthly demands $D_{i,t}$ imposed upon each of the reservoirs could be re-evaluated using Equation 5.25:

$$D_{i,t} = \sum_{j=1}^{N_d} \alpha_{i,j} \cdot d_{j,t}\ , \quad \forall i,t \tag{5.25}$$

and the decomposition-based optimization/simulation algorithm could be applied to derive the reservoirs' SDP operating policies. Consequently, within the C-GA-D model, this process is executed for each newly created individual as a part of the respective GA fitness evaluation. On the other hand, the A-GA-D model uses a simple simulation to evaluate the fitness of individuals and the SDP policies are derived only once. That is, the iterative SDP optimization is carried out only for the most promising combination of $\alpha_{i,j}$ coordinates identified by the GA search.

Chromosome representation. Regardless of the type of fitness evaluation approach, the adopted chromosome representation utilizes the classical binary mapping whereby each coordinate $\alpha_{i,j}$ is represented by an L-bit-long binary string. The relationship between the value of $\alpha_{i,j}$ and the respective binary map and thus achieved representation precision $\delta^{(L)}(\alpha_{i,j})$ are given by Equations 5.26 and 5.27, respectively (cf. Equations 4.15 and 4.16 in Section 4.5.1, assuming $\alpha_{max} = 1$ and $\alpha_{min} = 0$ as defined by Equations 5.22 and 5.23):

$$\alpha_{i,j} = \frac{1}{2^L - 1} \cdot \sum_{l=1}^{L} b_{i,j,l} \cdot 2^{l-1}\ , \quad \forall i,j \tag{5.26}$$

$$\delta^{(L)}(\alpha_{i,j}) = \frac{1}{2^L - 1}\ , \quad \forall i,j \tag{5.27}$$

where

$b_{i,j,l}$	the lth bit position value of the $\alpha_{i,j}$'s L-bit-long binary representation ($b_{i,j,l} \in \{0,1\}$, $\forall l \in \{1,2,\ldots,L\}$).

Since the entire chromosome is created by concatenating sub-strings representing individual solution coordinates and the coordinates are represented by equal L-long binary maps, the total length of the individual in the GA model is $N_\alpha \cdot L$, where N_α depicts the number of coordinates of the solution vector (cf. Equations 4.17 and 4.18 and Table 4.1 in Section 4.5.1).

GA operators. The developed models employ the three basic GA operators: proportional selection, one-point crossover and bitwise complement mutation. Since all of the three GA operators have already been described in detail in Section 4.5.1, their introduction is not going to be repeated here. It should only be noted that the employed crossover operator allows chromosome splitting at any bit position, and not only between neighbouring sub-strings representing different $\alpha_{i,j}$ solution coordinates.

Repair algorithm. Since both the crossover and mutation are essentially binary operators, the ultimate outcome of their application is virtually always a binary string consisting of at least one set of sub-strings representing a subset of $\alpha_{i,j}$ coordinates which do not meet the constraint given by Equation 5.23. That is, a newly created individual is likely to map onto such a set of coordinates $\alpha_{i,j}$ which, for a certain demand j, reflects a case of either a permanent undersupply:

$$\sum_{i=1}^{N_r} \alpha_{i,j} < 1.0 \qquad (5.28)$$

or a steady policy which would allocate more water to demand j than really needed:

$$\sum_{i=1}^{N_r} \alpha_{i,j} > 1.0 \qquad (5.29)$$

Therefore, once a new individual is created, the developed GA model employs a repair algorithm to test the feasibility of all of the individual's sub-strings (Equation 5.23) and, if necessary, to rectify the existing feasibility problems. The adjustment of an infeasible parameter subset is performed neither on the infeasible coordinates $\alpha_{i,j}$ nor on their binary maps, but rather on their integer representations (cf. Equation 5.26; and also Equation 4.13 in Section 4.5.1):

$$\beta_{i,j} = \sum_{l=1}^{L} b_{i,j,l} \cdot 2^{l-1}, \quad \forall i,j \qquad (5.30)$$

With regard to the definitions given by Equations 5.23 and 5.26, the desired feasibility condition can be written as:

$$\sum_{i=1}^{N_r} \beta_{i,j} = 2^L - 1, \quad \forall j \qquad (5.31)$$

where 2^L-1 is the maximum integer an L-bit-long binary number can represent.

Consequently, an infeasible subset of $\alpha_{i,j}$ coordinates which depicts a case of undersupply of demand j (Equation 5.28) causes the aggregate of the respective integer representations to fall short of the maximum L-bit-long integer:

$$\sum_{i=1}^{N_r} \beta_{i,j} < 2^L - 1 \tag{5.32}$$

Similarly, the case of oversupply (Equation 5.29) results in the respective integer sum overshooting the maximum L-bit-long integer target:

$$\sum_{i=1}^{N_r} \beta_{i,j} > 2^L - 1 \tag{5.33}$$

The repair procedure selects at random a $\beta_{i,j}$ member from the infeasible subset and increases or decreases its value by one, depending on whether the sum of the respective $\beta_{i,j}$ representations is smaller or larger than required (Equations 5.32 and 5.33, respectively). This process is repeated until the condition on the aggregate of parameter values is met (Equation 5.31). Thereafter, the adjusted $\beta_{i,j}$ values are mapped back onto their respective binary representations, thus ensuring the feasibility of the newly created chromosome.

Fitness scaling. The efficiency of a search is improved within the developed GA models by applying linear fitness scaling. It has been found during the development and calibration of the GA models that the GA which uses raw individual's fitness requires the creation of approximately 100 new generations before it manages to achieve the comparable levels of solution convergence of a 20-generation run of the, otherwise identical, GA search with linear fitness scaling. Although fitness scaling generally does bring about the improvement of GA searches, it should be emphasized here that these ratios must be viewed only with respect to the particular problem addressed in this study. The fitness scaling procedure employed in the GA models developed in this study is identical to the one described in Section 4.5.1 and, therefore, is not going to be repeated here.

Termination conditions. The developed GA models apply two criteria for the termination of their search. The run terminates when either of the following two conditions is met:

1. The search has reached the maximum number of newly created generations.
2. The relative improvement of the running average of the mean generational fitness has not been higher than the prespecified minimum threshold (n.b. this condition is checked only if the running average of the mean generational fitness has not deteriorated, i.e. $\overline{F}_{1,G} \geq \overline{F}_{1,G-1}$):

$$\frac{\overline{F}_{1,G} - \overline{F}_{1,G-1}}{\overline{F}_{1,G-1}} \leq \varepsilon_t \tag{5.34}$$

where

G the index depicting the number of generations created so far;

ε_t the minimum relative improvement threshold of $\overline{F}_{1,G}$.

After a GA search has performed the creation of G generations, the running average of the mean generational fitness can be estimated from:

$$\overline{F}_{1,G} = \frac{1}{G}\sum_{g=1}^{G}\overline{F}_g, \quad \forall G \tag{5.35}$$

where

$\overline{F}_g$ the mean generational fitness defined as the average fitness among N_c chromosomes in generation g ($f_i^{(g)}$ is the fitness of individual i in generation g):

$$\overline{F}_g = \frac{1}{N_c}\sum_{i=1}^{N_c} f_i^{(g)}, \quad \forall g \tag{5.36}$$

GA parameters. Genetic algorithms require that a number of parameters be calibrated to ensure the highest possible efficiency of their search. A set of GA parameters identified during the development and calibration of the GA models used in this study is given in the following:

1. The binary representation of each solution coordinate $\alpha_{i,j}$ consists of $L = 8$ bits. The achieved representation precision is thus $\delta^{(8)}(\alpha_{i,j}) \approx 0.004$. Together with the number of unknown solution coordinates, the individual coordinate representation length determines the total length of a single chromosome. As it will be shown in Section 6.4, there are 20 unknown solution coordinates $\alpha_{i,j}$, thus resulting in the total chromosome length of $20 \cdot 8 = 160$ bits.

2. The number of individuals in a generation is set to 30 and it has been found that very little improvement in the serach could be gained if the GA is run over more than 100 generations.

3. The crossover and mutation probabilities are set to 0.75 and 0.005, respectively.

4. The fitness scaling factor is set to 2.0.

5. The convergence criteria adopted in the models are the already mentioned maximum number of generations (i.e. 100), and the relative improvement threshold for the running average of the mean generational fitness which is set to 0.00005.

6. The value for the seed required by the pseudo-random number generator is taken from the system clock of the computer. Recall that random numbers (i.e. uniform deviates) are used to create the initial population, and within the three GA operators (i.e. selection, crossover and mutation) and the repair algorithm. The pseudo-random number generator employed in the developed GA models is based on the *subtractive method* which is implemented in this particular computer code as a slightly modified version of the code given by Press et al. (1988:212-213).

5.5.2 Fitness Evaluation Within the Genetic Algorithm

As already mentioned earlier, fitness evaluation within the C-GA-D model relies on the already described decomposition-based optimization/simulation approach. On the other hand, the appraisal of an individual's fitness within the A-GA-D release allocation model is carried out by simulating the system's operation assuming the release distribution pattern as given by that particular chromosome. Namely, given a certain set of solution coordinates (Equation 5.21) the total demand imposed upon a reservoir can be computed using Equation 5.25. Since the inflow time series and the aggregate demands are known for each of the reservoirs in the system, it is possible to use simulation to estimate the fitness of this particular individual.

Standard reservoir operating rule. To simulate the operation of individual reservoirs, the A-GA-D release allocation model employs the standard reservoir operating rule (SOR) as a common operating strategy for all the reservoirs in the system (Figure 5.9). According to this rule, a reservoir should release as much water as possible to meet the targeted demand, provided that the physical constraints on the resulting storage and release volumes are not violated.

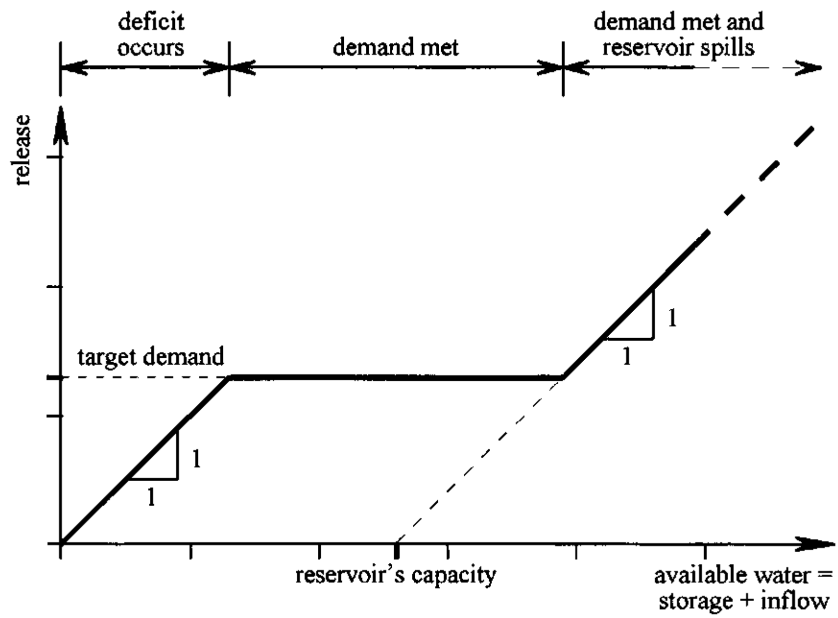

Figure 5.9 Standard reservoir operating rule

The estimation of the total release from a reservoir operated according to the SOR rule can be mathematically formulated as follows (n.b. it is assumed that there are no other but the capacity-related restrictions on the release from the reservoir):

$$r_{i,t} = \max[r_{i,t,\min}, \min(r_{i,t,\max}, \sum_{j=1}^{N_d} \alpha_{i,j} \cdot d_{j,t})], \quad \forall i,t \tag{5.37}$$

where

$r_{i,t,min}$ the minimum release from reservoir i during time step t defined with respect to the maximum allowable storage of the reservoir:

$$r_{i,t,\min} = \max(0, s_{i,t} + q_{i,t} + \sum_{k=1}^{N_r} \rho_{i,k} \cdot w_{k,t} - e_{i,t,\max} - s_{i,t+1,\max}), \quad \forall i,t \tag{5.38}$$

$r_{i,t,max}$ the maximum release from reservoir i during time step t defined with respect to the minimum allowable storage of the reservoir:

$$r_{i,t,\max} = \max(0, s_{i,t} + q_{i,t} + \sum_{k=1}^{N_r} \rho_{i,k} \cdot w_{k,t} - e_{i,t,\min} - s_{i,t+1,\min}), \quad \forall i,t \tag{5.39}$$

The Equations 5.37 through 5.39 are all describing the reservoir's balance during a single time step. The variables involved are introduced in the following:

$s_{i,t}$ the storage volume of the reservoir at the beginning of time step t;

$s_{i,t+1,min}$ the minimum allowable storage volume of the reservoir at the end of time step t;

$s_{i,t+1,max}$ the maximum allowable storage volume of the reservoir at the end of time step t;

$e_{i,t}$ the evaporation loss from the reservoir during time step t; the values of $e_{i,t,min}$ and $e_{i,t,max}$ are estimated under the assumption that the reservoir's storage volume underwent a transition from $s_{i,t}$ at the beginning of t to $s_{i,t+1,min}$ and $s_{i,t+1,max}$ at the end of time step t, respectively; the evaporation loss is computed from:

$$e_{i,t} = \frac{1}{2} e_{i,t,0} \cdot [a_i(s_{i,t}) + a_i(s_{i,t+1})], \quad \forall i,t \tag{5.40}$$

where

$e_{i,t,0}$ the expected evaporation loss per unit of the reservoir's surface area during time period t;

$a_i(s_{i,t})$ the surface area of the reservoir corresponding to storage volume $s_{i,t}$;

$q_{i,t}$ the own, unregulated inflow into the reservoir during time step t;

$\rho_{i,k}$ the factor indicating the existence of a serial connection between reservoirs i and k is defined as:

$$\rho_{i,k} = \begin{cases} 1, & i \text{ and } k \text{ are serially linked and } k \text{ is upstream} \\ 0, & \text{otherwise} \end{cases}, \quad \forall i,k \tag{5.41}$$

$w_{i,t}$ the excess, non-utilized release from reservoir i during time step t:

$$w_{i,t} = \max(0, r_{i,t} - \sum_{j=1}^{N_d} \alpha_{i,j} \cdot d_{j,t}), \quad \forall i,t \tag{5.42}$$

Once the total release is known, the storage volume of the reservoir at the end of a time step can be computed from:

$$s_{i,t+1} = s_{i,t} + q_{i,t} + \sum_{k=1}^{N_r} \rho_{i,k} \cdot w_{k,t} - e_{i,t} - r_{i,t}\,, \quad \forall i,t \tag{5.43}$$

Obviously, the total release $r_{i,t}$ consists of two components: the utilized and non-utilized release volumes. In this particular case, the SOR rule ensures that the non-utilized component $w_{i,t}$ may occur only due to unavoidable spilling when the reservoir is filled at the end of time step t. In fact, the total release can be represented as:

$$r_{i,t} = \sum_{j=1}^{N_d} \alpha_{i,j} \cdot d_{j,t} - \sum_{j=1}^{N_d} \Delta d_{i,j,t} + w_{i,t}\,, \quad \forall i,t \tag{5.44}$$

where

$\Delta d_{i,j,t}$ the deficit reservoir i encounters towards meeting the desired supply $\alpha_{i,j} \cdot d_{j,t}$ of demand j in time step t can be estimated from:

$$\Delta d_{i,j,t} = \max\left[0, \min\left(\alpha_{i,j} \cdot d_{j,t}, r_{i,t} - \sum_{k=0}^{v(j)-1} \alpha_{i,u(k)} \cdot d_{u(k),t}\right)\right], \quad \forall i,j,t \tag{5.45}$$

The parameter $v(j)$ in the upper limit of the sum indicates the rank of demand j in reservoir i's demand hierarchy whereas the index $u(k)$ depicts all those demands associated with reservoir i whose rank is higher than that of demand j (n.b. $\alpha_{i,u(0)} = 0$ and $d_{u(0),t} = 0$, by definition).

Thus, with regard to Equations 5.42, 5.44 and 5.45, the total supply deficit of a reservoir during a single simulation time step can be obtained from:

$$\sum_{j=1}^{N_d} \Delta d_{i,j,t} = \max(0, \sum_{j=1}^{N_d} \alpha_{i,j} \cdot d_{j,t} - r_{i,t})\,, \quad \forall i,t \tag{5.46}$$

System decomposition. The simulation of the entire system's operation is carried out one time step after another by coupling the SOR for individual reservoirs and a variation of the SDD decomposition (cf. Section 5.1.1). The extension of the SDD refers to the principles upon which the operation of serially linked reservoirs is modelled. The flow chart of this decomposition approach, named *extended sequential downstream-moving decomposition* (ESDD), is given in Figures 5.10 and 5.11 and its application to the seven-reservoir case study system is presented in Figure 5.12.

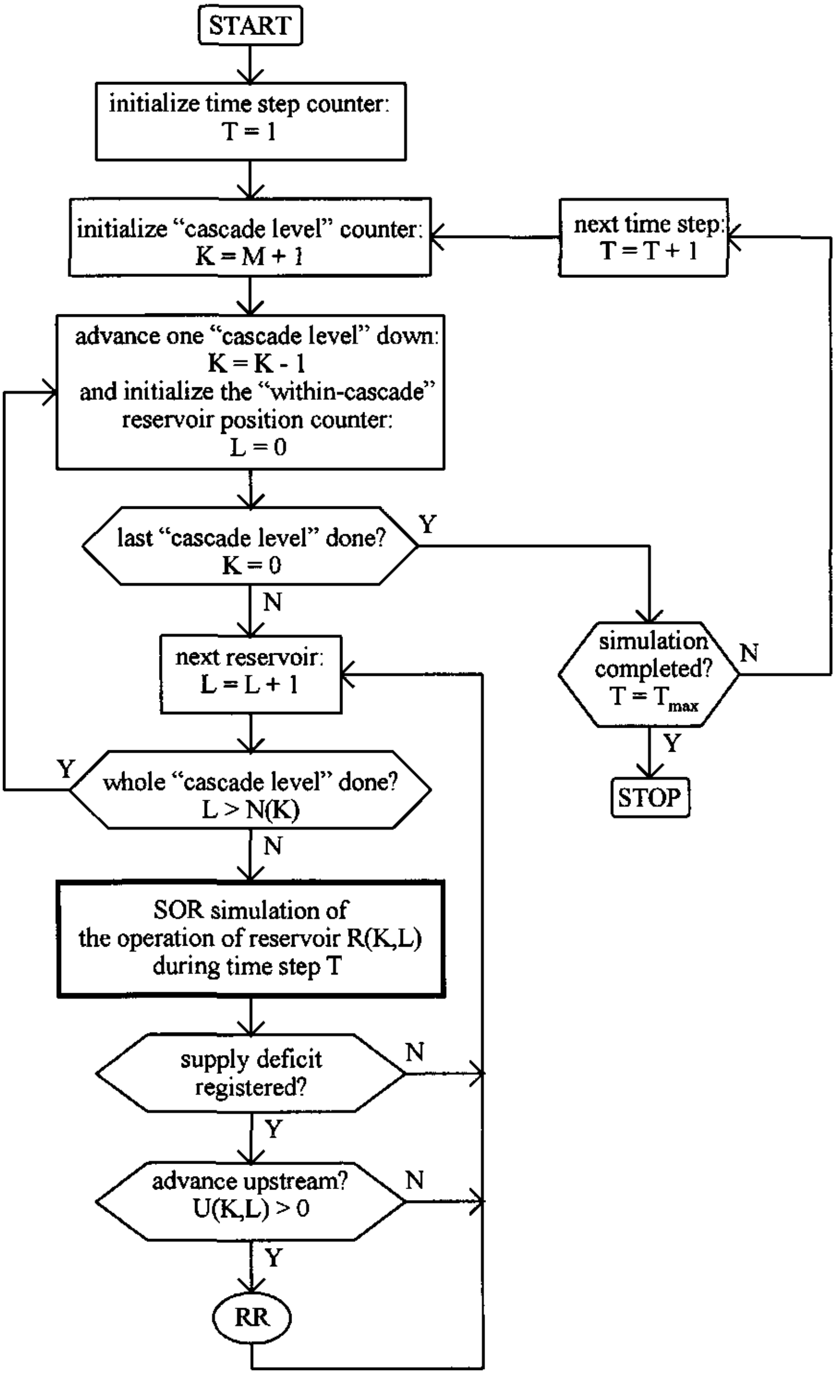

Figure 5.10 Flow chart of the extended downstream-moving decomposition approach for the SOR-based simulation of a multiple-reservoir system operation (1)

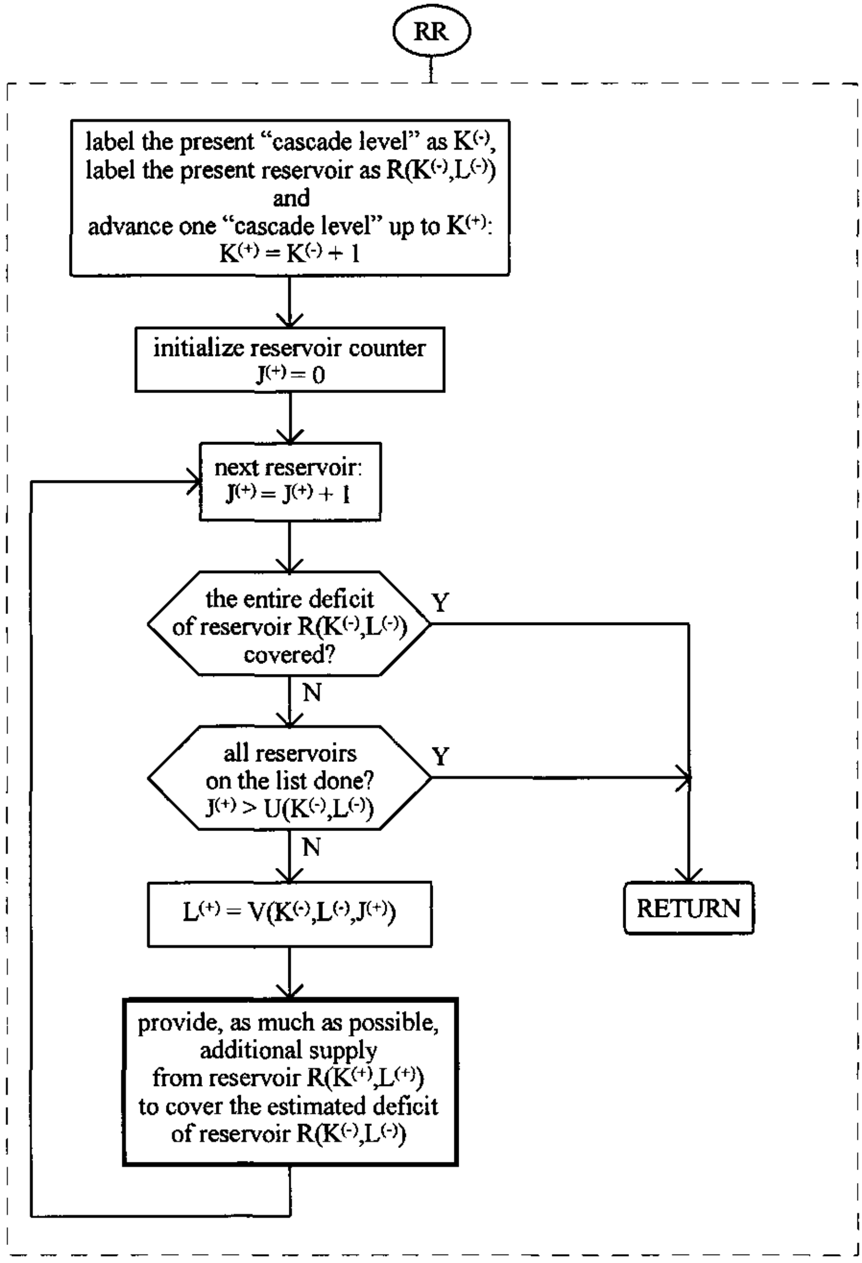

Figure 5.11 Flow chart of the extended downstream-moving decomposition approach for the SOR-based simulation of a multiple-reservoir system operation (2)

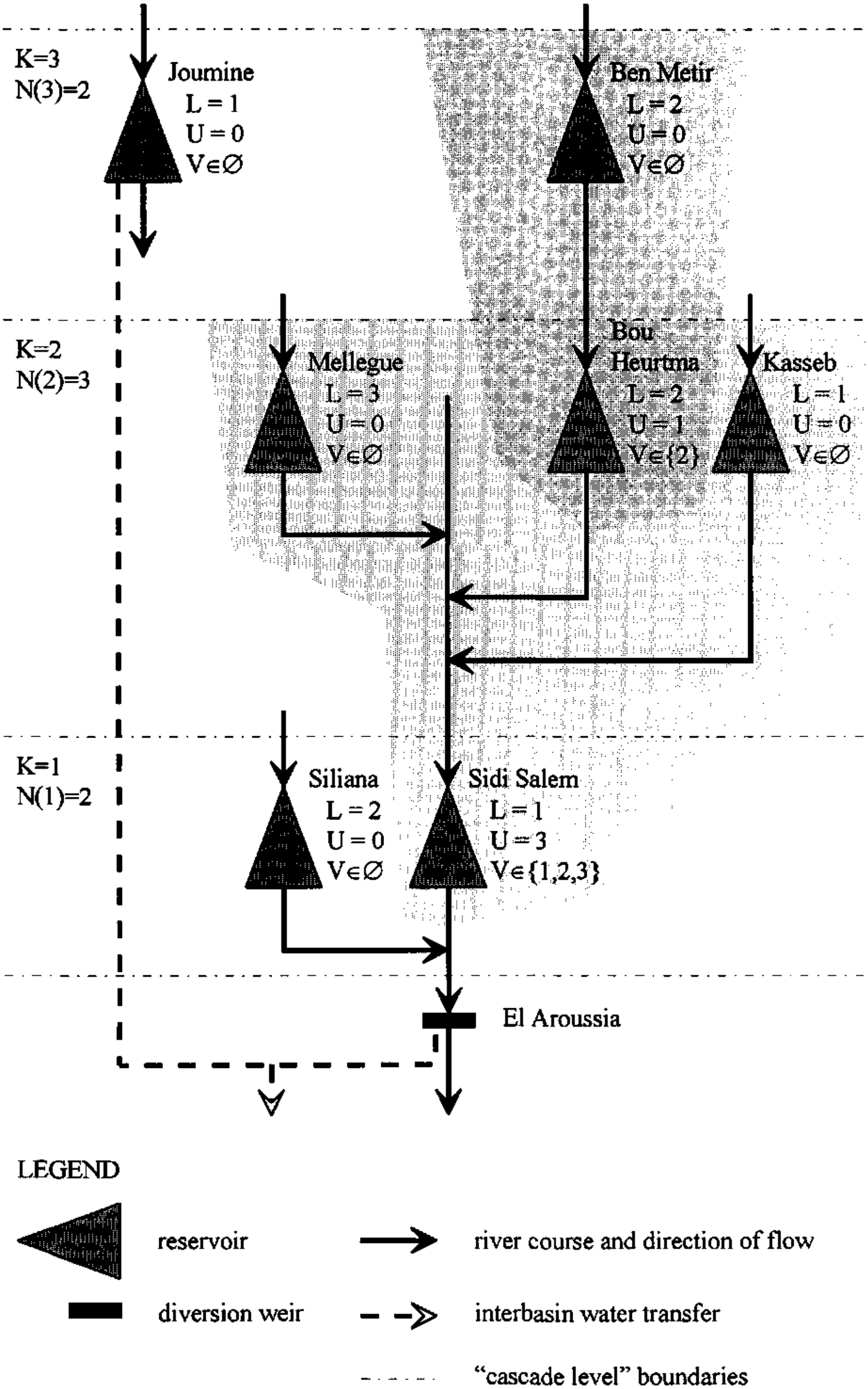

Figure 5.12 Extended downstream-moving decomposition of the case study system

The basic downstream-directed reservoir sequence which includes reservoir clustering into cascade levels (*K*) and the definition of the respective within-cascade reservoir selection orders (*L*) is done in a similar way as presented in Section 5.1.1 for the SDD decomposition. In addition, if a particular reservoir is serially linked to one or more reservoirs from the immediate upstream cascade its attribute *U* is set to the number of its upstream counterparts. Consequently, the indices *L* of those upstream reservoirs become the elements of the set *V* of this particular downstream reservoir. Conversely, if such a serial link does not exist the reservoir's attribute *U* becomes zero and the respective set *V* is empty. Note that these upstream serial link definitions are identical to those used within the earlier described UDD decomposition (cf. Section 5.1.3).

The basic idea behind the consideration of upstream serial links (*V*) is to provide additional releases from the upstream reservoir(s) to compensate for any supply shortage that the respective downstream reservoir may encounter. Since the operations of the reservoirs from all upstream cascade levels have already been simulated for the presently considered time step, any additional release from those reservoirs directed for the compensation of the downstream reservoir's supply shortage would not affect their own supply records in the present time step.

Once a reservoir's total release and allocations to its demand centres during one time step have been estimated using the SOR simulation principles, the total supply deficit which results from these decisions is to be compensated from the immediate upstream reservoirs (*V*). The sequence upon which the upstream reservoirs (*V*) are taken into consideration follows their ordering (*L*) in their respective cascade. Note that the upstream reservoirs' operations for the present time step have already been determined, thus allowing any additional release to be made only from the volume of water estimated to be available in those reservoirs at the end of the time step (i.e. defined by their respective final storage volumes). Naturally, any additional release from an upstream reservoir has an upper bound defined with respect to the recognition of the respective minimum storage constraint. It should be noted here that a change in the final storage volume of an upstream reservoir which may result from the additional release is made by neglecting the incurred change of the respective evaporation loss in the reservoir's balance equation. On the one hand, this approximation is found to have an insignificant impact on the overall outcome of the simulation. Furthermore, as any additional release from a reservoir results in the reduction of the originally estimated final storage volume the re-evaluated evaporation loss would always be less than the originally obtained one, thus having the model use a conservative estimate of the evaporation loss represented by its originally computed value.

The reservoir ordering for the case study system within the ESDD decomposition approach is (Figure 5.12): Joumine, Ben Metir, Kasseb, Bou Heurtma, Mellegue, Sidi Salem and Siliana. It is clearly shown that, in each time step, upon simulating the operation of Bou Heurtma any registered supply shortage is attempted to be compensated by an additional release from Ben Metir. Similarly, Kasseb, Bou Heurtma and Mellegue are serving as potential contributors towards compensating supply deficits of Sidi Salem.

Fitness function. The developed GA models search the solution space trying to locate the set(s) of α_{ij} coordinates associated with the minimum value of the objective function, which is the squared monthly deficit of each of the demands, aggregated over the entire simulation period:

$$\text{minimize} f' = \sum_{t=1}^{N_t}\sum_{j=1}^{N_d}\left(\sum_{i=1}^{N_r}\Delta d_{i,j,t}\right)^2 \tag{5.47}$$

Since GAs are essentially maximization search procedures the above minimization problem is transformed into the equivalent maximization one by simply subtracting the obtained objective function value from the maximum possible value this function may achieve for the given problem. The theoretical maximum penalty can be estimated upon the assumption that none of the reservoirs has managed to provide any water for any of the associated demand centres over the whole simulation period:

$$f'_{\max} = \sum_{t=1}^{N_t}\sum_{j=1}^{N_d} d_{j,t}^2 \tag{5.48}$$

Ultimately, the fitness function used within both of the GA models becomes:

$$\text{maximize} f = f'_{\max} - f' \tag{5.49}$$

5.6 System Performance Evaluation

The decomposition based approaches and the genetic algorithm used in this study rely on a single objective criterion to arrive at the solutions to the respective multiple-reservoir operating problems. That is, the individual objective functions used in the tested approaches all take some form of the aggregated squared penalty incurred by the release failing to match the respective demand for water. Since the estimate of the objective function value represents the expected objective achievement given that the system operates according to the derived policy for an indefinitely long time it is obvious that it contains no information about, for instance, the reliability, resilience and vulnerability of the resulting performance of the system (cf. Section 2.4). Therefore, to reflect on those aspects of the operation of the entire system, the alternative optimization approaches developed in this study are compared not only on the basis of their respective optimization-based objective function achievements but are also weighed with regard to a number of additional simulation-based performance indicators (PIs). Namely, once an operating strategy of the system is derived, the system's operation is simulated and the resulting performance is appraised against a number of criteria. The selected set of PIs provide additional information about the respective performance of the entire system with regard to, for instance, the likelihood of the occurrence of insufficient supply, the probable severity of such a failure and the estimate of the likely duration of periods of full and insufficient supply, respectively. The chosen PIs include (n.b. the symbols used to describe the estimation of the PIs in this section are not related to the ones used in other parts of this dissertation):

1. *Expected annual supply deficit* (PI_1) is the simulation-based estimate of the mean annual magnitude of failure. It is thus the estimate of the long-term expectation of an annual supply deficit provided that the respective operating strategy is followed:

$$PI_1 = \frac{\sum_{t=1}^{T} \max(0, D_t - R_t)}{N_y} \tag{5.50}$$

2. *Time-based reliability* (PI_2) is the simulation-based estimate of the long-term probability that the system will be able to meet the targeted demand (consequently, the likelihood that the system will fail to provide sufficient supply is 1 - PI_2):

$$PI_2 = 1 - \frac{1}{T}\sum_{t=1}^{T} u_t \tag{5.51}$$

3. *Average recovery time* (PI_3) is defined as the average length of periods the system continuously fails to meet the targeted demand, thus stating the expected time required by the system to switch to an operating mode characterized by full supply once it has encountered a deficiency in supply during one time period:

$$PI_3 = \frac{\sum_{t=1}^{T} u_t}{\sum_{t=1}^{T} v_t} \tag{5.52}$$

4. *Average recurrence time* (PI_4) is defined as the average duration of periods the system sustains full supply before switching to a failure operating mode. In other words, it gives the estimate on how long the system may be expected to provide full supply once it has recovered from an operating failure:

$$PI_4 = \frac{T - \sum_{t=1}^{T} u_t}{\sum_{t=1}^{T} w_t} \tag{5.53}$$

5. *Average monthly deficit* (PI_5) measures the average magnitude of monthly deficits with regard to the total number of failure months:

$$PI_5 = \frac{\sum_{t=1}^{T} \max(0, D_t - R_t)}{\sum_{t=1}^{T} u_t} \tag{5.54}$$

6. *Maximum vulnerability* (PI_6) indicates the magnitude of the most severe supply shortage observed over the entire simulation period:

$$PI_6 = \max_t[\max(0, D_t - R_t)] \tag{5.55}$$

7. *Maximum duration of failure* (PI_7) is the longest interval Δt (in months) of consecutive failure events:

$$PI_7 = \max_t(\Delta t | v_t = 1 \wedge w_{t+\Delta t} = 1) \tag{5.56}$$

The notation used in Equations 5.50 through 5.56 is described in the following:

- t — the index depicting a time step (i.e. month);
- T — the length, in months, of the simulation time period;
- N_y — the length, in years, of the simulation time period.
- D_t — the total demand imposed upon the system in time step t;
- R_t — the total utilizable release the system provides in time step t;
- u_t — the *success/failure* descriptor which indicates whether the system has managed to meet the demand imposed upon it during time step t:

$$u_t = \begin{cases} 1, & D_t > R_t \\ 0, & D_t \le R_t \end{cases}, \quad \forall t \tag{5.57}$$

- v_t — the descriptor indicating a *success-to-failure* operating transition:

$$v_t = \begin{cases} 1, & D_{t-1} \le R_{t-1} \wedge D_t > R_t \\ 0, & otherwise \end{cases}, \quad \forall t > 1, \quad v_1 = u_1 \tag{5.58}$$

- w_t — the descriptor indicating a *failure-to-success* operating transition:

$$w_t = \begin{cases} 1, & D_{t-1} > R_{t-1} \wedge D_t \le R_t \\ 0, & otherwise \end{cases}, \quad \forall t > 1, \quad w_1 = 1 - u_1 \tag{5.59}$$

It should be noted here that the definitions and functional relationships of all the PIs have been presented assuming that the system's operation is characterized by both full supply and shortage events thus excluding a possibility of a division by zero in the estimation of any of the PIs (i.e. Equations 5.50 through 5.56). Similarly, it is assumed that the total demand imposed upon the system over the whole simulation span, as well as the length of the simulation period are not zero.

6 ANALYSES AND RESULTS

This chapter compiles the results and the respective discussions related to the application of the developed models for the long-term operational analysis of the case study system. The chapter is divided into five parts:

1. Section 6.1 describes the data used in the study.
2. Section 6.2 presents the comparison of the three proposed decomposition approaches:
   - Section 6.2.1: Sequential downstream-moving decomposition (SDD);
   - Section 6.2.2: Iterative downstream-moving decomposition (IDD); and
   - Section 6.2.3: Iterative up-and-downstream-moving decomposition (UDD).
3. Section 6.3 summarizes the findings regarding the impact different simulation approaches have on the case study system performance derived by the SDD decomposition model:
   - The SDD model which utilizes the strict policy compliance simulation (SDD). This alternative is identical to the one presented in Section 6.2.1.
   - The SDD model with the average demand threshold simulation (SDD-A).
   - The SDD model which used the monitored demand simulation (SDD-M).
4. Section 6.4 compiles the results of the application of the approximate genetic algorithm/SDD-A model (A-GA-D) for the derivation of the best water allocation pattern and the respective long-term performance of the case study system.
5. Section 6.5 presents the application of the complete genetic algorithm/SDD-A model (C-GA-D) for the analysis of the long-term operation of the case study system.
6. And finally, Section 6.6 summarizes the most relevant findings from the above analyses.

6.1 Data Availability

The case study system used as a basis for all the presented analyses is the existing seven-reservoir system in Northern Tunisia (cf. Chapter 3). The data for the study originate from Agrar-und Hydrotechnik (1992, 1993). For the modelling purposes, the system in question was assumed to serve primarily for water supply. The end water users were depicted by 18 distinctive demand centres representing urban areas, tourist centres, irrigation schemes and water requirements for the recharge of one natural lake. The available data include:

1. Incremental monthly inflow volumes for the individual reservoirs covered a period of 44 years (i.e. period 1946-89).

2. The average monthly elevation losses due to evaporation from the surface were used to account for water losses from each of the seven reservoirs. Since data about seepage were not available it was assumed that those losses were negligible.

3. The salient reservoir characteristics (i.e. minimum and maximum storage volumes, service outlet capacities, elevation-volume and elevation-surface area curves) were provided for each reservoir.

4. The estimates of the expected monthly water demand volumes were available for each of the 18 demand centres (cf. Table 3.5).

The available inflow data record is partitioned into two subsets, one consisting of the initial 33 years of flow data (i.e. 1946-78) and the other being 11 years long (1979-89). All of the developed models were initially run using the 33-year-long inflow data subset to derive the respective operating strategies of the system. Subsequently, the obtained operating policies were appraised and compared upon the respective simulated outcomes using both inflow data sets. Thus, the shorter, 11-year-long inflow subset was set aside for verification of the findings made upon the simulation over the longer subset, which was a basis for optimization. The particular choice of the inflow time series partition was based on the fact that the available incremental inflow records for individual reservoirs all consisted of two distinct parts (Agrar-und Hydrotechnik 1993). Namely, the records were complete for the period 1946-80 (35 years) whereas the remaining nine years (i.e. 1981-89) of reservoir inflow data were obtained by extending the existing time series by means of various statistical or water balance methods. The ultimate choice for the 33/11-year partition, rather than the 35/9 one, was made partially for the reason of the extension of the verification period, which provided a longer simulation basis for the estimation of the respective performance indicator values, and partially because the extended 11-year-long subset exhibited a slightly better match of the basic flow statistics with the respective policy determination subset. These findings were valid for the total system inflow, as well for the most of the individual reservoir inflows, both on monthly and annual scales. As an illustration, Table 6.1 summarizes the basic statistics of the annual inflows into the entire system for the 1946-80/1981-89 (i.e. 35/9) and 1946-78/1979-89 (i.e. 33/11) flow record partitions.

Table 6.1 The basic statistics of the alternative inflow record partitions

Alternative	*Period*	*Length* [years]	*Range* [10^6m^3/year]	*Mean* [10^6m^3/year]	σ [10^6m^3/year]	C_v [-]
1: 35/9	1946-80	35	335.3 - 2504.7	987.3	488.9	0.495
	1981-89	9	495.2 - 1156.3	872.7	226.8	0.260
2: 33/11	1946-78	33	335.3 - 2504.7	986.2	497.8	0.505
	1979-89	11	495.2 - 1318.2	896.8	252.2	0.281

Given the selected 33/11 inflow record partition, Table 6.2 displays the respective estimates of the relative number of months when the total system inflow falls short of the respective total demand for water imposed upon the system (i.e. system inflow deficiency). It shows, with only two exceptions, that the two inflow subsets exhibit similar characteristics with regard to the qualitative relation between water availability and the respective water demands.

Table 6.2 Relative number of months with the observed system inflow deficiency [%]

Inflow subset	*Sept.*	*Oct.*	*Nov.*	*Dec.-Feb.*	*March*	*Apr.*	*May*	*June*	*July*	*Aug.*
33: 1946-78	76	36	21	0	9	27	64	94	100	100
11: 1979-89	64	64	27	0	0	45	64	100	100	91

As to the quantitative comparison of the two, the most interesting, and most important as well, period is the hydrologically driest three-month sequence June-August, which is also characterized by the highest demand for water within an annual cycle. Table 6.3 summarizes the comparison of the total system inflow and the total water demand for this period. As it can be seen, except for a larger difference in June, the monthly inflow deficiency estimates for the 11-year-long verification and 33-year-long policy determination subsets do not differ significantly, both for individual months and the whole three-month period.

Table 6.3 Comparison of the mean total system inflow and the respective total water demand imposed upon the system in period June-August

Inflow subset	*Mean monthly inflow deficiency relative to the respective water demand* [%]			
	June - August (aggregate)	June	July	August
33: 1946-1978	70	58	82	66
11: 1979-1989	76	74	89	60

Table 6.1 reveals that the mean annual inflow for the selected verification period amounts to approximately 91% of the respective 33-year-long estimate. On the other hand, the variability of annual inflows for the 11-year subset is much less pronounced than that of the policy determination subset. However, due to generally lower monthly inflow volumes the 11-year subset represents a potentially less favourable hydrological scenario which is reflected in both the number of months with insufficient inflows (Table 6.2) and the relative magnitude of inflow deficiency (Table 6.3). Therefore, and not only due to the fact that the operating policies have been derived over the 33-year-long period, it can be expected that the performance of the system over the policy determination subset would invariably be superior to the respective performance over the verification subset.

6.2 Comparison of the Three Decomposition Alternatives

This section presents the outcomes of the optimization and the respective simulation analyses of the long-term operation of the case study system executed for the three alternative decomposition approaches introduced in Section 5.1 (i.e. SDD, IDD and UDD models). The three SDP-based decomposition models share a number of common features:

1. The number of characteristic discrete storage representations is set to 25 for each reservoir in the system (Table 6.4 displays the adopted discrete storage representations for individual reservoirs). The selected storage discretization is in agreement with the findings of Goulter and Tai (1985) who stated that 20 discrete storage classes were sufficient for reservoirs with capacity up to 170% of the mean annual inflow (cf. Tables 3.1 and 3.3 in Chapter 3). In addition, the chosen number of storage classes is well above the recommendation given by Savarenskiy (1940) and Doran (1975) who stated that the required minimum was between five and 10 classes and, at the same time, in agreement with the levels recommended by Klemeš (1977). It should be noted here that the sequential downstream-moving decomposition (SDD) was also tested using 48 storage classes (i.e. achieving a 50% reduction of the respective class sizes obtained with 25 discrete storage representations) producing almost no improvement of the system's operation as compared to the adopted coarser discretization level. This finding is similar to the conclusions made by Bogardi et al. (1988) who, upon the analyses of the operation of one single and two multiunit reservoir systems, suggested that one cannot expect that the increase of the number of discrete storage states would invariably bring about the improvement of the respective SDP-based system performance.

2. Monthly reservoir inflows are represented by the respective sets of discrete flow values. The maximum allowed number of discrete inflow classes is set to 12. Inflow discretization varies from reservoir to reservoir and from month to month. The number of discrete inflow representations is defined as a linear function of the reservoir's capacity and the range of inflow observations in that particular month. Upon defining the inflow classes for each month, the

stochasticity of monthly inflows into reservoirs is described by transition probabilities estimated for their respective discrete representations on the basis of the 33-year-long policy determination inflow subsets.

Table 6.4 Discrete storage representation for individual reservoirs [$10^6 m^3$]

Class	Joumine	Ben Metir	Kasseb	Bou Heurtma	Mellegue	Sidi Salem	Siliana
1	130.0	57.2	81.9	117.5	120.0	555.0	70.0
2	127.4	56.2	80.3	115.3	118.1	543.9	68.7
3	122.1	54.3	77.2	110.8	114.2	521.7	66.0
4	116.8	52.4	74.1	106.4	110.3	499.6	63.3
...	...	...	...	...	...	...	...
22	21.9	17.8	17.5	26.1	40.7	100.4	15.2
23	16.6	15.9	14.4	21.7	36.8	78.3	12.5
24	11.3	14.0	11.3	17.2	32.9	56.1	9.8
25	8.7	13.0	9.7	15.0	31.0	45.0	8.5

3. The objective function used in optimization of the operation of individual reservoirs is to minimize the expectation of the annual aggregate of the squared deviation of a monthly release from the respective target (cf. Equations 5.4 and 5.6 in Section 5.2).

4. The adopted simulation alternative within each of the three decomposition approaches assumed full compliance with the derived SDP policies, thus allowing no policy violations (cf. Sections 4.3 and 5.3).

Table 6.5 An example of a typical SDP-based operating policy table

Initial	*Inflow class*				
storage class	1	2	3	4	5
1	6	6	1	1	1
2	7	6	2	1	1
3	8	7	3	1	1
4	9	8	4	2	1
...	...	...	...	...	...
22	24	23	19	18	15
23	24	23	20	19	16
24	25	24	21	20	17
25	25	25	22	20	17

5. The individual reservoir operating policies derived by SDP within each of the three decomposition approaches are defined for each month within an annual cycle and are given in a form of a table indicating the class index of the recommended final storage volume as a function of the class indices of the initial storage volume and inflow for that particular month. An abridged example of a typical SDP policy table is presented in Table 6.5 (n.b. storage volume decreases with the increase of the storage class index whereas inflow volume increases with the increase of the inflow class index).

6.2.1 Sequential Downstream-Moving Decomposition

The SDD model reached a stable value of the termination criterion (i.e. the expected annual supply deficit of the entire system) after six iterative cycles, with the execution time of almost 3 minutes on a Pentium 120. Using the derived SDP policies, the simulated estimates of the expected annual supply deficit of the system were 19.376 and 17.523 (both given in $10^6 m^3$/year) for the 33 and 11-year-long policy determination and verification subsets, respectively. Table 6.6 further displays the obtained estimates of a number of performance indicators for both simulation runs.

Table 6.6 SDD model: Performance indicator estimates*

Inflow subset	PI_1 [$10^6 m^3$/year]	PI_2 [-]	PI_3 [months]	PI_4 [months]	PI_5 [$10^6 m^3$/month]	PI_6 [$10^6 m^3$/month]	PI_7 [months]
33	19.736	0.636	3.1	5.5	4.440	29.021	9
11	17.523	0.447	4.9	3.9	2.640	10.926	29

* PI_1: expected annual supply deficit; PI_2: time-based reliability; PI_3: average recovery time; PI_4: average recurrence time; PI_5: average monthly deficit; PI_6: maximum vulnerability; PI_7: maximum duration of failure

In addition, Figure 6.1 presents the simulated estimates of the expected monthly supply deficits for the entire system. It should be noted here that the performance indicator PI_5 is the average monthly supply deficit estimated over the months when the deficit really occurred whereas the individual monthly deficit expectations given in Figure 6.1 are derived for the entire simulation period, thus taking also into account those months when the system managed to achieve full supply. Consequently, the aggregate of the individual monthly deficit expectations represents in fact the estimate of the expected annual supply deficit given by PI_1.

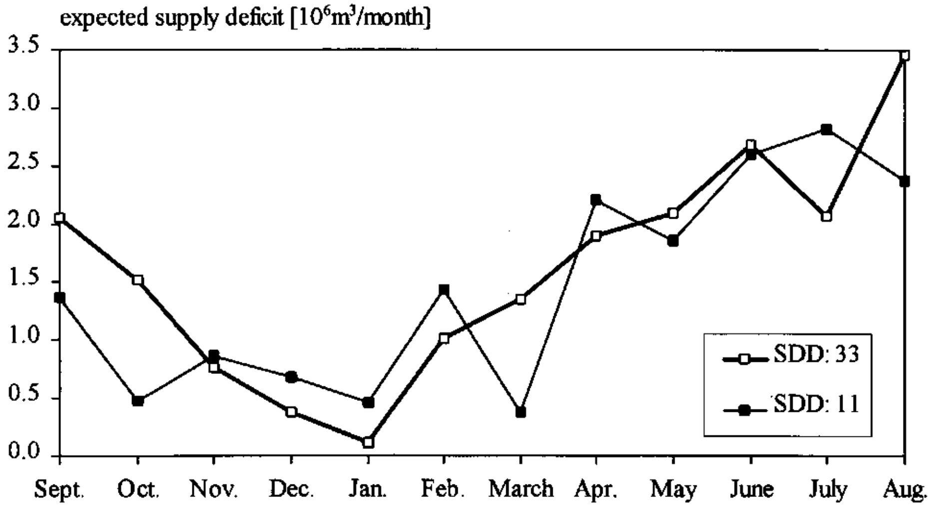

Figure 6.1 The simulated expected monthly supply deficits for the SDD model

6.2.2 Iterative Downstream-Moving Decomposition

The IDD model achieved a stabilization of the termination criterion after performing three iterative cycles, with the total execution time slightly over 2 minutes (Pentium 120). The simulation according to the derived SDP policies resulted in the estimates of the expected annual supply deficit of the system of 19.117 and 17.302 (10^6m^3/year) for the 33 and 11-year-long policy determination and verification subsets, respectively. Table 6.7 contains the respective estimates of a number of performance indicators for both simulation runs.

Table 6.7 IDD model: Performance indicator estimates

Inflow subset	PI_1 [10^6m^3/year]	PI_2 [-]	PI_3 [months]	PI_4 [months]	PI_5 [10^6m^3/month]	PI_6 [10^6m^3/month]	PI_7 [months]
33	19.117	0.634	3.1	5.3	4.351	28.403	9
11	17.302	0.432	4.7	3.6	2.538	10.926	29

Figure 6.2 displays the simulated estimates of the expected monthly supply deficits for the entire system, given the policies derived by the IDD model. The remark made in the preceding section about the difference between the estimates of PI_5 and the expected monthly supply deficits holds in this case too.

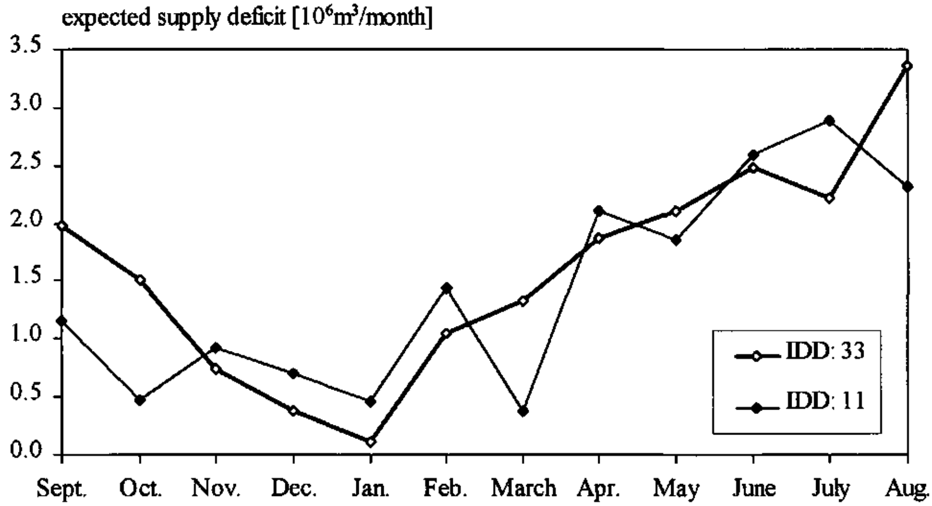

Figure 6.2 The simulated expected monthly supply deficits for the IDD model

6.2.3 Iterative Up-and-Downstream-Moving Decomposition

The UDD was the fastest among the three models. The stable value of the termination criterion was obtained already after the second iteration, resulting in the total execution time of approximately 1.5 minutes (Pentium 120). The derived SDP policies were used to simulate the operation of the system over both the policy determination and verification subsets, producing the estimates of the expected annual supply deficit of the system of 19.786 and 17.531 ($10^6 m^3$/year), respectively. The remaining performance indicator estimates are displayed in Table 6.8. In addition, Figure 6.3 displays the simulated estimates of the expected monthly supply deficits for the entire system. The remark made in Section 6.2.1 about the difference between the estimates of PI_5 and the expected monthly supply deficits holds in this case too.

Table 6.8 UDD model: Performance indicator estimates

Inflow subset	PI_1 [$10^6 m^3$/year]	PI_2 [-]	PI_3 [months]	PI_4 [months]	PI_5 [$10^6 m^3$/month]	PI_6 [$10^6 m^3$/month]	PI_7 [months]
33	19.786	0.636	3.0	5.3	4.534	31.009	9
11	17.531	0.447	5.2	4.2	2.642	10.920	29

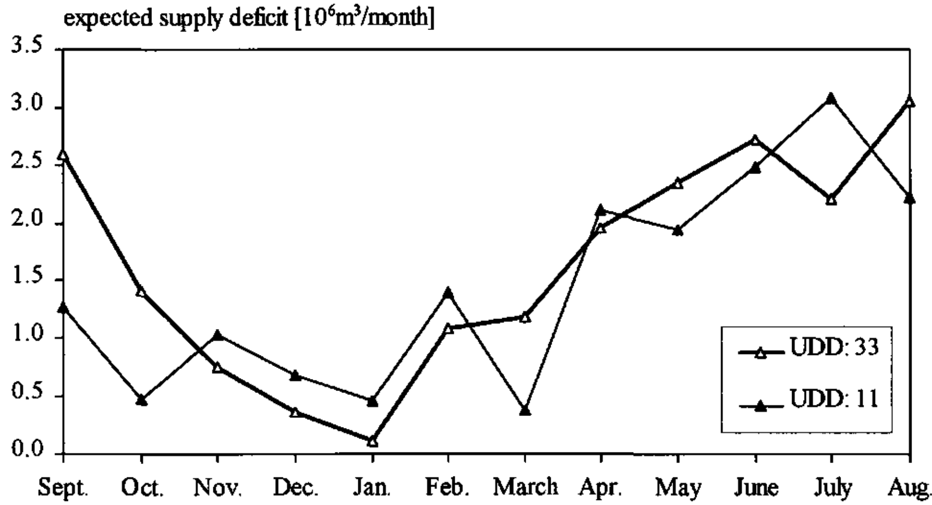

Figure 6.3 The simulated expected monthly supply deficits for the UDD model

6.2.4 Summary

According to the simulated estimates of the selected performance indicators (Table 6.9) the policies derived by the three decomposition models result in virtually identical system performances. The obtained values of PI_1 show that, for the 33-year-long inflow subset, the expected annual water supplies vary between 95.8% (SDD and UDD) and 95.9% (IDD) of the annual demand. As to the 11-year-long verification subset, the three models reach almost the same expected annual demand fulfilment (i.e. approximately 96.3% of the total annual demand).

Table 6.9 SDD, IDD and UDD models: Performance indicator estimates

Inflow subset	*Model*	PI_1 [10^{6}m^3/year]	PI_2 [-]	PI_3 [months]	PI_4 [months]	PI_5 [10^{6}m^3/month]	PI_6 [10^{6}m^3/month]	PI_7 [months]
	SDD	19.736	0.636	3.1	5.5	4.440	29.021	9
33	IDD	19.117	0.634	3.1	5.3	4.351	28.403	9
	UDD	19.786	0.636	3.0	5.3	4.534	31.009	9
	SDD	17.523	0.447	4.9	3.9	2.640	10.926	29
11	IDD	17.302	0.432	4.7	3.6	2.538	10.926	29
	UDD	17.531	0.447	5.2	4.2	2.642	10.920	29

The most significant differences among the three groups of PIs is related to the estimates of the maximum vulnerability (PI_6) obtained for the policy determination period where the UDD-related system performance exhibited the highest supply deficit in a single month. In general, it can be said that SDD and IDD models outperform UDD by a narrow margin, while IDD results in slightly more favourable PI values than SDD does. Similar conclusions can also be drawn by inspecting the estimated expected annual deficits of individual demands (Table 6.10).

Table 6.10 Expected annual deficits of individual demand centres for SDD, IDD and UDD models [$10^6 m^3$/year] (n.b. "-" indicates that no supply deficit has been observed)

Demand	*33-year inflow subset*			*11-year inflow subset*		
	SDD	IDD	UDD	SDD	IDD	UDD
TU	0.293	0.294	0.288	-	-	-
MO	0.022	0.022	0.023	-	-	-
NA	0.024	0.024	0.025	-	-	-
SO	0.065	0.065	0.066	-	-	-
SF	0.163	0.163	0.182	-	-	-
BI	0.065	0.065	0.065	0.066	0.066	0.066
JE	0.054	0.054	0.050	0.098	0.114	0.098
BE	0.052	0.051	0.050	0.107	0.116	0.099
MB	0.021	0.023	0.019	0.036	0.042	0.036
IMA	0.137	0.137	0.137	0.201	0.201	0.201
BLI	1.088	1.088	1.088	2.946	2.946	2.946
TO	0.282	0.282	0.283	-	-	-
IAEA	0.142	0.142	0.116	-	-	-
IBV	0.100	0.090	0.134	-	-	-
IMSC	5.524	5.413	5.810	0.109	0.060	0.126
INE	0.007	0.003	0.003	0.001	0.001	0.001
IBH	5.681	5.536	5.785	2.803	2.598	2.851
ISI	5.656	5.664	5.662	11.157	11.157	11.108

With regard to the resulting simulated estimates of the expected monthly supply deficits displayed in Figures 6.1 through 6.3, one may also conclude that the three decomposition models produce almost identical system performance outcomes. The simulation over the 33-year-long policy determination subset shows that the system is likely to fail more severely during dry summer months (i.e. June-August) when the imposed demand for water is at its peak. However, the derived SDP policies manage to reduce the magnitude of supply deficits in these months by "spreading" the inevitable shortage over the remaining nine months of an annual cycle. Quite logically, the largest "share" of this shortage is associated with the immediate neighbouring months (i.e. April-May and September-October). However, and despite the fact that the available inflow is almost invariably sufficient to cover the respective demands (cf. Table 6.2), a fraction of the deficit is even "transferred" to the period December-March. As to the simulation over the 11-year-long verification period, a slightly erratic form of the aforementioned mitigation of supply deficits can also be observed. This is entirely due to the fact that the stochastic properties of inflows occurring during this period were not taken into consideration within the optimization process.

Table 6.11 shows, however, that the three decomposition models achieve similar performances of the system on the basis of different operating policies. The only reservoir whose SDP policies do not differ from one model to another is Joumine. This is due to the fact that, in all of the models, Joumine is the first reservoir to be considered in a computational process, thus having always the same input sets of hydrological and demand variables irrespective of the chosen decomposition model.

Table 6.11 SDD, IDD and UDD models: Relative number of different decisions in monthly policy tables [%] ("*" indicates that some months are excluded from the comparison because the respective policies have different number of inflow classes)

Reservoir	*SDD vs. IDD*			*SDD vs. UDD*			*IDD vs. UDD*		
	min	*mean*	*max*	*min*	*mean*	*max*	*min*	*mean*	*max*
Joumine	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ben Metir	1.0	5.0	14.0	1.3	11.6	40.0	4.0	14.4	39.3
Kasseb	0.0	1.8	7.2	0.7	6.3	16.0	0.7	5.9	14.7
Bou Heurtma	1.1	8.6	21.0	6.0*	22.4*	40.0*	7.0*	20.5*	51.3*
Mellegue	1.3	3.4	6.3	0.8	4.8	13.1	0.0	5.1	14.7
Sidi Salem	0.0	4.8	20.7	1.6	14.7	40.7	3.2	14.5	46.7
Siliana	0.0	0.6	4.0	0.0	3.0	10.7	0.0	2.7	6.7

The fact that these three decomposition models arrive at similar system performances by using different operating strategies is also confirmed by the obtained values for the relative contributions individual reservoirs have towards supplying their common demand targets (Table 6.21). The three models, however, do agree that the contribution of Siliana towards supplying the TU, TO, NA, MO, SO, SF, IAEA, IBV and IMSC demands should be kept as low as possible. Similarly, none of them allocates any water from Sidi Salem to the TU demand and they all get the identical distribution of the NA, MO, SO and SF demands among Joumine, Sidi

Salem and Siliana on the one hand, and the IAEA demand between Sidi Salem and Siliana on the other.

Since the operating policies derived by the three models do differ, the total inflows (i.e. own incremental inflow augmented by the non-utilized release from the reservoirs situated immediately upstream) into Bou Heurtma and Sidi Salem should vary from one model to another. In that respect, Table 6.12 displays the relative differences among the respective total inflows to each of the two reservoirs obtained by simulation over the 33-year-long inflow subset. It should be noted here that the most pronounced relative differences between mean monthly inflows were observed in dry summer months thus indicating that the respective absolute differences of inflow volumes were not of a significant magnitude. That is also the reason why the relative difference among the respective annual mean inflows were rather low.

According to the simulated data, the mean annual inflow to Bou Heurtma derived by UDD is by 7.1% higher than the respective estimates for the SDD and IDD models. This outcome is quite expected since, unlike SDD and IDD, the UDD decomposition sequence progresses in the upstream direction, thus having the operation of Bou Heurtma optimized and simulated prior to that of the upstream located Ben Metir reservoir. Therefore, and starting from the initial iteration, Bou Heurtma's supply deficits and, consequently, Ben Metir's releases allocated to cover them are higher within the UDD model than those obtained by the other two models. On the other hand, a rather low variation of total inflows to Sidi Salem among the three models is mainly due to the fact that the available non-utilized resources of the three reservoirs situated immediately upstream of Sidi Salem (i.e. Kasseb, Bou Heurtma and Mellegue) cannot make a substantial contribution to the increase of the already huge unregulated inflow to this reservoir.

Table 6.12 SDD, IDD and UDD models: Relative difference between the corresponding monthly and annual inflows [%] (after simulation over the 33-year-long period)

Reservoir		SDD - IDD	SDD - UDD	IDD - UDD
Bou Heurtma	*Monthly range*	(-10.0, 2.4)	(-47.4, -0.3)	(-34.0, -0.1)
	Annual mean	-0.1	-7.1	-7.1
Sidi Salem	*Monthly range*	(-2.8, 3.3)	(-4.1, 1.3)	(-2.1, 2.4)
	Annual mean	0.0	0.1	0.1

As to the comparison of the system performance for the two inflow subsets (Table 6.9), it is apparent that the frequency of failure (cf. time-based reliability PI_2) is significantly greater for the verification inflow subset. Similarly, the respective estimates of the average duration of failure (PI_3), the average duration of full supply periods (PI_4) and the maximum duration of observed failures (PI_7) are inferior to those obtained upon simulation over the policy determination subset. This outcome is in agreement with the expected behaviour of the system performance since the operating policies have been derived on the basis of the latter data set. However, the comparison of the respective estimates of the expected annual deficit (PI_1), average monthly deficit (PI_5) and maximum vulnerability (PI_6) show that the failures are less severe for the verification period. This is likely to be caused by two factors. On the one hand, the variability of system inflows is less pronounced in the verification inflow subset. On the other, however, the critical sequence of dry years in the policy determination subset is longer and is characterized by significantly lower inflows in dry summer months. Furthermore, such an outcome can partially be attributed to the fact that SDP policies, if closely followed, ensure a certain level of "insensitivity" towards changing hydrological conditions. Quite contrary, "fine-tuned" operating policies, like those derived by the SDD model which allows demand-driven policy violations in simulation (cf. Section 6.3) and the GA-based strategies (cf. Sections 6.4 and 6.5), are more susceptible to alternating hydrological conditions.

To recapitulate, the presented results indicate that, for the adopted storage discretization and assuming a *strict policy compliance simulation*, there seem to be a number of operating strategies which all arrive at similar simulated performance of the case study system. Although the SDD model seems to require more iterations to converge to a stable solution to this particular operating problem it is chosen as the approach to be used further in this study for the analysis of the impact alternative simulation options may have on the resulting system performance (Section 6.3) and within the two couplings of the GA and decomposition models (Sections 6.4 and 6.5). This choice is made for three reasons. On the one hand, SDD is the simplest modelling approach among the three for the number of single-reservoir optimizations in one iteration always equals the number of reservoirs in the system which is not the case for the other two decomposition approaches. On the other hand, unlike in SDD, more complex systems with more serial and parallel reservoir interconnections and/or diversions, as well as with more complex demand/reservoir links may require major modelling effort within IDD and UDD. In addition, the case study system performance derived by SDD does not differ much from those obtained by the other two models. In fact, the SDD model outperforms the UDD one whereas it is only slightly inferior to the IDD model.

6.3 The Alternative Simulation Options

This section summarizes the results obtained by the application of three alternative SDD decomposition models, each utilizing a different simulation approach to appraise the operation of individual reservoirs within an iterative computational cycle (cf. Sections 4.3 and 5.3):

1. The SDD model employs the *strict policy compliance* simulation approach. This is, in fact, the model whose application has already been presented in Section 6.2.1.
2. The SDD-A model uses the average demand threshold simulation.
3. The SDD-M model relies upon the monitored demand simulation concept.

With the exception of the employed simulation alternative, the three models are otherwise identical. Thus, as described in Section 6.2 they apply the same principles with regard to storage and inflow discretization, inflow stochasticity, objective function and form of the resulting SDP operating policies for individual reservoirs.

Table 6.13 presents the PI estimates obtained upon 33 and 11-year-long simulation of the operation of the case study system using the operating strategies derived by the three variants of the SDD model. The SDD model achieved a stable system return after six iterations (i.e. almost 3 minutes on a Pentium 120) resulting in the simulated estimates of the expected annual supply deficits (PI_1) of the entire system of 19.376 and 17.523 (10^6m^3/year) for the policy determination and verification inflow subsets, respectively. On the other hand, both the SDD-A and SDD-M models reached their respective stable system returns after only three iterations (little over 1.5 minutes on a Pentium 120), ending up at the simulated PI_1 estimates of 0.787 and 7.729 (10^6m^3/year) for the 33 and 11-year-long inflow subsets, respectively. Thus, the achieved expected annual demand fulfilment varies between 95.8% (SDD) and 99.8% (SDD-A and SDD-M) for the policy determination period, and between 96.3% (SDD) and 98.4% (SDD-A and SDD-M) for the verification inflow subset.

Table 6.13 SDD, SDD-A and SDD-M models: Performance indicator estimates

Inflow subset	*Model*	PI_1 [10^6m^3/year]	PI_2 [-]	PI_3 [months]	PI_4 [months]	PI_5 [10^6m^3/month]	PI_6 [10^6m^3/month]	PI_7 [months]
	SDD	19.736	0.636	3.1	5.5	4.440	29.021	9
33	SDD-A	0.787	0.927	1.8	21.6	0.895	2.302	4
	SDD-M	0.787	0.927	1.8	21.6	0.895	2.302	4
	SDD	17.523	0.447	4.9	3.9	2.640	10.926	29
11	SDD-A	7.729	0.636	4.4	7.6	1.771	5.026	29
	SDD-M	7.729	0.636	4.4	7.6	1.771	5.025	29

The two models which allow limited policy violations in simulation clearly outperform the strict policy compliance SDD model. The superior system performance achieved by the SDD-A and SDD-M models can be confirmed from the figures given in Table 6.13, as well as in Table 6.14 which displays the simulated estimates of the distribution of the expected annual supply deficits among the individual demands for each of the three models. The same conclusion can be drawn by comparing the simulated expected monthly supply deficits for models SDD-A and SDD-M presented in Figure 6.4 with the respective estimates for SDD given in Figure 6.1. The only performance indicator (Table 6.13) where the SDD partially manages to match the other two models is the maximum duration of failure (PI_7). Namely, none of the three models could cope better with the extended three-year-long dry period at the end of the verification inflow subset, thus resulting in the same 29-month-long sequence characterized by continuous failure to meet the respective water demands.

Table 6.14 Expected annual deficits of individual demand centres for SDD, SDD-A and SDD-M models [$10^6 m^3$/year] (n.b. "-" indicates that no supply deficit has been observed)

Demand	*33-year inflow subset*			*11-year inflow subset*		
	SDD	SDD-A	SDD-M	SDD	SDD-A	SDD-M
TU	0.293	-	-	-	-	-
MO	0.022	-	-	-	-	-
NA	0.024	-	-	-	-	-
SO	0.065	-	-	-	-	-
SF	0.163	-	-	-	-	-
BI	0.065	0.018	0.018	0.066	0.053	0.053
JE	0.054	-	-	0.098	0.073	0.073
BE	0.052	-	-	0.107	0.075	0.075
MB	0.021	-	-	0.036	0.026	0.026
IMA	0.137	0.039	0.039	0.201	0.170	0.170
BLI	1.088	0.415	0.415	2.946	2.145	2.145
TO	0.282	-	-	-	-	-
IAEA	0.142	-	-	-	-	-
IBV	0.100	-	-	-	-	-
IMSC	5.524	-	-	0.109	-	-
INE	0.007	-	-	0.001	-	
IBH	5.681	-	-	2.803	-	-
ISI	5.656	0.314	0.314	11.157	5.187	5.187

The comparison of the system performance over the two inflow subsets shows that the policies derived by each of the three models result in the expected deterioration of the time-based reliability (PI_2), the average duration of failure (PI_3), the average duration of full supply periods (PI_4) and the maximum duration of observed failures (PI_7) when the simulation is carried out over the verification inflow subset. However, only the SDD-A and SDD-M models, as opposed to SDD, achieve inferior performance over the verification period with regard to the respective estimates of the expected annual deficit (PI_1), the average monthly deficit (PI_5) and the maximum vulnerability (PI_6). This is caused by the fact that the operating strategies derived by those two models exhibit "fine tuning" against the stochastic properties of the inflow set used in optimization, thus making them more sensitive to the changes of the hydrological conditions, which is not the case with the SDD model (cf. Section 6.2).

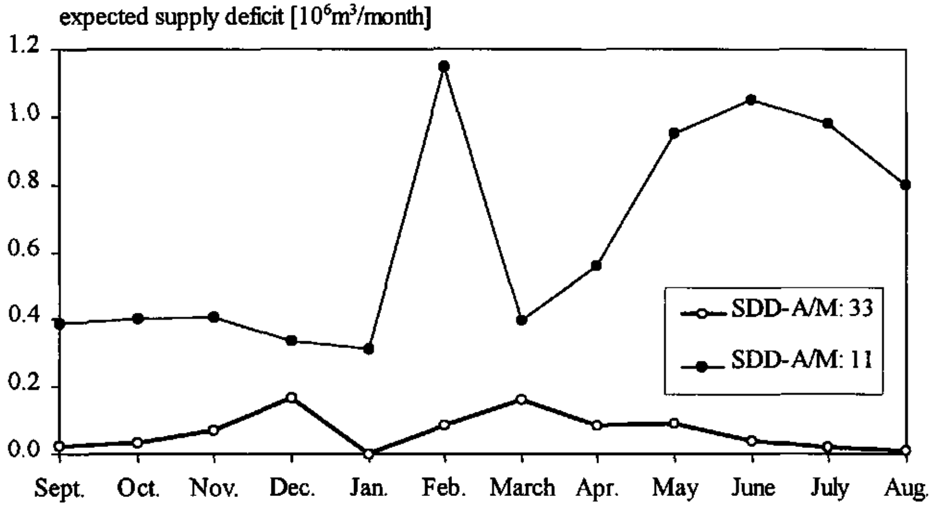

Figure 6.4 The simulated expected monthly supply deficits for the SDD-A and SDD-M models

Although they have identical PI values, the SDD-A and SDD-M models achieve those levels of system performance with different operating strategies (Table 6.15). The reason why they do arrive at identical PI values is revealed by the figures presented in Table 6.14. Namely, the policies derived by the two models result in the simulated system performance with the only supply deficits being associated either with Joumine (demands BI, IMA and BLI) and Siliana (demand ISI) in the policy determination subset, or with Joumine (again BI, IMA and BLI), Ben Metir (demands JE, BE and MB) and Siliana (again only ISI) within the verification subset. Since each of the aforementioned demands is supplied by only one reservoir and each of those reservoirs has no upstream counterparts to provide additional inflow volumes in times of need, the monitored demand simulation implemented within the SDD-M model cannot exercise the expected advantages it has over the average demand simulation used within the SDD-A model. As a direct consequence of the fact that these two models arrive at identical system performances, the respective relative contributions of individual reservoirs towards their common demand targets derived by them do not differ either (Table 6.21). It should, however, be stressed here that the conclusion about the identical performance of the two models is restricted only to the particular reservoir system and the two inflow subsets used in this study.

Table 6.15 SDD, SDD-A and SDD-M models: Relative number of different decisions in monthly policy tables [%] ("*" indicates that some months are excluded from the comparison because the respective policies have different number of inflow classes)

Reservoir	SDD vs. SDD-A			SDD vs. SDD-M			SDD-A vs. SDD-M		
	min	*mean*	*max*	*min*	*mean*	*max*	*min*	*mean*	*max*
Joumine	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ben Metir	2.5	10.7	18.7	2.0	12.2	21.3	1.3	5.4	12.0
Kasseb	0.0	5.4	13.3	0.0	5.3	11.2	0.0	1.5	4.0
Bou Heurtma	14.0*	31.5*	60.7*	18.0*	40.4*	69.3*	6.0*	21.4*	44.7*
Mellegue	0.8	4.4	8.8	0.0	3.9	10.9	0.0	3.4	8.7
Sidi Salem	24.7*	45.8*	70.0*	12.8*	38.5*	68.7*	3.3*	14.1*	33.7*
Siliana	0.0	5.6	10.4	0.0	5.6	10.4	0.0	0.0	0.0

Finally, Table 6.16 displays the simulated estimates of the relative difference between the corresponding means of total monthly and annual inflows to Bou Heurtma and Sidi Salem. As it can be seen, there is substantial difference between monthly inflow estimates obtained by the SDD model on one side and SDD-A and SDD-M models on the other. However, since these large discrepancies occur in dry summer months, their absolute values make little impact on the changes of the respective total annual inflows. As to the comparison of the figures obtained for the SDD-A and SDD-M models, it can be said that the difference in total inflow volumes to each of the two reservoirs can be regarded as insignificant.

Table 6.16 SDD, SDD-A and SDD-M models: Relative difference between the corresponding monthly and annual inflows [%] (after simulation over the 33-year-long period)

Reservoir		SDD - SDD-A	SDD - SDD-M	SDD-A - SDD-M
Bou Heurtma	*Monthly range*	(-9.7, 13.4)	(-13.9, 19.6)	(-3.8, 7.1)
	Annual mean	-2.6	-3.6	-1.0
Sidi Salem	*Monthly range*	(-22.0, 61.6)	(-21.9, 58.8)	(-7.6, 6.0)
	Annual mean	1.2	1.2	0.0

To conclude, the SDD-A model seems to be the most promising one for the analysis of the case study system operation under the given hydrological conditions. On the one hand, it outperforms the SDD model with strict compliance simulation. On the other, there is no difference between the SDD-A and SDD-M models with regard to the achieved levels of the case study system performance. Furthermore, from the modelling and computational point of view, SDD-A is markedly simpler and less computer storage and time consuming approach of the two. Therefore, SDD-A is further used within the analyses of the case study system operation by means of the two GA-based model couplings presented in Sections 6.4 and 6.5.

6.4 The Genetic Algorithm Model

The two GA-based models (A-GA-D and C-GA-D) used in this study have been developed to identify the most favourable water allocation patterns (i.e. the distribution of individual demand loads among the associated reservoirs) within a multiple-reservoir-multiple-demand water supply system (cf. Sections 4.5 and 5.5). The basic assumptions which are applicable to both models are described in the following:

1. Relative contribution a reservoir is expected to provide towards supplying a demand is not changing over a year.

2. To reduce the number of unknown variables, some subsets of demand centres are aggregated into single composite demands. These include:

- The aggregate demand AD1 consists of the BI, IMA and BLI demands which are the local water users of the Joumine reservoir. Thus, their aggregation cannot have any influence on the outcome of a GA search.
- The aggregate demand AD2 includes the NA, MO, SO and SF demand centres. These four are associated with Joumine, Sidi Salem and Siliana. As to their position in demand hierarchies of the three reservoirs, these demands always appear in the same order. Furthermore, each of these four demands is rather low (their annual aggregate amounts to only 2.9% of the respective total system demand). Thus their aggregation cannot have any significant influence on the outcome of the analyses.
- The aggregate demand AD3 consists of the BE, JE and MB demands which are all the local water users of Ben Metir. Therefore, their aggregation cannot influence the outcome of the analyses.
- The aggregate demand AD4 includes the IBV and IMSC irrigation demands. These two are associated with Sidi Salem and Siliana. As to their position in demand hierarchies of the two reservoirs, these demands always appear in the same order. Furthermore, since the annual volume of the IBV demand amounts to only 10.8% of the IMSC one, their aggregation cannot have any significant influence on the outcome of a GA search.

3. The solution sought by the GA consisted of 20 unknown variables describing the water allocation patterns related to demands covered by more than one reservoir. These are defined in the following:

- Five unknowns describe the relative contributions of Joumine, Ben Metir, Kasseb, Sidi Salem and Siliana towards the TU demand.

- Three variables depict the distribution of the TO demand load among Joumine, Sidi Salem and Siliana.
- Three unknowns represent the relative contributions of Joumine, Sidi Salem and Siliana towards the aggregate demand AD2.
- Two variables describe the portions of the IBH demand associated with Bou Heurtma and Mellegue.
- Two unknowns depict the distribution of the IAEA demand load between Sidi Salem and Siliana.
- Two more variables represent the relative contributions of Sidi Salem and Siliana towards the aggregate demand AD4.
- The additional three unknown variables are due to the fact that Kasseb, Bou Heurtma and Mellegue may contribute to the increase of the natural inflow of Sidi Salem. Thus, potential supply deficits of Sidi Salem are considered as a joint hypothetical demand imposed upon these three reservoirs.

4. Upon model calibration, a set of GA parameters has been adopted and kept unchanged throughout all the GA experiments (it is worth noticing here that the calibration process required about 150 GA runs):

- The binary representation of each solution coordinate is 8 bits long. Given 20 unknown solution coordinates, the total chromosome length is $20 \cdot 8 = 160$ bits.
- The number of individuals in a generation is set to 30 and the maximum number of generations is 100.
- The crossover and mutation probabilities are set to 0.75 and 0.005, respectively.
- The fitness scaling factor is set to 2.0.
- The convergence criteria adopted in the models are the already mentioned maximum number of generations (i.e. 100), and the relative improvement threshold for the running average of the mean generational fitness which is set to 0.00005.

6.4.1 Deriving the Best Water Allocation Pattern

This section presents the results obtained from the analyses of the applicability of the GA model which is an integral part of the GA/SDD-A coupling within the A-GA-D model. Recall that this GA model derives individual fitness values upon system simulation with the standard operating rule as the strategy adopted for individual reservoirs (cf. Section 5.5). The analyses consisted of 500 independent GA searches, each starting with a different initial population. The 500 runs were partitioned into 10 batches with 50 GA experiments each. A single best solution obtained in each of the 10 batches is selected into the final set of 10 alternative GA solutions for further analyses. The total execution time required to complete the 500 GA experiments, together with the identification of the 10 best solutions, was approximately 49 hours on a Pentium 120. Thus, a single GA run took a little less than 6 minutes to complete a search.

Figure 6.5 displays a typical progression of the convergence of a GA search. The two presented convergence parameters are the relative on-line and off-line performance measures (derived after De Jong 1975). The relative on-line performance is the running average of the mean fitness of each generation created so far in the run, divided by the maximum possible fitness for this particular problem. On the other hand, the relative off-line performance is the running average of the maximum observed fitness in each generation created so far in the run, also divided by the maximum possible fitness for this particular problem. As it can be seen, the on-line performance achieves the levels of 95% of the maximum possible fitness already within 15 to 20 generations while, in this particular problem, the off-line performance very quickly approaches a close neighbourhood of the absolute maximum fitness.

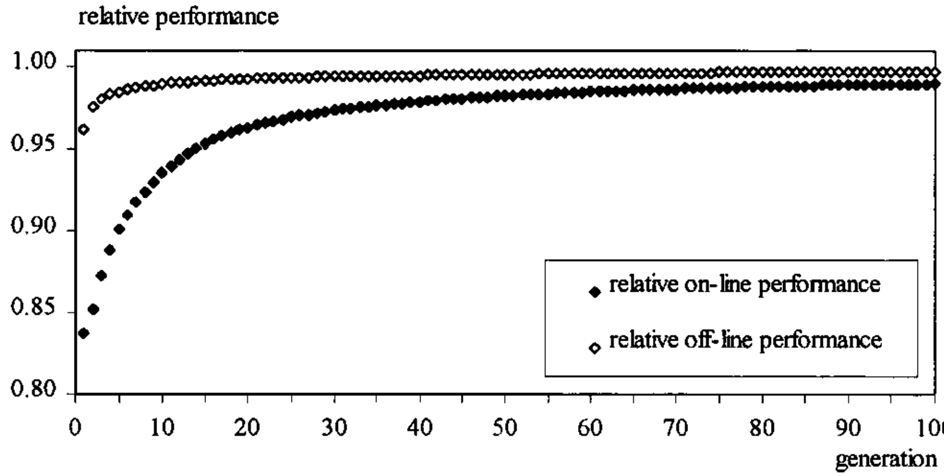

Figure 6.5 A typical convergence progression of a GA run

Table 6.17 displays some characteristic values of the mean annual fitness obtained for the 10 batches of the conducted GA searches. Based on the achieved fitness, this table also identifies the best solutions, together with their respective ranks, found in each 50-run batch. Obviously, the range of the obtained average annual fitness among the total number of 500 solutions offered by the GA model is remarkably close to the optimum (i.e. maximum) fitness value for this problem (n.b. the maximum possible value of the annual fitness is 5690.96 $(10^6 m^3)^2$/year). Namely, the worst solution found (i.e. batch number 8) achieves fitness which reaches the 99.5% level of the best possible one. Furthermore, the standard deviation of the average annual solution fitness is very low in each batch.

Table 6.17 GA experiments: Ranking of the best solutions

Batch	*Mean annual fitness* [$(10^6m^3)^2$/year]			*The best solution*			
	Minimum	*Mean*	σ	*Code*	*Fitness* [$(10^6m^3)^2$/year]	*Experiment*	*Rank*
1	5665.54	5682.17	3.93	0127	5688.02	27	6
2	5674.72	5683.03	3.48	0210	5688.05	10	5
3	5674.58	5682.85	3.44	0328	5688.85	28	3
4	5669.94	5681.50	4.09	0443	5687.94	43	8
5	5673.32	5682.62	3.85	0546	5689.61	46	1
6	5672.06	5681.74	3.80	0650	5688.01	50	7
7	5669.16	5681.89	3.75	0724	5687.56	24	10
8	5664.70	5681.60	4.83	0802	5689.02	2	2
9	5672.29	5681.73	3.97	0919	5688.79	19	4
10	5673.28	5682.16	3.68	1043	5687.89	43	9

The above conclusion regarding the stability of the achieved solution fitness is applicable to almost all the performance indicators obtained for the 10 best solutions (Table 6.18). For the policy determination period, the simulated estimates of almost all PIs are very close for all the proposed solutions. The most significant variation can be observed for the expected annual supply deficit (PI_1) which ranges from 0.445 to 0.940 (10^6m^3/year), the average monthly supply deficit (PI_5) which varies between 2.372 and 2.988 (10^6m^3/month), and the maximum vulnerability (PI_6) which is changing from 4.225 to 5.883 (10^6m^3/month). What is perhaps also interesting to point out is that the GA solution with the highest fitness (solution code 0546) is outperforming the other nine solutions over all but one performance indicator (i.e. PI_5).

As expected, the simulated PI estimates of the 10 solutions obtained for the 11-year-long verification inflow subset are all inferior to the respective PIs derived for the policy determination period. Consequently, the expected monthly supply deficits also exhibit the same behaviour, which is illustrated by Figure 6.6 (given for the solution 0546). Table 6.18 shows that the obtained 11-year estimates of PI_1, PI_5 and PI_6 exhibit the greatest variability among the 10 solutions. In this particular case, the derived values clearly indicate that some of the solutions, and not necessarily the best ones, are less sensitive to the changing hydrological conditions. Those more prone to failure under different input conditions include the solutions with codes 0546, 0802, 0328, 0127 and 0443. It should be stressed that the first three on this list occupy the top three positions with regard to the fitness rank, thus supporting the earlier formulated conclusions that "finer tuned" operating strategies are likely to exhibit higher sensitivity to the changing hydrological conditions (cf. Sections 6.2 and 6.3). Another characteristic shared by these five "sensitive" solutions is that, in addition to Siliana's failures, they all result in some supply deficit of the Joumine reservoir during the 11-year simulation period. These failures of Joumine are solely due to the estimated total demand this reservoir is expected to cover according to those five solutions. Namely, for the five "sensitive" cases, Joumine's total annual demand varies between 62.311 and 72.283 whereas the five solutions which do not result in its failure allocate an annual demand between 44.590 and 56.451 (all figures given in $10^6 m^3$/year) to this reservoir. In all other cases, and for both simulation periods, Siliana is the only reservoir which fails to meet the targeted demand in full. Siliana's failures are, however, of a different nature. Namely, in all of the 10 cases Siliana's annual demand target varies only from 30.441 to 32.863 ($10^6 m^3$/year), which is just slightly over its local irrigation demand ISI. Thus, Siliana's failures are entirely due to insufficient own resources.

Table 6.18 GA experiments: Performance indicator estimates for the 10 best solutions

Inflow subset	*Solution code*	PI_1 [$10^6 m^3$/year]	PI_2 [-]	PI_3 [months]	PI_4 [months]	PI_5 [$10^6 m^3$/month]	PI_6 [$10^6 m^3$/month]	PI_7 [months]
33	0546	0.445	0.985	2.0	97.5	2.447	4.225	3
	0802	0.575	0.980	2.7	97.0	2.372	5.281	4
	0328	0.634	0.982	2.3	97.3	2.988	5.428	3
	0919	0.634	0.980	2.7	97.0	2.617	5.354	4
	0210	0.772	0.977	3.0	96.8	2.829	5.800	4
	0127	0.750	0.975	3.3	96.5	2.475	5.710	4
	0650	0.791	0.975	3.3	96.5	2.609	5.811	4
	0443	0.826	0.975	3.3	96.5	2.727	5.846	4
	1043	0.848	0.975	3.3	96.5	2.799	5.814	4
	0724	0.940	0.972	2.8	96.3	2.819	5.883	4
11	0546	8.659	0.826	4.6	21.8	4.141	11.454	9
	0802	8.256	0.818	4.8	21.6	3.784	11.054	9
	0328	10.397	0.803	5.2	21.2	4.399	11.977	9
	0919	6.381	0.826	4.6	21.8	3.052	6.517	8
	0210	6.833	0.818	4.8	21.6	3.132	6.745	8
	0127	7.936	0.818	4.8	21.6	3.637	11.131	8
	0650	6.897	0.818	4.8	21.6	3.161	6.756	8
	0443	11.006	0.796	5.4	21.0	4.484	12.220	9
	1043	7.083	0.818	4.8	21.6	3.247	6.759	8
	0724	7.352	0.818	4.8	21.6	3.370	6.828	8

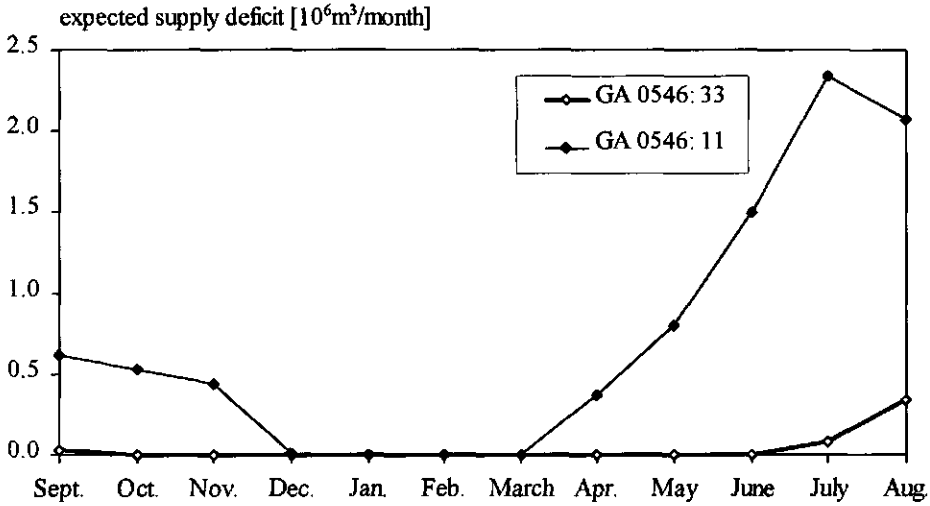

Figure 6.6 The simulated expected monthly supply deficits for the best GA solution

The above discussion has already implied that the 10 best solutions proposed by the GA do differ with regard to the respective water allocation patterns (cf. Table 6.21). However, there are two points common to all of the 10 solutions. Firstly, they all agree that Siliana represents a "weak" resource and that its contribution towards supplying the TU, TO, NA, MO, SO, SF, IAEA, IBV and IMSC demands should be kept as low as possible. And secondly, Mellegue should take at least a half of the IBH demand to cover to enable Bou Heurtma to operate without having any supply deficits.

6.4.2 Optimizing the System's Operation Under Different Water Allocation Strategies

The water allocation patterns identified by the 10 best GA solutions presented in the preceding section were further used to generate 10 different demand scenarios for the subsequent optimization of the case study system operation by means of the SDD-A decomposition model. The employed SDD-A optimization model retained all the characteristics of the one presented in Section 6.3. The execution of the SDD-A optimization constitutes the final phase of the analyses of the system operation for the 10 alternative water allocation patterns within the A-GA-D model coupling. Similarly to all of the methods tested so far, upon deriving the SDP policies, the operation of the system was appraised by simulation over both the policy determination and verification inflow subsets. Each of the 10 SDD-A runs converged to a stable system return within two iterative cycles (i.e. approximately 1 minute on a Pentium 120). Table 6.19 summarizes the PI estimates for the alternative simulation runs.

Table 6.19 A-GA-D experiments: Performance indicator estimates upon application of the SDD-A model using the water allocation patterns defined by the 10 GA solutions

Inflow subset	*Solution code*	PI_1 [10^6m^3/year]	PI_2 [-]	PI_3 [months]	PI_4 [months]	PI_5 [10^6m^3/month]	PI_6 [10^6m^3/month]	PI_7 [months]
33	0546	0.517	0.950	2.2	37.6	0.853	2.589	5
	0802	0.677	0.929	3.1	36.8	0.798	2.936	8
	0328	0.745	0.937	2.8	37.1	0.983	2.839	8
	0919	0.747	0.927	2.9	33.4	0.850	2.977	8
	0210	0.913	0.932	2.7	33.5	1.115	3.030	8
	0127	0.917	0.919	2.5	26.0	0.946	3.112	8
	0650	0.932	0.932	2.7	33.5	1.139	3.066	8
	0443	0.969	0.932	2.7	33.5	1.185	3.118	8
	1043	1.022	0.917	2.4	24.2	1.022	3.229	8
	0724	1.118	0.914	2.3	22.6	1.085	3.349	8
11	0546	6.174	0.652	3.8	7.2	1.476	5.224	11
	0802	6.543	0.623	4.9	8.3	1.469	5.232	13
	0328	6.885	0.636	4.8	8.4	1.578	5.423	11
	0919	6.622	0.629	5.4	9.2	1.487	5.320	18
	0210	7.065	0.636	4.8	8.4	1.619	5.544	11
	0127	7.110	0.629	5.4	9.2	1.596	5.453	18
	0650	6.967	0.644	4.3	7.7	1.631	5.555	11
	0443	7.515	0.636	4.8	8.4	1.722	5.591	11
	1043	7.178	0.636	4.8	8.4	1.645	5.566	18
	0724	7.458	0.629	4.9	8.3	1.674	5.637	18

The figures displayed in Table 6.19 show that the alternative SDP policies derived for the 10 water allocation strategies proposed by the GA exhibit relative stability over most of the PIs. Quite expectedly, there is a general trend of PI value deterioration with the drop of rank of the alternative GA solutions. The most interesting conclusions can, however, be drawn by comparing the PI estimates for the A-GA-D model with those obtained for the GA model alone (Table 6.18). In general, the values of the expected annual deficit (PI_1), time-based reliability (PI_2), average duration of full supply (PI_4) and the maximum duration of failure (PI_7) show that the system performance derived by applying the SDD-A optimization to the 10 alternative water allocation scenarios proposed by the GA is inferior to that obtained by the GA model alone. However, with respect to the estimates of the average duration of failure (PI_3), the average monthly deficit (PI_5) and the maximum vulnerability (PI_6), the additional SDP optimization seems to be bringing about the improvement in the system performance. This is, once again, the reflection of the "expectation-oriented" nature of SDP optimization. Namely, it is obvious that the final SDP-based system performance is characterized by shorter periods of continuous full supply and more frequently occurring failures, thus resulting in slightly higher total deficits over the entire simulation period. However, the deterioration along those performance aspects is to a certain extent compensated by the reduction of the magnitude of individual failure events.

Another interesting point can be observed by comparing the PIs obtained upon simulation over the 11-year-long verification period. Namely, the five "sensitive" GA solutions (i.e. 0546, 0802, 0328, 0127 and 0443; cf. Table 6.18) which exhibited the worst performance with regard to PI_1, PI_5 and PI_6 improved significantly upon the application of the SDP optimization to the respective water allocation scenarios (Table 6.19). It should be noted here that the distribution of supply deficits among the reservoirs remained virtually unchanged upon the application of the SDD-A optimization to the 10 alternative demand scenarios. Namely, Siliana remained the principal contributor to the deficit of supply (i.e. well over 95% of the total system supply deficit). The only change was observed with regard to the magnitude of Joumine's deficits, which were substantially lower upon the implementation of SDP policies. In general, it can be said that the additional SDP optimization has reduced the sensitivity and vulnerability of the "pure" GA strategies over both simulation periods. This is particularly noticeable for the verification inflow subset, which is also reflected in the obtained estimates of the expected monthly supply deficits for the application of the A-GA-D model to the 0546 GA solution displayed in Figure 6.7 (cf. Figure 6.6).

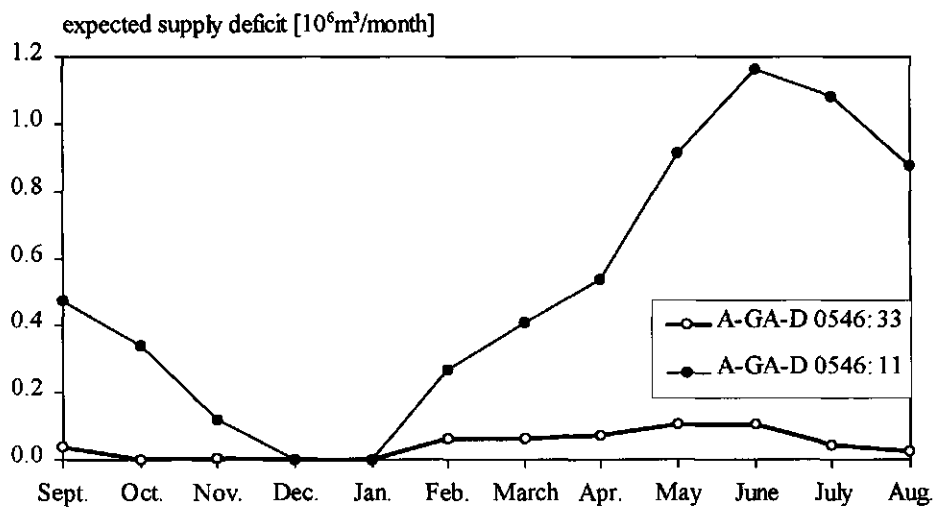

Figure 6.7 The simulated expected monthly supply deficits for A-GA-D with solution 0546

6.5 SDP-Based Fitness Evaluation Within a Genetic Algorithm

The final step in the analyses of the long-term operation of the case study system consisted of the application of the complete GA/decomposition model (C-GA-D). This most intricate coupling of the GA and SDD-A decomposition models involved the employment of the SDD-A as the principal fitness evaluation mechanism within the genetic algorithm. Thus, for each new individual created in the GA, the SDD-A model had to be run to derive the SDP-based operating strategy for that particular potential solution. Subsequently, based on the derived operating strategy, the system operation is simulated to obtain the respective fitness estimate. The GA model parameters used in this application remained unchanged from those presented in Section 6.4. Similarly, the basic SDD-A decomposition model settings were kept the same as those used in Section 6.4.2. Since the experiments described in Section 6.4.2 showed that the SDD-A optimization generally stabilizes after two iterations, this is introduced as a fixed number of iterative cycles for this model within the C-GA-D. Furthermore, this restriction was also made to reduce the execution time of the latter.

The C-GA-D model was run only once. The execution time was approximately 51.5 hours. Unlike in the previous GA experiments, the initial population for this GA run was not selected at random. Instead, the initial population was chosen to be the one which resulted in the best solution of the former GA model (i.e. solution code 0546). Upon completing the search, the C-GA-D achieved the expected annual fitness of the best solution of 5683.54 (given in $(10^6 m^3)^2$/year). The obtained water allocation pattern for the best solution found is given in Table 6.21. Upon the identification of the best solution, the system performance was appraised by simulation over the 33 and 11-year-long policy determination and verification periods, respectively. Table 6.20 displays the estimates of all the performance indicators obtained for these two simulation runs.

Table 6.20 C-GA-D experiment: Performance indicator estimates for the best solution

Inflow subset	*Solution code*	PI_1 [$10^6 m^3$/year]	PI_2 [-]	PI_3 [months]	PI_4 [months]	PI_5 [$10^6 m^3$/month]	PI_6 [$10^6 m^3$/month]	PI_7 [months]
33	0546-C	2.872	0.836	2.8	14.4	1.458	6.112	8
11	0546-C	10.476	0.576	6.2	8.4	2.058	6.394	20

The presented PIs indicate a superior performance of the system over the policy determination period to that derived upon the verification inflow subset. This fact is also reflected in the estimates of the respective expected monthly supply deficits displayed in Figure 6.8. Again, the earlier suggested sensitivity of "fine-tuned" operating strategies to the changing hydrological conditions (cf. Sections 6.2.4, 6.3, 6.4.1 and 6.4.2) is occurring in this case too.

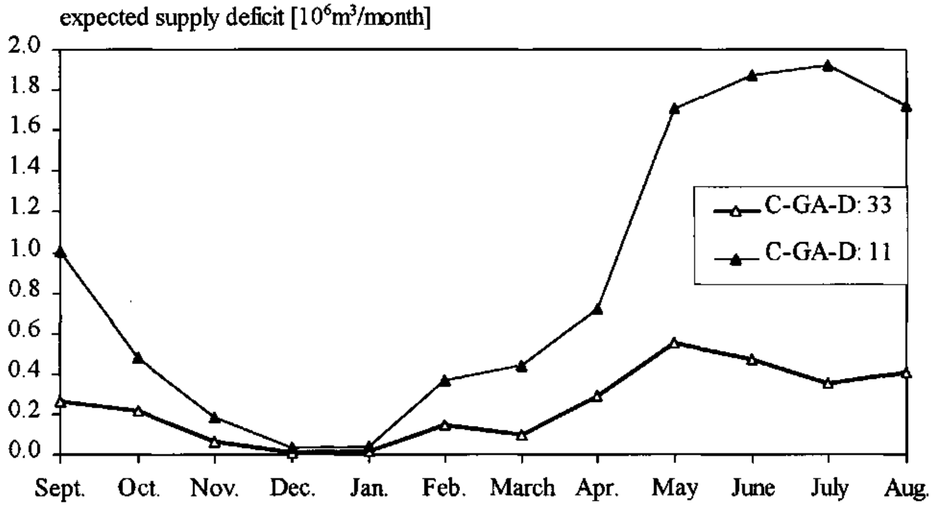

Figure 6.8 The simulated expected monthly supply deficits for C-GA-D

As to the performance of individual reservoirs suffice it to say that, in this case also, Siliana bears the largest burden of supply deficiency. Namely, over both simulation periods, its deficits amount to almost 99% of the total system deficit. The remaining 1% of shortage is attributed to Ben Metir.

6.6 Closing Remarks

The five sets of optimization experiments presented in this chapter reveal a number of interesting points. These include some general features of the different models used in the study, as well as a number of characteristics of the derived operating strategies and the respective system performances. The most pronounced ones are given in the following:

1. The overall performance of the system derived by the strict policy compliance-based SDP optimization models (i.e. SDD, IDD and UDD) is invariably inferior to the ones obtained by the models which are less, or not at all, reliant on the assumption that the system states and decision must be discretized (i.e. SDD-A, SDD-M, A-GA-D and C-GA-D). However, this does not mean that the use of the former results in totally unacceptable performance of the system. Namely, it should not be forgotten that, with regard to the imposed demands, none of the developed strict policy compliance models achieved less than 95.8% of the expected annual demand fulfilment.

2. The presented results also reflect that the SDP-based operating strategies (i.e. those derived by the SDD, IDD and UDD models), if strictly followed, exhibit less sensitivity to the changing hydrological conditions. On the contrary, "fine-tuned" policies derived by the SDD-A, SDD-M, A-GA-D and C-GA-D models seem to be more prone to failure if the simulation is carried out over inflow sets other than those used in optimization.

Table 6.21 Water allocation patterns obtained by different models [%]

Demand	*Reservoir*	*Decomposition models*		A-GA-D		C-GA-D
		The range within SDD, IDD and UDD	SDD-A and SDD-M	The best: 0546	The range among the 10 best	
TU	Joumine	83.1	91.9	47.5	(5.1, 54.9)	5.9
	Ben Metir	(0.0, 15.3)	8.0	2.7	(0.0, 34.1)	56.9
	Kasseb	(1.6, 16.9)	0.1	0.0	(0.0, 38.8)	6.3
	Sidi Salem	0.0	0.0	49.8	(14.5, 83.5)	31.0
	Siliana	0.0	0.0	0.0	(0.0, 1.2)	0.0
TO	Joumine	63.7	85.6	64.3	(23.1, 79.2)	40.4
	Sidi Salem	(35.9, 36.0)	14.4	35.7	(20.4, 76.9)	58.8
	Siliana	(0.3, 0.4)	0.0	0.0	(0.0, 7.1)	0.8
NA,	Joumine	59.9	82.7	22.4	(16.1, 90.6)	25.5
MO,	Sidi Salem	39.7	17.3	77.6	(8.2, 83.9)	59.2
SO, SF	Siliana	0.4	0.0	0.0	(0.0, 9.0)	15.3
IBH	Bou Heurtma	(76.2, 80.2)	80.8	45.1	(27.8, 45.1)	36.1
	Mellegue	(19.8, 23.8)	19.2	54.9	(54.9, 72.2)	63.9
IAEA	Sidi Salem	99.7	100.0	99.2	(95.7, 99.2)	95.7
	Siliana	0.3	0.0	0.8	(0.8, 4.3)	4.3
IBV	Sidi Salem	(97.7, 98.4)	100.0	99.6	(99.2, 100.0)	97.6
IMSC	Siliana	(1.6, 2.3)	0.0	0.4	(0.0, 0.8)	2.4

3. Another interesting point can be drawn with regard to the use of the SOR-based simulation for fitness evaluation within a GA search. Namely, as compared to the respective outcomes of SDP-based simulations, the expected increase of supply shortage in dry periods when SOR simulation is used (cf. Section 4.5.2) is substantiated by the values of the relevant PIs (cf. Tables 6.13, 6.18, 6.19 and 6.20). The analyses showed that whenever the operation of the case study system is optimized by the SDP-based decomposition model which allowed policy

violation in simulation (i.e. SDD-A and SDD-M models), and regardless whether this is done in combination with a GA model or not, the respective system performance almost invariably exhibited an improvement of the average duration of failure (PI_3), average monthly deficit (PI_5) and maximum vulnerability (PI_6) as compared to the one obtained by the SOR-based GA model alone. Such an outcome is due to the very nature of SOR which, although water availability in dry months can be rather low, allows maximum possible allocation of water in those periods regardless of the likely possibility that the shortage in subsequent months could become even more pronounced. On the other hand, the SDP-based policies derived on the basis of the chosen objective function do exhibit hedging and thereby try to distribute the expected supply shortage over a larger number of time steps, thus reflecting the basic, "expectation-oriented" facet of SDP. However, it should be noted here that the figures presented in Table 6.20 (i.e. PI estimates of the C-GA-D model) do not constitute a truly representative example of the above assertion. One reason for such an outcome is likely to be the fact that the C-GA-D search has been executed only once and, therefore, the results obtained in this single trial cannot be considered as the absolute reflection of the model's performance. Nevertheless, Table 6.20 still shows that the best solution found by the C-GA-D model represents a strategy which bears this "expectation-oriented" characteristic of SDP. Namely, the estimates of the time-based reliability (PI_2), average duration of failure (PI_3) and average duration of full supply periods (PI_4) from Table 6.20 do indicate that the resulting supply deficits are distributed over a greater number of time steps than it is the case with the solutions of the SOR-based GA model (Table 6.18). Furthermore, the estimate of the average monthly deficit (PI_5) for the C-GA-D model's best solution does outperform the respective performance indicator values of the 10 best solutions derived by the SOR-based GA. It is only that the respective estimates of maximum vulnerability (PI_6) do not show the expected behaviour as stated above (cf. Tables 6.18 and 6.20). Having all this in mind, it is not without reason to expect that an extensive experimentation with the C-GA-D model, as it has been the case with the A-GA-D model, would provide much stronger evidence to support the above assertion about the "expectation-oriented" characteristics of SDP policies. Unfortunately, such an exercise is confronted with almost prohibitive costs due to the excessive execution time of the C-GA-D model searches (cf. Section 6.5).

4. With regard to the particular operating problem addressed in this study, there seem to be a number of equally good long-term operating strategies for the case study system. Table 6.21 clearly exemplifies this fact. Namely, the water allocation patterns within the system derived by different models do differ along many points. However, there are still some operational features common to all, or most of the models:

- The contribution of Siliana towards supplying the TU, TO, IAEA, IBV and IMSC demands should be kept as low as possible. Similarly, all but one of the models (i.e. C-GA-D) do agree that the same strategy should be applied to the NA, MO, SO and SF demands. However, it should be noted that the C-GA-D's proposed 15.3% of Siliana's contribution to the four demands amounts to only 2.077 ($10^6 m^3$/year) in absolute terms. Therefore, and having in mind relatively poor inflows to this reservoir (43.1 $10^6 m^3$/year) and its substantial local water demand (29.5 $10^6 m^3$/year), it may be concluded that an additional storage facility could be envisaged in the system to ensure a more reliable water supply for these remote users of Siliana.

- All the models which involve a GA-based water allocation model suggest that Mellegue should take over more than a half of the IBH demand to cover, thus enabling Bou Heurtma to perform better with regard to its share of this demand. On the contrary, the decomposition based SDP models (i.e. SDD, IDD, UDD, SDD-A and SDD-M) allocate at least three-quarters of this demand to Bou Heurtma. This is entirely due to the fact that Bou Heurtma always precedes Mellegue in the adopted decomposition models.
- Unlike the GA-based models, the SDD, IDD, UDD, SDD-A and SDD-M models allocate no water from Sidi Salem to the TU demand. This is again a direct consequence of the adopted decomposition sequence in these five SDP models.

The existence of a multitude of solutions to this particular operating problem has also been confirmed in a separate exercise (Hendrix and Milutin 1997) which involved the derivation of the best water allocation patterns by applying the *multi single start search* (MSIS), a global optimization method developed by Hendrix and Roosma (1996). In short, the MSIS performs detailed local searches in the neighbourhood of the best potential solution point found in the previously generated random sample of points. The whole process consists of a number of random sample generations and the subsequent local searches around the respective most promising points. Ultimately, the search procedure ends upon completing a predefined number of local searches, thus identifying a set of solutions to the problem. In this particular case, the MSIS experiments showed that there exists a great number of water allocation patterns which all achieve the same objective function value. Furthermore, the subsequent simulation of the case study system operation revealed that, for all of the water allocation patterns found in the MSIS experiments, Siliana is the only reservoir which fails to meet the imposed water demands, which is almost entirely in agreement with the results presented in Sections 6.4 and 6.5.

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

The analyses carried out and presented in this study concentrated on the long-term operational aspects of a multiple-reservoir-multiple-demand water supply system. Due to the inherent complexity of this particular optimization problem, the focus is set to the appraisal of a family of decomposition techniques combined with stochastic dynamic programming optimization, simulation and water allocation models. Furthermore, since the discrete nature of SDP policies inevitably causes that the release decisions are also largely discrete and thus frequently overshoot the targeted water demands, the study proposes two policy violation-based simulation alternatives to reduce the amount of excess release from individual reservoirs. Consequently, the use of such simulation options in conjunction with SDP offers an improvement in the performance of the system without having violated the objective set in optimization. Furthermore, the shortcomings related to the decomposition-based determination of the sharing of common demand loads among groups of reservoirs are eliminated by deriving the best water allocation pattern within a system by means of a genetic algorithm search strategy. And finally, with regard to model assessment, the analyzed optimization and search methods are appraised and compared not only on the basis of a single system performance criterion but rather over an array of simulated performance indicator estimates describing different aspects of system operation.

The three sequential decomposition models which utilize the strict policy compliance simulation (i.e. SDD, IDD and UDD) have arrived at very similar simulated performance of the system. Although the number of iterations required to achieve a stable system return did vary from one method to another, this factor is not deemed significant due to the fact that the execution time of each of the models was of the order of magnitude of a couple of minutes only. It is rather the issue of suitability of one or more of the decomposition approaches to the particular system being analyzed that should play a decisive role in the selection of the method to be used. In this respect, it is believed that the relatively flexible and simple decomposition principles, together with the inherent system decomposition transparency pose a significant advantage to the applicability of this type of decomposition approaches to other, even substantially larger, reservoir systems. Furthermore, it is obvious that the proposed sequential decomposition methods do not set very rigid requirements with regard to the adopted reservoir orderings, nor do they explicitly require SDP as a choice of the optimization method to be used. Therefore, and despite the fact that the three decomposition models generally achieve a near optimum performance, rather than the global one, of the analyzed system, it is believed that the aforementioned advantages make them likely candidates for the derivation and assessment of alternative strategic operating plans of complex reservoir systems.

The two simulation alternatives which were devised to limit the excess release caused by the discrete nature of SDP decisions proved to be very influential to the resulting performance of the system. Namely, both decomposition models (i.e. SDD-A and SDD-M) which allowed limited policy violations in simulation arrived at substantially better system performance than their counterpart SDD which employed strict policy simulation. On the other hand, the identical performance of the system achieved by the SDD-A and SDD-M models was entirely due to the specific configuration of the system regarding the assumed reservoir-demand links, reservoir sizes and the inflow and demand records used. However, it is particularly important to emphasize that the ability to use policy violations was justified by the type of objective function used and the fact that the only consideration with regard to the system operation was given to water supply. Namely, the SDP objective function penalized both the deficiency and surplus of supply. If, however, the objective function had only been penalizing supply shortage it would have been totally unjustifiable to reduce the decision-based release volume to the level of the respective demand expectation, or the actual demand estimate, for that month because that would have been in clear violation of the pursued objective. Furthermore, if the optimization of the system operation had taken into account flood control, for instance, in addition to water supply it would also have been impossible to opt for such a type of policy violation. Nevertheless, the analyses did stress the importance of simulation within the adopted decomposition methods and showed that there is a possibility to act upon the improvement of system performance by using limited, simulation-based measures to refine the coarseness of SDP policies.

The applicability of genetic algorithms in complex water resources systems management was exemplified through their application to derive the best water allocation patterns within the case study system. The executed GA experiments showed that, for the given case study system, there exist a number of alternative water allocation strategies which all ensure almost identical system performance. This fact was also substantiated by the tests carried out using the Multi Single Start Search which belongs to the family of random search-based global optimization methods.

The development and use of genetic algorithms proved to be relatively uncomplicated. Perhaps the most demanding part of their development is related to the calibration of GA parameters which is generally a trial-and-error type of procedure. For instance, in this particular case, it took the equivalent of approximately one-third of the total time spent for the execution and analysis of 500 independent genetic algorithm runs. Nevertheless, genetic algorithms seem to be an appropriate choice for many types of water management problems. The primary advantage is due to their robustness and insensitivity to the size of the solution space they are expected to search. Secondly, they rely entirely on the objective criterion estimate which is derived by simulation, thus allowing more detailed simulation models to be used. Ultimately, genetic algorithms are fully capable of identifying a number of equally good alternative solutions, which is frequently the case in water resources management problems.

The two couplings of genetic algorithms and SDP-based decomposition models (i.e. the approximate A-GA-D and complete C-GA-D models) directly show the effects of the "expectation-oriented" nature of SDP optimization. Namely, in each of the cases, the system operation tends to have less reliable performance than any of the "pure" GA solutions. However, both model couplings exhibit a reduction of the average magnitude of those failures as compared to the respective estimates of the "pure" GA model.

As to the comparison of the approximate GA/decomposition coupling (i.e. A-GA-D) and the complete C-GA-D model, it is obvious that the latter is too costly to run. Namely, based on the execution times of the two models, the approximate A-GA-D outruns the C-GA-D at the rate of approximately 500:1. Thus, and this is also substantiated by the results, given the same execution time available for both models, this ratio may be used as a crude estimated of how higher a chance the approximate model has to identify a better solution than the complete one does.

Throughout the whole study, and especially when analyzing and comparing the alternative optimization and search models, instead of using the objective function achievement the emphasis was given on the use of simulated estimates of a number of system performance indicators. This has proven essential since some of the solutions proposed by different models seemed to be almost identical with regard to the objective criterion achievement. However, when the respective estimates of the remaining performance indicators were compared, it was frequently found that there were subtle, but still essential differences among the analyzed solutions. Furthermore, it is a widely acknowledged fact that the operation of a water supply system cannot be judged on the basis of a single performance measure which was used in optimization. The issues related to various aspects of performance reliability, resilience and vulnerability frequently prove to be vital in making the ultimate choice of the operating strategy to be used.

Ultimately, with regard to the applicability and suitability of the proposed decomposition, optimization, simulation and GA-based approaches to real-world reservoir systems, it should be noted here that the principles of the approximate GA/decomposition coupling (i.e. A-GA-D) have been adopted, with some problem specific extensions and modifications, as a basis for the development of the operational software for the complex reservoir system in Tunisia. The work on this operational model has already commenced within the second phase of the EAU 2000 project (Agrar-und Hydrotechnik 1992), which has been the sole source of the data used in this study.

7.2 Recommendations for Further Research

Obviously, since the proposed decomposition and search models have only been tested on the case study system, the primary recommendation for further research would be to appraise the applicability of these methods to different reservoir systems. As an initial suggestion, one may consider reservoir systems with more serial reservoir cascades and/or more complex reservoir-demand links. Furthermore, it is fully recognized that the three decomposition approaches presented in this study have not exhausted all of the possible reservoir orderings within the respective cascade levels. Therefore, another research area would be to investigate possible sensitivity of various decomposition approaches to the changes of within-cascade reservoir orderings.

The basic decomposition principle adopted in this study was to break down a complex system into individual reservoir units. One possible extension, or better to say relaxation, of this principle would be, if that is the case in reality, to acknowledge the existence of pairs of reservoirs with serial or parallel interconnections which are expected to operate in close conjunction with each other. The joint operation of such reservoir pairs could still be optimized by means of stochastic dynamic programming without falling into the trap of the "curse of dimensionality". It is believed that such considerations, if dictated by the real system configuration, would bring about the improvement into the derived performance of the system.

As to the incorporation of flood control as an integral part of reservoir operation, additional analyses are required to assess the changes of the system operation with regard to the inclusion of this important reservoir role. Furthermore, the consideration of flood control may prove essential to the changing view of the role of limited policy violation-based simulation options proposed in the study. For instance, seasonal flood control related storage volume targets may give ultimate thresholds as to how much, if at all, an SDP decision may be violated.

Further research regarding genetic algorithms applicability to operational problems of complex reservoir systems may be directed towards the use of niche and species methods

(Goldberg 1989:185-197). Since the results in this study indicate that there exist a multitude of solutions to the water allocation problem within the case study system, this becomes a particularly interesting area because niche and speciation GA methods can efficiently be used to identify all, or most of, the peaks of a multimodal objective function.

Furthermore, new areas of GA applicability may include the consideration of multiple objectives as the driving force in the search. In that respect, there have already been a number of proposals for the use of GAs in solving multiobjective decision making problems (e.g. Vector evaluated GA by Schaffer 1985; Pareto ranking GA by Goldberg 1989:199-201). Within the scope of the problem analyzed in this study, one may consider a number of performance indicators as the objective criteria in the serach for the most favourable water allocation patterns in the system. This may, for instance, be exemplified by the use of reliability and/or vulnerability in addition to the already employed squared deviation objective to identify the respective set of nondominated water allocation strategies.

In addition to water quantity, the quality of supply plays an equally important role in the operation of any water supply system. This is particularly important in the case of the system used in this study where the salinity of water poses a serious problem. In that respect, further work with genetic algorithms should concentrate on the issues regarding water quality as well. In fact, the initial steps in this direction have already been made and the obtained results seem to be quite promising (Milutin and Bogardi 1997).

With regard to the data used in this study, it is fully recognized that the time series of reservoir inflows, as provided by the EAU 2000 project, which covered the period 1946-89, would have provided a more reliable basis for the analyses, had they been extended beyond the year 1989. Since this was not possible to achieve during the course of this study, it should be born in mind that all the results, discussions and conclusions presented herein reflect the given inflow availability restriction. Therefore, further research involving the extended inflow time series is recommended. Similarly, the demand estimates and demand hierarchies adopted in this work closely follow the ones set up in the EAU 2000 project. In this respect, it is believed that, with regard to their impact on the optimum performance of the reservoir system, the alternative hierarchical arrangements of water demands, as well as the updated estimates of individual demand centres' water requirements, constitute an important framework for further research.

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