Adaptive models for operational use in dairy farming

Increasing economic results utilising individual variation in response

Thesis committee

Thesis supervisor
Prof. dr. ir. A.G.J.M. Oude Lansink
Professor of Business Economics
Wageningen University

Thesis co-supervisors
Dr. ir. P.B.M. Berentsen
Assistant professor, Business Economics Group
Wageningen University

Dr. B. Engel
Assistant professor, Biometris
Wageningen University

Other members
Prof. A. Weersink, University of Guelph, Canada
Prof. dr. ir. J.G.A.J. van der Vorst, Wageningen University
Prof. dr. ir. P.W.G. Groot Koerkamp, Wageningen University
Dr. ir. J. Dijkstra, Wageningen University

This research was conducted under the auspices of Mansholt Graduate School of Social Sciences

Adaptive models for operational use in dairy farming

Increasing economic results utilising individual variation in response

G. André

Thesis
Submitted in fulfilment of the requirements for the degree of doctor
at Wageningen University
by the authority of the Rector Magnificus
Prof. Dr. M.J. Kropff,
in the presence of the
Thesis Committee appointment by the Academic Board
to be defended in public
on Wednesday 15 June 2011
at 1.30 p.m. in the Aula.

G. André

Adaptive models for operational use in dairy farming
Increasing economic results utilising individual variation in response

Thesis Wageningen University, Wageningen, NL (2011)
With references, with summaries in English and Dutch

ISBN 978-90-8585-881-2

Voorwoord

Melkveehouders vragen veel van hun koeien. Soms vragen veehouders te veel en luisteren te weinig. De productieresultaten van hun koeien laten het zien. Dankzij automatisering worden die resultaten, meer en meer vastgelegd in databanken. En die data, hoe ook behept met fouten, vormen statistieken die niet liegen. Integendeel, ze tonen aan hoe iedere koe reageert op de voeding en het aantal keren melken. Zo geven de koeien zelf antwoord (respons) op de vraag hoe ze optimaal gevoerd en gemolken kunnen worden.

Optimalisatie is in de regel de vraagstelling van het landbouwkundig onderzoek. Jarenlang heb ik onderzoekers statistische ondersteuning mogen geven bij de opzet en verwerking van het onderzoek. Op wetenschappelijk verantwoorde wijze werden experimenten opgezet en uitgevoerd, gegevens verzameld en verwerkt. Dat leverde veel resultaten op, representatief voor de veehouderij: resultaten in de vorm van theorieën en modellen die goed voorspellen (weergeven) wat je gemiddeld genomen (normaal gesproken) mag verwachten. Zo werd praktisch toepasbare kennis en informatie gegenereerd: normen en adviezen die een bijdrage leverden aan verdere optimalisatie en vooruitgang in de veehouderij.

Maar in het onderzoek bleek ook dat er veel spreiding is in landbouwkundige gegevens. En een substantieel deel van die spreiding kon niet worden verklaard. Modellen en theorieën schieten tekort, hoewel het gemiddelde nauwkeurig kan worden voorspeld, kent de voorspelling van een individuele uitkomst een grote onnauwkeurigheid. Het is zoals de Belgische weerman Armand Pien vaststelde: “al mijn weersvoorspellingen waren steeds juist … maar het weer volgde mijn voorspellingen niet altijd.”[1]

En met vee is het net als met het weer, ook landbouwhuisdieren volgen de voorspellingen van landbouwkundigen lang niet altijd op. Veehouders hebben dagelijks met deze variatie te maken, daarom volgen ze de productieresultaten van hun dieren en niet de voorspellingen van modellen. Al in 1905 werd geschreven: “In den regel geven … koeien niet evenveel melk. … Dit kan door een beschouwing der melkteekens en een blik in de

---

[1] Roth, G.D. 1981. Elseviers gids van het weer. 2e druk. p. 8

melklijsten wel vermoed, maar slechts door een proef bewezen worden. Deze eischt tijd, moeite en zorgvuldige waarneming. Men kiest de meest geschikt lijkende dieren uit en geve ze 2-3 KG. krachtvoeder per 1000 KG. levend gewicht meer dan te voren, … Geven de dieren nu niet meer dan te voren, dan keere men tot het oorspronkelijk rantsoen terug. Doen zij dit wel, dan ga men na, hoeveel krachtvoeder men nog met voordeel kan geven."[2]

Het bovenstaande schetst de achtergrond en aanleiding voor mijn (onder-)zoektocht van innoveren tot promoveren. Maar zowel innoveren als promoveren doe je samen! Daarom dank aan al mijn collega's, met name: Gert van Duinkerken, Kees de Koning, Agnes van den Pol - van Dasselaar, Theun Vellinga – dank voor jullie steun en sturing; Martin de Bree, Roelof Stapel, Wijbrand Ouweltjes en Ronald Zom – dank voor jullie inzet en inbreng als pioniers; Gerrit Braakman, Helmert Werkman, Leo Tjoonk en Harrie van Vliet – dank voor de introductie in de praktijk; Alfons Oude Lansink, Paul Berentsen en Bas Engel – dank voor jullie leiding en lessen in de wetenschap; Johan van Riel en Edwin Bleumer – dank, gewoon omdat jullie er zijn en mogen wezen!

De (onder-)zoektocht bestaat ook uit moeilijk begaanbare trajecten. Hans Jonkhout en Carla Plas – dank voor jullie professionele coaching.

Tot slot, dank aan de thuisbasis: jullie waren, zijn en blijven onmisbaar.

Geert André

Dronten, juni 2011

---

[2] Wolff, E., 1905. OORDEELKUNDIGE VOEDERING VAN HET VEE. In verband met de nieuwste physiologische onderzoekingen op het gebied der dierkunde. 7e druk.

Contents

Chapter 1.	General introduction	2
Chapter 2.	Economic potential of individual variation in milk yield response to concentrate intake of dairy cows	18
Chapter 3.	Increasing the revenues from automatic milking by using individual variation in milking characteristics	50
Chapter 4.	Adaptive models for on-line estimation of individual milk yield response to concentrate intake and milking interval length of dairy cows	80
Chapter 5.	Quantifying the impact of heat stress on daily milk yield and monitoring dynamic changes using an adaptive dynamic model	116
Chapter 6.	General discussion	142
Summary		156
Samenvatting (Summary in Dutch)		160
Curriculum Vitae		164
Completed Training and Supervision Plan		166

THE FUTURE

We need help from the academic statisticians. We are gathering more data and are being asked to help interpreting it. We need readily interpretable methods of analyzing large datasets and effective means of presenting our results. Our best management practices (BMPs) in the past defined best as highest yields. We are now redefining best in terms of yield, environment, soil characteristics, and even sociological issues. Agricultural producers and food and fiber processors (and consumers) are asking us for decision aids in determining what to produce and how to process it while achieving sustainability on the land, economic health for the industry, and a plentiful, safe, and nutritious food supply (Nelsen, 2002).

1 General introduction

During the last century in the Netherlands milk production per cow has almost tripled. Accordingly, the amount of concentrates yearly fed per cow strongly increased. Furthermore, automation and robotisation has changed dairy management, especially by the introduction of automatic concentrate feeders and milking systems. These developments put high demands on feeding and management, in order to keep the cows in good health and welfare and to retain the profitability of dairy farming. Economically, environmentally and socially sustainable dairy farming systems are also desired in society. A new management concept, emerging in the last decades, is Precision Livestock Farming (PLF). The objective of PLF is to optimize livestock production, by on-line monitoring and control of the production process, utilizing the technical possibilities of automation and robotisation.

In this general introduction, the historical development of dairy farming in The Netherlands is described first. Thereafter present methods for control and monitoring of milk production are described. These methods are based on standards, ignoring individual variation in milk yield response on concentrate intake and milking frequency. This leads to the main hypothesis for the research in this thesis that profitability of dairy farming can be improved by utilizing information on individual variation in response. In the last section of this chapter, the research objectives are described and an outline of this thesis is given.

1.1 Historical development of dairy farming in The Netherlands

1.1.1 Milk production

Since 1900, potential milk yield per cow increased substantially by breeding and selection and higher yield was realized by a combination of improved nutrition and management. In the Netherlands, milk yield per cow increased from 2770 kg/yr in 1905 to 7919 kg/yr in 2009.

In Figure 1.1, the development of milk production per cow per year is shown.

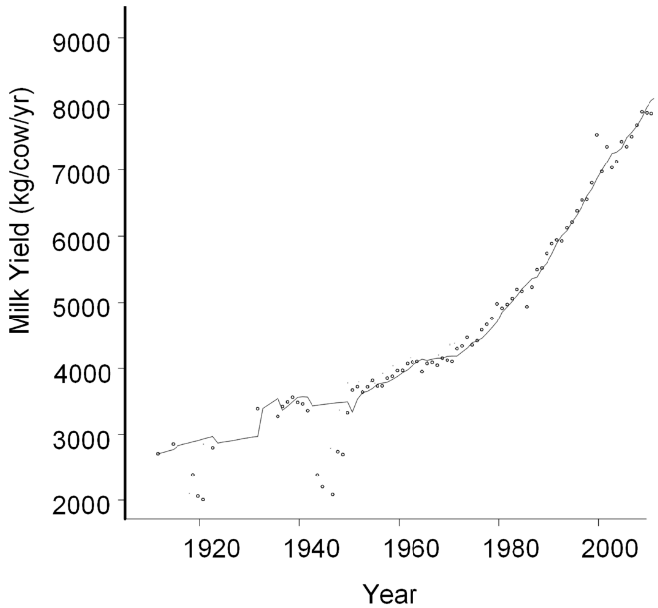

Figure 1.1 Development of yearly milk yield per cow in the Netherlands from 1905 to 2009. Source: CBS, 2010.

Milk yield per cow per year increased from 1910 to 1975 slowly with 20 to 40 kg per year. Thereafter, the incremental growth increased to 120 kg per year in 2009. It is expected that this increase will continue in the next years.

1.1.2 Concentrate feeding

According to the increased milk yield per cow, the nutrient requirement has increased and increasing amounts of concentrates were fed. Coppock et al. (1981) mentions an increase in grain and other concentrates yearly fed to dairy cows from 798 kg in 1955 to about 2270 kg in1980 in the United States. In Figure 1.2, the development of the amount of concentrates yearly fed to dairy cows in The Netherlands is showed from 1954 to 2009.

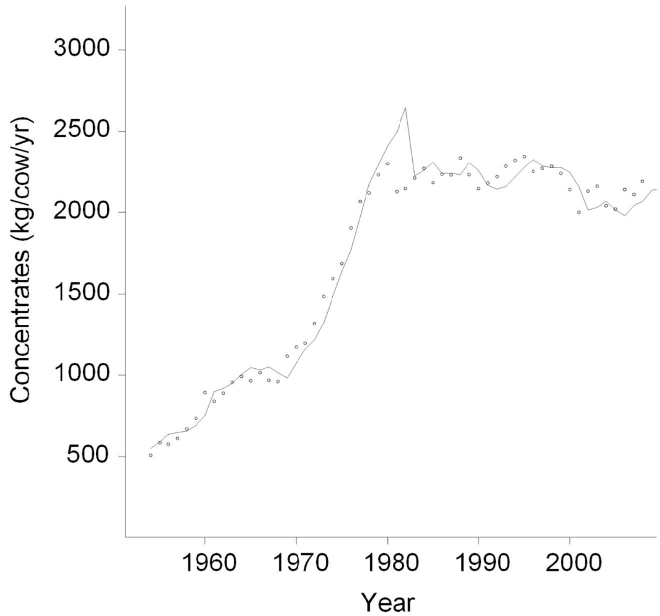

Figure 1.2 Development of yearly fed concentrates per cow in the Netherlands from 1954 to 2008. Source: Anonymus, 1969.

From 1954 to 1969, the amount of yearly fed concentrates increased with 45 kg per year from 500 to 1000 kg/cow/yr, followed by a higher increase up to more than 100 kg per year to 2300 kg/cow/yr in 1980. Thereafter, the amount of yearly fed concentrates per cow is almost constant around 2200 kg/cow/yr during the last decades, suggesting an increasing efficiency in the use of concentrates. Besides genetic improvement, there were other factors that have contributed to the increased milk production. Berentsen et al. (1996) indicate that in the last decades improvements in grass and silage production have contributed to the increased milk production, and mention also changes in housing, milking and health management. Also, changes in grazing management and the increased feeding of by-products might have played a role.

1.1.3 Economic aspects

The efficiency of concentrate feeding is often expressed as the input-output ratio of fed amounts of concentrate intake to realized milk yield. But the profitability of dairy farming depends on the milk and concentrate prices. Therefore, in this thesis the gross margin (milk revenues minus concentrate costs) is used, combining the prices with the milk yield and fed amounts of concentrates. The development of the prices of milk and concentrates are shown in Figure 1.3 for the period 1990 to 2009.

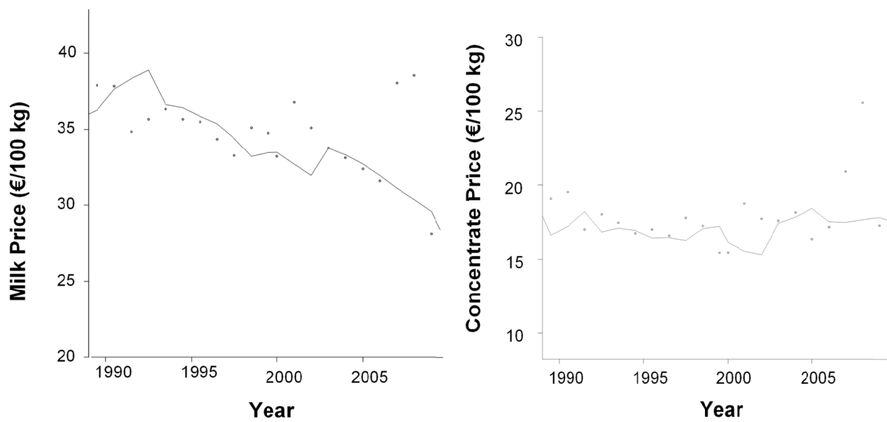

Figure 1.3 Development of the prices of milk (left) and concentrates (right) in the Netherlands from 1990 to 2009. Source: Anonymus, 1969.

During the last decades, the milk price has been decreasing while the concentrate prices remained almost constant. In 2007 and 2008 the milk price was extraordinary high and also the concentrate price appears to be higher. The development of the gross margin is shown in Figure 1.4.

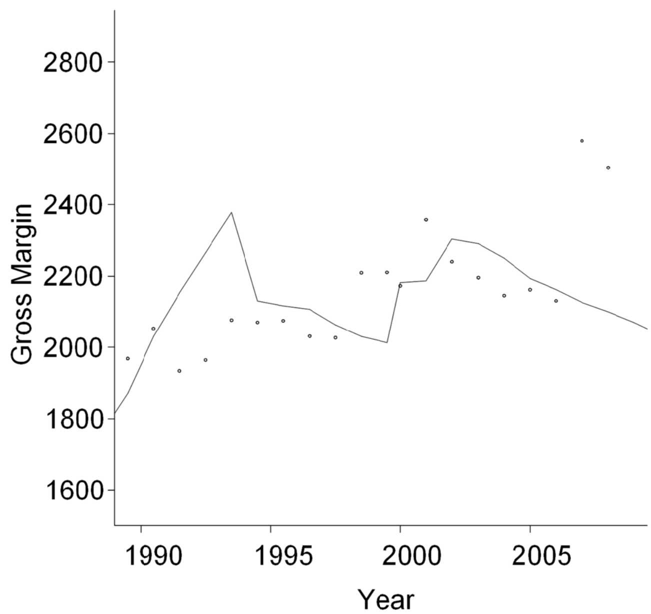

Figure 1.4 Development of the gross margin milk returns minus concentrate cost per cow per year in The Netherlands from 1990 to 2008.

The gross margin is high in 2007 and 2008 due to the higher milk prices. However, it is uncertain how the milk price will evolve the coming years. With increasing energy prices, concentrate prices might increase and if the milk price remains constant or decreases in the coming years this puts pressure upon the gross margin. Lower gross margins imply that farmers need to improve their efficiency in order to secure their income. During the last decades, the concentrates costs were about 30% of the milk returns. Given the high share of concentrate costs, it is particularly important to focus on improvement of concentrate efficiency.

1.1.4 Automation and robotisation

Dairy management substantially changed during the last century due to technological developments. Mechanization replaced human labor and increased farm sizes because of economies of scale (Bieleman, 2008). Consequently, the number of farms has decreased, and the number of cows per farm has increased. Automation and robotisation, like automated concentrate feeders and automatic milking systems (AMS) were increasingly used. Nowadays, on 94% of the farms a personal computer is used. In Table 1.1, automation trends on dairy farms with more than 30 cows in The Netherlands during the last decade are shown (Stormink and van Buiten, 2009).

Table 1.1 Number and (percentage) of dairy farms with more than 30 cows in The Netherlands using different applications from 1997 to 2008

Application	**1997**		**1999**		**2001**		**2008**	
Management information system	6.300	(25)	8.500	(35)	10.000	(44)	11.730	(69)
Automatic concentrate feeder	13.500	(53)	14.500	(59)	14.900	(66)	12.920	(76)
Automatic milk meters	2.800	(11)	3.200	(13)	4.800	(21)	4.250	(25)
Automatic milking system	50	(0.2)	125	(0.5)	325	(1.4)	2.550	(15)

In 2008, on 76% of the dairy farms use automated concentrate feeders and 25 % of the farms apply automatic milk measurement. The highest increase is in automatic milking systems; nowadays almost half of the new sold milking installations are automatic systems.

Dairy cows can visit the automated concentrate feeders and AMS freely during daytime and each cow is identified by the system. It depends on individual settings if the cow is milked and/or concentrates are supplied. Milk yield per milking and supplied amounts of concentrates, including the times of the visits, are recorded by the system, resulting in large amounts of process data. On 69% of the farms, the process data are stored and processed in management information systems, including a decision support system to determine the individual settings for concentrate allocation and milking frequency.

1.1.5 *Precision Livestock Farming*

A recent development in dairy farming is the introduction of Precision Livestock Farming (PLF). The goal of PLF is on-line control of the production process (Cox, 2002). Wathes (2009) states the following definition for PLF: application of the principles and techniques of process engineering to livestock farming to monitor, model and manage animal production. Wathes (2009) mentions three conditions for successful implementation of PLF:

1. the technology to be developed should be based on robust, low cost sensing systems and data-based models with meaningful parameters that enable process control;
2. appropriate applications must be identified with clearly stated targets/trajectories;
3. for the implementation at commercial scale, reliable technology should be available to demonstrate the investment returns.

Wathes et al. (2005) give a review of PLF and mention as potential advantages for dairy farming that it optimizes milk yield by tailoring milking frequencies to individual cows and also that the PLF technology encourages disease monitoring. To that, tailoring concentrate supply to individual cows can be added.

1.2 Individual settings for concentrate allocation and milking frequency

1.2.1 *Current standard guidelines for concentrate allocation and milking frequency*

In most systems for feeding dairy cows, roughage is fed ad lib and the ration is enriched by adding concentrates to the roughage mixture on herd or group level and/or by supplying extra concentrates to the individual dairy cow. Standard guidelines for feeding (CVB, 2010) are such that the amount of energy offered is in line with the energy requirement for maintenance, pregnancy and production (e.g. VanEs, 1978). Within this system there is uncertainty both on the requirement and on the intake side.

The energy requirement for production is derived from recorded milk yields, i.e. past performance, but there is uncertainty about the expected milk production in the future. Furthermore, there is uncertainty in the prediction of the requirement for maintenance, because body weight and weight change are usually unknown in practice.
The energy intake by the cow depends on the feed intake and the energy content of the feed components in the ration. Feed intake consists of concentrates and roughage, but roughage intake is usually unknown. Therefore roughage intake is predicted using a cow model (Zom et al., 2002), accounting for roughage replacement by concentrates. The cow model predicts the performance of dairy cows, using general relationships from the population the individual belongs to. However, within the population of cows, there is considerable variation in feed intake (Duinkerken et al., 2006). Moreover, the energy content of the feed components are derived from standard tables or from laboratory analysis from small samples of a much larger whole. Consequently, there is a large degree of uncertainty about the predicted energy intake.
Due to the large degree of uncertainty both on energy requirement and intake, this approach is less useful for managing feeding and production of individual cows in the actual situation. Despite the uncertainty, this approach is frequently applied in feeding advisory systems for individual concentrate allocation in the actual situation.

With conventional milking systems, dairy cows are usually milked twice per day. With AMS individual setting of milking frequency is possible. Standard guidelines for milking frequency take lactation stage and production level into account, because milk yield is effected by the milking interval. It is commonly advised, that cows early in lactation and high yielding cows should be milked more frequent than cows later in lactation and low yielding cows. Hogeveen (2001) investigated several aspects of an AMS and observed that it is important to optimize the milking interval and to consider the effects on milk production, udder health and the capacity of the AMS. The capacity of an AMS can be a limiting factor when the herd size is about 60-70 cows per milking robot. For that reason also milking duration, that depends on milk yield and milking frequency, should be taken into account. Ouweltjes (1998) observed large differences between cows regarding the effect of interval length on milk production and consequently on milking duration. These differences are not taken into account in the standard guideline for milking frequency.

1.2.2 Individual variation in efficiency

Individual differences in milk yield response on concentrate intake implies variation in efficiency in the use of concentrates. Variation in efficiency can be utilized by setting the input proportional to the efficiency, such that it works both ways: the losses can be decreased and the profits can be increased, while the overall input remains constant (see Figure 1.5).

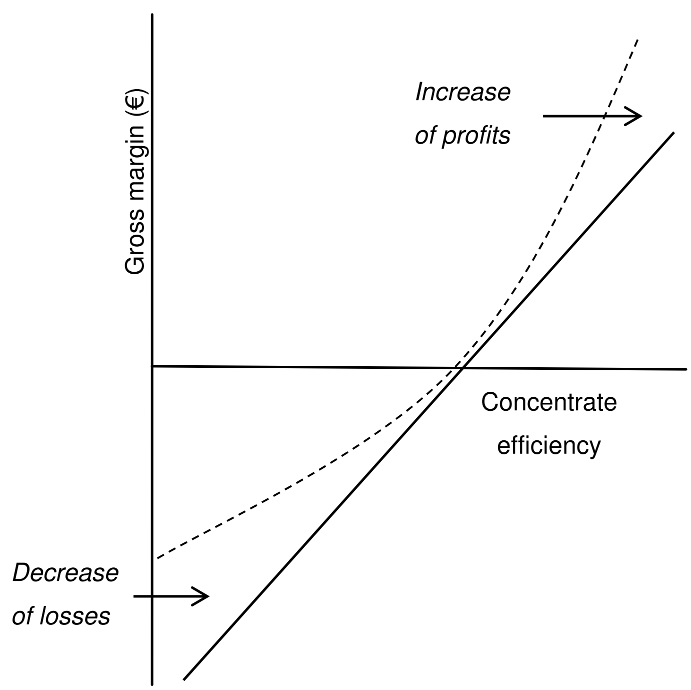

Figure 1.5 Relationship between gross margin and concentrate efficiency with concentrate input constant (solid line) and proportional to efficiency (dashed line).

This principle is not applied in currently used decision support systems for concentrate feeding and consequently the recommended settings for concentrate supply will often be suboptimal. The same line of reasoning applies to the individual settings for milking frequency.

1.2.3 Optimal settings for concentrate supply and milking frequency

The main disadvantage of current standard guidelines for concentrate allocation and milking frequency is that individual variation in milk yield response on concentrate intake and milking frequency is ignored. Regarding concentrate feeding, Broster and Thomas (1981) stated among other things that "the approach is retrospective, rather than predictive; … individual variation from cow to cow in efficiency of conversion has to be considered; … needs clarification in terms of the economics of feeding." Using the prices of milk and concentrates the gross margin (i.e. milk revenues minus concentrate costs) can be calculated, this is shown in Figure 1.6. And so the optimal setting is determined as the level of concentrate intake at which the gross margin is maximized (André et al., 2007).

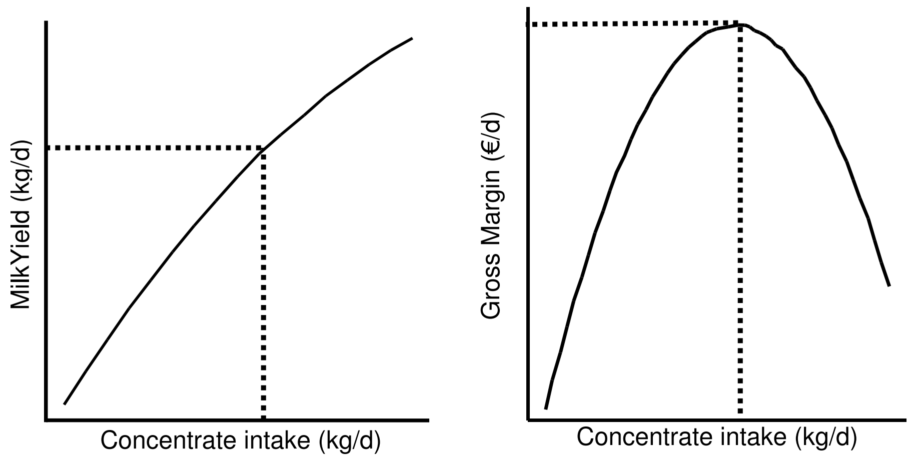

Figure 1.6 Response in milk yield on concentrate intake (left) and gross margin milk returns minus concentrate costs (right). The dotted line marks the optimal level of concentrate intake at which the gross margin is maximal.

Based on the individual response the optimum for each cow within the herd can be determined and so the gross margin is maximized at herd level. In the situation with AMS the capacity of the AMS might be a limiting factor in relation to the herd size. The capacity of an AMS is expressed in hours per day that the system is available for milking. So, besides the effects of milking frequency on milk yield, also the effects on milking duration should be taken into account to maximize the gross margin within the restricted capacity of an AMS.

1.2.4 Management tool for Precision Dairy Farming

A management tool for Precision Dairy Farming should consist of two components. The first component estimates the actual individual milk yield response on concentrate intake and milking interval length from the process data, using an adaptive (i.e. self-learning) model. The second component is a control algorithm that determines the individual optimal settings for concentrate allocation and milking interval in the actual situation. In Figure 1.7, a schematic overview of the management tool is given.

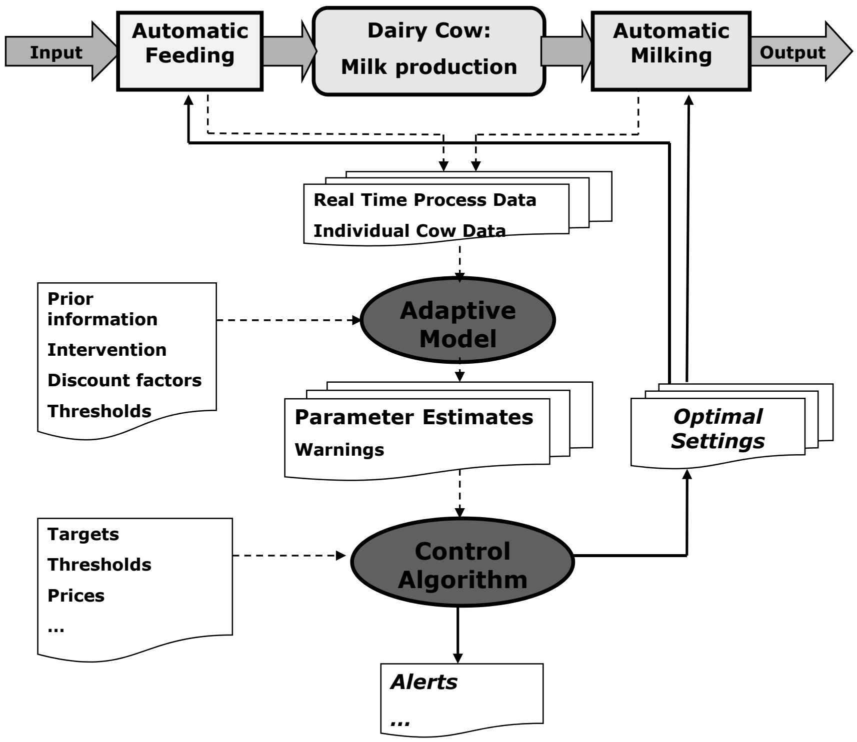

Figure 1.7 Schematic overview of the components of a management tool. (André et al., 2007, after Aerts et al., 2003).

In the foregoing it is concluded that fully specified models (with known parameter values) are not suitable for control purposes. This is confirmed by Wathes et al. (2005) and they state also that currently used estimation procedures in PLF that stem from technical engineering (Young, 1984; Goodwin and Sin, 1984; Ljung, 1987) are less suitable for biological processes that occur mostly in a complex dynamic environment. West and Harrison (1997) developed a Bayesian approach to time series analysis that can deal with a complex dynamic environment. This Bayesian approach consists of a recursive procedure for parameter estimation. Information from the past is used as prior to forecast the actual situation. Thereafter, observation of the actual situation is used to update the information to a posterior. The posterior is used as prior for the next time point and the estimation procedure is repeated recursively. This procedure is extended with a facility to detect process deteriorations, followed by automatic intervention to ensure properly continuation of the estimation procedure. The detected process deteriorations can be used as alerts to the farmer for process control. Based on this Bayesian approach, Duinkerken et al. (2003) tested a prototype for recommending concentrate allocation to dairy cows and they concluded that it was worthwhile to refine this prototype.

1.3 Research objectives

The first objective of this research is to quantify the individual variation in milk yield response to concentrate intake and milking interval length, in order to assess the economic prospects of applying individual optimal settings for concentrate supply and milking frequency. The second objective is the development of adaptive models for on-line estimation of the actual individual response in milk yield to concentrate intake and milking interval length. Furthermore, potential for monitoring and control of milk production is investigated, also at herd level.

1.4 Outline of the thesis

The first research objective is elaborated in Chapters 2 and 3 of this thesis. Chapter 2 focuses on the individual variation in concentrate efficiency. Strickland and Broster (1981) stated that the milk yield during the first 14 days of lactation is a strong guide to a cow's potential yield and that this guide could be used in practice to determine the level of feeding. The individual variation in milk yield response to concentrate intake during the first weeks of lactation is quantified. Next, the potential economic prospects of applying individual optimal settings are assessed. Chapter 3 focuses on milking frequency. The individual variation in milk yield and milking duration response to milking interval length is quantified. Next, the results are used to optimize the utilization of an AMS and to assess the potential economic prospects.

The second research objective is elaborated in Chapters 4 and 5 of this thesis. In Chapter 4, different adaptive models for on-line estimation of the actual individual milk yield response to concentrate intake and milking interval length are developed and compared. To illustrate the potential of adaptive models for a variety of practical problems, in Chapter 5 the dynamic approach is applied at herd level in order to evaluate the impact of heat stress. In Chapter 6 benefits and consequences of the dynamic approach for interrelated farm processes are discussed.

1.5 References

AERTS, J-M., C.M.WATHES AND D. BERCKMANS. 2003. Dynamic data-based modelling of heat production and growth of broiler chickens: Development of an integrated management system. *Biosystems Engineering*, **84**, 257-266.

ANDRÉ, G., W. OUWELTJES, R.L.G. ZOM, AND E.J.B. BLEUMER. 2007. Increasing economic profit of dairy production utilizing individual real time process data. In *Precision Livestock Farming '07* (Ed. S. Cox), pp. 179–186. Wageningen: Wageningen Academic Publishers.

ANONYMUS, 1969. *Agricultural Figures, several volumes* (in Dutch). Agricultural Economic Research Institute and Central Bureau of Statistics, The Hague, The Netherlands.

BERENTSEN, P.B.M., G.W.J. GIESEN AND J.A. RENKEMA. 1996. Scenarios of technical and institutional change in Dutch dairy farming. Neth. *J. of Agric. Sci*. **44**, 193-208.

BIELEMAN, J. 2008. *Boeren in Nederland. Geschiedenis van de Landbouw 1500 – 2000*. Boom. Amsterdam.

BROSTER, W.H. AND C. THOMAS. 1981. The influence of level and pattern of concentrate input on milk output. In: *Recent Advances in Animal Nutrition* (Ed. W. Haresign), pp. 76–96. London: Butterworth.

COPPOCK, C.E., C.H. NOLLER AND S.A. WOLFE. 1974. Effect of forage-concentrate ratio in complete feeds fed ad libitum on energy intake in relation to requirements by dairy cows. *J. Dairy Sci.* **57**, 1371-1380.

COX, S. 2002. Information technology: the global key to precision agriculture and sustainability. Comp. and Elec. in Agric. **36**, 93-211.

CVB. 2010. *Tabellenboek Veevoeding 2010. Voedernormen landbouwhuisdieren en voederwaarden veevoeders*. Productschap Diervoeder CVB, Lelystad.

DUINKERKEN, G. VAN, G. ANDRÉ AND R.L.G. ZOM. 2003. *Prototype van een Dynamisch Krachtvoer Advies Systeem voor Melkvee*. Praktijkrapport 37, Praktijkonderzoek Veehouderij, Lelystad.

DUINKERKEN, G. VAN, G. ANDRÉ, E.J.B. BLEUMER AND R.L.G. ZOM. 2006. *Actualisatie Voeropnamemodel Melkvee, fase 2*. Vertrouwelijk rapport 07, Animal Sciences Group, Wageningen UR.

GOODWIN, G.C. AND K.S. SIN. 1984. *Adaptive filtering, Prediction and Control*. Prentice Hall, New-York.

HOGEVEEN, H. 2001. Milking interval, milk production and milk-flow rate in an automatic milking system. *Livestock Production Science*, **72**, pp. 157-167.

LJUNG, L. 1987. System Identification. Theory for the user. Prentice-Hall, New-York.

NELSEN, T.C. 2002. The state of statistics in Agricultural Science. *J. of Agric. Biol. and Env. Stat*. **7**, 313-319.

OUWELTJES, W. 1998. The relationship between milk yield and milking interval in dairy cows. *Livestock Production Science* **56**, 193-201.

STORMINK, H. AND A. VAN BUITEN. 2009. *Gebruik & Trends. Automatisering in de Veehouderij*. Rapport 7. Animal Sciences Group, Wageningen University and Research Centre. Lelystad.

STRICKLAND, M.J. AND W.H. BROSTER. 1981. The effect of different levels of nutrition at two stages of the lactation on milk production and live-weight change in Friesian cows and heifers. J. *Agric. Sci*. **96**, 677-690.

YOUNG, P.C. 1984. *Recursive Estimation and Time-series Analysis*. Springer-Verlag. Berlin.

VAN ES, A.J.H. 1978. Feed evaluation for ruminants. I. The systems in use from May 1977 onwards in the Netherlands. *Livestock Production Science* **5**, 331-345.

WATHES, C.M., Kristensen, H.H., Aerts, J-M. and D. Berckmans. 2005. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? In *Precision Livestock Farming '05*, Wageningen Academic Publishers, Wageningen, pp. 33-47.

WATHES, C.M. 2009. Precision livestock farming for animal health, welfare and production. In: *Sustainable animal production. The challenges and potential developments for professional farming*. (Eds. A. Aland and F. Madec), pp. 411-419 Wageningen: Wageningen Academic Publishers.

WEST, M. AND J. HARRISON. 1997. *Bayesian Forecasting and Dynamic Models*. Second Edition. Springer-verlag, New York.

ZOM, R.L.G., J.W. VAN RIEL, G. ANDRÉ AND G. VAN DUINKERKEN. 2002. *Voorspelling voeropname met Koemodel 2002*, Praktijkrapport 11, Praktijkonderzoek Veehouderij, Lelystad.

2 Economic potential of individual variation in milk yield response to concentrate intake of dairy cows[3]

Summary

The objectives of the current study were to quantify the individual variation in daily milk yield response to concentrate intake during early lactation and to assess the economic prospects of exploiting the individual variation in milk yield response to concentrate intake. In an observational study, data from 299 cows on four farms in the first 3 weeks of the lactation were collected. Individual response in daily milk yield to concentrate intake was analysed by a random coefficient model. Marked variation in individual milk yield response to concentrate intake was found on all four farms. An economic simulation was carried out, based on the estimated parameter values in the observational study. Individual optimization of concentrate supply is compared with conventional strategies for concentrate supply based on averaged population response parameters. Applying individual economic optimal settings for concentrate supply during early lactation, potential economic gain ranges from €0.20 to €2.03/cow/day.

2.1 Introduction

Economic profit of dairy farms largely depends on milk revenues and feeding costs. In 2006, Dutch dairy farming feed costs averaged € 6.49/100 kg milk. This represented 0.207 of the milk revenues of € 31.28/100 kg milk (LEI, 2004). Concentrate purchases are a

---

[3] Paper by G. André, P.B.M. Berentsen, G. van Duinkerken, B. Engel and A.G.J.M. Oude Lansink; published in Journal of Agricultural Science (2010) **148**, 263–276.

major cost entry for farms feeding concentrates. Optimal supply of concentrates from the beginning of the lactation is important to achieve a good economic result.

During early lactation, when feed intake and daily milk yield increase, energy intake is often insufficient to meet the cow's energy requirements (DeVries & Veerkamp, 2000; Coffey *et al.,* 2002; Beerda *et al.,* 2007). The difference between a cow's net energy intake and its net energy requirement is the energy balance. Early in lactation dairy cows enter into a negative energy balance and body reserves are mobilized to avoid loss in milk yield. Concentrates are fed to reduce the negative energy balance (Van Arendonk *et al.,* 1991). Energy intake is increased by feeding substantial amounts of energy-rich concentrates, especially during early lactation. In addition, this challenges the cows to increase their peak yield (Ekern & Vik-Mo, 1983).

A common strategy on Dutch dairy farms is to start with a low level of concentrates at calving, followed by a linear increase during the first weeks of the lactation (Kokkonen *et al*., 2004). Around the lactation peak, from week 3 until weeks 10–14, concentrate supply is kept at a constant level related to the cow's parity. After that, concentrate supply is lowered corresponding to the decline in daily milk yield. The amount of concentrates fed during the decline in milk yield is based on the expected net energy requirement. This expectation is based on a feed evaluation system (e.g. Van Es, 1978), utilizing a model that predicts the net energy requirement of a dairy cow according to the cow's actual milk yield and an assumption of the cow's roughage intake. Feed evaluation systems are primarily intended for comparison of different feedstuffs (Cant, 2005) and are used in retrospect to evaluate the actual feeding (Okine *et al*., 2001). Feed evaluation systems are also used for the planning of rationing at the herd level over a certain period for managing farm resources. For these herd level decisions feed evaluation systems perform well, especially when the prediction or measurement of feed intake and determination of energy content of ration components are accurate (Buckmaster & Muller, 1994). However, the use of feed evaluation systems for determining daily individual concentrate supply is not feasible due to a lack of information on individual roughage intake and body weight change.

Two strategies for individual allocation of concentrates were investigated by Maltz *et al.* (1991, 1992) in comparison with total mixed rationing. The first strategy was based on the rule that 1 kg concentrates corresponds to 2 kg milk and it was concluded that milk yield cannot serve as the sole criterion for concentrate supplementation and that changes in body weight should also be taken into account. The second strategy accounted for changes in body weight, but the results of Maltz *et al.* (1991, 1992) were inconclusive regarding the superiority of individual supplementation of concentrates. Although in both trials, individual performance was evaluated afterwards, actual individual milk yield response to concentrate intake was not assessed nor used to forecast future individual performance.

The main objective of the current study is to determine the economic optimal concentrate supply for each individual cow after 3 weeks in lactation. For this the relationship between milk yield and increasing concentrate intake during early lactation will be established. This relationship in the current study is regarded as milk yield response to concentrate intake. The response is influenced by several factors, e.g. roughage intake, mobilization etc. Estimated individual response parameters will include all these effects and will be used to determine the individual economic optimum. Economic prospects will be assessed by comparing results of individual optimization with current strategies for concentrate supply.

2.2 Materials and methods

The study consists of two parts. In the first part, the observational study, a random coefficient model is presented to quantify individual variation in milk yield response to concentrate intake. In the second part, the simulation study, the economic prospects of exploiting individual variation is assessed, based on the estimated individual response parameters in the observational study.

2.2.1 Observational study

Data were collected in 2006 at four research farms in The Netherlands: ‘Aver Heino’ (AH), ‘Bosma Zathe’ (BZ), ‘High-tech’ (HT) and ‘Zegveld’ (ZV). Aver Heino was an organic dairy farm. AH, BZ and HT were farms milking with an automated milking system and ZV was a conventional dairy farm. Some farm characteristics are specified in Table 2.1.

Table 2.1 Farm characteristics

Farm:	Aver Heino	Bosma Zathe	High-tech	Zegveld
Cattle:				
dairy	103	200	80	101
young stock	80	140	45	45
breed	Red Holstein	Holstein Friesian	Holstein Friesian	Holstein Friesian
Milk yield (kg/cow/year)	6815	8853	9001	8361
Automatic milking	yes	yes	yes	no
Land:				
grassland (ha)	88	115	24.5	72
maize land (ha)	17	47	10.5	-
soil type	sand	clay	clay	peat
Roughage:				
summer grazing	limited	no	no	unlimited
silage	0.70 grass 0.30 maize	0.70 grass 0.30 maize	0.55 grass 0.45 maize	1.00 grass
Concentrates:				
steaming up period (days)	21	10	21	14
maximum (kg/cow/day)	6*	6*	8*	10*
	6†	10†	9†	12†
concentrates (kg/100 kg milk)	18.8	27.1	38.4	33.1

* primiparous † multiparous

The datasets, one for each farm separately, consist of daily milk yield (M) and concentrate intake (C) /cow/day during the first 3 weeks of lactation. At calving the concentrate supply was 1–3 kg/day and after calving, concentrate supply was linearly increased over 2–3 weeks to a maximum that depended on parity. At BZ, HT and ZV conventional concentrates were supplied with 6.486 MJ NE_L/kg dry matter (DM). AH is an organic farm where organic concentrates were used with the same energy content but with a higher amount of grains. At AH both the increase rate and the maximum supply for organic concentrates were lower than the maximum for conventional concentrates, because the content of glucogenic compounds is higher in organic concentrates. At BZ the period after calving lasted 14 days and so the increase was more rapid than on the other farms. After 10 days the concentrate supply was kept constant at the maximum level. At HT the period after calving lasted 21 days. At ZV the period after calving lasted 14 days and the maximum level of concentrate supply was higher than at BZ and HT, because the energy content of the roughage (entirely grass) was lower.

Concentrates were partly fed with external self-feeders and partly fed in the automatic milking systems on the robot milking dairies (AH, BZ and HT) or in the milking parlour on the conventional milking dairy (ZV). At AH, BZ and HT cows were milked on average 2.38 times/day during early lactation. At ZV milking was performed twice daily. Data from cows at ZV that calved in the summer of 2006 were not used, because concentrate intake was strongly limited due to extensive grazing.

Outliers in milk yield, defined as observations that differed more than three times the standard deviation from the expected value for daily milk yield, e.g. because of illness, were excluded. Only cows with at least 15 complete daily records were used in the analysis. The remaining dataset for analysis consisted of 5629 records from 299 cows; 102 primiparous and 197 multiparous cows. The numbers/farm/parity are given in Table 2.2.

Table 2.2 Numbers of cows and daily cow records per farm.

	Primiparous cows		**Multiparous cows**	
Farm:	No. cows	No. records	No. cows	No. records
Aver Heino	28	546	54	1058
Bosma Zathe	47	895	75	1391
High-tech	14	234	45	838
Zegveld	13	243	23	424
Total	102	1918	197	3711

In Figure 2.1 mean profiles of concentrate intake and milk yield/day are given for the four different farms, for primiparous and multiparous cows separately. Milk yield is also plotted against concentrate intake to indicate the response in milk yield to concentrate intake. At BZ, after 10 days, concentrate supply was kept constant while milk yield continued to increase. The same phenomenon was observed, though to a lesser extent, at ZV.

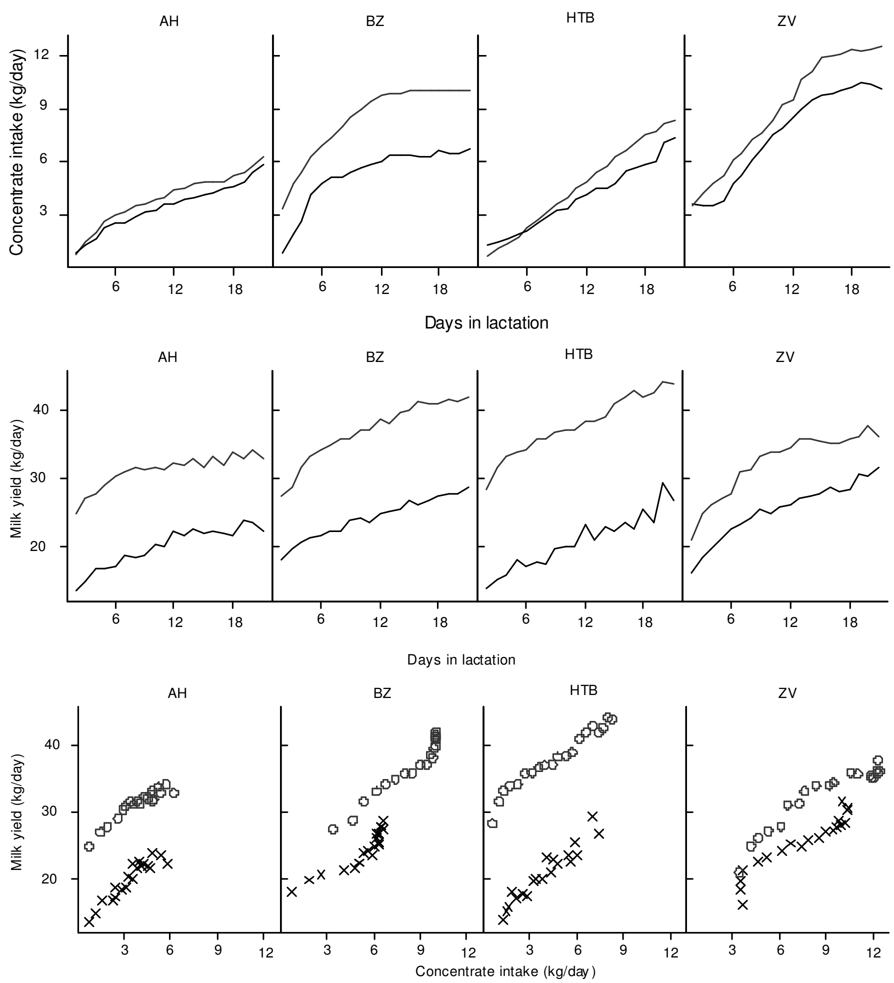

Figure 2.1 Averaged concentrate intake *vs.* days from calving (first row), averaged daily milk yield *vs.* days from calving (second row). Averaged milk yield *vs.* averaged concentrate intake at different days after calving (third row). Upper lines and symbols (o) are multiparous cows and lower lines and symbols (x) are primiparous cows.

2.2.2 *Modelling milk yield response to a linear increase in concentrate intake during early lactation*

During early lactation daily milk yield increases rapidly from around calving to a peak a few weeks later. After parturition the growth of active alveoli increases to a maximum, 0.88 of the proliferation occurs in the first 2 weeks of lactation (Vetharaniam *et al*., 2003). This process is seen as the 'inner drive' for the cow to produce milk. The number of active alveoli, together with the maximum secretion rate, determines the *potential* milk yield. Milk secretion is inhibited by the udder filling which in turn depends on the alveolar and cysternal storage capacity of the udder in relation to milking frequency (Mepham, 1976; Knight, 1982; Thornley & France, 2007, pages 560–569, following Neal & Thornley, 1983). Therefore, *maximal* milk yield depends on the number of milkings and cannot equal *potential* milk yield. The degree to which *maximal* milk yield is reached depends on the energy status of the cow (Vetharaniam *et al.,* 2003), i.e. the amount of metabolizable energy above maintenance requirement supplied by feeding concentrates and roughage (Broster & Thomas, 1981). When no concentrates are fed, energy is only supplied by roughage intake and there will be only a slight increase in milk yield during early lactation due to mobilization of body reserves (Broster & Thomas, 1981). Concentrates are fed to increase energy supply and to enhance milk production. At higher levels of energy supply daily milk yield will increase, the mobilization rate will decrease and bodyweight will increase. Consequently, with increasing daily concentrate intake, milk yield increases and approaches *maximum* milk yield. The profiles of *potential* (no limitations), *maximal* (only limited by number of milkings), *base* (feeding only roughage) and *actual* milk yield (feeding roughage and linear increasing concentrates) during early lactation are shown in Figure 2.2.

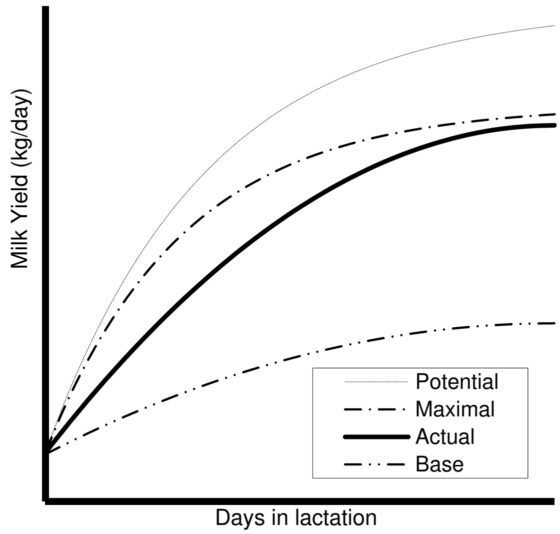

Figure 2.2 Development of potential, maximal, actual and base milk yield during early lactation.

The development of milk production during early lactation is a complex non-linear dynamic system in which daily milk yield (and body weight change) are response (dependent) variables and concentrate intake is a controllable (independent) variable. The following model was used for the development of milk yield during early lactation. The model is a two-dimensional response surface, omitting higher order interactions:

$$M(t,C)=\left\{\alpha_0+\alpha_1 t-\alpha_2 t^2\right\}+\left\{\beta_1 C-\beta_2 C^2\right\}+\gamma Ct \qquad (2.1)$$

where $M(t,C)$ milk yield (kg/day) at lactation day t and concentrate intake C (kg/day), α_0 intercept, milk yield at lactation day $t=0$ and concentrate intake $C=0$, α_1,α_2 coefficients for linear and quadratic effect of time (days in lactation), β_1,β_2 coefficients for linear and quadratic effect of concentrate intake, γ coefficient for interaction between time and concentrate intake.

In the current study, concentrate supply was increased linearly from the start of the lactation to a maximum, starting at a low level after parturition. Assuming that concentrate intake equals supply:

$$C = c_0 + c_1 t \tag{2.2}$$

with c_0 the intake at calving $(t = 0)$, linear increasing with c_1 kg/day.

The aim of the current study is to predict the optimal concentrate supply, in order to maximize gross margin (milk revenues minus concentrate costs).

Figure 2.3 offers an example where the optimum is not reached because the increase in concentrate supply is stopped too early. Alternatively, in practice the rate of concentrate increase could be too fast or the duration of concentrate increase could be too long, such that the level of concentrate supply has to be decreased to achieve the optimum.

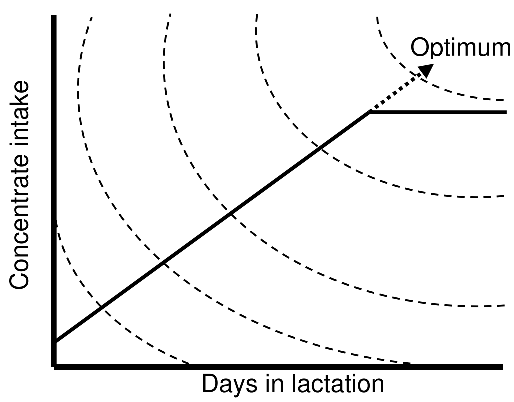

Figure 2.3 Response surface of milk yield (dashed contour lines) during early lactation in relation to concentrate intake. Concentrate supply is increased in a linear manner to a plateau (solid line), but the optimum will be achieved if the increase is continued (dashed arrow).

Substitution of model (2.2) into model (2.1) yields a quadratic function describing the development of milk yield over time in terms of concentrate intake:

$$M\left(C\right)=\beta_0^*+\beta_1^*C-\beta_2^*C^2 \tag{2.3}$$

Due to the linear relationship between concentrate intake and time, the effect of concentrate intake and time on milk yield cannot be estimated separately. Note that estimating the effects of concentrate intake and time separately is not the aim of the study, but to predict $M\left(C_{Opt}\right)$, where milk revenues minus concentrate costs are maximal. The associated day in lactation is calculated using model (2.2). Please refer to Appendix A for details. Considering milk yield as a function of concentrate intake rather than time is analogous to Parks (1982) who considered weight of young growing animals as function of cumulative feed intake explicitly, without taking time into consideration.

2.2.3 *Incorporating individual variation in milk yield response to concentrate intake*

To account for variation in response in milk yield to concentrate intake, model (2.3) is extended with fixed effects for parity and random effects for individual variation on the level of milk yield and response to concentrate:

$$M_{ij}\left(C\right)=\beta_0+\tau_{0j}+b_{0i}+\left(\beta_1+\tau_{1j}+b_{1i}\right)C+\left(\beta_2+\tau_{2j}+b_{2i}\right)C^2+\varepsilon_{it} \tag{2.4}$$

where M_{ij} daily milk yield (kg/day) for cow i of parity j, C concentrate intake (kg/day), β_0 intercept for a primiparous cow (kg/day), τ_{0j} effect of parity of the cow in intercept (kg/day), b_{0i} random effect of individual i in intercept (kg/day), β_1 mean effect of linear concentrate intake for primiparous cows (kg/kg), τ_{1j} effect of parity in the coefficient of linear concentrate intake (kg/kg), b_{1i} random effect of individual i in the coefficient of linear concentrate intake (kg/kg), β_2 mean coefficient of quadratic concentrate intake for primiparous cows (kg/kg^2), τ_{2j} effect of parity in the coefficient for quadratic concentrate intake (kg/kg^2), b_{2i} random effect of individual i in the coefficient of quadratic concentrate intake (kg/kg^2), ε_{it} residual at day t (kg/day), representing residual variation.

Individuals' random effects b in the model are assumed to follow a multivariate normal distribution with mean 0 and covariance matrix Σ_b. The residuals ε are assumed to be normally distributed with mean 0, variance σ_ε^2 and (auto) correlation ϕ within an animal over time. Random effects b and ε are assumed to be mutually independent. Random effects for different animals are also assumed to be independent. Parameters β_0, β_1 and β_2 are the population means for the primiparous cows, i.e. $\tau_{01} = \tau_{11} = \tau_{21} = 0$.

2.2.4 *Statistical analysis*

Because there were structural differences between the farms in milking and feeding strategy, model (2.4) was fitted for each farm separately. Parameters were estimated by restricted maximum likelihood (REML) (Searle *et al.,* 1992). Calculations were performed with Genstat (Genstat Committee, 2006). Only parameters that were statistically significant ($P < 0.05$) were retained in the model.

2.2.5 *Simulation study*

To assess the economic prospects a simulation was carried out for each farm separately, based on the estimated variance components from the observational study. Individual optimal settings (IOS) were compared with two other strategies assuming equal concentrate allocation for all individuals of the same parity. The first strategy was based on the current settings (CS) for concentrate supply at the end of the steaming up period on the research farms. The second strategy was based on the averaged optimal setting (AOS) for concentrate supply, ignoring individual random effects.

Optimal settings for concentrate allocation were determined by maximizing the gross margin (S), i.e. milk revenues minus feeding costs:

$$\begin{aligned} S_{ij}(C) &= \pi_M M_{ij}(C) - \pi_C C \\ &= \pi_M \theta_{0,ij} + (\pi_M \theta_{1,ij} - \pi_C) C + \pi_M \theta_{2,ij} C^2 \end{aligned} \tag{2.5}$$

Here π_M and π_C are milk and concentrate prices (€/kg) and $\theta_{0...2,ij}$ were the estimated parameters of an individual. Concentrate intake is optimal when marginal milk revenues are equal to marginal concentrate costs. Individual optimal settings followed from $\frac{\mathrm{d}S(C)}{\mathrm{d}C} = 0$:

$$C_{Opt,ij} = -\frac{(\pi_M \theta_{1,ij} - \pi_C)}{2\pi_M \theta_{2,ij}} \tag{2.6}$$

Economic evaluation could be based on first order approximations, as presented in Appendix B. However, some constraints have been included to allow for a solution of the optimization problem. Firstly, there must be an optimum, $\theta_{2,ij} < 0$. Secondly, in practice, the concentrate supply is limited to avoid digestion problems, $C_{Opt,ij} \leq 20$. Therefore, the IOS for concentrate supply, corresponding milk yield and gross margin were calculated using a parametric Bootstrap method (Efron & Tibshirani, 1993). The profit of individual concentrate feeding was calculated as the differences in gross margins between the different strategies. Details of the bootstrap are presented in Appendix C. The 0.95 range and standard deviation were calculated for concentrate supply, milk yield and economic gain in order to display the potential variation between individuals for IOS.

For BZ, HT and ZV the following prices (LEI, 2006) were used: $\pi_M = 0.3256$ €/kg milk and $\pi_C = 0.1814$ €/kg concentrates. Prices were higher for the organic farm AH: π_M = 0.3829 €/kg milk and $\pi_C = 0.2209$ €/kg concentrates.

2.3 Results

2.3.1 Observational study

Parameter estimates and standard errors of model (2.4) are given in Table 2.3. The parameters of the systematic part of the model characterize the global population response curve including the effects of parity, consisting of the intercept and the linear and quadratic effect of concentrate intake on milk yield. The parameters of the random part consist of the variance components that quantify the individual variation in intercept and milk yield response on concentrate intake.

Table 2.3 Parameter estimates and standard errors per research farm.

Farm: **Parameter**	**Aver Heino** est. (S.E.)	**Bosma Zathe** est. (S.E.)	**High-tech** est. (S.E.)	**Zegveld** est. (S.E.)
		Systematic part of the model:		
Intercept β_0	10.6 (1.07)	16.7 (0.92)	12.4 (1.40)	12.6 (1.61)
Effect parity on int. τ_0	9.9 (0.10)	4.2 (1.35)	14.4 (1.47)	3.1 (1.95)
Linear effect β_1	3.7 (0.28)	1.6 (0.20)	2.7 (0.24)	2.2 (0.22)
Effect parity on lin. τ_1	n.s.	0.65 (0.18)	n.s.	0.43 (0.16)
Quadratic effect β_2	–0.27 (0.03)	–0.04 (0.02)	–0.11 (0.02)	–0.07 (0.01)
		Random part of the model:		
Var. intercept σ_0^2	47 (9.9)	22 (6.0)	24 (6.5)	26 (8.4)
Var. linear σ_1^2	3.0 (1.05)	0.2 (0.07)	0.2 (0.09)	0.1 (0.05)
Var. quadratic σ_2^2	0.02 (0.012)	n.s.	n.s.	n.s.
Residual variance σ_ε^2	5.5 (0.30)	11.9 (0.57)	10.5 (0.87)	4.0 (0.48)
Corr. int. with lin. ρ_{01}	–0.82	–0.43	–0.33	–0.45
Corr. int. with quad. ρ_{02}	0.76	-	-	-
Corr. lin. with quad. ρ_{12}	–0.92	-	-	-
Autocorrelation ϕ	0.4 (0.03)	0.5 (0.02)	0.6 (0.03)	0.6 (0.05)

The intercept predicts milk yield at the start of lactation when no concentrates are fed $(C = 0)$. The intercept is lowest for AH, 10.58 kg M/day, and highest for BZ, 16.65 kg M/day. As expected the intercept for multiparous cows is higher than the intercept for primiparous cows. Multiparous cows at ZV had the lowest intercept (12.56 + 3.06 = 15.62 kg M/day) and multiparous cows at HT the highest intercept (12.40 + 14.38 = 26.78 kg M/day). This is related to the energy intake from forage, at ZV the roughage consists exclusively of grass silage and at HT 0.45 of the roughage is maize silage.

The milk yield response to concentrate intake at AH (organic) differs from the other farms; the linear effect (3.67 kg M/kg C) was higher, but there was a much more pronounced curvature, given the lowest quadratic effect (–0.267 kg M/kg^2 C). This difference may be explained by the fact that organic concentrates consist mainly of grains and that the herd at AH consists of cows from a breed with a lower production level. The curvature at BZ was the least pronounced, probably underestimated due to a linear increase of concentrates during only 10 days. At the farms BZ and ZV multiparous cows showed a significantly higher coefficient for linear concentrate intake than primiparous cows. Differences in milk yield response to concentrate intake between farms might also be explained by interaction with different forages across farms. Parity did not significantly affect the curvature. The fitted global response curves/farm/parity are given in Figure 2.4.

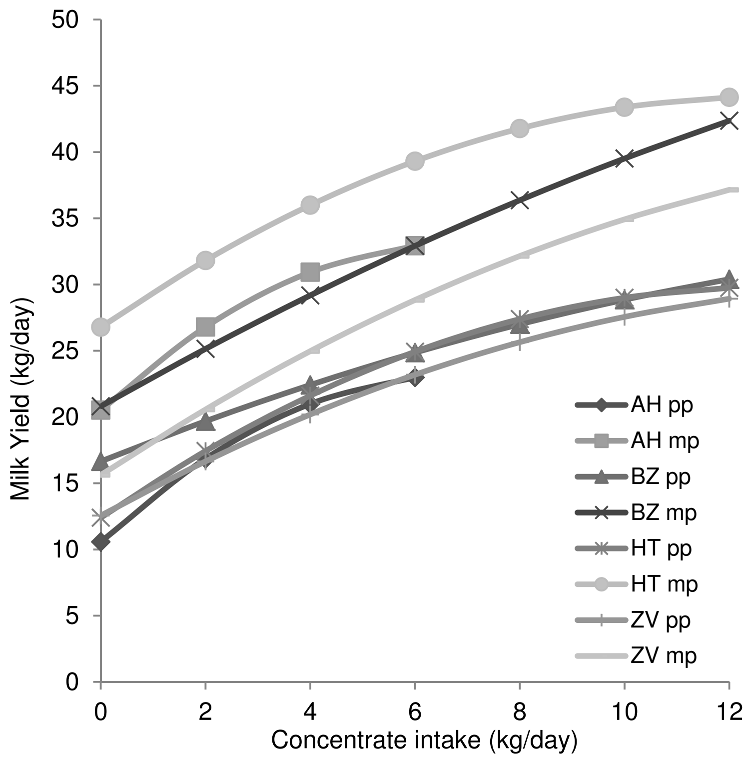

Figure 2.4 Fitted mean milk yield response curves *vs.* concentrate intake/farm/parity.

In addition to systematic differences in response between farms random variation between individuals was found on all farms. A considerable amount of individual variation was captured by individual variation in the intercept (σ_0^2), but there was also variation in the coefficient for linear concentrate intake (σ_1^2). Individual variation in the coefficient for quadratic concentrate intake (σ_2^2) was only significant at AH, at the other farms this variance component appeared to be negligible. Variation between individuals in intercept, linear and quadratic coefficients was highest at AH. Individual random effects were negatively correlated, e.g. the higher the intercept the lower the linear response to concentrate intake.

Figure 2.5 displays the estimated individual response curves, based on predicted random effects, the so-called best linear unbiased predictions (BLUPs) (Robinson, 1991; Searle *et al.,* 1992) for all individuals.

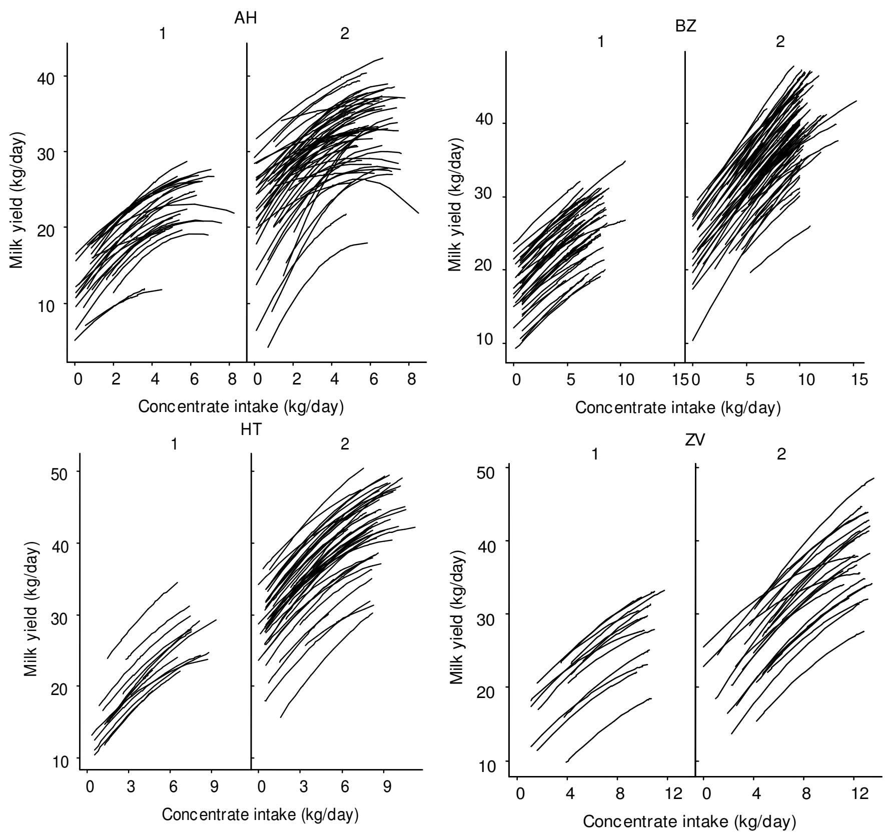

Figure 2.5 Fitted individual milk yield response curves *vs.* concentrate intake/farm. Different lines represent different cows (1 = primiparous cows and 2 = multiparous cows).

The residual variance (σ_ε^2), that quantifies variation around the individual profiles, was higher at BZ and HT than at AH and ZV. This indicates that the variation within an individual over time was higher at BZ and HT than at AH and ZV. The estimated autocorrelation (ϕ) was approximately the same for all farms, showing that the residuals were positively correlated over time.

Observations and fitted values for a high- and low-responding multiparous cow at HT are given in Figure 2.6, to illustrate the fit of the model. The figure shows the difference in response to concentrate intake. At the beginning of the lactation there is only a slight difference in production level between these two cows. However, there is a quite large difference in milk yield increase during early lactation indicating a difference in response to linearly increasing concentrate intake. The linear response to concentrate intake for the high-responding cow was $\hat{\beta}_1 + \hat{b}_1 =$ 2.73+0.68 = 3.41 kg M/kg C and for the low-responding cow $\hat{\beta}_1 + \hat{b}_1 =$ 2.73–0.57 = 2.16 kg M/kg C.

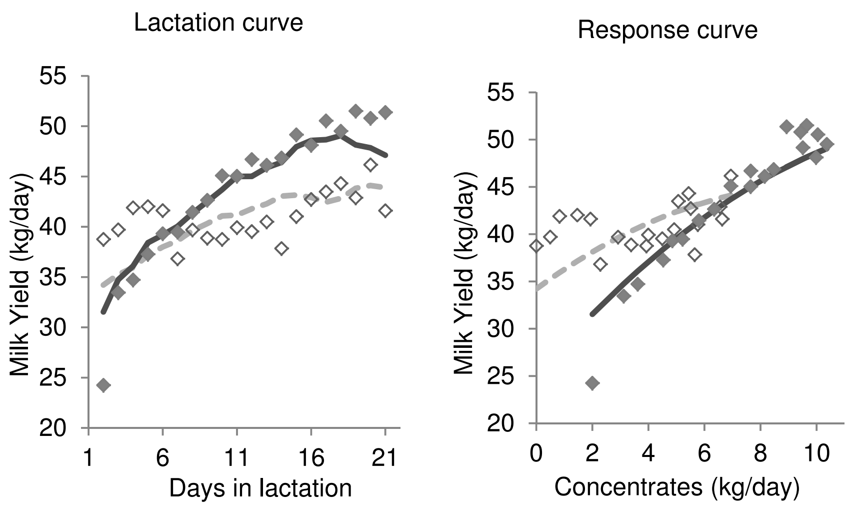

Figure 2.6 Lactation curve (left) and response curve (right) for two multiparous cows at High-tech. High-responding cow: observations (♦) and fitted values (solid line). Low-responding cow: observations (◊) and fitted values (dotted line).

2.3.2 Simulation study

Table 2.4 contains a comparison of the results of different strategies for the setting of concentrate supply. With CS individual variation in response is not exploited. Results for CS are compared with AOS, based on the global optimum of the mean response curve and compared with the IOS, based on the individual optimum of each individual response curve.

At AH, concentrate supply for CS approximates the supply for AOS and IOS. At the other farms concentrate supply for CS is below the supply for AOS and IOS, particularly at BZ. The mean concentrate supply differed only slightly between AOS and IOS. For IOS the 0.95 range and standard deviation for concentrate supply are given to illustrate the potential variation between individuals.

Table 2.4 Average concentrate supply (kg/day), milk yield (kg/day) and economic profit (€/day) after 3 weeks in lactation per farm and parity (**P** primiparous, **M** multiparous), compared using different strategies of concentrate supplementation (CS, AOS, IOS). Including 0.95 range and standard deviation (S.D.) for IOS.

Farm:	**Aver Heino**		**Bosma Zathe**		**High-tech**		**Zegveld**	
Parity:	**P**	**M**	**P**	**M**	**P**	**M**	**P**	**M**
Concentrate supply:								
- CS	5.7	6.1	6.9	9.6	7.2	8.2	10.2	12.2
- AOS	5.8	5.8	13.9	20.0*	10.2	10.2	12.0	15.2
- IOS	6.0	6.1	13.5	18.9	10.2	10.2	12.0	15.1
0.95 range	(2.1;12.1)	(2.0;11.9)	(3.0;20.0)	(11.9;20.0)	(6.5;13.9)	(6.4;13.9)	(7.1;16.8)	(10.3;20.0)
S.D.	2.39	2.40	4.88	2.30	1.90	1.91	2.49	2.44
Milk yield:								
- CS	23	33	26	39	27	42	28	38
- AOS	23	33	32	52	29	44	29	40
- IOS	24	34	32	50	30	44	29	40
0.95 range	(14;36)	(24;46)	(19;48)	(34;65)	(18;41)	(33;56)	(19;41)	(28;53)
S.D.	5.7	5.8	7.5	7.9	5.9	5.8	5.5	6.2
Economic profit:								
- AOS *vs.* CS	0.00	0.01	0.59	1.95	0.32	0.13	0.07	0.19
- IOS *vs.* AOS	0.25	0.25	0.35	0.08	0.13	0.13	0.14	0.14
- IOS *vs.* CS	0.25	0.27	0.93	2.03	0.45	0.26	0.20	0.32
0.95 range	(0;1.53)	(0;1.51)	(0;3.58)	(0.07;4.64)	(0;1.59)	(0;1.14)	(0;0.97)	(0;1.34)
S.D.	0.554	0.531	0.989	1.237	0.441	0.316	0.269	0.368

* truncated, the calculated value is 22 kg

Milk yield means differed slightly between CS, AOS and IOS at AH. At the other farms the mean milk yield for AOS and IOS was higher than for CS, especially at BZ. For IOS the 0.95 range and standard deviation for milk yield are given to illustrate the potential variation between individuals.

Profit was computed as the difference in gross margins for AOS *vs.* CS, IOS *vs.* AOS and IOS *vs.* CS. At AH, concentrate supply for CS was close to optimal, so the application of AOS did not increase profit. At BZ concentrate supply for CS was far from optimal, so the application of AOS can increase profit. At all farms a further gain in gross margin was possible between IOS and AOS. The total gain in gross margin for IOS *vs.* CS ranged from € 0.20/cow/day to € 2.03/cow/day. For profit in IOS *vs.* CS the 0.95 range and standard deviation are given to illustrate the potential variation between cows. In Figure 2.7 the distribution of simulated gain in profit for IOS *vs.* CS is given for HT multiparous cows. It is demonstrated that in 0.60 of cases the profit will be greater than € 0.10/cow/day and that profit can be as high as € 1.10/cow/day in about 0.03 of cases.

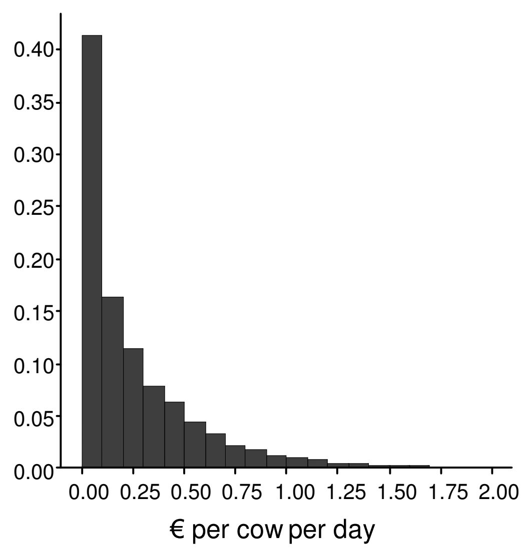

Figure 2.7 Distribution of simulated profit IOS *vs.* CS for High-tech multiparous cows.

2.4 Discussion

In the current study, only data from the first 3 weeks of the lactation were analysed. In early lactation, several factors influence milk production, e.g. concentrate intake, roughage intake and mobilization rate (body weight change). The effects of all these factors and interactions between them were not completely modelled. Modelling of the complete system of feed energy utilization is complex and estimating all partial efficiencies for individuals is not feasible with limited data (Tess & Greer, 1990). Moreover, it is unnecessary to use the energy balance equation, because individual response on concentrate intake can be estimated during lactation and optimal concentrate supply can be predicted in combination with the associated time point, given the linear relationship between concentrate supply and days in lactation during the first weeks in lactation.

Feeding at optimal levels at the beginning of and during peak lactation will reduce negative energy balance and loss of body weight and body tissues in that period (Bines, 1976). This might also contribute to improved health and reproduction (DeVries *et al*., 1999). Optimal individual concentrate allocation applying IOS was in most cases higher than CS, so IOS seems to be clearly sufficient for milk production and maintenance of body condition. Application of IOS, particularly at BZ, resulted in extremely high optimal settings. At BZ the period of linear increase of concentrates after calving was short compared to the other farms and this may have led to overestimated response parameters, especially the low curvature. For this reason the profit estimated at BZ is based on extrapolation and should be viewed with caution.

High levels for concentrate supply are (on average) not normally recommended because of the risk to digestion, such as acute and sub-acute ruminal acidosis (Owens *et al.,* 1998; DeBrabander *et al*., 1999). But with an individual dynamic approach higher levels for concentrate supply are applicable, as long as milk yield continues to respond to increasing concentrate supply and no digestive problems arise. In an individual dynamic approach, response is continuously evaluated and the optimum is automatically reduced if response decreases.

It is unlikely that milk yield response to concentrate intake remains constant after the first 3 weeks in lactation, because roughage intake, body weight and condition change over time. In addition factors at farm level that influence individual response might change over time, e.g. silage constitution. For these reasons the estimated individual response should be updated by recursive estimation during the remaining period of lactation. The individual optimum established after 3 weeks in lactation can be used as cow-specific prior information. Such a dynamic approach (West & Harrison, 1997) is part of precision dairy farming (Wathes *et al*., 2005). Prototypes of the dynamic approach to monitoring of response in milk yield to (changes in) concentrate allocation have been developed and tested by Duinkerken *et al.* (2003) and André *et al.* (2007).

An individual dynamic approach is only useful if there is sufficient variation between individual responses and if the economic prospects are encouraging. The current study demonstrates that individual variation in response exists and could be exploited to improve economic results during early lactation. However, these results have been derived as a first indication of the potential of a dynamic approach and are not intended for extrapolation over the whole lactation. Parameter estimates and economic results concern only the situation after 3 weeks in lactation. Further long term research is essential to evaluate all the aspects and prospects of a fully individual dynamic approach to concentrate feeding of dairy cows during the whole lactation. In future research, on-farm characteristics, such as milk quota, stocking rate, use of land, roughage acquisition and sale will also be taken into account.

Individual optimal settings are aimed at maximizing gross margins, but this is only valid if there are no limiting conditions such as milk quota. In the situation where milk quotas limit farm production levels, the strategy should be to minimize feeding costs. However, in the current study the focus is on data from early lactation and it is not advisable to reduce milk production by limiting energy supply during this period.

Total feeding costs do not consist only of concentrate costs. A more complete approach should also consider substitution of roughage. However, measurement of roughage intake including determination of the substitution rate is not yet common practice, neither at individual level nor at herd level. Ignoring roughage costs will cause a small error in the optimal setting for concentrate supply, if the actual market price of roughage is low and/or the substitution rate is low. In situations where roughage intake is measured individually or at herd level it is possible to evaluate the substitution of roughage by concentrate intake. Variation between individuals in milk composition, including effects of feeding, is ignored in the current study, but this variation affects the milk price. The model can be extended with an individual milk price to account for differences in milk composition.

Daily milk yield also depends on the length of the milking interval (Ouweltjes, 1998). In the current study, during the first weeks of the lactation the settings for milking frequency were constant within the cows and by consequence there is not enough variation in interval length to estimate the individual response. Individual variation in response to interval length is studied by André *et al.* (2010) to show that revenues from automatic milking can be increased by using this variation.

A considerable part of the individual variation in daily milk yield increase during early lactation is related to differences between cows in their response to increasing concentrate intake. It is possible in practice to estimate individual response in milk yield to concentrate intake after a few weeks in lactation using real time process data. This period should last at least 3 weeks to provide proper estimates of the response parameters.

Individual optimal settings for concentrate supply can be derived using individual response parameters. After 3 weeks in lactation, the averaged potential gain of IOS ranges from € 0.20 to € 2.03/cow/day.

Individual response parameter estimates can be used to construct cow-specific prior information for response to concentrate intake, for further use in an individual dynamic approach later on in lactation. The model and strategy can be extended to account for other sources of individual variation, such as roughage intake and substitution, milk composition and price, milking interval, etc. Positive effects on health and reproduction are also anticipated.

Acknowledgements

The authors wish to thank Edwin Bleumer for gathering the data. This project was funded by the Dutch Commodity Board for Dairy Products and the Dutch Ministry of Agriculture, Nature and Food Quality.

2.5 References

ANDRÉ, G., OUWELTJES, W., ZOM, R. L. G. & BLEUMER, E. J. B. (2007). Increasing economic profit of dairy production utilizing individual real time process data. In *Precision Livestock Farming '07* (Ed. S. Cox), pp. 179–186. Wageningen: Wageningen Academic Publishers.

ANDRÉ, G., BERENTSEN, P. B. M., ENGEL, B., DE KONING, C. J. A. M. & OUDE LANSINK, A. G. J. M. (2010). Increasing the revenues from automatic milking by using individual variation in milking characteristics. *Journal of Dairy Science* **93**, 942–953.

BEERDA, B., OUWELTJES, W., ŠEBEK, L. B. J., WINDIG, J. J. & VEERKAMP, R. F. (2007). Effects of genotype by environment interactions on milk yield, energy balance, and protein balance. *Journal of Dairy Science* **90**, 219–228.

BINES, J. A. (1976). Regulation of food intake in dairy cows in relation to milk production. *Livestock Production Science* **3**, 115–128.

BROSTER, W. H. & THOMAS, C. (1981). The influence of level and pattern of concentrate input on milk output. In *Recent Advances in Animal Nutrition* (Ed. W. Haresign), pp.76–96. London: Butterworth.

BUCKMASTER, D. R. & MULLER, L. D. (1994). Uncertainty in nutritive measures of mixed livestock rations. *Journal of Dairy Science* **77**, 3716–3724.

CANT, J. P. (2005). Integration of data in feed evaluation systems. In *Quantitative Aspects of Ruminant Digestion and Metabolism* (Eds J. Dijkstra, J. M. Forbes & J. France), 2nd edn, pp. 707–726. Wallingford, UK: CAB International.

COFFEY, M. P., SIMM, G. & BROTHERSTONE, S. (2002). Energy balance profiles for the first three lactations of dairy cows estimated using random regression. *Journal of Dairy Science* **85**, 2669–2678.

DE BRABANDER, D. L., DE BOEVER, J. L., VANACKER, J. M., BOUCQUÉ, CH. V. & BOTTERMAN, S. M. (1999). Evaluation of physical structure in dairy cattle nutrition. In *Recent Advances in Animal Nutrition* (Eds P. C. Garnsworthy & J. Wiseman), pp. 111–145. Nottingham, UK: Nottingham University Press.

DEVRIES, M. J., BEEK, S. VAN DER KAAL-LANSBERGEN, L. M. T. E., OUWELTJES, W. & WILMINK, J. B. M. (1999). Modeling of energy balance in early lactation and the effect of energy deficits in early lactation on first detected estrus postpartum in dairy cows. *Journal of Dairy Science* **82**, 1927–1934.

DEVRIES, M. J. & VEERKAMP, R. F. (2000). Energy balance of dairy cattle in relation to milk production variables and fertility. *Journal of Dairy Science* **83**, 62–69.

DUINKERKEN, G. VAN, ANDRÉ, G. & ZOM, R. L. G. 2003. *Prototype van een Dynamisch Krachtvoer Advies Systeem voor Melkvee*. (Prototype of a Dynamic Model for Concentrate Feeding to Dairy Cows, in Dutch, with English abstract). Praktijkrapport 37, Lelystad: Praktijkonderzoek Veehouderij.

EFRON, B. & TIBSHIRANI, R. (1993). *An Introduction to the Bootstrap*. Boca Raton, USA: Chapman & Hall.

EKERN, A. & VIK-MO, L. (1983). Standard and lead feeding of dairy cows. *Livestock Production Science* **10**, 443–455.

GENSTAT COMMITTEE (2006). *Genstat® Release 9 Reference Manual*. Hemel Hempsted, UK: VSN International.

KOKKONEN, T., TESFA, A., TUORI, M. & SYRJÄLÄ-QVIST (2004). Concentrate feeding strategy of dairy cows during transition period. *Livestock Production Science* **86**, 239–251.

KNIGHT, C. H. (1982). The mammary cell population in relation to milk yield. In *Hannah Research Institute Report 1989*, pp. 89–95. Ayr: Hannah Research Institute.

LEI (2006). *Cost Price of Milk at Dairy Farms*. Den Haag, the Netherlands: LEI Bedrijven-Informatienet.

MALTZ, E., KROLL, O., SPAHR, S. L., DEVIR, S., GENIZI, A. & SAGI, R. (1991). Milk yield, parity, and cow potential as variables for computerized concentrate supplementation strategy. *Journal of Dairy Science* **74**, 2277–2289.

MALTZ, E., DEVIR, S., KROLL, O., ZUR, B., SPAHR, S. L. & SHANKS, R. D. (1992). Comparative responses of lactating cows to total mixed rations or computerized individual concentrates feeding. *Journal of Dairy Science* **75**, 1588–1603.

MEPHAM, B. (1976). *The Secretion of Milk*. London: Edward Arnold Publishers.

MOOD, A. M., GRAYBILL, F. A. & BOES, D. C. (1974). *Introduction to the Theory of Statistics.* Singapore: McGraw-Hill.

NEAL, H. D. St C. & THORNLEY, J. H. M. (1983). The lactation curve in cattle: a mathematical model of the mammary gland. *Journal of Agricultural Science, Cambridge* **101**, 389–400.

OKINE, E. K., WANG, Z., GOONEWARDENE, L. A., MIR, Z. & LIU, M. F. (2001). Residual metabolizable feed consumption as a method of comparing feed efficiency in steers fed silage and silage-grain diets. *Journal of Animal Feed Science and Technology* **92**, 87–93.

OWENS, F. N., SECRIST, D. S., HILL, W.J. & GILL, D. R. (1998). Acidosis in cattle: A review. *Journal of Animal Science* **76**, 275–286.

OUWELTJES, W. (1998). The relationship between milk yield and milking interval in dairy cows. *Livestock Production Science* **56**, 193–201.

PARKS, J. R. (1982). *A Theory of Feeding and Growth of Animals*. Berlin: Springer-Verlag.

ROBINSON, G.K. (1991). That BLUP is a good thing: The estimation of random effects. *Statistical Science* **6**, 15–32.

SEARLE, S. R., CASELLA, G. & MCCULLOUCH, C. E. (1992). *Variance Components*. New York: Wiley.

TESS, M. W. & GREER, R. C. (1990). Considerations for the specification and statistical estimation of differences among animals in the partial efficiencies of feed energy utilization. *Journal of Dairy Science* **73**, 3297–3305.

THORNLEY, J. H. M. & FRANCE, J. (2007). *Mathematical Models in Agriculture: Quantitative Methods for the Plant, Animal and Ecological Sciences,* revised 2nd edn. Wallingford, Oxon: CAB International.

VAN ARENDONK, J. A. M., NIEUWHOF, G. J., VOS, H. & KORVER, S. (1991). Genetic aspects of feed intake and efficiency in lactating dairy heifers. *Livestock Production Science* **29**, 263–275.

VAN ES, A. J. H. (1978). Feed evaluation for ruminants. I. The systems in use from May 1977 onwards in the Netherlands. *Livestock Production Science* **5**, 331–345.

VETHARANIAM, I., DAVIS, S. R., UPSDELL, M., KOLVER, E. S. & PLEASANTS, A. B. (2003). Modeling the effect of energy status on mammary gland growth and lactation. *Journal of Dairy Science* **86**, 3148–3156.

WATHES, C. M., KRISTENSEN, H. H., AERTS, J-M. & BERCKMANS, D. (2005). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? In *Precision Livestock Farming '05* (Ed. S. Cox), pp. 33–47. Wageningen, The Netherlands: Wageningen Academic Publishers.

WEST, M. & HARRISON, J. (1997). *Bayesian Forecasting and Dynamic Models*, 2nd edn. New York: Springer-Verlag.

Appendices

A. Reduction of the 2-dimensional response surface to a quadratic polynomial

If $M(t,C)=\{\alpha_0+\alpha_1 t-\alpha_2 t^2\}+\{\beta_1 C-\beta_2 C^2\}+\gamma Ct$ and $C=c_0+c_1 t$ then substituting the associating days $t=(C-c_0)/c_1$ into $M(t,C)$ gives:

$$
\begin{aligned}
M(t,C) &= \left\{\alpha_0+\alpha_1\left(\frac{C-c_0}{c_1}\right)-\alpha_2\left(\frac{C-c_0}{c_1}\right)^2\right\}+\{\beta_1 C-\beta_2 C^2\}+\gamma\left(\frac{C-c_0}{c_1}\right)C \\
&= \left\{\alpha_0-\frac{\alpha_1 c_0}{c_1}-\frac{\alpha_2 c_0^2}{c_1^2}\right\}+\left\{\frac{\alpha_1}{c_1}+\frac{2\alpha_2 c_0}{c_1^2}+\beta_1-\frac{\gamma c_0}{c_1}\right\}C-\left\{\frac{\alpha_2}{c_1^2}+\beta_2-\frac{\gamma}{c_1}\right\}C^2 \\
&= \beta_0^*+\beta_1^* C-\beta_2^* C^2 \\
&= M(C)
\end{aligned}
$$

This quadratic function can be used to predict $M(C_{Opt})$ where the gross margin milk revenues minus concentrate costs is maximal. The associating day in lactation is $t=(C_{Opt}-c_0)/c_1$.

Milk yield M_t at day t depends on concentrate intake x_t at current and previous days t, $t-1$, … To account for the delay in response the following transfer function is used:

$$C_t=\lambda_0 x_t+\lambda_1 x_{t-1}+\lambda_2 x_{t-2}+\ldots$$

We assumed that weights from day $(t-3)$ and before are nearly 0. The remaining weights λ_0,λ_1 and λ_2 were chosen equal (to 1/3). Unless the real, but unknown, weights would markedly differ, the choice of weights is not critical. This results in a moving average for concentrate intake.

B. Comparison between two input strategies

The yield S for an input C is assumed to be:

$$S(C) = \gamma_0 + \gamma_1 C + \gamma_2 C^2$$

where

$$\gamma \sim MVN(\mu_\gamma, \Sigma)$$

for a random animal from the herd.

B1. Constant input based on average yield

The expected yield, which is the population average, for a fixed input C is:

$$E(S(C)) = \mu_0 + \mu_1 C + \mu_2 C^2$$

Here, we assume that $\mu_2 < 0$. Consequently, the expected yield is optimal for:

$$C_{aver} = -\frac{1}{2}\frac{\mu_1}{\mu_2}$$

which yields $S(C_{aver})$ with expected value

$$E_{aver} = E(S(C_{aver})) = \mu_0 - \frac{1}{4}\frac{\mu_1^2}{\mu_2}$$

B2. Input based on individual yield

For a random individual from the herd, when $\gamma_2 < 0$, an optimal input can be calculated:

$$C_{ind} = -\frac{1}{2}\frac{\gamma_1}{\gamma_2}$$

The associated individual optimal yield is:

$$S\left(C_{ind}\right) = \gamma_0 - \frac{1}{4}\frac{\gamma_1^2}{\gamma_2}$$

and the expected individual yield is:

$$E_{ind} = E\left(S\left(C_{ind}\right)\right) = \mu_0 - \frac{1}{4}E\left(\frac{\gamma_1^2}{\gamma_2}\right)$$

The latter expectation E_{ind} can be approximated by Taylor expansion around the mean, up to and including terms of order 2 (Mood *et al*. 1974):

$$E_{ind} \approx \mu_0 - \frac{1}{4}\left(\frac{\mu_1^2}{\mu_2} + \frac{Var\left(\gamma_1\right)}{\mu_2} + \frac{\mu_1^2}{\mu_2^3}Var\left(\gamma_2\right) - \frac{2\mu_1}{\mu_2^2}Cov\left(\gamma_1,\gamma_2\right)\right)$$

Here, we assume that the distribution of γ_2 largely concentrates on negative values. When $\lambda_2 \geq 0$, or when C_{ind} is unrealistically high, we might imagine that some standard input value C_{Max} is applied. The value C_{Max} is a sensible upper bound for the input (possibly depending on the individual in a dynamic setting). When $C_{Max} > C_{aver}$, this would give a higher yield than the strategy based on a constant input.

When variation in γ_2 is negligible, the covariance term will be equal to 0 and the result will be exact. The average input for the individual strategy is:

$$E\left(C_{ind}\right) = -\frac{1}{2}E\left(\frac{\gamma_1}{\gamma_2}\right) \approx -\frac{1}{2}\left(\frac{\mu_1}{\mu_2} - \frac{1}{\mu_2^2}Cov\left(\gamma_1,\gamma_2\right) + \frac{\mu_1}{\mu_2^3}Var\left(\gamma_2\right)\right)$$

B3. The difference between the two input strategies

$$E_{ind} - E_{aver} \approx -\frac{1}{4}\left(\frac{Var\left(\gamma_1\right)}{\mu_2} + \frac{\mu_1^2}{\mu_2^3}Var\left(\gamma_2\right) - \frac{2\mu_1}{\mu_2^2}Cov\left(\gamma_1,\gamma_2\right)\right)$$

When variation in γ_2 is negligible the result will be exact. While $\mu_2 < 0$ and when $Cov\left(\gamma_1,\gamma_2\right) < 0$ but relatively small the expected yield will be larger under the individual input strategy compared with the constant input strategy.

C. Bootstrap

Although an analytical solution can be derived, a parametric bootstrap was carried out to investigate the consequences of the different strategies for concentrate allocation. The bootstrap was based on the estimated fixed response parameters $\hat{\beta}$ and $\hat{\tau}$ according to primiparous or multiparous cows/farm. The random parameters b (n=10000) were sampled from a multivariate normal distribution $\left(b_0 \quad b_1 \quad b_2\right)' \sim MVN\left(0;\hat{\Sigma}_b\right)$. The bootstrap comprises the practical constraints $\theta_{2,ij} < 0$ and $0 \le C_{Opt,ij} \le 20$, which is more complicated to include in an analytical derivation. In next table the number of cases out of 10 000 is given that the bootstrap is bound by the constraints.

Farm	**Parity***	**Constraint**		
		$\theta_{2,ij} > 0$	$C_{Opt,ij} < 0$	$C_{Opt,ij} > 20$
Aver Heino	P	391	268	115
	M	412	274	128
Bosma Zathe	P	0	54	1302
	M	0	0	6863
High-tech	P	0	0	0
	M	0	0	0
Zegveld	P	0	3	0
	M	0	0	261

*P = primiparous; M = multiparous

3 Increasing the revenues from automatic milking by using individual variation in milking characteristics[4]

Abstract

The objective of this study was to quantify individual variation in daily milk yield and milking duration in response to the length of the milking interval and to assess the economic potential of utilizing this individual variation for optimizing the use of an automated milking system. Random coefficient models were employed to describe the individual effects of milking interval on daily milk yield and milking duration. The random coefficient models were fitted on a dataset consisting of 4,915 records of normal uninterrupted milkings collected of 311 cows kept in 5 separate herds during 1 week. The estimated random parameters showed considerable variation between individuals within herds in milk yield and milking duration in response to milking interval. In the actual situation the herd consisted of 60 cows and the automatic milking system operated at an occupation rate (OR) of 64%. When maximizing daily milk revenues per automated milking system by optimizing individual milking intervals, the average milking interval was reduced from 0.421 day to 0.400 day, the daily milk yield at herd level was increased from 1,883 to 1,909 kg/day and milk revenues increased from € 498 to € 507 per day. If an OR of 85% could be reached with the same herd size, the optimal milking interval would decrease to 0.238 day, milk yield would increase to 1,997 kg/day and milk revenues would increase to € 529 per day. Consequently more labor for fetching the cows would be required and milking duration would increase. Alternatively, an OR of 85 % could be achieved by increasing herd size from 60 to 80 cows without decreasing the milking interval. Then milk

---

[4] Paper by G. André, P.B.M. Berentsen, B. Engel, C.J.A.M. de Koning and A.G.J.M. Oude Lansink, published in Journal of Dairy Science (2010), **93**, 942–953.

yield would increase to 2,535 kg/day and milk revenues would increase to € 673 per day. For practical implementation on farm a dynamic approach is recommended by which the parameter estimates regarding the effect of interval length on milk yield and the effect of milk yield on milking duration are regularly updated and also the milk production response to concentrate intake is taken into account.

3.1 Introduction

Presently, on around 5,000 farms world-wide, cows are milked using an automatic milking system (AMS), and this number is rapidly increasing. Although an AMS requires a higher investment than a conventional system, increased milk yields per cow and reduced labor costs may result in lower costs per kg milk produced (De Koning and Rodenburg, 2004). From the point of economic efficiency of the AMS, maximizing milk production per AMS is crucial (Sonck and Donkers, 1995).

Daily milk yield per cow increases with the number of milkings per day (De Koning and Ouweltjes, 2000). On the other hand, sum of milking time of all cows in the herd is restricted by the AMS capacity. The AMS capacity is defined as the time that an AMS is available for milking per day of 24 hours. This capacity can also be expressed as an Operation Rate (OR) defined as the percentage of hours the milking system is available per day. When the AMS for example has an OR of 70%, the AMS is available 16.8 hr/day for milking the cows, while the remaining 7.2 hours are reserved for rinsing and cleaning the AMS, for handling non-milking visits and for idle time. Inclusion of idle time is necessary to avoid crowding of cows waiting to be milked, which could easily lead to hold back cows from visiting the AMS. Given the OR, the question is then how to allocate the total time available for milking to the individual cows in the herd such that milk revenues per day of the AMS are maximized. Allocation of time is made operational by setting minimum values for the milking interval (the time between two milkings). In practice simple guidelines based on daily milk production and parity are used for this but there might be possibilities for fine tuning. Milk flow (the amount of milk leaving the udder per time unit) and the relation between number of milkings per day and daily milk production vary considerably between cows (Ipema and Hogewerf, 2004). These milking characteristics are hereditary, but also depend on parity and lactation stage. By continuous monitoring of the automatic milking process milking characteristics per cow can be determined on a daily base, and utilized to optimize allocation of total milking time to individual cows.

Previous research in this area was focused on determining total milk production per AMS. Using simple guidelines for time allocation, De Koning and Ouweltjes (2000) assessed a potential total milk production ranging between 600,000 and 750,000 kg of milk/yr. Bijl et al. (2007) found for 31 Dutch farms with an AMS in 2003 an average milk production of 494,442 kg of milk/yr per AMS. They concluded that the capacity of most of the AMS was not yet fully utilized and that there was scope for growth within the existing capacity.

The objective of this study was twofold. The first objective was to quantify the variation between individuals in milk yield response to milking interval and the corresponding individual variation in milking duration, which also includes variation in milk flow. The second objective was to study the potential economic prospects of utilizing individual variation in milking characteristics including milk price by maximizing daily milk revenues of an AMS.

3.2 Materials and methods

3.2.1 Data

Data used in this study were obtained from the research farm "De Waiboerhoeve" of the Animal Sciences Group in Lelystad, a dairy farm with Holstein Frisian cows. Within this farm 5 groups of about 64 lactating cows per group were managed as different herds and housed in separated sections, 4 herds were housed in 4 adjacent sections and 1 herd in a separated section of a free-stall (Figure 3.1). Apart from differences in floor type (Table 3.2), housing conditions were similar for all herds.

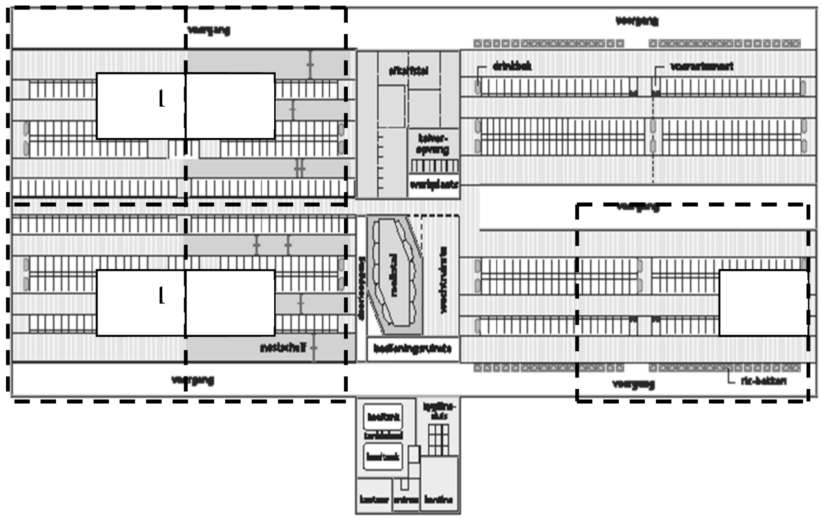

Figure 3.1 Lay out of the research farm "De Waiboerhoeve". The numbers 1101 to 1501 refer to the different herds and indicate the location of the automatic milking systems.

Cows from each herd were milked with a single stall AMS (Lely Astronaut A2, Rotterdam, the Netherlands) with an average production of 657,000 kg of milk/yr per robot. The vacuum level was 48 kPa and the pulsation ratio was 65:35. The cows received 1 to 6 kg concentrates during milking, depending on their production level. Water and a partially-mixed feeding ration were available ad libitum. Partially-mixed ration was a mixture composed (on dry matter basis) of 8.0 kg grass silage, 7.0 kg corn silage, 0.4 kg grass seed hay, 1.3 kg sugar beet pulp (pressed, ensiled), 2.0 kg soya bean meal, 1.5 kg wheat meal (fine) and 0.2 kg of minerals.

The data were real time process data registered by the AMS. At each milking, milk yield, milking duration (time taken from entry to exit of the AMS, i.e. the total box-visiting time) and milking interval (time between the starts of two consecutive milkings) were observed. The actually realized milking intervals resulted from settings for the admittance interval advised by the manufacturer (Table 3.1) and the cow collection strategy of the herds man. Cows that exceeded a 12 hour interval were fetched during three different times per day.

Table 3.1 Admittance interval settings for different categories of dairy cows milked by an Automatic Milking System

Milk yield (kg/day)		**Admittance interval** (day)
primiparous	multiparous	
M[1] ≤ 20	M ≤ 25	0.40
20 < M ≤ 27	25 < M ≤ 33	0.29
27 < M ≤ 30	33 < M ≤ 40	0.25
M > 30	M > 40	0.22

[1]milk yield (kg/day)

Data were collected over a period of 1 week from 30/4/2007 until 6/5/2007. Because this is only a short period, it was assumed that some cow characteristics like feed intake and efficiency remained constant. The dataset consists of 4,915 records of normal uninterrupted milkings following normal uninterrupted milkings. Deviating observations due to registration errors were excluded from the dataset. In total 311 cows (122 primiparous and 189 multiparous cows) were observed. Descriptive statistics of the data, comprising herd size H, milk yield per milking M in kg, milking duration per milking D in min, length of the preceding milk interval I as a fraction of the day (hours/24) and derived statistics such as daily milk yield M/I per cow are presented in Table 3.2.

Table 3.2 Descriptive statistics of the dataset. Standard deviation between ()

Herd number		**1101**	**1201**	**1301**	**1401**	**1501**
Floor type		solid concrete	slatted concrete	slatted rubber	solid rubber	slatted concrete
Herd size	H	63	62	61	59	66
Days in lactation		190	210	263	202	164
		(114)	(122)	(138)	(109)	(120)
Primiparous cows (%)		33	44	28	61	32
Parity		2.35	2.13	2.79	1.70	2.76
Per milking:						
Milk yield (kg/milking)	M	13.0	12.6	11.7	12.1	14.0
		(3.66)	(3.40)	(4.18)	(3.20)	(4.55)
Duration (min./milking)	D	6.76	6.21	6.31	5.54	6.44
		(1.75)	(1.53)	(2.06)	(1.73)	(1.75)
Per cow:						
Milking interval (day)	I	0.425	0.425	0.444	0.402	0.420
		(0.109)	(0.098)	(0.113)	(0.078)	(0.110)
Milk yield (kg/cow/day)	M/I	30.6	29.6	26.4	30.1	33.3
		(11.7)	(9.3)	(11.4)	(9.5)	(11.5)
Duration (min./cow/day)	D/I	15.9	14.6	14.2	13.8	15.3
AMS capacity utilization:						
Milkings (per day)	H/I	148	146	137	147	157
Occupation rate (%)	I	69	63	60	57	70
Duration (hr/day)	HD/60	16.7	15.1	14.4	13.6	16.8
Milk yield (kg/day)	HM/I	1,928	1,835	1,610	1,776	2,198

3.2.2 Effect of milking interval on milk yield and milking duration per milking

Milk yield per milking depends on the length of the preceding interval; this is referred to as the interval sensitivity. Stelwagen (2001) found that compared to two milkings per day, milking three times a day increases milk yield by 18%, whereas milking once per day decreases milk output by 20%. Ouweltjes (1998) showed that milk production per hour is higher for short intervals (during the day-time) than for long intervals (during the night-time) when cows were milked two times per day. Delamaire and Guinard-Flament (2006) found that daily milk yield decreased curvi-linearly with increasing intervals from 8 to 24 hours. France and Thornley (1984) used a non-linear Michaelis-Menten curve to describe the decreasing milk secretion rate by increasing intervals, due to udder filling which in turn depends on the storage capacity of the udder. Based on these insights from the literature, the relationship between milk yield per milking M and interval length I was approximated by a quadratic curve $M = \mathrm{B}_1 I + \mathrm{B}_2 I^2$ with B_1, B_2 being the coefficients for the linear and quadratic effect of interval length, respectively. There is no intercept in the model, because at the start of the interval $(I = 0)$ directly after milking, the udder is empty. The linear coefficient represents the milk secretion rate at the start of the interval and the quadratic coefficient represents the interval sensitivity.

An entire milking consists of several phases. When the cow enters the AMS time is needed for identification, udder preparation and teat cup attachment. The required time for milking depends on the milk yield and flow rate of the individual cow (De Koning and Ouweltjes, 2000). After milking, teat disinfection, cluster cleansing and exit of the cow from the AMS take time. Therefore, it was assumed that milking duration D consists of a constant proportion of time and a variable proportion of time depending on milk yield, $D = \mathrm{A}_0 + \mathrm{A}_1 M$ with A_0 the intercept and A_1 the slope.

The effect of milking interval on milk yield per milking and the effect of milk yield per milking on milking duration per milking are displayed in Figure 3.2. Dividing milk yield per milking and milking duration per milking by the interval length results in milk yield per day and milking duration per day. Milk yield per day increases linearly with decreasing the interval length between milkings (increasing milking frequency), but milking duration per day increases exponentially. The potential increase in milking duration is restricted by the available AMS capacity. During the day a certain amount of time is needed by the AMS for rinsing and cleaning, handling interrupted milkings and additional non-milking visits. Furthermore some more idle time is needed for good functioning of the AMS. The remaining time per day is the available AMS capacity for milking, i.e. the maximum milking duration. The maximum milking duration D_{Max} in relation to herd size determines the optimal milking interval length I_{Opt} and consequently maximal daily milk yield M_{Max}.

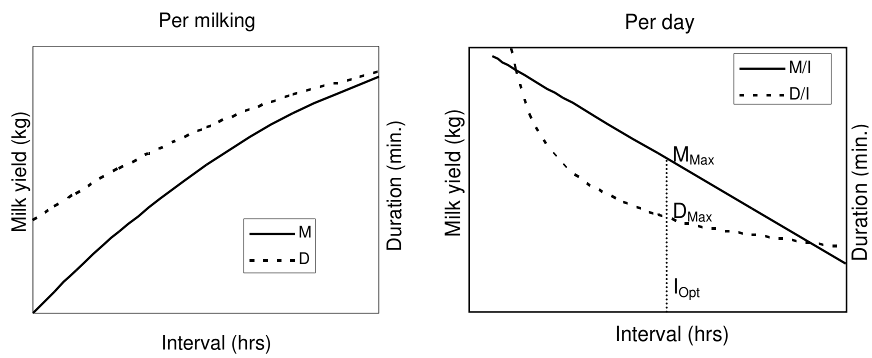

Figure 3.2 Relation between milk yield M (solid line, left axis) and milking duration D (dashed line, right axis) per milking (left figure) and per day (right figure) with interval length I. The right figure shows the maximal milking duration D_{Max}, determining the optimal interval length I_{Opt} and maximal daily milk yield per day M_{Max}.

3.2.3 Statistical models incorporating individual effects

Yield per milking

The coefficients B were formulated in more detail, distinguishing between systematic population effects and random individual effects. Because daily milk production at a certain moment during lactation depends on feeding and energy status (Vetharaniam, 2003) and parity, the systematic effects in coefficients B comprise main effects and interaction terms for herd and parity. The coefficients B were assumed to be constant (for each cow) during the short period of 1 week of data collection. The model for milk yield per milking is given in model (3.1):

$$\begin{aligned} M_{ijkl} &= \mathrm{B}_{1ikl}\, I + \mathrm{B}_{2ikl} I^2 + \varepsilon_{ijkl} \\ &= \left(\beta_1 + \kappa_{1k} + \lambda_{1l} + \gamma_{1kl} + b_{1i}\right) I + \left(\beta_2 + \kappa_{2k} + \lambda_{2l} + \gamma_{2kl} + b_{2i}\right) I^2 + \varepsilon_{ijkl} \end{aligned} \quad (3.1)$$

with:

M_{ijkl} yield at milking j of cow i from herd k with parity l (kg),

I interval length (day),

β_1 coefficient linear interval effect, representing milk production rate at the start of the interval (kg/ day),

κ_{1k} effect of herd k on coefficient of linear interval length (kg/day),

λ_{1l} effect of parity l on coefficient of linear interval length (kg/day),

γ_{1kl} interaction effect of herd k and parity l (kg/day) on coefficient of linear interval length (kg / day),

b_{1i} individual random effect on coefficient for linear interval length for cow i (kg/day).

Likewise, for the coefficient B_2 of the quadratic interval effect, systematic effects β_2, κ_{2k}, λ_{2l}, γ_{2kl} and individual random effects b_{2i} were introduced. Finally, ε_{ijkl} is the residual term.

A cow's individual random effects b_1 and b_2 were assumed to follow a bivariate normal distribution with mean 0 and covariance matrix Σ_B. Individual random effects of different animals were assumed to be independent. Residuals ε were assumed to be independently normally distributed with mean 0 and variance σ_ε^2. Random effects b and ε were assumed to be mutually independent. The so-called corner stone parameterization was adopted, expressing the differences between herds and parities relative to primiparous cows of herd 1101., i.e. $\kappa_{11} = \lambda_{11} = \gamma_{11l} = \gamma_{1k1} = \kappa_{21} = \lambda_{21} = \gamma_{21l} = \gamma_{2k1} = 0$.

<u>*Duration per milking*</u>

Similar, the coefficients A were formulated in more detail, incorporating systematic effects for parity and herd and individual random effects. Again, in the short data collection period of 1 week, intercept A_0 and slope A_1 were assumed to be constant. The model for duration per milking is given in model (3.2):

$$\begin{aligned} D_{ijkl} &= \mathrm{A}_{0i} + \mathrm{A}_{1i} M + \delta_{ijkl} \\ &= \left(\alpha_0 + \tau_{0k} + \upsilon_{0l} + \eta_{0kl} + a_{0i}\right) + \left(\alpha_1 + \tau_{1k} + \upsilon_{1l} + \eta_{1kl} + a_{1i}\right) M + \delta_{ijkl} \end{aligned} \tag{3.2}$$

with:

D_{ijkl} duration of milking j of cow i in herd k with parity l (min.),

M yield per milking (kg),

α_0 intercept (min.),

τ_{0k} fixed effect of herd k on intercept (min.),

υ_{0l} fixed effect of parity l on intercept (min.),

η_{0kl} interaction effect of herd k and parity l on intercept (min.),

a_{0i} individual random effect on intercept for cow i (min.).

Likewise, for the slope A_1, systematic effects α_1, τ_{1k}, υ_{1l}, η_{1kl} and individual random effects a_{1i} were introduced. Finally, δ_{ijkl} is the residual term.

A cow's individual random effects a_0 and a_1 were assumed to follow a bivariate normal distribution with mean 0 and covariance matrix Σ_A. Individual random effects of different animals were assumed to be independent. Residuals δ were assumed to be independently normally distributed with mean 0 and variance σ_δ^2. Random effects a and δ were assumed to be mutually independent. Again, systematic effects were expressed relative to primiparous cows of herd 1101: $\tau_{01} = \tau_{11} = \upsilon_{01} = \upsilon_{11} = \eta_{0k1} = \eta_{01l} = \eta_{1k1} = \eta_{11l} = 0$.

Parameters were estimated by restricted maximum likelihood (REML) (Searle et al., 1992). Calculations were performed with Genstat (2006). Only statistically significant (P<0.05, Wald test) parameters were retained in the model. Residual analysis was performed to detect outliers and to check model assumptions such as normality and temporal independence of residuals.

Individual cow parameters A_i and B_i were estimated by $\hat{\mathrm{A}}_i$ and $\hat{\mathrm{B}}_i$: the best linear unbiased predictors or BLUP's (Robinson, 1991). These estimates comprise the relevant systematic effects of herd and parity and the individual random effects.

3.2.4 Optimization of the AMS utilization

Individual optimal milking intervals $I_{Opt,i}$ were found by solving the non-linear programming problem of maximizing the daily milk revenues $\sum_i S_i$ subject to the constraint that the total milking duration per day $\sum_i \hat{D}_i / I$ cannot exceed the available AMS capacity D_{Max}. Duration and also milk yield *per milking* were divided by interval length to achieve duration and milk yield *per day*. Note that dividing by interval length is equivalent to multiplying by milking frequency. The individual optimal milking intervals were found by solving the nonlinear programming problem with GAMS (Rosenthal, 2006). Daily milk revenues were computed as the sum of the individual milk revenues, which is a function of individual milk yield and individual milk price $\pi_{M,i}$. The objective function was:

$$\sum_i S_i = \sum_i \left\{ \pi_{M,i} \hat{M}_i / I \right\} = \sum_i \left\{ \pi_{M,i} \left(\hat{\mathrm{B}}_{1,i} + \hat{\mathrm{B}}_{2,i} I \right) \right\}$$

with:

S_i	milk revenue of cow i (€/day),
$\pi_{M,i}$	individual milk price of cow i (€/kg),
$\hat{M}_i / I$	predicted milk yield of cow i (kg/day),
$\hat{\mathrm{B}}_{1,i}$, $\hat{\mathrm{B}}_{2,i}$	individual parameter estimates of cow i, see model (3.1).

Calculation of the individual milk price was based on the deviation of the individual fat F_i and protein content P_i from the averaged contents at herd level, fat 4.133% and protein 3.416%.

$$\pi_{M,i} = 1.06\left\{\bar{\pi}_M + \pi_F\left(F_i - 4.133\right) + \pi_P\left(P_i - 3.416\right)\right\} / 100$$

with $\bar{\pi}_M$ averaged milk price at herd level, $\pi_F = 2.78$ €/kg fat price and $\pi_P = 5.49$ €/kg protein price (Friesland Foods, price levels may 2007). The factor 1.06 is the rate of value-added tax.

The constraint for total milking duration was:

$$\sum_i \hat{D}_i / I = \sum_i \left\{\hat{\mathrm{A}}_{0,i} I^{-1} + \hat{\mathrm{A}}_{1,i}\left(\hat{\mathrm{B}}_{1,i} + \hat{\mathrm{B}}_{2,i} I\right)\right\} \leq D_{Max}$$

with:

$\hat{D}_i / I$	predicted milking duration of cow i (min/day),
$\hat{\mathrm{A}}_{0,i}$, $\hat{\mathrm{A}}_{2,i}$	individual parameter estimates of cow i, see model (3.2),
D_{Max}	maximum total milking duration (min/day).

Individual optimal milking intervals were restricted such that cows were milked at least once per day, i.e. $0 < I < 1$. Results for the individual optimal intervals were calculated for each herd separately given the herd size in the actual situation.

D_{Max} was set to the milking duration for each herd, achieved in the actual situation (Table 3.2). Individual optimal milking intervals were calculated for the actual situation to demonstrate the effect of individual optimization. Subsequently, the actual situation was compared with increasing settings for D_{Max} (1,008 to 1,224 min. per day with steps of 72 min.) according to 4 occupation rates (OR's) of the AMS: 70, 75, 80 and 85%. This demonstrates the effect of increasing OR in combination with individual optimization.

3.3 Results and discussion

3.3.1 Yield per milking

Parameter estimates and standard errors for the effects of milking interval on yield per milking are given in Table 3.3. Terms that were not statistically significant were removed from the model. The systematic part of the model describes the average effects at population level. The linear interval effect, representing the milk production rate at the start of the interval, differed significantly between herds: herd 1301 had the lowest and herd 1501 the highest production rate, which is in agreement with days in lactation (Table 3.2). The production rate for multiparous cows was significantly higher than for primiparous cows. The quadratic interval effect represents interval sensitivity and differed significantly between herds: herd 1501 displayed the greatest sensitivity and herd 1201 the lowest. This difference may be explained by the stage of lactation, and consequently the milk yield. The effect of parity on interval sensitivity was not significant. There were no significant interactions between parity and herd, and equal effects of parity among herds was assumed.

Table 3.3 Parameter estimates and standard errors milk yield per milking

Parameter		**Estimate**	**Standard error**
Systematic part of the model:			
Linear interval effect β_1		29.9	1.5
Linear interval effect of herd κ_{1k}	1101	0	-
	1201	- 0.24	1.98
	1301	- 2.03	1.42
	1401	+ 2.74	2.04
	1501	+ 5.82	1.95
Linear interval effect of parity λ_{1l}	primiparous	0	-
	multiparous	5.09	1.02
Quadratic interval effect β_2		- 8.72	1.26
Quadratic interval effect of herd κ_{2k}	1101	0	-
	1201	+ 1.87	1.79
	1301	- 0.61	1.67
	1401	- 2.75	1.88
	1501	- 3.27	1.74
Random part of the model:			
Variance linear effect σ^2_{B1}		212	19
Variance quadratic effect σ^2_{B2}		86.0	12.9
Residual variance σ^2_{δ}		0.615	0.013
Correlation linear with quadratic ρ_{B01}		- 0.741	0.104

The average relationship between milking interval and yield per milking is shown per herd for primiparous and multiparous cows separately in Figure 3.3.

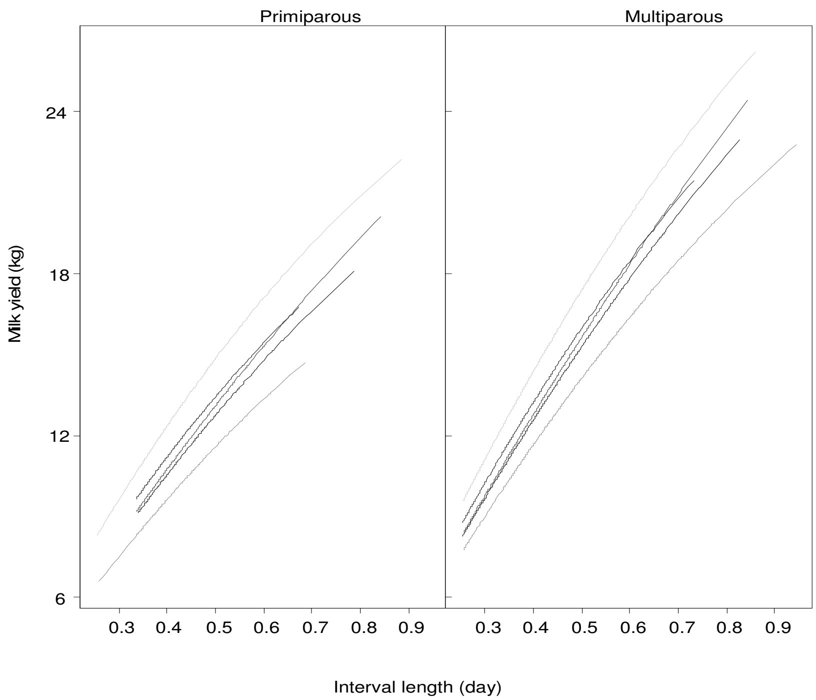

Figure 3.3 Fitted milk yield per milking vs. interval length for different herds (of above down: 1501, 1401, 1201, 1101 and 1301).

The random part of model (3.1) for milk yield per milking, represents the individual variation in the cows coefficients for linear and quadratic effects of milking interval, i.e. the variation between individual curves, and the residual variation, i.e. the variation between cows around their curves. Variation was expressed in terms of three variances (variance components), representing variation between cows in coefficients of linear and quadratic terms, i.e. linear increase and curvature, and variation within cows. Figure 3.4 demonstrates that there was a considerable variation between individuals in milk yield per milking. The variation was mainly related to the linear effect of interval (initial milk secretion rate) and to a smaller extent to the quadratic effect (curvature, interval sensitivity).

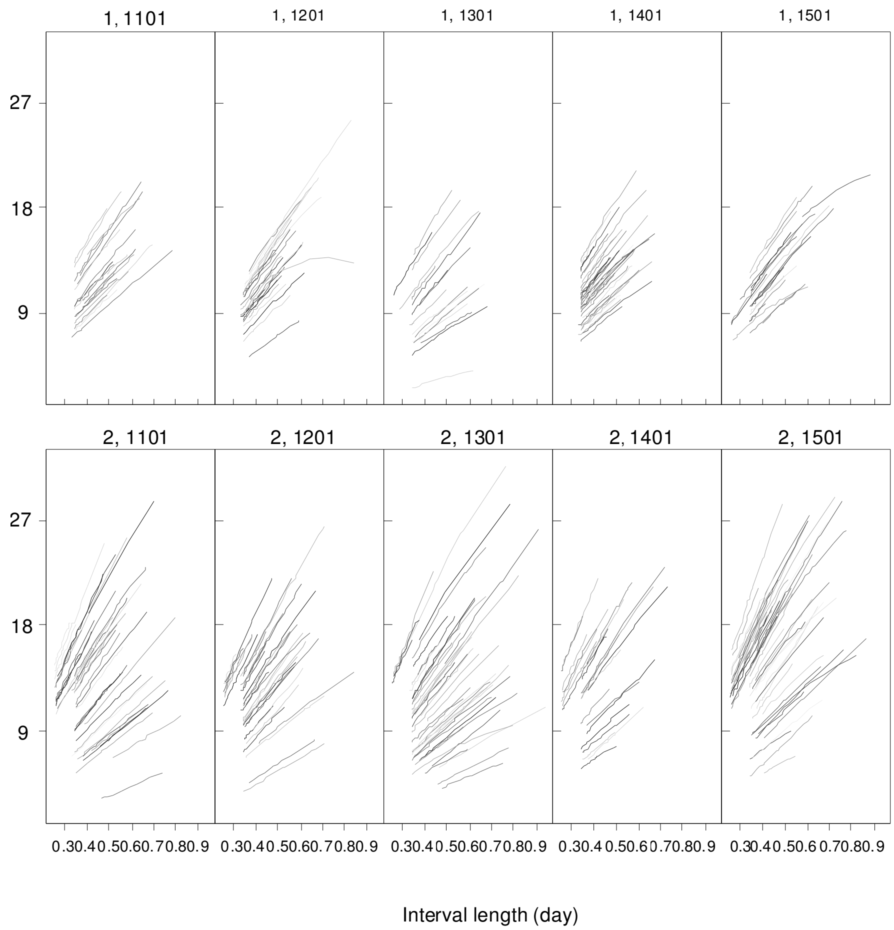

Figure 3.4 Fitted milk yield per milking vs. interval per cow for different herds (left to right). Primiparous (upper row) and multiparous (lower row).

The assumption of a zero intercept was checked by fitting model (3.1) for milk yield per milking, expanded with an intercept. The additional intercept did not statistical significantly differ from 0. Moreover, the model without an intercept produced more stable parameter estimates. Residual analysis by testing the autocorrelation between the residuals within a cow showed no significant interdependency.

3.3.2 *Duration per milking*

Table 3.4 contains the parameter estimates and standard errors for the effects of milk yield on milking duration. In the systematic part of the model the intercept differed significantly between herds: herd 1101 showed the highest intercept and herd 1401 the lowest. The linear coefficient did not differ significantly between herds. Parity had no significant effect on intercept and slope and there were no significant interactions.

Table 3.4 Parameter estimates and standard errors milking duration

Parameter		Estimate	Standard error
Systematic part of the model:			
Intercept α_0		3.34	0.17
Fixed effect of herd τ_{0k}	1101	0	-
	1201	- 0.483	0.224
	1301	- 0.098	0.207
	1401	- 0.948	0.226
	1501	- 0.506	0.222
Linear effect α_1		0.264	0.009
Random part of the model:			
Variance intercept σ^2_{A0}		4.19	0.58
Variance linear effect σ^2_{A1}		0.0322	0.0044
Residual variance σ^2_{δ}		0.444	0.010
Correlation intercept with linear effect ρ_{A01}		- 0.525	0.117

Again, variance components represent the variation in intercept and slope between individuals and residual variation. Figure 3.5 shows considerable variation between individuals which was not explained by parity and herd.

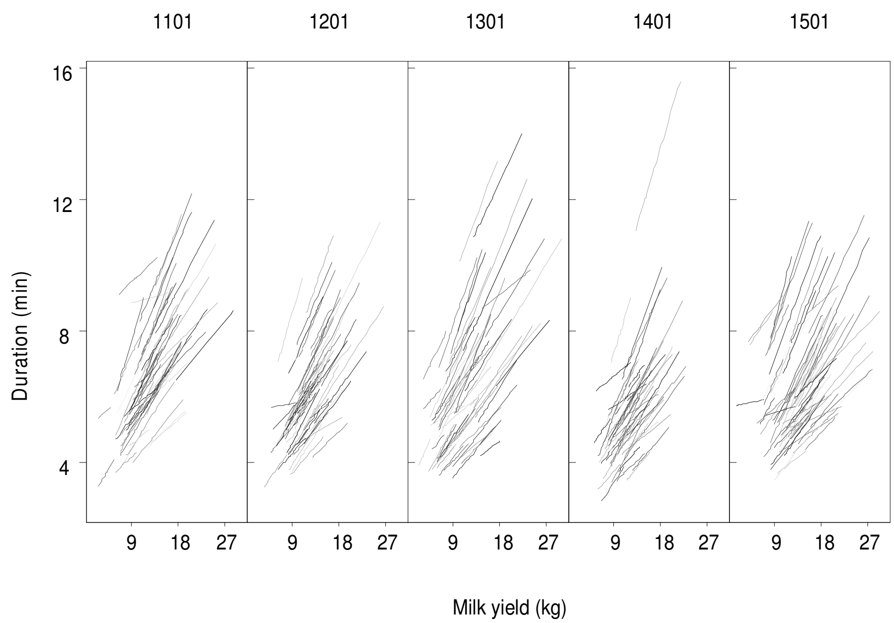

Figure 3.5 Fitted milk duration per milking vs. milk yield per cow for the different herds (left to right).

3.3.3 Optimization of the AMS capacity utilization

Individual optimal milking intervals, found by solving the nonlinear programming problem, depend on the estimated individual parameters: intercept, slope, milk production rate, interval sensitivity and the individual milk price. Table 3.5 contains results at herd level after applying individual optimal intervals in comparison with actually realized individual milking intervals.

Table 3.5 Results at herd level for actually realized individual intervals at current occupation rates (OR) compared with results achieved at optimal individual intervals

Herd:	1101	1201	1301	1401	1501	Averaged
Current OR (%)	70.3	63.0	60.1	56.5	70.7	64.2
Milking interval (day)						
Actual	0.416	0.425	0.449	0.401	0.418	0.421
Optimal	0.411	0.416	0.431	0.371	0.379	0.400
Relative change (%)	- 1.2	- 2.1	- 4.0	- 7.5	- 9.3	- 5.0
Milk yield (kg/day)						
Actual	1,960	1,835	1,595	1,774	2,249	1,883
Optimal	1,980	1,861	1,615	1,789	2,298	1,909
Relative change (%)	1.02	1.41	1.25	0.85	2.18	1.38
Milk revenues (€/day)						
Actual	530	492	430	458	582	498
Optimal	535	499	442	463	596	507
Relative change (%)	0.94	1.42	2.79	1.09	2.41	1.81

Applying individual optimal milking intervals to the studied herds resulted, in on average, 5% lower intervals than realized milking intervals in the actual situation. In other words, without increasing the OR, milking frequency increases with optimal intervals, with a better distribution of the available AMS capacity over the individual cows. Daily milk yield increased with 1.38% and daily milk revenues increased with 1.81%. The increase in milk revenues was relatively greater than the increase in daily milk yield, because the individual optimal milking intervals were aimed to maximize daily milk revenues.

Increase of daily milk yield and daily milk revenues was caused by shortening milking intervals, i.e. increase of the number of milkings. Note that this did not result in an increase in milking duration, while the OR is kept constant. Results are given in Table 3.6 where a distinction is made between the parts of the duration that are related to the milk yield (accumulated yield effect) and not related to the milk yield (accumulated intercept).

Table 3.6 Number of milkings, milking duration in terms of accumulated intercept and yield effect over herds for actually realized individual milking intervals compared with optimal individual milking intervals

	Number of milkings	**Accumulated intercept**		**Accumulated yield effect**	
Individual intervals	n	min	%[1]	min	%[1]
Actual	148	433	30	491	34
Optimal	155	425	29	499	35
Change	7	- 8	- 1	8	1

[1] 100 % = 1 day = 1,440 min.

Application of optimal individual milking intervals resulted in an increase in the total number of milkings per day at herd level of 7 milkings, but in spite of that the accumulated intercept was reduced by 8 min. (1%) in favor of the accumulated yield effect. This shows that optimizing the intervals resulted in milking cows with a low intercept more often than cows with a high intercept.

The results in Table 3.7 show that by increasing the OR it is possible to increase daily milk yield and daily milk revenues by shortening the milking interval.

Table 3.7 Herd level results for optimal individual intervals at different occupation rates (OR). The change is relative to results achieved with actually realized individual intervals

Herd:	1101	1201	1301	1401	1501	Averaged	Relative change (%)
Milking interval (day)							
OR 70%	0.413	0.339	0.332	0.250	0.386	0.334	- 20.1
OR 75%	0.365	0.300	0.297	0.222	0.337	0.295	- 29.9
OR 80%	0.325	0.267	0.267	0.199	0.297	0.264	- 37.3
OR 85%	0.292	0.241	0.243	0.180	0.265	0.238	- 43.5
Milk yield (kg/day)							
OR 70%	1,978	1,890	1,662	1,873	2,292	1,939	3.0
OR 75%	2,005	1,906	1,679	1,892	2,331	1,963	4.2
OR 80%	2,028	1,918	1,692	1,908	2,362	1,982	5.3
OR 85%	2,046	1,928	1,704	1,920	2,387	1,997	6.1
Milk revenues (€/day)							
OR 70%	534	507	447	484	594	513	3.0
OR 75%	541	511	452	489	604	519	4.2
OR 80%	548	514	456	493	612	525	5.3
OR 85%	552	516	459	497	619	529	6.1

The effect of milking interval on milk accumulation in the udder has been studied by Davis et al. (1998), whereas Bruckmaier and Hilger (2001) studied the effects on milk excretion. These studies show that short intervals have a negative effect on milk excretion and lengthening of the intervals increases the risk of milk loss. Applying the individual optimal intervals as proposed in our research will guarantee a good udder filling, thus reducing the risk of negative effects on milk excretion. Milk loss due to long intervals is part of the interval sensitivity which is accounted for in determination of the optimal intervals. In our approach both long and short intervals are avoided and this may also have positive effects on udder health.

Table 3.8 shows that increasing the OR resulted in an increase of the number of milkings and milking duration. Accordingly, idle time was reduced. The accumulated intercept increased much more than the accumulated yield effect.

Table 3.8 Number of milkings, accumulated intercept and yield effect, milking duration averaged over herds at different occupation rates (OR)

OR	**Number of milkings**	**Accumulated intercept** (a)		**Accumulated yield effect** (b)		**Milking duration** (a)+(b)	
%[1]	n	min	%[1]	min	%[1]	min	%[1]
70	185	502	35	506	35	1,008	70
75	210	568	39	512	36	1,080	75
80	235	635	44	517	36	1,152	80
85	260	703	49	521	36	1,224	85

[1] 100 % = 1 day = 1,440 min.

The duration that not depends on daily milk yield (the accumulated intercept) is a considerable part, anywhere from 30% up to almost 50%, of the total milking duration. This part consists mainly of time needed for handling. Handling time is required for cleaning the teats, teat detection and attachment of the teat cups and to a lesser extent for identification, entrance and exit of the cows. In this study we found an average intercept of 2.4 to 3.3 min. per milking per herd, which is in agreement with the handling time of 2.23 min. reported by de Koning and Ouweltjes (2000). Hogeveen and Ouweltjes (2001) reported a preparation time of approximately 1 min. up to 5 min per milking. Note that preparation time does not include the time a cow needs to exit the AMS. Cooper and Parsons (1999) reported 4.05 min. for cow movement through the AMS (excl. machine-on time), based on data from milking trials by Mottram et al. (1995), Sonck (1996) and Rossing (1997). Additionally, they used the relationship $t = 2.75 + 0.207M$ after Clough (1977) for milk-out time. So in total their estimate for handling time was 4.05 + 2.75 = 6.8 min. which is approximately twice as long as the estimated intercept in our study. In contrast, the parameter they use for inversed milk flow, 0.207 min/kg, is lower than the estimated value 0.264 min/kg found in our study. Reduction of handling time will increase

the AMS capacity (Gygax et al., 2007) and it is recommended that AMS developers pay attention to this aspect.
The counterpart of handling time in the milking duration is the milk yield related time, i.e. the yield effect. The yield effect on milking duration time corresponds with machine-on time and depends on technical aspects such as detachment level, vacuum level and milk flow dependent pulsation ratio (Ipema and Hogewerf, 2004). These technical aspects were not considered in this study. Although machine-on time was not measured in this study, the slope parameter can be used as an indication for the reciprocal of the milk flow and the calculated yield effect gives an indication for machine-on time.

In a simulation model of an AMS developed by Cooper and Parsons (1998, 1999) factors depending on the milking interval were used to correct daily milk yield. The factors after Parsons (1988) were based on quantitative studies conducted by Dodd and Griffin (1977). The correction factors are given in Table 3.9 and compared with correction factors derived from the parameter estimates presented in Table 3.3.

Table 3.9 Correction factors for daily milk yield depending on milking interval

Milking interval (day)	**Correction factor for daily milk yield**	
	After Parsons (1988)	Based on parameter estimates
1.00	0.69	0.84
0.50	1.00	1.00
0.33	1.14	1.05
0.25	1.20	1.08

Table 3.9 shows that Parsons (1988) found a much higher effect of milking interval on daily yield. In comparison with our results they predicted higher milk yields after short intervals and lower milk yields after long intervals. A possible explanation is that since the studies conducted by Dodd and Griffin (1977), milk yield per cow has increased together with an increase in the storage capacity of the udder. Cooper and Parsons (1999) found maximum profit for a single stall AMS, relative to conventional milking, for a herd of 55 cows. They predicted sharp reductions in profit with increasing herd size. They state that

the fall is caused by decrease in milk yield as a consequence of longer intervals between milkings.

In the situation at the experimental farm, AMS capacity was not limiting. However, the interval settings by the herdsman (Table 3.2) were much shorter than the actually realized intervals and also shorter than the individual optimal intervals (Table 3.5). The visiting frequency of the cows was too low and so it becomes necessary to collect and bring the cows to the AMS to achieve the desired intervals. The research farm's management strategy was to fetch cows three times per day, when the actual milking interval exceeded a fixed threshold, e.g. 12 hr. A better strategy for fetching would be to set the threshold proportional to the individual optimal milking interval to ensure that only the right cows are collected. When short milking intervals are aimed for, the cows have to be collected more frequently. To achieve an OR of 85% the milking interval should be substantially decreased to 0.238 day and this is only feasible in practice by fetching the cows more often and consequently more labor is required for collection of the cows and the time not related to milk yield is substantially increased.

Alternatively, an OR of 85% could be achieved by increasing herd size, without increasing the milking frequency. To achieve this, the herd size should increase from 60 to 80 cows, proportional to the increase in OR from 64% to 85%. Then milk yield increases proportionally to 2,535 kg/day and milk revenues to € 673 per day. So, our research suggests that it is feasible to milk much more cows with a single stall AMS then stated by Cooper and Parsons (1999). Increasing the herd size is usually not possible in the actual situation because it depends on the specific farm situation, there might be limiting conditions from land use, housing, milk quota etc.

Increase of milking frequency and increase of herd size improve the revenues from automatic milking, but which strategy is the most profitable depends on the costs of producing an extra unit of milk. These costs are not considered here, because this study is mainly focused on optimization at operational level given the herd size in the actual situation.

This study used milk production data from 1 week to quantify the variation in milking characteristics between individual cows and to gain insight into the potential benefits from improving the capacity utilization of an AMS. Milk yield and milking duration data during this one-week period were used to estimate the individual parameters, representing the actual situation for each cow at that moment during lactation. At other moments during lactation milk yield and milking duration will probably be different. As a consequence the parameter estimates for each cow should be regularly updated during lactation. This is possible following an approach based on dynamic linear models (West and Harrison, 1997). With a dynamic approach the optimal intervals are regularly updated and automatically adapted to changing herd size and herd characteristics over time.

Individual variation in milk production response to feeding has not been taken into account in this study. Feed intake and milk production were assumed to be constant during the short period of data collection. Moreover, 1 week is considered to be too short to allow for estimating the effects of feeding. Individual variation in milk production response to feeding is studied by André et al. (2009). Within a dynamic approach it is possible to estimate continuously the individual milk production response to concentrate feeding from real time process data (André et al., 2007). The optimal individual milking interval should be determined in combination with the optimal individual concentrate supply to maximize the gross margin milk revenues minus feeding costs.

3.4 Conclusions

This study showed that there is marked variation between individual cows in the effect of interval length on daily milk yield and consequently on milking duration. The efficiency of an AMS can be increased by applying individual optimal milking intervals, milk revenues increased from 498 to 507 €/day for a herd of about 60 cows, without increasing the OR. By increasing the OR from 64% to 85% a further increase in milk revenues to 529 €/day is possible. Alternatively, when an OR of 85% is obtained by increasing the herd from 60 to

80 cows, milk revenues increase to € 673 per day. For practical implementation on farm a dynamic approach is recommended where parameter estimates regarding effects of interval length on milk yield and of milk yield on milking duration are regularly updated and response of milk production to concentrate intake is also taken into account.

Acknowledgements

The authors are grateful to Edwin Bleumer for gathering the data. This project was funded by the Dutch Commodity Board for Dairy Products and the Dutch Ministry of Agriculture, Nature and Food Quality. We also thank the reviewers for their helpful comments.

3.5 References

ANDRÉ, G., W. OUWELTJES, R.L.G. ZOM, AND E.J.B. BLEUMER. 2007. Increasing economic profit of dairy production utilizing individual real time process data. In *Precision Livestock Farming '07*. (Ed. S. Cox), pp. 179-186, Wageningen Academic Publishers, Wageningen, the Netherlands.

ANDRÉ, G., P.B.M. BERENTSEN, G. VAN DUINKERKEN, B. ENGEL, AND A.G.J.M. OUDE LANSINK. 2010. Economic potential of individual variation in milk yield response to concentrate intake of dairy cows. *J. Agric. Sci*. **148**, 263–276.

AYADI, M., G. CAJA, X. SUCH, M. ROVAI, AND E. ALBANELL. 2004. Effect of different milking intervals on the composition of cisternal and alveolar milk in dairy cows. *J. Dairy Res*. **71**, 304-310.

BIJL, R., S.R. KOOISTRA, AND H. HOGEVEEN. 2007. The Profitability of Automatic Milking on Dutch Dairy Farms. *J. Dairy Sci*. **90**, 239-248.

BRUCKMAIER, R.M., AND M. HILGER. 2001. Milk ejection in dairy cows at different degrees of udder filling. *J. Dairy Res*. **68**, 369-376.

CLOUGH, P.A. 1977. Milking in cowsheds and parlours. In: *Machine Milking*. *Milking* (Eds. C.C. Thiel, F.H. Dodds). Shinfield: National Institute for Research in Dairying.

COOPER, K. AND D.J. PARSONS. 1998. A Simulation Model of an Automatic Milking System Applying Different Management Strategies. *J. Agric. Engng. Res*. **69**, 25-33.

COOPER, K. AND D.J. PARSONS. 1999. An Economic Analysis of Automatic Milking using a Simulation Model. *J. Agric. Engng. Res.* **73**, 311-321.

DAVIS, S.R., V.C. FARR, P.J.A. COPEMAN, V.R. CARRUTHERS, C.H. KNIGHT, AND K. STELWAGEN. 1998. Partitioning of milk accumulation between cisternal and alveolar compartments of the bovin udder: relationship to production loss during once day milking. *J. Dairy Res.* **65**, 1-8.

DELAMAIRE, E., AND J. GUINARD-FLAMENT. 2006. Longer Milking Intervals Alter Mammary Epithelial Permeability and the Udder's Ability to Extract Nutrients. *J. Dairy Sci.* **89**, 2007-2016.

DE KONING, C.J.A.M., AND W. OUWELTJES. 2000. Maximising the milking capacity of an automatic milking system. In *Robotic Milking*, Proc. Int. Symp. (Eds. H. Hogeveen and A. Meijering), pp. 38-46, Wageningen Pers, Wageningen, the Netherlands.

DE KONING, K., AND J. RODENBURG. 2004. Automatic milking: State of the art in Europe and North America. In *Automatic milking: A Better Understanding*. (Eds. A. Meijering, H. Hogeveen and C. J. A. M. de Koning), pp. 27-37. Wageningen Academic Publishers, Wageningen, the Netherlands.

DODD, F.H. AND T.K. GRIFFIN. Milking routines. In: *Machine Milking*. (Eds. C.C. Thiel, F.H. Dodds) Shinfield: National Institute for Research in Dairying.

FRANCE, J. AND J.H.M. THORNLEY. 1984. *Mathematical Methods in Agriculture. A quantitative approach to Problems in Agriculture and Related Sciences*. pp. 220 ff. Butterworths, London.

GENSTAT COMMITTEE. 2006. *GenStat® Release 9 Reference Manual*. Published by VSN International.

GYGAX, L., I. NEUFFER, C. KAUFMANN, R. HAUSER, AND B. WECHSLER. 2007. Comparison of Functional Aspects in Two Automatic Milkng Systems and Auto-Tandem Milking Parlors. *J. Dairy Sci.* **90**, 4265-4274.

HOGEVEEN, H., W. OUWELTJES, C.J.A.M DE KONING, AND K. STELWAGEN. 2001. Milking interval, milk production and milk flow-rate in an automatic milking system. *Livest. Prod. Sci.* **72**, 157-167.

HOGEVEEN, H. AND W. OUWELTJES. 2001. Sensors and management support in high-technology milking. *J. Anim. Sci*. **81**, 1–10.

IPEMA, A.H., AND P.H. HOGEWERF. 2004. Effects of milking machine parameters on the mean milk flow rate in a robotic milking system. In *Automatic milking: A Better Understanding*. (Eds. A. Meijering, H. Hogeveen and C. J. A. M. de Koning), pp. 450-456, Wageningen Academic Publishers, Wageningen, the Netherlands.

OUWELTJES, W. 1998. The relationship between milk yield and milking interval in dairy cows. *Livest. Prod. Sci*. **56**, 227-232.

PARSONS, D.J. 1988. An Initial Economic Assessment of Fully Automatic Milking of Dairy Cows. *J. Agric. Engng. Res*. **40**, 199-214.

ROBINSON, G.K. 1991. That BLUP is a Good Thing: The Estimation of Random Effects. *Stat. Sci*. **6**, 15-32.

ROSENTHAL, R.E. 2006. *GAM-system – A User's Guide*. GAM-system Development Corporation, Washington, DC, USA.

ROSSING, W. 1997. Freiheit oder "Weltraumfahrer"? *Zwei Melkrobotersysteme im Vergleich* [Liberty or Astronaut? A comparison of two robotic milking systems]. Die Landtechnische Zeitschrift. **10**, 82-86.

SEARLE, S.R., G. CASELLA, AND C.E. MCCULLOUGH. 1992. *Variance Components*. Wiley, New York.

SONCK, B.R., AND H.W.J. DONKERS. 1995. The milking capacity of a milking robot. J. *Agric. Engng. Res*. **62**, 25-38.

SONCK, B.R. 1996. *Labour organization on robotic milking dairy farms*. PhD Thesis, Agricultural University Wageningen, The Netherlands.

STELWAGEN, K. 2001. Effect of Milking Frequency on Mammary Function and Shape of the Lactation Curve. *J. Dairy Sci*. **84**, E204-E211.

VETHARANIAM, I., S.R. DAVIS, M. UPSDELL, E.S. KOLVER, AND A.B PLEASANTS. 2003. Modeling the Effect of Energy Status on Mammary Gland Growth and Lactation. *J. Dairy Sci*. **86**, 3148-3156.

WATHES, C.M., H.H. KRISTENSEN, J-M. AERTS, AND D. BERCKMANS. 2005. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? In *Precision Livestock Farming '05*. (Ed. S. Cox), pp. 33-47, Wageningen Academic Publishers, Wageningen, the Netherlands.

WEST, M., AND J. HARRISON. 1997. *Bayesian Forecasting and Dynamic Models*. Second Edition. Springer-Verlag, New York.

4 Adaptive models for on-line estimation of individual milk yield response to concentrate intake and milking interval length of dairy cows[5]

Summary

Automated feeding and milking of dairy cows enables application of individual cow settings for concentrate supply and milking frequency. Currently, general settings are used, based upon knowledge about energy and nutrient requirements in relation to milk production at group level. Individual settings based on the actual individual response in milk yield, has the potential for a marked increase in economic profits. In this study adaptive dynamic models for on-line estimation of milk yield response to concentrate intake and length of milking interval are evaluated. The parameters in these models may change in time and are updated through a Bayesian approach for on-line analysis of time series. The main use of dynamic models lies in its ability to determine economically optimal settings for concentrate intake and milking interval length for individual cows at any day in lactation. Three adaptive dynamic models are evaluated, a model with linear terms for concentrate intake and length of milking interval, a model that also comprises quadratic terms, and an enhanced model in order to obtain more stable parameter estimates. The linear model is only useful for forecasting milk production and the estimated parameters of the quadratic model turned out to be unstable. The parsimony of the enhanced model leads to far more stable parameter estimates. This study shows that the enhanced model is suitable for

---

[5] Paper by G. André, B. Engel, P.B.M. Berentsen, G. van Duinkerken and A.G.J.M. Oude Lansink, Journal of Agricultural Science, published on-line (2011)

control and monitoring, and therefore promises to be a valuable tool for application within precision livestock farming.

4.1 Introduction

During the last century in The Netherlands milk production per cow has almost tripled. Accordingly, the amount of concentrates yearly fed per cow has strongly increased. Furthermore, automation and robotisation changed dairy management, especially by the introduction of automatic concentrate feeders and milking systems (Bieleman, 2005 and 2008). A new management concept, emerging in the last decades, is Precision Livestock Farming (PLF). The objective of PLF is to optimize livestock production, by on-line monitoring and control of the production process, utilizing the technical possibilities of automation and robotisation (Cox, 2002). PLF is an embryonic technology with great promise, but one that requires considerable research and development before uptake (Wathes et al., 2008). Wathes et al. state that the new technology to be developed should consist of integrated monitoring and control systems for biological processes. Monitoring and control systems are already successfully implemented for industrial processes that most-times can be effectively controlled, because the objects are inanimate and predictable and the targets can be precisely defined and set independently of time and weather. By contrast, biological processes are more difficult to control because they are inherently more variable due to differences between individuals, and dynamic changes through age, reproduction and environment. Moreover, livestock producers are only prepared to adopt new technology when there is sound economic justification to do so (Frost et al., 1997).

Within dairy farming automated concentrate feeders and milking systems are increasingly used, enabling the use of individual daily setting of concentrate intake and milking interval. Although current settings are based upon knowledge about energy and nutrient requirements in relation to milk production, they do not account for variation between and within individual dairy cows. André et al. (2010a,b) found considerable variation in milk yield in response to concentrate intake and milking interval length among individual dairy cows. They concluded that individual variation in response can be exploited to improve economic profitability of dairy farming by optimization of individual feeding, enhancing utilisation of automatic milking systems. They recommended an individual dynamic approach to utilize the individual variation in response within management decision support systems for dairy farming.

Milk yield response to concentrate intake depends on stage of lactation. Woods et al. (2003) developed models that predict the response in milk yield to metabolisable energy intake with reasonable precision in vivo situations. However, there are various physiological factors that complicate attempts to model milk yield response to changes in (net) energy and/or nutrient intake during lactation. Ingvartsen and Andersen (2000) reviewed and summarized changes in hormones and tissues during pregnancy and lactation that affect the response. Van Knegsel et al. (2005) analyzed milk yield response on energy intake, especially in early lactation. During lactation net energy partitioning shifts away from milk yield towards retention of net energy in body reserves (Van Knegsel et al., 2007a,b). Garnsworthy et al. (2008a,b) and Ingvartsen and Andersen, (2000) studied the influence of pregnancy on energy partitioning. Because of these physiological factors, in general, milk yield response to concentrate intake is highest in early lactation and decreases towards the end of lactation. In addition there are the unpredictable causes for changes in the actual response in milk yield due to e.g. mastitis or lameness.

Within a dynamic approach, historical outcomes of the production process are analyzed in order to estimate the actual response on the control variables. Time series analysis of daily milk yield and on-line recursive estimation during the lactation has been applied in several studies. A Bayesian approach was applied by Goodall and Sprevak (1985) to estimate the parameters of the Wood-curve (Wood, 1967) early in lactation. DeLuyker et al. (1990) applied time series analysis to provide short term forecasts for daily milk yield. Lark et al. (1999) applied times series analysis for monitoring milk yield for detection of a disease (e.g. ketosis). De Mol et al. (1999) combined time series analysis of daily milk yield with a Kalman filter for detection of oestrus and diseases, also considering milk temperature and electrical conductivity as well. Bebber et al. (1999) introduced a recursive mixed model for monitoring milk yield at group and individual level. The focus of the models used in these studies was either on long-term forecasts of milk yield, e.g. for early estimation of the whole lactation curve, or on short-term forecasts, for monitoring and detection purposes.

However, the models used in these studies did not estimate actual individual response in milk yield on concentrate intake and interval length. Such information we consider vital to obtain optimal individual settings for concentrate supply and milking frequency on a daily base.

In this study, time series of daily milk yield of individual cows are analysed following a Bayesian approach, using dynamic models proposed by West and Harrison (1997). A dynamic model consists of an observation and a system equation. The observation equation is a linear regression model describing the relation between milk yield and concentrate intake and milking interval length. However, in contrast to ordinary regression models, the parameters in the observation equation are time dependent. Thus dynamic models have the advantage of being more flexible in accounting for changes in response during lactation.

The objective of this study is the development of an adaptive dynamic model for on-line estimation of the actual response in milk yield to concentrate intake and milking interval length, in order to determine economically optimal settings for concentrate supply and milking frequency.

First, two dynamic models will be presented that can be considered as 1^{st} and 2^{nd} order Taylor approximations (linear and quadratic approximations) of a more intricate non-linear model describing the underlying mechanistic and physiologic concepts of milk production such as the model presented by France and Thornley (1984). A third model is derived by applying constraints upon the parameters of the quadratic model.

Second, the predicted responses of these three adaptive models will be evaluated, with particular attention for the quality of the parameter estimates, because this relates to the choice of proper optimal settings for concentrate supply and milking interval. Third, the usefulness of the models for monitoring of daily milk production is evaluated.

4.2 Materials and methods

4.2.1 Modelling milk yield response to concentrate intake and milking interval

Milk yield per milking depends on the time between the starts of two consecutive milkings, i.e. upon the interval length I (in days). France and Thornley (1984) described the process of milk secretion using a mechanistic model in which at the start of a milking interval ($I = 0$) the rate of milk secretion (kg/day) by the alveoli in the udder is maximal.

The milk secretion rate approaches zero when the amount of milk M_m (kg) in the udder approaches the maximum udder capacity $M_{\max}$ (kg). The milk secretion rate depends on the number of active alveoli and the energy status of the cow (Vetharaniam et al., 2003). Therefore, the maximum milk secretion rate can be regarded as a function of feed intake. Feed intake consists of roughage and concentrates. Roughage intake, usually unknown, defines the intercept, and the response on concentrate intake C (kg/day) will be curvilinear, following the law of diminishing returns (Broster and Thomas, 1981). Milk yield per milking is obtained by integration:

$$M_m = M_{\max}\left(1 - e^{-\frac{f(C)I}{M_{\max}}}\right) \tag{4.1}$$

Because non-linear system equations are difficult to handle, model (4.1) is linearized by Taylor expansion around $I = i_0$ and $C = c_0$, the 2nd order approximation being $M_m \approx \alpha_0 + \alpha_1 C + \alpha_2 I + \alpha_3 C^2 + \alpha_4 I^2 + \alpha_5 CI$. Note that the 1st order approximation consists of the first three terms. Imposing the constraint that $M_m = 0$ at $I = 0$, implies that $\alpha_0 = \alpha_1 = \alpha_3 = 0$. But then the quadratic effect of concentrate would be lost and for that reason André et al. (2007) added a 3rd order term $\alpha_6 C^2 I$ to the constrained model.

The realised milk yield per day M_d (kg/day) is achieved by accumulation of the milk yields per milking over the number N of milkings per day. The following response models for milk yield per day will be considered:

$$M_d \approx \alpha_0 N + \alpha_1 NC + \alpha_2 \sum_N I \tag{4.2}$$

$$M_d \approx \alpha_0 N + \alpha_1 NC + \alpha_2 \sum_N I + \alpha_3 NC^2 + \alpha_4 \sum_N I^2 + \alpha_5 C \sum_N I \tag{4.3}$$

$$M_d \approx \alpha_2 \sum_N I + \alpha_4 \sum_N I^2 + \alpha_5 C \sum_N I + \alpha_6 C^2 \sum_N I \tag{4.4}$$

The 1st and 2nd order Taylor approximations, in equations (4.2) and (4.3), will be referred to as model T1 and T2 respectively. The enhanced model in equation (4.4) will be referred as model EM. Usually, when all the milkings on a day are successful, the sum of the interval lengths $\sum_N I \approx 1$ day, and therefore α_2 is regarded as the intercept and the other parameters as regression coefficients for the effects of concentrate intake and milking interval length on milk yield.

In models T1, T2 and EM, only the response to one diet component, i.e. compound concentrate, is estimated. The models can be easily extended to allow for more diet components, e.g. roughage or an extra concentrate component. However, it should be taken into account that an increase in diet components in the model, and thereby in the number of model parameters, will also increase the risks of multicollinearity. This is especially the case when applying additive models like quadratic response surfaces, where each extra term results in at least two extra parameters.

4.2.2 Dynamic model and on-line time series analysis

So far, the linear models T1, T2 and EM are representing the situation at some moment during the lactation without any dynamics yet. We make T1, T2 and EM dynamic, by allowing their parameters to be time-dependent. This involves an observation equation and a system equation. The observation equation describes the relation between milk yield and concentrate intake and milking interval length as in equations (4.2), (4.3) and (4.4), but with time dependent parameters ($\alpha_{\cdot t}$ instead of $\alpha_{\cdot}$), and an added random error term with an associated observational variance. The system equation describes the dynamic change of the parameters. In our research, we focus upon short-term forecasting. Therefore, the coefficients are assumed to be locally constant: current coefficients equal coefficients of the day before plus independent random error terms (a random walk) with an associated system variance. In appendix I technical details are provided, following Harrison and West (1997).

The time series of individual accumulated daily milk yields is analysed on-line, following a Bayesian approach. The philosophy of Bayesian statistics (Gelman et al., 1995) encompasses the idea that information (in research) is constantly updated (from one experiment to another). This is reflected by the use of a prior distribution, that summarizes current knowledge, based on observations from the past. When new data are collected, the information in the data is combined with the information in the prior, leading to a new distribution: the posterior distribution. The posterior is an up to date summary of the current and past information. The posterior will become the new prior in any subsequent calculations, when yet new data are collected. The analysis starts with an initial prior distribution for the parameters. This process of prior, plus data, becoming the posterior, where the posterior is the new prior for subsequent calculations, makes Bayesian statistics eminently suitable for monitoring purposes. So, within time series analysis, Bayesian statistics are applied as a way of sequential learning.

Discount factors allow for additional uncertainty when the posterior information from the last time point evolves into prior information for the next time point: basically by making the new prior somewhat wider than the last posterior. This way the system is able to discount information from the past, and to adapt to the present situation. A high discount factor (close to 1) implies a slow decay of information, such that the on-line parameter estimates are based on a long series of observations from the past and by consequence the dynamic change of the parameters (system variance) is low. A low discount factor (close to 0) would imply the opposite where almost nothing from the past is retained. Harrison and West (1997) recommend to use values between 0.8 and 1.0 for the discount factors, with the value for the regression part of the model being somewhat higher than for the intercept. According to this guideline, in the present study values of 0.95 and 0.975 were used for the intercept and the regression parameters, respectively. The observation variance is estimated in an adaptive way from the forecast errors with a discount factor for variance learning of 0.9. More details about the dynamic system and the use of discount factors may be found in Harrison and West (1997).

4.2.3 Monitoring followed by automatic intervention

The discrepancy between forecast and observation is judged by the Bayes' factor, expressing the likelihood that the observation fits into the actual routinely used model relative to an alternative and exceptional outlier model with a 3 times higher observation variance. When the Bayes' factor is lower than 0.15, the observation is classified as an potential outlier. Additionally, a cumulative Bayes' factor and a run length are calculated, to detect deteriorations in the series that are more gradually introduced. When the cumulative Bayes' factor is lower than 0.15 or the run length is higher than 3 a signal for deterioration is given. Potential outliers are discarded when parameter estimates are updated. After detection of a potential outlier or after a signal for deterioration, automatic intervention is carried out by applying once-only exceptional discount factors. The exceptional discount factors are lower than the routinely used discounts factors, resp. 0.8 for intercept, 0.9 for regression parameters and 0.8 for variance learning, allowing the system to adapt faster to possible changes in the process.

4.2.4 Assessment of model adequacy and retrospective analysis

Model adequacy, in terms of goodness of fit of the models, is evaluated using the standardized forecast errors and calculation of the root mean squared error, the log likelihood and the autocorrelation between successive forecast errors. The forecast error is the difference between the observation and the forecast and is standardized by dividing the forecast error by the square root of the forecast variance. The goodness of fit measures mainly relate to the forecast performance of the models. However, the quality of the on-line parameter estimates needs careful scrutiny as well, because these are used to calculate optimal settings of concentrate supply and milking frequency in the actual situation. The on-line parameter estimates, based on observations in the past only, are compared with retrospective parameter estimates. The retrospective parameter estimates are based on information from the whole series and can be used as reference for the on-line estimates. For details about on-line and retrospective estimation of the parameters we refer to West and Harrison (1997).

Potential problems due to multicollinearity, like inflated variances of and/or high correlation between parameter estimates, are assessed by calculation of the condition number of the correlation matrix of the on-line parameters estimates (Montgomery and Peck, 1982). The condition number is always greater than 1 and a high condition greater than 30 is considered evidence for inflated variance and/or high correlation.

The appropriateness of the model for monitoring is also assessed by judgment of the forecast errors. Deviating forecast errors are classified as potential outlier or yield a signal, as explained before, the other errors are classified as normal. Results of this classification are discussed, in order to assess the appropriateness for an alert system to the farmer.

4.2.5 Data

The data set consists of time series of 15 cows of 238 to 310 daily observations of daily accumulated milk yield, milking interval length and concentrate intake. Daily concentrate intake is calculated as the moving average of the intakes of the current day and the two days before. A moving average is used to reduce day to day variation in intake and to account for a delay in response in milk yield. The 15 cows were selected out of a herd of 66 cows because these cows realized a lactation length of more than 200 days from calving. Summarizing results over the whole time series will be given for the 15 selected cows that calved in the period February to April 2006. To clarify details of the analysis, daily results will be given for one random selected cow. The time series for this cow starts at day 22 and ends at day 260 after calving. In total, there are 238 observations, because one observation is missing at day 170. Milking frequency was on average 3.26 milkings per day (s.d. 0.80). Daily concentrate intake (kg/day) for this cow during the lactation is displayed in figure 4.1.

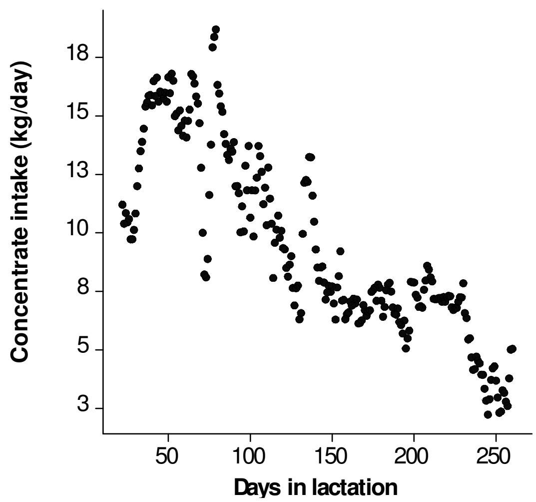

Figure 4.1 Daily concentrate intake (kg/day) during lactation (DIM) for the randomly selected cow.

4.2.6 Farm situation: feeding and milking

Data used in this study were collected by André et al. (2007) during the development and testing of a prototype for dynamic feeding and milking on a research farm in The Netherlands. The research farm was equipped with a robotic milking system and a robotic feeding system for individual feeding of roughage-concentrate mixtures and an automatic concentrate feeder. On average, this farm had 66 Holstein Frisian cows in milk, with an average milk yield of 29.8 kg per day and an average milking frequency of 2.5 times per day. The cows were milked with a single unit Lely Astronaut® automatic milking system (AMS) and remain indoors year round. Individual milking start time, milking duration and milk yield were recorded at each milking. The AMS was equipped with manufacturer software (T4C management system, Lely, Rotterdam, The Netherlands) to determine whether cows visiting the milking unit should be milked or not. In this software, production level, days in lactation and parity were the main criteria to determine preferred settings for milking permit. Fixed interval thresholds were set for fetching; three times per day cows with prolonged milking intervals were fetched.

Cows were individually fed with roughage-concentrates mixtures using an Atlantis® robotic feeder (Lely, Rotterdam, The Netherlands). The diet consisted of maize silage, grass silage and soy bean meal, supplemented with commercial compound concentrates. Between 10 days prepartum and 90 days postpartum the ratio between maize silage, grass silage and soy bean meal was 13 : 4 : 3 on a dry matter basis. Beyond 90 days in milk (DIM), the proportions of maize silage and soy bean meal in the ration were gradually reduced to zero in the last trimester of the lactation, depending on the development of body condition. The cows were given unrestricted access to the robotic feeder, so the intake of concentrates-roughage mixture was ad lib. Feed intake was recorded individually at each meal. Most of the concentrates were fed individually in the AMS and automatic concentrate feeder, so the mixtures contained only small amounts of concentrates.

4.3 Results and discussion

First, the forecasting performance of the models T1, T2 and EM will be evaluated. The models describe daily milk yield as a two-dimensional response surface on concentrate intake and milking interval length. The estimated response parameters are input for a control algorithm that calculates the daily individual optimal settings for concentrate supply and milking interval. Next, the quality of the estimated response parameters will be evaluated by evaluation of the predicted responses. Finally, detection of outliers and other deteriorations that can be used for monitoring will be evaluated.

4.3.1 Evaluating the forecasting performance

For models T1, T2 and EM, observations and forecasts with associated 90% probability intervals are given in figure 4.2.

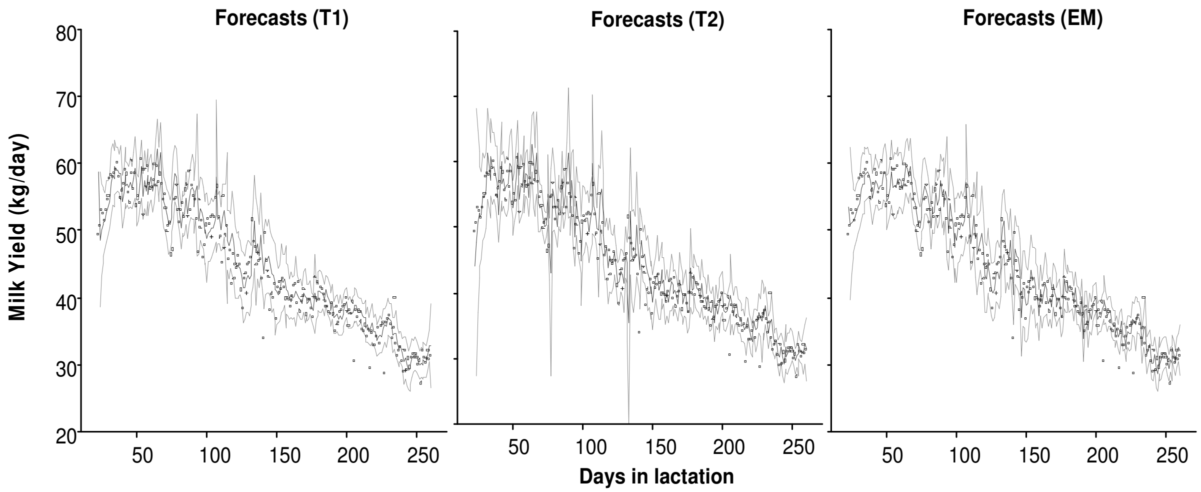

Figure 4.2 Milk yield (kg/day) during lactation (DIM) for model T1, T2 and EM. Observations (points), forecasts (centre line) and 90% probability interval (upper and lower line), for the randomly selected cow.

The graphs show that most of the observations lie within the 90% probability interval for all models. All models provide reasonable forecasts during the lactation, but the forecasts of model T2 show more variation from day to day than the forecasts in model T1 and EM. Incidentally there are big changes in level of the forecasts of model T2, but also the probability interval of the forecasts is occasionally substantially increased. This suggests that model T2 adapts too fast.

Standardized forecast errors are displayed in figure 4.3 and normal errors, potential outliers and signals for deterioration are indicated.

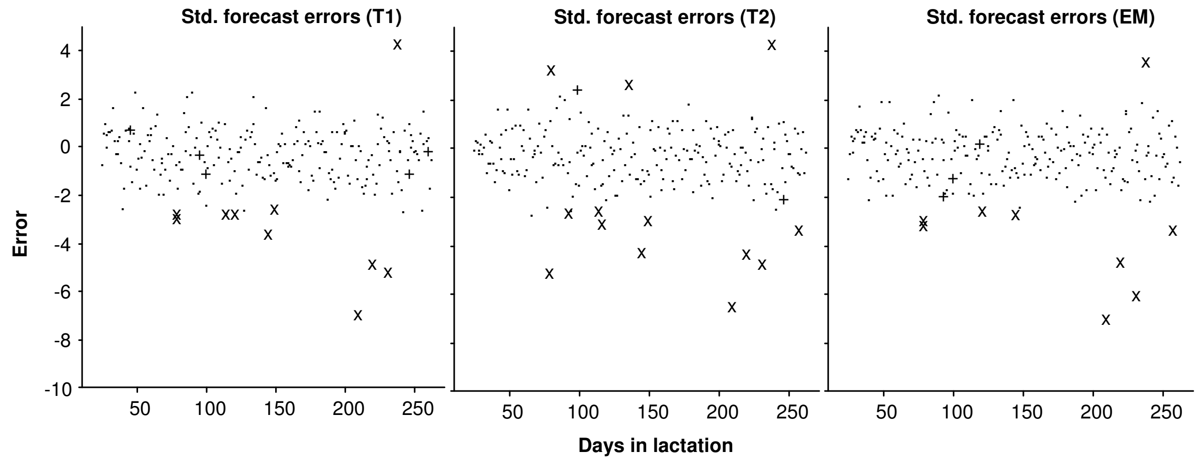

Figure 4.3 Standardized forecast errors versus days in milk for model T1, T2 and EM. Normal error (.), potential outlier (x) and signal for deterioration (+).

The majority of the normal errors lies between ± 2 and there are no trends indicating lack of fit. Most errors deviating more than 2 times are classified as potential outliers. Note that there are relatively more negative outliers, these are caused by interrupted and incomplete milkings.

In table 4.1 characteristics and statistics for the goodness of fit are given for the different models.

Table 4.1 Average goodness of fit statistics for the different models based on results of 15 cows. The range over the 15 cows is given in parentheses

	Model T1	**Model T2**	**Enhanced model**
potential outliers (%)	8.7	7.1	5.8
	(4.2 ; 14.1)	(3.6 ; 11.6)	(3.7 ; 10.2)
signals (%)	2.0	1.8	1.5
	(1.1 ; 3.0)	(0.8 ; 3.7)	(0.6 ; 2.2)
outliers and signals (%)	10.7	8.9	7.3
	(6.7 ; 15.1)	(4.7 ; 12.7)	(5.2 ; 11.3)
root mean squared error	2.045	2.308	2.089
	(1.567 ; 3.014)	(1.685 ; 3.220)	(1.673 ; 2.779)
log likelihood	-273.7	-359.2	-330.5
	(-387.4 ; -200.0)	(-578.7 ; -242.5)	(-586.9 ; -217.5)
autocorrelation	0.085	-0.160	-0.078
	(-0.057 ; 0.397)	(-0.327 ; 0.049)	(-0.227 ; 0.185)

The observations are classified as potential outlier or signal for deterioration based on the forecast errors. Model EM shows a lower percentage of deviating observations than model T1 and T2. The root mean squared error of model T2 is higher than the root mean squared error of models T1 and EM. Model T1 shows the highest log likelihood and model T2 the lowest. The lowest log likelihood and highest root mean squared error for model T2 indicate that model T2 fits worse than model T1 and EM. The autocorrelation of successive forecast errors is low for all models. The negative correlation of model T2 and EM suggests that these models adapt too fast. On the other hand it appears that model T1 adapts too slow.

In figure 4.4 the estimated observation variance during lactation is displayed for the randomly selected cow. Results from model T1 and EM show that the observation variance during the middle part of the lactation is higher than in begin and end of the lactation. This suggests that the observation variance depends on production level.

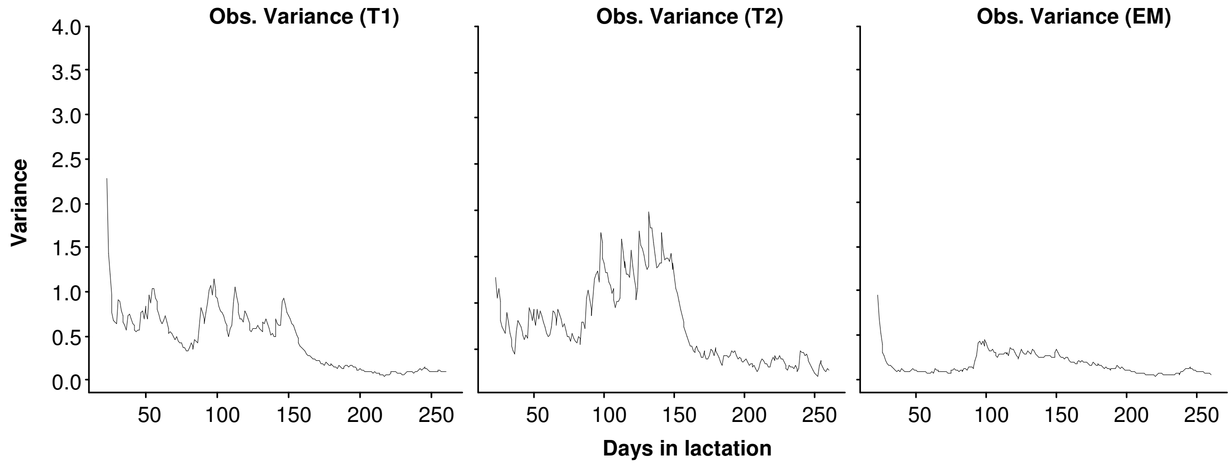

Figure 4.4 Estimated observation variance during lactation (DIM) for models T1, T2 and EM, for the randomly selected cow.

In model T1, the estimated observation variance is higher and in model T2 lower than in model EM. In other words, in model T1 and EM a relatively greater part of the random variation is attributed to the observation variance than to the system variance of the model parameters. This relates to the stochastic change in the parameters and the rate of adaptation of the models, model T1 and EM are adapting slower than model T2.

4.3.2 Evaluation of the predicted responses

Parameter α_0 in model T1 and T2, represents the linear effect of the number of milkings per day on accumulated daily milk yield, but during almost the entire lactation the estimates of this parameter are not significantly different from zero. Parameter α_1 in model T1 and T2 represents the linear effect of concentrate intake in relation to the number of milkings and this effect is positive and increasing during lactation. As mentioned before, parameter α_2 in models T1, T2 and EM, practically is an intercept. The development of the on-line and retrospective parameter estimates of α_2 during lactation, is illustrated in parallel in figure 4.5 for the randomly selected cow. The retrospective estimates are based on information of the whole series, observations from the past as well from the future, while on-line parameter estimates incorporate only information from past observations.

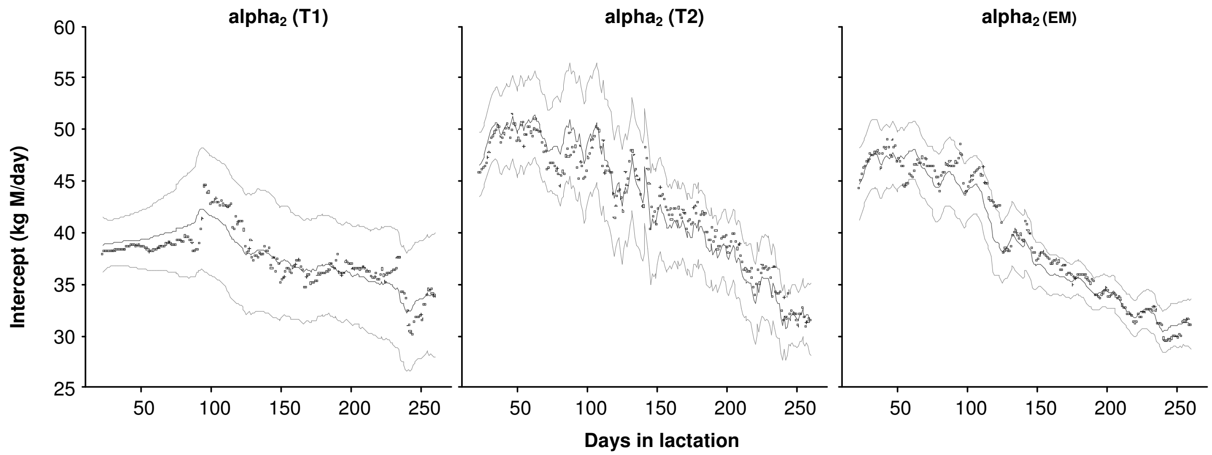

Figure 4.5 Development of the estimated intercept during lactation (DIM), parameter α_2 in models T1, T2 and EM, for the randomly selected cow. On-line (points), retrospective (centre line) and 90% confidence interval of the retrospective parameter estimates (lower and upper lines).

Figure 4.5 reflects the lactation curve, although the typical shape of a lactation curve is less apparent for model T2 where estimates tends to be less precise.

Parameter α_3 representing the quadratic effect of concentrate intake in relation to the number of milkings in model T2, is significant and negative in the second part of the lactation. Parameter α_4, representing the quadratic effect of interval length on accumulated daily milk yield in model T2 and EM, is poorly estimated in model T2. Parameter α_5, representing the linear effect of concentrate intake in relation to accumulated interval length in model T2 and EM, is mostly insignificant in model T2. Parameter α_6, representing the quadratic effect of concentrate intake in relation to accumulated interval length in model EM, is negative during almost the entire lactation. This implies convex curvature, which agrees with the law of diminishing returns. However, to the end of the lactation, the curvature diminishes and its precision decreases.

The effects of interval length and concentrate intake on daily milk yield are partitioned over different terms in model T1 and T2, consequently the parameters are difficult to interpret or to compare with the parameters of model EM. By contrast, the parameters α_4, α_5 and α_6 of model EM can be interpreted as the interval sensitivity, and the linear and quadratic effect of concentrate intake, respectively. The development of these parameters is shown in figure 4.6.

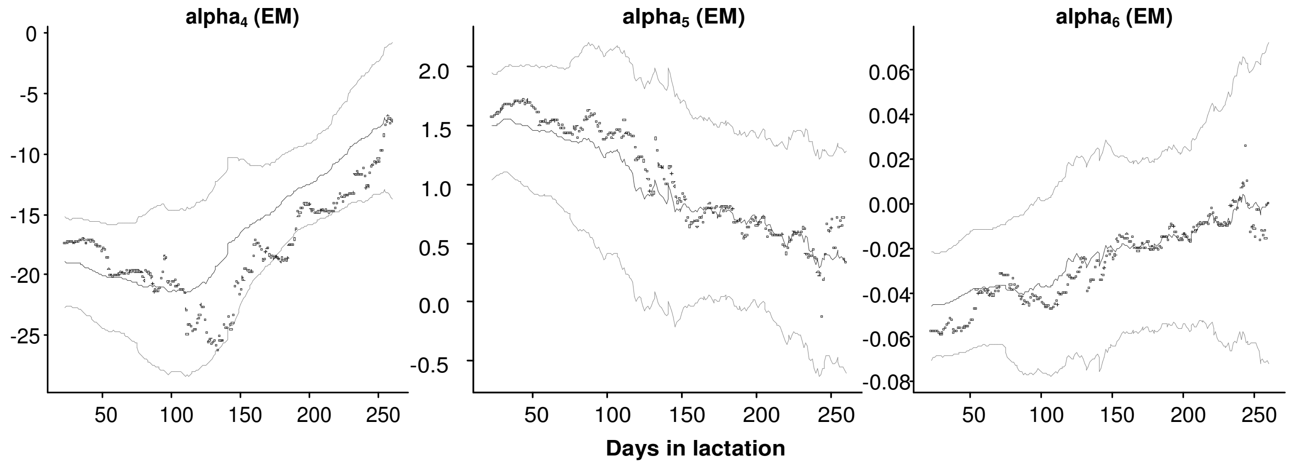

Figure 4.6 Development of parameter estimates α_4, α_5 and α_6 during lactation (DIM) in model EM, for the randomly selected cow. On-line (points), retrospective (centre line) and 90% confidence interval of the retrospective parameter estimates (lower and upper lines).

Some of the parameters, especially in model T2, show relatively a low precision. Differences between the on-line and retrospective estimates occur in model T1: parameter α_1 ; in model T2: parameters $\alpha_{0,1,4}$ and in model EM: parameter α_4 . Using the retrospective estimates as reference, because they are based on information from the whole series, a great difference with the on-line estimates suggests bias in the on-line parameter estimates.
The quality of the parameter estimates can also be assessed from their variance covariance matrix. A low quality, caused by a high variance and/or correlation, is reflected by a high condition number (Montgomery and Peck, 1982). For the different models the condition numbers of the correlation matrix on day 50, 100, 150, 200 and 250 in lactation are given in table 4.2.

Table 4.2 Averaged condition numbers of the correlation matrix of the parameter estimates for models T1, T2 and EM, including the range for the 15 cows in parenthesis.

Days in milk	Model T1	Model T2	Enhanced model
50	74	809	142
	(22 ; 106)	(358 ; 2126)	(69 ; 275)
100	102	1034	267
	(53 ; 163)	(189 ; 3259)	(114 ; 712)
150	71	1317	301
	(21 ; 141)	(108 ; 3353)	(37 ; 832)
200	63	1823	408
	(32 ; 111)	(338 ; 5126)	(82 ; 1115)
250	83	3951	858
	(29 ; 179)	(955 ; 19080)	(55 ; 3681)

The condition numbers increase during lactation. The lowest values are found for model T1. For model T2, condition numbers are extremely high. Hence, particularly in model T2, the parameter estimates are strongly correlated. This multicollinearity is due to relationships between the regression variables in the model. In this dataset regression variables are the realized concentrate intakes and milking intervals that depend on the behaviour of a cow in the on-farm situation. Settings for concentrate supply and interval length are not controlled as in experimental testing following an experimental design that pursues orthogonality. In a practical setting, multicollinearity may arise naturally from the nature of non-experimental data. Moreover, in the practical situation, settings are only moderately changed to avoid negative consequences for the cows' performance, thereby complicating the estimation of the response on concentrate intake and milking interval. These aspects together not only hamper the estimation of the parameters but also complicate the interpretation on the basis of estimated parameter values. Multicollinearity can be dealt with in a sensible way by changing to a more sparse adaptive model as is achieved with model EM relative to model T2. Model T1 has the smallest number of parameters and lowest condition numbers, but provides no information about the curvature of the response.

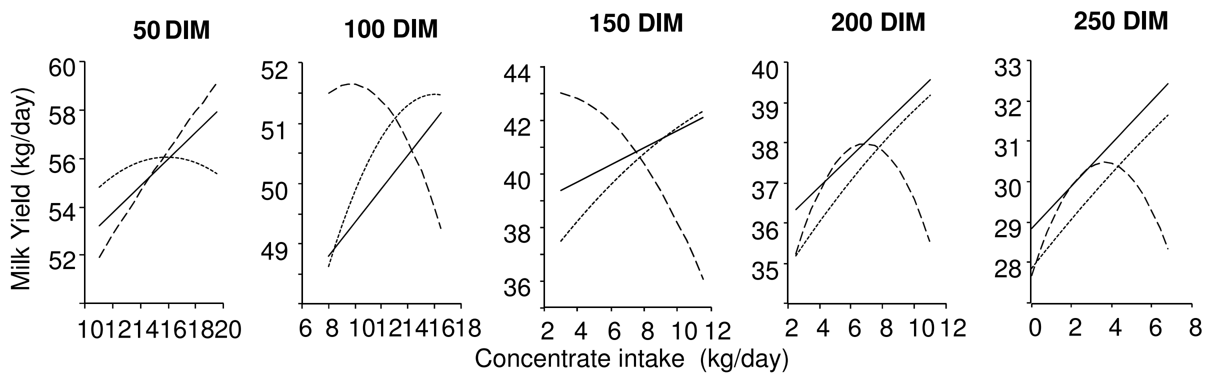

Figure 4.7 Estimated response curve of daily milk yield (kg/day, Y-axes) for one cow milked 2.85 times per day on concentrate intake (kg, X-axes) at 50,100, 150, 200 and 250 DIM for model T1 (solid line), T2 (dashed line) and EM (dotted line).

In figure 4.7, the predicted response in milk yield on concentrate is given for the different models at 50, 100, 150, 200 and 250 days in lactation. In early lactation, concentrate supply was directed to achieve maximum milk yield per day. The predicted response from model EM at 50 days in lactation shows that the maximum milk yield is reached around 15 kg concentrate per day, but model T1 and T2 show a higher response. Later on in lactation, concentrate supply was lowered towards an economic optimum where the marginal milk returns equals the marginal costs of concentrate, i.e. $dM/dC = 0.5$ according to a milk price of 0.30 €/kg and a concentrate price of 0.15 €/kg. From figure 4.7, it can be seen that the slope, that is the marginal response to concentrate intake based on model EM is about 0.50 kg milk per kg concentrates at days 150, 200 and 250 in lactation. At day 100, the marginal response is somewhere between the economic optimum and the maximum milk yield.

Because the milk yield response on concentrate intake follows the law of diminishing returns, convex curves are expected for model T2 and EM. Hence, the parameters α_3 in model T2 and α_6 in model EM should be negative. However, α_3 in model T2 is positive around 50 days in milk and α_6 in model EM is positive around 250 days in milk. So, the response curve is concave and an optimum for concentrate supply is not defined and an advice for increase or decrease of supply must be based on the first derivative of the estimated response curve. Note that this also applies to model T1 where only the linear effect is estimated.

The predicted responses based on model T1 and EM correspond well and are in agreement with the expectation that the response decreases during lactation. However, the predicted response by model T2 is clearly different and not in agreement with the expectations according to stage of lactation. During the top of the lactation, from 100 to 150 DIM the response is mainly negative and at the end of the lactation the curvature seems to be severely overestimated.

In figure 4.8 the predicted milk yield response on number of milkings at 50, 100, 150, 200 and 250 DIM is displayed for the different models. Model T1 and T2 predict a higher response at 50 DIM and a lower response later on in lactation than model EM. The predicted curvature in response in model EM is more pronounced than in models T1 and T2 and can be explained by the constraints in model EM.

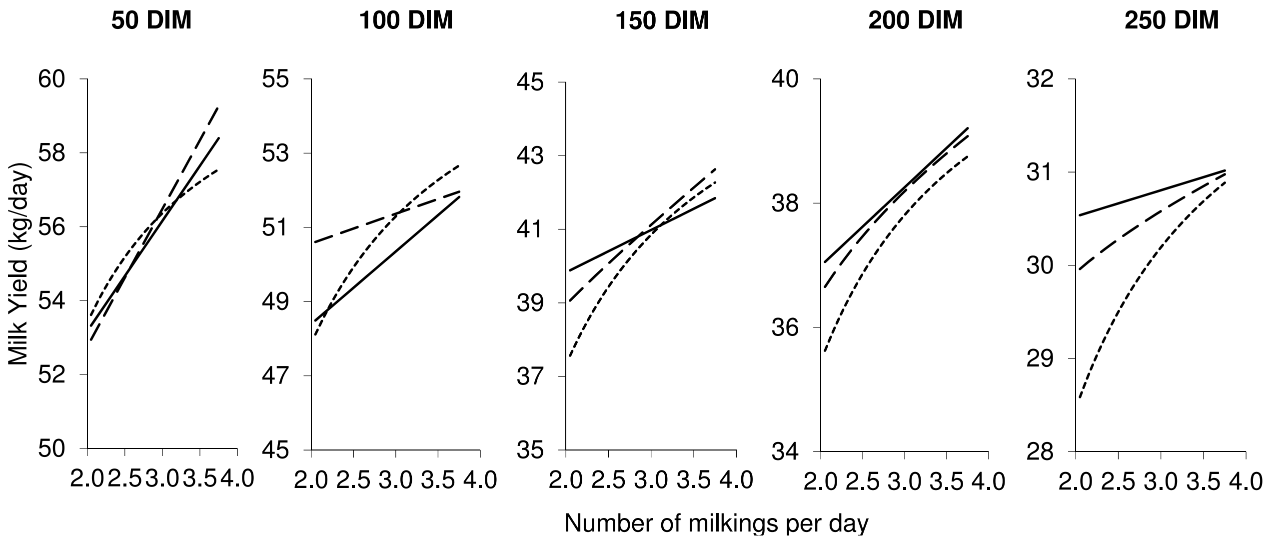

Figure 4.8 Estimated response curve of daily milk yield (kg/day, Y-axes) on number of milkings per day (X-axes) at 50,100, 150, 200 and 250 DIM for model T1 (solid line), T2 (dashed line) and EM (dotted line).

4.3.3 *Usefulness for control and monitoring*

From the foregoing section it is seen that model EM provides reasonable results, while model T2 shows poorer results. Model T1, obviously, lacks information about the curvature of the response. Here, we discuss results of model EM for the 15 cows to illustrate the usefulness of model EM for control and monitoring. Three cows were primiparous and the other 12 cows were multiparous. In table 4.3 the parameter estimates for model EM are presented at 100 and 200 DIM to show the variation between individual cows.

Table 4.3 Parameter estimates of model EM for 15 cows at 100 and 200 DIM. Standard errors in parentheses are given for the first primi- and multiparous cow

	100 DIM				**200 DIM**			
Parameter	α_2	α_4	α_5	α_6	α_2	α_4	α_5	α_6
Cow								
<u>*Primiparous*</u>								
1	43.0	-21.6	0.75	-0.046	33.8	-14.9	0.04	0.025
	(3.5)	(3.3)	(0.87)	(0.060)	(2.2)	(2.3)	(0.95)	(0.095)
2	33.8	-16.6	0.68	-0.030	26.2	-6.2	-0.11	0.045
3	29.8	-22.4	1.12	-0.048	20.1	-2.8	0.25	0.006
<u>*Multiparous*</u>								
4	49.5	-24.1	1.11	-0.037	31.8	-6.5	0.28	0.01
	(3.1)	(2.7)	(0.57)	(0.028)	(2.4)	(2.0)	(0.58)	(0.044)
5	46.5	-16.7	1.50	-0.061	37.1	-21.7	0.64	-0.031
6	43.2	-17.3	1.38	-0.069	30.3	-6.4	0.59	-0.026
7	46. 7	-22.1	1.72	-0.038	40.8	-14.8	1.10	-0.044
8	47.3	-20.6	1.43	-0.045	38.7	-14.0	0.62	-0.012
9	45.4	-19.6	1.36	-0.054	38.2	-26.2	-0.33	0.034
10	43.8	-30.1	1.96	-0.062	35. 8	-28.8	0.98	-0.028
11	42.0	-18.8	1.49	-0.050	32.2	-14.6	0.26	-0.005
12	37.4	-17.4	1.09	-0.041	32.2	-16.2	0.49	-0.021
13	39.9	-20.6	1.08	-0.052	30.0	-10.3	0.93	-0.022
14	43.7	-24.2	1.38	-0.063	35.1	-19.8	0.60	-0.004
15	44.6	-16.4	1.11	-0.045	30.7	-6.3	0.21	-0.019

The primary aim is to control the milk production process by providing actual parameter estimates of the milk yield response as a basis for determination of daily settings for concentrate supply and milking interval length during lactation. The settings chosen, are economically optimal settings that account for the actual milk and concentrate prices. Also milking duration is taken into account to ensure that the total milking time fits within the restricted capacity of the AMS. The method to calculate the preferred settings is described in Andre et al. (2010a,b). The preferred settings overcome several disadvantages of currently used standard guidelines for concentrate allocation and milking frequency. Currently used standard guidelines are based on models that predict the performance of dairy cows (eg. Thomas, 2004, Zom et al., 2002), using general relationships from the population the individual belongs to. Individual variation in milk yield response on concentrate intake and milking frequency is ignored. Consequently, there is a large degree of uncertainty about the predicted performance. Besides milking duration in relation to capacity of the AMS, also economic aspects like the milk and concentrate prices are not taken into account in currently used advisory systems. Consequently, the advised settings using standard guidelines are often suboptimal. Another disadvantage of existing practice is that the settings are manually adjusted periodically with intervals up to 4-6 weeks, while the preferred settings can be automatically updated daily. The preferred settings are continuously tailored to the performance of an individual cow in the actual situation. So, the profitability of dairy production can be improved and additionally, positive effects on health and reproduction are expected.

Next to control of the production process, the model and associated time series analysis is also an useful tool for monitoring. Automatic intervention and temporary change of discount factors, ensures that the model adapts faster after detection of potential outliers and other deteriorations. The detected potential outliers and signals for deteriorations can also be used as alert to the farmer that milk production is disturbed, possibly due to illness, heating or failure of equipment. In figure 4.9 the distribution of the forecast errors is given, classified as normal error, signal for deterioration or potential outlier.

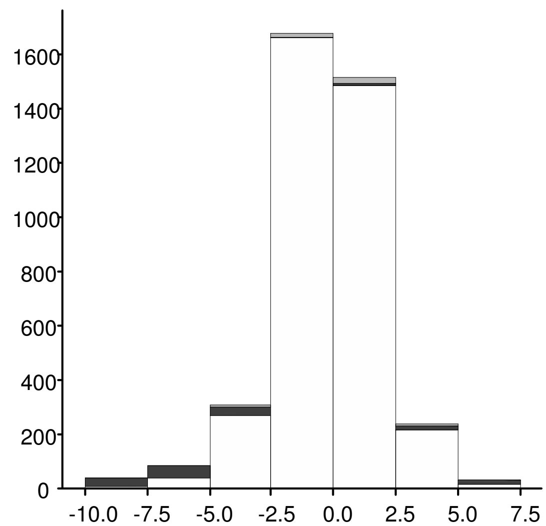

Figure 4.9 Histogram of forecast errors (kg milk per day) classified as normal (white), signal for deterioration (grey) or potential outlier (black) for all data of the 15 cows together.

Out of 4013 forecast errors, 1.5% were classified as signal for deterioration and 5.8% as potential outlier. In currently used decision support systems, attentions on deviating milk yield are commonly based on fixed thresholds for deviations between observed and expected milk yield, e.g. ±2.5 kg milk per day or a fixed percentage of expected daily milk yield. Figure 4.9 shows that many forecast errors deviating more than ±2.5 kg milk were not classified as potential outlier nor as signal for deterioration, while a small part of deviations lower than ±2.5 kg milk were classified as potential outlier or signal for deterioration. This is because model EM in concert with the time series analysis is more specific: forecast errors are evaluated fully taking account of the realized milking intervals and actual individual variance that may differ between and within cows.

Signals and potential outliers occurred in 222 series of length 1, 20 series were of length 2 and only 7 series of length 3 or longer. This indicates that it is likely that most of the signals for deterioration and potential outliers were false positives, resulting from technical failures of the equipment or registration errors. Nevertheless, the Bayesian procedure for monitoring offers a good starting point for an appropriate alert system, when the length of series of sequential outliers and/or signals is taken into account.

4.4 Conclusions and recommendations

This research shows that the actual individual milk yield response to concentrate intake and milking interval can be adequately estimated on-line from daily accumulated real-time process data, with an adaptive dynamic linear model. A two-dimensional quadratic response surface can be used, that can be regarded as an approximation to more intricate non-linear models. It is recommended to modify the quadratic model, as was done for the enhanced model (EM) in this paper, for the sake of sparseness and interpretability of parameters in the model.

Model assessment showed that the daily individual response parameter estimates from model EM can be used in an algorithm to determine the daily individual optimal settings for concentrate supply and milking frequency. The algorithm can be built in decision software and fits within the concept of precision livestock farming. Model T1, as a first-order Taylor approximation, has limited use for defining an economic optimum, and is only useful for forecasting milk production. Furthermore, evaluation of the predicted responses suggested that model T1 adapts relatively slow. Model T2, the second-order approximation, apparently adapts too fast and by consequence the parameter estimates proved to be unstable, with severely biased estimates for curvature.

Monitoring signals and potential outliers provide a base for useful alerts to the farmer, but the length of the series of sequential signals and/or outliers should be taken into account.

Acknowledgements

The authors are grateful to Edwin Bleumer for gathering the data. This project was funded by the Dutch Commodity Board for Dairy Products (Zoetermeer) and the Dutch Ministry of Agriculture, Nature and Food Quality (The Hague).

4.5 References

ANDRÉ, G., BERENTSEN, P.B.M., DUINKERKEN, G. VAN, ENGEL, B., OUDE LANSINK, A.G.J.M. 2010a. Economic potential of individual variation in milk yield response to concentrate intake of dairy cows. *Journal of Agricultural Science* **148**, 263-276.

ANDRÉ, G., BERENTSEN, P.B.M., ENGEL, B., KONING, C.J.A.M. DE, OUDE LANSINK A.G.J.M. 2010b. Increasing the Revenues from Automatic Milking by Using Individual Variation in Milking Characteristics. *Journal of Dairy Science* **93**, 942-953.

ANDRÉ, G., OUWELTJES, W., ZOM, R.L.G., BLEUMER, E.J.B. 2007. Increasing economic profit of dairy production utilizing individual real time process data. In: S. Cox (ed.) *Precision Livestock Farming '07,* Wageningen: Wageningen Academic Publishers, pp. 179-186.

BEBBER, J. VAN, REINSCH, N., JUNGE, W., KALM, E. 1999. Monitoring Daily Milk Yields with a Recursive Test Day Repeatability Model (Kalman Filter). *Journal of Dairy Science* **82**, 2421-2429.

BIELEMAN, J. 2005. *Technological innovation in Dutch cattle breeding and dairy farming, 1850-2000.* Agricultural History Review **53**, 229-250.

BIELEMAN, J. 2008. *Farmers in The Netherlands. History of agriculture 1500 – 2000.* [*Boeren in Nederland. Geschiedenis van de Landbouw 1500 – 2000].* In Dutch. Boom. Amsterdam.

BROSTER, W.H., THOMAS, C. 1981. The influence of level and pattern of concentrate input on milk output. In: W. Haresign (ed.), *Recent advances in animal nutrition.* London: Butterworths, pp. 76-96.

COX, S. 2002. Information technology: the global key to precision agriculture and sustainability. *Computers and Electronics in Agriculture* **36**, 93-211.

DELUYKER, H.A., SHUMWAY, R.H., WECKER, W.E., AZARI, A.S., WEAVER, L.D. 1990. modelling Daily Milk Yield in Holstein Cows Using Time Series Analysis. *Journal of Dairy Science* **73**, 539-548.

FRANCE, J., THORNLEY, J.H.M. 1984. *Mathematical models in agriculture. A quantitative approach to problems in agriculture and related sciences*. London: Butterworths, pp. 227-232.

FROST, A.R., SCHOFIELD, C.P., BEAULAH, S.A., MOTTRAM T.T., LINES, J.A., WATHES, C.M. 1997. A review of livestock monitoring and the need for integrated systems. *Computers and Electronics in Agriculture* **17**, 139-159.

GARNSWORTHY, P. C., LOCK, A., MANN, G.E., SINCLAIR, K.D., WEBB, R. 2008a. Nutrition, metabolism, and fertility in dairy cows: 1. Dietary energy source and ovarian function. *Journal of Dairy Science* **91**, 3814-3823.

GARNSWORTHY, P. C., LOCK, A., MANN, G.E., SINCLAIR, K.D., WEBB, R. 2008b. Nutrition, metabolism, and fertility in dairy cows: 2. Dietary fatty acids and ovarian function. *Journal of Dairy Science* **91**, 3824-3833.

GELMAN, A., J.B. CARLIN, H.S. STERN AND D.B. RUBIN. 1995. Bayesian data analysis. Chapman and Hall. London.

GOODALL, E.A., SPREVAK, D. 1985. A Bayesian estimation of the lactation curve of a dairy cow. *Animal Production* **40**, 189-193.

INGVARTSEN, K.L., ANDERSEN, J.B. 2000. Integration of metabolism and intake regulation: a review focusing on periparturient animals. *Journal of Dairy Science* **83**, 1573-1597.

LARK, R.M., NIELSEN, B.L., MOTTRAM, T.T. 1999. A time series model of daily milk yields and its possible use for detection of a disease (ketosis). *Journal of Animal Science* **69**, 573-582.

MOL, R. DE, KEEN, A., KROEZE, G., ACHTEN, J.M.F.H. 1999. Description of a detection model for oestrus and diseases in dairy cattle based on time series analysis combined with a kalman filter. *Computers and Electronics in Agriculture* **22**, 171-185.

MONTGOMERY, D.C., PECK, E.A. 1982. *Introduction to linear regression analysis*. New York: Wiley.

THOMAS, C. (Ed) 2004. *Feed into Milk: A new applied feeding system for dairy cows.* 72 pp. Nottingham, United Kingdom: Nottingham University Press.

VAN KNEGSEL, A.T.M., DE VRIES REILINGH, G., MEULENBERG, S., VAN DEN BRAND, H., DIJKSTRA, J., KEMP, B., PARMENTIER, H.K. 2007a. Natural antibodies related to energy balance in early lactation dairy cows. *Journal of Dairy Science* **90**, 5490-5498.

VAN KNEGSEL, A.T.M., VAN DEN BRAND, H., DIJKSTRA, J., TAMMINGA, S., KEMP, B. 2005. Effect of dietary energy source on energy balance, production, metabolic disorders and reproduction in lactating dairy cattle. *Reprod. Nutr. Dev.* **45**, 665-688.

VAN KNEGSEL, A.T.M., VAN DEN BRAND, H., DIJKSTRA, J., VAN STRAALEN, W.M., JORRITSMA, R., TAMMINGA, S., KEMP, B. 2007b. Effect of glucogenic vs. lipogenic diets on energy balance, blood metabolites, and reproduction in primiparous and multiparous dairy cows in early lactation. *Journal of Dairy Science* **90**, 3397-3409.

VETHARANIAM, I., DAVIS, S.R., UPSDELL, M., KOLVER, E.S., PLEASANTS, A.B. 2003. Modeling the effect of energy status on mammary gland growth and lactation. *Journal of Dairy Science* **86**, 3148-3156.

WATHES, C.M., KRISTENSEN, H.H., AERTS, J.-M. & BERCKMANS, D. 2008. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture* **64**, 2-10.

WEST, M., HARRISON, J. 1997. *Bayesian Forecasting and Dynamic Models*. 2nd edn. New York: Springer-Verlag.

WOOD, P.D.P. 1967. Algebraic model of the lactation curve in cattle. *Nature*, Lond. **216**, 164-165.

WOODS, V.B., KILPATRICK, D.J., GORDON, F.J. 2003. Development of empirical models to describe the response in lactating dairy cattle to changes in nutrient intake as defined in terms of metabolisable energy intake. *Livestock Production Science* **80**, 229-239.

ZOM, R.L.G., RIEL, J.W. VAN, ANDRÉ, G., DUINKERKEN, G. VAN. 2002. *Prediction of feed intake using the 2002 Dairy Cow model. [Voorspelling voeropname met Koemodel 2002]* In Dutch. Praktijkrapport 11, Praktijkonderzoek Veehouderij, Lelystad, The Netherlands.

Appendix

An univariate dynamic linear model consists of an observation and system equation. The observation equation is:

$$Y_t = \mathbf{F}_t'\theta_t + \nu_t$$

linking the observations milk yield per day Y_t to the regressor variables for concentrate intake and interval length in matrix $\mathbf{F}_t$.

The system equation is:

$$\theta_t = \theta_{t-1} + \omega_t .$$

The system error follows a Student T distribution: $\omega_t \sim \mathrm{T}_{n_{t-1}}\left[0, \mathbf{W}_t\right]$. The analysis starts with an initial prior for the parameters and the on-line parameter estimates are sequentially updated based on information of the past. The decay of information is regulated by discount factors for the intercept ($\delta_I = 0.95$) and for the regression parameters ($\delta_R = 0.975$) assuming that dynamic change of the intercept is greater than the dynamic change of the regressor variables.

The observation variance is unknown and estimated from information from the past using a discount factor for variance learning $\delta_V = 0.9$. The observation error is assumed to be normally distributed $\nu_t \sim \mathrm{N}\left[0, N_t/\phi_t\right]$ with precision $\phi_t = \eta_t \phi_{t-1}/\delta_V$; $\eta_t \sim \mathrm{Beta}\left[\delta_V n_{t-1}/2, (1-\delta_V) n_{t-1}/2\right]$ and n_t degrees of freedom. The number of milkings per day N_t is used as weighing factor, because the observation Y_t results from the accumulation of several milkings per day.

Detection of outliers and other deteriorations is based on monitoring of the cumulative Bayes' factor. After detection of potential outliers or signals for deterioration, automatic intervention is carried out applying once-only exceptional discount factors, $\delta_I = \delta_V = 0.8$ and $\delta_R = 0.9$. These exceptional discount factors are lower than the routinely used discounts factors resulting in an extra loss of information so that the system parameters adapt faster to a probable change in the process.

5 Quantifying the impact of heat stress on daily milk yield and monitoring dynamic changes using an adaptive dynamic model[6]

Abstract

Automation and robotisation are increasingly being used within dairy farming and result in large amounts of real time data. The information in these data provides a base for the new management concept of precision livestock farming. From 2003 to 2006, on six experimental research farms in The Netherlands, time series of herd mean daily milk yield were collected. In this study, these time series were analyzed with an adaptive dynamic model following a Bayesian method to quantify the impact of heat stress. The impact of heat stress was quantified in terms of critical temperature above which heat stress occurred, duration of heat stress periods and resulting loss in milk yield. In addition dynamic changes in level and trend were monitored, including the estimation of a weekly pattern. Monitoring comprised detection of potential outliers and other deteriorations.

The adaptive dynamic model fitted the data well; the root mean squared error of the forecasts ranged from 0.55 to 0.99 kg milk/day. The percentage of potential outliers and signals for deteriorations ranged from 5.5 to 9.7%. The Bayesian procedure for time series analysis and monitoring provides a useful tool for process control. On-line estimates (based on past and present only) and retrospective estimates (determined afterwards from all data) of level and trend in daily milk yield showed an almost yearly cycle that was in agreement with the calving pattern: most cows calved in winter and early spring. Estimated weekly patterns in terms of week day effects could be related to specific management actions. For impact of heat stress, the mean estimated critical temperature above which

---

[6] Paper by G. André, B. Engel, P.B.M. Berentsen, Th.V. Vellinga and A.G.J.M. Oude Lansink, under review by the Journal of Dairy Science (2011)

heat stress is expected to occur was 17.8 oC. the average estimated duration of the heat stress periods was 5.5 d, and the estimated loss was 31.4 kg of milk/cow/year, averaged over the farms and years. Farm specific estimates are helpful to identify management factors like grazing, housing and feeding, that affect heat stress. The impact of heat stress can be reduced by modifying these factors.

5.1 Introduction

Heat stress occurs when dairy cows suffer from hyperthermia when they fail to maintain thermo neutrality with increasing ambient temperature and/or humidity. Higher producing cows are more at risk than lower producing cows (Bianca, 1965), because high feed intake results in increased metabolic heat increment. Heat stress leads to reduced milk production and changes in milk composition (Schneider et al., 1988; Abdel-Bary et al., 1992) as fat and protein content decrease (Bandaranayaka and Holmes, 1976; McDowell et al., 1976). Besides temperature, wind speed and humidity play a role, and McDowell et al. (1976) included humidity in their index for heat stress. Apart from climatological factors, impact of heat stress depends on housing conditions and management, e.g. whether cows remain indoors or not (Bohmanova et al., 2007). Accurate measurement of the entry stage of heat stress is complicated (Kadzere et al., 2002). Berman et al. (1985) found an upper control temperature of 25-26 ^{o}C for the cows' thermo neutral zone. In the aforementioned studies, heat stress is related to a cows' ambient temperature, registered near the cows. However, in practice the ambient temperature is commonly not registered on farms. Therefore, for operational on-farm use it is expedient to relate heat stress to daily temperature as registered on meteorological stations in the region in which the farm is situated; when daily temperature does not vary too much within this region. This could help in timely signaling the risk of heat stress and reduction of its negative effects.

The impact of heat stress depends on the specific farm situation. Hence, it is recommendable to quantify the impact of heat stress using milk production data, collected in the farm specific situation. Milk production data are to a growing extent available from management information systems that are increasingly used within dairy farming. Management information systems provide the basis for Precision Livestock Farming (PLF), which is believed to contribute to more sustainable dairy production, both in ecological and economic terms (Wathes, 2009 ; Banhazi and Black, 2009). Wathes et al. (2005) concluded that PLF is an ‘embryonic technology’ with great promise, but one that requires considerable research and development of models of the key biological and physical processes, with meaningful parameters to control and monitor the production process (Frost et al., 1997).

Quantitative methods, developed and implemented for quality control of industrial processes (Montgomery, 2005) were proposed for animal production processes (Reneau and Lukas, 2006). Industrial processes usually can be fully controlled. However, biological processes are inherently variable through dynamic changes due to age, reproduction and interactions with the environment. Dynamic changes in level, trend and cyclical patterns from serial process data can be estimated by time series analysis (Pankratz, 1991). DeLuyker et al. (1990) used time series analysis for modeling daily milk yield of individual cows, but focused only on level and trend. André et al. (2010) used a dynamic model to describe the effects of concentrate intake and milking interval length on individual daily milk production. This dynamic model was fitted following a Bayesian procedure for time series analysis (West and Harrison, 1997). This Bayesian procedure comprises a procedure for process monitoring and control and can be applied to herd mean milk production data.

The objective of this study is to develop a dynamic adaptive model that provides an integrated method for: (i) estimation of the impact of heat stress on milk production in the actual on-farm situation and (ii) monitoring of level, trend and weekly pattern of milk production. The approach also allows for the detection of unexpected changes in daily milk production due to unanticipated events like illness etc.

5.2 Materials and methods

5.2.1 Data from experimental farms

The data set consists of time series of observations of herd mean daily milk production, from six experimental dairy farms during the period from 1-1-2003 to 31-12-2006. Milk yield per milking per cow was recorded electronically on each farm. The milk meters were checked at least once per year and calibrated by the suppliers of the milking equipment.

Table 5.1 provides a number of farm characteristics such as the feeding strategy, grazing during the summer and roughage mixture of the silage during the winter. The roughage mixture was also fed in summer when the cows were not grazing during the night and/or day. Aver Heino (AH) is an organic farm with Red Holstein cows. The other farms, Bosma Zathe (BZ), Cranendonck (CD), Hoorn (HO), Hightech (HT) and Zegveld (ZV) were conventional farms with Holstein Friesian cows. At CD and ZV the cows were kept in one group and milked twice a day in a milking parlor. At HT the cows were also kept in one group, but milked with an automatic milking system (AMS). At BZ, the cows were kept in three separate groups, two groups were milked in an AMS, and one group was milked twice a day in a milking parlor. At HO, there were five groups, four milked in an AMS and one group milked twice a day in a milking parlor. The groups within a farm were pooled to calculate the herd mean daily milk production. At all farms, cows were kept in free stalls. The barns at HT and HO were ventilated barns with open side walls and during warm days, mechanical ventilators were used to stimulate air circulation. The barns at AH, BZ, CD and ZV were naturally ventilated by openings in the top of the sidewalls without using mechanical ventilation.

Table 5.1 Farm characteristics over the period 2003-2006

Farm	**Region in the Netherlands**	**Soil type**	**Summer grazing**	**Roughage mixture**[1]	**Herd size**	**Milk yield** (kg/d)
AH	middle-east	sand	day and night	0.70 grass, 0.30 maize	83.8	22.2
BZ	north	clay	limited during the day	0.70 grass, 0.30 maize	125.0	26.4
CD	south	sand	day	0.55 grass, 0.45 maize	84.3	26.2
HO	middle	clay	no	0.55 grass, 0.45 maize	344	29.4
HT	middle	clay	no	0.55 grass, 0.45 maize	68.2	30.4
ZV	middle	peat	day and night	1.00 grass	85.4	27.4

[1]Silage in the winter and in the summer when the cows were not grazing.

The farms were located at different regions in the Netherlands, and average daily temperature was registered at meteorological stations nearest to the farms. The distances between the farms and the meteorological stations range from 10 km (BZ) to 55 km (AH). Figure 5.1 shows the average daily temperature registered from 2003 to 2006 on the meteorological stations in the different regions of the Netherlands.

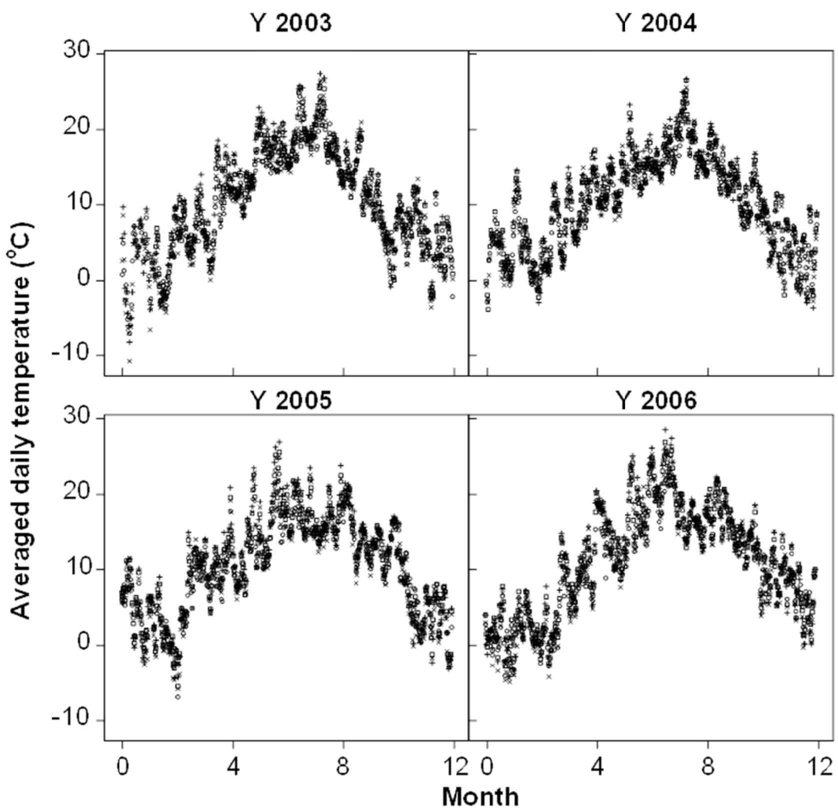

Figure 5.1 Averaged daily temperature registered from 1-1-2003 to 31-12-2006 at meteorological stations in different regions in the Netherlands: × middle-east, ○ north, + south, □ middle.

5.2.2 Dynamic model

Herd mean daily milk yield depends on several factors, like feeding, lactation stage, and mastitis outbreaks. Furthermore, the effect of high temperatures on herd mean daily milk yield interacts with other factors like humidity, solar radiation, and physiological state. These factors and interactions depend on the farm-specific situation and change over time. For that reason we utilized a dynamic model, with time changing parameters. Parameter estimates are updated daily to adapt to the actual on-farm situation. Hence, level and trend of herd mean daily milk adapt to e.g. changes in feeding, lactation stage, mastitis outbreaks etc. The parameter for the effect of high temperatures is also dynamic and adapts to the actual situation influenced by e.g. humidity and solar radiation.

A dynamic linear model consists of an observation and a system equation. The observation equation (5.1) expresses herd mean daily milk yield Y_t in terms of level μ_t, week day effect $\phi_{t,i}$ and heat stress effect γ_t of a variable X_t, and an observation error $\upsilon_t \sim N(0, V_t)$ with unknown variance V_t.

$$Y_t = \mu_t + \phi_{t,i} + \gamma_t X_t + \upsilon_t \tag{5.1}$$

The variable X_t for heat stress, as derived by eq. (5.2), represents the accumulated temperature degrees above critical temperature τ during the past κ days:

$$X_t = \sum_{j=0\ldots\kappa} (T_{t-j} - \tau) I_{T_{t-j} > \tau}, \tag{5.2}$$

with T the average daily temperature and indicator function I equal to 1 for $T > \tau$, and 0 otherwise. The system equation describes the evolution of the parameters. The series level μ_t at time *t* is modelled as a locally linear trend, see eq. (5.3), with an incremental growth β_{t-1} based on equidistant time points. The random errors $\omega_{t,1}, \omega_{t,2}$ represent random change in level and trend.

$$\begin{aligned} \mu_t &= \mu_{t-1} + \beta_{t-1} + \omega_{t,1} \\ \beta_t &= \beta_{t-1} + \omega_{t,2} \end{aligned} \tag{5.3}$$

Some management actions, like replacement of cows, change of pasture etc., are performed at specific days of the week, which might affect milk yield at those days. Therefore, the model comprises an effect $\phi_{t,i}$, for each week day i. These week day effects $\phi_{t,i}$, as the departures from the series level μ_t, are assumed to sum to zero: $\sum_i \phi_{t,i} = 0$. Moving from time *(t-1)* to time t, we move from one week day to another cf. eq. (5.4), where $\omega_{t,3}...\omega_{t,9}$ represent random changes in the week day effects.

$$\begin{aligned} \phi_{t,i} &= \phi_{t-1,i+1} + \omega_{t,3+i} \\ \phi_{t,6} &= \phi_{t-1,0} + \omega_{t,9} \end{aligned} \tag{5.4}$$

The effect of heat stress γ_t is assumed to be locally constant, see eq. (5.5), involving random error $\omega_{t,10}$.

$$\gamma_t = \gamma_{t-1} + \omega_{t,10} \tag{5.5}$$

The system errors $\omega_{t,1}...\omega_{t,10}$ were assumed to be normally distributed, with zero mean and variance matrix W_t. The system variance W_t was estimated proportional to the covariance matrix of the model parameters. West and Harrison (1997) refer to this dynamic model as a second-order polynomial/form-free seasonal effects/regression model.

5.2.3 Parameter estimation

The dynamic model was fitted for each farm separately following a forward and backward procedure. In the forward procedure, only data of the series up to time t were used to provide on-line parameter estimates by using updating recurrence relationships. So, the on-line parameter estimates are based on information from the past only. In the backward procedure, the retrospective parameter estimates, were calculated using retrospective recurrence relationships, a form of backward filtering (smoothing). The retrospective parameter estimates are based on information from the whole series, resulting in a higher precision. For details about the calculation of the on-line and retrospective estimates we refer to West and Harrison (1997).

The Bayesian method for parameter estimation allows for decay of information from the past by using several discount factors, adjustable for different parts of the model. Values for discount factors are usual chosen between 0.8 and 1, and the higher the factor, the smaller the decay. In this study, the discount factors were chosen according to the guidelines given by West and Harrison (1997): 0.9 for level and trend, 0.99 for effect of heat stress and 0.975 for week day effect. Level and trend were assumed to be more variable than the effects of heat stress and week day, so for the latter a higher discount factor was chosen. For heat stress a relatively high discount factor was chosen because the effect can only be adequately estimated from data from a relatively long period that includes high temperatures. The unknown observation variance was estimated from the data using a discount factor of 0.95. After detection of potential outliers and/or other deteriorations (see Bayesian monitoring below), discount factors were temporarily lowered to 0.85, 0.975, 0.95 and 0.9. This resulted in an extra loss of information, to allow the system to readjust.

Duration κ and critical temperature τ are non-linear parameters and cannot be simply estimated using the recurrence relationships. To estimate these parameters, an iterative procedure was followed by sequentially fitting models with fixed values for duration, increasing with steps of 1 d, from 4 to 10 d, and for critical temperature, increasing with steps of 0.5 degrees, from 15.5 to 20 ^{o}C. The values that maximized the log-likelihood were retained as the maximum likelihood estimates for these non-linear parameters and kept constant during the whole series. The total yearly loss in milk yield is obtained by accumulation of the daily effects of heat stress $\gamma_t X_t$ within years. The variance of the linear parameter γ_t for the effect of heat stress is estimated and enables the calculation of a 95% confidence interval for total yearly loss in milk yield. This interval is somewhat too narrow, because it does not reflect variability in the estimators for κ and τ, which is hard to assess.

5.2.4 *Bayesian monitoring*

Detection of outliers and other deteriorations was based on calculation of the Bayes factor, the ratio of the likelihood that an observation fits well into the assumed (usual) model or into an alternative (outlier) model with a considerably inflated variance. Besides the Bayes factor, a cumulative Bayes factor and a run length were calculated, to detect whether the series of most recent observations shows evidence for slowly growing deterioration. When the Bayes factor was below the threshold 0.15 the observation was diagnosed as a potential outlier and discarded in the update of the parameters. When the cumulative Bayes factor was below the threshold 0.15 and/or the run length was longer than 3, the last observation was not discarded, but an alert for slightly growing deterioration was given. In case of a potential outlier or an alert, the lower discount factors were used for updating parameter estimates. Consequently, the model parameters adapt faster to a possibly changed situation in the production process.

5.2.5 *Assessment of model adequacy*

Goodness of fit of the model was judged by graphical inspection of the forecast errors. The root mean squared error of the forecasts gives an indication of the variance of the errors in forecasts. The autocorrelation coefficient of successive forecast errors was calculated to evaluate the appropriateness of the choice of discount factors. For instance, a positive correlation would suggest that the discount factors were too high, and consequently the model adapted too slowly. The retrospective parameter estimates provided an additional criterion for goodness of fit of the model in a comparison with the on-line parameter estimates.

5.3 Results

Summarizing results are presented for all farms in the tables to show the farm specific impact of heat stress. Daily results showing the development of the time series are shown in more detail for farm HO to clarify aspects of the analysis.

5.3.1 Goodness of fit, forecasting and process control

In Table 5.2, the goodness of fit statistics are given per farm, over the whole period from 2003 to 2006. The root mean squared error of the forecast errors (rMSE) ranged from 0.55 to 0.99 kg milk/day indicating that the variation coefficient was about 3% and a 90% probability interval for the forecasts ranged from 1 to 2 kg milk/day. As expected the rMSE was lower for farms BZ and HO that had larger herds.

Table 5.2 Goodness of fit statistics

Farm	**rMSE**[1] (kg / d)	**Rho**[2]	**potential outliers** (%)	**signals** (%)
AH	0.8496	0.1240	3.08	2.12
BZ	0.6645	0.2354	8.21	1.44
CD	0.8472	0.2201	5.31	3.29
HO	0.5456	0.1183	6.67	2.04
HT	0.9874	0.1274	4.31	2.46
ZV	0.8568	0.2749	6.02	2.19

[1]Root Mean Squared Error
[2]Autocorrelation coefficient between successive forecast errors

The autocorrelation (rho) between successive forecast errors ranged from 0.12 to 0.27. The percentage of potential outliers and signals for deteriorations ranged from 5.5 to 9.7%.

In Figure 5.2, for farm HO the observed milk yield per day is given together with the forecasts and the 90% probability interval over the whole period. The graphs show a yearly cyclical pattern with a maximum in spring and summer and a minimum in late autumn and winter. The week day effects can be noticed in the short term day-to-day variation of the forecasts. And also a decay in production during summer, caused by heat stress, can be seen, for instance around day 225 in 2004. Detailed results of these effects are presented next.

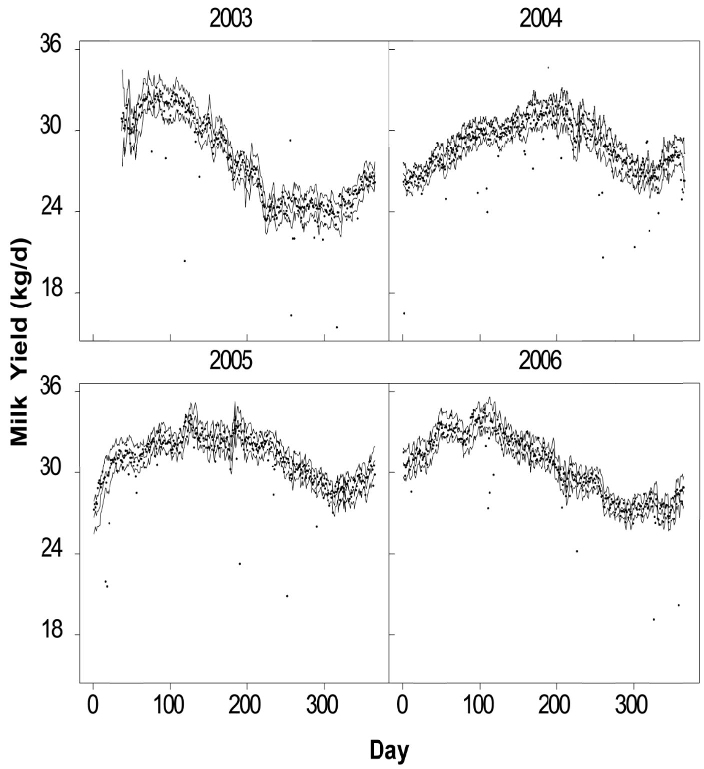

Figure 5.2 Observations (points) and forecasts (centre line) with 90% probability interval (upper and lower line) for herd mean daily milk yield on farm HO from 1-1-2003 to 31-12-2006

The observed milk yields per day were the raw data provided by the management systems on the farm. In Figure 5.2 it is seen that extremely low values occurred and that there were also a small number of positively deviating values that lie outside the forecast probability interval. In Figure 5.3, the forecast errors are displayed and labelled to distinguish between normal forecast errors and potential outliers or other signals for deteriorations.

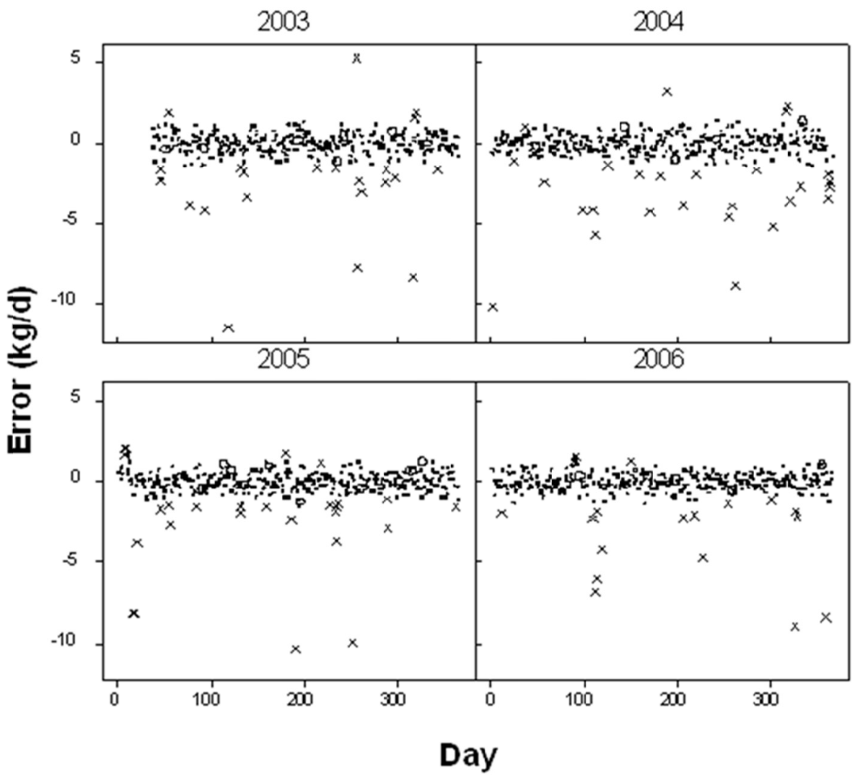

Figure 5.3 Forecast errors (·), potential outliers (x) and other signals (o) for farm HO

Large errors, deviating more than 2.5 kg milk/day were detected as potential outliers in most cases. These large errors were mainly due to technical failure of the equipment resulting in registration errors in milk yield and/or number of cows. Also small errors were detected as potential outliers and even small errors that lie within the forecast probability interval generated a signal for deterioration.

5.3.2 Level and trend

The yearly cyclic pattern, already apparent in the forecasts (Figure 5.2), can be studied in more detail by decomposition of the development over time in level and trend. In Figure 5.4 the on-line and retrospective daily estimates for level and trend for farm HO are shown.

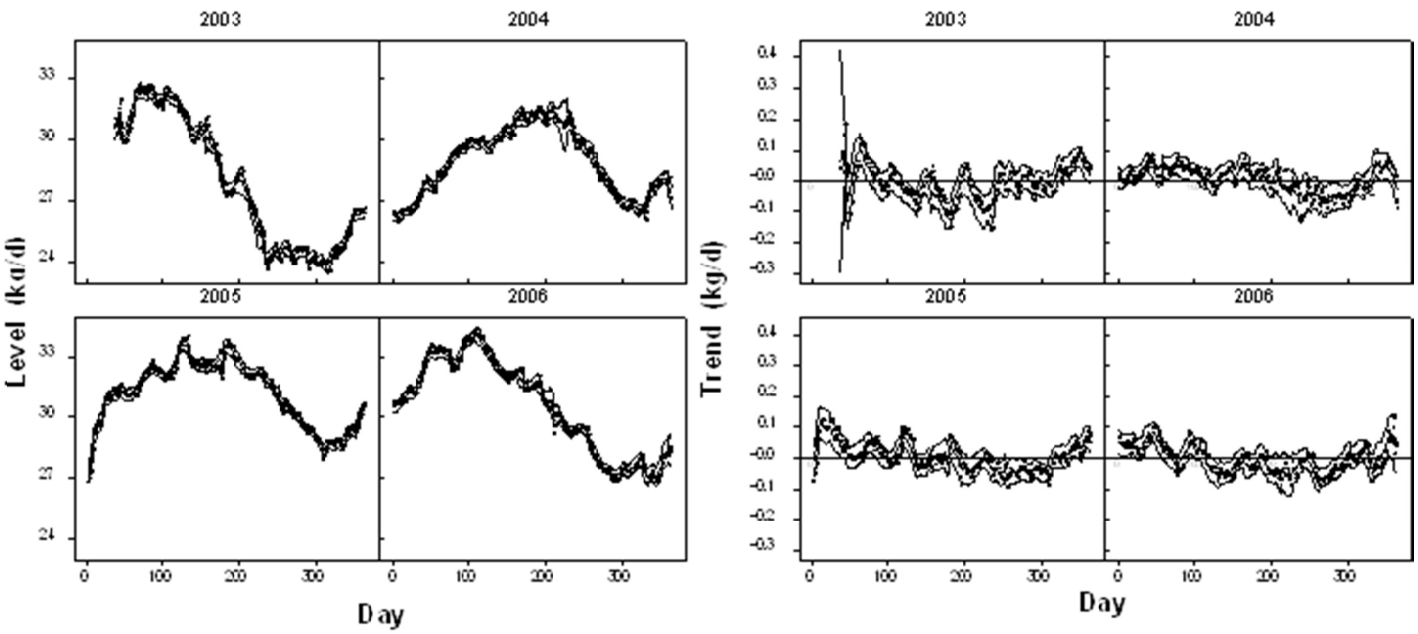

Figure 5.4 Estimated level (left) and trend (right) for herd mean daily milk yield on farm HO from 1-1-2003 to 31-12-2006. On-line estimates (points), retrospective estimates with 90% confidence interval (lines)

The increase in level, i.e. positive trend, during the winter and spring period were in agreement with the calving pattern. Besides this global development, also short term fluctuations in level and trend are noticeable. It should be noted that effects of heat stress and week day were not incorporated in the estimated level and trend. The 90% confidence interval for the retrospective estimates for level is considerable smaller than the 90% probability interval for the forecasts (see Figure 5.2). The averaged standard error for the retrospectively estimated level was 0.19 kg, which is much lower than the average standard deviation of the forecasts of 0.55 kg. So, retrospective estimates for level do indeed provide much more precise information about production level than observed and forecasted milk yield per day.

The averaged standard error for the retrospective estimated trend was 0.026 kg which means that in general an incremental change in level of about 0.05 kg milk/day can be noticed as statistically significant. So, the retrospective estimated level and trend provide more precise information, which enables effective evaluation of herd mean daily milk yield, but afterwards of course and not in real time.

5.3.3 Weekly pattern

On all farms, a significant cyclic pattern of week day effects was found during the period 2003 to 2006. However, the cyclic patterns differed between farms and also changed over time within farms. In Figure 5.5, the retrospective estimated week day effects on the farms ZV and HO are shown for May 2006 by way of an illustration.

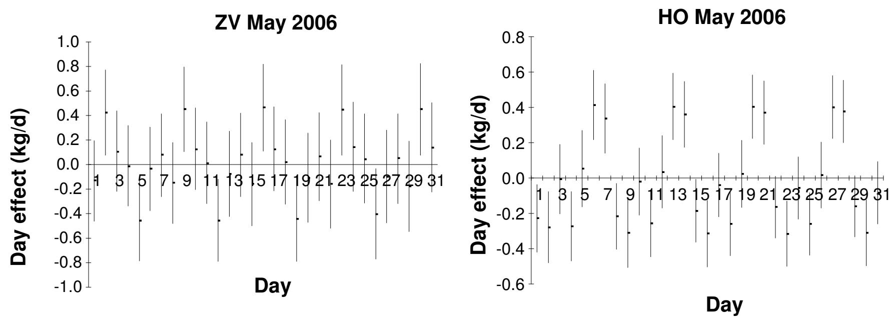

Figure 5.5 Retrospective estimates (points) with 90% confidence interval (vertical bars) for week day effects on farms ZV (left) and HO (right) during May 2006. May 1 is a Monday

At ZV there was a positive effect of 0.45 kg/day at Tuesdays decreasing the days thereafter to -0.45 kg/day at Fridays. From Saturday to Monday, there was almost no effect. This pattern can be explained by the pasture grazing strategy: the cows were changed from pasture after three to four days, mostly on Tuesdays and Fridays. Similar patterns were found during the summer at the other farms that applied grazing (AH, BZ and CD).

An explanation for the week day pattern at HO, where grazing did not occur, is that each Mondays a footbath with formaldehyde was placed in the entrance to the automatic milking system, with a negative effect on the number of visits of the cows to the milking system, resulting in a lower milk yield per day. At HT, a foot bath was applied in the same way and a negative effect on milk yield was found on Mondays. An alternative explanation might be that on Saturdays and Sundays there were less management activities in the stable, with a positive effect on average milk yield.

5.3.4 Heat stress

The impact of heat stress is described in the model with the non-linear parameters for critical temperature τ and duration κ and the linear parameters γ_t for loss in milk yield. The estimates for these parameters are given in Table 5.3. Variable X_t counts the number of degrees above the critical temperature during the last κ days. The daily loss in milk yield was calculated as the product of this variable with the linear parameter γ_t for the effect of heat stress. In Figure 5.6, the daily loss in milk yield is given for farm HO based on the on-line and retrospective parameter estimates for heat stress, including the 90% confidence interval. The yearly accumulated daily loss is the area under the curve and gives the total loss in milk yield per cow per year as presented for all farms in Table 5.3.

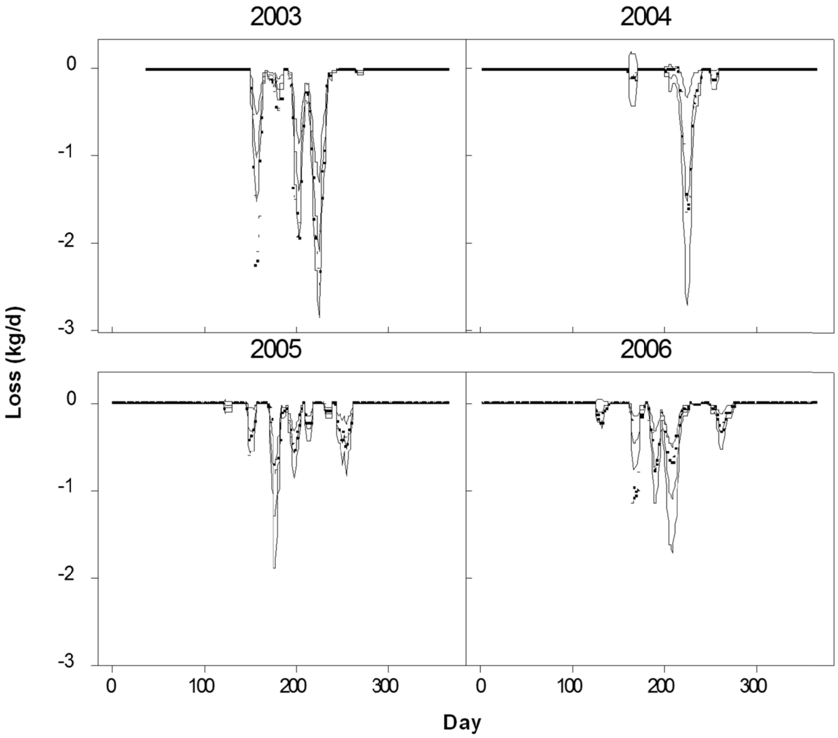

Figure 5.6 On-line (points) and retrospective (lines, including upper and lower 90% confidence limits) estimated daily loss in milk yield (kg/day) due to heat stress on farm HO in the years 2003 to 2006

In the Netherlands, loss in milk yield due to heat stress can occur during the summer from begin-April (day 100) to end-October (day 300). From Figure 5.4, it is seen that during each summer, in 2003 to 2006 at HO there were 3 to 7 periods with high temperature and that this had a negative impact on daily milk yield up to almost 2 kg/day (summer 2003).

The total loss in milk yield due to heat stress per cow per year was 31.4 kg, averaged over farms and years, but differed between years due to the variation in the weather conditions. The differences between farms were larger than the differences between years (see Table 5.3) and can be explained by the specific situations and management strategies on the farms. The lowest losses were found at HT and BZ, mainly because at these farms the estimated duration of the heat stress periods is low. At HT, the cows were kept indoors during summer in a modern open ventilated barn and during warm days, mechanical ventilators were used to stimulate air circulation. This explains the high critical temperature τ at HT. Moreover, at HT the roughage mixture was enriched with more concentrates to ensure energy intake by the cows during warm periods. The lowest loss in milk yield at BZ can also be related to the location in the north of the Netherlands where temperature is relatively low and wind speed is high.

Moderate losses were found at HO and AH. At HO and AH the duration was longer than at the other farms, indicating that cows recovered slower from heat stress. The housing at HO is similar to HT, but the barn and herd of HO were more than four times bigger than of HT, as a result of which ventilation might have been less effective. At CD and ZV the highest losses were found. The estimated critical temperature was lower than on the other farms, but the estimated duration was moderate. Both farms performed grazing during summer, and in combination with the losses found at AH, it can be concluded that grazing during warm days may increase the negative impact of heat stress.

Table 5.3 Farm specific estimates of critical temperature τ, duration κ and retrospective estimated effect of heat stress γ_t ($t =$ 1 Aug). The accumulated loss in milk yield per year per cow is calculated using the transfer function and the retrospective parameter estimates.

			γ_t (g) (s.e.)				**Loss in milk yield** (kg/year/cow) (90% c.i.[1])				
Farm	τ (°C)	κ (days)	2003	2004	2005	2006	2003	2004	2005	2006	Mean
AH	18.0	9	-23.5 (13.5)	-12.5 (16.8)	-22.7 (15.5)	-26.9 (11.1)	-30.7 (-62.1;0.6)	-9.7 (-32.0;12.6)	-18.9 (-42.3;4.5)	-55.8 (-92.1;-19.4)	-28.8 (-57.1;-0.4)
BZ	17.5	3	1.3 (20.4)	-33.8 (21.1)	-79.8 (21.5)	-9.9 (18.8)	-0.3 (-13.6;13.0)	-8.1 (-14.7;-1.6)	-15.7 (-23.3;-8.2)	-2.9 (-18.4;12.6)	-6.8 (-17.5;4.0)
CD	17.0	5	-1.9 (12.5)	-44.6 (13.7)	-35.1 (11.7)	-70.1 (14.8)	-0.3 (-36.4;35.8)	-33.7 (-51.1;-16.3)	-36.3 (-57.3;-15.4)	-108.9 (-151;-67.0)	-44.8 (-73.9;-15.7)
HO	18.5	8	-51.3 (11.6)	-38.1 (23.9)	-49.1 (13.6)	-23.8 (7.8)	-48.1 (-68.0;-28.2)	-19.5 (-38.1;-1.0)	-29.1 (-44.6;-13.6)	-31.8 (-51.4;-12.3)	-32.1 (-50.5;-13.8)
HT	20.0	3	5.8 (42.7)	-79.4 (61.1)	-178.8 (52.9)	26.2 (24.0)	0.2 (-13.7;14.2)	-7.6 (-15.1;-0.0)	-16.8 (-25.4;-8.1)	8.1 (-5.8;21.9)	-4.0 (-15.2;7.1)
ZV	16.0	5	-52.6 (12.5)	-34.7 (19.3)	-41.4 (11.9)	-75.3 (11.1)	-75 (-121;-40)	-31.8 (-62.9;0.8)	-47.3 (-78.4;-24.4)	-133 (-184;-105)	-71.8 (-112;-42.2)
Mean	17.8	5.5					-25.7 (-52.4;-0.8)	-18.4 (-35.7;-0.9)	-27.4 (-45.2;-10.9)	-54.1 (-83.8;-28.3)	-31.4 (-54.3;-10.2)

[1] Confidence interval

5.4 Discussion

The dynamic model presented in this paper fitted well to the time series of average daily milk yield per farm. The forecast errors were relatively small and the autocorrelations between successive forecast errors were small but positive for all farms, indicating that the chosen discount factors, especially for level and trend, may have been somewhat too high. A choice of lower discount factors is an option, consideration of a higher order model for level and trend is another option. The changes in level and trend resulted from an almost yearly cycle, related to the calving pattern: most cows calved in winter and early spring. The period of this cycle is usually longer than a year, but is also effected by replacement of the cows. This might explain the backward shift of the peak production in 2006 at HO, see Figures 5.2 and 5.4. Incorporating average stage of lactation in the model may provide more insight how level and trend are related to the calving pattern. In addition, level and trend depend on feeding, suggesting that variables representing the feeding strategy may also be incorporated. The same applies for weekly cyclic patterns, where week day effects could be related to specific management actions. These actions can also be incorporated in the model to provide more specific estimates of the related effects. So, there are several alternatives for model formulation, providing more specific information about the production process. The choices to be made with model formulation depend on the farmers objectives for operational use. On-line estimates of level, trend and week day effects can help the farmers to evaluate the actual situation. Retrospective estimates have a higher precision and are helpful to evaluate the farm specific situation afterwards. The results of this research led to the following recommendations. For farm HO it was recommended to find another location for the footbath to reduce the negative effect on the number of visits of the cows to the milking system. For farm CD and ZV it was recommended to reduce grazing during warm days to reduce the negative impact of heat stress.

In our research, although attention was given to modeling and explanation of level, trend and weekly cyclic pattern, the focus was on evaluation of the impact of heat stress on milk production at herd level. The dynamic model can be applied at individual level, comparable to André et al. (2010), to estimate cow specific impact of heat stress. But since management actions to reduce the impact of heat stress are mostly applied at herd level, there is little need to gain insight into individual variation. Furthermore, estimation of individual impact requires long series of data and it might be difficult to estimate the effects of heat stress from individual daily milk yield data within a lactation. Negative effects of heat stress on milk production occurred when the average daily temperature was higher than the estimated critical temperature ranging from 16 to 20 ^{o}C. These values are lower than the upper critical temperature of 25-26 ^{o}C for ambient temperature found for heat adapted cows in the literature (Berman et al., 1985). The upper critical temperature varies with physiological state and other environmental conditions (Kadzere et al., 2002). Dairy cows in The Netherlands possible are less heat adapted. Furthermore, when cows are calving during winter and early spring, high temperatures in summer coincide with the peak of the lactation when cows are more sensitive to heat stress. This might explain the relatively lower critical temperatures that we found in our study. In the studies from the literature, ambient temperature was measured inside the barns near the dairy cows. The average daily temperature used in this study was derived from the outside temperature which is often lower than the temperature inside naturally ventilated barns. Furthermore, it should be noted that the ambient temperature ranges from a minimum at night to a maximum at day. So, the ambient temperature of the cows might be above the upper control temperature during a considerable part of the day, even when the average daily outside temperature is between 16 to 20 ^{o}C. A low critical temperature indicates that the cows are earlier and longer at risk. The lowest values were found at the farms, where the cows were grazing during summer. This indicates that it is recommendable to keep the cows inside the barn during the hot periods of warm days, at least when the barn is cool and well ventilated. Environmental conditions that effect the critical temperature and the impact of heat stress are humidity, wind speed (outside) and air change rate (inside), cloudiness and solar radiation (Kadzere et al., 2002). These factors are interrelated and depend on the actual farm situation. With the dynamic modeling approach as applied in this study, there is no need to model the effects and interactions of all these factors explicitly, because critical temperature and duration are estimated per farm. Furthermore, the dynamic parameter for the effect of heat stress γ_t adapts to changes in environmental conditions within a farm.

In most studies the temperature humidity index (THI) is used. However in the Netherlands within a site-specific on-farm location, humidity does not vary much during a hot period. Using only temperature has the advantage that temperature measurements of the meteorological stations can be replaced by on-farm measurements of temperature. Furthermore, temperature of the weather forecasts can be compared with the farm specific estimated critical temperature to indicate the risk for heat stress in the near future and the expected loss in milk yield can be calculated using the parameter estimates for duration and effect of heat stress.

The estimated duration of the heat stress periods ranged from 3 to 9 d. A high duration means that cows recover slowly from heat stress. An explanation might be that the reduced feed intake cause residual effects. The delayed effects of heat stress are in agreement with literature. West et al. (2003) showed that mean air temperature and temperature humidity index (THI) of two days earlier had the greatest impact on milk yield and feed intake. Settivari et al. (2007) showed a negative effect on daily milk production up to 4 d after the end of an induced heat period. Linvill and Pardue (1992) used variables that counted the hours above a fixed threshold for THI up to the last 4 days to predict the effect of heat stress on milk production. The advantage of the model presented in this study is that the threshold and delay are both estimated from operational data, providing a farm specific critical temperature and duration. Together with the linear parameter for heat stress, these parameters determine the total yearly loss in milk yield due to heat stress.

The loss in milk yield in the Netherlands due to heat stress of 31.4 kg /cow/year is low in comparison to losses in the United States (St-Pierre, 2003), ranging from 68 (Wyoming) to 2072 (Louisiana) kg/cow/year. In The Netherlands the loss is 0.32% in relation to a year production of 9855 kg/cow/year. From an economic point of view the loss in milk returns is a modest 10.98 €/cow/year, assuming a milk price of € 0.35 per kg. On the other hand, heat stress results also in a diminished feed intake, which might save some costs. Furthermore, there might be effects on weight and body condition, health, reproduction and animal welfare and for a full economic evaluation, all these aspects should be taken into account.

The dynamic model was fitted following a Bayesian method for time series analysis, accompanied with a monitoring procedure for detection of outliers and/or other deteriorations. Not only large errors were detected, but also small errors caused alerts. Of course, in case of alerts, it remains up to the herdsman to diagnose the situation. Timely finding and correcting causes for unexpected changes in daily milk production aids the farmer in improving the production process.

5.5 Conclusions

The adaptive dynamic model presented in this paper is appropriate for quantification of the impact of heat stress for each farm in its specific situation in terms of critical temperature, duration and effect on milk production. The related parameter estimates provide information that can be used for management improvement. The critical temperature can be used as an indicator for the risk on heat stress based on daily weather forecasts. The duration can be used to evaluate and improve management regarding grazing, feeding and housing during warm periods. The adaptive dynamic model presented in this paper is appropriate for evaluation and monitoring level and trend of herd mean daily milk yield, including the estimation of week day effects. The on-line estimates provide useful information to the farmer to evaluate the actual situation and the retrospective estimates provide a good insight afterwards. The Bayesian procedure for time series analysis, accompanied with the monitoring procedure followed by automatic intervention is useful for process control. Detection of potential outliers and other deteriorations in the milk production process can be used as alerts to the farmer and might be helpful for improvement of dairy farm management.

Acknowledgements

The authors are grateful to Edwin Bleumer for gathering the data. We thank the editor and the referees for their helpful comments. This project was funded by the Dutch Ministry of Agriculture, Nature and Food Quality (The Hague).

5.6 References

ABDEL-BARY, H.H., M.M. MAHMOUD, H.I. ZAKY AND A.A. MOHAMED. 1992. Effects of season and month of calving on oestrous performance, services conception and milk yield of Friesian cows in Egypt. Egypt. *J. Anim. Prod*. **29**, 229–253.

ANDRÉ, G., P.B.M. BERENTSEN, G. VAN DUINKERKEN, B. ENGEL AND A.G.J.M. OUDE LANSINK. 2010. Adaptive models for on-line estimation of individual milk yield response to concentrate intake and milking interval length in dairy cows. *J. Agric. Sci.*, accepted for publication.

BANDARANAYAKA, D.D., AND C.W. HOLMES. 1976. Changes in the composition of milk and rumen contents in cows exposed to a high ambient temperature with controlled feeding. *Tropical animal health and production*. **8**, 38-46.

BANHAZI, T.M., AND J.L. BLACK. 2009. Precision livestock farming: A suite of electronic systems to ensure the application of best practice management on livestock farms. *Australian J. of Multi-disciplinary Engin*. **7**, 1-14.

BERMAN, A., Y. FOLMAN, M. KAIM, M. MAMEN, Z. HERZ, D. WOLFENSON, A. ARIELLI, Y. GRABER. 1985. Upper critical temperatures and forced ventilation effects for high-yielding dairy cows in a subtropical climate. *J. Dairy Sci*. **68**, 1488-1495.

BIANCA, W. 1965. Reviews of the progress of dairy science. Section A. Physiology. Cattle in a hot environment. *J. Dairy Res*. **32**, 291–345.

BOHMANOVA, J., I. MISZTAL, AND J. B. COLE. 2007. Temperature-humidity indices as indicators of milk production losses due to heat stress. J. Dairy Sci. **90**, 1947–1956.

DELUYKER, H.A., R.H. SHUMWAY, W.E. WECKER, A.S. AZARI AND L.D. WEAVER. 1990. Modelling daily milk yield in Holstein cows using time series analysis. *J. Dairy Sci*. **73**, 539-548.

FROST, A.R., C.P. SCHOFIELD, S.A. BEAULAH, T.T. MOTTRAM, J.A. LINES AND C.M. WATHES. 1997. A review of livestock monitoring and the need for integrated systems. *Comp. and Elec. in Agric*. **17**, 139-159.

KADZERE, C.T., M.R. MURPHY, N. SILANIKOVE AND E. MALTZ. 2002. Heat stress in lactating dairy cows: a review. *Livest. Prod. Sci*. **77**, 59 – 91.

LINVILL, D. E. AND F. E. PARDUE. 1992. Heat stress and milk production in the South Carolina coastal plains. *J. Dairy Sci*. **75**, 2598-2604.

MCDOWELL, R. E., N. W. HOOVEN AND J. K. CAMOENS. 1976. Effect of Climate on Performance of Holsteins in First Lactation. *J. Dairy Sci*. **59**, 965-971.

MONTGOMERY, D.C. 2005. *Introduction to statistical process control*. Third edition. Wiley. New York.

PANKRATZ, A. 1991. *Forecasting with dynamic regression models*. Wiley. New York.

RENEAU, J.K., AND J. LUKAS. 2006. Using statistical process control methods to improve herd performance. *Vet. Clin. North Am. Food Anim. Pract*. **22**, 171-93.

SCHNEIDER, P. L., D. K. BEEDE AND C. J. WILCOX. 1988. Nycterohemeral patterns of acid-base status, mineral concentrations and digestive function of lactating cows in natural or chamber heat stress environments. *J. Anim. Sci*. **66**, 112-125.

SETTIVARI, R. S., J. N. SPAIN, M. R. ELLERSIECK, J. C. BYATT, R. J. COLLIER, AND D. E. SPIERS. 2007. Relationship of thermal status to productivity in heat stressed dairy cows given recombinant bovine somatotropin. *J. Dairy Sci*. **90**, 1265–1280.

ST-PIERRE, N.R., B. COBANOV, AND G. SCHNITKEY. 2003. Economic losses from heat stress by US livestock industries. *J. Dairy Sci.* **86**, E52-E77

WATHES, C.M. 2009. Precision livestock farming for animal health, welfare and production. In: *Sustainable animal production*. The challenges and potential developments for professional farming. (Eds. A. Aland and F. Madec), pp. 411-419, Wageningen: Wageningen Academic Publishers.

WATHES, C.M., H.H. KRISTENSEN, J-M. AERTS AND D. BERCKMANS. 2005. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? In: *Precision Livestock Farming '05*. (Ed. S. Cox), pp. 33-47, Wageningen: Wageningen Academic Publishers.

WEST, J. W., B. G. MULLINIX, AND J. K. BERNARD. 2003. Effects of hot, humid weather on milk temperature, dry matter intake, and milk yield of lactating dairy cows. *J. Dairy Sci.* **86**, 232–242.

WEST, M. AND J. HARRISON. 1997. *Bayesian Forecasting and Dynamic Models*. Second edition. Springer.

6 General discussion

Methods and results are discussed in each chapter of this thesis. In this final chapter the methods and results are discussed in a broader context. In section 1, quantitative methodological aspects are discussed, regarding the data, modelling and parameter estimation. In section 2, the results are discussed with respect to the overall objective to develop a decision support system for control of the dairy production process using real time process data. In section 3, conclusions and in section 4, implications and recommendations are given.

6.1 Methodological aspects

The first objective of this research was to quantify the individual variation in milk yield response to concentrate intake and milking interval length. The second objective was the development of adaptive models for on-line estimation of the actual individual response. The results of this research were used to develop a decision support system for control of the dairy production process using real time process data. Real time process data differ in several aspects from data as usual collected for research, and by consequence the modelling approach and statistical analysis differ. These differences are discussed in the next sections.

6.1.1 Real time process data versus research data

Within research, complete data sets are collected according to a design of an experiment or a survey and are analysed afterwards. The power of the research is ensured by control of the environmental conditions, the settings of the explanatory variables, the accuracy of the measurements and the completeness of the data collection. In the on-farm operational situation the level of control is much lower. The environmental conditions are less controlled, outcomes of explanatory variables depend on the behaviour of the cows, advanced measurement methods are less available and the completeness of the data depends on the technical functioning of hard- and software. So, operational data have more uncontrollable variation and are more erroneous than research data.

Furthermore, research to investigate a process, is conducted such that the entire process is observed, resulting in complete time series, e.g. from begin to end of the production process. However, in an on-line approach in the operational situation, only historical data up to the actual time point are available and future outcomes of the process are unknown. By consequence, parameter estimation can only be based on information from the past and should be regularly updated during the on-going of the process.

The above suggests there are several shortcomings in the quality of real time process data in comparison to data collected for research. However, but this research shows that these shortcomings are no serious limitations for estimating the response in milk yield. The data used in the first two chapters cover only a short period of the lactation. In Ch. 2, only data of the first 3 weeks of lactation are used and in Ch. 3 only data of one week during lactation were used, but the results show that this short time series of data provide enough information to estimate the individual response in milk yield to concentrate intake and milking interval length. In Ch. 4 and 5 longer time series were used and the on-line estimates, based on information of past outcomes of the process only, confirm that it is possible to estimate the actual response.

6.1.2 Dynamic modelling of the dairy production process

Within dairy science empirical and mechanistic models are commonly used to describe the dairy production process (France and Thornley, 1984). The focus of empirical models is on prediction of the mean profiles of milk yield and feed intake during lactation. In empirical models, the dynamic aspects are incorporated by using time varying variables, like days in milk and/or age (parity) to describe the long term dynamics. Short-term dynamics are incorporated by extending the models with Box-Jenkins ARIMA components to account for serial dependency.

The scope of mechanistic models is to provide insight in the underlying physiological and biological processes of digestion and milk production. In mechanistic models, the dynamic aspects are incorporated by differential equations. Mechanistic models are more complex than empirical models, because they describe a lot of variables and relationships that are often non-linear.

In this research, we did not follow the approach of empirical or mechanistic model building. The main reason therefore is the difference in scope. For process control, the scope is on modelling the input – output relation in the actual situation. The only variables of interest are the controllable inputs: concentrate supply and milking frequency and there is no need to model the long-term effects in order to predict the entire lactation. The response in milk yield to concentrate intake and milking interval length can be described by simple linear models with a low number of parameters (regression coefficients) that can be regarded as linear approximations to more intricate non-linear models. Of course, there are a many other (uncontrolled) factors that influence feed intake and milk production, and moreover there are many interactions with environmental conditions and the state of the dairy cow. All these aspects change from time to time and by consequence, the response in milk yield is dynamic. Both in empirical and mechanistic models the parameters and covariance structures are assumed to be constant (stationary) during the production process, which makes these models less useful for modelling the dynamic milk production process of an individual cow. Within adaptive models, the dynamic aspects are incorporated in the model parameters following a self-learning routine. The model parameters are continuously updated, by discounting information from the past, in order to describe the response in the actual situation. So, there is no need to model in detail the entire process of digestion and milk production. Adaptive dynamic models offer the possibility to focus on the controllable input variables in a flexible way taking into account all the dynamics of the milk production process of an individual cow.

6.1.3 Parameter estimation and process control

Quantitative methods for on-line data analysis are developed for technical process engineering and are widely applied for control purposes of industrial (mechanical and chemical) processes. New outcomes of the process response variable(s) are predicted based on past observations of the response in relation to past and intended future values of (adjustable) explanatory (control) variables. The optimal future settings of the control variables can for example be found by maximizing a gross margin function to determine the target trajectory for the input and output variable(s). This approach, known as Model Predictive Control, relies on dynamic models of the process, most often linear transfer function models obtained by system identification (Ljung, 1987). The dynamic models are state-space models that accurately represent dynamic behaviour of a system. The models are often black or grey box models, because the parameters in these models are difficult to interpret. The parameters are estimated by filtering techniques or iterative recursive least squares (Young, 1984). Within the engineering approach separate routines are used for quality control to detect process disturbances, like control charts (Montgomery, 2005).

This engineering modelling and estimation approach is also suggested for control of biological processes (Aerts et al., 2003), but biological processes differ in several aspects from technical processes. Technical processes can be almost fully controlled, by accurately and intensively observation and monitoring during the production process. Furthermore, the environment is highly conditioned and finally, process deteriorations and disturbances occur at a fair low rate. By contrast, biological processes and their conditions are less easily controlled and more frequently disturbed, resulting in more variation and consequently a low signal to noise ratio. For that reason the Bayesian approach to time series analysis, developed by West and Harrison (1997), is chosen in this research. In their approach a system equation is used to model the dynamic changes of the parameters and an observation equation to model the observation variance. The Bayesian approach for time series analysis comprises a monitoring routine for detection of process deterioration and outliers. Detection of process disturbances is followed by automatic intervention to ensure that the model adapts to a possible changed situation by an extra decay of information from the past. So, within the Bayesian approach to time series analysis, both estimation of the dynamic response and detection of process disturbances are combined, which makes the Bayesian approach well suited for process control of biological production processes.

6.2 Results

6.2.1 Individual variation in milk yield response

The results of Ch. 2 and 3 show that there is considerable variation between individual cows in the effect of concentrate intake and interval length on daily milk yield and, consequently, on milking duration. Differences between individual cows in level of milk yield provide the base for selection and breeding and have contributed to the increased milk production per cow in the past century. From the estimated individual effects, the differences in level of milk yield can be divided in effects of concentrate intake and milking frequency and a remaining intercept that is related to the base ration of mainly roughage. In the operational situation, this information is used to determine the optimal settings for concentrate supply and milking interval in order to maximize the gross margin milk returns minus concentrate costs. The daily estimated individual response can also be used to derive indicators for the individual efficiency in terms of concentrate feeding and milking (interval sensitivity and milking duration). This new information enables more specific objectives for selection and breeding to improve dairy production accounting for the specific farm situation.

6.2.2 Potential economic gain

The outcomes from the studies in Ch. 2 and 3 show that the potential economic gain of applying individual optimal settings for concentrate supply ranges from 0.20 to 2.03 €/cow/day and that milk revenues increase from 498 to 507 €/d by applying individual optimal settings for milking frequency. These outcomes are achieved by simulation based on the estimated response using models that approximate the true response. Furthermore, it depends on several factors to what extent the estimated potential gain can be realized in practice. First, it should be noted that the gain regarding concentrate supply represents the situation after 3 weeks in lactation and not during the entire lactation. Furthermore, the actual economic gain depends on the actual prices for milk and concentrates, that might differ from the prices used in the studies. Finally, the individual settings applied in the studies are exact, but the realization of these settings in the operational situation depends on the response of the cows.

The potential economic gain represents the direct and short term effects of applying optimal settings, but there might be also indirect and long term effects. A change in level of concentrate feeding effects roughage intake and total milk yield. This might have consequences for interrelated farm processes like roughage cultivation, purchases or sales of roughage; land use; herd size and/or leasing milk quota. These aspects are also influenced when a change in efficiency of an AMS leads to a change of herd size.

The optimal individual settings correspond with the actual response of the dairy cow that fits to the actual performance of the cow regarding roughage intake and body weight change. Both, roughage intake and body weight change are controlled by the cow itself. Preliminary results of the application of the dynamic approach in practice (see section 6.4.1) show that the cows remain in good health and condition. This suggests that the optimal individual settings are in balance with the cows performance and that risks of feeding too much or too low levels of concentrates and/or milking too often or too infrequently are avoided. So, there might be positive effects on (udder-)health, welfare, body condition, living duration, fertility and reproduction. These indirect and long term effects might lead to a further improvement of the economic gains from dairy farming.

6.2.3 Practical applicability

The results from Ch. 2 and 3 show that the actual individual milk yield response to concentrate intake and milking interval can be adequately estimated from individual daily process data over a relatively short period of 1 to 3 weeks during the lactation. In Ch. 4 an adaptive dynamic linear model is developed for on-line estimation of the actual individual response from daily accumulated real-time process data. Based on the daily estimated actual individual response the optimal settings for concentrate supply and milking frequency can be determined. The algorithms for this dynamic approach to on-line estimation and optimization can be implemented in decision support systems for dairy management on dairy farms with automated concentrate feeders and automated milk meters or an AMS. In this way the individual optimal settings for concentrate supply and milking frequency are daily updated, in accordance with the actual individual response of the dairy cows. These individual optimal settings are essential different than advised settings from currently used feed evaluation systems, e.g. FiM (Thomas, 2004) and Norfor (Volden, 2011). With currently used systems the same supply of concentrates is advised, for comparable cows with respect to age, stage of lactation and daily milk yield, ignoring differences in response. For this reason it is difficult for the farmers to adopt this innovation (André et al., 2009).

6.2.4 Process control and monitoring

One of the objectives of this research was the development of an adaptive model for on-line estimation of the individual response in milk yield in order to control the individual settings of concentrate supply and milking frequency. The applied Bayesian procedure for time series analysis is not only useful for control of the individual settings, but turned out to be also a useful tool for monitoring. Process disturbances, like outliers and other deteriorations are detected by a monitoring procedure and are followed by automatic intervention in the estimation procedure. With the analysis of the daily individual milk yields (Ch. 4) 7.3% of the observations are detected as potential outliers or other deteriorations, with the analysis of daily herd mean milk yield (Ch. 5) this percentage was 8.4%. In this research we did not figure out the causes of these deviating observations, because the estimation procedure is made robust by automatic intervention. However, the detected deviating observation are useful alerts for the farmer for monitoring the production process. The major part of the deviations are incidental and indicate that these deviations are due to technical failures of the equipment or registration errors. The minor part of the deviations occur as successive alerts in series of length 2 or more and especially these alerts seem to be an indication for process disturbances. In Ch. 5 the possibilities of the Bayesian approach to time series analysis for process monitoring are further elaborated by explicit modelling level, trend, cyclical week day pattern and the effect of incidental high temperatures in order to quantify the impact of heat stress. The on-line estimates provide information for the farmer to evaluate the actual situation regarding several aspects that influence the production process. The on-line estimates are based on information from the past only and the estimates can be improved by backward filtering (smoothing) of the complete time series. The improved estimates are called the retrospective estimates and provide information for evaluation of the production process afterwards.

6.3 Conclusions

Between dairy cows there is considerable variation in milk yield, and consequently in milking duration, in response to concentrate intake and milking interval length (Ch. 2 and 3). This variation can be utilized to increase the profits from dairy farming. The gross margin per cow (milk revenues minus concentrate costs) can be increased by applying individual optimal settings for concentrate supply and milking intervals. The optimal settings are determined by the individual response in combination with the prices of milk and concentrates.

The actual individual response can be estimated from real time process data using adaptive dynamic models. The Bayesian approach to time series analysis, accompanied with the monitoring procedure followed by automatic intervention, is par excellence appropriate for dynamic modelling of the dairy production process (Ch. 4 and 5). The main reason for this is that within this kind of adaptive models, the functions of parameter estimation for process control and detection of disturbances for process monitoring are combined into one algorithm.

6.4 Implications and recommendations

The research described in this thesis is part of a larger project, involving the development and implementation of the individual dynamic approach in practice. The project started in 2006 with the development and testing of a prototype at a research farm (André et al., 2007). In 2007 and 2008, the prototype was built in a web application by a software company, developing management software for agricultural enterprises. This application, called "Dynamic Feeding" (www.dynamischvoeren.nl), was tested in a pilot on 4 dairy farms and thereafter distributed on a commercial scale in The Netherlands (Bleumer et al., 2009). Beginning 2011 about 550 dairy farms were participating and results were evaluated in order to improve and extend the application. In the next section, results of the implementation in practice are briefly summarized and in the sections thereafter implications are discussed and recommendations are given for research and farming.

6.4.1 Preliminary results of implementation in practice

The introduction of "Dynamic Feeding" (DF) in 2008 started in cooperation with two feed industry companies. Clients of these companies were invited to participate and feed specialists supported them during the implementation. Practical experiences from individual farmers were published in professional articles and on the web site www.dynamischvoeren.nl. To monitor the progress, the technical results of the dairy farmers applying DF were compared with the average results of all the participating farmers. Preliminary results indicate the following:

- A 5 to 10% lower use of concentrates
- Almost no difference in milk yield per cow
- So, more milk produced from roughage
- An higher income of 5 to 15 k€ per year, depending on farm size
- The cows remain in good health and condition
- The cows show a higher peak production
- An increase in efficiency of an AMS of 10%

6.4.2 Dairy research

Feeding

The individual dynamic approach is an on-line optimization method given the actual situation, so only short-term effects on milk yield are taken into account. Further long-term research is essential to evaluate the long-term effects of the individual dynamic approach on milk production, body weight development, roughage intake, health, fertility and reproduction.

Nowadays, roughage is commonly fed *ad lib* to dairy cows, but new technological developments enable controlled roughage feeding on herd and individual level. It is possible to extend the individual dynamic approach for control of roughage supply and therefore it is worthwhile to investigate the prospects of controlled roughage feeding.

The individual dynamic approach is directed on control of the level of milk yield and not on control of milk constitution, i.e. fat and protein content. Especially regarding milk composition the ratio concentrate to roughage is important (Gordin et al., 1971). Often, the complete ration of dairy cows consists of more than two components of different kinds of concentrates, roughage mixtures and additional by-products. An interesting research question is whether it is possible to reduce the number of components when applying the individual dynamic approach.

Disturbances

Disturbances in the milk production process, due to illness, heat, changes in environmental conditions are unavoidable. The adaptive model is made robust against these disturbances, by the monitoring procedure accompanied by automatic intervention. Up to now, the monitoring signals are not reported to the farmers yet. So, in practice the detection of disturbances is left to the farmers and when disturbances occur the farmers are advised to ignore the optimal settings and to act according to their own insights. However, the disturbances detected by the monitoring procedure might be useful for the farmer, and more research is needed to transform the signals into useful alerts, especially to distinguish between technical failures regarding the hard- and software and serious problems regarding the individual cow. In this context, it is important that hardware developers not only minimize the chances on technical failures of the equipment, but also try to minimize registration errors in order to avoid erroneous data.

However, disturbances in the production process might affect the parameter estimation and consequently the advised settings for concentrate supply and milking frequency. This aspect needs further research to ensure that the individual dynamic approach functions appropriately under all circumstances.

Breeding and selection

Application of the individual dynamic approach provides a host of new information about the individual performance of dairy cows in the form of estimates of individual response parameters. Based on these parameters, new indicators can be defined and used for selection and breeding. So, it is worthwhile to investigate the heritability of these parameters.

6.4.3 Methodological research

Adaptive models for on-line monitoring and control of biological production processes differ from empirical and mechanistic models that are commonly used within biological science. This is mainly due to the fact that within adaptive models is the parameter estimation is based on a relatively short series of recent observations only, which implies limitations for the estimation procedure and the modelling. The limitations are aggravated by the fact that the settings of the control variables are adjusted towards the optimal settings, resulting in a small range for estimating the response parameters. These limitations necessitate the use of sparse models, proper initial priors and discount factors as high as possible in order to get parameter estimates of good quality.

There are several aspects regarding the response models in Ch. 2,3 and 4 that need further investigation. Firstly, the models are additive without interaction between concentrate intake and milking interval length. Also, it is assumed that the effects of concentrate intake on the current day and the lagged effects of the past two days on the actual milk yield are equal. Finally, the time series of observations consists of daily accumulated milk yields in order to achieve an equidistant series. It is worthwhile to determine if the quality of the estimated response can be improved by investigating these aspects.

6.4.4 Precision farming

In management information systems large amounts of production data are stored and analyzed in order to improve the production process. The added value from management information systems on farms in The Netherlands is investigated by Verstegen and Huirne (2001) and Csajbok et al. (2005) and the results show a positive effect on profitability in the

long run. On dairy farms, an increased milk and protein production and a shortened calving interval was found, such that the payback period of a management information system was 5 years (Tomaszewsky et al., 2000). The process data collected during the production process are analysed afterwards when the process is completed (Banhazi and Black, 2009) i.e. at the end of the lactation, after a production cycle, a season or a year. In this way the information, produced afterwards from process data, is used to support tactical management decisions. With the on-line dynamic approach described in this thesis, real time process data are analysed to provide information on the current situation in order to optimize the production process at that moment and the near future. In this way, the information is used to support operational management decisions. This is an important principle of Precision Farming: control of the smallest controllable production unit in the actual situation.
Technological developments, like new hardware for process automation and new advanced sensors, provide large amounts of new data. This thesis research shows that control of milk production is possible using regular operational measurement data and actual prices of milk and concentrates. This information is sufficient in order to pursue the economic target of maximizing the gross margin: milk returns minus concentrate costs. Stating a clear target as a SMART-objective is also an important principle for Precision Farming, in order to determine which measurement data are needed.

Precision Farming is an innovative approach and especially the economic benefits are important to the farmer to adopt this new approach. Farmers avoid risks and as long there is uncertainty they are reluctant to change their management and they have to be learned the new insights and principles of an innovation (Marra et al., 2003). To introduce Dynamic Feeding in practice there was a tight cooperation between hard- and software developers, feed industry, education and science institutes in their efforts to be successful (Bleumer et al., 2009).

The Bayesian dynamic approach for monitoring and control of dairy production can be broadened to other processes and sectors. For example within dairy farming, the process of milking can be optimized by control of vacuum, pulsation rate and ratio. Within poultry and pig farming the Bayesian dynamic approach can be followed in order to optimize egg and meat production. The Bayesian dynamic approach is also applied for control of manure (co-)digestion (van Riel, personal comm.). And there might also be prospects for production processes in arable and horticultural farming. Bayesian adaptive models are ideal Precision Farming tools for monitoring and control of biological production processes in a stochastic dynamic environment.

6.5 References

AERTS, J-M., C.M.WATHES AND D. BERCKMANS. 2003. Dynamic data-based modelling of heat production and growth of broiler chickens: Development of an integrated management system. *Biosystems Engineering*, **84**, 257-266.

ANDRÉ, G., W. OUWELTJES, R.L.G. ZOM, AND E.J.B. BLEUMER. 2007. Increasing economic profit of dairy production utilizing individual real time process data. In: *Precision Livestock Farming '07* (Ed. S. Cox), pp. 179–186, Wageningen: Wageningen Academic Publishers.

ANDRÉ, G. E.J.B. BLEUMER AND G. VAN DUINKERKEN. 2009. Evaluation of an application for dynamic feeding of dairy cows. In: *Precision livestock farming '09* (Eds. C. Lokhorst and P.W.G. Groot Koerkamp), pp. 25-32, Wageningen: Wageningen Academic Publishers.

BANHAZI, T.M., AND J.L. BLACK. 2009. Precision livestock farming: A suite of electronic systems to ensure the application of best practice management on livestock farms. *Australian J. of Multi-disciplinary Engin*. **7**, 1-14.

BLEUMER, E.J.B., G. ANDRÉ AND G. VAN DUINKERKEN. 2009. Implementation of an application for daily individual concentrate feeding in commercial software for use on dairy farms. In: *Precision livestock farming '09* (Eds. C. Lokhorst and P.W.G. Groot Koerkamp), pp. 33-36. Wageningen: Wageningen Academic Publishers.

CSAJBOK, I., A. OUDE LANSINK AND R. HUIRNE. 2005. Effects of management information from FADN on profitability of Dutch potted-plant firms. *Agricultural Economics* **33**, 325-331.

FRANCE, J., AND J.H.M. THORNLEY. 1984. *Mathematical models in agriculture. A quantitative approach to problems in agriculture and related sciences*. London: Butterworths.

GORDIN, S., R. VOLCANI AND Y. BIRK. 1971. The effect of varying ratios of roughage to concentrates on composition and yield of cow's milk. *Journal of Dairy Research*, **38**, 295-302.

LJUNG, L. 1987. *System Identification. Theory for the user*. Prentice-Hall, New-York.

MARRA, M., D.J. PANNELL AND A.A. GHADIM. 2003. The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Agric. Systems* **75**, 215-234.

MONTGOMERY, D.C. 2005. Introduction to statistical process control. Third edition. Wiley. New York.

THOMAS, C. (Ed) 2004. *Feed into Milk: A new applied feeding system for dairy cows*. 72 pp. Nottingham, United Kingdom: Nottingham University Press.

TOMASZEWSKI, M.A., M.A.P.M. VAN ASSELDONK, A.A. DIJKHUIZEN AND R.B.M. HUIRNE. 2000. Determining farm effects attributable to the introduction and use of a dairy management information system in The Netherlands. *Agric. Econ*. **23**, 79-86.

VERSTEGEN, J.A.A.M., AND R.B.M. HUIRNE. 2001. The impact of farm management on value of management information systems. *Comp. and Elec. in Agric*. **30**, 51-69.

VOLDEN, H. (Ed.) 2011. *NorFor - The Nordic feed evaluation system.* EAAP Scientific Series Volume 130.

WEST, M. AND HARRISON, J. 1997. *Bayesian Forecasting and Dynamic Models*. 2nd edn. New York: Springer-Verlag.

YOUNG, P.C. 1984. *Recursive Estimation and Time-series Analysis*. Springer-Verlag. Berlin.

Summary

Individual variation in milk yield response to concentrate intake and milking interval length

During the last century in the Netherlands milk production per cow has almost tripled. Accordingly, the amount of concentrates yearly fed per cow strongly increased. Furthermore, automation and robotisation has changed dairy management, especially by the introduction of automatic concentrate feeders and milking systems. A new management concept, emerging in the last decades, is Precision Livestock Farming (PLF). The objective of PLF is to optimize livestock production, by on-line monitoring and control of the production process, utilizing the technical possibilities of automation and robotisation. Nowadays, individual settings for daily concentrate supply and milking frequency are based on standards, ignoring individual variation in milk yield response on concentrate intake and milking frequency. This leads to the main hypothesis for this thesis research that profitability of dairy farming can be improved by utilizing information on individual variation in response.

The first objective of this research was to quantify the individual variation in milk yield response to concentrate intake and milking interval length, in order to assess the economic prospects of applying individual optimal settings for concentrate supply and milking frequency.

In the first observational study (Ch. 2), data from 299 cows on four farms in the first 3 weeks of the lactation were collected. Individual response in daily milk yield to concentrate intake was analysed by a random coefficient model. During the first three weeks of lactation, considerable variation in individual milk yield response to concentrate intake was found on all four farms. An economic simulation was carried out, based on the estimated parameter values in the observational study. Individual economically optimized settings for concentrate supply were compared with conventional strategies for concentrate supply based on averaged population response parameters. Applying individual economic optimal

settings for concentrate supply during early lactation, potential economic gain ranges from 0.20 to 2.03 €/cow/day.

In a second observational study (Ch.3), data of normal uninterrupted milkings during one week from 311 cows kept in 5 separate herds on one farm were collected. The data set consisted of 4,915 records and random coefficient models were fitted to estimate the individual effects of milking interval on daily milk yield and milking duration. Between individuals, considerable variation in milk yield and milking duration was found in response to milking interval. Based on the estimated individual response, a simulation was carried out in order to optimize the utilization of an AMS for different herd sizes and occupation rates. Applying optimal individual milking intervals for a herd of 60 cows and an AMS operating at an occupation rate of 64%, the average milking interval reduced from 0.421 day to 0.400 day, the daily milk yield at the herd level increased from 1,883 to 1,909 kg/day, and milk revenues increased from 498 to 507 €/day. In the actual situation, the herd consisted of 60 cows. A further increase of daily milk revenues per AMS was possible by increasing the operation rate and/or herd size.

The conclusion is that between dairy cows there is a considerable variation in effects of concentrate intake and milking interval length on milk yield and, consequently, milking duration. A marked increase in economic profits of dairy production is possible by improvement of the concentrate allocation and/or the utilisation of an AMS, applying optimal individual settings based on the actual individual response in milk yield.

Development of adaptive models

The second objective was the development and testing of adaptive models for on-line estimation of the actual individual response in milk yield to concentrate intake and milking interval length. In Ch. 4 adaptive dynamic models for on-line estimation of the actual individual milk yield response to concentrate intake and milking interval length were evaluated. The parameters in these models may change over time and are updated through a Bayesian approach for on-line analysis of time series. Time series data of daily milk yield during the first 200 days of lactation from 17 cows were analysed with different adaptive dynamic models. Three models were evaluated: a model with linear terms for concentrate intake and length of milking interval, a model with linear and quadratic terms, and an enhanced model in order to obtain more stable parameter estimates. The linear model was only useful for forecasting milk production and the estimated parameters of the quadratic model turned out to be unstable. The parsimony of the enhanced model lead to far more stable parameter estimates.

In Ch. 5 an adaptive dynamic model was used for time series analysis of herd mean daily milk yield, in order to quantify the impact of heat stress and to assess the potential for monitoring and control of milk production. Time series data of daily milk yield from 2003 to 2006 were collected on six experimental research farms in The Netherlands. The impact of heat stress was quantified in terms of critical temperature, duration and loss in milk yield. The estimated critical temperature was 17.8 ^{o}C, the duration was 5.5 days, and loss in milk yield 31.4 kg milk/cow/year, averaged over farms. Besides estimation of the impact of heat stress, level and trend, including a weekly cyclical pattern were estimated to evaluate the production process. The Bayesian approach for on-line analysis of time series comprises also a procedure for the detection of potential outliers and other deteriorations that might be promising for monitoring the production process. Outliers and other process deteriorations are adequately detected by this monitoring procedure.

The conclusion is that on-line estimation of the actual individual response in milk yield and milking duration is possible following a Bayesian approach for time series using an adaptive dynamic model. Besides estimation of the actual response the Bayesian approach adequately detects process deteriorations. Therefore, adaptive dynamic models provide a useful tool for control and monitoring of the dairy production process.

Samenvatting

Verschillen tussen individuele koeien in melkproductierespons op krachtvoeropname en lengte melkinterval

In Nederland is in de afgelopen eeuw de melkproductie per koe bijna verdrievoudigd. In overeenstemming met de gestegen productie is ook de krachtvoeropname per koe sterk toegenomen. Verder is de melkveehouderij veranderd door automatisering, zoals de introductie van krachtvoerautomaten en melkrobots. Een nieuw management concept, dat inspeelt op deze ontwikkelingen, is Precisie Veehouderij. Het doel van Precisie Veehouderij is het optimaliseren van de dierlijke productie, door online monitoring en controle van het productieproces, gebruikmakend van de technische mogelijkheden die de automatisering in de veehouderij biedt. Tot nu toe, zijn de instellingen voor de individuele dagelijkse krachtvoergift en melkfrequentie gebaseerd op normen, waarbij te weinig rekening wordt gehouden met verschillen tussen dieren in melkproductierespons op krachtvoeropname en melkfrequentie. Dit leidt tot de belangrijkste hypothese voor het promotieonderzoek, namelijk dat de rentabiliteit van de melkveehouderij kan worden verbeterd door gebruik te maken van informatie over individuele variatie in respons.

De eerste doelstelling van het promotieonderzoek was het kwantificeren van de individuele variatie in melkproductierespons op krachtvoeropname en lengte melkinterval, om zodoende het economische voordeel vast te stellen dat kan worden behaald door de toepassing van optimale individuele instellingen voor krachtvoergift en melkfrequentie.
In de eerste observationele studie (Ch. 2), werden dagelijkse gegevens gedurende de eerste 3 weken van de lactatie verzameld, van 299 koeien afkomstig van 4 melkveebedrijven. De individuele melkproductierespons op krachtvoeropname werd geanalyseerd met een random coëfficiënten model. Op alle 4 bedrijven werd aanzienlijke variatie in individuele melkproductierespons op krachtvoeropname vastgesteld, tijdens de eerste drie weken van de lactatie.

Vervolgens werd een economische simulatie uitgevoerd, gebruikmakend van de resultaten van de observationele studie. Economisch optimale individuele instellingen voor de krachtvoergift werden vergeleken met instellingen volgens conventionele strategieën voor krachtvoeradvisering, die uitgaan van populatiegemiddelden. Toepassing van de optimale individuele instellingen voor krachtvoergift tijdens de eerste weken van de lactatie, kan een economisch voordeel opleveren, variërend van € 0,20 tot € 2,03 per koe per dag.

In een tweede observationele studie (Ch.3), werden van 311 koeien, gehouden in 5 aparte groepen op één veehouderijbedrijf, gedurende één week gegevens van normale niet onderbroken melkingen verzameld. Het databestand bestond uit 4.915 melkingen en de individuele effecten van intervallengte op de melkproductie en melkduur zijn geschat met random coëfficiënten modellen. Tussen individuen, werd aanzienlijke individuele variatie in het effect van de lengte van het melkinterval op melkproductie en melkduur gevonden.

Op basis van de geschatte individuele effecten, is een simulatiestudie uitgevoerd om het gebruik van een automatisch melk systeem (AMS), bij verschillende koppelgroottes en draaiuren per dag, te optimaliseren. Door toepassing van optimale individuele melkintervallen, kan het gemiddelde melkinterval teruggebracht worden van 0,421 dag naar 0,400 dag, de dagelijkse melkopbrengst op koppelniveau verhoogd worden van 1.883 naar 1.909 kg/dag, en de melkinkomsten stijgen van € 498 tot € 507 per dag. In die situatie bestaat de kudde uit 60 koeien en is het aantal draaiuren van het AMS 15,36 uur per dag. Een verdere verhoging van de dagelijkse melkopbrengst per AMS is mogelijk door de koppelgrootte en/of het aantal draaiuren per dag te verhogen.

De conclusie is dat er aanzienlijke individuele variatie is in effecten van krachtvoeropname en lengte melkinterval op de melkproductie en de melkduur. Het economisch resultaat in de melkveehouderij en/of het gebruik van een AMS kan verbeterd worden, door toepassing van optimale individuele instellingen voor dagelijkse krachtvoergift en melkfrequentie, gebaseerd op de individuele respons in melkproductie.

De ontwikkeling van adaptieve modellen

De tweede doelstelling van het promotieonderzoek was de ontwikkeling en het testen van adaptieve modellen voor het online schatten van de actuele individuele respons in melkproductie op krachtvoeropname en lengte van het melkinterval.

In Ch. 4 werden verschillende adaptieve dynamische modellen voor online schatting van de individuele respons in melkproductie geëvalueerd. De parameters in dynamische modellen kunnen veranderen in de tijd en worden dagelijks bijgesteld volgens een Bayesiaanse methode voor de analyse van tijdreeksen. Tijdreeksen van dagelijks melkgiften van 17 koeien, verzameld tijdens de eerste 200 dagen van de lactatie, werden geanalyseerd met drie verschillende modellen: een model met lineaire effecten van krachtvoeropname en lengte melkinterval, een model met lineaire en kwadratische effecten, en een aangepast model waarmee stabielere parameter schattingen kunnen worden verkregen.

Het lineaire model was alleen geschikt voor voorspelling van de melkproductie en de geschatte parameters van het kwadratische model bleken niet stabiel genoeg te zijn. Met het aangepaste model werden stabielere parameter schattingen verkregen en dit model bleek geschikt te zijn voor online schatting van de respons.

In Ch. 5 werd een adaptief dynamische model ontwikkeld en getest voor tijdreeksanalyse van de dagelijkse gemiddelde melkgift op koppelniveau. Het doel was om de impact van hittestress te kwantificeren en daarnaast te beoordelen of de dynamische aanpak geschikt is voor monitoren en controleren van het melkproductieproces.

Tijdreeksen met dagelijkse melkgiften, verzameld op 6 experimentele onderzoeksbedrijven in Nederland in de periode van 2003 tot 2006, werden geanalyseerd met een zelf lerend model. De impact van hittestress werd gekwantificeerd in termen van kritieke temperatuur waarboven hitte stress optreedt, duur van de hittestress periode en verlies in melkproductie. Gemiddeld over de bedrijven was de geschatte kritieke temperatuur 17,8 ^{o}C, de duur 5,5 dagen en het verlies in melkproductie 31,4 kg melk per koe per jaar. Naast de inschatting van de impact van hittestress, werden niveau en trend, met inbegrip van een wekelijks cyclisch patroon geschat om het melkproductieproces nader te evalueren. Voor dit doel is er binnen de Bayesiaanse methode voor online analyse van tijdreeksen een procedure voor het opsporen van potentiële uitbijters en andere verstoringen en lijkt veelbelovend voor het monitoren en controleren van het melkproductieproces. Potentiële uitschieters en andere verstoringen van het proces werden adequaat gedetecteerd met deze procedure.

De conclusie van het promotieonderzoek is dat online schatting van de actuele individuele respons in melkproductie en melkduur mogelijk is volgens de Bayesiaanse aanpak voor analyse van tijdreeksen, gebruikmakend van adaptieve dynamische modellen. Naast de schatting van de respons kunnen proces verstoringen adequaat worden vastgesteld met de Bayesiaanse procedure voor monitoring. Adaptieve dynamische modellen zijn daarom bij uitstek geschikt voor het monitoren en controleren van het melkproductieproces.

Curriculum Vitae

Gerrit André werd geboren op 29 januari 1959 in Harderwijk. In 1976 behaalde hij het diploma HAVO aan het Gereformeerd Lyceum te Groningen. Vervolgens behaalde hij in 1980 het diploma MAS aan de Christelijke Middelbare Landbouwschool te Groningen en in 1984 het diploma HAS aan de Christelijke Agrarische Hogeschool te Dronten. Hij begon zijn carrière als onderzoeksassistent bij het Instituut voor Veeteeltkundig Onderzoek (IVO) in Zeist. Daarna werkte hij bij het Praktijkonderzoek voor de Rundvee-, Schapen- en Paardenhouderij te Lelystad. In die periode volgde hij opleidingen voor statistiek bij de Vereniging voor Statistiek en Operationele Research en behaalde in 1993 het diploma Statisticus – VVS. Aan de onderzoekers gaf hij statistische ondersteuning bij de opzet en verwerking van het onderzoek en werkte hij mee aan de ontwikkeling van simulatiemodellen voor de veehouderij en grasgroei. In 2003 begon hij met het onderzoek naar de toepassing van adaptieve modellen voor krachtvoeradvisering bij melkvee. In 2006 ontwikkelde hij de toepassing Dynamisch Voeren en Melken, waarmee voor iedere koe dagelijks de optimale krachtvoergift en melkfrequentie wordt berekend. Deze uitvinding vormde de aanleiding voor zijn proefschrift, om zo de innovatieve dynamische aanpak, die reeds met gunstig resultaat wordt toegepast in de melkveehouderij, ook wetenschappelijk te onderbouwen. Momenteel werkt hij als onderzoeker Precisie Veehouderij bij Livestock Research - Wageningen UR, te Lelystad.

Geert André
PhD candidate, Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

	Name of the course	Department/Institute	Year	ECTS
I	**General part**			
1	Techniques for writing and Presenting a Scientific Paper	Animal Sciences Group	2006	1.2
2	Project and Time Management	Proefstation Rundveehouderij	1998	1.5
	Subtotal part I			**2.7**
II	**Mansholt-specific part**			
3	Mansholt Introduction course	Mansholt Graduate School		
4	Oral presentation 6 June 2007	Eur. Conf. Precision Livestock Farming	2007	1.0
5	Oral presentation 21 April 2009	Int. Symposium Dairy Cow Nutrition	2009	1.0
6	Oral presentation 6 July 2009	Eur. Conf. Precision Livestock Farming	2009	1.0
	Subtotal part II			**3.0**
III	**Discipline-specific part**			
7	a. Technical – scientific computer applications	Post Academisch Onderwijs Post Academisch Onderwijs	1986	2.4
	b. Applied Regression Analysis	Post Academisch Onderwijs	1986	1.6
	c. Computer applications and Quantitative Methods	Post Academisch Onderwijs	1986	1.6
	d. Design, analysis and interpretation of animal experiments	Ned. Org. voor Toegepast Natuurwetenschappelijk Onderzoek	1986	1.6
	e. Multivariate methods	Boerhave Instituut	1990	2.0
	f. Random-effect models for longitudinal data and correlated measuremen	Institute of Arable Crops Research	1998	0.4
	g. New Developments in REML ar its implementation in Genstat 5 Release 4.1	Biometris	1999	0.4
	h. Bayesian Statistics	Vereniging voor Statistiek	2003	0.8
	i. Statistical Analyst	Vereniging voor Statistiek	1989	13.0
	j. Statistician		1993	20.0
	Subtotal part III			**43.8**
IV	**Teaching and supervising activities**			**4.0**
			Total	**53.5**

Omslag: *En face*. Hans Buenk (Nijkerk, 1953) *De koe is van bijzaak, hoofdzaak geworden*.

Druk: GVO drukkers & vormgevers B.V. | Ponsen & Looijen