METHODS FOR SENSOR BASED FARROWING PREDICTION AND FLOOR-HEAT REGULATION

THE INTELLIGENT FARROWING PEN

APARNA UDUPI

PhD THESIS · SCIENCE AND TECHNOLOGY · 2014

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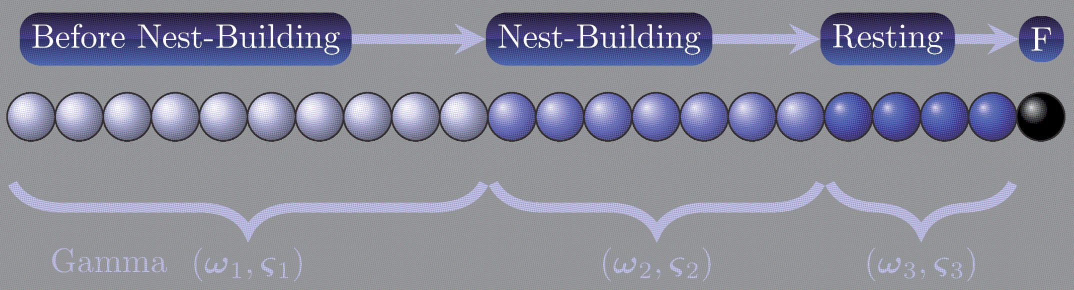

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PREFACE

This dissertation is submitted in partial fulfilment of the requirements for the Doctor of Philosophy (Ph.D.) degree at the Department of Animal Science, Aarhus University, Denmark. The dissertation presents the research work conducted between March, 2009 and September, 2012, initially, at the Department of Genetics and Bioinfomatics in the research group for Genetics, Bioinfomatics and Statistics (GBI-GBS) (which was later renamed to Biostatistics research group). In 2012, restructuring of the departments made some of us to move to the Department of Animal Science. This study has been a part of the main project 'The Intelligent Farrowing Pen' and supported by the 'Danish National Advanced Technology Foundation'.

The Ph.D. work is inter-disciplinary, i.e. it relies on the application of methods from disciplines such as Herd management, Statistics and Operations Research. Therefore, I have tried to formulate different parts of the dissertation to different audiences, e.g. focus on the final system for behavioural scientists and the farmers versus methodological focus for scientist with more mathematical background. The algorithms presented in the dissertation should be seen as the methodology for using the data to achieve the overall aim of the thesis.

The work would not have been completed without the main supervision of Erik Jørgensen and the co-supervisors Lene Juul Pedersen and Lars Relund Nielsen (while he was working in Foulum). Due to the circumstances, Ulrich Halekoh took over the main supervisor position at the later stage and encouraged my work.

My sincere thanks to Gang Jun Tu for filling up lots of energy in me, by supplying sugar whenever I needed it. I also extend my gratitude towards Lene Munskgaard who put up with me in all the circumstances.

I would like to acknowledge Uday Kumar Shetty and Prathap Shetty Halady who encouraged me to apply for a PhD position; a decision which led me to obtain the current position. In an unknown country, Karin Smedegaard and Goutam Sahana (and family) made my stay very pleasant from the first day in Viborg. My first journey from Copenhagen to Viborg stamped an impression of a live telecasting Black & White television show and reminded me of a silent Indian movie 'Pushpakavimana' (word to word translation is 'flowery aircraft'). I could hardly see any colourful or talkative people around me in the train. I took a deep breath after I was received by a colourful family called - Nørresø Kollegiet. First few days, I was running behind Chitra just like a child following the mother. Chitra, Smitha and Vinitha (and family) have been always with me during both good and bad days. I also have had a great time with Sebastiano, Gabrial, Joao, Emiliano, Sina, Vahid, Wentao, Rafael, Emmanuel etc. etc. etc.; trust me, it is a big list. The success of my PhD study should also be shared with them because it is their company which made each day *fresh* and a *special*. It is said that there won't be sorry and thanks between friends. But, friends, I take this opportunities to remember our golden days, once again.

I also have had some memorable 'discussion days' with Lars, Søren Højsgaard, Ulrich, Erik, David Edwards and Smitha in the corner of K21 and canteen; the topics included R, statistics, chilly, spices, wine, music and dance, cricket, crackers, car...; I never thought that those are discussable topics. I also have had a 'colourful' (I should admit it) office-mates who have tolerated me time to time. Being a British-English, it would have been hard for David to look at my Indian English + Statistical English (?) grammar. Thanks David, for the corrections.

Last but not the least, I'm also thankful to my family members and friends from back home who are still updating me with the Indian movies, songs and news and giving me the feeling that I am not far from them.

SUMMARY

Piglet mortality is a current issue in the pig production and the large variability between herds suggests a management component to the mortality. Studies show that the mortality may be reduced by the supervision of farrowing or through climate regulation in the farrowing pens. However, this is possible only if the farrowing time is known and thus provides sufficient time for the management to make and execute the decisions. The gestation period of a sow is approximately 115 (SD=2) days. However, an initial cost-benefit analysis recommended increased precision in the prediction of farrowing to make the increased management efforts cost-effective for the pig producer. Recently, a wide range of sensor technology have become available to monitor the behavioural and physiological changes of sow. Evidence show that appropriate utilization of sensor technology may increase the precision of prediction of onset of farrowing. Prediction is feasible only if the prediction is online and automated.

The thesis is focused on constructing a system that can give predictions about the expected time to farrowing of individual sows based on automatic sensor recordings such as water consumption, video based activity measurements, and photo-cells based activity measurements. The warnings could serve to activate the floor heating system to ensure a sufficiently high temperature for the new born piglets, as well as to help the farmer to organize extra surveillance around farrowing. The thesis is based on three submitted manuscripts, describing the system at different stages.

The kernel in the thesis is a Markov process with four subsequent states *Before Nest-Building Nest-Building*, *Resting* and the absorbing state *Farrowing*; the states were selected based on ethological knowledge about sow behaviour. However, the sojourn time distribution in each state is not exponential. There-

fore a continuous time discrete state semi-Markov process based on a Phase-Type distribution (in this case Erlang distributed) was formulated. Finally, the Markov process was transformed to a discrete time process. A Hidden Markov Model (HMM) was used for this process. The model is called Hidden Phase-type Markov Model (HPMM), and the time steps corresponded to each updating with sensor information at which the time to farrowing was predicted. The first paper describes and validates the use of the HPMM model for predicting the farrowing time based on an experimental data set of more than 30 sows. The second paper describes the estimation of model parameters (transitional parameters and parameters for the distribution of the sensor measurements conditioned on the state of the sow) using an adaption of estimation methods for Hidden Markov Models. The final paper demonstrates how to formulate the floor-heat regulation problem as a Partially Observable Markov Decision Process (POMDP), by supplementing the farrowing process model with a model for floor heating, a model for mortality model, and the relevant utilities. Approximate solutions for POMDP was found using so called greedy strategies (e.g. QMDP) and their rewards were evaluated against 'no-heating' strategy and a simple heuristic strategy.

The tools for the prediction of onset of farrowing, estimation of HPMM and optimal decision making provides a framework for handling a large amount of sensor data available and gives an overview of how to integrate information from several sensors on the pen level. The complexity of the models imply that the prediction algorithm and decision tool may be run on the herd level computer; whereas the parameters were estimated on the central level computers. Hence, the application is quite promising in precision livestock farming with the necessary customising for the end-user.

SAMMENDRAG

Pattegrisedødelighed er et konstant problem i svineproduktionen og den store variation mellem besætninger tyder på, at management er en vigtig årsag til dødeligheden. Undersøgelser viser, at dødeligheden kan reduceres ved overvågning af faringerne eller gennem klimaregulering i farestien. Men dette er kun muligt, hvis faretidspunktet er kendt og der dermed er tilstrækkelig tid til, at driftsledelsen kan tilrettelægge og gennemføre tiltag, som at allokere arbejdskraft til overvågning, eller at iværksætte klimaregulering . Drægtighedsperioden for en so er omkring 115 (SD = 2) dage og faringstidspunktet kan derfor prædiceres med samme præcision udfra løbetidspunktet. Imidlertid viste en cost-benefit-analyse, at der kræves øget præcision af faringsprædiktionen hvis de ekstra tiltag skal kunne svare sig for svineproducenten. For nylig, er en bred vifte af sensor-teknologier blevet tilgængelige til overvågning af adfærdsmæssige og fysiologiske ændringer hos soen. Undersøgelser viser, at hensigtsmæssig udnyttelse af sensorteknologi kan øge præcisionen af forudsigelsen af faringen, men en anvendelse at prædiktionen er kun praktisk mulig, hvis prædiktionen er online og automatiseret.

Afhandlingen fokuserer på konstruktion af et system, der kan give forudsigelser om den forventede tid til faring af individuelle søer baseret på automatiske sensorer, såsom vandforbrug, aktivitetsmålinger baseret på videooptagelser og fotoceller. Advarslerne kan for eksempel tjene til at aktivere et gulvvarmesystem der sikrer en tilstrækkelig høj temperatur for de nyfødte grise, eller til at hjælpe landmanden til at organisere ekstra overvågning omkring faring. Afhandlingen er baseret på tre manuskripter, der beskriver forskellige stadier af dette system. Alle tre manuskripter er indsendt til publikation.

Kernen i afhandlingen er en såkaldt Markov proces med fire tilstande som soen gennemløber *Før redebygning*, *Redebygning*, *Hvile* og en absorberende tilstand *Faring*; tilstandene blev udvalgt på grundlag af etologiske viden om soens

adfærd. Men soens opholdstid i disse tilstande er eksponentielt fordelt. Derfor blev modellen formuleret som en kontinuert, semi-Markov proces med diskret tilstandsrum baseret på Erlang fordelinger af opholdstiden i de enkelte tilstande. Endelig blev denne Markov proces omdannet til en process i diskret tid. En Hidden Markov model blev anvendt til at modellere denne proces. Denne model kaldes en Hidden Phase-type Markov Model (HPMM). Tidsskridtene svarer til hver opdatering med sensor oplysninger og falder således sammen med genberegning af faringsprædiktionen. Det første manuskript beskriver og validerer brugen af HPMM modellen til forudsigelse af faringstidspunktet baseret på et eksperimentelt datasæt på mere end 30 søer. Det andet manuskript beskriver estimering af modelparametre (parametre for overgangsintensititer og parametre for fordelingen af sensormålinger betinget på soens tilstand) ved hjælp af en modifikation af estimationsmetoder anvendt til Hidden Markov Models. Det sidste manuskript viser, hvordan problemet med regulering af gulvvarmen kan formuleres som en delvist observerbar Markov Beslutningsprocess (POMDP) ved at supplere modellen for faringsprocesen med en model for gulvvarme, dødelighed, og de involvere omkostninger. Approksimative løsning til POMDP blev fundet ved hjælp af såkaldte grådige (greedy) strategier (f.eks QMDP) og deres udbytter blev vurderet mod en strategi uden gulvvarme og en simpel heuristisk strategi.

Værktøjerne til forudsigelse af udbrud af faring, estimering af HPMM og optimal beslutningstagning giver en ramme for håndtering af den store mængder sensor data der er til rådighed, og giver et overblik over hvordan information fra flere sensorer kan integreres på stiniveau. Kompleksiteten i de anvendte modeller indebærer, at prædiktionsalgoritme og beslutningsstøtte/ reguleringsmodulet kan køres på besætningens egen computer, mens parameter estimation og beregning af beslutningstrategier kan gennemføres på computere med større kapacitet på det centrale niveau. Derfor er anvendelsen ganske lovende i fremtidens præcisionshusdyrbrug, efter en nødvendig tilretning mod slutbrugeren.

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CHAPTER 1

INTRODUCTION TO THE PH.D. THESIS

1.1 Introduction

Piglet mortality is one of the highly concerned issues among the farmers, scientists and politicians as it has high impact on the economy of many of the countries. An average of 13.7% of the live born piglets died before weaning in Danish sow herds in 2012 according to Vinther (2013). Although the variation between the Danish herds are not well documented, the Norwegian study (Andersen et al., 2007) has documented the mortality rates ranging from 5 to 24% and a Swedish study (Wallgren, 2013) has also discussed the variation between the herds and herd management. Baxter et al. (2011) reviews different studies in this field. The large variability between herds suggests a management component to the mortality, and several studies indicate that it is possible to reduce this mortality, especially in the herds with high mortality, either by increasing the supervision of the farrowings (Dyck and Swierstra, 1987; White et al., 1996; Andersen et al., 2009) or through improved climate regulation during farrowing and the following days (Malmkvist et al., 2006). It has been shown that birth surveillance combined with birth assistance at farrowing and care for weak and small piglets such as reheating and colostrum supplementation can reduce neonatal piglet mortality with up to 50% of the control level. Kirkden et al. (2013) reviewed the management solutions related to the piglet mortality. However, due to high labour costs such procedures are rarely performed on commercial farms in Denmark. The efficiency and cost of such a procedure would be considerably improved by a more precise prediction of farrowing time.

According to Berthon et al. (1994), the neonatal piglets suffer from hypothermia in the first 2 days of their life. During the body cooling, the heat production has increased initially; but started decreasing below the body temperature threshold of $34.4°C$ which may result in the death of the piglet (Lossec et al., 1998). Rewarming of the piglets, during the first 2 hours, was faster at an ambient temperature of $34°C$ as compared with $24°C$. Rewarming may be by supervising the farrowing which include drying and warming immediately after the birth (Andersen et al., 2009) or an improved climate regulation during the farrowing and the following days. Since, the newborn piglets spend most of their time close to the sow, many studies recommended to provide heating close to the sow.

A study by Malmkvist et al. (2006) showed the effect of floor heating on the vitality of the piglets in the first 12 to 24 hours of their early life in the loose house system and concluded that although the heating has no direct effect on the measures of newborn piglet vitality, it has a large effect on the early recovery of piglet body temperature and latency to first suckling and hence the survival of the piglets (see figure 1.1). The floor heating is beneficial if and only if the floor heat is around $34°C$ when the piglets were born. After few hours from birth, the piglets may have recovered their normal body temperature after the drop, and they will gradually begin to use the piglet hut over the next 12-48 hours, instead of staying close to the udder. However, floor heating implies a relatively long heating up period and hence, the evaluation of the costs and benefits become dependent on the energy costs involved. Moreover, in order to achieve optimal thermal-benefit, the floor heating should be started well in advance so as to achieve the comfort zone surrounding the piglets. As the thermo-neutral zone of the sow is between 16 and 20°C, she may easily suffer from heat stress if the surrounding temperature is increased above this level (Malmkvist et al., 2009) for longer periods. Therefore, if extra heat is to be added to save the piglets, the duration of extra heating must be as short as possible before the farrowing. However, Damgaard et al. (2009) found that the sows did not experience heat stress after farrowing for 1 to 3 days; indeed some studies have shown a preference for warm floor Phillips et al. (2000) .

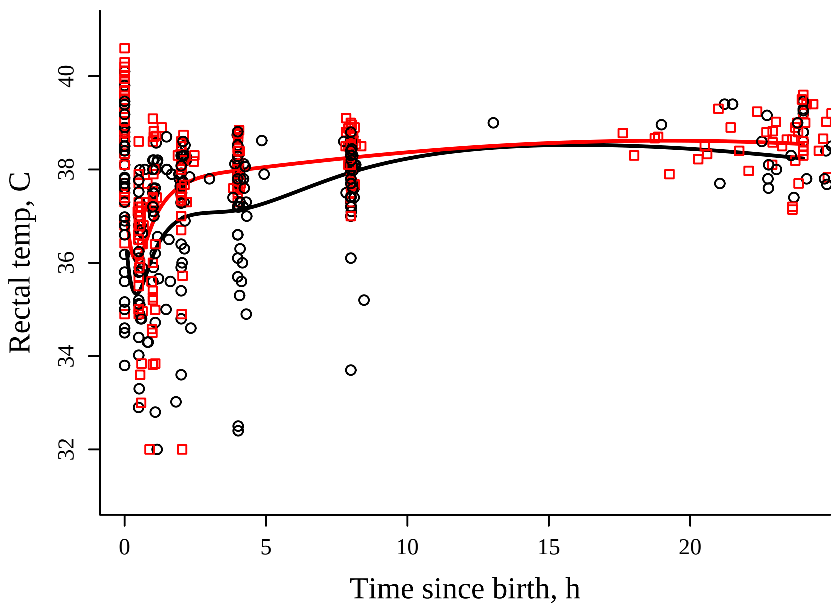


Figure 1.1: Rectal temperature of a piglet in the first 24 hours of life (Malmkvist et al., 2006). *Red points*: effect of floor-heating; *Black points*: control effect. The rectal temperature rises subsequently if the extra heating was provided at the time of piglet's birth and in the early life.

Hence the prediction of onset of farrowing is necessary regardless whether the purpose is the supervision of farrowing or the optimal climate regulation. In case of the optimal climate regulation, particularly for the floor heating, in addition to the precision of the prediction of the farrowing and the heating costs, the regulation strategy will also depend on the supply of heat energy, room temperature, floor type etc. Recording of mating time will give a vague prediction of 115 days with approximately ± 2 days. In the cost benefit analysis preceding this project, Jørgensen (2008) recommended improved precision of the prediction of onset of farrowing for an increased benefit. This was evaluated by considering different values of standard deviation in the range [0.5, 48] hours. Similar detailed quantification of costs and benefits related to the precision and timing of farrowing predictions could be made for the surveillance case, but, as the choice of method for the prediction will be the same in both cases, we will omit this in this context.

1.1.1 Objective New

The objective of the PhD study was to develop and validate a system that monitors the pre-parturition behaviour of the sow in the farrowing pen, and predicts the onset of farrowing using the data collected by different sensors, mounted at the pen level; further, developing a decision tool that uses the monitoring and predictions to make optimal decisions aiming at helping the farm-manager to solve the issues connected to parturition and post-parturition. To illustrate this we have chosen to demonstrate a decision tool for the optimal floor-heat regulation at the pen level prior to farrowing, using the sensors. The heat regulation maximizes the net return from the piglet production by minimizing the managemental and maintenance costs.

1.2 The desired system

In this section the desired intelligent system in the farrowing pen is described with references to the following chapters, which are the manuscripts, that give a detailed description of the important parts of the system.

The loose-housed farrowing pens in the herd are set up with a number of useful sensors from which the data may be recorded online and sent to the herd level computers, as illustrated in figure 1.2. The sensors are able to record the data in different time intervals, from seconds to minutes.

The pregnant sows are introduced into the farrowing pens approximately day-105 after mating. Recording of the sensor data starts from the day of insertion. The computer summarizes the data on, say, every half hour interval. Prediction of the time of farrowing also starts just after the insertion. At the start, the predicted distribution of the time to farrowing is based only on time since mating and possible other information from the herd data base, such as breed and parity of the sow. However, based on the summarized data from the sensors and the time spent in the farrowing pen, the prediction algorithm will dynamically update a state-vector for the sow. Based on the state-vector it is possible to calculate, for example, mean and variance of time to farrowing, and the state-vector captures all relevant information from the sensors. The prediction algorithm is applied individually for data from each sow in the herd. Since, the complexity of the prediction algorithm is low, it is expected to run on a herd level computer. The prediction algorithm is described in detail in chapter 2.

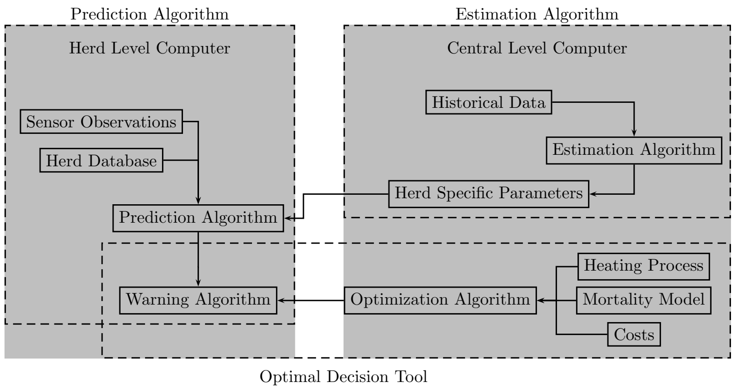


Figure 1.2: The desired climate controlling system and the framework of the PhD study. The gray regions on the left and right correspond to herd level and central level computers. Herd level computer predicts the onset of farrowing and makes decisions for individual sows, whereas the central level computer is meant to estimate the herd specific parameters and optimize the decision strategy. The whole system has been partitioned into three (representing the issues covered under the manuscripts of the thesis) and are separated by the dotted frames.

However, the prediction algorithm rely on a set of parameters specific for the herd as shown with the gray box to the right within figure 1.2. When a new herd starts, it will probably rely on the parameters estimated from the data of another similar farm; later these parameters are estimated using historical data from the herd itself. The herd specific parameters of the prediction model will be estimated using the 'estimation algorithm'. This algorithm uses complex models and learns from the data and hence the calculations are time consuming. Therefore, it is recommended to use central computing system for the estimation. The estimation algorithm is described in detail in chapter 3.

The basic output from the prediction algorithm is a state-vector (or belief state) which is the probability that the sow is in a set of successive behavioural phases. Given that the sow is in a given phase, the distribution of time to farrowing will be known and thus the mean time to farrowing may be calculated. For decision support or automatic climate regulation in the farm we will need a way of warning the farmers that the farrowing is approaching. In this study two approaches will be used: a simple heuristic warning strategy, and a warning strategy that is based directly on the model used for the prediction and estimation, and, furthermore, includes the relevant costs and benefit from the automatic floor heating. The heuristic strategies rely on average time to farrowing and probability of farrowing within a time interval. The calculations to find a heuristic strategy can easily be handled on the herd level computer. These strategies are used for validation of the prediction algorithm in chapter 2. Examples of the issues to be considered while formulating the heuristic strategies are included in sections 1.2.1, 1.2.2, 1.2.3 and 1.2.4. Ideally a warning/regulation strategy should be optimized by evaluating the associated preparation time, external factors, management costs and production benefit. For example, the floor-heat regulation strategy is associated with the thermodynamics of the heating process and mortality model and hence, it should be evaluated against the costs of energy supply and maintenance along with the benefit of increased production. In chapter 4, we demonstrate the formulation of such an 'optimal decision tool', with the prediction algorithm as the kernel. The optimization is an iterative procedure which uses complex models and hence, the calculations are time consuming. Therefore, it is recommended to use central computing system for the optimization. However, the optimization algorithm outputs a reward table (or simply, a look up table) of reasonable size that can be used in the local decision/warning algorithm. The decision for each sow at each time point is made based on this table. Therefore, the decisions are made along with the prediction of farrowing on the herd level computer.

We have not included the interaction between the prediction system and the heating system in figure 1.2. But in the following section the floor heating is described.

1.2.1 How improved prediction of farrowing can improve piglet survival and economic return

To illustrate the use of prediction system, in this section we will present the link between the improved farrowing prediction and the economic return of the pig production through better heating strategy. We follow the experimental results by Malmkvist et al. (2006), that has showed that floor heating has effect on initiating the first suckling, thermoregulation and the survival of piglets. Similar considerations could be made with respect to surveillance. We will base the description of work concerning cost-benefit to a report made for a Ph.D. course in animal health economics.

Ideal and real heat regulation system The prediction system will monitor the sows behaviour and when a warning triggers, the floor heating in the pen will be activated. The process is illustrated in figure 1.3. The start of Phase-(A) corresponds to the time of warning from the prediction system. At the start, the floor-temperature increases rapidly from the room temperature; but the increase will slow down as the floor-temperature asymptotically reaches an equilibrium where the temperature remains constant, if the supply of energy is constant. Normally, it would take too long time to reach equilibrium temperature. Most often it is interest to maintain a lower temperature that can be reached quickly, and is high enough to ensure that the piglets recover after the body-temperature drops after the birth. We will call this the *recovery* temperature. Thus floor-temperature can be maintained at this *recovery* level by supplying a lower amount of energy to the floor, for example, by turning the heat on/off using a thermostat. This will lead to the horizontal temperature line in Phase-(B) in the figure. Of course, it is optimal that the temperature reaches the *recovery* level just when the farrowing starts; but the success-rate for this depends on the precision of the prediction algorithm. Finally, as soon as the supply of energy is stopped/turned off, the floor temperature begins to drop (Phase-(C)) and reaches the room temperature, as shown in figure 1.5b. The optimal turn off time will be when the litter no longer gets benefit from heating.

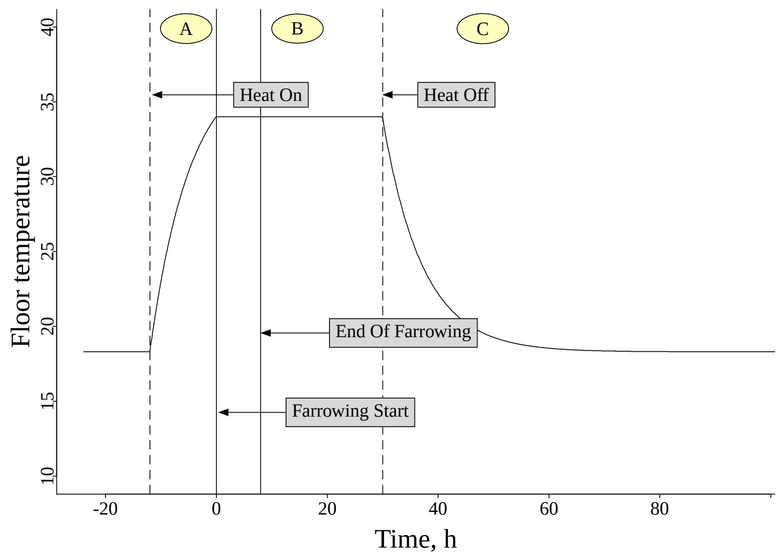


Figure 1.3: Illustration of heat regulation on a pen level. Phase-(A) starts from the heat on time until the floor was sufficiently warm; Phase-(B) is the period when the floor was maintained at sufficient temperature; Phase-(C) is the last phase when the heating was turned off and the temperature starts dropping down to the surrounding temperature.

In terms of the benefit of piglets, primarily, Phase-(B) in figure 1.3 is relevant. Phase-(B) starts when the floor is sufficiently warm for the piglet, that is, at the *recovery* temperature, and is maintained during Phase-(B). The strategy for a litter is illustrated in figure 1.4 for which the heat was supplied 24 hours after observing the farrowing.

In the example, the floor has reached the *recovery* temperature at hour 1.9, may be because of the delayed prediction of farrowing. Thus, heat is supplied only for 22.1 hours after the birth of first piglet and not for 24 hours as planned. First ten piglets were born before the temperature was sufficient; this is the result of sending too late warning/activation signal. For most piglets, Phase-(B) was

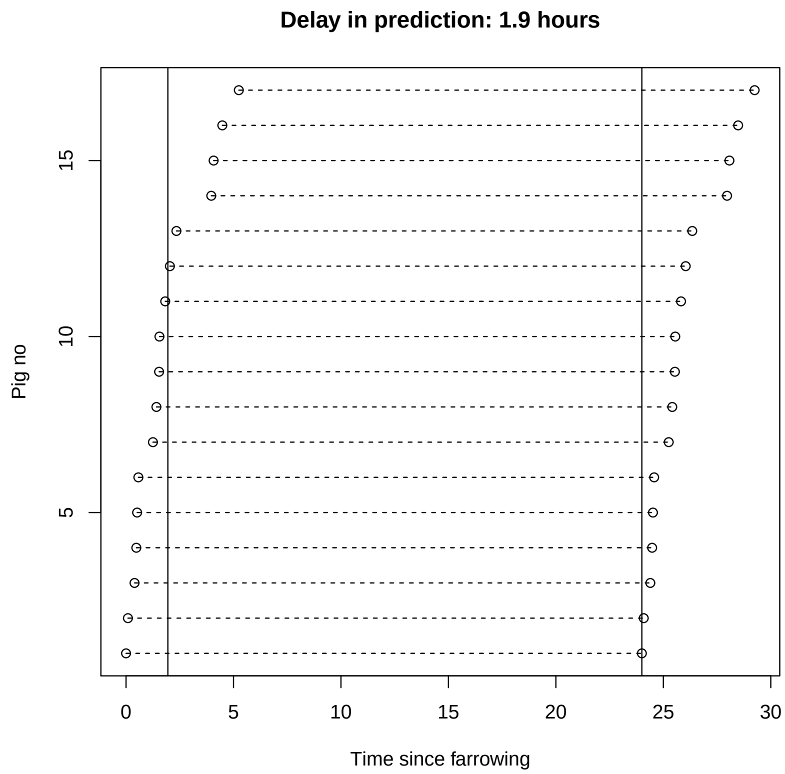


Figure 1.4: Illustration of heat supplementation to a litter. Each horizontal dotted-line corresponds to the first 24 hours life of a new born piglet for the litter. The rings on each horizontal dotted-line indicates the time of birth and the first 24 hours life of that piglet. Two vertical lines indicate the time since the floor has reached the *recovery* temperature and heat off after 24 hours from farrowing. The plot illustrates that the floor has reached *recovery* temperature 1.9 hours later the farrowing was observed. some of the new born piglets cannot benefit from the floor-heating in the first few hours of their early life and some, at the last part of their 24 hours age.

too short; they would have benefitted if the heat was turned off later than the 24 hours. Some piglets were without sufficient heat in the beginning and some at the end of their first 24 hours life. For example, first piglet was without heat for first 1.9 hours and the 10^{th} piglet for 0.4 hours, while the last born piglet had no heat for the last 3.3 hours.

The ideal case from a piglet survival point of view is that the Phase-(A) should be finished before the birth of the first piglet, and Phase-(B) should continue until 24 hours after the birth of the last piglet. The experimental results from Malmkvist et al. (2006) showed approximately a difference in mortality of one piglet per litter. The results shown in figure 1.1 indicated that heat just after birth was most important. However, the experimental design did not allow a direct evaluation of the precise relationship between the length of floor heating and risk of mortality. Similarly, it is expected that higher floor-temperature will have some positive effect, even though the temperature is less than the 34°C that was used in the experiment. The improvement in survival rate achieved by Malmkvist et al. (2006) was under circumstances where the floor temperature had reached the *recovery* temperature at the time of birth of first piglet, and the effect of heating was constant throughout the first 24 hours after birth.

1.2.2 Evaluating how to set threshold for the heuristic rules

Performance of floor heating process An important parameter for the heuristic warning strategy is when to send the message that activates the heating system. Based on the existing prediction model, the problem is to find the optimal time to turn on the heat so as to get the maximum benefit. This requires knowledge about how fast the floor-temperature changes. The mathematical formulation of the relation between the floor temperature C and time t with the uniform energy supply is given by,

$$C_t = C_0 + \mathbf{A}(1 - e^{-k_1 t}) + \epsilon_t, \tag{1}$$

where C_0 is the initial floor-temperature (when floor heating is off), often assumed to be equal to room-temperature, $\mathbf{A} = k_G/k_1$ such that $k_1 > 0$, is the time constant, and $k_G = \frac{Q_A}{C_v}$ where Q_A is the energy supplied (in Phase-(A)). C_v is the heat capacity of the concrete floor and is defined as the amount of heat required to change the temperature of the floor by a given amount (= 0.9 J/g/K). $\epsilon_t \sim N(0, \sigma_\epsilon^2)$ is the residual error-term. We refer to DOE Training Coordination Program (1992) for the terminologies of thermodynamics and heat transfer.

To evaluate the parameters in the experimental pens, one empty pen was used for a heating experiment. The heat was turned on and the floor-temperature was measured every 10 minutes. The parameters in (1) were estimated based on these data using a nonlinear regression analysis. Table 1.1 shows these estimated values and additional values from other sources. These were used for a small Monte Carlo simulation study.

Table 1.1: Parameter values of heating process estimated for a regression model based on (1) and other costs.

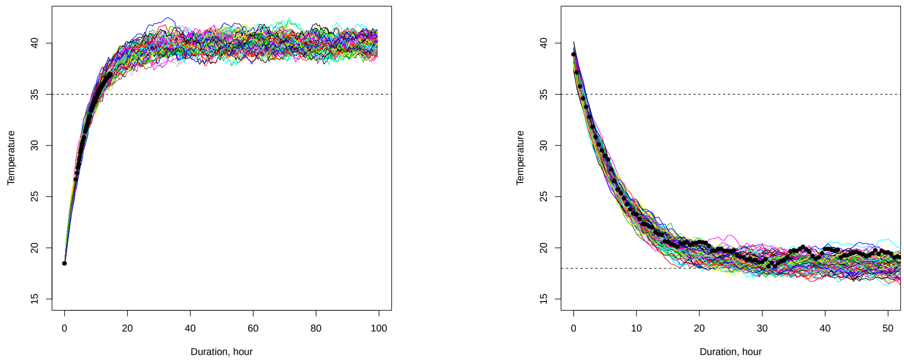
Estimated	Parameter description	Value
$+$	Surrounding (room) temperature, C_0 °C	18.34
	Recovery temperature, C_c °C	35
$+$	Thermal conductivity of concrete with flux, $k_1 \mathrm{mW/m^2/°C}$	0.038
$+$	Standard deviation of temperature per 0.25 hours, σ_ϵ	0.24
	Heat capacity, C_v, J/g/K	0.9
$+$	Input energy coefficient, $k_G \mathrm{mW/m^2/°C}$	0.83
	Energy consumption in Phase-(A) per hour, $Q_A \mathrm{W/m^2}$	4.5
	Heating cost in Phase-(A) per hour, $pr_A \mathrm{DKK}$	6.06
	Net return per piglet, NRP, DKK	300

In figure 1.5, the simulated heating and cooling process are shown for the estimated parameters. The energy input to floor-heating is able to raise the floor-temperature with approx. 22°C, leading to an equilibrium temperature of 40°C, from the room-temperature of 18°C. The figure 1.5a illustrates the rapid rise in the temperature and later slows down as the floor-temperature approaches the equilibrium.

Influence of energy input and room temperature on the floor heating process To see how the duration and costs of the heating process are influenced by the amount of input energy and the surrounding temperature, a Monte-Carlo simulation study was performed. The design of the simulation study with the parameter combinations used is shown in Table 1.2. The scenarios with different parameter combinations are numbered from 0 to 8, where No. 0 is the basic scenario with values in table 1.1. In Scenario No. 1, 2 and 3, the room temperature was fixed at $C_0 = 18.3°\mathrm{C}$, while k_G was varied as $\frac{k_{G0}}{2}$, $2k_{G0}$ and the energy required to raise the floor temperature to 35°C in 24 hours.

In Scenario No. 4, 5 and 6, the room temperature was lowered to 16 °C. The value k_G in Scenario No. 5 and 6, was the energy required to raise the floor-temperature to 35 °C in 12 and 24 hours. Finally, in Scenario No. 7 and 8, the room temperature was lowered to 14 °C and k_G were k_{G0}, the energy required to raise the floor temperature to 35°C in 12 hours, respectively.

For the above combination of parameters, the equilibrium floor-temperature, mean time to Phase-(B), energy consumption in Phase-(A) were calcualted and are shown in Table 1.2. For the values in the Scenario No. 0, the floor-temperature reaches 35°C in about 13 hours and the heating costs are 3.03DKK



(a) heating process

(b) cooling process

Figure 1.5: Simulation results of heating and cooling processes. *floor-heating process* (Left panel): the temperature starts increasing from the room temperature with the continuous supply of uniform energy (Phase-(A)) and reaches an equilibrium. The equilibrium temperature is such that the floor-temperature does not increase with the continued supply of the same amount of energy. *cooling process* (Right panel): when the energy supply was stopped, the floor temperature begins to decrease rapidly and then slowly drops to the surrounding temperature.

Table 1.2: Parameter scenarios and results of simulation study of heating and cooling processes. The objective of the simulation was to study the importance and influence of the heat parameters on the distribution of the event *time to Phase-(B)* and the energy consumption. $k_{G0} = 0.83\mathrm{mW/m}^2$ is the estimated value from the experimental pen

Scenario No.	Room temp. C_0°C	**A** $^\circ$C	k_G $(\mathrm{mW/m}^2)$	Equilibrium temp. $C_{\mathrm{eqm}}{}^\circ$C	Mean time to Phase-(B) hours	Energy Consumption Q_A, $\mathrm{W/m}^2$	Heating cost pr_A DKK
0	18.3	21.6	k_{G0}	40	10.6	2.25	3.03
1	18.3	10.8	$\frac{k_{G0}}{2}$	29	∞	NA	NA
2	18.3	43.3	$2k_{G0}$	62	3.6	4.49	6.06
3	18.3	17.3	0.67	36	22.4	1.79	2.42
4	16.0	21.6	k_{G0}	38	15.2	2.25	3.03
5	16.0	23.5	0.90	39	11.9	2.44	3.29
6	16.0	19.7	0.76	36	22.8	2.05	2.76
7	14.0	25.9	k_{G0}	36	24.1	2.25	3.03
8	14.0	25.9	1.00	40	11.9	2.69	3.63

during Phase-(A). However, for Scenario No. 1, the floor-temperature does not reach 35°C. Therefore, it is clear that for the available amount of energy, the floor-temperature may not reach to 35°C. If the energy supply was doubled, it takes only about 4 hours to reach 35°C; however, the heating cost was also doubled. Furthermore, for the room temperatures 14 and 16 °Cs, with k_{G0} amount of energy has resulted in approximately 24 and 15 hours, respectively, to reach 35°C. That is, decreasing the surrounding temperature implies, changing the distribution of *time to Phase-(B)*. However, the mean time to Phase-(B) may be controlled by supplying the appropriate amount of k_G as done for Scenario No. 3, 5, 6, 7 and No. 8.

1.2.3 The relation between temperature and mortality

The costs associated with establishing the right climate at the time of farrowing should be evaluated against the possible decrease in mortality. The heating strategy assumes that at least one piglet per litter can be saved by providing sufficiently warm environment for all the piglets. The most conservative approach is to consider only two levels of mortality; mortality without floor-heating, $p_0 = 0.2$ and reduced mortality due to floor-heating, $p_{red} = 0.16$. In other words, these probabilities correspond to two levels of floor-temperatures, $< C_c$ and $\geq C_c$ as found in Malmkvist et al. (2006).

However, a smooth curve is probably more realistic. The benefit of increased floor temperature will most likely show up, before the *recovery* temperature is reached. To investigate this effect, simulations using three mortality curves for mortality at varying floor-temperature were made. These mortality curves assumed logistic models for the relative mortality as shown in figure 1.6.

In these curves, the effect of heating starts at 33.5, 30 and 25 °C respectively. Further, we assume that the mortality is bounded in the region $[p_{red}, p_0]$. The mortality of each piglet was calculated based on the floor-temperature for each individual when they were born. The heating strategies were compared by varying 3 factors: starting time of heat supply, precision of the prediction of farrowing and mortality scenario. For each combination of the factors, the expected reward $\mathbb{E}[\Pi]$ and standard error of the rewards SE_Π were calculated. The *expected time to farrowing*, denoted by $\mathbb{E}_F$, was varied from 1 to 24 hours with an hour interval. The standard deviation SD_F of the prediction were chosen to be {0.05,1,2,5} hours, corresponding to the precisions of {400, 1, 0.25, 0.04}. These values are based on the prediction results of the current PhD study (chapter 2). The results of the above scenarios were presented for N=10000 number of simulations. The results are shown in figure 1.7.

As the figure shows, for the three lowest SD_F values, the optimal rewards lay close together. However, improved prediction of farrowing (lower SD_F) may result in an increased reward; at least the prediction SD_F of 5 hours is markedly

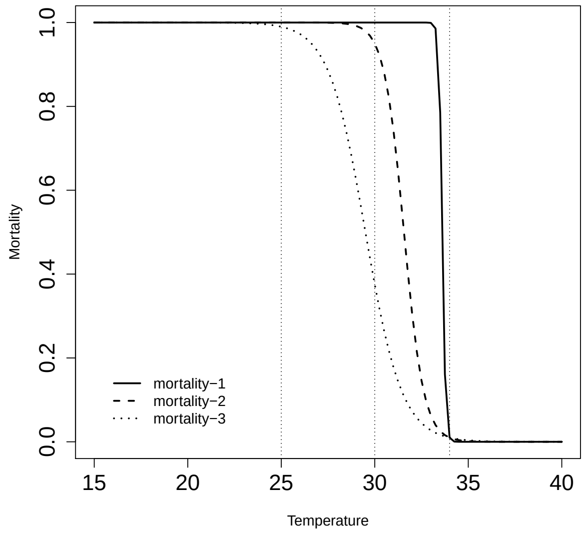
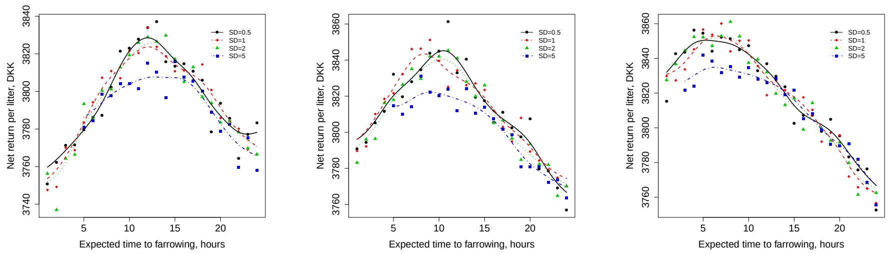


Figure 1.6: Mortality curves with respect to the floor-temperature. The heating effect starts at 33.5, 30 and 25°C for the curves mortality-1, 2 and 3, respectively.



(a) Rewards for mortality-1 (b) Rewards for mortality-2 (c) Rewards for mortality-3

Figure 1.7: Rewards of heating strategies versus *expected time to farrowing* for different mortality scenarios. Each line and symbols correspond to different standard deviations of the prediction. The time with maximum reward was recommended for the optimal heating strategy.

worse than the other scenarios. Therefore, if $SD_F = 2$ the precision seems to be adequate, and in that case there seems to be no need to improve the prediction model further. However, the optimum threshold value for the warning strategy decreases with increased precision. Low or high threshold values is far from optimal. Furthermore, if the effect of the floor heating on mortality starts at lower temperatures, the threshold value in the warning strategy can be lowered even more. The results also indicate the importance of getting a more precise relationship between the mortality of the piglet and the floor temperature just after it is born.

1.2.4 Implications for the Floor-heating Strategy

The simulation results for heating process showed that it is possible to fix the mean *time to Phase-(B)* and hence the threshold for the heuristic strategy, with varying room temperatures; it means the supply of energy should be varied accordingly. This also means that the heating up costs will increase with decreasing temperature. Thus the dimensioning of floor-heating system need to be adequate while establishing. At the minimum, the floor-heating system should be able to raise the temperature after the nest-building activity has been recognized by the prediction algorithm and before birth of the first piglet. However, a simple heuristic strategy with a threshold value around 12 hours is within the optimal range for the heating system used in the Research Center, Foulum, Denmark from where the training data was obtained. This is true only if the mortality changes at the *recovery* temperature.

However, if the piglets get benefit from the heating even at the temperatures below the *recovery* level, a decision to turn on the heat may result in an increased benefit as compared with no heating scenario, if the sow is close to farrowing.

1.3 Outline

The main contents of the thesis is a collection of three manuscripts, developed in stages in order to fulfill the objective of the thesis (sec. 1.1.1). In this section we will give brief presentation of the applied methods and results.

Chapter 2. Prediction Algorithm - *Hidden Phase-type Markov Model for the Prediction of Onset of Farrowing for the Loose-Housed Sows (Aparna et al., 2013b).*

Chapter 3. Estimation Algorithm - *An EM Algorithm to Estimate Parameters of a Hidden Phase-type Markov Model (Aparna et al., 2013a).*

Chapter 4. Optimal Floor-heat Regulation Algorithm - *POMDP for Automatic Floor-Heat Regulation using Sensors Prior to Farrowing (Aparna and Jørgensen, 2013).*

In this section we summarize and review each of these manuscripts. However, the three manuscripts rely on the same data set, which is briefly described below. A more detailed description is presented in chapter 2 and chapter 3.

1.3.1 The data set used for the study

The data used in this study were collected from late 2008 to early 2009 in the experimental farm at Research Center, Foulum, Denmark. 64 sows were introduced to the farrowing pen approximately seven days before expected farrowing. The sows were fed twice a day, 8:00 - 8:45 and 15:00 - 15:30, using an automatic feeding system. Management of the pen was restricted to a two hours period between 8:45 and 10:00, after the first feeding, where the pens were cleaned and 1kg straw was provided daily on the floor.

Each farrowing pen had a number of sensors installed as shown in figure 1.8. In addition, video-recordings of each pen were made from the time when the sow was introduced until after farrowing. Additional visual analysis of these recordings include identifying the start of farrowing (time of birth of first piglet) as well as a time point when the sow was nest-building. The onset of nest-building was recorded by an experienced observer and was identified based on the criteria described in Malmkvist et al. (2006), as the first occurrence of at least five front leg pawing per hour or repeated carrying of straw, without being interrupted by resting periods longer than 2 hours. The time of farrowing was used to validate the algorithm. The nest building time were used for confirming the model predictions but not directly for validation.

The sensor data include water consumption data, video based activity measurements and photo-cells (grid) based activity measurement. The data from the sensors were recorded with different time intervals, ranging from seconds to minutes. However, we consider the data pooled over half an hour intervals. Therefor a maximum of 48 observations were observed per day per sow. The water consumption, video-activity and grid-activity data were collected from 45, 64 and 45 sows, respectively. The experimental data were used in the first two manuscripts (chapter 2 and chapter 3). The sensor information collected before day-105 after mating were excluded from the study. Some sows were discarded from the study because of failure of sensors or the management data (such as time of nest building, time of farrowing as identified by the visual analysis of video recordings) were not available. For chapter 4, where the focus were on comparing the different approximations for the POMDP solutions, simulated data from estimated distributions where used. 2500 farrowing sows with the sensor observations were simulated for this purpose.

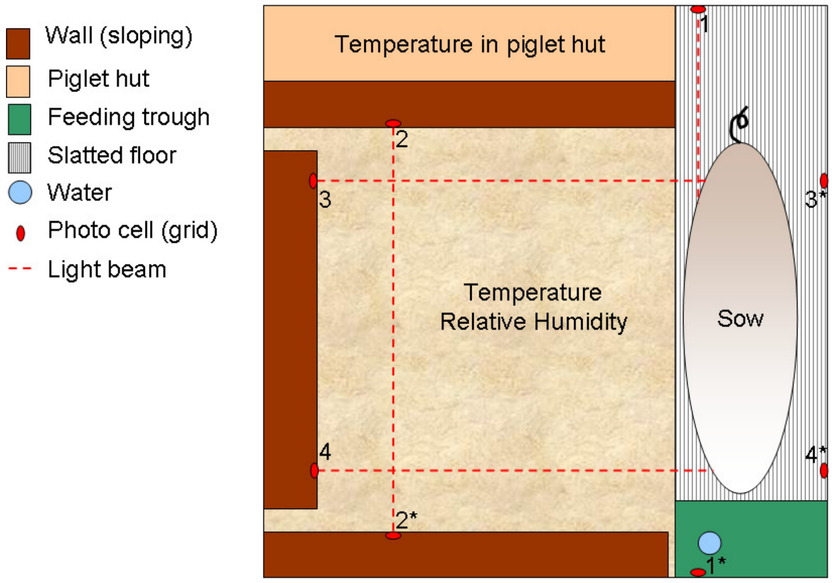


Figure 1.8: Sensor set up in the pen level.

1.3.2 Prediction Algorithm

This chapter, shortly called *prediction algorithm*, of the thesis describes the prediction of the onset of the farrowing, built based on the models used to evaluate the *time to failure*. The prediction system starts from the day the sow was mated. The pre-parturition physiological and behavioural changes of the sow were monitored and tracked since the sow was introduced into the farrowing pen which is approximately day-105 after mating. The pre-parturition period of a sow was classified into being in one of the three behavioural states named *Before Nest-Building, Nest-Building* and *Resting*, as illustrated in figure 1.9. We define the *farrowing process* as monitoring of the sow passing through these pre-parturition behavioural states in succession before it reaches *Farrowing*. This process is analogous to the Queuing theory with multiple service counters to be passed in succession in order to finish the assigned job, sojourn time being the service time at each counter. The behavioural states of the sow can be seen using both behavioural and physiological measures.

These states are latent or unobservable. However, the sensor technology has made it easier to capture the activity related to the behavioural changes of the sow, that is the distribution of the sensor measures will change conditioned on the hidden state. Using one of the well developed approach in the survival analysis called Hidden Semi-Markov processes, the probability of the phases of the sow were predicted. The semi-Markov part was handled using the Phase-type (PH) distributions for the sojourn times in each of the states (hence, Hidden Phase-type Markov Model (HPMM)). This was later used to estimate the mean

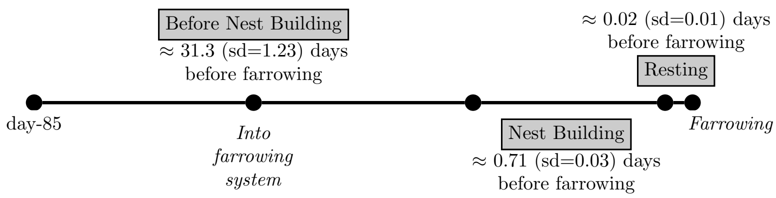


Figure 1.9: Pre-parturition Behavioural states of the sow (Not to scale)

time to failure, where failure in this context refers to the farrowing. Estimating the expected time to farrowing will give more flexibility to the management; for example, the farmer may decide to visit the farrowing pen 2 hours before farrowing instead of waiting for 24 hours in the herd, or he may make a decision to turn on the floor-heating prior to farrowing at the right time, so he can obtain the benefit of reduced mortality, while still keeping heating costs low. The prediction algorithm was validated against a test data set of about 35 farrowings.

The HPMM model was further extended to calculate the expected time to farrowing and probability of farrowing; hence the onset of farrowing was predicted. As an example of complete Herd Level Computation system as described in sec. 1.2, a warning system was discussed in the current chapter to use a thumb rule for generating alarms. The rule is that for a warning measure (either expected time to farrowing or probability of farrowing), a threshold was set and alarm was sent if the measure falls below the threshold. The validation was based on the period of alarm with respect to time of actual farrowing. The performance of combination of sensors in the prediction model were also tested in this chapter. Using only water observations in the prediction model gave very few true-warnings, whereas the video-activity sensors over predicted with a large standard deviation of warning time. When water and video-activity measures were combined it gave very good results in terms of true warnings, mean and standard deviation of time to farrowing and low duration of false alarm periods. There was not much changes by adding grid-activity data with water and video-activity, however, the true warnings were increased and standard deviations were further reduced after including grid-activity data with the other individual sensors.

The main signal in the data was the change of activity pattern when nest-building starts; but compared to other methods, the HPMM maintained the information necessary to calculate the expected time to farrowing as part of the model. This made it easier to validate the prediction methods and the applied heuristic strategy. However, it was recommended to include the precision of the prediction, thermodynamics and costs directly when considering the warning strategy, instead of the simple, fixed, heuristic strategy, if the prediction is for the floor-heating purpose.

From a computational point of view the prediction algorithm is based on few basic calculations and can easily be implemented on low costs computers.

1.3.3 Estimation Algorithm

The HPMM proposed for the prediction of the onset of farrowing belongs to the class of models for biological processes that have the characteristic that can be conceptualized as consisting of sojourns in discrete states or phases that the individuals pass through and where they will end up in an absorbing state (Titman and Sharples, 2010). Although there existed estimation methods for HMM and PH-distribution, there were some special characteristics of the farrowing process that needed to be considered in estimating the parameters of HPMM. Those included, that the main part of the process could be modelled as a discrete-time multi-state model because of the fixed interval between the observations; but the time from last observation to the absorption (farrowing) needed to be treated as a continuous variable; the number of phases and phase transition rate within the state should match with the sojourn time distribution of the state; for each sow, the sensor observations were continuous variables (in contrast to some other existing methods) and collected for about 10 days with 48 observations per day; the sensor observations should be modelled so as to distinguish between the diurnal rhythm and state effect of the sow. Furthermore, the estimation method should be able to use multiple sensor information simultaneously.

The current estimation algorithm was developed by adopting other existing methods. It is an EM algorithm, inspired by Baum-Welch algorithm and calculates forward and backward probabilities. However, since the M-step was not tractable, we have introduced a stochastic part by randomly allocating the phase of the sow, resulting in a Stochastic EM algorithm. The number of phases in each state and the transition rate were estimated by matching the first two moments of estimated sojourn time distribution of that state. The parameters were estimated to use the data with 50 farrowings. The algorithm has estimated 117 (SD=1.2) days of total gestation length with 31.3 (SD=1.23) days of *Before Nest-Building* in addition to 85 days after mating, 17.02 (SD=0.8) hours of *Nest-Building* state and 0.53 (SD=0.22) hours of *Resting* state. These are in agreement with the other biological knowledge and studies.

The video-activity and grid-activity measurements were modelled using simple linear models with four folded harmonic functions as the covariates interacting with the state variable. The models captured the effect of states on the diurnal rhythm successfully. However, there was a limited information about the

Resting state, as it is of short duration. The water observations showed different levels of consumption pattern and hence was modelled using a mixture model. Furthermore, the mixing proportions, showed association with the time of the day and hence used concomitant models with four folded harmonic function as the covariates. The best fitting mixture model of the water consumption had three mixture components with different levels of drinking pattern in the *Before Nest-Building* and *Nest-Building* states. The probabilities of water consumption showed a clear evidence of diurnal rhythm. The increased probabilities during the night time in the *Nest-Building* state gave a good supplementation to the other sensors in the prediction of farrowing. Thus the prediction algorithm operates with a combination of two time scales: time of the day and the time since mating. The models can be further extended to use, for example, phase number or sow variable.

The algorithm gave a straight forward approach to combine and handle different sensor information to estimate the parameters. Since it includes complicated models, algorithm is time consuming. Therefore, it is recommended to develop the algorithm to speed up the calculations before implementing in practice. The estimation of the model parameters relied on the observation of the exact time of farrowing as the "gold" standard, but in an applied setting the time when the farmer confirms the farrowing can be used as the gold standard. The identification of the hidden states was robust when both water and activity measures were included, and do not require independent confirmation that e.g. the nest-building has started.

1.3.4 Optimal Floor-heat Regulation Algorithm

When the algorithm for predicting the onset of farrowing was established, it gave the opportunity to extend the automated system beyond the prediction, e.g. an automated decision tool combining the prediction with climate controlling or management surveillance. The prediction model (HPMM) was built on the principles that made it easier to formulate a model for the decision and floor-heat regulation process to make sure that a floor-heating system could reduce piglet mortality. Therefore, an optimal floor-heat control system in the pen level, as discussed in sec. 1.2.1, was designed. A floor-heating strategy is nothing but to make sequential decisions to turn on or off the floor heater so as to bring the floor to the *recovery temperature* at the time of birth of the first piglet. As we have discussed in sec. 1.2.2 and 1.2.3, there is a clear relationship between the final rewards of pig production, prediction of farrowing, floor-heating process and the piglet mortality. Therefore, there are two Markov processes involved in the decision process: the farrowing process and the floor-heating process. Both decision/action and total rewards at a decision epoch are the function of behavioural phase and the floor-temperature. The decisions regulate the floor-temperature in individual pens, and thus answers the question, 'when' to start the floor heating and 'how long'. The optimal heating strategy was modelled as a *sequential decision process* or in particular, Markov Decision Process (MDP).

The floor-temperature at the time of decision will be known to the decision maker. However, in the HPMM, the behavioural phases of the sow are hidden or unobservable, but we can use the sensor information to find the belief state of the phases (probability of the phases conditioned on the sensor observations) at every prediction point (or decision epoch). Therefore, the decision process may be classified as a partially observable Markov decision process (POMDP). In this case, a decision only influences the next floor-temperature and neither the phase number nor the future sensor observations. The analogue of the floor-heating strategy is given in figure 1.10. The farrowing process has been addressed in chapter 2 and chapter 3, and the stochastic floor-heating process is established in chapter 4, along with the method for finding the optimal strategy. In addition, the paper specifies the costs of floor-heating and the reward from the reduction in mortality, based on the similar elements as described in sec. 1.2.2. As per the mortality model, chapter 4 considers a simple two-level model (mortality model-1 of sec. 1.2.3) with $C_c = 35°\mathrm{C}$ intended not to overestimate the value of sensor information and floor-heating.

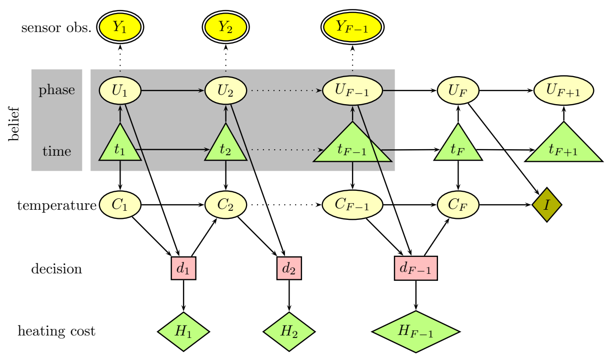


Figure 1.10: Analogue of POMDP for floor-heat regulation: The POMDP set up is similar to MDP except that the behavioural phases of the sow are not directly observable; indeed phases were modelled by HPMM using the sensor observations measured at each decision epoch and hence, the vector of belief state were predicted. Therefore, the decision is such that $d_t : (\mathcal{B} \times \mathcal{C}) \to \mathbf{D}$.

The approximate optimal solution of the POMDP was obtained by the so called greedy approaches: QMDP, 'Most likely phase', 'Random phase', 'Voting' and 'Random action'. All these approaches are based on the optimal solution of the completely observable MDP. That is, the decision process was solved by assuming both farrowing process and floor-heating process are observable. Furthermore, these greedy approaches are equal to the assumption that the phase number will be known from the next decision epoch and onwards. In problems where little is known about the distribution over phases, that is the distribution is close to uniform, they are expected to perform badly, and they are not suitable to evaluate the decisions that includes gathering of information (Littman et al., 1995). But as demonstrated in the paper this is not the case in the floor heating problem.

Heating versus no-heating strategies as well as POMDP versus simple heuristic strategy (SHS) were compared for different scenarios of heating parameters in terms of the rewards for 2500 simulated sow data. The greedy POMDP approaches behaved similarly. However, POMDP and SHS behaved similarly only if the SHS parameters matched the heat parameters; otherwise, the POMDP returned higher rewards. The results indicated that the POMDP approaches adapted to the different climate scenarios, and that it is able to detect the scenarios in which floor heating cannot give a positive reward.

The algorithm is adaptable for the changes in the input parameter values such as room temperature, energy source, mortality model. Furthermore, the algorithm gives a framework for integrating information about several sensors into a model for optimal decisions.

1.4 State Of Art and the present thesis

Since the sensor technology has been improved and feasible for studies in animal science, several studies have documented its significance in identifying and monitoring animal physiology and behaviour.

The biological studies imply that the sows internal or external behavioural and physiological state will cause an impact on sow's major behavioural activities such as food intake, drinking or sleeping pattern, physical activities, body temperature etc. Thus, it is possible to capture a large amount of data related to sow behaviour through the sensors mounted in the pens, or on the sow. Those sensors include feeding pattern, water consumption, temperature or humidity in the pen level, activity of the animal etc. As a result, this research area in pig production has been very active during the last decade. In this review we will focus on the methods developed for monitoring the sensor data, and the algorithms that lead to warning that a farrowing is closer.

Erez and Hartsock (1990) described a system based on photo-cells to monitor peri-parturient activity of sows, The measured activity pattern was supposed to be presented as a simple graph to the farmer. Bressers et al. (1994) showed significant changes in the ear base temperature around farrowing in a study using 5-7 sows. Bressers et al. (1994) described that the temperature increase started between 6-12 hours before farrowing probably based on visual inspection of the plots showing the relation between time before farrowing and temperature. Oliviero et al. (2008) has captured the increased activity in the last 24 hours before farrowing using a thin-film ferroelectret force sensor and photo-cell sensor in the pen level using 10 sows. In the experiment, the overall movement of the sow were measured by force sensor and the lying down and standing up behaviour were detected by photocells. They found significant increase in the measured variables on the farrowing day. They also claim that the movement sensors can be utilized to measure the activities preceeding the parturition and hence can be used in the development of a system to predict the onset of farrowing, but have not developed any algorithm. These studies have showed that it is possible to use the sensor information to improve the precision of the prediction of farrowing by monitoring the sow behaviour.

However, with the large amount of sensor information available online, it becomes more important to develop the systems to process and utilize the online sensor information by means of statistical models and inferences, (Wathes et al., 2005, 2008).

1.4.1 Methods and Models for the Prediction of Farrowing

The only study related to the prediction of farrowing is the recent paper by Cornou and Lundbye-Christensen (2012) and is focused on the development of two methods to detect the onset of farrowing by monitoring the activity of the sow in the farrowing pen using accellerometer measurements: 1. a generalized linear models with logistic link for diurnal variation in activity combined with two Dynamic Linear Models (DLM) models for the sow specific deviation from this variation, and 2. modelling of activity using a cumulative sum based on comparison between acitvity in the current hour with the activity in the same hour on the previous day. .

Thus, in both the methods in Cornou and Lundbye-Christensen (2012), the prediction of onset of farrowing is based on the detection of change in the activity pattern. To quote from the introduction in Cornou and Lundbye-Christensen (2012) "The systems that have been developed for detecting the onset of parturition are based on monitoring this re-directed nest building behaviour (or, more generally, an increase in activity) and changes of body temperature". Other studies show that these changing pattern occurs mostly when the sow starts nest building (Baxter, 1984; Oliviero et al., 2008). So a better categorization of the study would probably be 'change-point detection in activity pattern related to start of nest building'. The sow activities were monitored using three-dimensional acceleration data used in Cornou et al. (2011). The sow activities were classified using the multi-process Kalman filter (Cornou and Lundbye-Christensen, 2008). These classification has allowed to re-group the activities as total active and passive. The diurnal patterns for an average sow in either of the groups and the individual sow were obtained by modelling the logit transformation of the probability of a sow being active at the given time. The data smoothing indicated a clear diurnal rhythm with three dominant peaks around the feeding times and a less marked active period around evening. From the description it appears that the estimation of population diurnal rhythm was separated from estimation of sow-specific effects, which was finally used in the DLM. The study applied the methods in two groups of 9 sows which received straw and 10 sows which did not receive straw. Alarms were sent based on either a weighted distance measure between the activity levels predicted using DGLM and static models in 2 minutes interval, or the CUSUM value for the hourly differences between subsequent days. For each group and criteria a threshold value was chosen that maximized the sum of measures related to what is called sensitivity and specificity in the paper. Because the change-point detection occurs after the change in behaviour has taken place, the settings of these parameters as well as the precision in the sensor measurements must relate to the time from alarm to farrowing. It would have been interesting if the threshold parameter has been set for a given expected time to farrowing, or alternatively that alarms prior to 24 hours before farrowing was included in the results presented.

1.4.2 Studies related to the methodologies applied in this thesis

In the present study we have applied methods that has originated in life-time or time-to-failure studies. Thus the model is directly focused on predicting the remaining time to farrowing (which corresponds to the failure in the other studies). In the domains other than precision livestock farming, this is a standard approach. Dayanik and Goulding (2009) gave a framework of detection of the distribution of an unobservable disorder (or failure) time due to an unobservable cause. As they have discussed, most of the Bayesian approaches are limited to geometric or exponential prior distribution (depending on discrete or continuous time space) for the disorder time, mainly because of their memoryless property; whereas in reality not all the distributions can be approximated to these distribution and many times the distribution depends on the cause of the disorder which is, in many situations, unobservable. A Hidden Markov Model (HMM) is one of the well established technique for this purpose. However, if the sojourn times are distributed non-exponentially, then the process can be modelled as Hidden Semi-Markov Model (HSMM). O'Connell et al. (2011) have modelled the semi-markov part directly using Gamma sojourn distribution to monitor the reproductive status of cattle (sample size=58 cows) based on the hourly counts of pedometer and hourly approximated progesterone hormone concentration measurements. As they were interested in knowing the most likely sequence of states, Viterbi algorithm was used. Titman and Sharples (2010); Lange and

Minin (2013) have given a detailed description of using Phase-Type (PH) distribution in the semi-Markov part. A plus point of PH-distribution is that it is dense in the class of distributions defined on the positive real half line. Therefore, any distributions for the positive values of a random variable can be approximated to a PH-distribution. Different properties of PH-distribution and its uses in stochastic modelling can be found in Pérez-Ocón et al. (2010). Aalen (1995) has reviewed the applications of PH-distribution in survival analysis. One of the scenario is an acyclic Markov chain, means no state can be visited more than once. This is a very important aspect in the farrowing process because, a sow either continues to stay in the same pre-parturition behavioural state or moves on to the next state until the process is absorbed at farrowing. Recently, a lot of work has been done in the area of survival analysis to use PH-distribution. Garg et al. (2009) has compared Gaussian Mixture Models (GMM) with the Coxian PH-distribution (C-PHD), with one absorbing component, for clustering patient's length of stay. C-PHD is the process at which the process starts from the first transient state and transits sequentially through the states. However, the process may absorb from any transient state. According to the study, C-PHD provides some advantages over GMM such as its memoryless property. Furthermore, higher number of components of C-PHD can be approximated by a Normal distribution for the better fit of the data. Many more related studies have been carried out; some of those are McClean et al. (2011); Marshall and McClean (2003); Gillespie et al. (2011). García-mora et al. (2013) have used the sum of two independent PH-distributed variables in modelling the bladder carcinoma treatment data. Some authors (Callut and Dupont, 2007) have addressed similar process by the name Partially Observable Markov Models. However, most of these studies were focused on understanding the underlying process, rather than prediction of time to absorption.

Concerning the decision methods, within the livestock precision farming, the use of completely observable Markov Decision Processes (MDP's) (Puterman, 1994; DeGroot, 2004) are a well established practice and has been used for solving several decision problems, including Kristensen (1989, 1993b); Toft et al. (2005); Kristensen and Jørgensen (1997, 2000); Huirne et al. (1988); Kristensen (2003). While POMDP's are notorious for the resulting complexity, they have been used previously within Precision livestock farming. some of the examples of use have especially been focused on how to reformulate POMDP's problem into MDP's that can be handled (Kristensen (1993a); Jørgensen (1992); Kristensen and Søllested (2004); Nielsen et al. (2011); Jørgensen et al. (2012)). POMDP model was initially introduced by Sondik (1971); Smallwood and Sondik (1973) as the optimal control of partially observable Markov processes and since then, intensively used by the researchers in artificial intelligence, machine learning and computer engineering. The applications include, quality controlling in a production system (Ben-Zvi and Grosfeld-Nir, 2013; Grosfeld-Nir, 2007), robot navigation (Simmons and Koenig, 1995), aiding disabled people (Taha et al., 2007; Hoey et al., 2010). Littman (2009) has given a brief tutorial of POMDP for behavioural scientists. Zhang (2011) has used POMDP for investigating the optimal cancer screening policies.

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CHAPTER 2

PREDICTION ALGORITHM

Abstract

High piglet mortality is an issue in the pig production. Evidences indicate that if the time of farrowing can be predicted, the mortality can be reduced through planned supervision or improved climate regulation. The aim of the study was to improve the prediction of onset of farrowing by monitoring pre-parturient behaviour of sows with different sensors and by developing an automated system for the prediction of time to farrowing. The resulting prediction model, named as Hidden Phase-type Markov Model (HPMM), assumes that sow passes through the behavioural states *Before Nest-Building*, *Nest-Building* and *Resting* before reaching the *Farrowing* state. Each state was further split into phases, to allow a more realistic distribution of sojourn times. As these phases and states are unobservable, HPMM was used to calculate the probability of a sow being in given phase using the automatic sensor measures. Thus *time to farrowing* could be predicted at each time point. The prediction algorithm was validated on a data set (sample size is about 35) followed from day-105 to farrowing with half hourly mean and standard deviation of sensor recordings for activity measured by video and by a photo-cell grid, and water consumption. The algorithm was evaluated using heuristic warning strategies e.g. that a warning should be generated when the expected time to farrowing was less than 12 hours (inspired by the regulation of floor heating systems). The performance of the sensors was evaluated. The combination of different sensors outperformed the individual sensors. Using a combination of water and activity sensors the prediction algorithm gave a coherent warning period prior to farrowing (true warning) in 97 % of the cases with a mean duration of 11.5 (SD=4.6) hours and only 0.7 hours per sow with false warnings. The use of HPMM thus allowed a direct prediction of the time to farrowing, handling more than one sensor and a compact representation of historical sensor information.

keywords: Hidden Markov Model, Phase-type distribution, prediction of onset of farrowing, sensors, automated system, Precision livestock

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Hidden Phase-type Markov Model for the Prediction of Onset of Farrowing for Loose-Housed Sows

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2.1 Introduction

Piglet mortality is one of the major causes for economic loss in pig production. An average of 13.7% of the live born piglets died before weaning in Danish sow herds in 2012 according to Vinther (2013). Although the variation between the Danish herds are not well documented, the Norwegian study (Andersen et al., 2007) has documented the mortality rates ranging from 5 to 24% and a Swedish study (Wallgren, 2013) has also discussed the variation between the herds and herd management. Baxter et al. (2011) reviews different studies in this field. The large variability between herds suggests a management component to the mortality, and several studies indicate that it is possible to reduce this mortality, especially in the herds with high mortality, either by increasing the supervision of the farrowings (White et al., 1996; Andersen et al., 2009), or through improved climate regulation during farrowing and the following days (Malmkvist et al., 2006). However, management efforts are only efficient if the required time can be minimized, and this requires that the time of farrowing can be predicted fairly precisely, particularly in large herds where the management effort per animal is often reduced. Based on mating time, the time of farrowing can be predicted within approximately ± 2 days and this value is used to a large extent in farm planning. To obtain a better prediction of the time, it is necessary to include observations of the sows prior to farrowing. Thus new techniques and tools must be developed. In this paper we will use the term *prediction algorithms*, for computational techniques and tools that allow us to dynamically predict the time of farrowing and its distribution using new information as the farrowing approaches.

Early studies have indicated that it is possible to base predictions on automatically recorded sensor data. These prior studies suggest that the change in the sow behaviour is reflected in change in the pattern of the sensor measurements. Erez and Hartsock (1990) described a system based on photo-cells to monitor

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periparturient activity of sows, and the experiment described by Bressers et al. (1994) showed significant changes in the ear base temperature around farrowing. The temperature increase started between 6-12 hours before farrowing.

Since these studies, a range of other sensors have become available. Thus a management tool for farrowing prediction can now use the online sensor information including feeding pattern, water intake, temperature or humidity in the pen level, and activity of the animal. For example, Oliviero et al. (2008) have used movement sensors (photocells and a thin-film ferroelectret force sensors) to detect the onset of farrowing in the crates. Cornou and Lundbye-Christensen (2012) has used data from 3D accellerometers for detecting the onset of farrowing based on the classification method presented in Cornou et al. (2011).

The wide range of sensor technology has helped to record a huge amount of data; as a result statistical algorithms are necessary to extract behavioural patterns and combine measurements from multiple sensors into a useful information. Recently several studies have focused on statistical methods for handling data from online measurements. Different techniques have been used to extract the patterns, primarily different versions of the Kalman filter or Dynamic Linear Models (West and Harrison, 1997).

Madsen and Kristensen (2005); Madsen et al. (2005) looked at Dynamic Linear models for monitoring the health condition of young pigs by their drinking behaviour with an emphasize on diurnal drinking pattern. In this study a CUSUM approach based on the V-mask was used for detecting changes in the drinking pattern. In Cornou et al. (2008), electronic sow feeders were used for the automatic detection of oestrus and health disorders for group housed sows. Cornou and Lundbye-Christensen (2008) developed an algorithm for measurements from 3D accelerometers, using Multi-process Kalman filter to classify the sow activities such as feeding, walking, rooting, lying laterally and lying sternally during the reproductive cycle based on which the sows were monitored (Cornou et al., 2011). This classification was later used in Cornou and Lundbye-Christensen (2012) for development of two methods to detect the onset of farrowing by monitoring the activity of the sow in the farrowing pen: 1. logistic dynamic generalized linear models for diurnal variation, and 2. modelling of activity using a cumulative sum based on daily variation. The classification made it possible to re-group the activities as total active and passive. The diurnal patterns for an average sow in either of the groups and the individual sow were obtained by modelling the logit transformation of the probability of a sow being active at the given time. The data smoothing indicated three dominant peaks around the feeding times and a less marked active period around evening.

The warning signal for onset of farrowing, in either methods of Cornou and Lundbye-Christensen (2012), is based on the detection of change in the activity pattern. The studies show that these changing pattern occurs mostly when the sow starts nest building (Baxter, 1984; Oliviero et al., 2008). However, most managemental tasks such as climate regulation require a direct estimate of time to farrowing. In such cases, the warning signal of Cornou and Lundbye-Christensen (2012) requires additional information about the distribution of the time from change point detection to start of farrowing.

Another promising class of models is that used in the analysis of *time to failure*. These models have so far not been implemented in farrowing prediction. Dayanik and Goulding (2009) gave a framework of detection of the distribution of an unobservable disorder time due to an unobservable cause. This type of model has only been applied in very few cases within livestock production. One such method is to use the Phase-type (PH) distribution for the event *time to failure* (Cox, 1955; Neuts, 1975) or in farrowing context, *time to farrowing*. PH-distributions are a special type of a Markov models in which the time spent in a stochastic process is modeled with phases through which objects in the model progress until the process is absorbed. Thus, in the prediction of farrowing, we would assume that the sow passes through different phases and is absorbed at farrowing. However, these behavioural phases are unobservable or hidden. Perhaps the sensor observations recorded on the pen level are dependent on the current phase of the sow, and hence Hidden Markov Models (HMM) may be used. Such a combination with a PH-distribution furthermore gives an easy mechanism for aggregating and storing the information in historical registrations.

The purpose of the paper is to present and validate a prediction algorithm developed based on the above principles. The farrowing prediction algorithm is planned to be a part of a farm management information system. The system will automatically collect sensor data and do the necessary calculations to make real-time predictions of farrowings. The real-time part of the algorithm will consist of a continuous revision of the probability distribution over the phases of the HMM based on sensor and farmer observations.

The predictions will be based on parameters describing the distribution of the duration of each state of the farrowing process, as well as the distribution of the sensor observations. The estimation of these parameters is described in Aparna et al. (2013).

The model was evaluated by applying simple heuristic warning strategies related to the improved climate regulation during farrowing and the following days suggested in Malmkvist et al. (2006). These strategies include using the expected time to farrowing and the probability of farrowing. The method developed for the prediction algorithm makes it possible to utilize more than one kind of sensor for the prediction. Thus, this paper also compares the value of combining different sensor measures based on the prediction and warning accuracy.

2.2 Materials and Methods

In this section we will present the biological knowledge and principles used in the formulation of the algorithm, comprising the experimental setup and the different sensors used.

2.2.1 Experimental data

The data used in this study were collected from late 2008 to early 2009 in the experimental farm at the research center, Foulum, Denmark. 64 sows were introduced to the farrowing pen approximately seven days before expected farrowing. The sows were fed twice a day, 8:00 - 8:45 and 15:00 - 15:30, using an automatic feeding system. Management of the pen was restricted to a two hours period between 8:45 and 10:00, after the first feeding, where the pens were cleaned and 1kg straw was provided daily on the floor.

Each farrowing pen had a number of sensors installed as shown in figure 2.1. In addition, video-recordings of each pen were made from the time when the sow was introduced until after farrowing. Additional visual analysis of these recordings include identifying the start of farrowing (time of birth of first piglet) as well as a time point when the sow was nest-building. The onset of nest-building was recorded by an experienced observer and was identified based on the criteria described in Malmkvist et al. (2006), as the first occurrence of at least five front leg pawing per hour or repeated carrying of straw, without being interrupted by resting periods longer than 2 hours. The time of farrowing was used to validate the algorithm. The nest building time were used for confirming the model predictions but not directly for validation.

The different measurements used for the development of the algorithm are described in the following. The data from the sensors were recorded with different time intervals, ranging from seconds to minutes. However, for this paper we consider the data pooled over half an hour intervals. Therefor a maximum of 48 observations were observed per day per sow. The pattern of these observations were used in the specification of statistical models described later on. The water consumption, video-activity and grid-activity data were collected from 45, 64 and 45 sows, respectively. The sensor information collected before day-105 after mating were excluded from the study. Some sows were discarded from the study because of failure of sensors. Furthermore, those sows who have recorded the data less than 3 days before farrowing were also excluded from the prediction. The number of sows used in different scenarios of prediction algorithm are presented in table 2.2.

Water Consumption of sows: The sensor for water consumption measures the water consumed by the sow as the number of rotations of the water valve

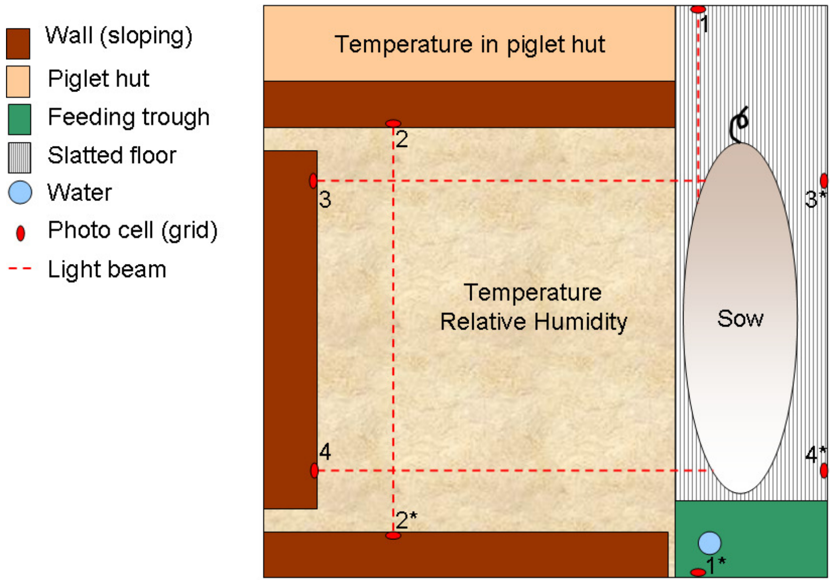


Figure 2.1: Sensor set up in the pen level.

(approx. 2ml of water per rotation). The water valve is situated on the food trough (see figure 2.1). For the current study, the counts were summed up over half hour intervals. We use the log-transformation of the water counts (denoted by $Y^{(w)}$) throughout the analysis. The pattern of water consumption is illustrated for one sow in figure 2.2a. The consumption pattern in sows was highly dependent on the time of the day. The sows consumed more water during feed intake and much less during the night. Furthermore, the water consumption occurred more frequently close to the farrowing, especially during the night. A disruption of the pattern was observed immediately prior to farrowing.

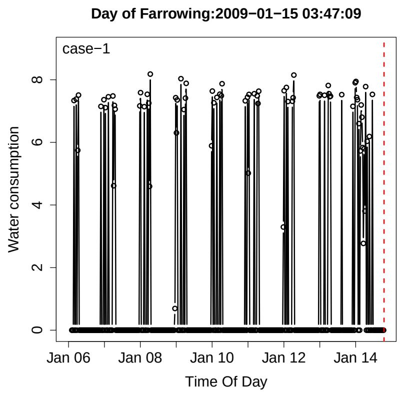
Activity of sows: Activity measures are based on the video recordings observations. The activity measure are the number of pixel changes from frame to frame in the video recordings. The preliminary studies indicated that, along with the mean of the activity over an interval it is realistic to consider the variation of the activities during the interval. Hence, in this paper, the sow activity was evaluated on two measures: mean (*meanActivity*) and the standard deviation (*sdActivity*) of the activity measures on half an hour interval. We use log-transformation of both the quantities through out the model and are denoted by $Y^{(Am)}$ and $Y^{(Asd)}$, respectively. We consider these as two independent measures. The patterns in the observations are illustrated in figure 2.2b and figure 2.2c. The sows were less active during the night time as compared with the day time. The *sdActivity* was also high during the day time. However, *sdActivity* shows more deviations during the night time, probably because of the changing lying position. In addition to this, both *meanActivity* and *sdActivity* have increased prior to and during parturition.

Grid measurement: Grid measurements are the interruption of photocell measurements due to the movements of sow in the pen. The grid set-up consists of four pairs of emitter and a receiver, {(1,1*), (2,2*), (3,3*) and (4,4*)} as shown in figure 2.1. If the sow is in the path of the beam, the beam is interrupted; for example, the receiver 1* (also the receivers 3* and 4*) in figure 2.1 doesn't receive the beam from the emitter 1 (3 and 4) and hence the beam is interrupted by the sow in its path. Thus, the grid measures it as an activity in that direction, at that time. However, if the sow was in the same position in the previous time of recording, then it is not considered as an activity. Furthermore, if the movements take place below the lane of photo cells, for example, lying, sleeping, it won't be measured by the grids. In this paper, the total activity measured by the four cells were summed up over half hour intervals. We use the log-transformed activity measure which we denote $Y^{(g)}$. The sows were less active during the night time and comparatively more active during the herd management. Also the sows showed significant activities before the parturition and deviation in the night time pattern (figure 2.2d).

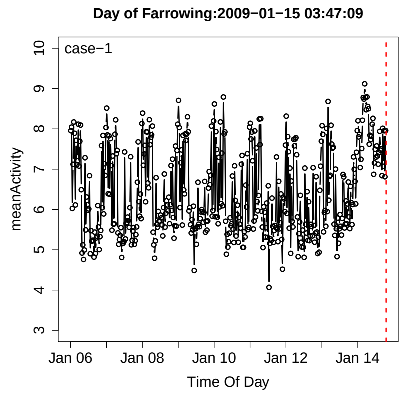
Time variables The data used for the prediction algorithm includes the date of mating. In addition, from the examples given in figure 2.2, it is evident that there is a clear diurnal rhythm with reduced activity during night time, at least in the the first days after introduction to the pen. Therefore, it was necessary to include a continuous time variable to denote the time of the day between 0 and 24 hours in addition to the time since the mating or time to farrowing. We denote this variable by $\mathbf{TOD}$ to indicate time of the day and it takes the values ζ such that $\zeta \in [0, 24)$. These values are used for generating the harmonic covariates while modelling the conditional distribution of sensors.

2.2.2 Behavioural knowledge and Statistical methods used to formulate the Prediction Model

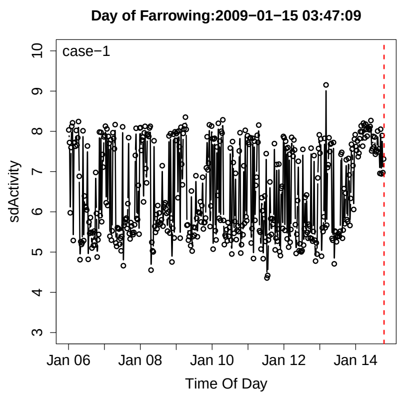
This section describes the biological and behavioural background of a sow during the pre-parturition and parturition states which lead to the formulation of a stochastic model for the prediction of the farrowing. The current understanding of the physiological and behavioural changes during the pre-parturition is based both on study in semi-natural conditions and under production conditions. The current section also describes the statistical background of the prediction model.



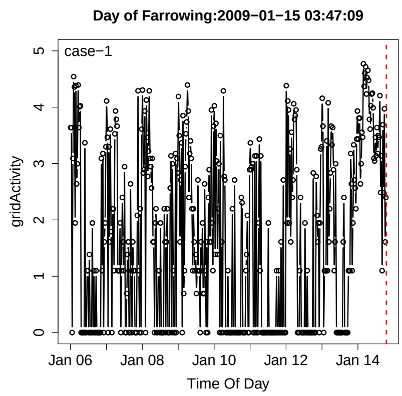
(a) water consumption



(b) meanActivity



(c) sdActivity



(d) grid-activity

Figure 2.2: Illustration of water consumption, *meanActivity, sdActivity* and grid-activity patterns for a sow, pooled over half hour intervals (on their log transformations). The dotted vertical line in the right indicates the actual time of farrowing.

Behavioural Background The relevant period for the prediction of farrowing in the production system is illustrated in figure 2.3. The period starts when the sow was mated. If she becomes pregnant she will farrow approximately 115 days after mating. At approximately day-105 after mating, the sow will be transferred into a farrowing pen or farrowing system (however, in the commercial farms the sows will be moved about day-110). The sensors will start recording the data as well as the automatic monitoring of the sow will start at this time. Thus, this is the interesting time period for the prediction algorithm.

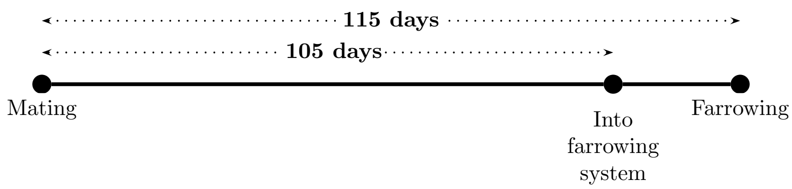


Figure 2.3: Time line for the gestation period of the sow (Not to scale).

From mating to 1-2 days prior to farrowing the sow will show a regular behavioural pattern with a clear diurnal rhythm. When the sows are being moved to the farrowing unit a temporary change in the behaviour may take place for 1-2 days due to a change of environment. As the time of farrowing approaches hormonal changes in the sows will motivate the sow to change behaviour. The behavioural changes will typically be present during the last 24 hours before parturition (Baxter, 1984; Jensen, 1989; Wischner et al., 2009). Such behavioural changes were expected to show up in the diurnal pattern in the sensor data. Nest building behaviour starts to decline about an hour before farrowing, partly due to an elevation in oxytocin (Castrén et al., 1993).

Thus the pre-parturition behaviour of a sow can be broadly classified into three states, *Before Nest-Building, Nest-Building* and *Resting*, as illustrated in figure 2.4. These three behavioural states of the sow can be seen using both behavioural and physiological measures. In addition, we have the *Farrowing* state, where the birth of the first piglet defines the beginning of the state. Thus, the *Resting* state could be the start of the parturition process.

The behavioural or motivational states are latent and not directly observable. It is well recognized between researchers that the states can be indirectly observed, by combining different behavioural and physiological observations (Thodberg et al., 2002; Malmkvist et al., 2006; Wischner et al., 2009), although a direct quantitative model has not been formulated. However, the use of different sensors mounted in the pen level have made it easier to automatically record the data whose distributions are influenced by the latent states. Hence it has become realistic to formulate such a quantitative model.

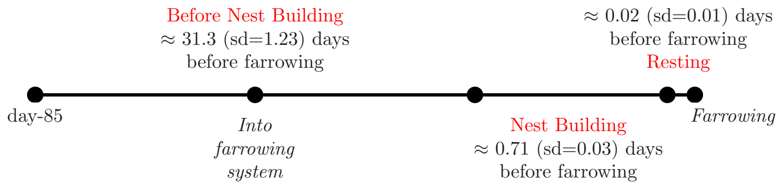


Figure 2.4: Pre-parturition Behavioural states of the sow (Not to scale).

Stochastic Model HMM is a well established technique for modelling processes similar to the pre-parturition behaviour of the sow, for example, monitoring disease progression, where a system progresses through different states. We may observe other variables, and because the distribution of these variables are different for different states, we may use these observations to improve our knowledge about the state of the system at each time step. However, in the usual formulation, HMM assumes that the sojourn times of the latent states are exponentially distributed. This is clearly not the case for the pre-parturition states. The mean duration of each of these states varies from study to study, but is typically approximately 24 hours for the *Nest-Building* state and 6 hours for the *Resting* state and 115 days of total gestation period. The variability of these durations is not well documented except for the total gestation period with a standard deviation of approximately 2 days. The distribution of total gestation period is close to (left-truncated) normal. Prior studies reveal that the sojourn times of these states are approximately Gamma distributed. Hence HMM can not be implemented directly for our purpose.

This was solved by splitting up the states into a number of smaller divisions called *phases* (as illustrated in figure 2.5) each of whose sojourn times follows exponential distribution such that the total sojourn time distribution of each state is a Gamma or more specific an Erlang distribution, as the number of phases in each state is an integer value.(An Erlang distribution is a sub-class of Gamma distribution with integer valued scale parameter). Therefore, HMM was constructed over the pre-parturition phases instead of states, and the parameters of the three Erlang distributions estimated using moment matching.

The distribution of the corresponding sensor measurements were conditioned on the phases. figure 2.6 shows an analogue of HMM. At time t, the sow will be at phase $U_t = u$, $u \in \mathbf{U}$ where $\mathbf{U}$ is the set of all pre-parturition phases. An observation Y_t was measured by a sensor from the distribution associated with the phase u. Since the process will be absorbed at the first phase of the *Farrowing* state, we assume only one phase in *Farrowing* and is denoted by u_F.

The HMM technique is typically used to predict the most likely phase of

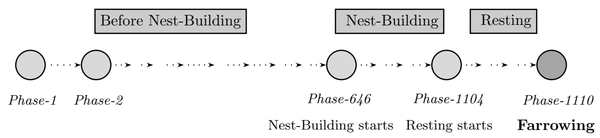


Figure 2.5: An illustration of Markov process with the states divided into phases. The phases, *Phase-1, Phase-646* and *Phase-1104* are the first phase of the states *Before Nest-Building, Nest-Building* and *Resting*. *Phase-1110* is the absorption phase or the first phase of *Farrowing*.

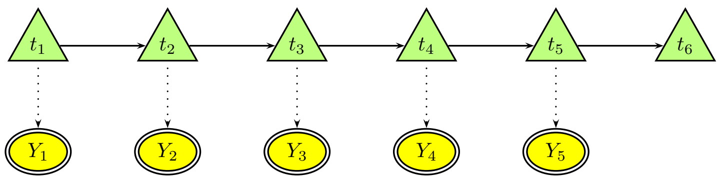


Figure 2.6: An analogue of the Hidden Markov process (HMM). The sequence $\{t\}$ denotes time instance at which an observation Y_t are observed. At time t the system stays in phase $U_t = u$ which is unobservable. However, Y_t's are observed from the distribution associated with the phase u. Y_t could be any measure such as water consumption, activity, temperature etc.

the system at a given time, whereas our objective is to predict the time of absorbtion (farrowing). Furthermore, the technique will usually not take the time since the start of the process into account, whereas the start (time of mating) is very important in the farrowing process. However, the HMM set up will help us to calculate the probability of each phase at a given time. The assumption of Erlang distribution as the sojourn time distribution of each of the three states means that the distribution of gestation period is the sum of three Erlang distribution which is nothing but PH-distribution. Therefore, an event *time to farrowing* can be modelled using PH-distribution. By the theory, PH-distribution itself is a Markov process with the transition probabilities given by (2). Hence, the variable corresponding to the time since mating will be handled by (2). Titman and Sharples (2010) give a detailed description of using PH-distribution as the sojourn time distribution in a Hidden Semi-Markov Models. An advantage of the PH-distribution is that it is dense in the class of distributions defined on the positive real half line. Therefore, any distributions for the positive values of a random variable can be approximated to a PH-distribution. In particular, the left truncated normality assumption of the total gestation period may be easily approximated to a PH-distribution. Therefore the transition probability of the phases were defined by a PH-distribution. Furthermore, the PH-distribution uses the updated phase probabilities to compute the expected time to farrowing at the time of prediction. The farrowing prediction model is a combination of HMM and PH-distribution and therefore, the model is named as Hidden Phase-type Markov Model (HPMM).

We introduce the basics of HMM and PH distribution in sec. 2.2.4 and 2.2.5.

2.2.3 Warning Strategies for validating the algorithm

The purpose of the prediction was to be able to send out warning signals that may, for example, activate the heating equipment or alert the farmer for the special attention. The algorithm we have presented, calculates the phase probabilities using all the available information at each time step, and can calculate the necessary statistics to predict the onset of farrowing. We now need a warning strategy to tell when to send out the warnings. A *warning strategy* is defined as a mapping between a probability distribution for time to farrowing at a given time and a decision to either send a warning or do-nothing.

Thus, the farrowing prediction model was evaluated by applying simple heuristic warning strategies inspired by the improved climate regulation around farrowing suggested in Malmkvist et al. (2006) and by the use of warning to increase management surveillance. The climate regulation requires that floor heating should be turned on prior to farrowing early enough to ensure that the floor temperature reaches the desired level before the start of the farrowing. Thus a natural warning strategy will be to send a warning signal to activate floor heating when the expected time to farrowing is less than or equal to the required time to heat up the floor. With respect to warning to start management surveillance another strategy could be to spend time on those sows that have a high probability of farrowing within a given time interval.

The validation will be made for different thresholds for the alarm criteria applied to the collected data. These will be based on different success criteria and different combinations of sensors, as described in detail in sec. 2.4.2.

2.2.4 Basics of a Markov Process and Hidden Markov Model

A stochastic process is said to have the *Markov Property* if the conditional probability of being in the next state depends only on the current state. It is also called *memoryless* property. A stochastic process satisfying the Markov property is known to be a *Markov Process*. A Markov process may have a discrete or continuous state space; it also may be over a discrete or continuous time space.

In particular, $\mathbf{U}$ is the state space of the *farrowing process* and is finite and discrete. The farrowing process will progress over a continuous time from mating to farrowing. However, the purpose of the prediction is to make certain managemental decisions before the farrowing and these will be based on sensor data which are sampled at discrete intervals. Hence the time space for the *prediction process* is discrete. Further the prediction process starts only after the sow was introduced into the farrowing pen. For simplicity, consecutive predictions were performed at an equal time interval of δ hours and the sensor observations were pooled to fit into the prediction time. The farrowing process ends with farrowing and hence, the prediction process. Therefore, the time space of the prediction process is finite and is $\mathcal{T} = \{t_I, t_I + \delta, \ldots, t_I + N\delta\}$ where N is such that $t_I + N\delta \quad (\leq t_F)$ is the time of last observation before farrowing. Since the time of farrowing (t_F) is unknown in reality, N or $t_I + N\delta$ is also unknown. The probability of a phase of the sow at time $t + \delta$ depends only on the phase of the sow at time t.

The amount of time a subject (a sow, in our case) will spend in a phase or state before it exits from there, is called *sojourn time* or *waiting time* or *first passage time*. Hence, by the memoryless property of a Markov process, the sojourn time distribution for a phase is exponential. Therefore, farrowing process is a *Markov Process* over phases.

A Markov Process is *absorbing* (Absorbing Markov Process or AMP) if there is at least one state of absorption and it is possible to reach this state from every other state (not necessarily in single step). In an AMP, the states which are not absorbing are known as *transient* states. The farrowing process terminates when the sow reaches u_F of *Farrowing* state. Hence, u_F is called an *absorbing* phase from which the process does not continue or in other words, the phase has zero probability of exiting.

Since the phases of the farrowing process are not directly observable, we call the process *hidden* or *latent*. These phases (or states) are associated with a probability distribution. We can calculate the probability that a sow will be in a certain phase or set of phases at a given time. (The time of absorption (birth of first pig) may be observed by the farmer, but not by the sensors.)

Thus, when we observe, for example, data from the water sensor at a given time, we know that the prior distribution of the observation will follow a mixture of conditional distributions for each phase weighed with the associated probability of being in that phase. In turn we may use the value of the observation to revise the phase probabilities. As shown in Aparna et al. (2013), it is possible to use historical data for estimation of both the number of phases, the transition intensities and the parameters of the conditional distributions.

Hence, a HMM over phases may be used to model the farrowing process. figure 2.6 illustrates such a process.

2.2.5 Phase-Type Distribution

Consider an $(\mathbf{M}+1)$-phase and continuous-parameter Markov process with $\{1, 2, \ldots, \mathbf{M}\}$, $\mathbf{M} \geq 1$, transient phases and an absorption phase $(\mathbf{M}+1)$, with rate matrix,

$$\mathbf{Q} = \begin{pmatrix} \mathbf{S} & \mathbf{S^0} \\ \mathbf{0} & 0 \end{pmatrix}$$

where $\mathbf{S_{M\times M}}$, corresponds to the transient phases; $\mathbf{S^0}_{\mathbf{M}\times 1}$, corresponds to the absorbing phase from the transient phases. In our case, $\mathbf{S_{M\times M}}$ is sparse and will only have non-zero values at the diagonal and super-diagonal.

Let $(\boldsymbol{\alpha}, \alpha_{\mathbf{M}+1})$ be the row-vector of initial phase probabilities with $\boldsymbol{\alpha}$ corresponding to the transient phases and $\alpha_{\mathbf{M}+1}$ corresponding to the absorption phase.

Then, a probability distribution of the time till absorption in the Markov chain $\mathbf{Q}$, on $(0, \infty)$ is,

$$\mathbf{Pr}(T \leq \delta) = 1 - \boldsymbol{\alpha}\mathbf{e}^{\mathbf{S}\delta}\,\mathbf{1}, \qquad \delta \in \mathcal{R}^+ \tag{1}$$

a *Phase-type distribution* (PH-distribution) (Neuts, 1978) and is represented by a pair $(\boldsymbol{\alpha}, \mathbf{S})$. Here, $\mathbf{1}$ is the unit column-vector and $\mathbf{e}$ is the matrix exponential (Bernstein, 2009).

For the farrowing process, the absorbing phase is at *Farrowing* and therefore, $\alpha_{\mathbf{M}+1} = (\alpha)_F = 1 - \boldsymbol{\alpha}\,\mathbf{1}$.

The transition probability matrix for the time interval δ is given by, (Asmussen et al., 1996),

$$\mathbf{P}_\delta = \mathbf{e}^{\mathbf{S}\delta}. \tag{2}$$

The moments of the distribution are given by

$$\mathbb{E}[T^n] = (-1)^n n!\boldsymbol{\alpha}\mathbf{S}^{-n}\,\mathbf{1} \qquad n = 1, 2, 3, \ldots$$

Therefore, the mean of the PH-distribution is

$$\mathbb{E}[T] = -\boldsymbol{\alpha}\mathbf{S}^{-1}\,\mathbf{1} \tag{3}$$

and the variance can be found from the second moment,

$$\mathbb{E}[T^2] = 2\boldsymbol{\alpha}\mathbf{S}^{-2}\,\mathbf{1}\,. \tag{4}$$

2.2.6 Notations

We denote the states *Before Nest-Building, Nest-Building, Resting* and *Farrowing* by $\mathcal{S}_1, \mathcal{S}_2, \mathcal{S}_3$ and $\mathcal{S}_4$ respectively. The number of phases in an i^{th} pre-parturition state $\mathcal{S}_i$ is denoted by m_i, $i = 1, 2, 3$. Therefore, there are $\mathbf{M} =$

$\sum_{i=1}^{3} m_i$ transient phases. We assume only one phase in the *Farrowing* state and is denoted by u_F. The successive phases are denoted by an ordered sequence *Phase-1, Phase-2,...* or simply $1, 2, \ldots$ such that *Phase-*m_1 is the last phase of state $\mathcal{S}_1$ and *Phase-*$(m_1 + 1)$ is the first phase of state $\mathcal{S}_2$; *Phase-*$(m_1 + m_2)$ is the last phase of state $\mathcal{S}_2$ and *Phase-*$(m_1 + m_2 + 1)$ is the first phase of state $\mathcal{S}_3$; *Phase-*$(m_1 + m_2 + m_3)$ is the last phase of state $\mathcal{S}_3$ and *Phase-*$(m_1 + m_2 + m_3 + 1)= u_F$ is the farrowing phase.

Let $\mathbf{U}$ denotes the set of all $\mathbf{M}$ phases and $\mathbf{U}_i$ denotes the subset of $\mathbf{U}$ and consists all the phases of state $\mathcal{S}_i$. i.e. $\mathbf{U}_1$, $\mathbf{U}_2$ and $\mathbf{U}_3$ has m_1, m_2 and m_3 number of phases, respectively. $u \in \mathbf{U}_i$ denotes any phase u in $\mathbf{U}_i$. Further, U_t is a random variable and denotes the phase of the sow at time t. $U_t = u$ implies that the sow occupies phase u at time t. The states are indexed by i or j and the phases by u or v.

The vector of probabilities over the transient phases at time t is denoted by $\boldsymbol{\alpha}_t$. Let $(\boldsymbol{\alpha}_t)_{\mathbf{U}_i}$ denote the elements of $\boldsymbol{\alpha}_t$ corresponding to all the phases in state $\mathcal{S}_i$. The vector of probabilities of the transient phases corresponding to the time when the farrowing process begins is denoted by $\boldsymbol{\alpha}_0$. The probability corresponding to the farrowing phase is denoted by $(\alpha)_F$.

Other notations were explained as and when they were introduced.

2.3 Prediction Algorithm

The following are the steps of the algorithm for the prediction of onset of farrowing for an individual sow.

2.3.1 Initializing the algorithm for a sow

In principle, the farrowing process starts on the day the sow was successfully mated. Thus we know that the sow is in the first phase. However the duration of the first phase has a very small standard deviation. Therefore, to avoid too many phases, the model for the first part of the gestation period is slightly modified. Initial evaluation studies showed that the distribution of sojourn time from mating to farrowing (gestation length) could be described adequately with a constant part of 85 days and a gamma distributed final part. This approximation lead to a markedly lower number of phases. Therefore, the model was reformulated, such that all the sows were entered into *Phase-1* on day-85 after mating, Thus, the phase probabilities, $\boldsymbol{\alpha}_0$, on the day 85 was defined as the vector with the first element 1 and the rest 0s. If δ_I is the time interval between day-85 after mating and the day the sow was introduced into the farrowing system, the transition matrix, $\mathbf{P}_{\delta_I}$ was found from (2) and the phase probabilities of the sow on the day of insertion were then calculated as,

$$\boldsymbol{\alpha}_{t_I}^{(0)} = \boldsymbol{\alpha}_0 \mathbf{P}_{\delta_I} \tag{5}$$

where t_I is the time that the sow was introduced into the farrowing system. We also assume that the sensors mounted in the pen starts recording the data from time t_I.

2.3.2 Half-hourly updating for a sow

As mentioned in sec. 2.2.1, the observations were pooled and measured at the fixed time interval δ. Therefore, the phase transitions of the sow were calculated on every interval δ after t_I, where $\delta = 0.5$ hours in this paper. If t is the current time then the phase transition of the sow at time $t + \delta$ is predicted as

$$\boldsymbol{\alpha}_{t+\delta}^{(0)} = \boldsymbol{\alpha}_t \mathbf{P}_{\delta}. \tag{6}$$

Here, the transition matrix, $\mathbf{P}_\delta$, is again found using (2). As the time interval δ is constant, we only need to calculate $\mathbf{P}_\delta$ once.

Furthermore, as mentioned the HMM technique allows us to use any sensor observation, measured at time t, to revise the phase probabilities of time $t + \delta$. Since we assume that the sensor measures are conditionally independent, the phase probabilities were revised for each sensor measure available at the given time. The conditional independence also means that the sequence of sensors in the revision is irrelevant and any missing sensor measure does not influence the revision of probabilities. Let there be N_s number of sensors available at time t (note that the time indicator is omitted in the notation N_s). Let $Y_t^{(n_s)}$ be the observation measured at time t by ${n_s}^{th}$ sensor. Then, the phase probabilities given the n_s number of sensors is,

$$\boldsymbol{\alpha}_{t+\delta}^{(n_s)} = \frac{\boldsymbol{\alpha}_{t+\delta}^{(n_s-1)} \cdot \mathbf{Pr}(Y_t^{(n_s)} \mid U)}{\mathbf{Pr}(Y_t^{(n_s)})}, \quad n_s = 1, 2, \dots, N_s \tag{7}$$

where $\mathbf{Pr}(Y_t^{(n_s)} \mid U)$ is the row vector of probabilities of $(Y_t^{(n_s)} \mid$ *Phase-1*$)$, $(Y_t^{(n_s)} \mid$*Phase-2*$), \dots (Y_t^{(n_s)} \mid$*Phase*-$\mathbf{M})$ and $\mathbf{Pr}(Y_t^{(n_s)}) = \boldsymbol{\alpha}_{t+\delta}^{(n_s-1)} \mathbf{Pr}(Y_t^{(n_s)} \mid U)^{\top}$. Here, $A^\top$ denotes the transpose of A and $A \cdot B$ is the element-wise multiplication of A and B.

In the current paper, the phase probabilities were updated for the sensor measures $Y_t^{(n_s)} \in \{Y_t^{(w)}, Y_t^{(Am)}, Y_t^{(Asd)}, Y_t^{(g)}\}$ and are discussed in sec. 2.3.3. Therefore, $\boldsymbol{\alpha}_t^{(n_s)} \in \{\boldsymbol{\alpha}_t^{(Am)}, \boldsymbol{\alpha}_t^{(Asd)}, \boldsymbol{\alpha}_t^{(g)}, \boldsymbol{\alpha}_t^{(w)}\}$ for $n_s = 1, \dots, N_s$.

The vector of final phase probabilities predicted for time $t + \delta$ is, $\boldsymbol{\alpha}_{t+\delta} = \boldsymbol{\alpha}_{t+\delta}^{(N_s)}$ if N_s sensor information is available; otherwise, $\boldsymbol{\alpha}_{t+\delta} = \boldsymbol{\alpha}_{t+\delta}^{(0)}$.

Therefore, the probability of farrowing phase is,

$$(\alpha_{t+\delta})_F = 1 - \boldsymbol{\alpha}_{t+\delta}\,\mathbf{1}\,. \tag{8}$$

The phase transition with time and the revision of the phase probabilities using the available sensor observations were continued alternatively for time $t = t_I, t_I + \delta, t_I + 2\delta, \ldots, t_I + N\delta$. At the end of each time step, before considering the next half-hourly updating of phase transition (as in (6)), the necessary statistics for raising the warning were calculated. Sec. 2.2.3 discusses some of such statistics used in this study.

The algorithm will proceed until farrowing has been observed by the farmer, and not directly by the sensor observations.

2.3.3 Updating $\boldsymbol{\alpha}_t$ Using the Sensor Information

The prediction algorithm was built and implemented to use the sensor information such as water observations, video-activity and grid-activity measures. As described in sec. 2.2.2 and sec. 2.2.4, the prediction process starts from the day the sow was introduced into the farrowing system. At time t, if any evidence from the sensors is available, it was used to update the phase probabilities $\boldsymbol{\alpha}_{t+\delta}$ as follows:

We assume that at a given time t, the conditional distribution of *meanActivity, sdActivity* and *grid-activity* are distributed as follows,

$$\begin{aligned}
(Y_t^{(Am)} \mid u \in \mathbf{U}_i) &\sim \mathcal{N}(\mu_i^{(Am)}, \sigma_i^{2(Am)})_\zeta \\
(Y_t^{(Asd)} \mid u \in \mathbf{U}_i) &\sim \mathcal{N}(\mu_i^{(Asd)}, \sigma_i^{2(Asd)})_\zeta \\
(Y_t^{(g)} \mid u \in \mathbf{U}_i) &\sim \mathcal{N}(\mu_i^{(g)}, \sigma_i^{2(g)})_\zeta
\end{aligned}$$

where $(\mu_i^{(Am)}, \sigma_i^{2(Am)})_\zeta$, $(\mu_i^{(Asd)}, \sigma_i^{2(Asd)})_\zeta$ and $(\mu_i^{(g)}, \sigma_i^{2(g)})_\zeta$ are the mean level of respective measures with the corresponding variances at time of the day ζ. We assume that $\sigma_{i\zeta}^{2\,(Y)} = \sigma^{2(Y)},$ for $i = 1, 2, 3$ for *meanActivity, sdActivity* and *grid-activity*.

These density functions were used in the expression (7) as the likelihood of $(Y_t^{(n_s)} \mid U)$ and the phase probabilities $\boldsymbol{\alpha}_{t+\delta}^{(Am)}$, $\boldsymbol{\alpha}_{t+\delta}^{(Asd)}$ and $\boldsymbol{\alpha}_{t+\delta}^{(g)}$ corresponding to meanActivity, sdActivity and grid-activity, respectively, were calculated.

The water observation measured at time t is assumed to be from a mixture distribution for the given state; the mixing is over a number of components. These components can be seen as different types of drinking behaviour that the sow may select. Furthermore, the mixing proportions were associated with the time of measurement. For the simplicity, we assume that the consumption pattern of one state is independent of other states and, within the state, the water consumption in each component follows a distribution independent of the other component. The probability of observing the water consumption in k^{th} component $\mathcal{C}_k^{(i)}$ of state $\mathcal{S}_i, \quad i = 1, 2, 3$ is defined as

$$\pi_k^{(i)} = \mathbf{Pr}(\mathcal{C}_k^{(i)} | \mathcal{S}_i), \quad k = 1, \ldots, K^{(i)}$$

where $K^{(i)}$ is the number of components in state $\mathcal{S}_i$.

Therefore, the density of observing $Y_t^{(w)}$ at time t as the k^{th} component of the i^{th} state is

$$(Y_t^{(w)} \mid \mathcal{C}_k^{(i)}, \mathcal{S}_i) \sim \mathcal{N}(\mu_i^{(w)^{(k)}}, \sigma_i^{2(w)^{(k)}})_\zeta.$$

For the simplicity, we assume that $\sigma_{i\zeta}^{2\,(w)^{(k)}} = \sigma_i^{2(w)^{(k)}}, \quad \forall\zeta$. Furthermore, we assume that $(Y_t^{(w)} \mid \mathcal{C}_k^{(4)}, \mathcal{S}_4) = (Y_t^{(w)} \mid \mathcal{C}_k^{(3)}, \mathcal{S}_3)$. Therefore, the likelihood of $Y_t^{(w)}$ given $\mathcal{S}_i$ is

$$\mathbf{Pr}(Y_t^{(w)} \mid \mathcal{S}_i) = \mathbf{Pr}(Y_t^{(w)} \mid \mathcal{C}_k^{(i)}, \mathcal{S}_i) \quad \mathbf{Pr}(\mathcal{C}_k^{(i)} | \mathcal{S}_i)_t \qquad i = 1, 2, 3, 4$$

Hence, by Bayes' theorem, the posterior of each state given the observation is

$$\mathbf{Pr}(\mathcal{S}_i \mid Y_t^{(w)}) = \frac{\mathbf{Pr}(Y_t^{(w)} \mid \mathcal{S}_i)\mathbf{Pr}(\mathcal{S}_i)_t}{\sum_{j=1}^4 \mathbf{Pr}(Y_t^{(w)} \mid \mathcal{S}_j)\mathbf{Pr}(\mathcal{S}_j)_t}; \qquad i = 1, 2, 3, 4.$$

where $\mathbf{Pr}(\mathcal{S}_i)_t = (\boldsymbol{\alpha}_t)_{\mathbf{U}_i}\mathbf{1}_{m_i}$ is the sum of $\boldsymbol{\alpha}_t$ elements corresponding to state $\mathcal{S}_i$, $i = 1, 2, 3$ and $\mathbf{Pr}(\mathcal{S}_4)_t = (\alpha_t)_F$. $\mathbf{1}_{m_i}$ is the unit vector of size m_i.

Hence, the phase probabilities were updated as

$$(\boldsymbol{\alpha}_t^{(w)})_{\mathbf{U}_i} = \mathbf{Pr}(\mathcal{S}_i \mid Y_t^{(w)}) \frac{(\boldsymbol{\alpha}_t)_{\mathbf{U}_i}}{\mathbf{Pr}(\mathcal{S}_i)}; \qquad i = 1, 2, 3$$

where $(\boldsymbol{\alpha}_t)_{\mathbf{U}_i}$ are the elements of $\boldsymbol{\alpha}$ corresponding to the phases in state $\mathcal{S}_i$; similarly the $(\boldsymbol{\alpha}_{t+\delta}^{(w)})_{\mathbf{U}_i}$.

2.4 Computational and validation plan

The prediction algorithm described above is tested for the experimental data described in sec. 2.2.1. For the validation of the algorithm, in the current paper, we use the same sow and sensor data as used for estimating the model parameters described in Aparna et al. (2013). For each sow, the sensor data were used sequentially, thus pretending that only the data from time of insertion up to the half hourly time of prediction was available at each prediction. If data from a sensor were missing at a given time the corresponding updating of the phase probabilities was omitted. Furthermore, if all the sensor observations were missing at the time of prediction, the algorithm handles it by calculating only the phase transition over time. The validation could have been made using a cross-validation approach where the observations from each sow was evaluated with parameters estimated from data for other sows. However, because of the sample size it was expected that each sow had so little influence on the parameter estimates that the large extra computing time for the cross-validation was not worth the effort.

2.4.1 Parameters and values

The model parameters were estimated by an EM-algorithm inspired by the Baum-Welch algorithm by updating Forward-Backward probabilities as described in detail in Aparna et al. (2013). In the present paper we skip the discussion of estimation of parameters. However, as the estimated parameters were used for the prediction algorithm they are briefly described in the following.

Sojourn Time Distribution, Number of Phases and Transition Rates

The sojourn times of the pre-parturition behavioural states were assumed to be Gamma distributed. The mean and variance for these states are given in table 2.1. The values can be interpreted as follows: on average, a sow spends 17.02 hours (SD= 0.80 hours) in the *Nest-Building* state; whereas the sojourn time for *Resting*, with the limited information, was estimated to be 0.53 hours (SD=0.22 hours) before farrowing. These values are in good agreement with published values for nest-building times, although in the low range. If the sojourn times were exponentially distributed, the SD would be equal to the mean. The low SD thus support the use of the PH-distribution. The total duration is approximately 32 days after day-85 or 117 days after mating.

Hence, the number of phases and the transition rates of a state are the parameters of the corresponding Erlang distribution. They are calculated to be $(m_1, m_2, m_3) = (645, 458, 6)$, so that the sow passes through 1109 phases before the farrowing and 1110^{th} phase is the beginning of *Farrowing*. The process exits at the rate $\lambda_1 = 0.86$ between the successive phases within the *Before Nest-Building* state and enters into the first phase of *Nest Building* state from the last phase of *Before Nest-Building*. Further, it transits between the successive phases of *Nest-Building* state with the rate $\lambda_2 = 26.91$ and enters into *Resting* state. The process will transit between the successive phases in the *Resting* state with the rate $\lambda_3 = 11.4$ and then enters into the *Farrowing* state.

Table 2.1: Mean duration (with their SD) of stay in each state for a sow.

State	Duration (hours) Mean	SD	Phases	Rate (per hour)
Before Nest-Building	751.20	29.58	645	0.86
Nest-Building	17.02	0.80	458	26.91
Resting	0.53	0.22	6	11.40

For these values, the phase transition probabilities were calculated using (2) by constructing the $\mathbf{S}$ matrix of PH-distribution. The $\mathbf{S}$ matrix can be divided into 3×3 sub-matrices corresponding to each pre-parturition state. The i^{th} sub-matrix on its diagonal is of size $m_i \times m_i$ such that, the values on the diagonal are $-\lambda_i$ and super-diagonal are λ_i; for $i = 1, 2, 3$. These correspond to the phases of i^{th} state. For example, for $(m_1, m_2, m_3) = (2, 3, 4)$, $\mathbf{S}$ is given by,

$$\mathbf{S} = \left[\begin{array}{cc|ccc|cc} -\lambda_1 & \lambda_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -\lambda_1 & \lambda_1 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & -\lambda_2 & \lambda_2 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\lambda_2 & \lambda_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\lambda_2 & \lambda_2 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & -\lambda_3 & \lambda_3 \\ 0 & 0 & 0 & 0 & 0 & 0 & -\lambda_3 \end{array}\right]. \tag{9}$$

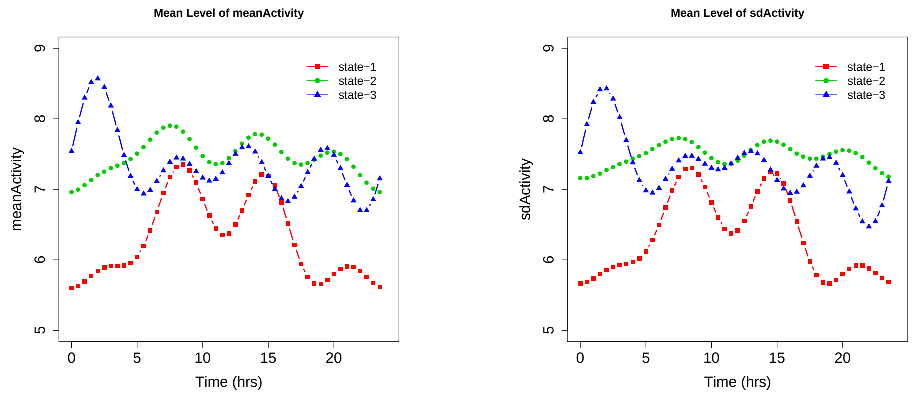
The corresponding $\mathbf{S^0}$ would have λ_3 as the last element, and all other elements 0. We will omit the illustration of the estimated matrix with $(m_1, m_2, m_3) = (645, 458, 6)$.

Conditional Distribution of Sensor Observations

The different patterns of the sensor measurement when the sow is in different states are what allow us to distinguish which state the sow is in. These conditional distributions are therefore important part of the algorithm. The prediction algorithm was implemented to use four different sensor measures, namely, water observations, meanActivity, sdActivity and grid activity. Note that we use the log-transformation of these variables throughout the model. The conditional distributions also capture the diurnal rhythm of the sow hidden in the sensor observation in addition to the pre-parturition behaviour.

Video-Activity The mean levels of the *meanActivity* and *sdActivity* were plotted against the time of a day, as shown in figure 2.7b. The lines indicating *state-1, state-2* and *state-3* correspond to *Before Nest-Building, Nest-Building* and *Resting* states. The mean levels were estimated with the SDs $\sigma^{(Am)} = 0.8$

and $\sigma^{(Asd)} = 0.9$. The peaks in the curves for *state-1* suggest the pronounced diurnal variation and the corresponding time of the day matches with the managemental records. In *state-2* the mean level reflects the highly active nest building behaviour of the sow, but *state-3* is almost identical. The pattern of the *meanActivity* and *sdActivity* is more or less identical.



(a) meanActivity (b) sdActivity

Figure 2.7: Mean level of meanActivity and sdActivity over a day in different states; state-1 (*Before Nest-Building*) and state-2 (*Nest-Building*) and state-3 (*Resting*).

Grid Activity The mean level of the grid activity was estimated with SD, $\sigma^{(g)} = 1.64$. The plot of $\mu^{(g)}$ over 24hours of a day is as shown in figure 2.8. For *state-1* the diurnal pattern is more or less identical. In contrast to the video-activity, the mean grid-activity shows a marked difference between *state-2* and *state-3*. The reason is probably that the grid activity only measures the activity while standing up. If the sow moves while lying down, it will not show up in grid measurements.

Water Consumption The conditional distribution of water consumption was the most complicated to model. The data suggested that the sows used the drinking nipple in different ways. Thus the final conditional model was a mixture model with three components corresponding to each way of drinking. The mean level of different components of *Before Nest-Building* state was estimated to be $\mu_1^{(w)} = [7.07, 2.09, 0]$ with the residual standard deviation ${\sigma_1}^{(w)} = [0.96, 1.14, 0.01]$. That is, the Component-1 corresponded to the most drinking per drinking episode, Component-2 may be a kind of redirected behaviour, e.g. playing with the drinking nipple, and Component-3 to almost no drinking activity. The corresponding mixing probabilities varied throughout the day and are shown in figure 2.9a (The x-axis of the plot denotes the 0-24 hours

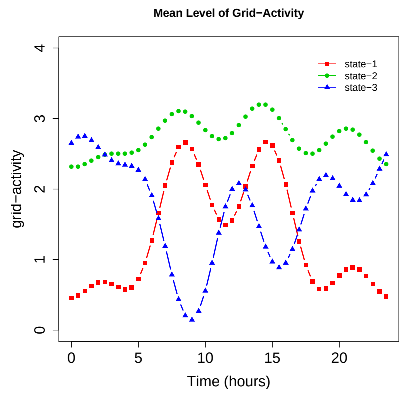


Figure 2.8: Mean level grid-activity over a day in different states: state-1 (Before Nest-Building), state-2 (Nest-Building) and state-3 (Resting).

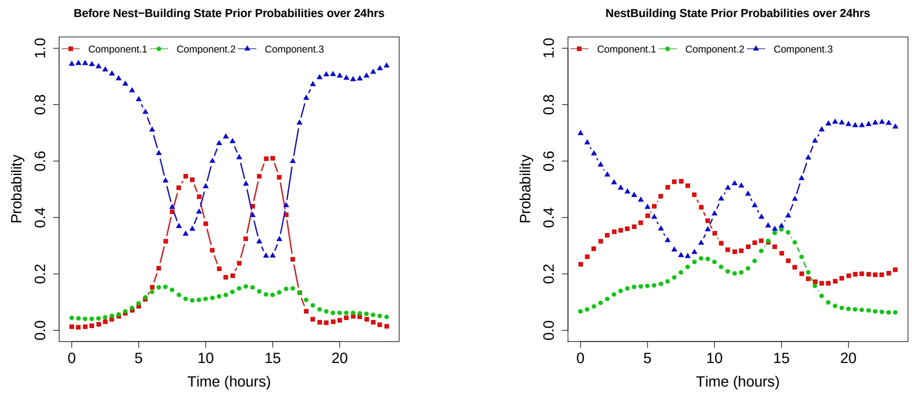
of a day). Early morning and mid-night, the water consumption level was very low compared to that during the day time (Component-3). Also, as the other measures the model captures the feeding times by showing large probability of drinking at around hour 8 and 15 of the day (the peaks for Component-1). Apart from this lower and higher level of water consumption, the sow has also intended to consume some water during the night/day time with the very low probability as denoted by the dots for Component-2. The estimates for mean level of water consumption for each component over a day for *Nest-Building* state were similar and are $\mu_2^{(w)} = [7.14, 3.61, 0.001]$ with residual standard deviation ${\sigma_2}^{(w)} = [0.74, 2.0, 0.02]$. But as the plot of probabilities for the *Nest-Building* state, figure 2.9b , shows, there is a notable change in the water pattern, though the mean level of water consumption was very close to that of *Before Nest-Building*. The plot shows more water activity even at the night time (after hour 20 and before hour 4)(Component-1), indicating a clear link between nest building activity and water intake.

Since the *Resting* state has very short duration we consider only one component for the water consumption with mean level estimated to be $\mu_3^{(w)} = 0.49$ (${\sigma_3}^{(w)} = 1.61$).

2.4.2 Validation of Warning Strategy

In the present paper, the prediction algorithm was evaluated using the prediction in two different kind of simple and heuristic warning strategies. The first is based on the expected time to farrowing, inspired by the use of the prediction for activation of the floor heating system,

$$\mathbb{E}[T]_{t+\delta} = -\boldsymbol{\alpha}_{t+\delta}\mathbf{S}^{-1}\,\mathbf{1}$$



(a) Before Nest-Building

(b) Nest-Building

Figure 2.9: The mixture probabilities for water consumption over a day for the components of *Before Nest-Building* and *Nest Building* states. The consumption behaviour was classified into components: Component-1 to 3 correspond to most-drinking to no-drinking activities. Furthermore, $\mathbf{Pr}$*(Component-1)* + $\mathbf{Pr}$*(Component-2)* + $\mathbf{Pr}$*(Component-3)* = *1*, at a given time.

as in (3).

The second was inspired by the management surveillance case, where it is natural to concentrate efforts on the sows that are most likely to farrow within a given time-period x. Thus we calculate the probability of farrowing in the next x hours as

$$\{(\bar{\alpha}_x)_F\}_{t+\delta} = 1 - \boldsymbol{\alpha}_{t+\delta}\mathbf{e}^{\mathbf{S}x}\,\mathbf{1}$$

as in (1).

Each of these strategies were illustrated in the sec. 2.5 by plotting the respective statistic value over the time of prediction. The warning or alarm was indicated by a dot over the prediction line. The evaluation was made for different scenarios. For each of the scenarios, different success criteria was measured.

To illustrate we refer to figure 2.11a. A warning is raised if the expected time to farrowing is less than 12 hours. Thus there are three periods of warning for the sow in the figure. Two of them are false, they were cancelled by later predictions, while the last one is OK. In other words, the first two are false warnings, while the last one is a true warning. That is, each sow can have only one true warning. For the true warnings, we calculate the mean and standard deviation of the warning duration for all the sows. For the false warnings we calculate the total duration for each sow and then the mean of these durations over all the sows. The later is called the Error. In the floor heating case, it would correspond to how long time the heat was turned on unnecessarily. The results are presented in the table 2.2. Note that these are different from the definitions of false alarms/warnings used in Cornou and Lundbye-Christensen (2012).

In the present paper, the first strategy was tested for the threshold value 12 hours. That is, an alarm was raised if the expected time to farrowing was less than 12 hours. For the same strategy and scenario, the performance of the prediction algorithm was evaluated for different combination of water, video-activity and grid-activity sensors; this include, {water and video-activity}, individual performances of water and video-activity, {water, video-activity and grid-activity}, {water and grid-activity}, {video and grid-activity}. Whenever *meanActivity* was calculated, *sdActivity* was also calculated. Therefore, we include both the measures if the combination consists video-activity.

For the combination of water and video-activity sensors, the performance of the algorithm was also compared by changing the threshold to 2 and 6 hours. Evaluating the algorithm and the strategy for the reduced thresholds is also necessary for the applications like climate controlling (for example, when a higher input energy was supplied), managemental surveillance.

The second strategy was tested by calculating the probability of farrowing in the next $x = 12$ hours. The warning results were compared by varying the probability threshold from 0.4 to 0.6.

2.4.3 Computational Environment

The prediction algorithm was implemented in the statistical computational environment R (R Development Core Team, 2010). Various functions supporting the algorithm were written. These functions have been collected into a package compatible with R.

2.5 Results

2.5.1 Illustration of use of algorithm for individual sows

The performance of the prediction algorithm for one sow is illustrated in figure 2.10a. The algorithm has used information from water and video-activity sensors. The time-axis starts from the time of insertion, and the horizontal line is drawn to indicate the threshold for the warning strategy. The vertical line indicates the actual day of farrowing of that sow. The expected time to farrowing was calculated at every prediction time step and are plotted against the time-axis. After the sow was introduced into the farrowing system, the expected time to farrowing has decreased linearly. The observations did not revise the probability distribution over phases, because the most likely state was the *Before Nest-Building*. As the time has passed, other states become more likely, and the prediction began to change. A small drop on January 13^{th} was the clear indication of the sow in the *Nest-Building* state. Visual inspection of the video recordings for the sow has confirmed the nest-building on January 14^{th}. The plot has also showed a sudden drop in the expected time when the sow was very close to farrowing and continued to decrease over time, indicating that the sow was approaching the farrowing state.

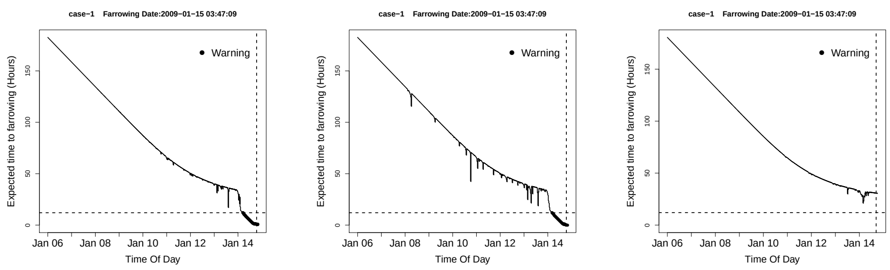
For this case, the warning threshold was set to 12 hours. However, the true-warnings were raised 13.3 hours before the actual farrowing. If the algorithm uses only video-activity data during the prediction, the true-warnings were raised 13.8 hours before the actual farrowing (see figure 2.10b). On the other hand, if only water consumption data was used in the algorithm, there would not have been any warnings (see figure 2.10c); indeed, if we assume that the farmer routinely visits the herd on every day at 10:30 am, then there would have been a delay of 6.7 hours in knowing the farrowing.

The algorithm may also give false-positive warnings, such as in figure 2.11. In the example figure 2.11a, around July 2, some of the observations led to a marked drop resulting in false-positive warnings; 2 times before farrowing. These false warnings were there for 2 and 5 hours respectively. The prediction was revised later on and hence, the warnings were retracted. On July 5, the observations clearly indicated a transition to the *Nest-Building* state (confirmed by the visual inspection of the video recordings), and the expected time to farrowing dropped below 12 hours. Therefore, a warning was raised 8.3 hours before farrowing and are indicated by the dots in the plot. However, in figure 2.11b, the false-positive warnings lead to a false-negative by raising no alarms during the farrowing. A vertical line was drawn on the prediction results in figure 2.11b, to indicate 24 hours before farrowing and will be used for discussion in sec. 2.6.

The strategy of probability of farrowing in the next 12 hours is illustrated in figure 2.12. The horizontal lines indicate different threshold points, from 0.4 to 0.6. The first alarm was produced on January 14^{th}, almost 14 hours before farrowing. The probability curve has sharpened as the algorithm approaches farrowing state.

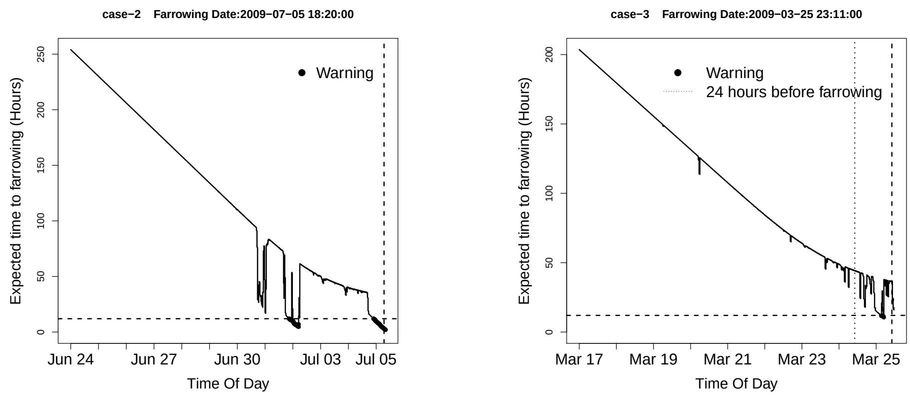
2.5.2 Validation of algorithm for different sensor combinations and heuristic strategies

The sample size, percentage of true-positive warnings, mean warning time and the error due to false-positive warnings for different warning strategies, threshold scenarios and combination of sensors are presented in the table 2.2. For the combination of water and video-activity, with threshold 12 hours for the expected time to farrowing strategy, 34 of the 35 sows (97%) gave satisfactory warnings



(a) water and video-activity (b) video-activity (c) water

Figure 2.10: Performance of the prediction algorithm for the combination of water and video-activity sensors for the *expected time to farrowing* based warning strategy.



(a) case-2 (b) case-3

Figure 2.11: Illustrating the performance of the prediction algorithm for the combination of water and video-activity sensors for the *expected time to farrowing* based warning strategy with case-2: both false-positive and true-positive warnings; case-3: false-positive and false-negative warnings.

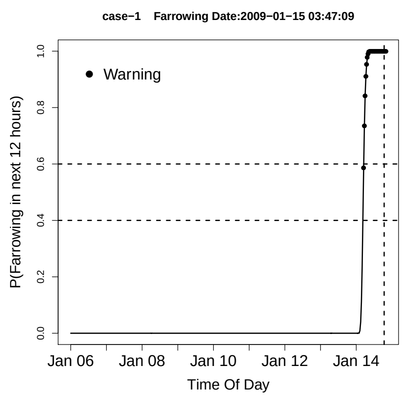


Figure 2.12: Plot of *probability of farrowing in next 12 hours* against time.

Table 2.2: Comparison of prediction algorithm for different combination of sensors and for different warning-strategies. (ETF: Expected time to farrowing based strategy (hours); PF: The warning strategy being Probability of farrowing in next 12 hours; Error: mean duration of false-positive warning (hours))

Strategy	Sensor	Threshold	Sample Size	True Warnings	Warning Time Mean	SD	Error
		12	35	97	11.5	4.6	0.7
ETF	Water and Video-Activity	6	35	83	6.9	3.4	0.1
		2	35	60	4.2	2.6	0.1
ETF	Water	12	38	21	11.7	2.2	3.4
	Video-Activity		55	98	14.4	12.5	1.6
PF	Water and Video-Activity	0.4	35	97	11.7	4.5	1.1
	Water, Video-Activity and Grid		34	97	11.6	4.8	0.8
ETF	Water and Grid	12	36	67	12.2	5.6	3.8
	Video-Activity and Grid		37	100	13.5	7.3	3.1

with mean 11.5 hours (SD=4.6 hours), with the mean error of 0.7 hours.

Using only water measures, the algorithm gave only 8 true-warnings out of 38 (21%) with mean of 11.7 hours (SD=2.2hours). However the error was increased to 3.4 hours. The algorithm which has used only video-activity information (*meanActivity* and *sdActivity*) gave 98% true-warnings and are penalized by the bias in the mean of 14.4 hours and the increased SD of 12.5 hours. The combination of water and video-activity sensors with grid-activity in the prediction algorithm did not improve the prediction results. When used with water or video-activity, the mean time of true-warnings did not improve much. However, with the water, the grid-activity sensor increased the number of true-warnings to 67% with SD=5.6 hours and error 3.8 hours. Using the grid-activity sensor with the video-activity sensor decreased in the SD warning time from 12.5 hours to 7.3 hours.

If the threshold was decreased to 6 hours for water and video-activity combination, only 29 of 35 sows gave true-warnings with mean warning time 6.9 hours (SD=3.4 hours) and an error 0.1 hours. If the threshold was further reduced to 2 hours, only 21 sows gave true-warnings with a biased mean warning time 4.2 hours (SD=2.6 hours). The prediction algorithm had in general low bias. The expected mean time to farrowing used as threshold was close to the observed mean value.

For the strategy of probability of farrowing in the next 12 hours, for the threshold 0.4, the algorithm predicted 36 true-warnings out of 38 with mean warning time of 11.4 hours (SD=4.2 hours). Since the probability curve sharpens as the algorithm approaches farrowing, comparison of different thresholds was not relevant.

2.6 Discussion and Conclusions

In the present study we applied methods that originated in life-time or time to failure studies. Thus the model is directly focused on predicting the remaining time to farrowing (which corresponds to the failure time in the other studies). The biological knowledge of change in behavioural states of the sow in the farrowing pen gave a good modelling framework for handling different patterns in the sensor measures. One of the characteristics of the sensor measurements was a marked diurnal variation. This has allowed a combination of two time scales in the prediction model; the time of the day and the time since mating. The latent state/phase allowed us to treat the different sensor measurements as independent given the state, and thus easily adapt the complexity of the modelling to each different sensor observations. Moreover, this prediction algorithm gives a framework to integrate information from different sensor types for the prediction. The prediction algorithm performed best using both activity and water consumption, although the individual performance of the information from the water sensor was not promising. Thus the combination of these sensors is recommended. Furthermore, because the prediction algorithm can update with values from any sensor, the farmer may choose a suitable sensor for his herd depending on the resources available. The prediction algorithm seems to be unbiased with respect to the threshold level, the mean time to farrowing corresponds to the threshold. For management surveillance a suggestion is also to use the probability based strategy to rank the sows with high chance of farrowing in, say, 12 hours. Later, the strategy based on expected time to farrowing may be used to make the decisions. However, since the earliest start of the *Nest-Building* state is later than 24 hours before farrowing, it is not advisable to use the probability of farrowing in 24 hours.

The algorithm performed satisfactorily based on the evaluation criteria and a cost-benefit analysis (not shown) has subsequently confirmed the use of the algorithm and the sensors is expected to be cost effective, after further product development.

Furthermore, the same algorithm can be used to predict the beginning of *Nest-Building* state. This may be done by considering the first phase of the *Nest-Building* state as an absorbing phase. Detection of the *Nest-Building* state may be helpful, say, in providing the nest building materials to the sow on time.

As mentioned in section 2.1 the study of Cornou and Lundbye-Christensen (2012) is the only one with similar aim of sending warnings about farrowings but uses a different methodology. In both the methods of Cornou and Lundbye-Christensen (2012), the criteria for alarm is related to the detection of change in activity pattern. It is clear that this change of pattern in the observations around start of nest building is what allows the relative precise prediction of time of farrowing in our algorithm. However, the new approach of using the PH-distributions have led to several advantages. We have been able to use different types of sensors and can even compare the success-rates using different combinations of sensors because the model gives direct predictions concerning the time of farrowing. Any detection of a change-point will include a delay between the actual change, and the time where it can be observed. If we want to predict the time of farrowing, we of course want to correct for this delay when we predict. For the sow the behaviour change and the time of farrowing occurs at the same time, no matter how we try to monitor it. The methods in Cornou and Lundbye-Christensen (2012) have a mean time from detection of change-point to farrowing ranging from 8.7 to 15.0 with very similar success-rate in terms of specificity and sensitivity as defined in the paper (note that some false positive results are excluded from these mean values). The difference between a mean time of 8.7 and 15.0 would cause a very large difference for our floor heating system. Our HPMM approach have similar observed mean values to farrowing as the thresholds used in the heuristic strategy. Thus in our case we can measure if, for example, the expected time to farrowing time is biased compared to the observed time, and we can directly compare the precision of the predictions. Of course the large sample size also gives us better possibility to compare different methods. Also note that our setting of threshold values are directly connected to the desired time of warning and independent of the data sample. In contrast, Cornou and Lundbye-Christensen (2012) operates with a threshold for the desired warning of 24 hours, and a subsequent optimized threshold value for the deviation criteria.

The intended use of the prediction algorithm for activation of a floor heating system made it clear that a relevant warning system should give warning in time for the floor to heat up and it also helped in defining relevant measures of success used in this paper. There may exist early periods where a warning is triggered, because the expected duration falls below the threshold, but later the expected duration increases above the threshold. This is clearly a false warning. From the heating point of view the heat will be turned on, but energy may be wasted because the floor temperature will return to room temperature before farrowing. Only when the warning period extends until start of farrowing, the energy will be used fully, leading to a true warning. At least in this context we only have false and true alarms. In contrast, Cornou and Lundbye-Christensen (2012) defines four types of alarms true-positive, false-positive, false-negative, and true-negative. This is possible by defining (arbitrarily ?) a gold standard where a sow is positive within the last 24 hours before farrowing and negative before that. Thus each sow is both negative and positive, and figures twice in the evaluation, e.g. a sow may be both false-positive and true-positive. Unfortunately, the description of an alarm in Cornou and Lundbye-Christensen (2012) is not specific enough to know if they also operate with time periods where the threshold criteria is full-filled. They define an alarm at time t when the deviation criteria at time t crosses over the threshold value. We cannot decide from this description whether an alarm refer to a period or only a single time point. The figures in the paper seem to indicate that alarm refers to a period.

It is possible that the alarm periods are interrupted by periods below the threshold during the final 24 hours as it is in our case figure 2.11b. On the other hand, true-positive is defined as when at least 1 alarm is given within the final 24 hours before farrowing, indicating that there may be more than one alarm in the period, and therefore also periods without alarms. In the calculation of time from alarm to farrowing, they seem to be using the earliest alarm within 24 hours before birth of first piglet, but this is only relevant if the alarm is not interrupted. So, for some sows, it is possible that the alarm periods are interrupted by periods below the threshold during the final 24 hours as it is in our case figure 2.11b. By their definition, this is a true-warning and according to us, it is within a positive period and should lead a false-negative score as there is no warning at the time of farrowing. These uncertainties makes it very difficult to compare the approaches. Another approach to compare is if the threshold selection was optimized to get as close to a given mean time to farrowing (e.g. for different time periods such as 12, 6 hours before farrowing.) instead of fixing the threshold value by optimizing sensitivity and specificity; but then again this needs to be done for each deviation criteria. In the case of warnings with the purpose of better surveillance, there is no doubt that the end of an alarm period will also lead to an end to the planned increased surveillance.

The discussion above illustrates the need for a clearer definition of how to treat the problems of sequential observations,that may lead to alarms.

One way is to make a more direct specification of the cost and benefits that may arise from the alarms. The phase-type formulation makes it possible to set up a decision support system or automatic heat regulation system based on the methods described in Lovejoy (1991); Aberdeen (2003). This system takes the sequential nature of the decision making into account and includes the expected outcome of future observations. This system allows a systematic approach to precision of prediction, false versus true alarms, and multiple alarms, in contrast to different heuristic strategies used in the present paper.

Similar system could be made with respect to warning to improve the efficiency of surveillance of farrowings, as seems to be the intention of the development of algorithms in Cornou and Lundbye-Christensen (2012).

The computational complexity of the algorithm is mainly related to the number of phases (approximately 1000), where the transition matrix will be of size 1000×1000. This should not give any problems on modern computers. Another issue could be to use a finer time interval for the observations than the half an hour interval. However, this may lead to a model with autocorrelation of the sensor observations, and if this is included it would increase the the model complexity significantly. In Cornou and Lundbye-Christensen (2012), in either approaches, with 2 min interval or 1 hour interval, observations were compared without large differences. However, in both cases there is an assumption of independence.

The algorithm may be revised to use some other information such as farmer's routine visit to the herd which in turn may be a better evidence about the farrowing. The success of the algorithm to adopt warning strategies makes the phase-type approach promising in other applications exploiting sensor information in precision livestock agriculture. In fact O'Connell et al. (2011) has applied a similar semi-Markov process to the problem of oestrus detection in dairy cows. Prediction of possible disease outbreaks and outbreak of behavioral problems such as tail-bite are other obvious candidates.

The low complexity of the prediction algorithm helps the farmer to use this on the herd level computer. The compact state representation makes it likely that the optimal warning strategy can be found by treating the problem as a sequential decision problem, where factors such as benefit from treatment, cost of false-positive and false-negatives as well as the value of future observations are taken into account.

2.7 Acknowledgements

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CHAPTER 3

ESTIMATION ALGORITHM

Abstract

Many biological processes have the characteristic that we can conceptualize them as consisting of sojourns in discrete states or phases that the individuals pass through and will end in an absorbing state. Very often it is interesting to predict the time of absorption such as, in our case, we are interested in predicting the time to farrowing. Even though we cannot observe the underlying states directly, we can monitor the history because we can observe the variables (sensor measurements) that will change with changing underlying states. Those techniques include Hidden Semi-Markov Models, in which semi-Markov part is modelled by a Phase-type distribution (HPMM). We used a model for the farrowing process based on HPMM with three latent states, and a number of phases within each state to match the sojourn time of the state. Existing estimation methods were adapted for estimating the HPMM parameters based on data from 50 farrowings. There was a clear evidence of diurnal rhythm in the sensor data which changed with the states. The algorithm has successfully estimated a total of 117 (SD=1.2) days of gestation length and sojourn times of the states which are in agreement with the biological knowledge. The algorithm can use multiple sensors for the estimation purpose. The estimated parameters have been validated using them in the HPMM based prediction model which is not discussed in this article.

keywords: EM algorithm, Hidden Phase Type Markov Model, Hidden Semi Markov Model, prediction of onset of farrowing, Stochastic estimation algorithm

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An EM Algorithm to Estimate Parameters of a Hidden Phase-type Markov Model

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3.1 Introduction

Mortality of piglets soon after the birth (farrowing) is a major problem in the pig production. Improved precision in the prediction of onset of farrowing is necessary in order to reduce the piglet mortality either by management surveillance or by improved climate regulation. However, prediction is feasible only if the system can be automated. This may be achieved by monitoring pre-parturient behaviour of sows. Advanced sensor technology has increased the range of information to monitor the animals physiology and behaviour. The biological studies imply that these changes will have an impact on the main behaviour patterns of the sow activities such as food intake, drinking or sleeping pattern, movements, body temperature. Several studies have confirmed the significant changes in the pattern of the sensor observations as the sow approached farrowing, e.g. Erez and Hartsock (1990); Bressers et al. (1994); Oliviero et al. (2008).

Recently several studies have focused on statistical methods for handling data from online measurements mainly to distinguish between behavioural patterns in the measurements. Different techniques have been used to extract these patterns, primarily different versions of the Kalman filter or Dynamic Linear Models (West and Harrison, 1997). Cornou et al. (2011) have monitored the sow behaviour during the reproductive cycle based on the classification method developed in Cornou and Lundbye-Christensen (2008) for 3D accelerometers. The method uses Multi-process Kalman filter to classify the sow activities such as feeding, walking, rooting, lying laterally and lying eternally during the reproductive cycle based on which the sows were monitored. The classification and monitoring was later used by Cornou and Lundbye-Christensen (2012) for detecting the onset of farrowing. Cornou and Lundbye-Christensen (2012) have developed two methods: 1) logistic dynamic generalized linear models for diurnal variation, and 2) modelling of activity using a cumulative sum based on daily variation. The prediction of onset of farrowing is based on detecting the

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change in activity pattern and studies show that the change occurs mainly due to the nest building behaviour of sows. These class of models use CUSUM method or V-mask to detect these changes.

On the other hand, many biological processes have the characteristic that we can conceptualize them as consisting of sojourns in discrete states or phases that the individuals pass through, as stated by Lange and Minin (2013). Such processes comprise disease processes and gestation processes. A characteristic of these processes is that they end in an absorbing state, such as death or birth. The absorption of an individual can be directly observed. Our main interest is to estimate individual's history, that is, when it passes through the intermediate states in the procession, either in order to reach a better understanding of the process, or to improve the estimate of when the individual will transit to the absorbing state. For example, in prediction problem, we are interested to estimate the remaining time to onset of farrowing. Even though we cannot observe the underlying states directly, we can monitor the history because we can observe the variables that will change with changing underlying state. According to Lange and Minin (2013), discretly observed continuous-time Markov models are successful in describing these processes. The techniques include Hidden Markov Models (HMM) and Hidden Semi-Markov-models (HSMM). See Aalen (1995); Faddy et al. (2009); Mandel (2010); Titman and Sharples (2010); Yu (2010); O'Connell et al. (2011) for further examples of using such a class of models.

However, this class of models have rarely been applied in precision livestock farming, and not within sow production. Recently, Aparna et al. (2013) have proposed Hidden Phase-type Markov Model (HPMM) to predict the onset of farrowing incorporating the knowledge about the sequence and duration of the behavioural changes of the sow before farrowing. The HPMM is a HSMM where the distribution of the sojourn time in the hidden states (the semi-Markov part) are approximated by a Phase-type (PH) distribution (see Neuts (1975)). The algorithm extracts the pre-parturition behavioural patterns of a sow from the sensor measurements, conditioned on the hidden states or phases of the sow. The algorithm used the sensor information from water consumption, activities based on video frames (video-activity) and photo-cell (grid) activity in the HMM set up to predict the distribution of underlying states and uses PH-distribution to model the event *time to farrowing*. The prediction model in Aparna et al. (2013) relies on a set of herd-level parameters that could be estimated for individual farms that uses the prediction system. In particular, when a new herd starts, it will probably rely on parameters estimated from the data of another similar farm, but later these parameters are estimated using historical data from the herd itself. The method that could handle the estimation of the parameters from observed sensor data was needed. Although estimation methods for HMM and

PH-distribution parameters (Asmussen et al., 1996; Johnson and Taaffe, 1989) are well established, the HPMM parameters need some modification in these methods. Examples of such modifications include Titman and Sharples (2010); Lange and Minin (2013). Furthermore, the farrowing process has some specific characteristics and are discussed in the present paper. For example, the main part of the process can be modelled as a discrete-time multi-state model because of the fixed interval between the observations; but the time from last observation to the absorption (farrowing) need to be treated as a continuous variable. The sensor observations should be modelled so as to distinguish between the diurnal rhythm and state effect of the sow.

Thus the aim of the study was to adapt the existing estimation algorithms to make parameter estimation feasible, and to apply this estimation algorithm on the collected data from the sensors.

3.2 Materials and Methods

In this section, we briefly describe the experimental data and the HPMM model used in the prediction of onset of farrowing. However, for the details of the prediction algorithm we recommend to read Aparna et al. (2013). At the end of this section, we discuss the need for PH-distribution, model assumptions and parameters.

3.2.1 Experimental data

The parameters were estimated for the data set collected from the same experiment as described in Aparna et al. (2013). The data for an individual sow consists of sow information such as mating time, farrowing time, and sensor data recorded from the day of insertion to the farrowing. 64 sows were introduced to the pen approximately seven days before expected farrowing. Each farrowing pen had a number of sensors installed as shown in figure 3.1. In addition, video-recordings of each pen were made from the time when the sow was introduced until after farrowing. Visual analysis of these recordings include identifying the start of farrowing (time of birth of first piglet) as well as a time point when the sow was nest-building.

The sensor data include water consumption data ($Y^{(w)}$), video based activity measurements (*meanActivity*, $Y^{(Am)}$ and *sdActivity*, $Y^{(Asd)}$) and grid based activity measurement (*grid-activity*, $Y^{(g)}$). The data from the sensors were recorded with different intervals, ranging from seconds to minutes. Such a data needs to consider autocorrelation while modelling. Therefore, in order to reduce the model complications, the observations were pooled over half an hour intervals. Therefor a maximum of 48 observations were observed per day per sow. Furthermore, the log transformation of the measures were used in the calculations.

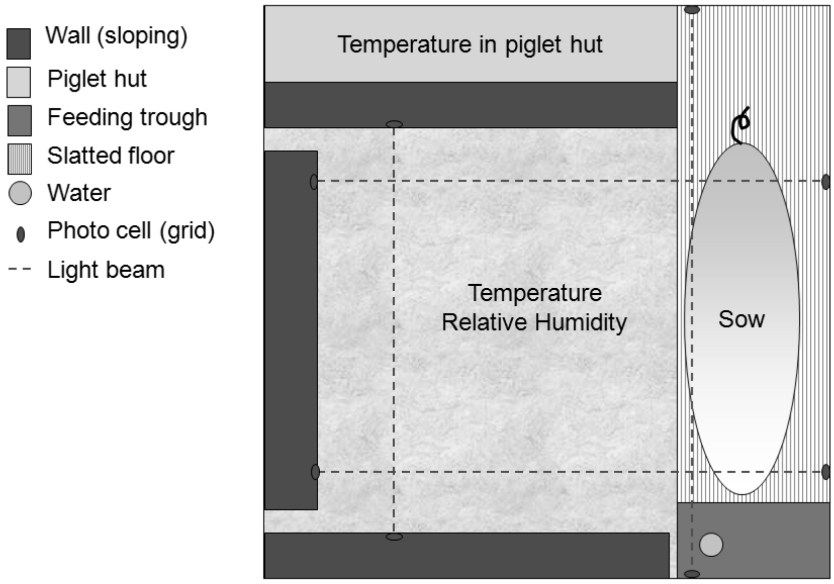


Figure 3.1: Sensor set up in the pen level.

For the detailed description of the sensor measurements we redirect to Aparna et al. (2013). The pattern of these observations were used in the specification of statistical models described later on. *meanActivity* and *sdActivity* are available together and were from video recordings; therefore, these measurements together are also referred as *video-activity* in the current article.

The sows inserted before day-105 were excluded from the study. Some sows without nest-building time, as identified by visual inspection, were also excluded. Because of failure of sensors, the number of sows with recorded data was different for different sensors as shown in Table 3.1. The water consumption data was collected from 45 sows, video-activity data from 64 sows and grid data from 45 sows. Out of these, 39, 48 and 44 sows were filtered with water, video-activity and grid-activity respectively. Only 37 sows had both water and activity data from day-105 after mating to farrowing. Altogether, 37 sows with both Water and video-activity, 11 sows with only video-activity and 2 sows with only water data (total 50 sow data) were used to estimate the parameters of the prediction model (HPMM). These estimates were then used with grid data for 44 sows to estimate the conditional distribution of grid-activity.

Since, these data are used to estimate the parameters of the HPMM, they are also called training data.

Time variables As discussed in Aparna et al. (2013), we also include a continuous time variable $\mathbf{TOD}$ to denote the time of the day between 0 and 24 hours in addition to the time since the mating or time to farrowing. $\mathbf{TOD}$

Table 3.1: Counts of the sows in the experiment and used in the estimation algorithm according to their availability of sensor information

Combination of Sensors	No. of Sows in expt.	No. of sows in algm.
Water	45	39
Activity	64	48
Grid	45	44
Water and Activity	-	37
Table	64	50 (water and video-activity) 44 (grid-activity)

takes the values ζ such that $\zeta \in [0, 24)$. These values are used for generating the harmonic covariates while modelling the conditional distribution of sensor measurements.

3.2.2 Hidden Phase-type Markov Model and Prediction of Onset of farrowing

Farrowing process starts from the day sow was mated until farrowing. The prediction process starts when the sow was introduced into the farrowing pen and continues until the farrowing was observed. The HPMM assumes that the preparturition behaviour of the sow may be defined in terms of behavioural states, *Before Nest-Building, Nest Building* and *Resting*. After the end of *Resting* state *Farrowing* state begins. *Farrowing* state is defined as the birth of the first piglet (See figure 3.2). Moreover, the state of the sow is hidden or unobservable directly. Hence, the farrowing process may be conveniently modelled by setting up HMM in which the latent states were modelled by means of observable facts from the sensors, except that the Markov models require that the sojourn time distribution is exponential. The variability in the durations of these states are not well documented except for the total duration of gestation length with a mean of approximately 115 (SD=2) days, which is clearly not exponential. Prior studies reveal that the sojourn times of the states are approximately Gamma distributed. Hence HMM can not be implemented directly to the farrowing prediction problem. Therefore, the states were split into a number of phases (as illustrated in figure 3.3) whose sojourn time follows exponential distribution so that the total sojourn time of each state will follow a Gamma (in particular, an Erlang) distribution which can be easily approximated to PH-distribution; so that the total gestation length is the sum of three PH-distributions. Furthermore, the model assumes that the sow passes through the phases successively and hence the states. The phases corresponding to the pre-parturition states are transients and the only phase in the *Farrowing* state is an absorbing phase. The PH approximation of

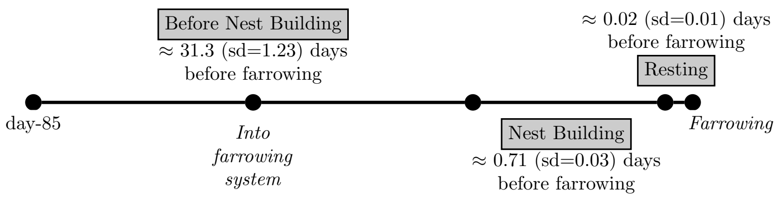


Figure 3.2: Pre-parturition Behavioural states of the sow (Not to scale).

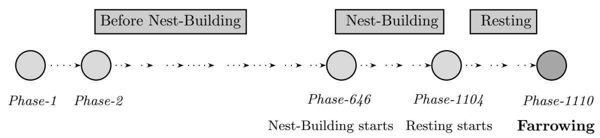


Figure 3.3: An illustration of Markov process with the states divided into phases. The phases, *Phase-1, Phase-646* and *Phase-1104* are the first phase of the states *Before Nest-Building, Nest-Building* and *Resting*. *Phase-1110* is the absorption phase or the first phase of *Farrowing*.

the gestation length leads to model the event *time to farrowing* and hence, the transitions of the sows between the phases were defined by the PH-distribution. This is possible because PH itself is a Markov process. The HMM was built over the phases so that it helps to revise the knowledge about the distribution of phases over the gestational period using the observable sensor measures and was then used to predict the remaining time to farrowing.

Readers are recommended to see Rabiner (1989) for the mechanism of HMM and Aparna et al. (2013) for some basic concepts of Markov process and HMM in context to the farrowing and prediction process. The notations of Aparna et al. (2013) follow the same description in the current paper unless or otherwise specified.

Choice of PH-distribution We have chosen to use PH-distributions for modelling the sojourn time in each state, instead of e.g. using the Gamma Distributions directly as suggested by O'Connell et al. (2011). It is mainly because,

- in the prediction algorithm we need to be able to calculate the distribution of time to farrowing (or failure, in general) after each sensor update (Asmussen et al., 1996). Thus, we need a compact representation of the state-space conditioned on the history. We may be able to include time since start of the process into each state in state-space; but it is expected to be at least as complicated and we need to discretize the time.

- The prediction algorithm is expected to become a part of a Markov Decision Process leading to same argumentation as above.

- The phase formulation of the process, makes sense also with a biological viewpoint. That is, it is possible that the sows are required to pass through several phases of nest building activities before farrowing is reached. The PH formulation allows us to model the conditional model for the sensor to include a phase dependent change in the distribution. In fact, such a development is more plausible than a strict dependency on calendar time.

Phase-Type Distribution Consider an $(\mathbf{M}+1)$-phase and continuous-parameter Markov process with $\{1, 2, \ldots, \mathbf{M}\}$, $\mathbf{M} \geq 1$, transient phases and an absorption phase $(\mathbf{M}+1)$, with rate matrix,

$$\mathbf{Q} = \begin{pmatrix} \mathbf{S} & \mathbf{S^0} \\ \mathbf{0} & 0 \end{pmatrix}$$

where $\mathbf{S}_{\mathbf{M}\times\mathbf{M}}$, correspond to the transient phases; $\mathbf{S^0}_{\mathbf{M}\times 1}$, correspond to the exit rates from transient phases.

Let $(\boldsymbol{\alpha}, \alpha_{\mathbf{M}+1})$ be the row-vector of initial phase probabilities with $\boldsymbol{\alpha}$ corresponding to the transient phases and $\alpha_{\mathbf{M}+1}$ corresponding to the absorption phase.

Then, a probability distribution $\mathbb{F}(.)$ of the time till absorption in the Markov chain $\mathbf{Q}$, on $(0, \infty)$ is,

$$\mathbf{Pr}(T \leq \delta) = \mathbb{F}(\delta) = 1 - \boldsymbol{\alpha} \mathbf{e}^{\mathbf{S}\delta} \mathbf{1_M} \qquad \delta \in \mathcal{R}^+ \tag{1}$$

a *phase-type distribution* (PH-distribution) (Neuts, 1978) and is represented by a pair $(\boldsymbol{\alpha}, \mathbf{S})$; where $\mathbf{1_M}$ is the unit column-vector of size $\mathbf{M}$ and $\mathbf{e}$ is the matrix exponential. The matrix exponential is as defined in (Bernstein, 2009).

Since, the distribution of total gestation period is the mixture of Erlang(m_1, λ_1), Erlang(m_2, λ_2) and Erlang(m_3, λ_3) corresponding to the states $\mathcal{S}_1, \mathcal{S}_2$ and $\mathcal{S}_3$, there are $\mathbf{M} = \sum_{i=1}^{3} m_i$ transient phases and $(\mathbf{M}+1)^{th}$ is the absorbing phase, denoted by u_F, and is in the *Farrowing* state. Therefore, $\alpha_{\mathbf{M}+1} = (\alpha)_F = 1 - \boldsymbol{\alpha}\,\mathbf{1}$. The $\mathbf{S}$ is given by,

$$\mathbf{S} = \left[\begin{array}{cc|ccc|cc} -\lambda_1 & \lambda_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -\lambda_1 & \lambda_1 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & -\lambda_2 & \lambda_2 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\lambda_2 & \lambda_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\lambda_2 & \lambda_2 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & -\lambda_3 & \lambda_3 \\ 0 & 0 & 0 & 0 & 0 & 0 & -\lambda_3 \end{array}\right] \tag{2}$$

for $m_1 = 2$, $m_1 = 3$ and $m_1 = 2$; each sub-matrix on the diagonal, separated by lines, represents phase transition within the state (in other words, state specific $\mathbf{S}$ matrix) and

$$\mathbf{S^0} = \left[\begin{array}{cc|ccc|cc} 0 & 0 & 0 & 0 & 0 & 0 & \lambda_3 \end{array}\right]' \tag{3}$$

is a column vector.

The transition probability matrix for the time interval δ is given by, (Asmussen et al., 1996),

$$\mathbf{P}_\delta = \mathbf{e}^{\mathbf{S}\delta} \tag{4}$$

The transition probability from phase u at time t to phase v in the time interval δ is the $(uv)^{th}$ element of $\mathbf{P}_\delta$,

$$\mathbf{Pr}(U_{t+\delta} = v | U_t = u) = (\mathbf{P}_\delta)_{uv} = \mathbf{p}_{\delta uv} \, .$$

Furthermore, $\mathbf{p}_{\delta \cdot v}$ denotes the v^{th} column vector of $\mathbf{P}_\delta$ corresponding to the phase v.

Model Specific Assumptions In the following we summarize the assumptions of the model.

1. In principle, the farrowing process starts on the day the sow was mated successfully and thus she becomes pregnant. Therefore, the sow is in the first phase on the day of mating. However, due to the complexity issue, the model for the first part of the gestation period is slightly modified. Initial evaluation studies showed that the distribution of sojourn time from mating to farrowing (gestation length) could be described adequately with a constant part of 85 days and a Gamma distributed final part. This approximation lead to markedly lower the number of phases. Therefore, the model was reformulated such that all sows entered *Phase-1* at day-85 after mating.

2. Each behavioural state consists of at least one phase. Furthermore, the sow passes through each phase in succession and hence the states in succession.

3. Since the HMM was built over the phases, it is more likely that the sensor observations will change with changing phase number within state. Since the number of phases is large, it is not convenient to estimate the conditional distribution of the sensor observations for each phase. Therefore, we assume that the conditional distribution of the sensor observations on the phases are identical for all the phases within the state.

$$\mathbf{Pr}(Y_t \,|\, u \in \mathbf{U}_i) \equiv \mathbf{Pr}(Y_t \,|\, \mathcal{S}_i). \tag{5}$$

However, it is still feasible to model the distributions as a continuous function of phase number.

4. Different sensor measures ($Y_t^{(w)}$, $Y_t^{(Am)}$, $Y_t^{(Asd)}$ and $Y_t^{(g)}$) observed at the same time point are independent given the phases.

5. Although the PH-distribution and the farrowing process are on continuous time scale, we are only interested in knowing the distribution of phase of the sow at the time of prediction and the prediction was made at discrete time steps. Therefore, the HPMM was set up on discrete time scale. Only the calculation of probability distribution over phases at the time of insertion into the farrowing pen and the time from final observation to farrowing require use of continuous formulation. On the other hand, prediction may be made at any time point, not necessarily at the fixed interval. However, fixing the time interval will reduce the calculation time and the complexity of the model.

6. In the PH-distribution, the transition rates may be allowed to vary between successive phases. However, the definition of phases within the states and Gamma distributed sojourn time of three states will result in only three different transition rates and hence a reduction in the model complexity.

Parameters of HPMM The parameters of HPMM are herd specific and are from both HMM and PH-distribution. They are,

1. the number of phases in each pre-parturition state, $\mathbf{m} = [m_1, m_2, m_3]$ and hence, the total number of phases in the farrowing process $\mathbf{M} = \sum_{i=1}^{3} m_i$. The scale parameter of an Erlang distribution gives the number of phases in each state.

2. the transition rates of the phases in each state , $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \lambda_3]$. The shape parameter of an Erlang distribution gives the transition rate of the phases in each state.
   Using the parameters $\mathbf{m}$ and $\boldsymbol{\lambda}$, the $\mathbf{S}$ matrix was constructed as in (2) and the transition probability matrix by (4). Since the intermediate transition time is fixed, $\mathbf{P}_\delta$ was calculated once in the beginning of the iteration.

3. the parameters of the probability distributions of the sensor observations $f(Y_t|\mathcal{S}_i)$, conditioned on the states and time of day (TOD).

For the convenience of further references, the above parameters were classified and denoted as `PH-PARMS`= $\{\mathbf{m}, \boldsymbol{\lambda}, \mathbf{S}\}$ which describes the PH-distribution (parameters 1 and 2) and `COND-PARMS` corresponding to the conditional distributions of all the sensor measures (parameters 3).

3.3 Estimation Algorithm

The parameters of the HPMM were estimated by an EM algorithm inspired by the Baum-Welch algorithm (Welch, 2003) which is a well established method for estimating HMM parameters. However, since the M-step was not tractable, we impute a stochastic part after E-step by randomly allocating the phase of the sow at the given time, resulting in a Stochastic EM (SEM) algorithm (Celeux et al., 1996). This iterative procedure, at each iteration, uses the training data to calculate forward and backward probabilities of phases and then estimates the parameters.

Algorithm 1 Estimation Algorithm

Initialize PH-PARMS$^{(1)}$ and COND-PARMS$^{(1)}$
Set iteration number: $\mathbf{k} \leftarrow 1$
repeat
  use PH-PARMS$^{(\mathbf{k})}$ and COND-PARMS$^{(\mathbf{k})}$
  for Every sow: $r = \{1 \to R\}$ **do**
    Find $\boldsymbol{\alpha}_{t_I}$ using (6)
    for Every time step: $t = \{t_I \to (t_N - \delta)\}$ **do**
      Forward propagation: $\boldsymbol{\alpha}_{t+\delta}$ using (7)
    end for
    Include farrowing time: find probability of absorption as in (8)
    for Every time step: $t = \{t_N \to t_I\}$ **do**
      Backward propagation: $\tilde{\boldsymbol{\alpha}}_t^{(0)}$ using (9)
      for Every sensor: $n_s = \{1 \to N_s\}$ **do**
        Find $\tilde{\boldsymbol{\alpha}}_t^{(n_s)}$ using (10)
      end for
      Randomly select the phase U_t
    end for
    for Every State: $i = \{1 \to 3\}$ **do**
      Find state duration ω_i^r
    end for
  end for
  Find mean and variance of sojourn time for all the states , using (11) and (12)
  Find PH-PARMS$^{(\mathbf{k+1})}$ from sow sojourn times as in sec. 3.3.5
  for Every sensor **do**
    Find COND-PARMS$^{(\mathbf{k+1})}$ as in sec. 3.4
  end for
  Set $\mathbf{k} \leftarrow (\mathbf{k+1})$
until Convergence of EM

The algorithm starts by initializing the parameter values (sec. 3.3.1). Each main iteration of the algorithm comprises 6 major steps (see Algorithm 1): For each sow,

Forward Propagation: calculating the phase probabilities at the time steps from day-85 until the time of last sensor recording (sec. 3.3.2). The phase progression only takes time since mating into account.

Evidence from Farrowing: entering the evidence of farrowing time (sec. 3.3.3).

Backward Propagation: calculating the phase probabilities by knowing the future phases for the sow, which were then revised by the sensor information available at that time. The calculations were performed from the time of last sensor recording to the day-85 (sec. 3.3.4, 3.3.4),

Phase Allocation: sampling the phase of the sow at each time steps.
Finally,

Estimation of Parameters: summarizing the phase allocation of all the sows and then estimating `PH-PARMS` and `COND-PARMS` (sec. 3.3.5 and 3.4).

Convergence: testing for the convergence and termination of the algorithm (sec. 3.3.6).

The phase probabilities calculated during the forward (backward) propagation will be called forward (backward) probabilities in the rest of the paper.

First three steps of the algorithm for one sow data and the approach to handle the iterations and convergence of the algorithm are presented in the current section. The conditional models for sensor measurements and the parameter estimation are presented in sec. 3.4.

A note about notation To keep the formulation simple, the sow indicator are excluded in the notation of different variables and values except in sec.3.3.5.

3.3.1 Initialization of the Parameters

The estimation algorithm starts by initializing the parameters `PH-PARMS`$^{(1)}$ and COND-PARMS$^{(1)}$. The time of nest-building confirmed by the video analysis (see sec. 3.2.1) was used as the beginning of the *Nest-Building* state. Since, *Resting* duration was unobservable, all the sows were assumed to be in the *Resting* state for an hour before farrowing. Based on this state allocation, `PH-PARMS`$^{(1)}$ and `COND-PARMS`$^{(1)}$ were calculated. The first run of the EM algorithm was performed for the conditional distribution of *meanActivity, sdActivity* and water consumption data with simple linear models. The structure of the conditional models were later refined based on the initial EM-run. We briefly discuss the model selection strategy in sec. 3.4.

Thus, for the current EM algorithm initial values of `PH-PARMS` were those estimated from the initial EM-run. According to this, the mean time that a sow spends in the states *Before Nest-Building, Nest-Building* and *Resting* are 31.2 (SD =1.2) days, 0.6 (SD = 0.2) days and 0.1 (SD = 0.05) days before farrowing, respectively. The number of phases in each state and the state transition rates were calculated by the method of moment matching with the Erlang distribution parameters. There were $\mathbf{m} = [676, 8, 4]$ phases in *Before Nest-Building, Nest-Building* and *Resting*, respectively, with rates $\boldsymbol{\lambda} = [0.90, 0.63, 1.67]$. These values specified the initial $\mathbf{S}$ matrix and the transition probability matrix $\mathbf{P}$, as described in sec. 3.2.2. This state classification was used to get the initial values of the conditional distribution parameters of the sensor observations.

3.3.2 Forward Propagation

Initializing for a sow By assuming that all the sows are in *Phase-1* on the day-85 from mating, the row-vector of phase probabilities, $\boldsymbol{\alpha}_0$ of size $\mathbf{M}$, on day-85 was defined as the vector with the first element 1 and the rest 0s. If δ_I is the time interval between the day-85 after mating and the time of insertion into the farrowing system, the row-vector of phase probabilities at the time of insertion was calculated as,

$$\boldsymbol{\alpha}_{t_I} = \boldsymbol{\alpha}_0 \mathbf{P}_{\delta_I} \tag{6}$$

where t_I is the time the sow was introduced into the farrowing system and $\mathbf{P}_{\delta_I}$ is as defined in (4). The time of insertion differs among the sows and hence, $\mathbf{P}_{\delta_I}$ is sow-specific.

Half-hourly updating for a sow The first sensor observation was measured at time t_I and then on at every fixed interval δ. In the current paper, $\delta = 0.5$ hours. Therefore, from this point onwards, forward probabilities were calculated on every interval δ until the last sensor observation was recorded at time $t_N = t_I + N\delta$, before farrowing. Here, N is a positive integer. If t is the current time then the vector of phase probabilities at time $t + \delta$ is

$$\boldsymbol{\alpha}_{t+\delta} = \boldsymbol{\alpha}_t \mathbf{P}_\delta, \quad t = t_I, t_I + \delta, \ldots, t_N - \delta. \tag{7}$$

where $\mathbf{P}_\delta$ is the transition probability matrix obtained using (4).

3.3.3 Evidence from Farrowing

In the training data, the time of farrowing is known for an individual sow. If t_F is the time of farrowing, define $\Delta = t_F - t_N$ as the time interval between the time of last sensor observation and the time of farrowing. The time of farrowing, thus, serves as an evidence to make the transition to phase u_F in time Δ. Therefore, the probability that the farrowing process is absorbed at phase u_F from the transient phases in time Δ is,

$$\mathbf{p}_{\cdot F} = \mathbf{P}_{\Delta}\mathbf{S}^0 \tag{8}$$

where $\mathbf{S}^0$ is as defined in (3) and $\mathbf{p}_{\cdot F}$ is the column vector of length $\mathbf{M}$. Again $\mathbf{P}_{\Delta}$ is sow specific.

3.3.4 Backward Propagation and Phase Allocation

Beginning of the Backward Propagation Since we know that the farrowing has happened at time $t_N + \Delta$, the vector of backward probabilities at time $t = t_N$ was calculated with the prior $\boldsymbol{\alpha}_t$ (calculated in (7)) and the likelihood $\mathbf{p}_{\cdot u} = \mathbf{p}_{\cdot F}$ as follows,

$$\tilde{\boldsymbol{\alpha}}_t^{(0)} = \frac{\boldsymbol{\alpha}_t \cdot \mathbf{p}_{\cdot u}^{\top}}{\boldsymbol{\alpha}_t \mathbf{p}_{\cdot u}} \tag{9}$$

where $A^{\top}$ denotes the transpose of A and $A \cdot B$ is the element-wise multiplication of A and B.

These probabilities were revised using all the sensor information available at that time, one by one. Let there be N_s number of sensors available at time $t = t_N$ (note that we omit the time indicator in the notation N_s). Let $Y_t^{(n_s)}$ be the observation measured by ${n_s}^{th}$ sensor. Then, the phase probabilities given n_s number of sensors is,

$$\tilde{\boldsymbol{\alpha}}_t^{(n_s)} = \frac{\tilde{\boldsymbol{\alpha}}_t^{(n_s-1)} \cdot \mathbf{Pr}(Y_t^{(n_s)} \mid U)}{\mathbf{Pr}(Y_t^{(n_s)})}, \quad n_s = 1, 2, \ldots, N_s \tag{10}$$

where $\mathbf{Pr}(Y_t^{(n_s)} | U)$ is the row vector of probabilities $(Y_t^{(n_s)} | \textit{Phase-1}), (Y_t^{(n_s)} | \textit{Phase-2}), \ldots$ $(Y_t^{(n_s)} \mid \textit{Phase-}\mathbf{M})$ and $\mathbf{Pr}(Y_t^{(n_s)}) = \tilde{\boldsymbol{\alpha}}_t^{(n_s-1)} \mathbf{Pr}(Y_t^{(n_s)} \mid U)^{\top}$. Since we assume that the sensor measures are conditionally independent, the sequence of sensors in the revision is irrelevant and any missing sensor measure does not influence the revision of probabilities.

In the current paper, the phase probabilities were updated for the sensor measures $Y_t^{(n_s)} \in \{Y_t^{(w)}, Y_t^{(Am)}, Y_t^{(Asd)}, Y_t^{(g)}\}$ and are discussed in detail at the end of this section. Therefore, $\tilde{\boldsymbol{\alpha}}_t^{(n_s)} \in \{\tilde{\boldsymbol{\alpha}}_t^{(w)}, \tilde{\boldsymbol{\alpha}}_t^{(Am)}, \tilde{\boldsymbol{\alpha}}_t^{(Asd)}, \tilde{\boldsymbol{\alpha}}_t^{(g)}\}$ for $n_s = 1, \ldots, N_s$.

The vector of final backward probabilities calculated for time t is, $\tilde{\boldsymbol{\alpha}}_t = \tilde{\boldsymbol{\alpha}}_t^{(N_s)}$ if N_s sensor measures are available; otherwise, $\tilde{\boldsymbol{\alpha}}_t = \tilde{\boldsymbol{\alpha}}_t^{(0)}$.

Note that the definition of forward and backward probabilities are different from that of Baum-Welch algorithm, mainly because evidence from the sensors were added in the backward step.

Phase allocation at t_N Phase allocation constitutes the S-step of the SEM algorithm. Final backward probabilities of the phases were used as the weights to randomly sample the phase of the sow at time t_N. If u is the phase number obtained from sampling, then we have $U_{t_N} = u$.

Half-hourly calculations for one sow Now the algorithm knows the phase of the sow at time t_F and t_N. This information was used to calculate the backward probabilities at time $t = (t_N - \delta)$. To generalize, by knowing the phase at time $t_F, t_N, \ldots, (t + \delta)$, the backward probabilities at time t were calculated in two steps: first, as the posterior probabilities $\tilde{\boldsymbol{\alpha}}_t^{(0)}$, with prior $\boldsymbol{\alpha}_t$ and the phase $U_{t+\delta} = u$ of the sow using (9). Here, $\mathbf{p}_{\cdot u}$ is the u^{th} column elements of $\mathbf{P}_\delta$ corresponding to $U_{t+\delta} = u$. Since we consider fixed time interval δ of transitions, we ignore the time index in $\mathbf{p}_{\cdot u}$.

In the second step, if an observation $Y_t^{(n_s)}$ was observed at time t as n_s^{th} sensor measurement then the backward probabilities were updated using the conditional distribution of sensor observations as the likelihood in (10), for all $n_s = 1, \ldots, N_s$.

Phase allocation at t Once, the final backward phase probabilities at time t were calculated at time t, the phase U_t of the sow was obtained by random sampling with weights $\tilde{\boldsymbol{\alpha}}_t$.

Half-hourly revision of backward phase probabilities and the allocation of phases were continued alternatively for time $t = t_N - \delta, \ldots, t_I + \delta, t_I$ for every sow.

Since there were very few information about the *Resting* state, we have restricted the phase at t_N to be in *Resting* state.

Updating Backward Probabilities by Sensor Observations In this section, we describe using individual sensor measures (*meanActivity* ($Y^{(Am)}$), *sdActivity* ($Y^{(Asd)}$), *grid-activity* ($Y^{(g)}$) and water consumption ($Y^{(w)}$)) to revise the backward probabilities. The assumption 4 of sec. 3.2.2 makes it is easier to calculate the conditional distribution of individual sensor measures.

We assume that the conditional distribution of *meanActivity, sdActivity* and *grid-activity* measures, observed at time t, are distributed as follows,

$$(Y_t^{(Am)} \mid u \in \mathbf{U}_i) \sim \mathcal{N}(\mu_i^{(Am)}, \sigma_i^{2(Am)})_\zeta$$
$$(Y_t^{(Asd)} \mid u \in \mathbf{U}_i) \sim \mathcal{N}(\mu_i^{(Asd)}, \sigma_i^{2(Asd)})_\zeta$$
$$(Y_t^{(g)} \mid u \in \mathbf{U}_i) \sim \mathcal{N}(\mu_i^{(g)}, \sigma_i^{2(g)})_\zeta$$

where $(\mu_i^{(Y)}, \sigma_i^{2(Y)})_\zeta$ correspond to the values $\mu_{i\zeta}^{(Y)}$'s and $\sigma_{i\zeta}^{2\ (Y)}$. This is possible due to the assumption 3. We assume $\sigma_{i\zeta}^{2\ (Y)} = \sigma^{2(Y)},$ for $i = 1, 2, 3$ for *meanActivity, sdActivity* and *grid-activity*.

These density functions were used in the expression (10) as the likelihood of $(Y_t^{(n_s)} \mid U)$ and $\tilde{\boldsymbol{\alpha}}_t^{(Am)}$, $\tilde{\boldsymbol{\alpha}}_t^{(Asd)}$ and $\tilde{\boldsymbol{\alpha}}_t^{(g)}$ were calculated.

Since we increase the level of complexity while modelling the water observations, the calculation of likelihood is not straight forward. The water observation of a sow, at time t, was assumed to be from a mixture distribution for the given state; mixing takes place over $K^{(i)}$ different components, within i^{th} state. Furthermore, the mixing proportions are associated with the time of measurement. Let $\pi_{ik\zeta}$ be the probability of observing the water consumption in k^{th} component $\mathcal{C}_k^{(i)}$ of state $\mathcal{S}_i$, $\quad i = 1, 2, 3$ and $k = 1, \ldots, K^{(i)}$, at time ζ, where $K^{(i)}$ is the number of components in state $\mathcal{S}_i$.

If a water observation was measured at time t, the density of observing $Y_t^{(w)}$ as the k^{th} component of the i^{th} state is,

$$(Y_t^{(w)} \mid \mathcal{C}_k^{(i)}, \mathcal{S}_i) \sim \mathcal{N}(\mu_i^{(w)^{(k)}}, \sigma_i^{2(w)^{(k)}})_\zeta.$$

Furthermore, we assume that $(Y_t^{(w)} \mid \mathcal{C}_k^{(4)}, \mathcal{S}_4) = (Y_t^{(w)} \mid \mathcal{C}_k^{(3)}, \mathcal{S}_3)$.

Therefore, the likelihood of $Y_t^{(w)}$ given $\mathcal{S}_i$ at time t is

$$\mathbf{Pr}(Y_t^{(w)} \mid \mathcal{S}_i) = \mathbf{Pr}(Y_t^{(w)} \mid \mathcal{C}_k^{(i)}, \mathcal{S}_i) \quad \pi_{ik\zeta} \qquad i = 1, 2, 3, 4$$

Hence, by Bayes' theorem, the posterior of each state given the observation is

$$\mathbf{Pr}(\mathcal{S}_i \mid Y_t^{(w)}) = \frac{\mathbf{Pr}(Y_t^{(w)} \mid \mathcal{S}_i)\mathbf{Pr}(\mathcal{S}_i)_t}{\sum_{j=1}^{4} \mathbf{Pr}(Y_t^{(w)} \mid \mathcal{S}_j)\mathbf{Pr}(\mathcal{S}_j)_t}; \qquad i = 1, 2, 3$$

where $\mathbf{Pr}(\mathcal{S}_i)_t = (\tilde{\boldsymbol{\alpha}}_t^{(n_s-1)})_{\mathbf{U}_i}\mathbf{1}_{m_i}$ is the sum of $\tilde{\boldsymbol{\alpha}}$ elements corresponding to state $\mathcal{S}_i$, $i = 1, 2, 3$ and $\mathbf{Pr}(\mathcal{S}_4)_t = 1 - (\tilde{\boldsymbol{\alpha}}_t^{(n_s-1)})\mathbf{1_M}$. Hence, the backward probabilities in (10) were calculated as

$$(\tilde{\boldsymbol{\alpha}}_t^{(w)})_{\mathbf{U}_i} = \mathbf{Pr}(\mathcal{S}_i \mid Y_t^{(w)}) \frac{(\tilde{\boldsymbol{\alpha}}_t^{(n_s-1)})_{\mathbf{U}_i}}{\mathbf{Pr}(\mathcal{S}_i)}; \qquad i = 1, 2, 3.$$

3.3.5 Estimation of Parameters

The parameters $\texttt{PH-PARMS}^{(\mathbf{k+1})}$ and $\texttt{COND-PARMS}^{(\mathbf{k+1})}$ were estimated at the end of the $\mathbf{k}^{th}$ iteration; after allocating the phases and states for each sow at every time points.

First of all, the state sojourn times were calculated as follows. Let ω_i^r be the duration of stay in i^{th} pre-parturition state for the r^{th} sow as calculated in $\mathbf{k}^{th}$ iteration. The assumption 2 of sec. 3.2.2 makes the calculation easier by noting down the time that the sow enters into different states. Since the sow was monitored on discrete time steps of fixed interval δ, the sow may pass through more than one phase in this interval. In such a case, there is a possibility that the sow was shifted from the last phase of one state to the first phase of the successive state. Therefore, the exact time of state shift is unknown. In such a case, the shifting time was estimated by interpolation based on the mean duration in each state.

If there are R sows, the mean sojourn time of the i^{th} state is

$$\boldsymbol{\omega}_i^{(\mathbf{k+1})} = \frac{\sum_{r=1}^{R} \omega_i^r}{R}, \quad i = 1, 2, 3 \text{ with variance} \tag{11}$$

$$\varsigma_i^{(\mathbf{k+1})} = \frac{\sum_{r=1}^{R} \left(\omega_i^r - \boldsymbol{\omega}_i^{(\mathbf{k+1})}\right)^2}{R-1}, \quad i = 1, 2, 3. \tag{12}$$

The mean sojourn times were used to define the convergence of the algorithm (see sec. 3.3.6) as well as for estimating the $\texttt{PH-PARMS}^{(\mathbf{k+1})}$ (sec. 3.3.5). Furthermore, state allocation was also used to estimate $\texttt{COND-PARMS}^{(\mathbf{k+1})}$ by grouping the observation by the allocated state number. Details of modelling and estimation methods are in sec. 3.4.

Number of Phases and Transition Rates (PH-PARMS) The Erlang sojourn time distribution of the states means, the mean and variance calculated in (11) and (12) are the mean and variance of corresponding Erlang distribution. Therefore, the transition rates $\boldsymbol{\lambda}$ and the number of phases $\mathbf{m}$ were calculated by the method of moment matching (Johnson and Taaffe, 1989) as follows,

$$\lambda_i^{(\mathbf{k+1})} = \frac{\varsigma_i^{(\mathbf{k+1})}}{\boldsymbol{\omega}_i^{(\mathbf{k+1})}}, \quad i = 1, 2, 3 \tag{13}$$

$$m_i^{(\mathbf{k+1})} = \text{round}[\frac{\boldsymbol{\omega}_i^{(\mathbf{k+1})}}{\lambda_i^{(\mathbf{k+1})}}], \quad i = 1, 2, 3 \tag{14}$$

where $\text{round}[A]$ is the closest integer value of A. The $\lambda_i^{(\mathbf{k+1})}$s were then corrected for $m_i^{(\mathbf{k+1})}$. However, if the calculated $m_i^{(\mathbf{k+1})}$ is 0, it was set to 1 and hence, the matching was restricted to the first moment (i.e. mean sojourn time). The total number of transient phases in the system is

$$\mathrm{M}^{(\mathbf{k+1})} = \sum_{i=1}^{3} m_i^{(\mathbf{k+1})}.$$

Hence, the PH-distribution was represented with the $\mathbf{S}$ matrix and the transition probability matrix $\mathbf{P}_\delta$ of dimension $\mathrm{M}^{(\mathbf{k+1})} \times \mathrm{M}^{(\mathbf{k+1})}$ as in (2) and (4), respectively.

3.3.6 Iterations and Convergence

The first iteration of the algorithm uses the initial parameter values (sec. 3.3.1). At the end of the $\mathbf{k}^{th}$ iteration, the parameters `PH-PARMS`$^{(\mathbf{k+1})}$ and `COND-PARMS`$^{(\mathbf{k+1})}$ were estimated. The convergence of the algorithm is defined as,

$$\sqrt{\sum_i \left(\boldsymbol{\omega}_i^{(\mathbf{k})} - \boldsymbol{\omega}_i^{(\mathbf{k+1})}\right)^2} \leq 0.3 \text{ for at least 20 successive iterations.} \qquad (15)$$

Typically, convergence is defined when the left-hand-side (LHS) of (15) is approximately 0. However, because of the stochastic nature of the algorithm, LHS varies in an interval. The upper limit of this variation was decided to be 0.3 because more than 80% of the LHS values, calculated for many iterations, were less than 0.3.

If the algorithm does not converge at $\mathbf{k}^{th}$ iteration, $(\mathbf{k}+\mathbf{1})^{th}$ iteration uses `PH-PARMS`$^{(\mathbf{k+1})}$ and `COND-PARMS`$^{(\mathbf{k+1})}$ for the allocation of phases including the calculation of forward and backward probabilities for all the sows.

3.4 Modelling and Estimating the Conditional Distribution of the Sensor Observations (COND-PARMS)

The modelling and estimation methods for individual sensor measurements are described in this section. We restrict the article to discuss statistical models to capture diurnal variation and state effects rather than discussing the model parameters and their estimates. We present the parameters based on the final EM-run with the final models for each sensor measures. The assumption 3 of sec. 3.2.2 made it easier to explore the models in state level instead of phase level and hence reduced the number of parameters. Moreover, the assumption 4 allowed us to use separate models for each measures.

Strategy for model selection The initial data exploration, showed a characteristic diurnal pattern that seemed to change as farrowing was approached. In the first EM-run, the diurnal rhythm was matched by 8 discrete levels of time periods, each of 3 hours duration, and *meanActivity* and *sdActivity* were modelled with the interaction of discrete time periods and state of the sow. But the final model strategy was based on the continuous variable of time $\mathbf{TOD}$ (see sec. 3.2.1). The time variable was used in the harmonic functions and different folding of these functions were tested to capture the pattern. For the model selection, the final state classification of first EM-run, for all the sows was used. Based on this, four folded harmonic function was selected for *meanActivity* and *sdActivity* observations. In the first run, water observations were assumed to be from a mixture model of two components, {drinking, no-drinking}; the probability of water consumption (or drinking) was calculated by classifying the data into binary levels {drinking, no-drinking} (drinking was defined as the number of rotations to be more than 9). However, the data showed off more than two components in the consumption behaviour. Furthermore, the probability of consumption was dependent on the time of measurement. The final model for water consumption was also tested for different folding of harmonic functions and also, with and without state interactions. Finally, separate models for *Before Nest-Building* and *Nest-Building* were selected each with a four folded harmonic functions as the covariates. The final model selections were based on the BIC criteria. The structure of these models were fixed through out the second (i.e. current) EM-run. However, for the water mixture model, the number of components in each state was selected at each iteration, separately. Based on the final classifications and estimates of the second EM-run, a model similar to *meanActivity* was selected with four folded harmonic functions as covariates for *grid-activity* observations.

3.4.1 Distribution of meanActivity and sdActivity

Let $Y_t^{(Am)}$ and $Y_t^{(Asd)}$ denote the meanActivity and sdActivity respectively, measured at time t. A linear regression models were used to extract the preparturition behaviour of sow for these data. In order to see the effect of states on sow's daily routine, interaction of states with the harmonic functions were also included as a covariate. The models are summarized and presented as,

$$Y_{it}^{(Am)} = \phi_i^{(Am)} + \sum_{h=1}^{H} [\beta_{ih}^{(Am)} \cos(h2\pi\omega) + \eta_{ih}^{(Am)} \sin(h2\pi\omega)] + \epsilon_{it}^{(Am)} \quad (16)$$

$$Y_{it}^{(Asd)} = \phi_i^{(Asd)} + \sum_{h=1}^{H} [\beta_{ih}^{(Asd)} \cos(h2\pi\omega) + \eta_{ih}^{(Asd)} \sin(h2\pi\omega)] + \epsilon_{it}^{(Asd)} \quad (17)$$

where $\omega = \zeta/24$, $H = 4$ is the number of harmonic components and ϵ are the residual term. The mean effect of meanActivity ($\mu_{i\zeta}^{(Am)^{(\mathbf{k+1})}}$) and sdActivity ($\mu_{i\zeta}^{(Asd)^{(\mathbf{k+1})}}$) at time ζ in state $\mathcal{S}_i$ were estimated with residual variances $\sigma^{2(Am)^{(\mathbf{k+1})}}$ and $\sigma^{2(Asd)^{(\mathbf{k+1})}}$.

3.4.2 Distribution of Grid-Activity

Let $Y_t^{(g)}$ be the grid-activity measured at time t. Similar to the video-activity models, the pre-parturition behavioural pattern was modelled by a linear regression with four folded harmonic functions and interaction of states. The model is summarized as,

$$Y_{it}^{(g)} = \phi_i^{(g)} + \sum_{h=1}^{H} [\beta_{ih}^{(g)} \cos(h2\pi\omega) + \eta_{ih}^{(g)} \sin(h2\pi\omega)] + \epsilon_{it}^{(g)} \text{ with } H = 4. \quad (18)$$

The mean effect ($\mu_{i\zeta}^{(g)^{(\mathbf{k+1})}}$) for the sow at time ζ and state $\mathcal{S}_i$ was estimated with the residual variance, $\sigma^{2(g)^{(\mathbf{k+1})}}$.

3.4.3 Distribution of Water Consumption Data

Water consumption pattern could not be captured using the linear model similar to those used for the video-activity and the grid-activity data. It is mainly because rather frequently the observations were recorded zero or close to zero, and a preliminary analysis of the data showed that the observations could be modelled by a mixture distribution. Furthermore, the mixing proportions were associated with the time of measurement. Therefore, the water consumption pattern was modelled by defining different latent levels of water consumption, called components. The number of components in state $\mathcal{S}_i$ is denoted by $K^{(i)}$. For the simplicity, we assume that the consumption pattern of a state is independent of other states. Hence, the data from each state was modelled independently. Furthermore, within the state, the water consumption in each component was assumed to follow a distribution independent of the other component and modelled linearly with $\mathbf{TOD}$ as the regressor.

Therefore, the mean water consumption, $\mu_{ik\zeta}^{(w)^{(\mathbf{k+1})}}$, of component $k = 1, 2, \ldots, K^{(i)}$ in state $\mathcal{S}_i$; $\quad i = 1, 2$ at time of the day ζ is given by

$$\mu_{ik\zeta}^{(w)^{(\mathbf{k+1})}} = \phi_{ik}^{(w)} + \beta_{ik}^{(w)}\zeta. \quad (19)$$

The proportions $\pi_{ik\zeta}{}^{(\mathbf{k+1})}$ of the components were modelled using the concomitant model (Dayton and Macready, 1988) with the harmonic functions to capture the diurnal rhythm. Therefore,

$$\pi_{ik\zeta}{}^{(\mathbf{k+1})} = \frac{e^{\Lambda^c_{ik\zeta}}}{\sum_{k=1}^{K^{(i)}} e^{\Lambda^c_{ik\zeta}}} \tag{20}$$

where

$$\Lambda^c_{ik\zeta} = \phi^c_{ik} + \sum_{h=1}^{H} [\beta^c_{ikh} \cos(h2\pi\omega) + \eta^c_{ikh} \sin(h2\pi\omega)] \text{ with } H = 4 \tag{21}$$

such that

$$\sum_{k=1}^{K^{(i)}} \pi_{ik\zeta}{}^{(\mathbf{k+1})} = 1 \qquad \text{and} \qquad \pi_{ik\zeta}{}^{(\mathbf{k+1})} > 0 \qquad \forall k.$$

The superscript 'c' in the parameters of (20) and (21) is to denote the concomitant model. For each component in state $\mathcal{S}_i$, we assume the same residual variance, $\sigma_i^{2(w)}$.

The observations corresponding to the *Before Nest-Building* and *Nest-Building* states were modelled separately using the above mixture model technique.

At every iteration, each model was tested for different number of components. For either states, number of components corresponding to the minimum BIC was chosen for the classification.

Since there were very few observations in *Resting* state, the mean level of water consumption was estimated by taking simple mean and variance of all the observations in that state (i.e. $K^{(3)} = 1$).

3.5 Computational Plan and Environment

For the current study, the data was available from four different sensor measures, water consumption ($Y^{(w)}$), *meanActivity* ($Y^{(Am)}$), *sdActivity* ($Y^{(Asd)}$) and *grid-activity* ($Y^{(g)}$). However, early on in the experiment, it was clear that the photo-cells (grids) required a comprehensive daily maintenance routine with cleaning and repositioning in order to keep on functioning. Therefore, the grids are not a likely candidate for product development, and the main interest was to document that the farrowing system could function without these sensors. Therefore, the EM algorithm was run to use *meanActivity, sdActivity* and water observations; later, these parameters and phase classification were used to estimate the grid-activity distribution. For discussing the results, we call it as Scenario-1. However, to evaluate the EM-algorithm, another run (Scenario-2) has been made with the grid data included with initial values based on the final iteration of the Scenario-1. We also summarize these results.

The estimation algorithm was implemented in the statistical computational environment R (R Development Core Team, 2010). Various functions supporting the algorithm were written. These functions have been collected into a package compatible with R. Apart from these, the basic function `lm()` was used to fit the activity models and the function `stepFlexmix()` of `flexmix` 2.2-8 package (Leisch, 2004; Grün and Leisch, 2007, 2008) was used for modelling the water observations.

3.6 Results

First we will present the results from estimation with only observations from *meanActivity, sdActivity* and water consumption sensors. This corresponds to the Scenario-1 of sec. 3.5.

3.6.1 Sojourn Time Distribution, Number of Phases and Transition Rates

The mean and variance of sojourn times for the pre-parturition states are given in Table 3.2. On an average, a sow spends 17.02 hours (SD= 0.80 hours) in the *Nest Building* state; whereas the sojourn time for *Resting*, with the limited information, was estimated to be 0.53 hours (SD=0.22 hours) before farrowing. For these sojourn times, the moment matching calculations gave 645, 458 and 6 phases in the states *Before Nest-Building, Nest Building* and *Resting*, so that the sow passes through 1109 phases before the farrowing and 1110^{th} phase will be the beginning of *Farrowing*. The process exits at the rate 0.86 per hour from each phase within the *Before Nest-Building* state. The process enters into the first phase of *Nest Building* state from the last phase of *Before Nest-Building* with the rate 0.86 per hour and exits from each phase of *Nest Building* state with the rate of 26.91 per hour. It enters into *Resting* state with the rate 26.91 per hour and continues in the *Resting* state with the phase transition rate 11.4 per hour. Finally, it enters into the *Farrowing* state. The sum of the mean state durations gives the total duration of the gestation period minus the 85 days and the sum of the variances is the variance of the gestation period. This results in a mean gestation length of 117 days with a standard deviation of 1.2.

The phases allocated for each sow during the backward propagation are showed in figure 3.4 against the time since mating. The variance in total gestation length appears to come from the *Before Nest-Building* state.

Table 3.2: PH-PARMS estimated using *meanActivity, sdActivity* and water consumption sensors in the EM algorithm

State	Duration (hours)		Phases	Rate (per hour)
	Mean	SD		
Before Nest-Building	751.20	29.58	645	0.86
Nest-Building	17.02	0.80	458	26.91
Resting	0.53	0.22	6	11.40
Gestation period, days	117	1.2	1109	-

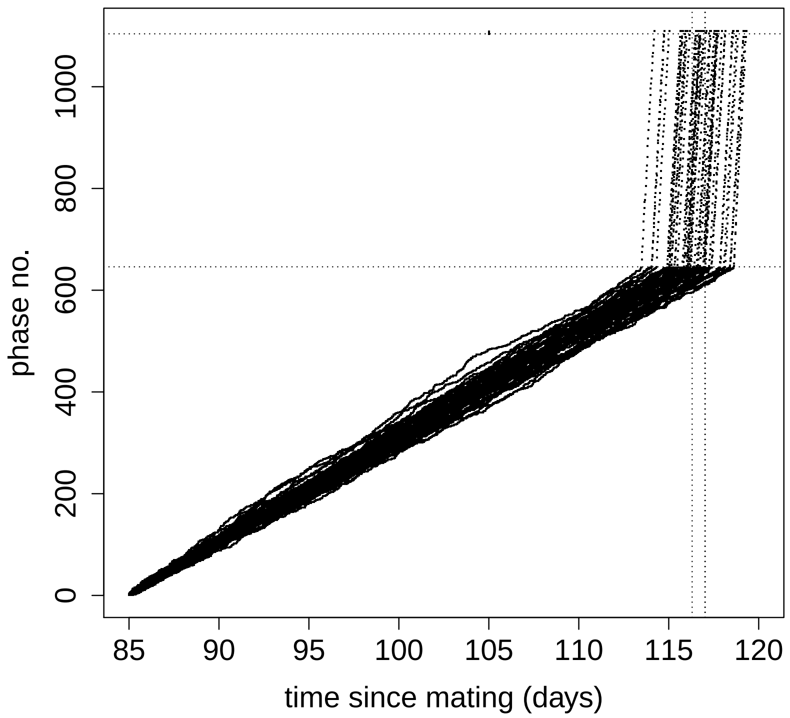
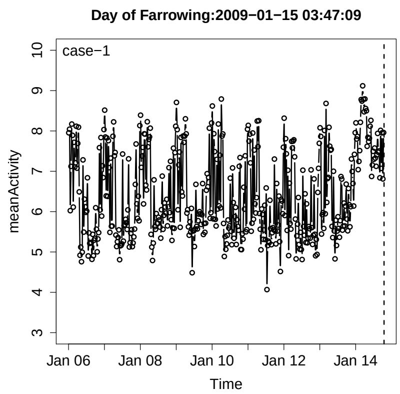


Figure 3.4: The phase allocation for the sows as in the final EM-iteration against the time since mating.

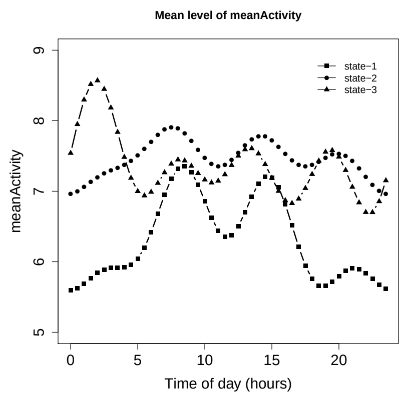
3.6.2 Conditional Distribution of the Sensor Information on Phase and Time

The estimates of parameters using the phase allocation in the final iteration of the EM-algorithm (iteration no. 586).

Video-Activity figure 3.5a and figure 3.6a illustrates the patterns of the (log-transformed) *meanActivity* and *sdActivity* for one sow. The corresponding conditional means ($\mu_{i\zeta}^{(Am)}$ and $\mu_{i\zeta}^{(Asd)}$) are shown in figure 3.5b and figure 3.6b.The figures show one diurnal cycle, that is the time of a day (ζ) varying from 0 to 24 hours. The lines for *state-1, state-2, state-3*, correspond to *Before Nest-Building*, *Nest-Building* and *Resting* states. The residual standard deviations of *meanActivity* and *sdActivity* were estimated to be 0.8 and 0.9, respectively. The line for *state-1* in figure 3.5b shows a marked rythm with sharp peaks in the morning and afternoon at times which coincide with the normal rhythm of sows and in this experimental herd, with the daily feeding and other management activities. In contrast to this, the mean levels of activity in the daytime were higher in the *Nest-Building* state and more constant with lower amplitudes. Similar patterns can be observed in figure 3.6b.



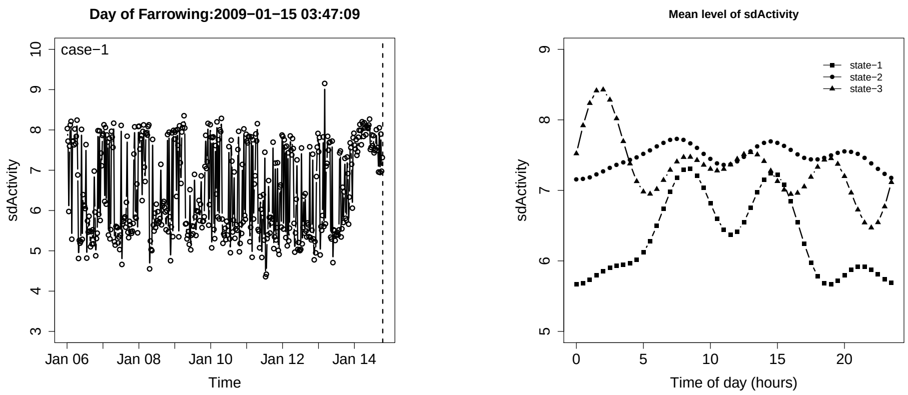
(a) data pattern



(b) mean level

Figure 3.5: Left panel: Illustration of *meanActivity* data pattern for a sow. The dotted vertical line in the right indicates the actual time of farrowing. Right panel: Mean level of *meanActivity* over a day in different states; state-1 (Before Nest-Building) and state-2 (Nest-Building) and state-3 (Resting).

Grid-Activity The mean level of grid-activity (with SD=1.64) over 24 hours of a day is as shown in figure 3.7b. The data pattern is illustrated for one sow in figure 3.7a. The lines for *state-1, state-2, state-3*, correspond to *Before Nest-Building*, *Nest-Building* and *Resting* states. The activities captured through grids

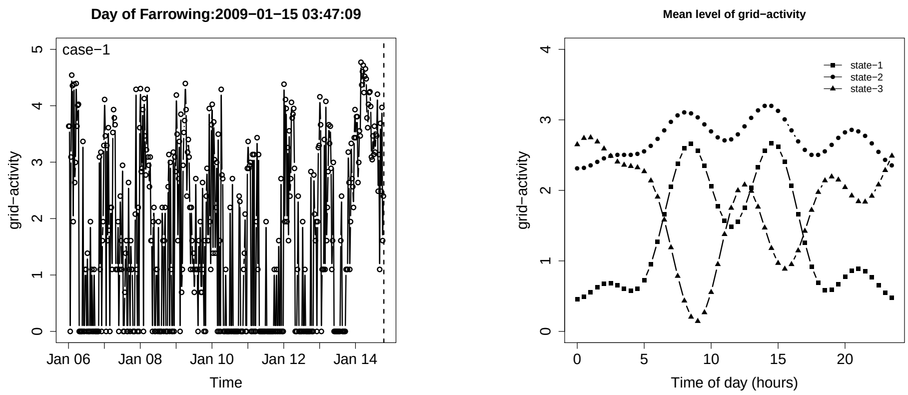


(a) data pattern (b) mean level

Figure 3.6: Left panel: Illustration of *sdActivity* data pattern for a sow. The dotted vertical line in the right indicates the actual time of farrowing. Right panel: Mean level of *sdActivity* over a day in different states; state-1 (Before Nest-Building) and state-2 (Nest-Building) and state-3 (Resting).

are low (*state-1* line) during the night indicating less movements of sow at the height of photo-cells; however, increased activity was observed twice a day, indicated by the clear peaks in the plot. The mean level (*state-2* line) has increased notably from that of *Before Nest-Building*, with low amplitudes at the peaks. The lower mean values were estimated during the day time for the *Resting* state (*state-3* line) and higher values in the night time. Note that data from this sensor was not included in the EM-algorithm, and the conditional distribution was therefore based on the phase allocation from the other sensors.

Water Consumption The models each with three components corresponding to lowest BIC for both *Before Nest-Building* and *Nest-Building* were selected at the last iteration. These components can be seen as different types of drinking behaviour that the sow may select. The mean level for three components of *Before Nest-Building* state was estimated to be [7.07, 2.09, 0] with the residual standard deviation [0.96, 1.14, 0.01]. That is, the Component-1 corresponded to most drinking and Component-3 to no drinking activity. The corresponding mixing probabilities varied throughout the day and are shown in figure 3.8b (The x-axis of the plot denotes the 0-24 hours of a day). Early morning and mid-night, the water consumption level was very low compared to that during the day time (higher probabilities of Component-3 indicate 0 mean consumption). Also, the model captures the feeding times by estimating large probability of drinking around hour 8 and 15 of the day (the peaks for Component-1). Apart from the lower and higher levels of water consumption, the sow has also intended to consume some water during the night/day time with very low probability as denoted



(a) data pattern

(b) mean level

Figure 3.7: Left panel: Illustration of *grid-Activity* data pattern for a sow. The dotted vertical line in the right indicates the actual time of farrowing. Right panel: Mean level of *grid-activity* over a day in different states; state-1 (Before Nest-Building) and state-2 (Nest-Building) and state-3 (Resting).

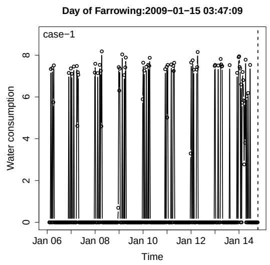
by the dots for Component-2. The estimates for mean level of water consumption over a day for *Nest-Building* state were [7.14, 3.61, 0.001] with residual standard deviation [0.74, 2.0, 0.02]. The plot of probabilities for the *Nest-Building* state (figure 3.8c) clearly confirms the assumption of notable changes in the water pattern, though the mean level of water consumption was very close to that of *Before Nest-Building*. The plot shows more water activity even at the night time (after hour 20 until 4) (Component-1). For the *Resting* state the mean water consumption level was estimated to be 0.49 (SD=1.61).

3.6.3 PH-PARMS estimated using all the sensor measurements available - Scenario-2

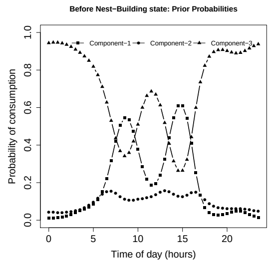
The EM-run for Scenario-2 has converged after 198 iterations. The sojourn times changed slightly; the mean *Nest-Building* duration has increased approximately by 1 hour to 18.2 hours, while the SD was reduced by 0.2 hours. The mean duration of the *Resting* state was increased to 0.7 (SD=0.37) hours. The lower SD of the *Nest-Building* state has almost doubled the number of phases. Furthermore, the conditional distributions of the sensor measurements showed only minor changes.

3.6.4 Computational Time

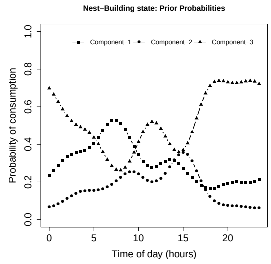
The estimation algorithm presented in this article was programmed to supplement an estimation methodology for the prediction model described in Aparna et al. (2013) and not focused on speeding up the run. The current version of the



(a) data pattern



(b) probabilities: Before Nest-Building



(c) probabilities: Nest-Building

Figure 3.8: Left panel: Illustration of water consumption data pattern for a sow. The dotted vertical line in the right indicates the actual time of farrowing. Middle and Right Panels: The mixture probabilities of water consumption pattern over a day for the components of *Before Nest-Building* and *Nest-Building* states. The consumption behaviour was classified into components: Components from 1 to 3 corresponding to most-drinking to no-drinking activities. Furthermore, $\mathbf{Pr}$*(Component-1)* + $\mathbf{Pr}$*(Component-2)* + $\mathbf{Pr}$*(Component-3)* = 1, at a given time.

Table 3.3: Time consumed by different parts of the EM algorithm in one iteration

Part of a iteration		Time
Forward propagation		2.5 mins
Backward propagation and Phase allocation	per sow	10 secs
	for 50 sows	8 mins
Estimation	water	15 mins
	meanActivity	< 1 sec
	sdActivity	< 1 sec
	grid-activity	< 1 sec
Total time per iteration		26 mins

programming takes about 3 mins for the forward and backward propagation with phase allocation. Because of the simple models, estimation parts for *meanActivity, sdActivity* and *grid-activity* takes less than a minute. However, estimation of water consumption data uses the function `stepFlexmix` separately for *Before Nest-Building* and *Nest-Building* states and takes about 15 mins. This is mainely because of another set of EM algorithm running within the function. Within the function, the models were tested for the components 3 and 4 for each state and each scenario was replicated 4 times. i.e. altogether 16 EM algorithms run while estimation of conditional distribution of water consumption in one iteration of the main algorithm. The time consumed by different parts of the algorithm in one iteration are given in Table 3.3. In total, the algorithm takes about 26 mins to complete one iteration.

3.7 Discussion

Our study indicates that HPMM may be successfully implemented in livestock production farming, with similar underlying biological processes as the farrowing process studied here. It gives a straight forward approach for the problem of combining and handling different sensor measurements in the monitoring system.

The estimates of the sojourn times or duration of each state matches quite good with the other studies, (for example, Castrén et al. (1993); Malmkvist et al. (2012)), though the duration of *Nest-Building* state, had a surprisingly low SD. The estimate of the duration of the total gestation period (117 days ± 1.2 days) is also in line with more recent studies. The low variability in the duration of *Nest-Building* state required many phases in order to match with the mean and variance of the distribution. The *Resting* state was harder to identify and of short duration. With two observations per hour, the 0.53 hours duration probably means that there were too few observations allocated to this state to give a precise estimate of the conditional distribution of sensor observations given the state. It may be considered to include sensor observations from the first hours after farrowing has started, where the patterns in the observations is similar to the resting state.

The models for sensor observations confirmed the hypothesis of significant changes in the behaviour of sows during the pre-parturition period. One of the characteristics of the sensor measurements was a marked diurnal variation at least at the days before nest-building start. The harmonic components in the models were well used to describe this diurnal rhythm. This has allowed a combination of two time scales in the prediction model: the time of the day and the time since mating, in addition to *time to farrowing*. The simple linear model for video-activity sensor and the photo-cell grids also indicated an overall increase in mean activity with changed state from *Before Nest-Building* to *Nest-Building*.

With respect to the water sensor, a more elaborate mixture model was needed, indicating different drinking behavioural patterns occurred with different probabilities throughout the day. First mixture component probably included dripping of the water nipple, e.g. if the tubes were pushed by the sow, or may be even when the water was released from the neighboring pens. The second component was probably due to play-full activities with the drinking nipple, and only the third component indicated dedicated drinking activity. The diurnal variation of the estimated mixture probabilities in this more complicated model was actually what distinguished the water consumption during the night in the *Nest-Building* state from the other states; thus it has given a good supplementation to the other sensors. Hence this model extension was necessary to give a clear identification of the *Nest-Building* state (especially at night) and thus a more precise prediction of the time of farrowing.

All the sensor observations showed a marked diurnal pattern during the *Before Nest-Building* state, consistent with the findings in Cornou and Lundbye-Christensen (2012). In our case two peaks were identified, while in Cornou and Lundbye-Christensen (2012) four peaks were identified on the days before nest-building. It is well known that these diurnal patterns are a combination of the management schedule on the farm and a basic pattern of sows. In contrast, in the *Nest-Building* state, the diurnal pattern has almost disappeared. Thus for most of the sensors, there were clear differences between the two states during the night, but very little difference during the peak activity periods. This must imply that the detection of the beginning of the *Nest-Building* state is easier if it takes place during the night.

We have assumed that different sensor measurements were independent given the state. However, the estimates for *meanActivity* and *sdActivity*, shown in the curves figure 3.5b and figure 3.6b, are almost identical, this assumption may be questioned. Furthermore, as there are many zero values in the *grid-activity* data, a mixture distribution similar to water observations may be suggested.

It would be easy to extend the modelling further, for example, 1) to use phase number as a covariate to capture changes in the behavioural pattern as the phase number progresses within the state, 2) to use the information of time of feeding to give a more precise diurnal modelling, or 3) to distinguish between the pattern of individual sows. Such extensions should be evaluated both for their improvement in prediction and the resulting increase in model complexity. The first two changes may have minor effects on the complexity of the modelling, while the last may significantly increase the complexity. Since the behavioural pattern may differ from sow to sow, the algorithm for the conditional distributions may be extended to do so as well; i.e. by including the sow effect as a random effect. However, this would imply a large increase in model complexity, as different types of sows should be included in the state space used for the prediction algorithm, in order to automatically learn the behavioural pattern of each sow. It would also require a larger data set in order to quantify how the sows differ, both within each of the states and across the states,as well as between gestation periods for the sow. One of the models specified in Cornou and Lundbye-Christensen (2012), attempts to estimate the diurnal pattern for the individual gestation periods, either with constant random terms for the sows/gestation period, or with the gestation periods deviance as autoregressive effects; but it is not clear, how the data supports this choice of models.

The estimation algorithm may be modified to utilize training data sets where the farmers observation that the sow has started farrowing replaces the exact start of farrowing based on video analysis. In such a set up, instead of using visual analysis of video recordings, the farmer can input whether the farrowing has started or not during his routine visits to the pen. Typically this will happen at least twice a day. In that case, the data about start of the farrowing will be interval censored and the algorithm should, therefore, be able to handle this as an input that the farrowing has taken place anywhere between the last two visits.

Use of the algorithm for behavioural studies We have applied the estimation algorithm to a data set with sensor observations that measures rather nonspecific effects of the sows behaviour changes. When ethologists try to define the beginning of nest-building and duration of nest-building activities, they rely on behavioural observations classified into much more detailed categories (Thodberg et al., 1999; Malmkvist et al., 2006, 2012). As an example, Malmkvist et al. (2012) defines nest-building behaviour as when the sow roots with the snout on the flour, carries straw, or paws with the front leg against the floor, and onset of nest building behaviour (used for turning floor-heating) as the first occurrence of at least 5 front-leg scratches within a 5 min interval or the first occurrence of carrying straw and/or branches, whichever was sooner. However, there seems to be no generally accepted way of defining the nest-building and most of the time it will be identified when the nest building activity becomes so high that the *Nest-Building* state has started. In the studies there will often be additional measurements such as temperature, feed intake and blood test for assessing the level of different hormones. Obviously, data from such studies containing the more detailed behaviour categories could also be treated with the present algorithm, allowing a better use of the data for understanding the behavioural process, with all measurements treated simultaneously, and a clear direct. It is expected that the algorithm presented here will give a more precise detection of potential treatment differences than the usual methods for analysing data, e.g., the diurnal variation in the measured variables are usually ignored.

Computational methods and recent developments The estimation algorithm presented here is time consuming as the EM technique needs many iterations to converge and each iteration takes about half an hour to complete. Within each iteration, the forward and backward propagations take about 40% of the total time, while the estimation of the conditional models is responsible for the rest; mainly the estimation of parameters in the mixture model for water consumption. However, some of the approaches have avoided large calculations, for example,

- The sow was assumed to be in *Phase-1* on day-85 after mating. This has reduced m_1 being larger than one we have now.
- Since the forward probabilities, for each sow, are based only on the time of transition from day-85 to farrowing, they were calculated only once in

the beginning of the iteration for the time steps $\{day - 105, day - 105 + \delta, \ldots, t_{\mathbf{N}}\}$ such that time of insertion and the time of last observation for the r^{th} sow is such that $day - 105 < t_I^r$ and $t_{\mathbf{N}} \geq t_N^r$, for all $r = 1, 2, \ldots, R\}$. This has saved about 2 hours of calculations.

- By fixing the time interval to δ, the large transition probability matrix (of about 1000×1000) was calculated only once in the beginning of the iteration.
- By sampling the phase of the sow at each time step before calculating the next backward probabilities.

However, it may be necessary to speed up the algorithm further if the system should be brought into practice. Recently some studies implementing the HSMM as a Phase-type model has appeared in the literature, e.g. Titman and Sharples (2010); Lange and Minin (2013), where especially Lange and Minin (2013) demonstrates how to speed up the calculations. However, the suggestions in Lange and Minin (2013) is not necessarily relevant in our case. In the application, they operate with relatively small (known) number of phases and the observations are univariate diagnostic test of the hidden phase at each time point. It is not obvious how their algorithm will scale to larger problems. As an example, the observations in their study occur with relatively long intervals, and the duration between observation varies between patients. In our application we have more than 500 observations per sow, and we use a total of about 1000 phases. In the estimation algorithm of Lange and Minin (2013) the expected number of transitions between phases in each time step is calculated, which will probability be too time-consuming in practice.

In general, the available packages for estimation purposes in a programming environment such as R seems to be focused on a specific application area, restricting e.g. the structure of the PH-distribution, the model for the conditional distributions (emission distributions), the possibilities for further calculations for prediction purposes, e.g. the distribution of time to absorbtion, or the expected utility until the absorbtion. Currently we are aware of at least five different R-packages used for handling HMM, HSMM and HPMM. If our algorithm should be used on larger scale in Danish sow production units, we will, therefore, suggest that these recent algorithmic developments may lead to improvements when evaluated on our specific case.

3.8 Acknowledgements

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CHAPTER 4

OPTIMAL FLOOR-HEAT REGULATION ALGORITHM

Abstract

Many piglets suffer from hypothermia just after birth and this increases mortality. Studies show that maintaining the farrowing pen-floor temperature at sufficiently high level at the time of farrowing may increase the survival of the piglets. However, heating the floor from room-temperature to the necessary temperature consume time. Therefore, the heating should be started well before farrowing to achieve the goal. In addition to the reward of extra surviving piglets, the heating requires energy costs. This floor-heat regulation process was modelled based on a Partially Observable Markov Decision Process (POMDP). The model includes two Markov processes: a partially observable farrowing process with belief states calculated using the sensor information in Hidden Phase-type Markov Model, and a completely observable floor-heating process. The POMDP solutions were approximated via greedy approaches, e.g. QMDP, based on the optimum solution for a completely observable MDP. Heating versus no-heating strategies as well as POMDP versus simple heuristic strategy (SHS) were compared for different scenarios of heating parameters in terms of the rewards for the 2500 simulated sow data. The greedy POMDP approaches behaved similarly. However, POMDP and SHS behaved similarly only if the SHS parameters matched the heat parameters; otherwise, the POMDP returned higher rewards. The current decision algorithm, along with HPMM, solved the problem of optimal heating and gives a framework for integrating the information from different sensors. It is expected that other problems such as optimization of management

surveillance can be handled within a similar framework.

keywords: Partially Observable Markov Decision Process, Hidden Phase type Markov Model, Piglet mortality, climate regulation, sensors, Precision livestock farming

Manuscript submitted to *Annals of Operations Research*

POMDP for Automatic Floor-Heat Regulation using Sensors Prior to Farrowing

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4.1 Introduction

In pig production, differences in piglet mortality is one of the main determinants of the net return from the farms. A major cause of mortality is that the neonatal piglets suffer from hypothermia within the first 2 days of their life (Berthon et al., 1994). As an example, Malmkvist et al. (2006) studied the effect of floor heating on the vitality of the piglets in a loose house farrowing system and concluded that floor heating had an effect on the early recovery of piglet body temperature and latency to first suckling and hence the survival of piglets. In the study it was estimated that approximately one more pig would survive in each litter if heat was turned on. The necessary increase in floor temperature was between 10-20°C; therefore, the heating needed to be turned on some time before the farrowing if the newborn piglets should benefit from the extra heat. Thus the regulation of the heating need to be based on some kind of prediction of the farrowing time. In this case a heating strategy may be based on existing information (mating date) or additional sensor information about the sow, allowing the floor temperature in each pen to be regulated individually. Without sensor information, only a relatively coarse heating strategy can be followed. The farrowing can only be predicted within ± 2 days, if it is only based on mating day and without additional observations. Thus the heating needs to be turned on for a relatively long period if a sufficient number of piglets in the litter should benefit from it. A preliminary cost benefit analysis showed that the use of climate regulation requires an improved precision of the prediction of farrowing to be cost-effective. The analysis indicated that such additional floor-heating could give a positive economic return. However, this required that the heating period should be short, which will only be feasible if the prediction of farrowing could be made precisely enough to synchronize the heating-up period with the birth of the piglets. Research had indicated that such a precise prediction might be possible using online measures of e.g. the sows behaviour before farrowing.

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Thus a project was started with the aim of making a prediction system based on cheap sensors, such as video activity measures, and water consumption measurements. As a result, Aparna et al. (2013b,a) have described the development, parameter estimation and validation of a farrowing prediction system based on a Hidden Phase-Type Markov Model (HPMM). HPMM is a Hidden Semi-Markov model where the time dependency of the transition rates within states were handled by a Phase-Type (PH) distribution. The model validation in Aparna et al. (2013b) was based on simple heuristic decision rules for regulating the floor heating system based on the algorithm; the rules like, *when the estimated time to farrowing is below 12 hours, turn on the floor heating*. The validation was based on definitions of true warnings and how much floor heating was applied with no use. However, the calculations indicated that there could be a need for a more comprehensive heating strategy, where the timing of the heating takes the expected time to farrowing, precision of the prediction and the resulting costs and benefits directly into account. An evaluation of such sequential decision strategies, is not possible within the simple heuristic framework. Furthermore, such a floor-heat regulating system is feasible only if it can be automated in the pen level by optimizing the production profit. This may be achieved by treating the problem as a *sequential decision problem* or a Markov Decision Process (MDP) in which the value of future observations are taken into account.

Because the model in Aparna et al. (2013b) was developed using the HPMM, it could be directly treated as a Hidden Markov model in the decision context. However, the farrowing prediction model needed extension to reflect the effect of the floor heating decisions on the actual floor temperature. While the floor temperature at the time of decision making will be known to the decision maker, the hidden phases/states are not observable except for the absorbing state at farrowing; thus the problem should be classified as a Partially Observable Markov Decision Process (POMDP). POMDP model is intensively used by the researchers in artificial intelligence, machine learning and computer engineering. The applications include, quality controlling in a production system (Ben-Zvi and Grosfeld-Nir, 2013; Grosfeld-Nir, 2007), robot navigation (Simmons and Koenig, 1995), aiding disabled people (Taha et al., 2007; Hoey et al., 2010). Littman (2009) has given a brief tutorial of POMDP for behavioural scientists. Within livestock precision farming the use of (completely observable) Markov Decision Processes (MDP's) is a well established practice and has been used for solving several decision problems, including Kristensen (1989, 1993b); Toft et al. (2005); Kristensen and Jørgensen (1997, 2000); Huirne et al. (1988); Kristensen (2003). While Partially Observable Markov Decision Processes (POMDP's) are notorious for the resulting complexity, some of the examples of use have especially been focused on how to reformulate POMDP's problem into MDP's that can be handled (Kristensen (1993a); Jørgensen (1992); Kristensen and Søllested

(2004); Nielsen et al. (2011); Jørgensen et al. (2012)). These techniques can, however, not be applied in this case. Instead we will use other, approximate solution method based on so called greedy approaches.

The aim of the present article is to demonstrate how the farrowing prediction and heating problem can be formalized as a POMDP and to implement variants of the QMDP strategies (Littman et al., 1995) to reach an approximate solution to the decision problem. It will focus on a more elaborative decision strategy which uses the production and managemental costs and the prediction results to a profitable heating strategies. Finally, we will evaluate the benefit of heating versus no-heating as well as the benefit of adopting the (PO)MDP heating strategy versus a simple heuristic strategy described in Aparna et al. (2013b).

4.2 The POMDP representation of floor-heat regulation on a pen level

The benefit of floor heating for piglet survival is at the maximum if the floor is sufficiently warm when the the piglets are born. Malmkvist et al. (2006) indicate that the floor should stay at this temperature during their first 12-24 hours. Therefore, the floor heating must be turned on well before the farrowing starts. If the floor-temperature of each pen can be regulated individually, the development of floor-temperature during the heating and no-heating periods can be illustrated by figure 4.1.

The heat regulation may be divided into three phases. The first Phase-(A) is the interval from the start of the heating until the floor is sufficiently warm. We call this temperature as *recovery temperature* and denote it by C_c. The second Phase-(B) is where the floor-temperature is maintained at C_c. Finally, in Phase-(C) the heat is turned off and the floor temperature slowly returns to the room temperature level. The ideal case is that the Phase-(A) should be finished before the birth of the first piglet, and Phase-(B) should continue to give the later born piglets sufficient time on the heated floor. However, in practice, due to the uncertainty attached to the prediction of farrowing, Phase-(B) may not yet be reached by the time of farrowing. The relation between floor temperature and mortality indicates that even if not all the piglets can get benefit of floor-heating due to delayed heat on, the total piglet mortality may still be reduced, if the floor heating continue after the farrowing. In such a case, Phase-(A) may either start after farrowing and/or may continue after the farrowing was observed, if doing so is profitable.

Therefore, it is challenging to turn on the heater at the right time, perhaps before farrowing so as to get maximum benefit from piglet survival after deducting the associated costs and expenses. In the figure, the heater is on throughout Phase-(A). But, because sensor information will continue to give evidence about

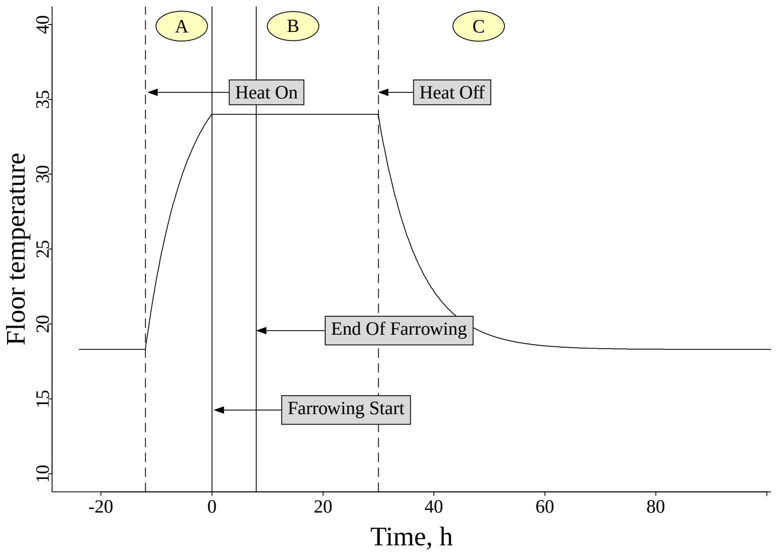


Figure 4.1: Illustration of heat regulation on a pen level. Values on the x-axis are the time with reference to the time of farrowing (hours)and on y-axis are the floor-temperature (°C). Phase-(A) starts from the heat on time until the floor was sufficiently warm; Phase-(B) is the period when the floor was maintained at sufficient temperature; Phase-(C) is the last phase when the heating was turned off and the temperature starts dropping down to the surrounding temperature.

the time of farrowing, it is natural to revise the decision every time new information arrives, i.e., the heating strategy is a sequence of decisions made during the pre-parturition period, in order to provide a friendly environment to the new born piglets. The decisions will lead to the actions either *Heat On* or *Heat Off*.

4.2.1 Floor-Heat Regulation as a POMDP

As mentioned earlier, the prediction of onset of farrowing was modelled by HPMM. The HPMM was originally formulated as a continuous time semi-Markov process with three transient states (*Before Nest-Building, Nest-Building* and *Resting*) and one absorbing state (*Farrowing*). The sojourn time of each state was modelled as Erlang distributions, that is the transient states were split into a number of phases with exponentially distributed sojourn times. These behavioural states and phases are unobservable. The information about the states/phases was obtained by a set of sensor observations, from water consumption, video-activity and grid-activity sensors, updated at half hourly interval ($\delta = 0.5$ hours). Based on this, the continuous time Markov model was converted into a discrete time Markov process; the time points corresponding to the time of observations and with homogeneous transition probabilities. From the floor-heat regulation point of view, the decisions were made at these time points after the belief of the phases were updated using the available observations. These time points are called *decision epochs*. The period for the decision process starts on the day sow was introduced into the farrowing system (i.e. t_I) and continues until the farrowing was observed at t_F. Furthermore, if the sow is pregnant, the probability of farrowing in a finite time period is asymptotically one. Therefore, the decision process is a finite horizon. The time space for the decision process is given by $\mathcal{T} = \{t_I, t_I + \delta, t_I + 2\delta, \ldots t_I + N\delta\}$ where N is such that $t_I + N\delta$ ($< t_F$) is the time of last sensor observation recorded before farrowing was observed. At each of these decision epochs, HPMM predicts the onset farrowing in terms of phase probabilities ($\boldsymbol{\alpha}_t$) which further serve as the belief state to the decision process. The decisions made at each decision epoch will lead to the actions either to turn on the heater or off, i.e., the action space is $\mathbf{D}$={*Heat On*, *Heat Off*} or simply {1,0}. Furthermore, the decision requires the knowledge on current floor-temperature, which are observable. Thus, the floor-heat regulation problem involves both partially observable (phases) and observable (floor-temperature) Markov processes. Therefore, the problem may be treated as a POMDP.

A *decision rule* at a decision epoch t is a mapping to specify the choice of decision when the sow occupies the phase U_t and the floor-temperature is C_t, i.e. $d_t : (\mathbf{U} \times \mathcal{C}) \rightarrow \mathbf{D}$ where $\mathbf{U}$ is the set of behavioural phases of a sow and $\mathcal{C}$ is the discrete set of floor-temperatures. Therefore, the heating strategy or policy is a set of decisions taken at each decision epoch of a sequential dynamic process. The policy is denoted as,

$$\pi = \{d_t = d(U_t, C_t), \quad d_t \in \mathbf{D} \text{ and } t \in \mathcal{T}\}.$$

That means, the floor-temperature at the next decision epoch depends on the current action either to *Heat On* or *Heat Off*. Therefore, the floor-temperature at the next decision epoch is governed by the transition probabilities depending on the current decision. In contrast to the heating process, the farrowing process is independent of the decisions, i.e. the current decision has no influence on the phase of the sow at the next epoch. Furthermore, the sensor measurements are also independent of the current decision and the action.

Each decision and action at the epochs are furthermore associated with certain reward in terms of heating cost, H_t. If the decision is to *Heat On*, H_t is the value to be paid for supplying the energy to keep the floor temperature more than the room temperature; if the decision is to *Heat Off*, $H_t = 0$. In addition to these negative rewards, the decision maker will achieve a revenue due to the piglets production, I_π, which can only be gained after the farrowing. Therefore, although *Farrowing* is the absorption state of the HPMM, the decision process will be absorbed at the first phase after farrowing, denoted by u_{F+1}. Therefore, the decision process consists $\mathbf{M}_{adj} = \sum_{i=1}^{3} m_i + 2$ phases and the corresponding set of phases is $\mathbf{U}^{\text{adj}} = \{\mathbf{U}, u_F, u_{F+1}\}$ where $\mathbf{U}$ is the set of all transient phases of HPMM as in Aparna et al. (2013b). The corresponding transition probability matrix is given by,

$$\mathbf{P}_{\delta}^{adj} = \begin{pmatrix} \mathbf{P}_{\delta} & \mathbf{P^0}_{\delta} & \mathbf{0} \\ \mathbf{0}^{\top} & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix} \tag{1}$$

where $\mathbf{P}_{\delta}$ is as defined in Aparna et al. (2013b) for HPMM, $\mathbf{P^0}_{\delta} = \mathbf{1} - \mathbf{P}_{\delta}\,\mathbf{1}$, $\mathbf{1}$ is the unit column-vector and $\mathbf{0}$ is the zero column-vector of size $\mathbf{M}$. For this extension, the vector of phase probabilities at time t was adjusted as $\boldsymbol{\alpha}_{t+\delta}^{\text{adj}} = (\boldsymbol{\alpha}_{t+\delta}, 0, 0)$, where $\boldsymbol{\alpha}_t$ is a row vector of phase probabilities corresponding to the transient phases of HPMM, so that $\boldsymbol{\alpha}_{t+\delta}^{\text{adj}}\,\mathbf{1} = 1$.

The net profit due to the policy π for a sow is the production profit after deducting the total heating cost i.e.

$$\Pi_{\pi} = I_{\pi} - \sum_{t \in \mathcal{T}} H_t.$$

We define the reward of heating strategy as the increased profit due to the strategy against 'no heating' in the pen. The MDP and POMDP for climate regulation are illustrated in figure 4.2 and figure 4.3. In case of MDP, the decision d_t at the decision epoch t is the function of the phase U_t and the floor-temperature C_t. However, in POMDP d_t is the function of $\boldsymbol{\alpha}_t$ and C_t.

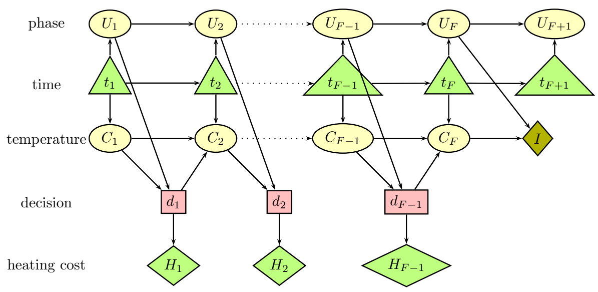


Figure 4.2: Analogue of MDP for floor-heat regulation: The decision process is featured by two Markov process: farrowing process and heating process. Farrowing process determines the behavioural phases of the sow from mating to farrowing. Heating process specifies the transition of floor-temperature. The decision rule d_t at time t is the function of the current phase, U_t and current floor-temperature, C_t. Furthermore, the floor temperature at the next decision epoch is only influenced by C_t and d_t. Each decision is penalized by a heating cost H_t. The pig production will result in a revenue, I, which can only be enjoyed after farrowing. Therefore, the net profit of a heating strategy is $I - \sum_{t \in \mathcal{T}} H_t$.

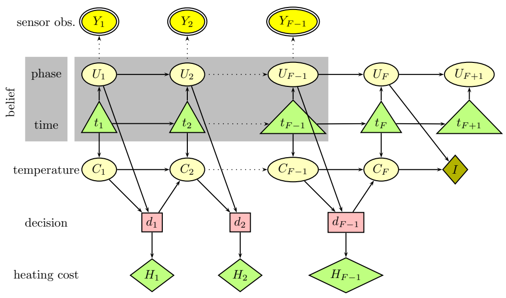


Figure 4.3: Analogue of POMDP for floor-heat regulation: The POMDP set up is similar to MDP except that the behavioural phases of the sow are not directly observable; indeed phases were modelled by HPMM using the sensor observations measured at each decision epoch and hence, the vector of belief state were predicted. Therefore, the decision is such that $d_t : (\mathcal{B} \times \mathcal{C}) \rightarrow \mathbf{D}$.

The problem is to find an optimal decision policy π^* that maximizes the expected production profit. Since we do not the exact distribution of the belief states, we use Q_{MDP} approach in which the problem was first optimized by assuming completely observable MDP and then using belief state to find the optimality of POMDP.

The Elements of Floor-heat Regulation System Following are the elements of POMDP, summarized from the above description.

The floor-heat regulation system involves two Markov process.

- Markov Process-A: The farrowing process in which the the process is over the behavioural states/phases of the sow which are not observable and are directly governed by HPMM. The vector of phase probabilities $\boldsymbol{\alpha}_t \in \mathcal{B}, \forall t \in \mathcal{T}$ where $\mathcal{B}$ is the set of all belief states, serves as the belief state for POMDP which are updated by the sensor observations available at time t (see Aparna et al. (2013b)). Furthermore, $\mathbf{Pr}(U_t \mid U_{t-\delta}, d_{t-\delta}) = \mathbf{Pr}(U_t \mid U_{t-\delta})$ and $\mathbf{Pr}(Y_t^{(n_s)} \mid U_t, d_{t-\delta}) = \mathbf{Pr}(Y_t^{(n_s)} \mid U_t)$ for any n_s^{th} sensor measure available at time t.
- Markov Process-B: The floor-heating process with states discretized into $\mathbf{N}$ temperature levels from room-temperature C_0 to *recovery temperature* C_c. Since, the floor-temperatures depend on the current action, the two transition probability matrices are $\mathbf{pC_1}$ with elements $\mathbf{Pr}(C_t \mid C_{t-\delta}, d_{t-\delta} = 1)$ and $\mathbf{pC_0}$ with elements $\mathbf{Pr}(C_t \mid C_{t-\delta}, d_{t-\delta} = 0)$.
- Decision epochs: although the successive decision epochs may be of unequal length, we fix the interval to δ and sensor observations were also

recorded at these epochs.

- Action space: is a binary set with $\mathbf{D}$ ={*Heat On, Heat Off*} $= \{1, 0\}$.
- Heating Costs: are the function of the action (as well as the floor-temperature) at a decision epoch.
- Revenue: is the income due to survived piglets and it depends on the floor-temperature at the time of farrowing.
- Decision Rule: is the mapping from $(\mathcal{B} \times \mathcal{C})$ to $\mathbf{D}$.

4.2.2 Markov Process-B: Floor-Heating Process

The final optimization model consists of the farrowing process model (Markov Process-A) and a model describing the floor-temperature as a result of the heating strategy (Markov Process-B). The Markov Process-A of behavioural phases of the sow are already established in Aparna et al. (2013b) and estimation of parameters are discussed in Aparna et al. (2013a). In this section we describe (Markov Process-B), that is, a discrete time and discrete state stochastic model of floor-temperature, fitted to the floor-heating system where the study was performed.

Deterministic Heat Equation

The floor of the pen was heated up using an electric heating grid, placed 2cm below the surface of the concrete floor of area 3m^2. When the heat is turned on certain amount of energy was supplied. The resulting marginal change in floor temperature consists of two parts. The first part is the heat transfer from/to the surroundings which is proportional to the difference in temperature, and the second is proportional to the energy input. Thus the differential equation of temperature is given by,

$$\frac{dC}{\delta} = -k_1(C - C_0) + k_G \tag{2}$$

where C is the temperature, C_0 is the surrounding temperature, $k_1 > 0$, is the time constant, and $k_G = \frac{Q}{C_v}$ where Q is the energy (Q/area is the heat flux) supplied. C_v is the heat capacity of the concrete floor (=0.9 kJ/kg/K) and is defined as the amount of heat required to change the floor temperature by a given amount. We refer to DOE Training Coordination Program (1992) for the terminologies of thermodynamics and heat transfer.

Therefore, the temperature at time t is

$$C(t) = C_0 + \frac{k_G}{k_1}(1 - e^{-k_1 t}) \; . \tag{3}$$

In practice the temperature development will not follow this deterministic curve, but will show a random fluctuation due to the variation in the energy supply, temporary covering of the floor (water, straw, sow) etc.

Stochastic Heat Equation

Estimation of parameters for the heating process: A pilot experiment was performed in the experimental farm in Research Center, Foulum, Denmark and the data set consist of the floor temperature of the pen, measured every 10 mins for about 11 hours with the heat turned on. At the start of the experiment the floor temperature was similar to the room-temperature. The heating and cooling process parameters were estimated using the non-linear regression model,

$$C_t = C_0 + \mathbf{A}(1 - e^{-k_1 t}) + \epsilon_t \tag{4}$$

with a noise $\epsilon_t \sim \mathcal{N}(0, \sigma^2_{\epsilon 10})$, $\mathbf{A} = k_G/k_1$ and $\sigma^2_{\epsilon 10}$ is the noise measured on 10 mins span. The function `nls()` of software R (R Development Core Team, 2011), with the initial values $C_0 = 18, \mathbf{A} = 10.4$ and $k_1 = 0.25/(60 * 60)$, was used to establish the heat relation. The estimates correspond to the heating process in Phase-(A) of figure 4.1 and are given in table 4.1. The residual SD for δ hours was calculated as $\sigma_\epsilon = \sigma_{\epsilon 10} \times \delta \times 60/10$. We assume $\sigma^2_C = \sigma^2_\epsilon$.

Table 4.1: Parameter values of heating process, estimated and calculated based on 4.

Parameters	Value
Surrounding temperature, C_0°C	18.34
Maximum temperature, C_c°C	35
Thermal conductivity of concrete with flux, k_1 mW/m^2/$^\circ$C	0.038
Time interval of observation, δ hours	0.5
Standard deviation of temperature per δ, σ_ϵ°C	0.24
Heat capacity, C_v kJ/kg/K	0.9
Input energy coefficient in Phase-(A), k_G mW/m^2/$^\circ$C	0.83
Input energy coefficient in Phase-(B), k_{G2} mW/m^2/$^\circ$C	0.64
Energy consumption in Phase-(A) per δ, Q$_A$ kW/m^2	2.25
Energy consumption in Phase-(B) per δ, Q$_B$ kW/m^2	1.73

In Phase-(B), the floor temperature was maintained at $C_c = 35^\circ$C, for example, by supplying a reduced, but constant energy, i.e. $\frac{dC}{\delta} = 0$. Therefore, the coefficient k_G takes the new value k_{G2} such that, from (2), $k_{G2} = k_1(C_c - C_0)$. An alternative regulation method would be to use a thermostat for the regulation with the same expected energy use.

Furthermore, during the cooling process (in Phase-(C)), no extra energy was supplied. Therefore, $k_G = 0$.

Discretization of time Since the heating strategy assumes a discrete set of decision epochs, it is necessary to calculate the change in the floor temperature in δ hour intervals. However, $\delta = 0.5$ hours is very large for approximation of the differential equations for the heating or cooling process. Therefore, the instant change in the floor-temperature was observed for a shorter interval τ hours. In order to make it simple, τ was chosen such that τ is a positive divisor of δ i.e. $r = \delta/\tau$ is a positive integer. The instant change in the floor temperature $dC_t^{(1)}$ due to heating up process (Phase-(A)), in an interval τ, is given by,

$$C_t = C_{t-\tau} + dC_t^{(1)} \tag{5}$$

such that the floor-temperature raises from C_0 to C_c in $(\mathbf{N}-1)$ time steps, each with an interval τ. We denote the series of these temperatures as $\{C_1, C_2, \ldots, C_{\mathbf{N}}\}$ where $C_1 = C_0$ and $C_{\mathbf{N}} \approx C_c$. Consequently, (5) can be re-written as,

$$C_n = C_{n-1} + dC_n^{(1)} \text{ where } n = 2, 3, \ldots, \mathbf{N}; \quad n \equiv t \text{ and } (n-1) \equiv (t-\tau). \tag{6}$$

The floor temperature further fluctuates on its mean level, θ_n with variance σ_C^2.

Discretization of floor-temperature For the fixed supply of energy, the floor-temperature in the pen takes the real values in the range $[C_0, C_c]$. For the simplicity of the model, we assume discrete state space of floor-heating process. The floor-temperatures were discretized by dividing the interval $[C_0, C_c]$ into $\mathbf{N}$ sub-intervals such that $F_1 = (-\infty, C_1]$, $F_2 = (C_1, C_2], \ldots, F_N = (C_{N-1}, C_N]$.

Furthermore, for heating up process, we have $C_n \sim \mathcal{N}(\theta_n^{(1)}, \sigma_C^2)$ where

$$\theta_n^{(1)} = \frac{C_{n-1} + C_n}{2} + dC_n^{(1)}.$$

Since the first sub-interval is only right-bounded, $\theta_1^{(1)}$ is undefined. We overcome this problem by correcting (approximating) the assumption of initial floor-temperature to be less than the room-temperature, denoted by C_{0^-}. Therefore, we define a new series of floor-temperature as $\{C_{0^-}, C_1, C_2, \ldots, C_{\mathbf{N}}\}$ where C_n for $n = 1, 2, 3, \ldots, \mathbf{N}$, were calculated from (6) in $\mathbf{N}$ steps as explained earlier. The sub intervals were re-defined as $F_1 = (C_{0^-}, C_1]$, $F_2 = (C_1, C_2] \ldots, F_{\mathbf{N}} = (C_{\mathbf{N}-1}, C_{\mathbf{N}}]$. The series of these interval is denoted by $\mathcal{F}$. Note that, in the new series $C_1 \neq C_0$.

For the cooling process (Phase-(C)), the drop in floor-temperature $dC_n^{(0)}$, from the temperature C_n, $n = 1, 2, \ldots, \mathbf{N}$ in the interval τ were calculated using (2) and (6) with $k_G = 0$. For cooling process, $C_n \sim \mathcal{N}(\theta_n^{(0)}, \sigma_C^2)$, where

$$\theta_n^{(0)} = \frac{C_{n-1} + C_n}{2} + dC_n^{(0)}$$

.

Transition Probabilities Due to the discretization of the floor temperatures, the transition in time τ was assumed to be from the interval F_m to F_n. Therefore, the $(m,n)^{th}$ element of the transition probability matrix $\mathbf{pC_1}^{(\tau)}$, for the heating process in time τ is

$$\begin{aligned}(\mathbf{pC_1}^{(\tau)})_{mn} &= \mathbf{Pr}(C_t \in F_n \mid C_{t-\tau} \in F_m, d_{t-\tau} = 1) \\ &= \Phi(C_n; \theta_m^{(1)}, \sigma_C^2) - \Phi(C_{n-1}; \theta_m^{(1)}, \sigma_C^2), \quad \forall m = 1, 2, \ldots, (\mathbf{N}-1)\end{aligned} \tag{7}$$

$n = 1, 2, \ldots, \mathbf{N}$

$$(\mathbf{pC_1}^{(\tau)})_{\mathbf{N}n} = \begin{cases} 1 & \text{if } n = \mathbf{N} \\ 0 & \text{if } n \neq \mathbf{N} \end{cases} \tag{8}$$

where $\Phi(C_{n-1}; \theta_m^{(1)}, \sigma_C^2) = 0$ for $n = 1$, C_t is the floor-temperature at time t and Φ is the Normal distribution function. Similarly, for the cooling process in time τ, the $(m,n)^{th}$ element of the transition probability matrix $\mathbf{pC_0}^{(\tau)}$ is

$$\begin{aligned}(\mathbf{pC_0}^{(\tau)})_{mn} &= P(C_t \in F_n \mid C_{t-\tau} \in F_m, d_{t-\tau} = 0) \\ &= \Phi(C_n; \theta_m^{(0)}, \sigma_C^2) - \Phi(C_{n-1}; \theta_m^{(0)}, \sigma_C^2), \quad \forall m, n = 1, 2, \ldots, \mathbf{N}\end{aligned} \tag{9}$$

with $\Phi(C_{n-1}; \theta_m^{(0)}, \sigma_C^2) = 0$ for $n = 1$. The respective transition probability matrices for the heat transition in δ hours were calculated by r-step matrix multiplication of $\mathbf{pC_0}^{(\tau)}$. That is,

$$\mathbf{pC_1} = \left(\mathbf{pC_1}^{(\tau)}\right)^r, \text{ and} \tag{10}$$

$$\mathbf{pC_0} = \left(\mathbf{pC_0}^{(\tau)}\right)^r. \tag{11}$$

Note that the n^{th} row (or column) of $\mathbf{pC_1}$ and $\mathbf{pC_0}$ correspond to the interval F_n.

Distribution of time to reach C_c from C_F As discussed before, in ideal conditions, the floor-temperature $C_F = C_c$. However, the uncertainty in the prediction model may delay the prediction of farrowing, and hence, $C_F < C_c$. We assume that, the farmer will manually turn on the heater as soon he observes the farrowing. Let T_B be the time required for the floor to reach C_c from C_F. Here, we describe how to calculate the distribution of T_B. Because of the discretization of time and floor-temperature, the distribution was established using the transition probability matrix $\mathbf{pC_1}$, for each beginning temperature in $\mathcal{F}$. The

$\mathbf{N}^{th}$ column of $\mathbf{pC_1}$ matrix gives the distribution of $T_B = \delta$ hours. This may be written as,

$$\mathbf{pT_B}(\delta) = (\mathbf{pC_1})_{\cdot\mathbf{N}}$$

where $(\mathbf{pC_1})_{\cdot\mathbf{N}}$ is the $\mathbf{N}^{th}$ column elements of the matrix $\mathbf{pC_1}$.

The distribution of $T_B = (2\delta)$ hours is given by

$$\mathbf{pT_B}(2\delta) = (\mathbf{pC_1})^2_{\cdot\mathbf{N}} - (\mathbf{pC_1})_{\cdot\mathbf{N}}.$$

By induction, the distribution of $T_B = (l\delta)$ hours is given by

$$\mathbf{pT_B}(l\delta) = (\mathbf{pC_1})^l_{\cdot\mathbf{N}} - (\mathbf{pC_1})^{l-1}_{\cdot\mathbf{N}}$$

for any positive integer l. Therefore the matrix of distribution function is constructed by binding the above column vectors such that

$$\mathbf{pT_B} = [\mathbf{pT_B}(\delta), \mathbf{pT_B}(2\delta), \ldots, \mathbf{pT_B}(l\delta)]. \tag{12}$$

l is chosen to be large enough to establish the distribution function for the lowest beginning temperature C_{0^-} in the series. The n^{th} row- vector of $\mathbf{pT_B}$ is the distribution of T_B for $C_F = F_n$ for $F_n \in \mathcal{F}$.

Summary of floor-heating process in MDP The floor-heating process is summarized as follows for developing the (PO)MDP. As a basic formulation, the floor-temperatures were classified into intervals $\mathcal{F} = \{F_1, F_2, \ldots, F_N\}$. However, without loss of generality, at a decision epoch t, the floor attains the temperature $C_t \in \mathcal{C}$, where $\mathcal{C}$ is the set of floor-temperature states and the decision maker will know the value of C_t before making the decision d_t. The floor-temperature $C_{t+\delta}$ will, thus, be governed by the transition probabilities $\mathbf{pC_d}$ ($\mathbf{pC_1}$ or $\mathbf{pC_0}$) depending on $d_t = \{1, 0\}$. Since, the action due to d_t will be implemented until the next decision epoch, the heating costs are given by,

$$H_t(C_t \mid d_t) = \begin{cases} pr_A\delta & \text{if } C_t < C_c \text{ and } d_t = 1 \\ pr_B\delta & \text{if } C_t = C_c \text{ and } d_t = 1 \\ 0 & \text{if } d_t = 0, \end{cases} \tag{13}$$

where pr_A is the price of energy for heating up the floor and pr_B is the price for maintaining the floor temperature per hour.

4.2.3 Merging Two Markov Processes in MDP

From the formulation of two Markov processes and (PO)MDP, it follows that the state space of the combined MDP will be the Kronecker product of $\mathbf{U}^{\mathrm{adj}}$ and $\mathcal{C}$; thus the transition matrices will be of size $\mathbf{M}^{\mathrm{adj}}\mathbf{N} \times \mathbf{M}^{\mathrm{adj}}\mathbf{N}$. As we know from Aparna et al. (2013b), there are about 1000 behavioural phases and about

50 floor-temperature states, the resulting size of the state transition probabilities and the MDP will be huge (around 2.5 billion). However, behavioural phases of the sow are independent of the decisions, actions and the floor-temperature at any decision epoch (figure 4.2). This allows us to treat farrowing process and floor-heating process independently. These two processes are governed by independent sets of transition probabilities: the phase transition matrix is ${\mathbf{P}_{\delta}^{adj}}_{\mathbf{M}^{\mathrm{adj}} \times \mathbf{M}^{\mathrm{adj}}}$ and the two temperature transition matrices $\mathbf{pC_1}$ or $\mathbf{pC_0}$ are of $\mathbf{N} \times \mathbf{N}$, given the decisions (*Heat On* and *Heat Off*). This has reduced the problem into size $\mathrm{M}^{\mathrm{adj}} \times \mathbf{N}$ as illustrated in table 4.2 and the utilities were defined as the function of phases and floor-temperatures.

Table 4.2: The look up decision table based on MDP value iteration with full information about the phase of the sow and floor-temperature of the pen.

Floor-temperature	Behavioural Phase	$\Delta\mathbf{f}_{\mathrm{opt}}$	$\mathbf{d}^{\mathrm{opt}}$
C_1	Phase-1		
C_1	Phase-2		
$\vdots$	$\vdots$		
C_1	Phase-1000		
C_2	Phase-1		
C_2	Phase-2		
$\vdots$	$\vdots$		
C_2	Phase-1000		
$\vdots$	$\vdots$		
$C_5 0$	Phase-1000		

4.2.4 Utility Criteria

At each decision epoch there is an immediate reward of making the decision. If the heat is turned on the reward will be the heating cost until next decision epoch as specified in eq. 13. There is also a final reward that will be given when the farrowing starts. This positive reward depends on the reduction in piglet mortality, and is a function of the floor temperature at farrowing.

Reward at farrowing

The management gets the complete benefit of heating strategy if the floor-temperature at the time of farrowing (C_F) is C_c and the duration of heating is sufficient to give maximal benefit to the last born piglet. In this paper we assume that this is fulfilled if the heat is on for 24 hours after start of farrowing.

Then, the income or revenue is the added value due to an extra surviving piglet. However, if $C_F < C_c$, the strategy is to turn on the heater at farrowing, so that recovery temperature will be reached as soon as possible. The distribution of time (decision epochs) to reach this temperature is given by $\mathbf{pT_B}$ in eq. 12. Given $T_B = t_{A24}$, the heating cost in the first 24 hours after farrowing is,

$$H_{24}(t_{A24}) = pr_A t_{A24} + pr_B(24 - t_{A24}). \tag{14}$$

In such a scenario, a penalty is payed in terms of no effect on mortality, until the floor temperature reaches C_c. Therefore, the revenue, I, may be seen as the function of t_{A24} and C_F, i.e.

$$\begin{aligned} I(t_{A24}, C_F) = & \text{ No. of survived piglets per litter} \times \text{price of each piglet} \\ & = \text{LS}(1 - \bar{p}_{mortality}(t_{A24}, C_F))\text{pr}_{\text{piglet}} \end{aligned} \tag{15}$$

where $\bar{p}_{mortality}(t_{A24}, C_F)$ is the mean mortality during the first 24 hours as a function of t_{A24} and $\text{pr}_{\text{piglet}}$ is the net return per piglet. Calculation of $\bar{p}_{mortality}$ is explained in 'mortality models' of sec. 4.3.2. The average revenue was calculated by simulating the farrowing events as in sec. 4.3.2.

Therefore, the net income for the temperature t_{A24} is,

$$h(t_{A24}, C_F) = I(t_{A24}, C_F) - H_{24}(t_{A24}) \tag{16}$$

and the expected income with respect to the distribution of T_B, for the given C_F, is,

$$h(C_F) = \sum_{T_B} \mathbf{pT_B}[C_F, T_B] h(T_B, C_F) \quad \forall C_F \in \mathcal{C} \tag{17}$$

where $\mathbf{pT_B}[C_F, T_B]$ is the value in $\mathbf{pT_B}$ (see sec. 4.2.2, Eq. (12)) corresponding to the row C_F and the column T_B. If $h(C_F) < 0$, it is set to 0, i.e. no heat costs and no improvement in mortality or in other words, the final heating will only be made, if it will give a positive return.

Moreover, the income due to pig production can only be gained at the time of farrowing. Therefore the utility matrix, with columns corresponding to the behavioural phase and the rows corresponding to the floor-temperature states, is given by,

$$\mathbf{h}_0[C_F, u_F] = h(C_F), \quad \forall C_F \in \mathcal{C} \text{ and,} \tag{18}$$

$$\mathbf{h}_0[C_F, u] = 0, \quad \forall C_F \in \mathcal{C} \text{ and, } u \in \{\mathbf{U}, u_{F+1}\} \tag{19}$$

where u_F is the farrowing phase, u_{F+1} is the first phase after u_F.

The total utility of N steps sequential decision problem is given by

$$\mathbf{h}_0[C_F, u] - \sum_{t}^{t_I + N\delta} H_t(C_t \mid d_t)$$

for $t \in \mathcal{T}$, $u \in \mathbf{U}^{\text{adj}}$ and $C_F \in \mathcal{C}$.

Optimization of the Utility Function with Known Phases If the phase of the sow is known, an optimal decision rule may be obtained by maximizing the total expected utility,

$$\bar{\mathbf{h}}_\pi = \mathbb{E}_F \mathbb{E}_U [\sum_{t \in \mathcal{T}} \mathbf{h}_t(u, C \mid d)] \tag{20}$$

with respect to the policy π. Here $\mathbf{h}_t$ is the utility at the decision epoch t for $U_t = u \in \mathbf{U}^{\text{adj}}$, $C_t = C \in \mathcal{C}$and $d_t = d \in \mathbf{D}$; $\mathbb{E}_F$ and $\mathbb{E}_U$ are the expectations with respect to the floor-temperatures and behavioural phases of the sow, respectively.

The function in (20) was maximized with respect to the functional equations given in (21) and (22) using the value iteration method (Bellman, 1957) in which the optimality was reached by backward induction (DeGroot, 2004). That is, the set of initial values for the first iteration assumes that the sow is in the farrowing phase, u_F. Therefore, $\mathbf{f}_0 = \mathbf{h}_0$ is the revenue associated with the pig production if energy was supplied to the pen floor after the farrowing was observed (see (18) and (19)). The first iteration, $\mathbf{k} = 1$ corresponds to the decision epoch before the farrowing, that is at time $t_{F-\delta}$, second iteration $\mathbf{k} = 2$ corresponds to the time $t_{F-2\delta}$, etc. At the $\mathbf{k}^{th}$ iteration, for each combination of sow phase and the floor temperature, the total expected utility until $\mathbf{k}$ epochs (in backwards) was calculated using the functional equations,

$$\mathbf{f}^d_{\mathbf{k}} = \mathbf{pC_d}(\mathbf{P}^{adj}_\delta(\mathbf{f}^d_{\mathbf{k}-1})^\top)^\top + \mathbf{h}_0 - \mathbf{H}^d_\delta; \quad d = 0, 1 \text{ and,} \tag{21}$$

$$\mathbf{f}_{\mathbf{k}} = \max_{d_{\mathbf{k}} \in \mathbf{D}} \{\mathbf{f}^1_{\mathbf{k}}, \mathbf{f}^0_{\mathbf{k}}\} \tag{22}$$

with dimensions of 21 as,

$$(\mathbf{N} \times \mathbf{M}^{\text{adj}}) = (\mathbf{N} \times \mathbf{N})((\mathbf{M}^{\text{adj}} \times \mathbf{M}^{\text{adj}})(\mathbf{N} \times \mathbf{M}^{\text{adj}})^\top)^\top + \mathbf{N} \times \mathbf{M}^{\text{adj}} - \mathbf{N} \times \mathbf{M}^{\text{adj}},$$

where $\mathbf{A}^\top$ denotes the transpose of $\mathbf{A}$, $\mathbf{P}^{adj}_\delta$ is as defined in (1), $\mathbf{H}^d_\delta$ is the matrix of heating costs whose elements are such that for any phase $u \in \mathbf{U}^{\text{adj}}$,

$$\mathbf{H}^d_\delta[C, u] = \begin{cases} pr_A\delta & \text{if } C < C_c \text{ and } d = 1 \\ pr_B\delta & \text{if } C = C_c \text{ and } d = 1 \\ 0 & \text{if } d = 0, \end{cases} \tag{23}$$

$$\mathbf{pC_d} = \begin{cases} \mathbf{pC_1} & \text{if } d = 1 \\ \mathbf{pC_0} & \text{if } d = 0, \end{cases} \tag{24}$$

$\mathbf{f}^1_{\mathbf{k}}$ and $\mathbf{f}^0_{\mathbf{k}}$ are the total expected utilities for the decisions *Heat On* and *Heat Off*, respectively, for the given phase and floor temperature at the $\mathbf{k}^{th}$ stage.

The iterations were terminated at $\mathbf{k}^{th}$ iteration, if $\sqrt{\sum_{C,u} (\mathbf{f}_{\mathbf{k}} - \mathbf{f}_{\mathbf{k}-1})^2} \approx 0$. The corresponding $\mathbf{f}_{\mathbf{k}}[C, u \mid d)$ are the optimum total expected utility for the decision d and are denoted by $\mathbf{f}^d_{\text{opt}}$ for $d = 0, 1$ which can be presented as in the table 4.2 where $\Delta\mathbf{f}_{\text{opt}} = \mathbf{f}^1_{\text{opt}} - \mathbf{f}^0_{\text{opt}}$ and $\mathbf{d}^{\text{opt}} = 1$ if $\Delta\mathbf{f}_{\text{opt}} > 0$, else 0.

4.2.5 Approximate POMDP methods

In a complete MDP, the optimal decision d_t with known phase $U_t = U^*$ and the floor-temperature $C_t = C^*$ is such that

$$d_t^{\text{opt}} = \arg\max_{d \in \mathbf{D}} \{\mathbf{f}_{\text{opt}}^d [C^*, U^*]\}.$$

In other words, the decision maker will look up the table 4.2 for the floor-temperature $C_t = C^*$ and the phase $U_t = U^*$; if the corresponding $\Delta \mathbf{f}_{\text{opt}} > 0$ then the decision is to *Heat On* or else *Heat Off*.

However, in POMDP, the behavioural phase of the sow is unknown for the decision maker; indeed, he has the belief state $\boldsymbol{\alpha}_t^{\mathbf{adj}}$. In principle, it is possible to obtain the exact solution to such a POMDP; but in a problem of the size implemented here, finding an exact solution is expected to be impossible in practice. Several authors have suggested methods for obtaining approximate solutions (Littman et al., 1995; Boutilier, 2002; Aberdeen, 2003; Braziunas, 2003; Shani et al., 2005). We will evaluate some of these that are based on, so called, greedy approaches.

QMDP (Expectation of utilities): The value Q_{MDP} is the general notation used for $\mathbf{f}_{\text{opt}}^d$, optimized for the complete MDP. According to this method, the POMDP optimal decision is,

$$d_t^* = \arg\max_{d \in \mathbf{D}} \{\boldsymbol{\alpha}_{t+\delta}^{adj} \mathbf{f}_{\text{opt}}^d [C^*, \cdot]^\top\}. \tag{25}$$

where $\mathbf{f}_{\text{opt}}^d [C^*, \cdot]$ is the row-vector of $\mathbf{f}_{\text{opt}}^d$ for the floor temperature C^*. This approach was first suggested in Littman et al. (1995).

Most likely phase: the decision was chosen from the look up table 4.2 for the floor-temperature C^* and the most likely phase,

$$U^{likely} = \arg\max_{u \in \mathbf{U}^{\text{adj}}} \{\boldsymbol{\alpha}_{t+\delta}^{\text{adj}} [u]\}.$$

Random phase: the choice of d^* is similar to the previous method except that the phase was chosen randomly as,

$$U^{random} = \underset{u \in \mathbf{U}^{\text{adj}}}{\text{random}} \{\boldsymbol{\alpha}_{t+\delta}^{\text{adj}} [u]\}$$

where the values inside the operator 'random' are the sampling weights in order.

Voting: the decision corresponds to the one recommended by most of the phases, weighted by the belief, i.e.

$$d^* = \arg\max_{d \in \mathbf{D}} \{\boldsymbol{\alpha}_t^{\text{adj}} \boldsymbol{\delta}^d\}$$

where $\boldsymbol{\delta}^d$ is a column-vector with elements corresponding to the phases such that $\boldsymbol{\delta}^1[u] = 1 \Leftrightarrow$ ***Heat On*** = $\arg\max_{d \in \mathbf{D}}\{\mathbf{f}^d_{\text{opt}}\}$, else 0 for all $u \in \mathbf{U}^{\text{adj}}$ for the given floor-temperature ($\boldsymbol{\delta}^1[u]$ is equal to $\mathbf{d}^{\text{opt}}$ in table 4.2. Similarly, $\boldsymbol{\delta}^0$. In this case, it is possible that $\mathbb{E}^d_t = \boldsymbol{\alpha}^{\text{adj}}_t \boldsymbol{\delta}^d = 0.5$. In such a situation, by assuming that the belief will be improved in future, d^*_t was chosen randomly.

Random action: the decision d^* is randomly chosen with weights $\mathbb{E}^d_t = \boldsymbol{\alpha}^{\text{adj}}_t \boldsymbol{\delta}^d$ for $d = 1, 0$, i.e.

$$d^* = \underset{d \in \mathbf{D}}{\text{random}}\{\mathbb{E}^d{}_t\}.$$

For the given $\boldsymbol{\alpha} \in \mathcal{B}$, table 4.2 will reduce to table 4.3. The optimal policies reached by these methods are denoted by π^Q, π^{ML}, π^{RP}, π^V and π^{RA}, respectively. However, in general, these greedy approaches assume that the phase number will be known from next decision epoch and onwards. In problems where little is known about the distribution over phases, that is the distribution is close to uniform, they are expected to perform badly, and they are not suitable to evaluate the decisions that includes gathering of information Littman et al. (1995). The two approaches, π^{RP} and π^{RA}, based on random sampling are expected to perform equivalently because the sum of the selection probabilities of the set of phases which lead to a given decision is the same as the sum of the probabilities of selecting the decision.

Table 4.3: An example of POMDP look up decision table for the given $\boldsymbol{\alpha} \in \mathcal{B}$.

Floor-temperature	$\mathbf{d}^{\text{opt}}$
25	Heat On
26	Heat On
27	Heat Off
28	Heat Off
29	Heat Off
31	Heat Off

4.3 Computational Plan

4.3.1 Simulated Data

For evaluating the floor-heat regulation system under different parameter scenarios and with different optimization methods, we have used data set with phase number at each decision epoch, and sensor data for a single sow, simulated from the distributions estimated in Aparna et al. (2013a), The values of the parameters such as number of phases in different pre-parturition behavioural states of a sow, phase transition rates and the conditional distributions of different sensor measures were also taken from Aparna et al. (2013a). In total 2500 simulated data set corresponding to 2500 sows were generated. The mating date and time of insertion into the pen were taken from the 50 sows used in Aparna et al. (2013a). The simulation process assumes that on the day of mating, the sow will be at phase *Phase-1*; since then she passes through the other phases in succession and hence the pre-parturition states (*Before Nest-Building, Nest-Building* and *Resting*) in succession until the farrowing. For simulating the data, the phase transition of the sows were considered on an equidistant half-hourly time interval. The phase transitions are governed by the PH-distribution for farrowing process, described in Aparna et al. (2013b,a). At every interval, the phase probabilities were used to sample the next phase of the sow, and hence the state. From the time of insertion into the farrowing pen to the simulated time of farrowing, each data set also contains a series of observations for the sensor measures *water consumption*, *meanActivity* and *sdActivity* pooled over half hour intervals corresponding to the decision epochs.

For the simulated data, the Belief Management system described in Aparna et al. (2013b) was used to generate the current belief of the phases $\boldsymbol{\alpha}_{t+\delta}$ at each decision epoch for each simulated sow. These believes have served as an input to the decision algorithm.

4.3.2 Biological Elements of Heating Strategy

Central for the economic evaluation of the heating strategy is how the floor temperature during and after farrowing affects the average piglet mortality, $\bar{p}_{mortality}$. We assume that the piglet friendly environment is around $C_c = 35°\mathrm{C}$, based on the recommendations from Malmkvist et al. (2006). The calculation of $\bar{p}_{mortality}$ was based on Monte Carlo simulation. The floor temperature has its effects only in the early life-time of the individual piglet. Thus the timing of birth of the individual piglets in the litter needs to be considered. The intra-birth interval shows considerable variability, but in general the total duration of the farrowing will increase while the intra-birth interval will decrease. To model this we choose farrowing event model as simple as possible, still reflecting the variability in the timing of the individual births. The birth time of each piglet were calculated based on a model where the birth duration of each piglet followed exponential distribution with identical parameter (mean birth duration, 1.5 hours). The model of litter size is based on a simple binomial distributions, with number of ovulations and embryo mortality as parameters. The expected litter size and number of ovulations were assumed to be 16 and 27 respectively. These simulated value of the birth times of each piglet was the basis for the average mortality and utilities.

Mortality model A simple two level mortality model was used. The mortality rate (or hazard rate of dying) could attain two levels, corresponding to the two levels of floor-temperature. If the floor-temperature was less than C_c, the mortality was p_0 (also referred as *general mortality*) and if it was at least C_c the mortality was reduced to p_{red} (referred as *reduced mortality*). This model is inspired by the studies of Malmkvist et al. (2006).

The total mortality in the first 24 hours depends on the length of the period with floor heating. We assume that 1 extra piglet will survive in each litter, if all the piglets can enjoy the extra heating during the first 24 hours after their birth. We assume that the mortality rate is constant within the 24 hours period if the heating regime does not change. However, delayed heating might result in piglets being born before the heat reaches C_c. Hence, for some of the piglets heat is available only for the part of their first 24 hours life. Therefore, the mortality model for the first 24 hours life of a piglet was divided into three periods; 1) From the time of birth to the time at which full heat is available. 2) From the time heat is available to the 24 hours since the observed farrowing (the time heat the is turned off), and 3) Since the end of heat to the first 24 hours life of the piglet.

Period-1 and Period-3 follow general mortality rate and Period-2 follows reduced mortality rate. Moreover, any of these periods may be of 0 hours. The total mortality in 24 hours, $\bar{p}_{mortality}$, was calculated by combining the risk of dying in each of these three periods. The values used for the mortality without heating, was 20% and for the mortality with heating was 13.75%.

4.3.3 Economic Evaluation of the simulated decision

Values of energy consumptions and different costs associated with the reward of heating strategy are given in table 4.4. These are used both in utility part of the MDP process and while evaluating the reward from each of the decision strategies for each simulated sow.

Table 4.4: Values of heating process parameters and costs involved in the basic scenario of the decision process. Values in the gray area are not the input parameters

Variable	Value
Price per kW, pr_{kW} DKK	0.75
Heated floor area per pen, A, m^2	3
Heating cost per pen in Phase (A) per hour, pr_A DKK	6.06
Heat maintenance cost per pen in Phase (B) per hour, pr_BDKK	4.68
Duration of heating from observed farrowing, hours	24
Net return per piglet, NRP, DKK	300

Heating Costs The heating costs include the cost associated with the amount of energy required to increase the floor from room temperature to the recovery temperature i.e. pr_A associated with Phase-(A) of figure 4.1 and the cost associated with the amount of energy required to maintain the floor at C_c i.e. pr_B associated with Phase-(B). We assume that pr_A is fixed through out the process and it is different from pr_B. These costs were calculated by fixing the price of energy, pr_{kW}, to be 0.75 DKK per kilo Watt. If the area of the pen-floor to be heated is A and if C_v is the heat capacity of the concrete floor, then by neglecting the thickness of the floor, the amount of energy consumption per hour is $Q = k_G C_v A$ where Q is Q_A for Phase-(A) and Q_B for Phase-(B). Thus the cost of heating up the floor for one hour in Phase-(A) is $pr_A = Q_A pr_{kW}$ and that for Phase-(B) is $pr_B = Q_B pr_{kW}$. Let the number of *Heat On* decisions in Phase-(A) and Phase-(B) before observing the farrowing be t_A and t_B, respectively (t_B may be equal to 0 if C_c is not reached before farrowing). Therefore, total heating cost before observing the farrowing, due to the policy π^* is given by

$$H_{\pi^*} = (pr_A t_A + pr_B t_B)\delta. \tag{26}$$

Revenue and Profit of Pig Production We assume that the net return per piglet (NRP) is $\mathrm{pr}_{\mathrm{piglet}} = 300$DKK. Therefore, the revenue due to the pig production by implementing the policy π^* is,

$$\begin{aligned} I_{\pi^*} &= \text{ No. of survived piglets per litter} \times \text{price of each piglet} \\ &= \mathrm{LS}(1 - \bar{p}_{mortality})\mathrm{pr}_{\mathrm{piglet}} \end{aligned} \tag{27}$$

and hence the net profit of pig production due to the policy π^* is,

$$\Pi_{\pi^*} = I_{\pi^*} - H_{\pi^*} - H_{24\pi^*} \tag{28}$$

where $H_{24\pi^*}$ is the total heating cost in the first 24 hours after farrowing was observed and calculated as in (14).

Reward of No Floor-heating The heating strategies are evaluated by calculating the net reward of the strategy compared to the reward without floor heating. If p_0 is the general mortality, then the revenue due to no floor heating is given by,

$$R_0 = \mathrm{LS}_0(1 - p_0)\mathrm{pr}_{\mathrm{piglet}} \tag{29}$$

where $\mathrm{LS}_0(1 - p_0)$ is the litter size survived under general mortality risk.

Reward of Strategy π^* The reward R_{π^*} of the heating strategy π^* is the increased profit due to floor-heating, i.e.

$$R_{\pi^*} = \Pi_{\pi^*} - R_0. \tag{30}$$

The average reward for the simulated data for each of the selected scenarios and decision strategies are presented in sec. 4.4.

4.3.4 Comparison of POMDP strategies and Simple Heuristic Heating Strategy

The floor-heat regulation strategy in the pen level was compared for the 5 greedy approaches of POMDP described in sec. 4.2.5, for 1250 simulated sows, based on the reward of heating. The rewards of POMDP strategies were also compared with the simple heuristic strategy (SHS) (π^{SHS}) based on the prediction of expected time to farrowing ($\mathbb{E}[T]_t$) at each decision epoch as presented in Aparna et al. (2013b).

According to the simple heuristic strategy, the optimal decision at the epoch t is such that,

$$d_t^{\mathrm{SHS}} = \begin{cases} 1 \text{ (Heat On)} & \text{if } \mathbb{E}[T]_t \leq \mathbb{E}_F \\ 0 \text{ (Heat Off)} & \text{if } \mathbb{E}[T]_t > \mathbb{E}_F \end{cases} \tag{31}$$

where $\mathbb{E}_F$ is the threshold value fixed for the process. We choose the threshold value to be $\mathbb{E}_F = 12$ hours, inspired by the duration of Phase-(A) for the continuous supply of energy $k_{G0} = 0.83\mathrm{mW/m}^2$. Similar economic evaluation of the strategy (see sec. 4.3.3) was performed by calculating the net profit $\Pi_{\pi^{\mathrm{SHS}}}$ and reward $R_{\pi^{\mathrm{SHS}}}$ of simple heuristic strategy. POMDP greedy strategies were compared with the simple heuristic strategy by calculating the *gain* as,

$$G = R_{\pi^*} - R_{\pi^{\mathrm{SHS}}}. \tag{32}$$

4.3.5 Scenarios of Heating Parameters

The two heating strategies, 1) QMDP (π^Q), and 2) simple heuristic strategy (π^{SHS}), were examined and evaluated for 6 scenarios of heating parameters, for 2500 simulated sows; the parameter scenarios are given in table 4.5. The scenario are numbered from 0 to 5, to make it easier to compare the results. The Scenario No. 0 (also called basic scenario) corresponds to the estimated values of the model in (4). The value of σ_C^2 was varied by 0.05 in Scenario No.1 and No.2. In No.3, the value k_G was doubled. In Scenario No.4, the value $k_G = 0.66\mathrm{mW/m}^2$ corresponds to the minimum input energy required to raise the floor temperature from $C_0 = 18.34$°C to $C_c = 35$°C in 24 hours. In Scenario No.5, the room temperature was set to be 16°C (heat parameters are not changed).

For each of these scenarios, $\Delta\mathbf{f}_{\mathrm{opt}}$s were calculated for the combination of floor-temperature and behavioural phase number to formulate the complete MDP and the look up table 4.2. Based on the prediction of the phase of the sow at different decision epochs, heating period prior to farrowing, the reward of the strategies and the gain of POMDP strategy with respect to simple heuristic strategy were also calculated for 2500 sows, individually. Mean of these values and the first and second quartiles of the floor-temperature at the time of farrowing are presented in sec. 4.4, along with the mean heating periods. The Monte Carlo standard errors are shown to indicate the numerical precision of the comparisons.

The performance of the POMDP greedy strategies described in sec. 4.2.5, were also evaluated in terms of their rewards and gains for the Scenario No. 0, 3 and 5.

Table 4.5: The scenarios of heat parameters (SD of the heating process, room temperature and energy input) used to evaluate the decision strategies. $k_{G0} = 0.83\mathrm{mW/m}^2$.

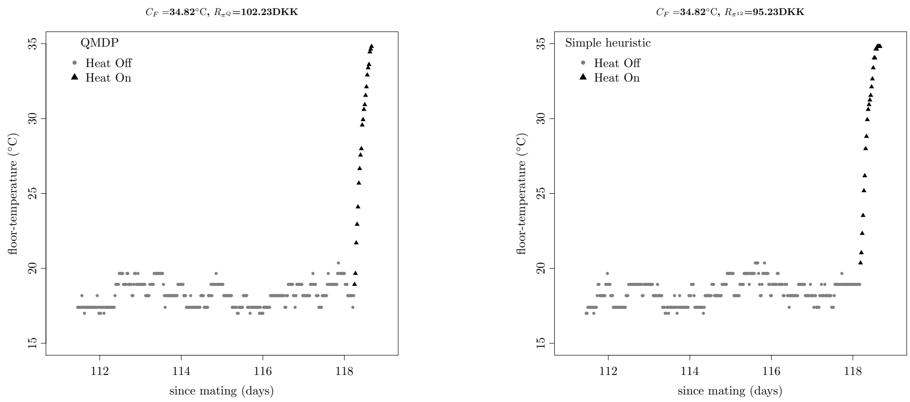
Scenario No.	σ_C	T_0	k_G	k_G/k_{G2}	$\mathbf{A} = k_G/k_1$
0	0.24	18.34	k_{G0}	1.30	21.63
1	0.15	18.34	k_{G0}	1.30	21.63
2	0.10	18.34	k_{G0}	1.30	21.63
3	0.24	18.34	$2k_{G0}$	2.59	43.26
4	0.24	18.34	0.66	1.04	17.29
5	0.24	16	k_{G0}	1.14	21.63

The optimization algorithm was implemented in the statistical computational environment R (R Development Core Team, 2011). Various functions supporting the algorithm were written. These functions are being collected into a package compatible with R (not yet published).

4.4 Results

4.4.1 Illustration of floor heat regulation of individual pen

The floor-heat regulation was similar in both the POMDP and heuristic strategies. The decisions made at different decision epochs and the corresponding change in the floor-temperature are illustrated in figure 4.4 and figure 4.5 for POMDP (in particular, QMDP) and simple heuristic strategy. The x-axis correspond to the time since mating and the floor-temperatures are in y-axis. The floor-temperature at the time of farrowing (C_F) and the reward of heating strategy are also mentioned on the plot. The points in the plot correspond to the decision either *Heat On* or *Heat Off* (see the legend). The floor-temperature was kept close to the initial level (room temperature) and was raised as the sow approached the time of farrowing. In figure 4.4, for the parameter Scenario No. 0, the heating was turned on almost at the same time and the floor was almost at the same temperature at the time of farrowing in either strategies. However, when more energy was supplied (in Scenario No. 3), the POMDP strategy delayed the heat on (figure 4.5a) and hence, the heater was on for shorter period before farrowing in contrast to the heuristic strategy in figure 4.5b. That is, according to POMDP, keeping the pen floor temperature higher than the room temperature was expensive than risking the piglet mortality due to lowered floor-temperature. This was possible since the floor can be heated up in a shorter time.



(a) POMDP

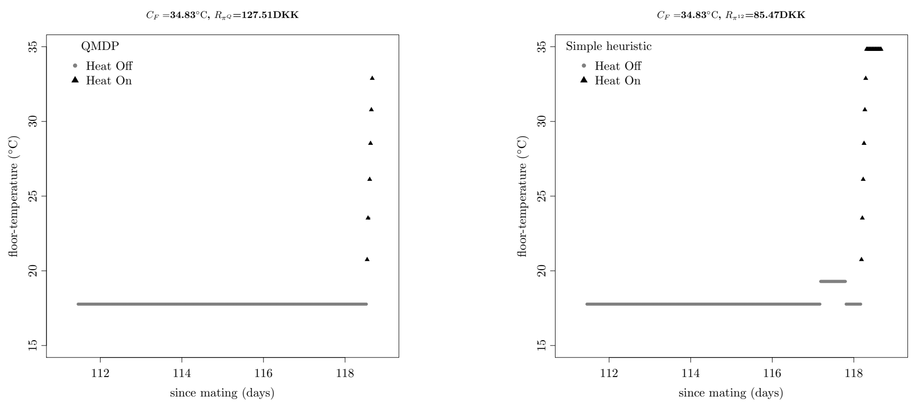
(b) Simple heuristic strategy

Figure 4.4: Illustration of POMDP (left panel) and SHS (right panel) with the floor-temperature (y-axis) before farrowing versus days since mating as observed for the parameter Scenario No. 0 of table 4.5. The two strategies perform similar and the gain of POMDP is very small.

4.4.2 Decision versus Floor-temperature and Behavioural Phase

We have chosen to illustrate the optimized complete MDP model in figure 4.6 (as in table 4.2). The $\Delta \mathbf{f}_{\mathrm{opt}}$ (on y-axis) values were plotted as the function of phase number for selected floor-temperatures, to show how the (PO)MDP decisions are based on the floor-temperature (each line), behavioural phase number (on x-axis) and the heat parameter scenarios (each panel). The dotted vertical line indicates the beginning of the *Nest-Building* state. For the given floor-temperature and the phase number, a $\Delta \mathbf{f}_{\mathrm{opt}}$ value above the 0-line (the horizontal dotted line), i.e. positive $\Delta \mathbf{f}_{\mathrm{opt}}$, corresponds to the decision *Heat On* and negative value corresponds to the decision *Heat Off*.

As it can be seen from the plots, the first change point (not necessarily from negative to positive) of $\Delta \mathbf{f}_{\mathrm{opt}}$s occur when the state of the sow shifts to the *Nest-Building* state. In Scenario No. 0 (figure 4.6a), the first and the third quartiles at which the (PO)MDP makes the decision *Heat On* are at Phase-881 and Phase-976, respectively. Whereas, in Scenario No. 3 (figure 4.6b), the decision to heat on will be delayed until the sow is around phase-1070 (the first and third quartiles being Phase-1052 and Phase-1080) as higher energy supply will raise the floor temperature faster than Scenario No. 0. Furthermore, the gain in the



(a) POMDP

(b) Simple heuristic strategy

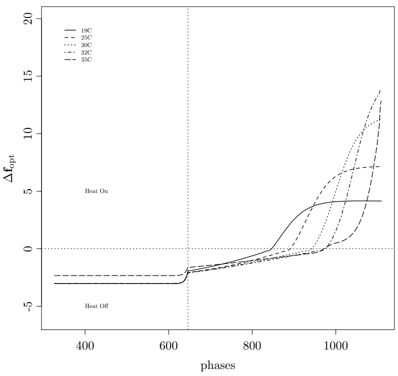
Figure 4.5: Illustration of POMDP (left panel) and SHS (right panel) with the floor-temperature (y-axis) before farrowing versus days since mating as observed for the parameter Scenario No. 3 of table 4.5. In spite of the delay in turning on the heater, POMDP has resulted in an increased reward.

utility of *Heat On* is less compared to that of Scenario No.0. This is mainly due to the increased cost of energy. In Scenario No. 5 (figure 4.6d), for the floor-temperatures below 25°C, 75% of those suggest floor heating before reaching Phase-740 and 25% of those fall below 0-line after Phase-970 and 75% of those after Phase-1062, i.e. at the latter phases the strategy suggests not to supply any energy to the pen floor if the floor is still below 25°C. For the floor-temperatures 25°C or more, the first and third quartiles of *Heat On* start are at Phase-792 and Phase-848, respectively. The utilities of *Heat On* are comparatively higher than the other two scenarios. In Scenario No. 4, figure 4.6c, MDP suggests floor heating before starting the *Nest-Building* state if and only if the floor-temperature around that period is above 30°C. Moreover, unless the floor-temperature raises to $C_c = 35°\mathrm{C}$ by the time the sow reaches Phase-806, the decision of *Heat On* will be retracted.

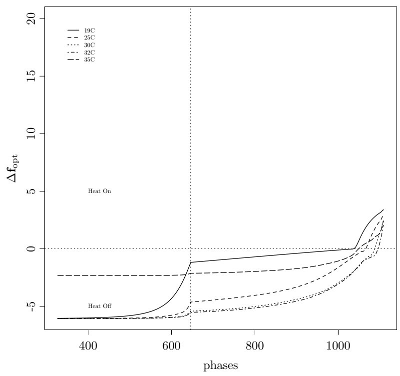
Thus, for most scenarios, it is optimal to turn on the heater as the phase number increases. However, if the floor-temperature has not increased sufficiently as the farrowing gets closer, it is no longer profitable to turn on the heater to the floor with low temperature. In such cases, the recovery temperature is not likely to be reached soon enough to improve the mortality of the piglets.

4.4.3 Decision versus Belief state for the given Floor-temperature

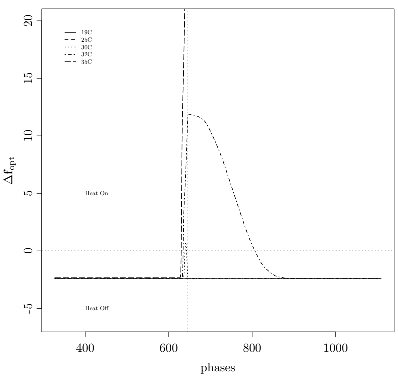
Use of mating date as well as the sensor information for the prediction of farrowing means that the uncertainty in predicting the behvaioural phase at a given decision epoch is relatively minor. This means that for most of the decision



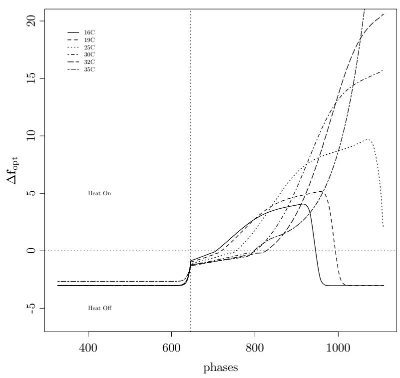
(a) Scenario No. 0



(b) Scenario No. 3



(c) Scenario No. 4



(d) Scenario No. 5

Figure 4.6: Plot of optimized $\Delta\mathbf{f}_{\mathrm{opt}}$ values of complete MDP against the pre-parturition behavioural phases for selected floor-temperatures and heat parameter scenarios. Positive $\Delta\mathbf{f}_{\mathrm{opt}}$ indicates the decision *Heat On* and the negatives correspond to *Heat Off*. These optimized utilities were used for making the decisions for all the sows under the same conditions.

epochs, the decision is identical for all likely phases. The functioning of the POMDP with the belief state and floor-temperature is illustrated in figure 4.7. Each line in the plot is the belief state (or phase probabilities, $\boldsymbol{\alpha}_t$) predicted from the HPMM at different decision epochs t, for a simulated sow which has started nest-building on day-117.9 and farrowed after day-118.7 from mating. In the beginning, the decision *Heat Off* was optimal for all likely phases (solid line). At the decision epoch t= day-118.3, the decision was no longer clear cut; some phases led to *Heat Off* (solid line) and some phases to *Heat On* (dashed line). The POMDP approximation is therefore important here. The decision was clear again after 8 decision epochs (that is after 4 hours); all the phases leading to *Heat On*. To illustrate the uncertainty, Shannon's entropies (H_α and H_d) were calculated for the phase probabilities $\boldsymbol{\alpha}_t$ and for $[\mathbb{E}_t^d, 1 - \mathbb{E}_t^d]$; the plots of these measures are shown in figure 4.8. The entropy for $\boldsymbol{\alpha}_t$ (figure 4.8a) starts increasing rapidly from day-117.9 after mating (the mean sojourn time of the *Nest-Building* state is much shorter than *Before Nest-Building*), for a period of about 16 hours. On the other hand, the entropy for $\mathbb{E}_t^d$ (figure 4.8b) is more than 0.4 from day-118.2, for a period of 3.5 hours and is more than 0.2 for a period of 4.5 hours.

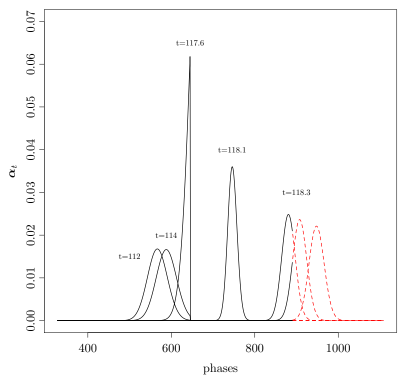
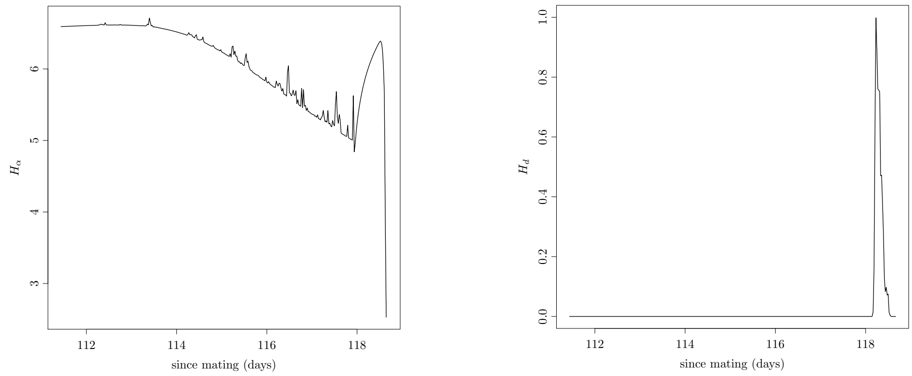


Figure 4.7: Plot of phase probabilities ($\boldsymbol{\alpha}_t$) calculated from HPMM prior to farrowing at different decision epochs for a simulated sow which has farrowed after day-118.7 after mating. The decision *Heat On* for the floor-temperature 25°C are denoted by the dotted part of the line. The decision is uncertain around day-118.3.

4.4.4 Economic Evaluation of the Heating Strategies

The results from the evaluation of different heating strategies based on the simulated sows and data are shown below. Note that the economic evaluations are not dependent on the expected returns found by the complete MDP-optimization, except through the effect on the decisions.



(a) entropy of $\boldsymbol{\alpha}_t$ (b) entropy of $\mathbb{E}_t^d$

Figure 4.8: Shannon entropy for $\boldsymbol{\alpha}_t$ (left-panel, $H_{\boldsymbol{\alpha}}$) and $[\mathbb{E}_t^d, 1-\mathbb{E}_t^d]$ (right-panel, H_d). The $H_{\boldsymbol{\alpha}}$ rapidly increases from day-117.9 after mating for the next 16 hours, whereas, H_d increases from day-118.2 and is more than 0.2 for a period of 4.5 hours.

QMDP versus SHS The reward of no heating strategy was calculated to be $R_0 = 3840$DKK with mean litter size 16.

The comparisons between the QMDP strategy and the heuristic strategy for the 6 scenarios are shown in table 4.6. The table shows the mean heating durations (t_A and t_B) prior to farrowing, the first and second quartiles of the floor-temperature at the time of the farrowing, the reward due to heating (R_π) for QMDP (π^Q) and SHS (π^{SHS}), gain of QMDP against SHS (μ_{gain}) with the standard error (SE_{gain}) for the 2500 simulated sows.

For the initial temperature $C_0 = 18.34°\text{C}$ and the energy input k_{G0} (i.e. Scenario No. 0, 1 and 2), both QMDP and SHS have performed similar with a margin of 3DKK. The two strategies have brought the floor-temperature close to C_c by the time of farrowing. Decreasing σ_C^2 by an amount of 0.05 has resulted in a small increase in the mean gain and has also decreased the SE_{gain}.

Doubling the value of the energy input per time unit, k_G, in Scenario No.3, QMDP has reduced the Phase-(A) heating period by an hour and the Phase-(B) heating period by 8 hours as compared to SHS, in spite of second quartile of C_F being 32.9°C. However, this has raised the gain, μ_{gain} into 36.1 (SE=0.15) DKK, about 10 times more than that for Scenario No. 0 to 2.

Furthermore, for the Scenario No. 4, *QMDP* strategy does not take any decision to *Heat On* through out the pre-parturition period; this seems to be fair enough as the supplied energy takes about 24 hours to raise the floor-temperature from $18.34°\text{C}$ to C_c and, moreover, the net production profit due to heating is less than that for no-heating. However, SHS is ignorant to these issues and raises the floor-temperature whenever the prediction of *time to farrowing* falls below the threshold and hence, it has resulted in a loss of 56.4 (SE_{gain}=0.12) DKK.

If the initial floor-temperature of the farrowing pen was $T_0 = 16°\mathrm{C}$ (Scenario No. 5), the QMDP has taken extra 2.6 hours of Phase-(A) period and 0.6 hours of Phase-(B) as compared to SHS, resulting in a gain of about 10 (SE=0.53) DKK. Thus, SHS is very sensitive to room temperature changes. The t-tests for the gain in rewards for all the parameter scenarios are statistically significant.

Table 4.6: Comparison of QMDP (π^{Q}) and SHS (π^{SHS}) heating strategy in terms of the quartiles of the floor-temperature at the time of farrowing, Phase-(A) and Phase-(B) heating periods prior to farrowing, rewards and gains, summarized for 2500 simulated sow data. Reward of no-heating strategy is $R_0 = 3840$DKK with mean litter size 16.

Scenario No.	Strategy	Floor-temperature (°C)		Heating (hours)		Reward (DKK)	Gain (DKK)	
		Quartile-1	Quartile-2	t_A	t_B	R_π	μ_{gain}	$\mathrm{SE}_{\mathrm{gain}}$
0	π^Q	33.8	34.6	9.8	0.4	102.3	2.2	0.22
	π^{SHS}	34.6	34.8	10.4	1.3	100.2		
1	π^Q	34.1	34.6	10.0	0.4	101.2	3.1	0.13
	π^{SHS}	34.8	34.8	10.4	1.2	98.1		
2	π^Q	34.1	34.6	10.0	0.3	101.4	3.5	0.10
	π^{SHS}	34.8	34.8	10.6	1.1	97.9		
3	π^Q	29.7	32.9	2.7	0.1	125.0	36.1	0.15
	π^{SHS}	34.8	34.8	3.6	8.1	88.9		
4	π^Q	17.6	17.6	0.0	0.0	0.0	56.4	0.12
	π^{SHS}	31.3	32.2	11.6	0.0	-56.4		
5	π^Q	34.1	34.6	14.2	0.6	43.5	9.8	0.53
	π^{SHS}	32.4	33.4	11.6	0.0	33.7		

Comparison of POMDP Greedy Strategies The mean reward of POMDP greedy strategies and the mean gain (with SE) as compared to SHS, for 1250 simulated sow data, are tabulated in table 4.7. The marginal differences between the rewards and gains of different greedy strategies are very small. However, it appears that QMDP (π^{Q}) and 'Most Likely' methods (π^{ML} and π^{V}) perform better than the random methods (π^{RP} and π^{RA}). The two random methods, π^{RP} and π^{RA} behave equivalently and have resulted in the same rewards, within the numerical precision given by the $\mathrm{SE}_{\mathrm{gain}}$, as expected.

Table 4.7: Comparison of POMDP greedy strategies based on their reward and gain against SHS, summarized over 1250 simulated sow data.

Scenario No.	Quantity	QMDP π^{Q}	Most likely Phase π^{ML}	Random Phase π^{RP}	Voting π^{V}	Random Action π^{RA}	SHS π^{SHS}
	Reward	98.06	97.58	95.45	96.88	95.02	95.49
0	μ_{gain}	2.57	2.09	-0.03	1.39	-0.47	-
	SE_{gain}	0.32	0.36	0.39	0.35	0.38	-
	Reward	125.48	125.63	124.23	125.57	124.29	89.01
3	μ_{gain}	36.47	36.62	35.22	36.55	35.28	-
	SE_{gain}	0.19	0.21	0.22	0.21	0.22	-
	Reward	44.45	44.53	43.65	45.30	43.23	34.96
5	μ_{gain}	9.48	9.57	8.69	10.34	8.27	
	SE_{gain}	0.76	0.76	0.75	0.74	0.76	

4.5 Discussion

The study has been successful in demonstrating the implementation of sequential decision problem as an extension to the farrowing prediction model in Aparna et al. (2013b). This has given a framework to integrate sensor information from multiple sources into an optimal decision making and has also taken care of the costs and rewards associated with the problem. Since the prediction model was built using Hidden (Semi) Markov Model, the task of finding the belief state in the decision process is identical to the calculations performed in the prediction model and has been omitted here; indeed, the belief state has carried all the historical information along with and the extra effort in decision making has markedly reduced. The estimated model and parameters have been directly used in the decision model; however, it has been necessary to formulate the model part concerning the floor heating.

Even though the combined decision model is large, it is still tractable; especially when the phase numbers are assumed to be known. This has been possible mainly because the farrowing process is independent from the floor heating process.

The simple heuristic strategy ($\pi^{(\text{SHS})}$) as introduced in Aparna et al. (2013b) is a rule-of-thumb relying on previous experiences of time to heat up the floor. Thus it has performed slightly worse, under the basic scenario of heat parameters. However, when some of these parameters have changed, there was a marked difference to the POMDP based strategy. The main drawback of the heuristic strategy is the threshold value $\mathbb{E}_F$ to be adjusted frequently. If the surrounding temperature is varying or if more energy for heating was feasible then it is hard to decide on the $\mathbb{E}_F$ value. On the other hand, the (PO)MDP strategy automatically adapts to the changes in the values such as the surrounding temperature, energy supply, cost of heating and also the floor-area. For example, supplying more energy to the pen floor means increasing the heating cost; and meanwhile the floor-temperature rapidly reaches to C_c. Therefore, the decision to *Heat On* may be delayed as compared to the heuristic strategy. If optimal, (PO)MDP will avoid making *Heat On* decision through out the entire process. Sometimes, the supplied energy would not be sufficient to bring the floor-temperature to C_c on time. In such a case, the (PO)MDP strategy takes the distribution of heating process into account and hence may not advice to *Heat On*. Furthermore, the (PO)MDP strategy incorporates the mortality model. If no piglets may be able to get the benefit of floor heating, then it is not worth to *Heat On*.

About the belief state, we only know that they are distributed between 0 and 1 and they sum up to 1 over all the phases. Therefore, as first attempt we have used the greedy approximations of POMDP solution and these approximations seem well suited to the heat regulation problem. The information from the sensors were relatively narrowly distributed over phase numbers. The likely phases (the phases with more than negligible probability) would all lead to the same decision for most of the decision epochs. Only for few decision epochs there was substantial doubt about the optimal decision. As the POMDP is based on fixed amount of information from the sensors, there is no decision about gathering extra information. Thus the caveats mentioned in Littman et al. (1995) does not refer to our use of the approximation. It should also be noted that even if we knew the phase number at certain decision epoch, there would still be considerable uncertainty about the future development in phase numbers. However, the current model specification and the belief states calculated for the simulated data could be used as a realization to apply the methods for finding the exact solution to the POMDP (Littman et al., 1995). Since, underlying process is dynamic, the realization should take the time of decision with respect to mating or farrowing as well as the relation with the floor-temperature into account. This would lead to an intensive computational problem, which has been outside the scope of the current work. Moreover, although we do not know how the other local approximation methods will perform, we expect it to be similar to the current greedy approaches.

In comparison, the greedy strategies differed only slightly. The QMDP method seemed more natural as a criteria, but if the methods are evaluated based on their performance, 'Most likely' and 'Voting' methods are similar to QMDP. Similar comparison was also performed by Shani et al. (2005). From an implementation point of view the 'Most likely' will be very easy to use. If the prediction algorithm described in Aparna et al. (2013b) is available on the farm-level, the most likely phase at each decision epoch will be known. In addition, only the decision table 4.2 is needed on the farm-level, and the measurement of the current floor temperature. A simple look up in the table for the most likely phase, and the floor-temperature will give the optimal decision.

With respect to building the model of the farrowing process, we have had access to sufficient empirical data. However, there is a need for a better understanding of the interaction between the floor and room temperatures and the mortality rate both with and without any heating strategy. We have used a conservative approach that were intended not to overestimate the value of sensor information and floor heating. Therefore, we expect the real reward to be higher than that calculated here. The structure of the decision algorithm is flexible to adopt to other formulations of the reward from the heating process. Furthermore, the heating strategy can be modified by considering the heat supply for the period from the time of farrowing to the first 24 hours life of the last piglets birth so that all the piglets will get maximum benefit of thermal regulation.

Other studies, such as Cornou and Lundbye-Christensen (2012) has been addressing the use of sensors for giving farrowing alarms, and it has been a problem to define when an alarm or absence of alarm should be considered false. However, the problem may be avoided by framing the problem as a decision problem by defining the costs/rewards, similar to our approach. In this paper, we have focused on making the optimal decisions for the floor-heat regulation problem using the prediction of farrowing. However, the underlying decision model will also be suitable for other uses, such as to improve the management surveillance of the farrowings. In management surveillance problem, the problem should consider the time for preparation (similar to Phase-(A) of floor-heating process) such as the issues involved in allocating the personnel, in addition to the costs and rewards.

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CHAPTER 5

DISCUSSION AND PERSPECTIVES

The objective of the PhD study has been achieved in the three stages. First of all, a method for the prediction of onset of farrowing was developed using sensor information that has significantly improved the precision of the prediction. This stage was based on a statistical model for various phases that the sow goes through up to farrowing. The new approach of using the PH distributions to take the distribution of the sojourn time into account have lead to several advantages. We have been able to use different type of sensors in the same model at the same time and can even compare the success-rates using different combinations of sensors. The success rate is comparable with the similar work by Cornou and Lundbye-Christensen (2012).

Because the model directly predicts the farrowing time it can be validated based on the observed farrowings. Thus we were able to measure the bias of the expected time to farrowing compared to the real time, and hence, directly able to compare the precision of the predictions. Of course, the large sample size in the study has also allowed better possibility to compare different methods. From a calculation point of view, the CUSUM method with the group-wise weighings of the differences (Cornou and Lundbye-Christensen, 2012) is the most easy to handle (and should be identical with a method without weighing), but the increase in complexity in our method is minor and could be handled in modern computers.

Furthermore, the HPMM distribution approach allowed us to revise the prediction if new sensor information contradicted the current prediction, because it is the part of the model, although the simple heuristic strategy defined to validate our prediction algorithm does not give any option to turn off the floor heating if necessary except when the prediction of time to farrowing was more than the threshold value.

The decisions taken based on the prediction of farrowing should consider the planning and preparation time. For example, if the prediction should be used for management surveillance, the timing of the alarm should consider the time required to allocate the personnel so they are available at the time of farrowing; from the floor-heat regulation point of view, the decisions should be based on the time required to heat up the floor from room temperature to the required temperature. But, in the more heuristic based methods, there is no way of making the timing of the alarm fit with neither the heating up time or the management preparation time. Therefore we choose to set up an automatic floor-heat regulation system combined with thermodynamical knowledge about the floor heating and the energy costs. This system allows a systematic approach to precision of prediction, false versus positive alarms, and multiple alarms, in contrast to more heuristic strategies. Due to the properties of the farrowing process, we were able to treat the HPMM as an HMM over phases in the decision context, with the phase probability distribution at each time step as the belief state.

Based on the existing literature about sow behaviour around farrowing, we had a clear expectation that the behavioural changes would show up in the simple sensors' data pattern. However, there was no experimental evidence about the amount of changes to expect in the sensor information such as water consumption and movements, with changing behavioural phases/ stages of the sow. There was no clear agreement which behavioural measures to use in order to detect the change in states and thus the changes in the patterns of sensor measurements; especially, where little evidence was available about the duration of the states and how it affected, e.g., the diurnal rhythm. The current estimation of conditional distribution of the sensor information has quantified these effects and found out that the diurnal rhythms are distinguishable between the states. Especially, model for water consumption data has shown that mixture models with the concomitant model (with harmonic functions as covariate) are the better candidate for this purpose which also estimates the probability of consumption. Extension of these models may be useful in solving many other issues in the livestock farming and animal welfare such as how much water to provide and at what period. Obviously these model types are candidates for analyzing experiments of sow behaviour.

In the desired system illustrated in chapter 1, the same prediction and decision tool parameters will be used for all sows in a batch. Thus, the complexity and the time consumption of the estimation and optimization algorithms are not an issue at the farm level, as these tasks will be done on the central level computer. In addition to this, prediction algorithm can be used as a stand-alone solution performing independent of the decision tool. This allows the developers to focus on the individual algorithms rather than the whole system. Apart from this, from the farmers or product point of view, there may be more than one decision tools running (e.g. one for climate regulation and another for management surveillance) for the same pen/sow which uses the common prediction model.

The modelling techniques have allowed us to integrate several sensor information into the single framework. It also indicates that it may be important to combine different sources of information in order to obtain a sufficient identification of the problem. It is interesting to note that if the water consumption data and the activity measurement had been evaluated in two different studies, neither of the studies would have shown potential value. In addition, sensors integration has also allowed the farmer to choose a sensor(s) set up suitable for his availability. it would be very natural to develop, especially, the prediction algorithm to include the information from farmer's routine visit to the herd. With minor changes, the set up may also be able to predict the beginning of the nest-building behaviour which would help the farmer as well as the behavioural scientists, e.g., to provide nest building materials. The decision tool illustrated in this study, does not take the cost of the sensors and their installation into account while optimizing the rewards, as these costs are irrelevant for these operational decisions. However, the cost-benefit calculations discussed in chapter 1, indicated that the increase in reward from each farrowing would make these investments in equipment economically sound. The sows are in the farrowing pen for so short interval, that the reward will be gained 7-8 times a year.

The success of the algorithm in our application seems promising for future applications using the phase-type approach in sensor based monitoring in precision livestock/agriculture production. Prediction of possible disease outbreaks and outbreak of behavioural problems such as tail-bite are candidates for the modelling approach.

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"A busy pig farmer may appreciate if he has a system that can send alarms to his smart-phone as his sows approach farrowing stage or can automatically control various tasks around the farrowing. By this, he can avoid spending 2 days or overnight, far away from his weekend parties, just waiting for the sows to farrow. Of course, he doesn't want to be disturbed by the false alarms!!!"

The thesis has developed an automated system for the prediction of farrowing based on the online sensor information that sends warning alarms to the farmer. The prediction system was further extended to a decision tool to automatically control the floor-heat regulation system at the pen level. The decision tool evaluates the costs involved in heating and the pay-off for the false-alarms into account; and hence, aims at making a strategy that would yield maximum reward to the farmer.