A SURVEY OF COMPUTER-BASED APPROACHES FOR GREENHOUSE CLIMATE MANAGEMENT

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Abstract

This study recapitulates research efforts that have addressed the restricted problem of greenhouse climate management. This problem is first analyzed by looking at the current working method of the grower and the characteristics of this management task. The different attempts to automate parts of management problem are presented. The systems and methods considered use problem solving techniques from either artificial intelligence or control theory. Advantages and drawbacks of both classes of problem solving approaches are pointed out. The surveyed papers show that most efforts have been directed towards an assessment of the applicability of particular problem solving techniques. Unfortunately, most systems have not been validated under circumstances that are comparable with those of a commercial grower.

1. Introduction

Management of greenhouse production systems requires identification and execution of suitable actions along the production time scale in order to obtain the desired crop and production conditions. The actions include the proper supply of water, minerals, heat, carbon dioxide and radiation to the crop, as well as manual operations (e.g. deleafing, truss pruning).

The desired properties include timing, quality and volume of production, minimization of heating-energy expenditure, absence of disease, and any suitable physiological state of the plants at particular stages of growth (e.g. state of good balance between reproductive and generative functions). The management task is a difficult decision problem because:

- it depends on an essentially uncontrolled external environment (solar radiation, wind, temperature);
- several complex and interacting factors (biological, physical, human) come into play;
- the knowledge and modeling capabilities concerning some biological and even some physical processes are still insufficient.

Despite these intricacies the recent past has seen a number of attempts to resolve this problem using computer-based decision support and/or decision making systems. There is little doubt that such systems will become indispensable for proper management of greenhouse production systems of the next generation.

The purpose of the present study is to examine the main existing approaches that have addressed the restricted problem of climate management which is a quite complex and central problem in greenhouse production. In this survey we will not consider decision support systems (DSSs) which primary purpose is to supply the grower with information about his crop. Simulation models and special measuring systems, the latter being central in the so-called "speaking plant approach" e.g. Hashimoto et al. (1981), have been widely suggested to supply the grower with better information. The management systems that are dealt with in this

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survey should have decision making capabilities. Likewise we will not address approaches that discuss the problem of regulation (Udink ten Cate (1987) or Young et al. (1993)). These approaches aim at the better realization of either device-dependent or climate setpoints through the use new control engineering techniques and/or climate models. Although those systems take decisions as part of the climate management process they only consider physical processes and are therefore not specifically oriented towards crop production management.

In the next section we describe our understanding of the management problem and the criteria that discriminate the approaches considered. Section three briefly describes and evaluates according to the criteria of section two a certain number of systems that address the climate management problem. We end with a discussion of some important attributes that a system should possess in order to be expected to have a commercial perspective.

2. Crop production management

Before we will discuss the different approaches addressing the problem of greenhouse climate management we would like to clarify our view on this problem.

2.1. Activities involved crop production management

Generally, management can be seen as the collection of activities which are executed to accomplish certain goals. Management, related to greenhouse production systems, can be subdivided in relation to its planning horizon as depicted in Challa and van Straten (1993). In this framework crop production management is an activity within operational management.

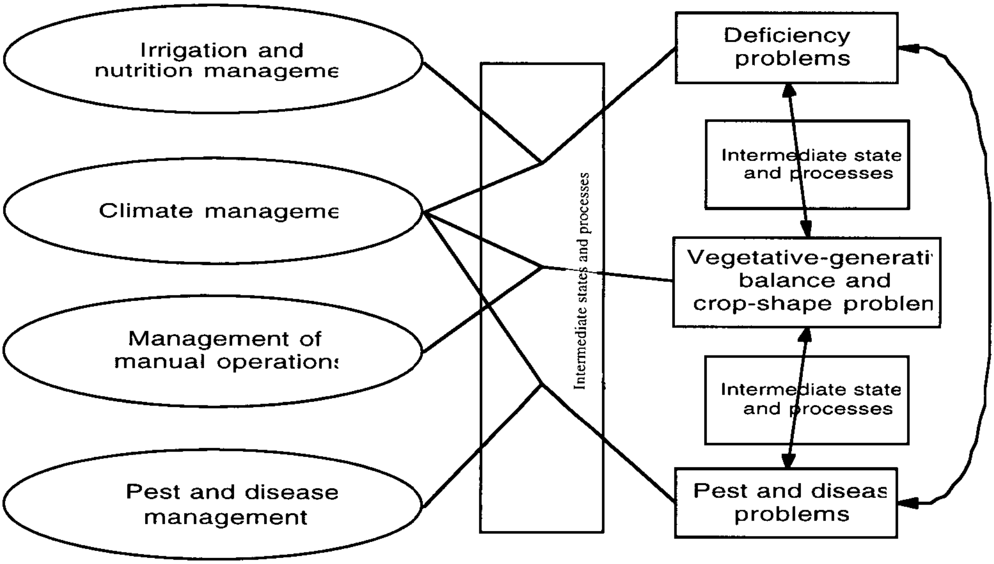

Figure 1. The relationship between management tasks and key crop problems.

We define crop production management as the collection of management activities, that directly influence the crop. The most important activities are: climate management, nutrition and irrigation management, pest and disease management and management of manual operations (harvesting, branch-pruning, plant-spacing, etc.). In order to be able to automate a certain management task, one has to have a thorough understanding of the activity itself and it's interactions with the other crop-related management activities. Figure 1 shows the connection of specific management activities with the key problem classes in greenhouse production. It can be seen that climate management is especially important because it directly plays a role in the possible emergence of a problem in any of the problem classes. Note that the occurrence of a problem in one class may cause other problems in other classes to occur. Given a problem-related goal there may likely be several possibilities to influence the state of the crop in the desired direction. An experienced grower will have such a multi-facetted viewpoint on his crop production management task.

2.2. The current working method of the grower concerning climate management

With the introduction of analog and digital controllers the regulation of the greenhouse climate became automated. Growers no longer operate the control mechanisms themselves but enter device-related desired values for one or more of the climate variables like temperature, CO_2-concentration, humidity and possibly light-intensity into their control system. Since then determination of the proper device-related setpoints (or an array of setpoints over a particular period) became an important management activity.

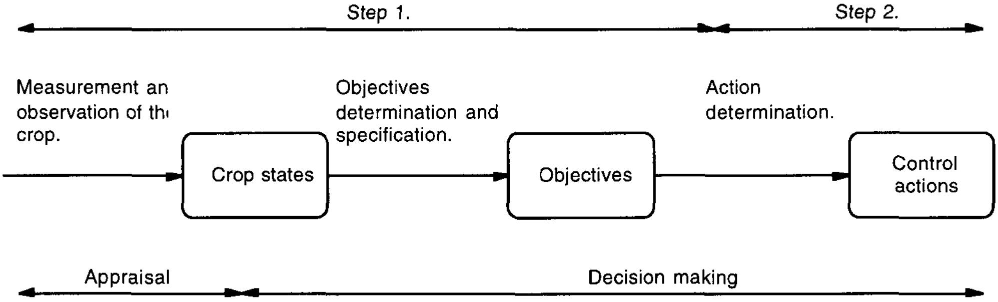

Figure 2 Activities involved in day-to-day climate management.

The day-to-day activities related to climate management can be seen as a two step process in which three activities take place (Figure 2). During the first step the grower is heavily involved and executes the first two activities namely, the appraisal of the state of the crop and the determination and/or specification of the objectives he wants to pursue from that particular point in time. However, owing to the limited expressiveness that the currently available control systems allow, the grower has to translate his higher level objectives, often related to crop characteristics, into device-related setpoints. The second step corresponds mainly to the automated part of the management task and is performed by climate control systems that regulate the control mechanisms in order to satisfy the objectives of the grower. The typical actions decided upon by the control system concern opening of windows, opening of hot water pipe valves and activation of CO_2 source.

The objectives are set up to influence the growth process in the desired direction or to avoid undesirable situations that can be observed or anticipated from the current state as it is perceived. Assessing the state of the crop properly, and assigning adequate objectives requires agronomic competence and experience that determine in part the difference in performance between growers.

2.3. Characteristics and discrimination features between the approaches

2.3.1. Broadness and scope

The systems surveyed differ as to the broadness and scope of the management problem addressed. In particular, the following features may be considered:

- which sub-part of the overall management task is addressed;
- which climate factors are dealt with;
- is the system developed for the management of one greenhouse zone or for a complete greenhouse complex involving several zones and possibly several crops.

Figure 3 shows a decomposition of climate management problem in a sequence of five subtasks. The ambition of management approaches grows with the number of subtasks that are taken over by a management system. A further dimension of comparison concerns the possibilities of communication between the grower and the management system. For instance, some systems require some input from the grower about desired states, others operate on an implicit notion of goals that makes interaction with the grower on this subject superfluous.

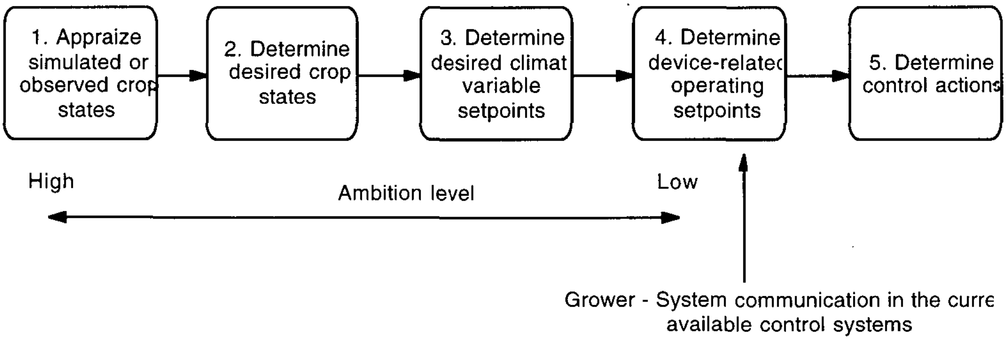

Figure 3 Climate management as a sequence of tasks.

2.3.2. Knowledge classes used in the system

We discriminate between two main sources of knowledge: the growers and the specialists in the fields of horticulture, crop physiology, greenhouse physics and control theory. The grower is trained to assess the current state of his crop, specify his objectives and to decide about what entries to put in his control system (figure 1). From the second author's interviews with growers and also from publications in professional literature we believe that the growers' explanation and argumentation for his control actions can occasionally be doubtful. Although their explanation is sometimes wrong the chosen actions are often rather correct. Scientists specialized on different aspects of crop production and growth are better sources for knowledge about specific crop processes . However those specialists lack the necessary overview of the entire production process, and are therefore not the appropriate persons for advice concerning the decision-making tasks.

The systems could be based on heuristic knowledge, which comes from growers, or model-based knowledge, which has it roots in the scientific community, or a combination of both.

2.3.3. Planning capabilities of the system

In the broad sense solving the management problem consists of choosing actions over time to influence the crop production process. A particularly useful dimension to categorize the approaches considered in this survey is the one of planning depth or deliberative power. Planning generally calls for a broad consideration of the potential consequences of candidate sequences of control actions. Potentially, planning allows for optimal management; however planning has proven to be difficult because one cannot easily represent all the relevant knowledge. In practice this approach has proven to be hard. Optimal control systems that consider the climate management task as the problem of finding a sequence of actions that optimize a numerical performance index belong to the class of systems that execute a form of planning. An alternative idea to planning is to address the management task as the problem of finding the appropriate reaction to a given situation by choosing in a set of pre-defined procedures that tell how to control things. The essential task of the management system is then to choose what decision procedure should run and when and, when several are applicable at the same time, to ensure that they are properly coordinated. Rule-based systems are developed in this spirit. Because this approach is short-sighted, theoretical optimality cannot be reached. Nevertheless this approach has the advantage of being closer to the working practices of the grower and thus facilitates the representation of knowledge.

2.3.4. The system's problem solving method

In the section 3 we will discuss the systems along the lines of the problem solving methods they use. We discriminate two main classes, the systems within the first class use techniques from the field of Artificial Intelligence (AI), the systems belonging to the second class use some form of mathematical optimization.

2.3.5. Integration with the currently available control systems

The suggested systems can either be a replacement of, or a complement to the currently available control systems. For some approaches integration is neither logical nor possible.

2.3.6. Robustness of the approach

The possibility to augment a system with new functionality (in either the greenhouse or the control system) or additional knowledge depends on the problem solving technique used, and the architecture in which it is embedded. Some approaches are intrinsically more difficult to expand. A related dimension is the one of ease of transportability from one application context to another; how difficult is it to adapt the knowledge base assembled for one application context to a similar context.

3. Computer-based approaches for greenhouse climate management.

The viewpoints in Section 2 lead the way to appraise the suggested approaches and should give some insight in their applicability outside the research context. In this section we try to classify the considered systems within the two main problem solving frameworks provided by artificial intelligence and the theory of optimal control. In each class that contains more than one system we examine mainly the most significant one, that is the one that seems to be the most typical and advanced.

3.1. Artificial Intelligence approaches

The use of artificial intelligence techniques in climate management has been considered as a means to exploit both (*i*) practical know-how in solving the specific problems and (*ii)* qualitative knowledge about bio-physical processes. Essentially two approaches have been applied. In the first, knowledge is represented in rules that express either the logical dependencies (causality) between the bio-physical variables or decision-making patterns that associate observed states (facts provided by the grower and sensors) to what should be done in terms of executable actions or changes in goals. The resolution mechanism that works on this kind of representation is what is called an inference engine. An inference engine aims at applying and chaining the appropriate rules depending on the situation. In the second approach, the domain knowledge is represented as a set of numerical constraints on the values that can be taken by the variables involved in the problem. The resolution mechanism is a constraint solver that searches assignments of values to the variables such that all constraints are satisfied. This way of addressing problems is quite general and is gaining in popularity in many application domains (e.g. scheduling, resource allocation).

The two approaches are considered in turn and the first one is subdivided according to the kind of knowledge (either qualitative bio-physical models or reactive decision rules) it relies on.

3.1.1. Rule-based approaches

3.1.1.1. Rules as a support of model-based decision making

In this approach we are aware of one system that has been described by Harazono (1988). The problem of real time management of the photosynthesis process is considered. The system is run periodically (every 10mn) or every time a significant event occurs. The goal of the system is to modify appropriately and continuously the setpoints for air temperature, relative humidity and CO_2 concentration. Each execution starts with an evaluation of the change in plant activity (photosynthesis and transpiration rates) and environmental parameters (air temperature, relative humidity and CO_2 concentration). If the present conditions are judged inappropriate (i.e. if the activity or response of the plant does not follow the change in the environment), then the system turns to symbolic reasoning and tries to infer new setpoint values by firing and chaining the rules in its knowledge base. A typical rule is telling, for instance, that in order to increase the photosynthetic rate, one could increase the CO_2 concentration, decrease the stomatal resistance, decrease the mesophyll resistance and act on the air temperature according to the actual context. Others tell how to decrease or increase stomatal resistance, mesophyll resistance and transpiration. Some of these rules specify how to achieve changes in terms of actions on directly accessible environmental parameters. Thus, the knowledge base composed of such rules constitutes a qualitative model of the photosynthetic activity. In order to return setpoints the system has to combine and transform in numerical terms the qualitative suggestions (e.g. increase CO_2 concentration, increase air temperature) inferred via different rules. This is done by a process that sums up positive and negative changes for each climate variable and computes a setpoint value as the product of this sum by a unit of correction of the concerned climate variable (e.g. 2°C for temperature). This system has the sole and implicit objective of optimizing the photosynthetic process.

The Harazono (1988) paper reports on a short (one day) and preliminary experiment conducted in a growth chamber with a lettuce crop. The plant activity was assess by use of an assimilatory box covering a representative leaf. The results proved the feasibility of the approach in this particular setting. The environmental changes decided by the system were found reasonable (agronomically) and gradual (no sharp changes). Besides its reliance on a model of the photosynthetic activity, another interesting aspect of this method is that it is not very sensitive to measuring-errors owing to its use of variations rather than absolute values of the variable. It seems, however, that the method is rather weak and criticizable on the combination process that synthesizes by an average operation the conclusions provided by several rules advising on the same climate variable. Apparently no large scale experiments in a real greenhouse and with a more elaborate knowledge base was planned.

3.1.1.2. Rules as an implementation of reactive behaviors

The idea of using rules as a repository of precompiled procedural knowledge about what to do in a given situation was first proposed by Kozai (1985). The management of the greenhouse climate subtask addressed by the systems belonging to this approach is under the responsibility of a mechanism that must continuously select and coordinate the rules to apply depending on the current situation and the available data. Here we provide a more detailed description of the GX system (Gauthier 1992, 1993) that embeds this approach in a generic greenhouse management platform and seems to be the most advanced systems falling in this category. Others are briefly mentioned.

GX is a greenhouse climate management shell designed to support knowledge-based control of the greenhouse environment. It supports the specification and deployment of dynamic strategies defined as setpoint adjustment based on context sensitive information such as outside climatic conditions, crop value, energy costs, weather forecasts. The management capabilities of GX are essentially embedded in heuristic rules that convey directly applicable procedural knowledge telling what to do in a given context. In every sample period (typically 10 minutes), the GX system looks for applicable rules and chooses among them those that should be applied. Apparently GX has not been designed to support goal-directed reasoning; it has mainly been used as a purely reactive system. GX directly jumps from observed or simulated states of the crop and the climate to decisions expressed in terms of climate setpoints or executable tasks.

A powerful feature of the GX system stems from its explicit representation (Gauthier, 1992) of the objects and concepts that have to be dealt with in the resolution of the management problem. This includes the important physical entities found in a greenhouse complex as, for instance, the zones, sensors, crops, actuators, communication devices. These entities are defined as general objects or classes in the Smalltalk object-oriented environment on which the GX system has been built. A particular greenhouse configuration can be described through a set of specific instances of these classes. The dynamic behavior of these objects may be described in procedures attached to them. In addition to the objects describing the physical greenhouse context GX encompasses a set of virtual entities that are repository of the control strategy knowledge (i.e. the decision rules) and information processing tools (e.g. for periodic updating of statistics). The explicit and modular knowledge representation framework used in the GX facilitates incremental development of the system and reuse of part of the system for different production contexts. This feature is well suited to accommodate different greenhouse configurations and different user-dependent climate management strategies. Other management activities than those related to climate management (e.g. pest and disease management, nutrition and irrigation management) can potentially be incorporated in the GX knowledge-based approach. A definite advantage of the GX approach is that it addresses the management problem at the greenhouse complex level rather than at the level of a particular zone, potentially this allows for more complicated management issues to be addressed. Another nice feature of the system is that some justifications of the decisions can be provided, thus making them more acceptable to the growers. Moreover the effect of the control strategies can be tested in a simulated environment before they are actually applied in a real greenhouse management task.

The management capabilities of GX have been tested in an industrial size experiment in which hydroponic lettuce where grown year round. So far no detailed experimental results have been reported concerning the performance of GX climate management capabilities. What has been tested, apparently with success is the architecture of GX; the part of the knowledge base actually concerned with strategies was quite small in this experiment. Although GX offers a clean and powerful representation framework for a greenhouse production complex it seems that a thorough evaluation of its aptitude to accept the expression and to permit effective application of sophisticated management strategies has still to be done.

Several other attempts to exploit precompiled reactive behaviors through a rule-based encoding have been reported. Jacobson et al. (1987) have implemented a system for the generation of device-related setpoints (temperature and CO_2-concentration) for a tomato crop. The originality of this system is that it is combined with a mathematical models for calculation of optimal setpoints. The rule-based part acts as a supervisor to ensure robustness and reliability of the calculated setpoints. The paper by Jones et al. (1988) describes the system MISTING, which is an autonomous rule-based controller for the frequency and duration of misting events in plant-propagation environments. The system overcomes the limitations of the dual timer controller which does not take the value of one or more climate variables into account. The rules in the system are based on the knowledge of a grower and replicate his problem solving behavior. Test experiments show different patterns of both frequency and duration of the misting events. Whether it resulted in a better crop is not stated. Ehler and Karlsen (1993) outline the system OPTICO, which is dedicated to CO_2 optimization. It uses a small set of rules and an objective function in which the ventilation rate and the photosynthesis production are the important variables. The system, which has been tested with a sweet pepper crop, increased the number of fruits but reduced the average fruit size. The main problem with such a system is the integration with other systems managing other climate aspects. Recently, Chao et al. (1994) have applied the inference mechanism developed in fuzzy control to the daily management of temperature and CO_2 concentration for a single stem rose production. They essentially take into consideration the development status of the roses and the cost of heating and ventilation. They report more profitable results than those obtained by conventional practices; however, their approach was tested in a simulated context only.

3.1.2. Constraint satisfaction approach

The commercial greenhouse computers of the current generation essentially execute climate control actions according to the device-related setpoints that have to be specified by the growers. It has been observed that this daily setpoint specification task is difficult for many growers and that significant improvement of production performance could be expected from a keener determination procedure. This is precisely what the SERRISTE system aims at.

More specifically, SERRISTE (Martin-Clouaire et al., 1993a) which has so far been developed for tomato crops is an artificial intelligence software designed to be used once every morning. Essentially, it chooses for the three different periods (day, night, and dawn) of a 24 hour cycle the temperature thresholds that specify the situations in which the heating (of air and soil) and ventilation systems should be used. Practically, SERRISTE tries to plan the most appropriate distribution of temperature over the cycle. The determination of these device-related setpoints is done according to a set of implicit objectives such as avoiding problems (diseases, infestations, loss of vegetative - generative balance), creating climatic conditions that are appropriate for a good growth and development of the crop (e.g. no sharp change of climate from one day to the other) and limiting the cost of energy to be provided. Others are directly set-up in response to the current situation (e.g. the default mean temperature over 24 hours that mainly depends on the predicted solar radiation). Some can be specified by the growers, for instance, to lower or to increase the default mean temperature of the next 24 hours (in order to comply with the desired degree-day program over a growth stage). Besides some objectives, the SERRISTE systems takes as daily input a qualitative description of the crop (vigor), the weather forecast for the next 24 hours and the weather conditions of the close past.

The setpoint determination process embedded in SERRISTE relies on a combination of scientific and practical know-how of experts in the domain (Martin-Clouaire et al., 1993b). The main part of the knowledge is expressed in a set of constraints on numerical variables that are mean temperatures over different periods and the different setpoint variables that corresponds to the inputs required by the commercial climate control computers. The constraints are of the form ${}_i\, a_i X_i$ F where the a_i's are numerical values, the X_i's are the variable and F is a fuzzy interval. Each variable has a domain of acceptable values and this domain is also a fuzzy interval. Fuzzy intervals permits a faithful representation of the available knowledge. As a simple example of a fuzzy constraint used in SERRISTE consider the piece of knowledge stating that the difference between mean day and night temperatures should be between 2 and 6 with some flexibility on these bounds. The constraints to be used a particular day are context dependent, in other words, the prevailing conditions induce what constraints should be taken into account. The SERRISTE system is equipped with a constraint solver that returns all the combinations of values of the variables that satisfy all constraints (though may be partially). The resolution mechanism is based on classical filtering and tree search algorithms that have been extended to deal with the flexibility (fuzziness) of the constraints (Martin-Clouaire and Kovats, 1993c). Once all combinations of acceptable values are obtained SERRISTE chooses the best one according to a context dependent hierarchy of criteria, the most common of which concerning the limitation of energy cost.

A prototype of SERRISTE has been implemented on PC and tested in a real greenhouse in the period going from mid December 1993 to the end of May 1994. In this experiment the setpoints provided by SERRISTE were applied in one zone. The control was managed independently by an expert who had not been involved in the elaboration of the SERRISTE knowledge base. It was observed that the yield, fruit size and timing were comparable in the two zones with a slightly better performance in the reference one. The crop was looking better (better vigor) in the SERRISTE zone and about 10% less energy was spent in the SERRISTE zone than in the reference zone. The main practical limitation of the approach comes from the fact that part of the knowledge base is equipment dependent. Thus a new knowledge base has to be developed for each new application. So far there is no methodology for doing this easily. In the next two years other tests are planned outside the specific context considered so far in the research phase. Up to now SERRISTE is the sole attempt to use constraint satisfaction approach for greenhouse climate management.

3.2. Optimal control

According to our understanding, optimal control approaches are defined by the use of a numerical model of the system (crop + greenhouse), of a performance criterion (a scalar function) and the definition of a time interval over which optimal control is determined. Such approaches are young in the horticultural field because they need accurate models of both the greenhouse climate and the profit production rate. This rate is an economic measure of the crop response to climate manipulation and was first derived by Challa (1980) and developed by Challa and Schapendonk (1986) and Challa and Heuvelink (1993). Because the optimization is performed using a composite model extending from the crop behavior to the greenhouse climate, most of these approaches intrinsically cover step two and three of figure 3, namely determining the desired crop state and climate set-points. The following subsections are arranged in increasing complexity of the model used.

3.2.1. Single state variable models

Two main lines of work are reported here. The first concerns the temperature exposure problem where the crop state is represented by a physical variable (degree-day). This method covers only step three of the climate management problem. The second method deals with crops in which vegetative growth is the only factor considered.

The temperature exposure problem is based on the fact that many crops show the same growth rate for various temperature regimes providing the same daily (or even weekly) mean. The crop state is thus represented by its temperature exposure (expressed in degree-day or degree-hour). The controls for heating and ventilation (that cannot be operated simultaneously) are calculated from algebraic equations (simple energy balance) and the constraint that says that the temperature must be around a mean value. Bailey and Seginer (1989) applied Pontryagin's Maximum Principle to obtain the best economic operation of heating and found a sub-optimal solution to this problem, while stressing on the need to incorporate weather predictions to obtain better results. Gutman et al. (1993) produced a solution to the minimization of the heating cost, using a limited time horizon of a few days for which weather forecasts are considered available, based on linear programming. The solution oscillates between state-constrained and state-unconstrained greenhouse operation. State-constrained means that the greenhouse operation is not driven by the criterion function but by the constraint function on the state variables. The authors point out that each state-unconstrained interval can therefore be considered as an independent optimal control problem, thus allowing to shorten the prediction horizon, an interesting feature given the reliability of weather predictions.

The second type of approach is based on a simple model of a vegetative crop (lettuce or young tomatoes) that can be used to simulate the dry matter accumulation. One special characteristic of this crop model is that its formulation is such that the crop (s) and the climate (f) functions can be separated: $dw/dt = s(w)f(u)$ (where w is the crop state and u the control and external input vector). The greenhouse model is algebraic and static (as in the previous case), adding no state variable to the problem. Gal et al. (1984) set up a solving method which results in an analytical optimal condition, meaning that the optimization problem can be solved for each time instant independently. Whether one is interested in CO_2 enrichment only, or in the control of both temperature and CO_2, the crop state has no influence on the greenhouse operation. Lookup tables, where the various combinations of outside weather conditions are the entries and the greenhouse operation are the outputs, can thus be defined. This result, that relies on the specific formulation of the model, can be found in Seginer (1980) and has been confirmed by further works (Seginer et al., 1986; Seginer, 1989; Critten, 1991).

3.2.2. Two state variable models

These studies are based on a vegetative crop model describing dry matter accumulation and leaf area expansion of lettuce. Although this is a dynamic model, it does not include any operational storage of dry matter which would allow for growth during the night. At night, temperature simply controls the rate of respiration, i.e. dry matter loss. Therefore the night temperature set-point is not considered in the optimization process and taken as low as possible. A first attempt to find economically optimal day-temperature setpoints was drawn by Marsh and Albright (1991), using a sequential search method. The optimal day-temperature for day ***d*** is found after successive evaluation of the criterion (income - cost) over the whole growing season for various temperatures on day ***d*** and assuming a constant and reasonable future greenhouse operation for the subsequent days (***d*** + 1 and on). Seginer and McClendon (1992) reformulated the problem in order to compare solutions obtained with this sequential search method and the classical Pontryagin's Maximum Principle. They obtained similar solutions to this lettuce production problem: effort is first put into extending the plant leaf area with high temperatures (to increase light interception) and then into maximizing photosynthesis to achieve the proper harvest weight. They showed that the sequential search method of Marsh and Albright (1991) is rather insensitive to assumptions made on future operation of the greenhouse. Seginer and McClendon (1992) also present a simplification of the maximum principle solution that considers a subset of the state variables of the original model in the hamiltonian function. This simplification, which aims at allowing the use of larger models, is found to be very sensitive to the state variable retained in the hamiltonian. Seginer and Sher (1993) draw the same conclusion using the TOMGRO model of Jones et al. (1991) that has over 50 state variables, retaining only two of them for calculating the sub-optimal control actions.

3.2.3. Complex models

Larger models of the crop and greenhouse system have also been used, without simplification, to design an optimal greenhouse controller. Van Henten and Bontsema (1991) used a lettuce model, in which shoot and root states have been modeled separately. They added an operational storage of non-structural dry matter, allowing for structural dry matter increase during night, and thus giving value to the night operation of the greenhouse. The optimal day/night temperatures and CO_2 levels for the whole growing season are obtained by non-linear programming techniques. It is shown that the use of average weather data as forecasts results in a better performance than the classical blueprint method, while exact knowledge of the future weather would increase performance even more. No improvements could be obtained by applying a repeating optimization scheme that recomputes the solution every ten days on the basis of an updated crop state.

Tchamitchian et al. (1993) and Tap et al. (1993) put emphasis on the physical model of the greenhouse. While previously reported studies used simple algebraic equations, they used a dynamic model that included heat capacities of soil aerial components in the greenhouse. The goal was to investigate what could possibly be gained by short-term (within the day) optimal control of the greenhouse. Tchamitchian et al. (1993) used a static, algebraic model for the crop (a tomato crop in reproductive phase). The optimal solution found with Pontryagin's Maximum Principle adapts the CO_2 level to the light level, with some anticipation, and shows the need to incorporate the daily dynamics of the crop (operational storage of non-structural dry-matter). Tap et al. (1993) combined this dynamic greenhouse model with the lettuce model of van Henten and Bontsema (1991). The dynamic model of the greenhouse gives better results than the static one, especially if the daily weather forecasts are available for each couple of hours (hourly forecasts are already available for some locations in Europe).

3.2.4. Concluding remarks

Except for the temperature exposure problem, one must notice that these approaches consider the climate management problem as ranging from desired crop states to desired climate variable setpoints although the greenhouse model often considers device-related setpoints (heat supply essentially). In the temperature exposure problem, no crop model is used; the required temperature integral is in this case an implicit crop model. The models used by these approaches, and especially the greenhouse models, are rather simple ones compared with models produced in the last decade. There is agreement that these models would improve the results of optimal control, if they can be dealt with computationally (see Seginer and Sher, 1993).

Although these approaches are described as promising by all authors, almost none has been used in real greenhouse operation and so no real appraisal of their feasibility is available. This can result from the fact that some of these approaches have been developed by control engineers looking for application fields rather than by plant modelers. Their relative youth might be another reason. Our feeling is that combined approach or constrained approach where the unmodeled part of the crop behavior is taken into account through state constraints are the more likely to develop and to lead to practical implementations.

4. Discussion and conclusions.

As it has been the systems discussed here vary widely in the broadness and scope of the problems they try to solve. Systems range from reactive systems that do not perform any goal reasoning to systems with planning capabilities; or, systems ranging from ones that control a simple device to elaborate ones that take over the complete set of activities of the grower. Planning should be an important attribute in the latter, since it is necessary to reason over time about the consequences of fast changing control actions, via the resulting inside climate, on slowly changing crop states.

4.1. Characteristics of the problem solving methods.

Table 1 Advantages and drawbacks of AI and optimal control problem solving approaches.

Optimal control approaches	
advantages	drawbacks
• theoretical optimality guaranteed with respect to the objective function chosen	• neither models nor objective function are perfect: the solution is probably not optimal and
• planning capabilities intrinsically present	• the resolution mechanism may be very sensitive to inaccuracies in the models
• capability to exploit advanced knowledge of bio-physical processes	• tractability problem with respect to the number of state-variables, the number of decisions and the handling of uncertainty
• intrinsic capability of handling conflicting objectives	• representation difficulty to find an adequate objective function and to integrate incommensurable quantities
AI approaches	
advantages	drawbacks
• solutions are rational in the sense of the user	• no notion of optimality with respect to process models
• appropriate for goal generation	• planning's engine must be defined; existing ones are not powerful enough
• capability to exploit practical know-how and qualitative knowledge about processes	• conflict resolution between inconsistent decisions requires case-based exploitation
	• explicit and understandable representation of knowledge

Table 1 shows some advantages and drawbacks of the problem solving approaches considered. From this table it is not possible to conclude that methods from one problem solving approach are clearly better than the ones from the other, however one can clearly notice the difference in spirit between the approaches. As for desirable enhancements, optimal control approaches need supervisory systems to compensate for incompleteness in the models and simplification in the objective functions. In addition, the approaches based on numerical models (e.g. optimal control) require identification systems that can adjust model parameters in order to reduce inaccuracies. When appropriate, AI approaches need better integration with numerical models and optimization procedures. Some constraint processing approaches found in recent AI-literature may provide this enhancement. Extending AI approaches with a fuzzy knowledge representation is a possibility to create a built-in conflict resolution system. One might conclude that through such enhancements the approaches are converging toward an integrated one.

4.2. General remarks.

It is noticeable that, to our knowledge, no research has been reported on the specification of the objectives of grower. None of the systems discussed here address this problem. Many approaches, especially among the ones that are based upon a form of optimization use maximization of the dry matter production as their one and only objective. However, we can be sure that maximizing dry matter production does not summarize the objectives of the grower completely. We already pointed out that for those approaches the design of a system that performs optimization under constraints may well be a solution. However, defining constraints that both summarize the grower's objectives truthfully and can be used by an optimization system is not at all a trivial problem.

No or only limited validation of almost every system that was mentioned in this paper with respect to situations comparable to that of modern commercial growers has been reported. Therefore the real value of these systems remains unknown. For this kind of research we need a validation procedure which unfortunately has not been developed yet .

Climate management is often considered as an independent problem in the systems considered. However, as pointed out earlier, other management activities like pruning, changing planting distance and activities related to pest management or water and nutrition management can definitely interfere and should thus be taken into account especially in those systems that aim at the replacement of the grower. For optimal crop production it can be argued that in modern sophisticated greenhouses both shoot and root environments should be controlled simultaneously. Treating the climate management problem independently of the other management problems may be an acceptable approach in some specific situations, but one should first verify that indeed the current conditions fit these particular cases.

Emerging techniques like neural networks or genetic algorithms can be of help to alleviate some of the problems listed in Table 1. For instance, it is possible to model processes with a neural net; this can be done either dynamically or statically (Seginer et al., 1994). Genetic algorithms can for instance be used for identification of model parameters (Sequeira et al.,1993). Using such techniques can result in better models or models which might run faster.

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