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Prediction of Illness in Sheep on Body Temperature

Master's thesis in Datateknologi
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Master's thesis

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Abstract

Each year thousands of sheep are free range grazing during the summer. While this practice is good utilization of land and has many health benefits for sheep, it is not without it's troubles. When the sheep are on free range pastures it becomes incredibly difficult to have a good understanding of the individual sheep's health and welfare, and to detect illness or injuries. Illness can lead to slower growth, and in serious cases to death, which both would cause loss of revenue for the farmer.

Tools that could predict, warn, and give information of the health and welfare of the grazing sheep could be of immense value to farmers, especially as farms and the amount of livestock per farmer is increasing. Not only could such tools improve animal welfare, but also possibly lead to increased farmer revenue.

In this thesis we have analyzed temporal data, collected from lamb during a period where the lamb were on a free range pasture. Based on these analyses we have tried to make models and software that could be able to detect abnormalities and detect illness in sheep. These models were tested against benchmarks and compared, showing advantages for models that take the circadian rhythm and its changes in consideration.

Sammendrag

Hvert år gresser tusenvis av sau på sommerbeite. Mens denne praksisen er god utnyttelse av utmark og har gode helsefordeler for sauen er det ikke uten problemer. Når sau er på beite blir det vanskelig å ha en god oversikt over sauens helsetilstand og å oppdage sykdom eller skade. Sykdom kan medføre nedsatt vekst og i alvorlige tilfeller død. Både nedsatt vekst og dødsfall sørger for nedsatt omsetning for bonden.

Verktøy som kan forutsi, varsle og gi informasjon om helsen til gressende sau kan være til stor hjelp for bonden. Antall dyr per bonde er økende i forbindelse med økte krav om effektivitet og sammenslåing av gårder, hjelpemidler for overvåking av sauens helse blir da mer nødvendig for å sørge for god dyrevelferd. Hjelpemidler kan også lede til økt omsetning for bonden dersom de forhindrer dødsfall og/eller nedsatt vekst.

I denne tesen har vi analysert temperatur data, innsamlet fra lam på sommerbeite. Basert på disse analysene har vi forsøkt å lage modeller og programvare for å detektere unormaliteter og sykdom i sau. Disse modellene er testet og sammenlignet, og viser nytte av å modellere for den circadiske rytmen og dens endringer over tid.

Acknowledgements

This is my master thesis for the study Computer Science at the Faculty of Information Technology and Electrical Engineering at the Norwegian University of Science and Technology.

A lot of work has been put into this thesis, however it wouldn't have been possible without the help of several people that I would like to thank.

Professor Svein-Olaf Hvasshovd was my supervisor through my work on this thesis, and has been guiding and reviewing my work. We have had regular meeting were I have received valuable input on my work, and good suggestions of what I should look into next. He has also been very helpful in organizing meetings with Lise, Borris, Kristin, and Kjell.

Further, a group of scientists that have been helpful are Lise Grøva and Unni Støbet Lande from NIBIO, Borris Fuchs from University Innland, and Kristin Sørheim from NORSØK. They have all been very helpful by teaching me new stuff on sheep illness, directing me to sources, and giving me information on the data we applied, and about the sheep the data was recorded on.

Professor Emeritus Kjell Bratbergsengen has provided interesting point-of-views and valuable findings that I have found very helpful, and that helped me look at the data in a different view, and investigating new possible dependencies.

This thesis couldn't have been possible without the data we used, which was provided by the Norwegian Institute of Bioeconomy Research (NIBIO).

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Chapter 1

Introduction

Every summer thousands of sheep are released to free-range pastures for grazing all over Norway, so each year thousands of sheep are grazing on free-range pastures. While this practice has many good health benefits for the sheep, and utilizes land that is not usable for other agricultural purposes, it is not without risks. Each year many of the grazing sheep die of injuries and illnesses, and some are killed by predators. Sheep illness can be a direct cause of death, can lead to slowed down growth, weakening, and making them easier prey. All resulting in loss of revenue for the farmer, as well as loss of food and resources. Farmers reported in 2016 a total loss of 75,275 sheep, of which 17,794 were compensated, in other words less than 24% of the lost sheep were compensated. Of all the lost sheep, less than 3,000 had a documented cause of death [1]. For reporting causes of death to authorities or insurance companies, the current situation could be improved by a computer system that creates a report based on the data that is collected on the individual.

Loss of sheep is naturally varying from year to year, however the yearly loss of lamb has been between 5 % and 7 % since 2010, and in some grazing areas ranging above 30 % [1]. This is quite a substantial amount of loss, and tools that would decrease this, would be very helpful.

The pastures are often huge, in which the sheep move a lot, and the sheep usually don't go in one big herd. Once they are spread it can be difficult to get up close to them. This makes it almost impossible to systematically locate and inspect all the sheep. Finding visual illness signs in the sheep can also be seriously difficult. Diagnosing is also something that might require medical knowledge, which we can't expect a general farmer to possess. There is also a general trend of increased productivity and increased farm sizes, which leads to more animals per stockperson [2]. Farmers will need help of tools to keep control of the health and welfare of the increasing size of his livestock.

In order to have an accurate idea of the health of the animals we deem it necessary to use sensors that are able to detect and communicate this information to the farmers. Sensors would be able to follow the individual animal, and control its status at any time of the day. If the farmers then could be warned when their sheep get ill, it could result in getting the sheep help when needed, ensuring fewer deaths, and stronger and quicker growing animals.

Our work is based on data, that is collected and used in an ongoing research project [3]. The aim of the research is to investigate the potential for early detection of Tick Born Fever in sheep. In the project they also attempt to establish baseline values for the diurnal- and seasonal trends of core temperature and heart rate for domestic, free-ranging sheep. They also aimed to estimate the impact of the implantation process on the growth performance of sheep, and the quality of the heart rate measurements.

The study found a difference between the heart rate of adult females and the heart rate of juvenile females and males [3]. The results suggested a slight seasonal effect on the core temperature in the second half of July. The core temperature displayed significant rhythmicity in all lambs. 24-hour circadian rhythms were present in 80.7% of the periods, and 12-hour ultradian rhythms in 9.9% of the periods [3] .

We also see a use of this type of sensor technology outside the field of sheep. There are more farmed animals it could be useful for, such as e.g. cows, who also have a much higher value. This type of technology could also be used on humans, e.g. patients, elderly, infants, and possibly used in popular technology such as training watches. Our goal is to discover more about the temperature of sheep, how it changes, how it is affected, and if it is possible to predict illness based on disturbances in the core temperature of the animals. We will investigate whether it is possible to make this type of software for the sensors, and in that case see whether we can make a general model or if the model would need to be individually fitted.

Chapter 2

Total System

In this thesis we will explore the possibilities of making a system that is able to detect illness in sheep. This is meant to be part of a bigger system that will aid and help farmers to look after their sheep, and to give information about the animals well-being and status. Due to limitations of both time and resources we narrow down the problem which we address and attempt to solve.

2.1 This Subsystem

The part of the entire system we focus on is illness detection. To detect illness we will use sensors measuring the core temperature of the sheep. These measurements will be analyzed to check if the sheep is ill or not. These measurements will be transmitted so that the farmer can be informed of the illness, and be given the opportunity to take appropriate actions. We will only be able to detect illnesses that have an impact on the core temperature of sheep.

We would also like to be able to give a possible prediction of the illness, and to mark the illness' severity. This is because not all illnesses are critical, and they might therefore need to be treated differently.

2.2 Bigger Picture

When the sheep are on free range pastures it experience more dangers than illnesses. It could therefore be useful for the farmers with more information than the health of the sheep. Knowing the position of the sheep can be very important; the pastures are often very large, and aimlessly looking for a specific sheep can be very demanding if not almost impossible. It can be important to be able to locate a specific sheep for several reasons; if it is hurt, ill, has been attacked, etc. It will be important to find this sheep to inspect and/or treat it. Also, when sheep are dead it can be important to find them to find the reason of death.

Predator attacks also kill many grazing sheep each year, so knowing that sheep are attacked can be important so that one can perform preventive measures against more attacks. These measures can be to increase surveillance of the sheep, increase the presence of humans in the area, and/or make the sheep leave the area where these attacks occur.

The sheep will have a radio sender around their neck that collects the relevant information, and at specific time intervals broadcast this information. These signals will be traveling via relays until it reaches an end-station. The data will then be available for the farmer through an interface, giving them an overview of the status of his sheep, and their location.

Chapter 3

State of the Art

3.1 Illnesses Affecting Sheep

As we are trying to detect sheep illness we need to know what illnesses are likely to affect free ranging sheep. We will focus on the illnesses that are relevant to the breed of sheep and the geographical locations we have covered. Useful information about illnesses that are likely to affect sheep in Norway was provided by **Lise Grøva** [4] and **Kristin Sørheim** [5].

Tick born fever (TBF) is one of the illnesses that affect lamb in parts of Norway. This is a very prevalent disease in coastal areas, like Tingvoll. Lamb can also suffer from **listeriosis**, **arthritis**, **pneumonia**, and **poisonings**. For adult sheep, illnesses such as mastitt can also occur, however as all the sheep we have data on are lamb this will not be relevant for us.

Cocciosis is a parasitic disease that occurs mainly in lamb between the age of 1 and 6 months [6], and is usually contracted orally through infected feces. In sheep this disease is caused by the parasite genus Eimeira, which is harboured by other sheep. Lamb, that are previously unexposed to the geuns Eimeira parasite, can develop cocciosis from exposure to large amounts of this parasite [7]. After having suffered the disease, they will become resistant to it in the future, however can still harbour the parasite, infecting other sheep. This disease can often affect a high percentage of the herd, and can be difficult to get rid of, as medicine is needed to be given orally for 3-7 days [7].

Sheep suffering from cocciosis often don't show signs of illness, but generally suffer from reduced food consumption. If the condition worsens the lambs can get diarrhea with streaks of blood. Cocciosos can be a deadly disease, and should be treated at first signs [6] [7], however most sheep survive it.

Pneumonia in sheep comes in different forms, and can cause symptoms such as fever, weight loss, coughing, isolation from the herd, and quick breathing. Acute pneumonia can lead to life-long effects on sheep, such as reduced lung capacity and reduced weight gain, and can in worst case lead to death. Chronic non-progressive pneumonia (CNP) is a form of pneumonia that affects for the most part lambs between 3 and 10 months of age. CNP has few clinical signs and can be difficult to detect [8]. Pneumonia is known to reduce weight gain by up to more than 50 % [9].

Arthritis in sheep affects especially lamb, and can cause fever, depression, less movement, and lessen the appetite leading to lower weight gain. Joints that are affected will often be painful, swollen and warm. Arthritis is caused by bacteria entering the blood stream, often from cuts, but can also accompany TBF. When arthritis accompany TBF, the sheep can suffer from both illnesses at the same time [10].

Bacteria causing **listeriosis** can be found in the soil, and can affect sheep of all ages. Symptoms of listeriosis in sheep can include walking in circles, partial facial paralysis, inability to drink and eat, fever, confusion, and uncoordinated motion [11]. Listeriosis can be transmitted to humans, which can be sever in case of children, elders, and pregnant women [12].

Lamb are also considered to be at greater risk of **hypothermia**. Lamb are more vulnerable to the weather as they have less fat reserves than adult sheep. This makes it more difficult for the lamb to maintain a stable core temperature in especially cold weather [13].

3.2 Effects of Illness on Sheep Core Temperature

The normal temperature range for sheep is [38.5°C – 40°C], however lamb can have a somewhat higher temperature range [14]. Signs of illness in sheep are often deviations from the norm. These deviations can be with regards to the behavior and the values such as the temperature and heart frequency [14].

High temperatures can be observed in cases of infections and severe injuries, however can also occur due to stress, physical activity, and high, environmental temperature [14]. Low temperature in sheep might be due environmentally induced hypothermia. For lamb a low temperature might be an indication that it has received too little milk. Illnesses or other cases that cause low blood circulation will at the same time cause low temperatures. Sheep in the death phase can also have low temperatures [14].

TBF is known to be characterized by a sudden onset of very high fever, with temperatures above 41°C [15]. Pneumonia can be an acute illness that cause high fever temperatures [8], listeriosis cause fever [11], and arthritis can cause fever, normally up to 40.5 °C [10].

As we started to read up on other illnesses, we noted, not surprisingly, that the core temperature often was affected by illness. In one paper, [16], they described how an infection of the Bhanja virus effected sheep. The body temperature of the infected sheep were significantly higher than that of the control specimen, and the temperature rise was visible before other symptoms were visible. However the temperature difference wasn't constant, and varied how much it differed from day to day. This paper also only presented us with one measurement a day, and we can see from the graph that the different animals had different core temperature already from the start, in addition there was a relatively small sample size, so it is difficult to say whether these differences are purely because of the infection or whether individual differences has also played a role. It is also not certain if these results are based on this specific illness, which will not be especially prevalent in our groups of sheep.

Another paper we looked at was investigating the effects of sheep- and goatpox, [17], in both sheep and goats. This paper showed that the body temperature started differentiating from the control animals after 3-4 days after inoculation, and the biggest difference occurred around 6-7 days after which the temperature started to drop.

Sheep-pox is shown to affect the core temperature in sheep [17]. The body temperature of infected sheep start to differ to that of healthy sheep after 3-4 days of inoculation. The biggest difference of the core temperature between infected and healthy animals occurred 6-7 days after inoculation, after which it started to decrease. The infected sheep had elevated temperature compared to the healthy sheep. Mortality in the animals was observed after 7 days, and not all animals survived the experiment. From this we can see that mortality was observed shortly after reaching the maximum core temperature, which means that, in case other illnesses follow the same pattern in regards to temperature difference and mortality, we have to be able to detect differences from the normal quite early in order for our model to be able to save the sheep. Also this decease is not likely to have affected our groups of sheep, and it is not certain that the results can be generalized to be accurate for other deceases, although they do seem to co-align with the other information we have gathered so far.

3.3 Other Effects on Sheep Core Temperature

As well as the differences in body temperature due to illness, we were also interested in which other factors could effect the core temperature of sheep. In [18], they found that the body temperature changed with the season on sheep in tropical climates; in the summer the body temperature was higher than in the winter. The change throughout the year of the environmental temperature was similar to that of the body temperature, however the maximum- and minimum points of the environment was shifted somewhat in relation to the body temperature, suggesting that maybe the light has more impact on the circadian rhythm than the temperature.

These finds are interesting, and something we might have to take into consideration when developing our models. If our models are to change based on the length of day, it will likely need to take the latitude into consideration as well. The phase shift between summer and winter, as seen in the study, was approximately 1.5 hours [18]. This is not a lot, and considering we have data from an 3 month period we might not see a big change. In this study they used one breed of sheep, and only in one location with a specific climate, thus it is difficult to say if these finds would have been the same had one used a different breed in different climate zones and longitudes. Similar changes can also be seen in related species such as alpine ibex [19] and red deer [20]. We might need to take the seasonal changes in consideration later.

The effects of shearing sheep were investigated in another of the papers [21]. In this paper they showed that the shearing had significant effect on the circadian rhythm of the sheared sheep, that lasted for at least a month. They discussed the change in temperature most likely was an adaptation to the new circumstances as the sheared animals no longer had their fleece that insulated them, however the stress of having been sheared might also have had some influence, at least in the first hours or days after shearing. These finds are interesting as it shows that outer conditions can influence the core temperature in sheep. However we are unsure whether this will be relevant for our study as our sheep are not shared before going to the pasture.

Starvation was also found in another paper [22] to lower the core temperature. This was tested in both goats and sheep, and although they had some difference in the reaction to starvation, both animals got a lower core temperature. While we would expect the sheep that are grazing to always have enough food, some illnesses might make the sheep eat less, as seen in Chapter 3.1, and starvation symptoms might occur because of that.

3.4 Other Findings of Effects on Core Temperature of Illness

A paper, [23], we found quite interesting looked at the change of body temperature before minor illnesses in (human) infants. They were able to see differences from the normal core temperature during night up to 7 days before other symptoms were visible, and the biggest difference was 3 days prior. The abnormal temperatures were usually within the normal temperature range, however it didn't fit the pattern of temperature oscillation. We find this very interesting as it might tell us that illnesses can be (at least in some cases) detected by temperature oscillation abnormalities before other symptoms are visible, even when the temperature isn't high enough to be categorized as fever [23]. It was also mentioned that before sudden-infant-death, similar changes had been observed. How useful this paper will be for us is debatable as this concerns human infants, and not sheep. However as the circadian rhythm is present in all animals it is not unimaginable that similar reactions to illnesses are present in different species.

Poisonings can have severe effects on animals, and possibly lead to death. Some cases of poisonings can lead to the animal not eating and being inactive [24], not eating/starvation can induce hypothermia in sheep [22]. Severe poisonings have also been showed to cause hypothermia in both people and animals, even in conditions where development of hypothermia would be unlikely [25] [26]. In humans we know that different poisonings have different effect on the core temperature. While some poisonings cause hypothermia, some cause fever [27]. Similar effects might be present in sheep.

3.5 Existing Digital Tools for Looking after Sheep

While we don't expect to end up with a finished product, it can be useful to see what tools are already in place to help the farmers to look after their sheep while they are on pasture. This can also serve as inspiration for which technologies we might pair the illness detection with.

We found two products, that are rather similar, that offer the farmers help in the form of GPS-tracking. These products are Findmy [28] and Telespor [29]. Both these products use GPS senders that are mounted around the neck of the sheep, and send information about the individuals location at a specified and adjustable time interval, for example once a day. These products also offer additional features like alarms that notifies the farmer in case an individual has been moving too little and/or is going towards boundaries that are digitally set.

These products can be very helpful for the farmers as it can help locating the sheep, and the added functionalities of the alarms can give some rudimentary surveillance of the sheep. The location becomes especially useful at the end of the grazing season, when the sheep are going to be retrieved from the pastures.

While these products can be of great help, they have some limitations. The sampling frequents is low, at most a few readings a day, which makes it difficult to pinpoint the exact position of the animal at all times. While the frequency is changeable, an increased frequency comes at the cost of lowered battery life, which can result in the need of changing batteries through the grazing season. The senders and the equipment that is needed is costly, especially considering that sheep are not of great value, so only a minority of the sheep will be equipped with the senders.

Chapter 4

Data

The data we used for our analysis, was provided by the Norwegian Institute of Bioeconomy Research (NIBIO), and contained about 4.3 million records. The temperature was recorded once every minute for each of the sheep throughout a period, in which the sheep were grazing. There were some variations when the period started and ended, but generally the period was from the first half of June until the first half of September.

4.1 Study Animals

The data was collected from selected lamb in two different herds. The specie was Norwegian White Sheep (NWS)[3], and the two herds were located at Tingvoll (62.9861 N, 8.2482 E), and Tynset (62.3169 N, 10.9534 E). Tingvoll is a coastal area, while Tynset is an inland mountain area, thus the climate and conditions are somewhat different. Another difference between the locations is that Tingvoll has a high incidence of tick-born fever, while Tynset has no incidences of this illness [30].

There were surgically implanted temperature and heart rate sensors in the sheep. However, as we only look at temperature in this thesis, we will only be discussing the data collected by the temperature sensors.

The temperature sensor (Centi-T version 14, Star Oddi, Gardabaer Iceland) was sterilized by using a 12 hour gas sterilizer that used propylene gas, and then surgically implanted [3]. The sensors were retrieved at slaughter. The herd at Tingvoll had the sensors implanted at a mean age of 49 days, while for the herd at Tynset the mean age was 51 days. The sex distribution was 11 females and 9 males at Tingvoll, and 8 females and 12 males at Tynset [3].

At slaughter not all sensors were found. From the Tingvoll herd 17 out of 20 sensors were found, and from the Tynset herd 15 of 20 sensors were found. The mean age at slaughter were 136 and 144 days respectively for the Tingvoll and Tynset herds. The data was retrieved from the sensors using a communication box and the Mercury software 4.5 (Star Oddi, Gardabaer Iceland) [3].

4.2 Follow-up of the Test Animals

After the insertion of the sensors, the lamb were kept for observation and looked after. The herd at Tingvoll was first kept in a barn for two days post-operation, and then kept in a fenced pasture for 4 more days. During this period the sheep were clinically examined morning and evening. After these six days, the lamb were collected and examined. If the lamb showed signs of TBF, they were treated with antibiotics. The same procedure was repeated fifteen days post-operation. The lambs were observed every morning and evening until they were moved to a summer range pasture, where they stayed until the end of August. During the time the lamb were at the summer pasture, they were observed 2-3 times a week [3].

The herd at Tynset was kept in a fenced pasture until they were released on the free-range pasture. During the initial, post-operation period, they were looked after twice a day, and were given antibiotics to prevent inflammation in the surgery wounds [3].

4.3 Structure of Data Set

The data set that was provided consisted of records of the temperature. Each record had information of the ID of the sheep, its gender, the time of recording, date of birth, herd, and the ID of its mother. This is quite a lot of information, and gives us the ability to analyze the temperature in regards to several different variables, and thus we might be able to discover dependencies that can be crucial in order to make an accurate model.

4.4 Evaluation of Data Set

Our data set is quite big and contains a lot of measured temperatures. It also contains information that allows us to analyze on attributes, such as age, gender, location, etc., which is very positive. However we think this data set is still too small to give any definitive conclusions as the number of animals is only 31, data is only collected from 2 herds/locations, and we only have data from lamb and not fully grown sheep.

In an ideal world we would have had access to more data, however this would demand more time for analysis, and possibly more computing power than we have available. We think, despite our objections, that the data set is big enough to at least give a picture of the situation, and give us some valuable information about the nature of temperature in lambs and how illness affects it.

Chapter 5

Analysis

We analyze the data set to find evidence supporting or contradicting the information we have found. Through analysis we want to find dependencies and factors that influence the temperature and circadian rhythm of the sheep. In order to make an effective model for predicting illness in sheep, based on temperature alone, we need to know what to look for, and what would be considered normal and abnormal.

5.1 Tools and Methods used for Analysis

In our analyses we use Python[31] as a tool for modifying, extracting and analyzing the data. For visualization of the results we use the plugin PyPlot[32]. We use these tools during the analysis as they offer good support for our intended analyses, and because we are already familiar with the use of these tools.

Our analyses are for the most part directed towards the circadian rhythm, and changes/differences in this. As we want to find a general solution that will fit all sheep, our analyses often revolve around group differences, and trying to define what is a normal pattern. Our analyses do however also include more individualistic and long-term analyses.

5.2 Initial Experimental Analysis

Our first analyses must be seen as experimental as we were still trying to find out how we were to analyze the data, and what we were trying to find. In this early period of analysis we were also still getting to know the data. Nevertheless some of our results seem to be of importance, especially as they made the foundation of our later analyses.

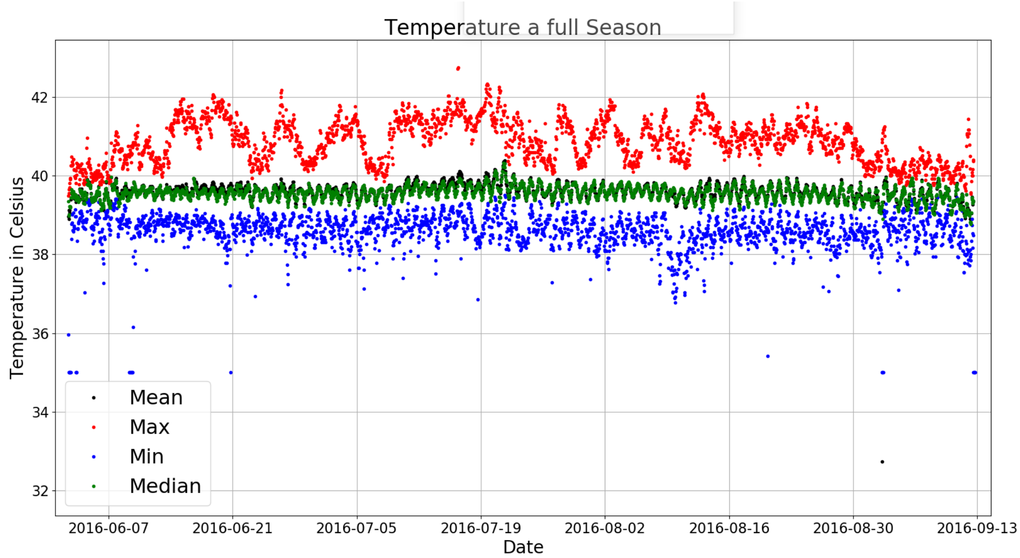

Figure 5.1: Changes of body temperature throughout season

This figure plot the maximum, median, mean, and minimum temperatures of all the sheep throughout the season.

5.2.1 Entire Season

In Figure 5.1 we have plotted maximum, minimum, mean and median values from the data from all the sheep for the entire period we have measurements. As we can see from this the maximum and minimum measurements each day vary a lot, however the mean and median temperatures seem more stable. The minimum temperatures sometimes go so low that they are not even in the plot, and the maximum temperatures are also very high. We also see that there are a lot of these very high and low values, implying that there are lots of outliers in our data set. Something we think is very interesting is how the variance in temperature is much lower at the beginning and at the end of the measured period. Our assumption is that the procedure of inserting the sensors has affected the sheep in the first days after the insertion. We know that the sheep were retrieved from pasture, and eventually slaughtered at the end of the period, something that also likely have affected their temperature. We know from earlier that the circadian rhythm and the core temperature can be affected by shearing, see Chapter 3.3. In the beginning of the depicted period, we only have data from the herd at Tingvoll, while at the end we only have data from the Tynset herd. This might have had an effect.

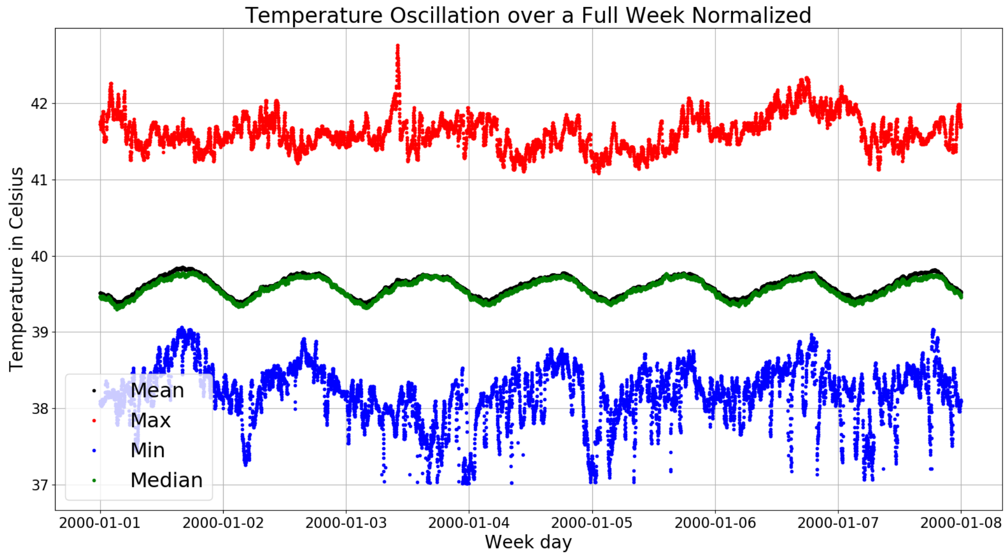

Figure 5.2: Temperature changes through week

This depicts a "typical" week for all individuals. It shows the maximum, median, mean, and minimum temperatures of the week.

5.2.2 Weekly Temperature Oscillation

We also analyzed how the temperature oscillated through a typical week, the results of which is depicted in Figure 5.2. In this analysis we put all the records from the entire period into a time frame of one week, preserving the original time of each record.

The temperature oscillation through the week seems quite stable, and follows a clear pattern, with the daily maximum being recorded during the day, and the daily minimum during the night. This strongly indicates that the circadian rhythm is both present and stable in the lambs. The problem with this analysis where we have combined data from different periods and individuals, is that the pattern we have is only an average. This might not fit the individuals patterns if they seem to differ to a large degree. This analysis will neither take the possible development in the circadian rhythm over time into account.

5.2.3 Abnormalities in Data

As we started to look at the temporal history of the individual lamb, we noticed that there were several periods that differed significantly from what could be described as a normal temperature. We also noticed that the tem-

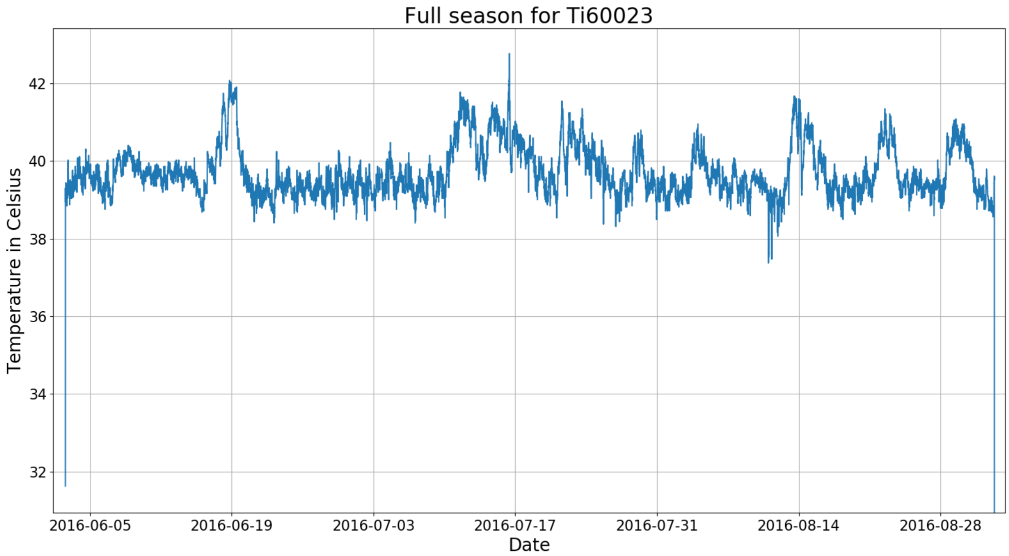

Figure 5.3: All temperature data of Ti60023 through the season

This is temporal data for the individual Ti60023. It shows how the temperature has changed throughout the season

perature the first 2 weeks at the beginning and last 2 weeks at the end of the measured period were quite low for all lamb. This is might be due to the sensor being implanted, and the lamb getting slaughtered. Figure 5.3 illustrates this, where we show the temporal history of the individual Ti60023 through the season. We see from this that the temperature has been in periods significantly elevated in rather large parts of the measured time period. If we want to define a normal daily oscillation, these abnormalities can undermine our results as they are present to such a large degree.

In order not to let abnormal records, of which we know there are many, affect our data, we decided to created a new data set. The new data set would be based on the existing one, and differ by removing the abnormal periods. We selected these periods based on simple visual analysis. We have depicted the mean and average temperature through a day, based on all the data, for both the data sets in Figure 5.4.

When using the full data set we can see from the figure that the mean value is too much affected by the outliers to be a good representation of a normal day, the median value is more robust against these outliers, so it gives a better representation we will therefore used the median value of analysis on the full data set. When comparing the mean and median value of the data set without abnormal periods, we see that there is not so much difference.

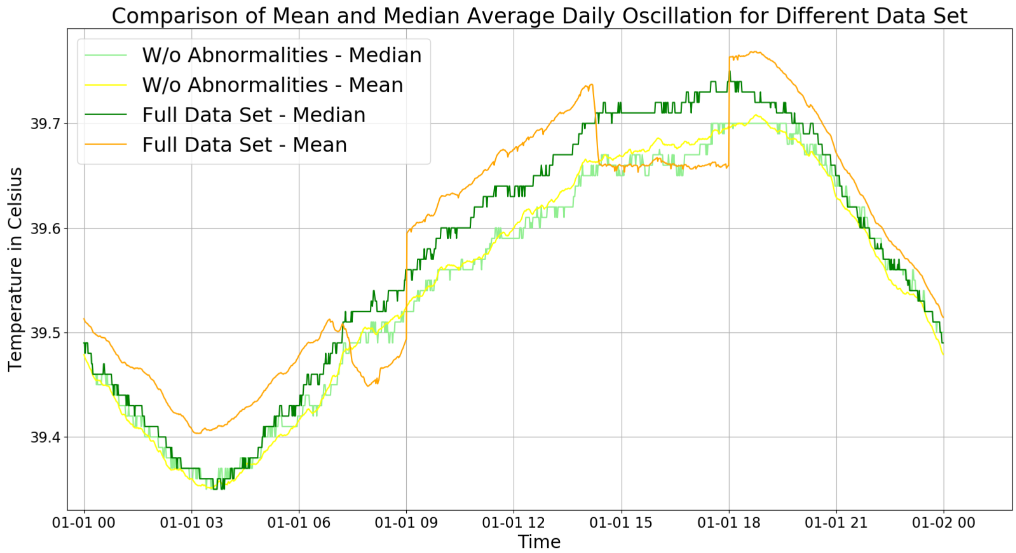

Figure 5.4: Comparison of mean and median temperature through day

This figure compares the average daily oscillation by using the mean values or the median values for both the full data set and the data set in which all abnormal periods are removed.

Here we chose to continue with using the mean value as it seems to give a smoother curve.

5.2.4 Individual Differences

In Figure 5.5 we have depicted an average daily oscillation of all the individual lambs. As we have data from 31 lambs, we decided to depict the curves in several plots, as plotting all 31 curves in a single plot would be very difficult to read. We can't see anything in great detail in this figure, however we are able to see that the average day for the different individuals vary greatly. Between some of the individuals the temperature varies by half a degree, which is quite significant. We can also by this figure see that the amount of oscillation and the nature of the curve is different from individual to individual. These big individual differences might mean that in order to efficiently and accurately detect illness in sheep, we might have to fit the prediction algorithm to each individual. These changes might also be caused by other factors. Some individuals were more sick than others, so this might have affected the results of the analysis greatly.

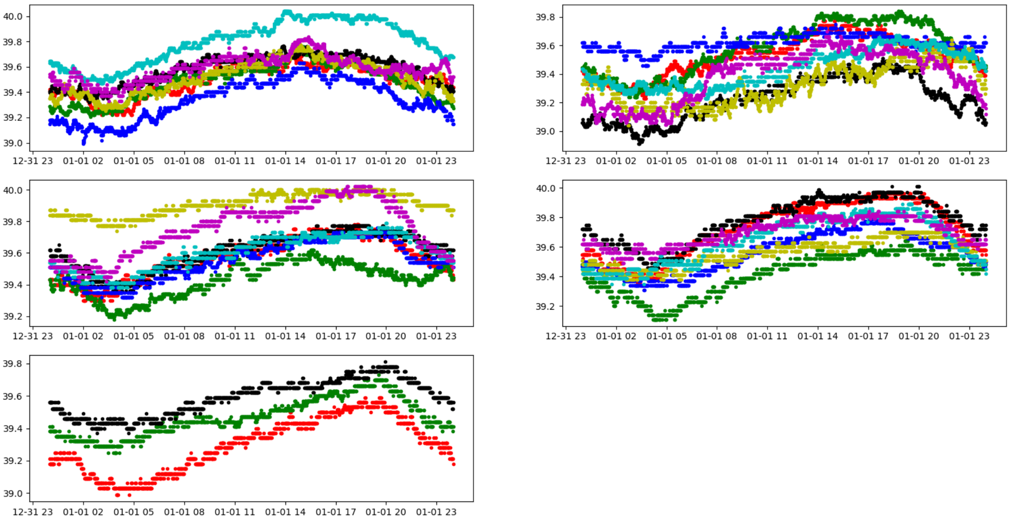

Figure 5.5: Comparison of an average day for all individuals

The average daily oscillation for each individual. This illustrates how great the individual difference is.

5.2.5 Average Core Temperatures

We computed the mean temperature by using the data set where the abnormal periods are removed. The mean temperature for all lamb was 39.52°C with a standard deviation of 0.17°C. The mean standard deviation for the individuals average temperature is 0.3°C, implying some variation is normal as seen in Figure 5.4. However, in Figure 5.4 we see that the difference between the maximum and the minimum is approximately 0.35°C. This difference gives a variation from the average temperature of approximately half that of the mean standard deviation. We can therefore expect there to be larger differences than what we see for the average temperature curves.

We did also calculate the mean temperature for both herds and discovered a rather large difference. The Tynset herd had a mean temperature of 39.6°C with a standard deviation of 0.17°C and a mean standard deviation from the individuals average temperature of 0.25°C. The Tingvoll herd had a mean temperature of 39.46°C with a standard deviation of 0.13°C and a mean standard deviation from the individuals average temperature of 0.34°C.

The mean temperatures differ significantly between the herds. A possible explanation is that they have been exposed to illnesses at a different rate as discussed in Chapter 3.1. Interestingly we see that while the Tynset herd has standard deviation from the mean temperature, the individuals standard deviation from its mean temperature is lower than for the Tingvoll herd.

When comparing results for the two herds, we must take into consideration that the amount of illness was likely different for the herds, see Chapter 3.1, and we might therefore have less data for one of the herd as abnormal periods had been removed.

5.3 Age Group Based Analyses

We analyzed the data to see if there was changes in the temperature and circadian rhythm as the lamb grew and got older. As the lamb grow they get fattier and bigger[13], something which might have had an affect on the core temperature and its oscillation. The nature of the fleece also changes a bit, which is another possible cause for change.

5.3.1 Average Temperature for Age Groups

We divided the temperature records into age groups, of the size of one week, and measured the average for these. This way we wanted to see if the temperature generally changed through the season, and the results of this analysis can be seen in Figure 5.6. Throughout the season there is little change in the average temperature, with the exception of the very beginning and end of the period, where the temperature is elevated. The difference of the start and end of the period to the rest of the period, might be explained by what happened in both these periods. During the start it is likely that the temperature has been elevated due to light infections, and other causes related to the operation, while the elevation at the end is probably due to stress and other causes related to retrieval from pasture, shearing, transport, handling, and eventually slaughter.

There might be fewer individuals in the youngest and oldest age groups as the lamb were born on different days. A smaller sample size at the ends of the age spectrum could have influenced these results.

5.3.2 Daily Oscillation in Age Groups

Possible change in the daily oscillation of the core temperature was also something of great interested to us. We analyzed to look for signs of changes in our data set. We sorted the temperature records in age groups, that were 3 weeks long, and compared their daily oscillation. Part of the reason to now use larger age groups was to get more data forming the foundation for each group, and to easier compare the groups. Results of this analysis can be seen

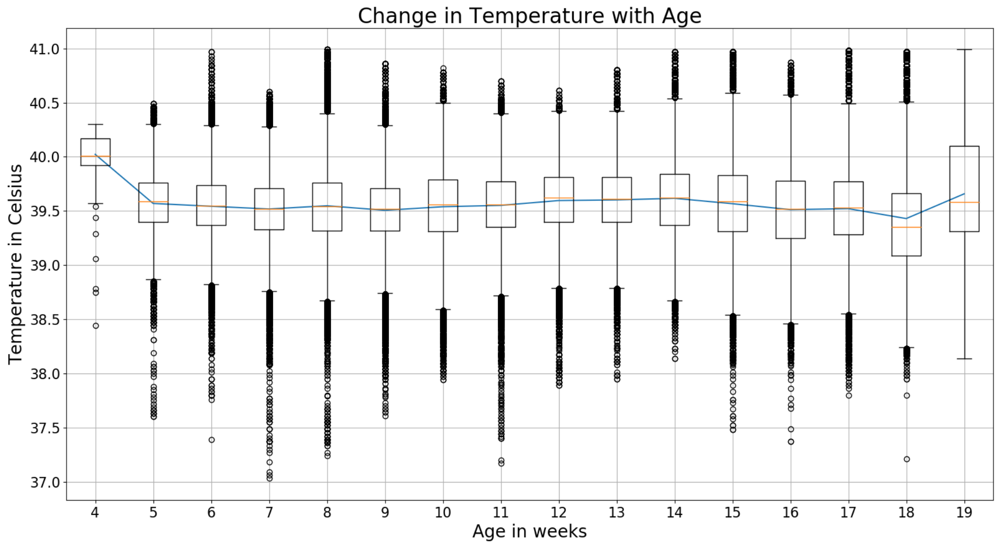

Figure 5.6: Average temperature based on age

The plot shows the average temperature for each week of age, excluding all temperatures above 41°C, or below 37°C. Temporal data from all individuals from both herds are included.

in Figure 5.7. We calculated the average of one hour intervals through the day, and left out values that were over 41.0°C or under 37°C.

Younger age groups have a lower amplitude than older groups, indicating a change in the amplitude over time. The change in amplitude will not by itself create a change in the average temperature, so this result is consistent with our previous discoveries. The oscillation seem to become smoother with age.

We notice in our results a clear change in the phase of the oscillation, where young lambs reach their maximum and minimum temperature later in the day than the older sheep. This change, especially regarding the maximum, is interesting, as the phase seems to be shifted approximately 5 hours. While we see a change as the lamb age, it is not certain whether this is a causality or a correlation. The lamb are born in a relatively short time frame, so the changes we see over time could very well simply be caused by seasonal variance that happen to correlate with the aging in our case.

During the year, it is normal that the temperature changes, most likely due to the change of length of day [18]. However seasonal change was found to be around 1.5 hours between winter and summer, which is much less than the change we observe. It could be that the seasonal change in sheep in

Norway are different, due to different lighting and climate conditions. The seasonal change of length of day is much greater in Norway than it is in a tropical environment as seen in the paper, [18].

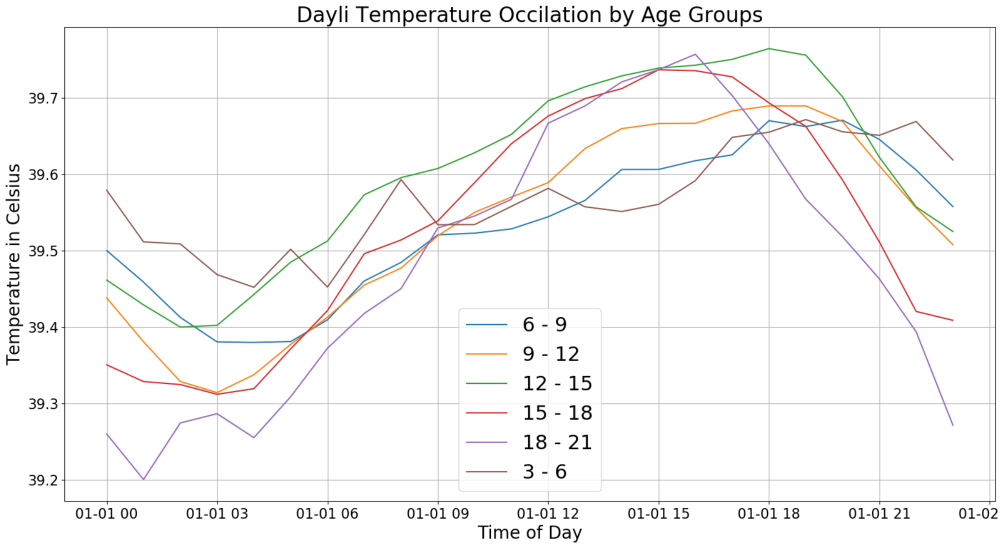

Figure 5.7: Comparison of daily oscillation differences based on age groups

The average daily temperature oscillation for different age groups of lamb. The average temperature was measured per hour, and only temporal data in the range of [37°C - 41°C] were used in the analysis.

5.3.3 Differences of Average Temperature Change between the Herds

In Figures 5.8 and 5.9 we have depicted how the average temperature changes for the different herds through out the season. While we didn't find this type of plot as shown in Figure 5.6 very helpful, however we see here that there are some differences between the herds. Most notably there are differences at both ends of the periods; in the start the herd at Tynset, see Figure 5.9, has an elevated average temperature, while the average temperature of the herd at Tingvoll, see Figure 5.8, seems normal. At the end of the period the average temperature of the herd at Tingvoll increases, while the average temperature of the herd at Tynset decreases. We find these differences rather puzzling.

The difference that we see at the ends of the measured periods is the most puzzling; both herds experience a change in the average temperature, but the

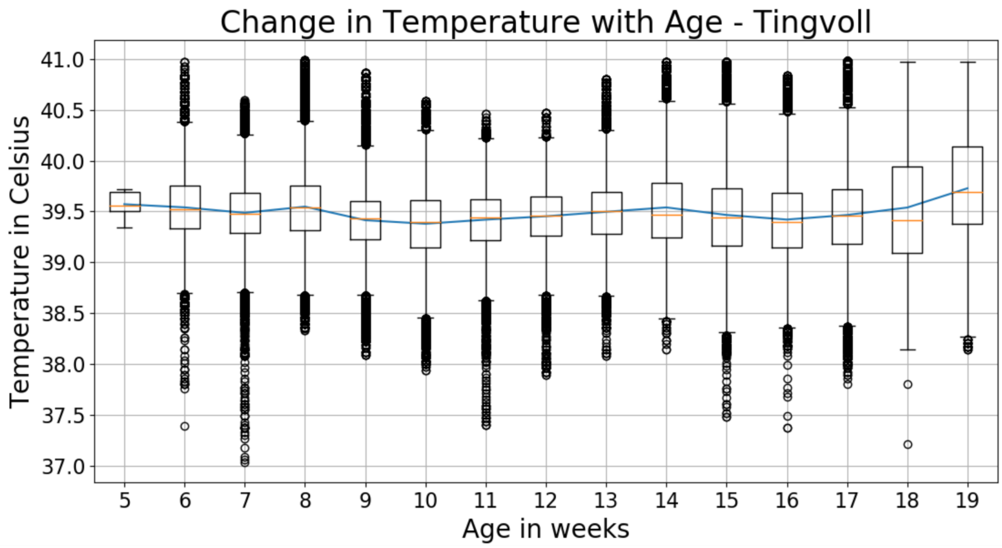

Figure 5.8: Average temperature based on age - Tingvoll

The average temperature per week of age for the herd at Tingvoll. Only temporal data in the range of [37°C - 41°C] were used in the analysis.

changes are opposite of each other. Maybe this could be caused by different handling before slaughter and different pre-slaughter conditions? We know that the herd at Tynset was slaughtered in a large scale facility, while the herd at Tingvoll was slaughtered in a small scale slaughterhouse.

From both figures we see that there are relatively few data points at the youngest and oldest age groups. This suggest comparably little data for these periods, making them less reliable and individual differences and outliers have greater impact.

5.3.4 Differences of Changes of Daily Oscillation between the Herds

We did also plot the changes of the daily temperature oscillation for both the herds, the results of which can be seen in figures 5.10 and 5.11. In these plots we have shown the average temperature for 1-hour intervals through a day for each of the age groups of each of the herds. We did not include temperatures that were over 41°C or under 37°C.

Straight away we can see that there are clear differences in the change of the daily oscillation between the herds, and we also see that these plots doesn't resemble the change for both herds combined as shown in Figure 5.7. We don't see the steady phase shift and change in amplitude in Figure 5.10

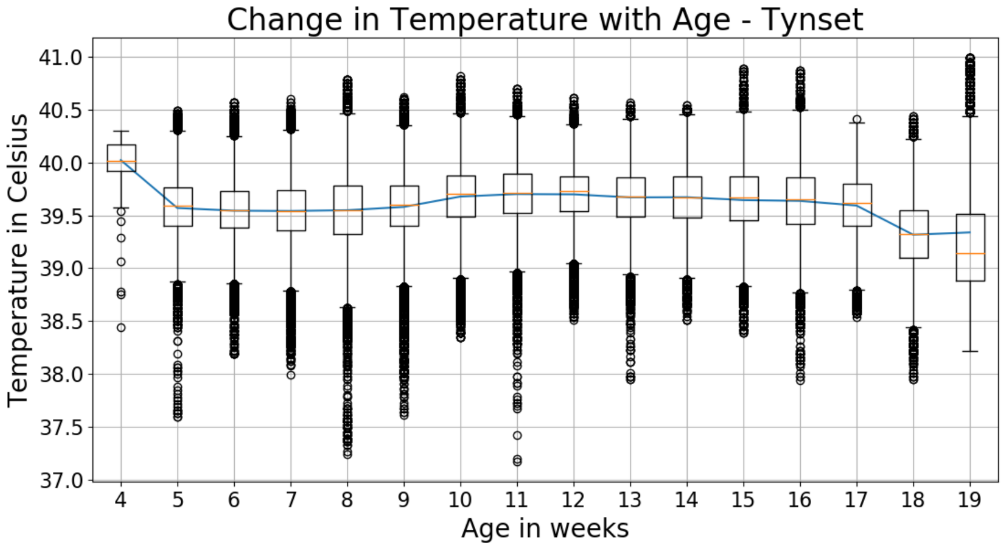

Figure 5.9: Average temperature based on age - Tynset

The average temperature per week of age for the herd at Tynset. Only temporal data in the range of [37°C - 41°C] were used in the analysis.

and 5.11 as we do in Figure 5.7.

We do see change in the amplitude for the herd at Tingvoll, see Figure 5.10; with age the amplitude increases, which coincides with the results for the analyses in figure 5.7. However, it doesn't change as much for most of the age groups. There is some change in the phase, however not as much as we have previously seen, and it seems to stabilize already after 9 weeks of age. We also see that the oldest age group is the one that differs the most from the others, and the temperatures here are quite high; at the maximum the average temperature is 39.9°C. This is reflected in the results we see in figure 5.8 where the average temperature in the last weeks are higher than normal. We can therefore consider it likely that the curve we see for the age group "18-21" is abnormal, and that it has been influenced by outer factors as we have previously discussed regarding gathering the sheep from the pastures, shearing and eventually slaughter. In Figure 5.8 we see that there are no lamb over the age of 19 weeks, telling us that there are few data points in this age group.

In the results for the herd at Tynset, see Figure 5.11, we also see that it is the last age group that differs the most from the others. Here the temperatures in the last age group is much lower than the other, and also in this herd this coincides with the average temperature in the last weeks, however we think it is strange that the temperature drops for one of the herds while it increases for the other. As we discussed in Chapter 5.3.3, there are less data at both ends of the age spectrum, making the results for these ages less reliable. Similarily to the Tingvoll herd there are no lamb in the Tynset herd above the age of 19 weeks, as cen be seen in Figure 5.9.

For the herd at Tynset we do also see a slight phase shift, however unlike the herd at Tingvoll it doesn't change as early, and for the majority of the periods it remains un-shifted. If we compare the two herds we see that in the age group "15-18", the temperature has a similar range $[39.2°C - 39.7°C]$ for the herd at Tingvoll and $[39.4°C - 39.8°C]$ for the herd at Tynset. The same age group has it's peak at slightly different times, approximately 15.00 for the herd at Tingvoll and 17.00 for the herd at Tynset, which is a difference of 2 hours. This difference indicates that age alone is not responsible for the phase and temperature change in the circadian rhythm, but that it is affected by other factors as well.

5.3.5 Differences between the Herds During Same Time Periods

As previously discussed it is assumed that the amount of daylight plays a bigger part in the seasonal change in the circadian rhythm than the environmental temperature [18]. The herd at Tynset was younger than the herd at Tingvoll, however the amount of recorded time, and age of insertion were approximately the same. This would lead the age groups of the herd at Tynset to be shifted later than the same age group of the herd at Tynset. As most of our records are from after summer solstice, a certain age group of the herd at Tingvoll would for the most part have longer days than that of the same age group at Tynset. Thus when we compare the circadian rhythms of the different herds we would expect the herd at Tynset to reach its maximum temperature earlier than the herd at Tingvoll, however we see the opposite happening. Does this mean that the amount of daylight is irrelevant for the circadian rhythm, or are other factors simply more important or more pronounced in our data?

We have previously shown that there are quite a lot of individual differences, and in this analysis we are splitting our data into two groups, consisting approximately of 15 sheep in each, we then break down the data into even smaller groups based on the age. What's more is that there are large amounts of abnormal temperature records, that we remove so that the abnormalities doesn't influence the results too much, resulting in even less amount of data for the analysis. We must therefore ask ourselves if the data we use for these analyses are sufficient, and whether or not the data set is big enough to hide

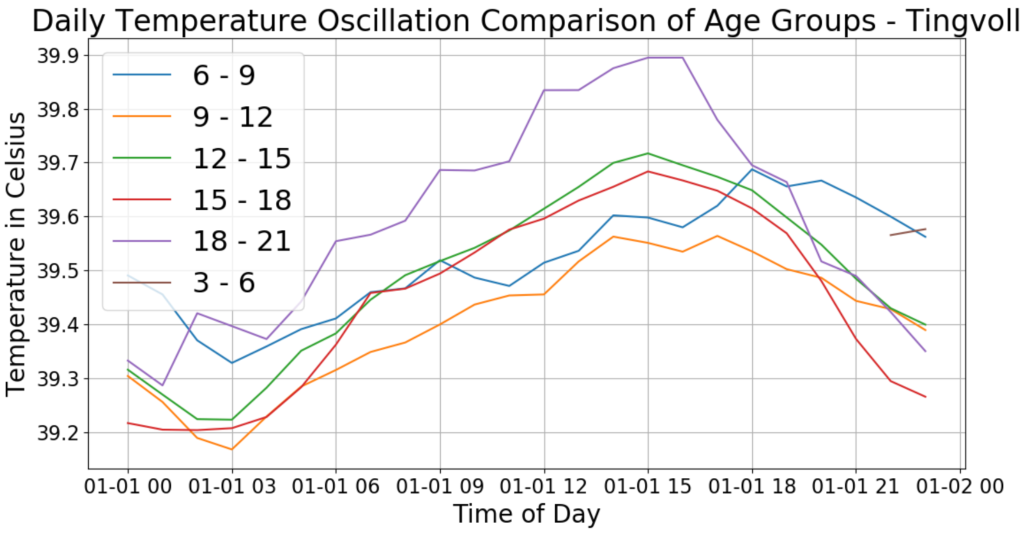

Figure 5.10: Differences in daily temperature oscillation between different age groups - Tingvoll

The average daily temperature oscillation for different age groups of lambs at Tingvoll. The average temperature was measured per hour. The abnormal periods were removed.

the individual differences.

To easier compare the change and the temperature oscillation between the herds, we selected two time periods, in which we measured the average daily oscillation for each of the herds, and plotted them together. The results can be seen in Figure 5.12. In this analysis we tried to choose time periods that were far apart in order to maximize the potential change, and at the same time we tried to avoid the periods we had seen giving abnormal temperatures, which were visible for both herds at the ends of the collection of data. For this analysis we used the data set without abnormal periods. We decided not to use the full data set because we didn't want the results to be affected by abnormalities, although this comes at the cost of less data for our analyses which is unfortunate considering the already relatively small sample size.

In the results from this analysis we see that the different curves show more similarities with the other curve of the same herd than any of the curves for the other herd. We do also see some changes in both the herds with time, however this change is slight. Strangely the amplitude of the herd at Tynset seems to decrease rather than to increase as we would have expected based on our previous analyses. We find this rather strange. Because of this we decided to do the same analysis, but this time we would use the entire data

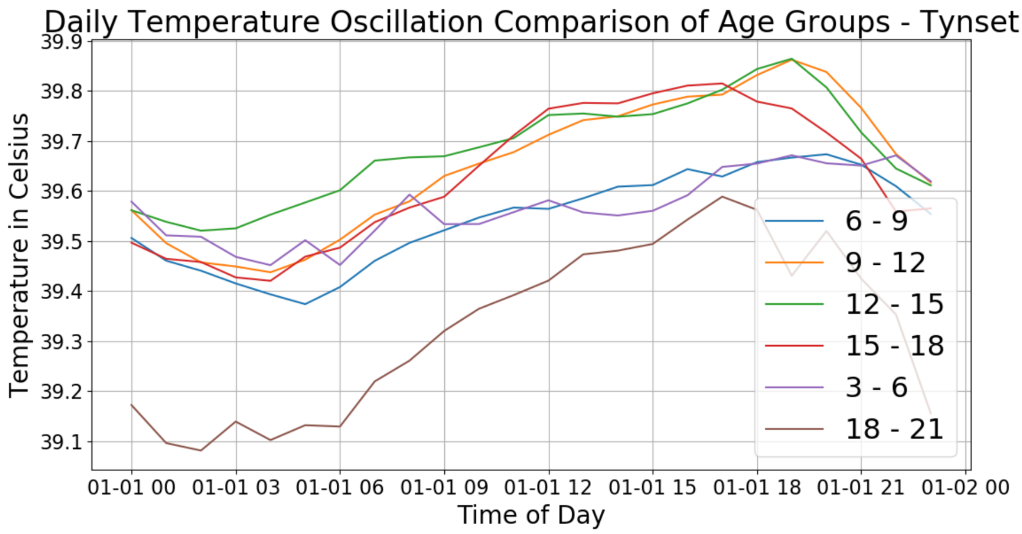

Figure 5.11: Differences in daily temperature oscillation between different age groups - Tynset

The average daily temperature oscillation for different age groups of lambs at Tynset. The average temperature was measured per hour. The abnormal periods were removed.

set including the abnormalities. The results can be seen in Figure 5.13.

In this new analyses we see that the different time periods for the same herd are now more similar to each other than they were previously. We also see that the lowered amplitude in the herd at Tynset seems to have disappeared, we therefore think that by removing all the abnormal periods, we probably removed too much data for that time period for the herd at Tynset.

We see in both Figure 5.12 and 5.13 the phase is changed for both herds; for the herd at Tingvoll the maximum is shifted to a bit later in the day, however this is hard to see as the top of the curve for the latest period for the herd at Tingvoll is quite flat. For the herd at Tynset the change is opposite; the maximum is shifted a bit earlier, approximately an hour. The minimum for both the herds in both the analyses seems not to change at all, which is interesting. This leads us to think that while the circadian rhythm has a period of 24 hours, it doesn't follow that the temperature rises and falls for an equal amount of time. So that if we imagine the rising period to be the day and the falling period to be the night, day and night isn't of equal length and does vary with time.

It is very difficult to draw conclusions based on these age based analyses

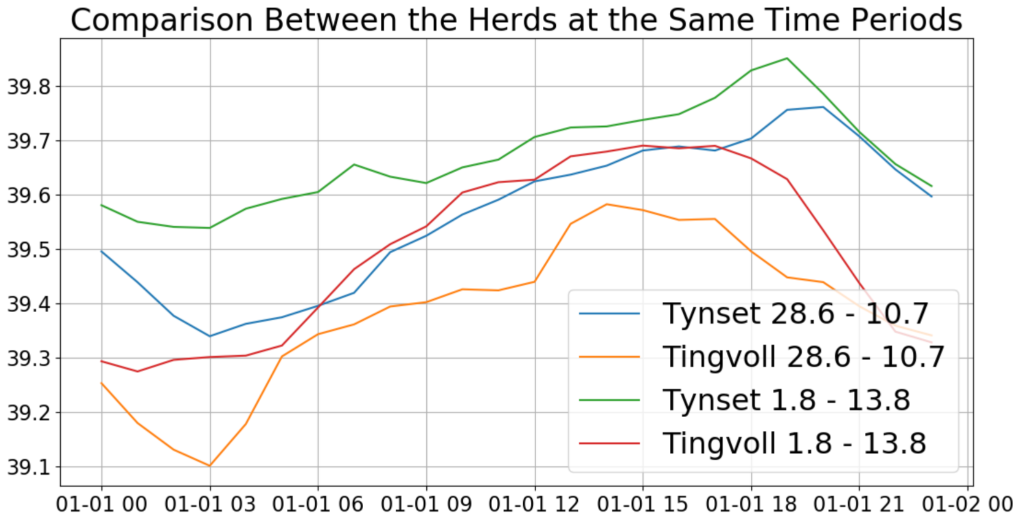

Figure 5.12: Comparison of average daily oscillation between the herds during same intervals

Comparison of average daily oscillation for both the herds over two different time periods. Data sets used do not include abnormal periods.

both due to the small sample set, but also as the results are ambiguous and sometimes contradict each other. However, the fact that the different herds had quite different profiles during the same time periods, and in areas with very similar amount of daylight, leads us to think that while the amount of daylight do influence the circadian rhythm, there are also other important factors. It is hard to say how much of these changes are due to age, if anything at all, as the aging of the sheep coincides with the change in season. There might be other factors that also change with time, such as availability and quality of food, downfall, and so on. Although we do see a change with age here, we cannot be sure if this is caused by or coincides with age.

5.4 Gender Based Analyses

We thought that it might be interesting to see if there is any differences based in the gender of the lambs. We therefore made a graph showing the differences through out an average day. We have the results depicted in Figure 5.14, here we have used both the full data set, and the data set where the abnormalities are removed. From the graph we can see that for the full data set there are some differences; the female lambs have a lower

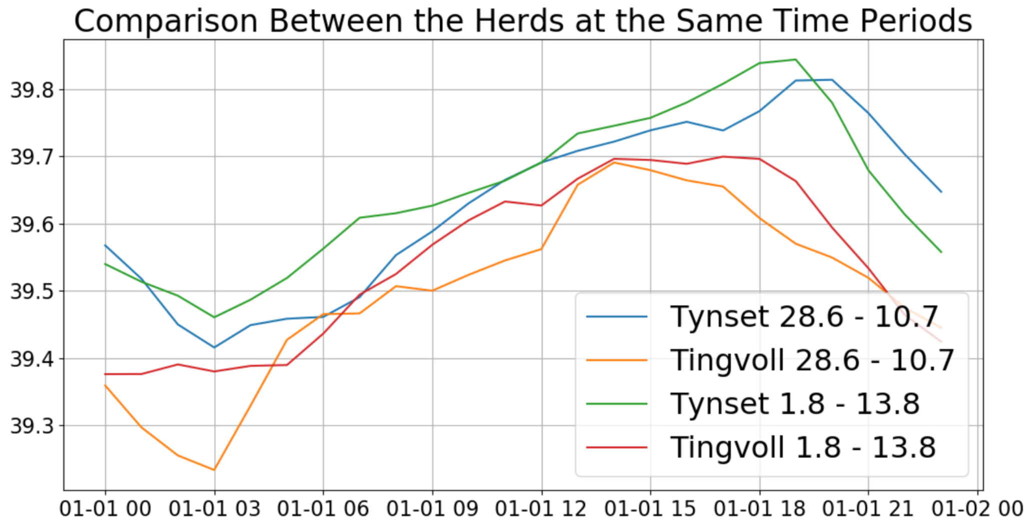

Figure 5.13: Comparison of average daily oscillation between the Herds during same intervals with abnormal values

Comparison of average daily oscillation for both the herds over two different time periods. The full data set is used.

amplitude than the male lambs, however when we remove the abnormalities this difference almost disappears. After removing the abnormalities we can still see some difference in the low point. The male lambs have, during the night, a lower temperature than the female labs, however this difference is approximately 0.05°C. As we have in total data from 31 lambs, where about half were female and the other half naturally were male, we are fortunate that both sides are approximately evenly represented. However we don't have enough data to be able to definitively state that there in fact are differences between the genders. As we have earlier stated, the individual difference is quite big, so such a small difference is well within the natural individual variance.

5.5 Analyzes Based on Herds

Analysis on differences in the daily oscillation specifically on the two groups, without regarding age, were also performed. We wanted to see if there were any significant changes from one herd to another, not taking age into consideration, as they were exposed to a different climate, surroundings, and most likely faced different illnesses. The results from this analysis can be seen in Figure 5.15 where we have compared the results with the full data set and

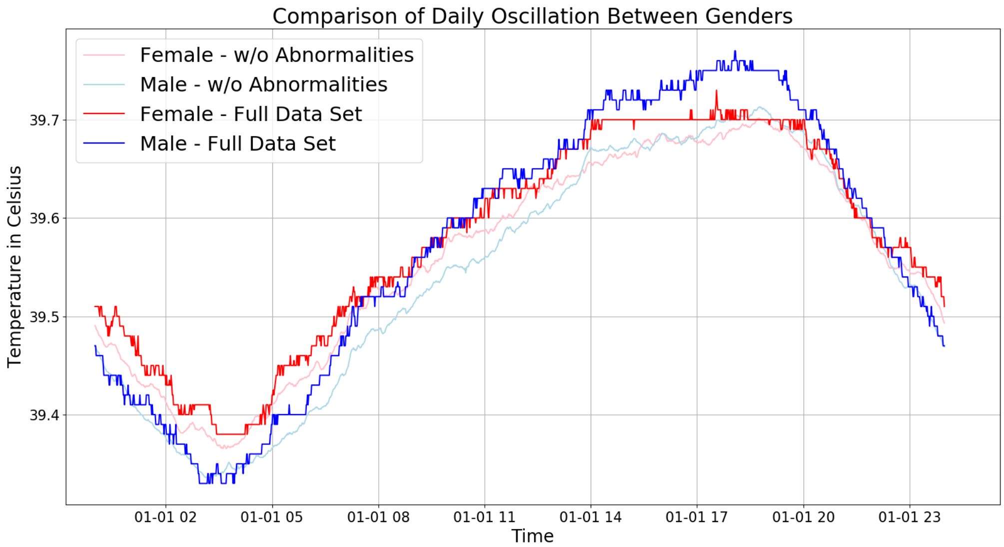

Figure 5.14: Comparison of gender differences based on different data sets

Comparison of the average daily oscillations between the genders. Comparison with both the full data set and the data set without abnormal periods. For the full data set median values are used, while for the data set without abnormalities mean values are used.

the data set where we had removed the abnormalities. We do see in these results a quite significant difference between the herds both when using the full data set and when using the data set where we had removed the abnormalities. The herd that was on Tynset had a higher temperature through out the day than the herd at Tingvoll. Whats more is that the herds have a different phase; compared to the phase of the herd at Tingvoll, the herd at Tynset have a phase that is shifted significantly forward. These results was also seen in Chapter 5.3.2.

It might be outer factors of these locations that have affected the herds into having both different temperatures and phases, or maybe this is just a result of individual variances. We know that the lambs at Tingvoll had the sensors inserted around 2 weeks before the herd at Tynset, this was because the lambs had been born at different dates, so they were approximately the same age at insertion of the sensors. This shift can have caused these herds to differ at least in the phase; we have read [18], and discussed that the change in phase might be due to differences in the length of the day. In this case the herd at Tynset would have gotten the sensors implanted just before summer solstice, while the herd at Tingvoll would have already been measuring more data before summer solstice. Thus this difference in the phase might be caused by a difference in the period that was measured. We also know that both herds were measured for about the same amount of time, however it might be that measuring 2 weeks at the beginning of June and 2 weeks in the beginning of September will give different records.

What is more puzzling is the difference in temperature; it is quite significant, and is constant through out the day. The question is whether this is caused by the same factors we have discussed that might have caused the difference in the phase, or if this is caused by something else. In the comparison of the different age groups we did see a clear difference in the phase, however the difference in temperature was nowhere near what we see here. This leads us to think that there are other factors that are to blame for the temperature difference, and that this is, at least to a degree, a separate issue. It might also be that this temperature difference is caused by individual differences as the difference in temperature we can see here is less than the difference we saw between individuals. Given the relative small sample size of each location we cannot rule out that individual differences has caused the average measurements to be different between the herds.

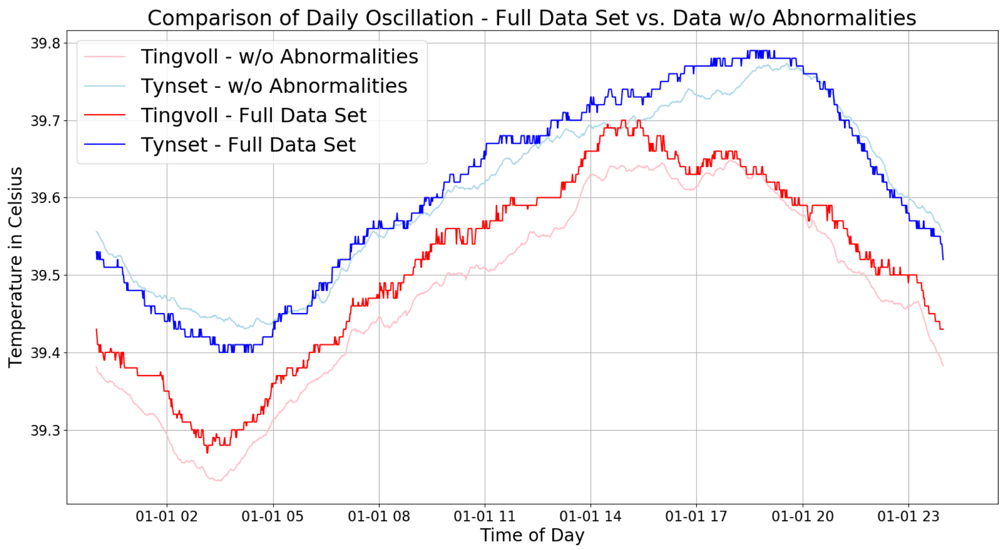

Figure 5.15: Comparison of differences in location based on different data sets

Comparison of the average daily oscillation between the herds. Comparison with both the full data set and the data set without abnormal periods. For the full data set median values are used, while for the data set without abnormalities mean values are used.

5.6 Period Based Analysis

After doing several group based analyses we started to look at the individual lamb, and comparing different periods of the individuals. By doing this individual comparison we look for patterns that otherwise would be lost due to averaging.

In Figure 5.16 we have compared two periods in which there are fever, and a seemingly normal period for the individual "Ti60023". We can here quite clearly see that the fever periods substantially differ from the normal period, both in terms of the lack of any daily rhythm and in terms of the elevated temperature.

We do also see quite a big difference in the different fever periods, and we see that they are very different. The 2nd fever period (green) seem to last longer and have a temperature that climbs and stay more steadily than that of the 1st fever period (blue). The 1st fever period is characterized by sudden big changes to the temperature, and we can see that some days before the first sudden temperature increase the circadian rhythm is off, and the nightly temperature is much higher than normal. We can also see that the temperature lowers just before the first sudden increase. We don't see the same in the 2nd fever period.

In the 2nd period we see that the temperature drops half way through the period but then climbs again, at at a certain point it suddenly reaches temperatures well above 42°C before plummeting to temperatures under 40 °C, and then going back up to around 41°C. This probably isn't a good sign for the lamb's health.

The big variation between the two fever periods leads us to think that the sheep was suffering from different illnesses during these two periods, and that different illnesses will have a different temperature pattern. This might mean that there is no one way to predict all illnesses, but it can also mean that it might be possible to predict the illness based on the temperature. If this is the case, and if we would be able to implement it, we could give the farmers even more information, easing the decision making and ensure that the sheep can get the most efficient care.

In Figure 5.17 we have compared one period where there was fever, one normal period, and one period where there were a lot of low temperatures for the individual "Ty60001". The period that differ the most from the others here is the period with fever, where we can clearly see the elevated temperature.

The fever period begins with a rapid increasing temperature that reaches almost 42°C. The temperature stays high for some time before it slowly starts to decline. We see that after the temperature has declined within the normal temperature range, it still takes a few days for the temperature to stabilize. Before the temperature starts to rise, we do not see any big disturbance. This fever period is also rather different from both the fever periods depicted in Figure 5.16. The temperature climbs quicker, seems more stable at the top, and falls quicker. Whether these differences are due to the periods being caused by different illnesses, or if it is due to different individual responses is difficult to say and based on our data we cannot make an informed conclusion on this.

The period with low temperatures doesn't differ much from the normal period; it follows more or less the same pattern. We see that the low temperatures happens usually around the expected minimum from the circadian rhythm, and they don't last long. In the period with low temperatures we see that on one occasion the temperature drops as low as 38°C, while it doesn't last long, it last for enough time for us not to assume it was an error. Before this temperature drop there seems to be a slight disturbance in the circadian rhythm a day before it occurs. We also see some slight disturbance at the end of this period. Whether or not these disturbances are of any significance is hard to say, as there are some differences from day to day even in the normal period. We also see that the abnormally low temperatures occurs during the night, when the core temperature of the sheep is supposed to be low. During the night, the environmental temperature is also at it's lowest, so it would make some sense that the temperature sometimes drops lower than usual due to inactivity and low environmental temperature.

As we know, low temperatures can be a sign of very poor health and/or very serious illness as discussed in Chapter 3.1, however due to the short periods and no sign to fever before and after each temperature drop, we do not think that illness is the cause for these low temperatures. Poisoning can also cause lowered temperatures, see Chapter 3.3, and in case of food poisoning the short time frame could possibly be explained by the time this poisonous food is in the digestive system, however this builds on the assumption that the sheep only reacts to the food as long as it is in the digestive system. Another similar possible explanation could be that the short time frame is related to the time it takes for the body to break down the toxins. Both of these possible explanations are purely hypothetical, and we have no data supporting these hypotheses as we don't know what they were eating before and around the time of these incidents.

Outer factors such as temperature, humidity, wind, and downfall could possibly also have an effect on the temperature of the lamb. The incidences of low core temperatures might just have been cases where the lamb were simply cold, without any causes related to the lamb's general health.

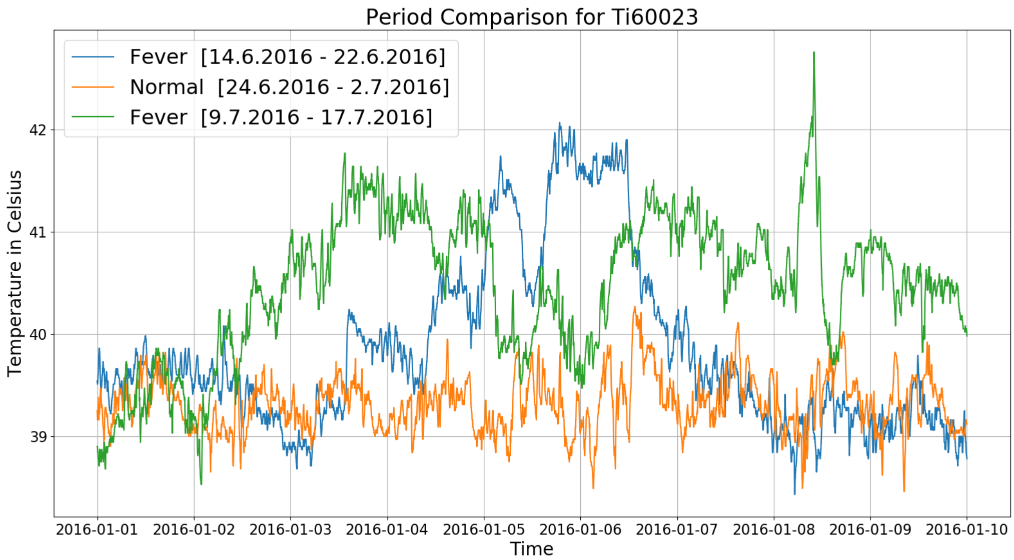

Figure 5.16: Comparisons of different periods for Ti60023

Comparison between 3 different time periods for the individual Ti60023. Plotted are two periods, in which there were fever, compared to a seemingly normal period. The labels on the time axis does not show the actual date of the recordings, but is related to the amount of time after the first record in each of the time periods.

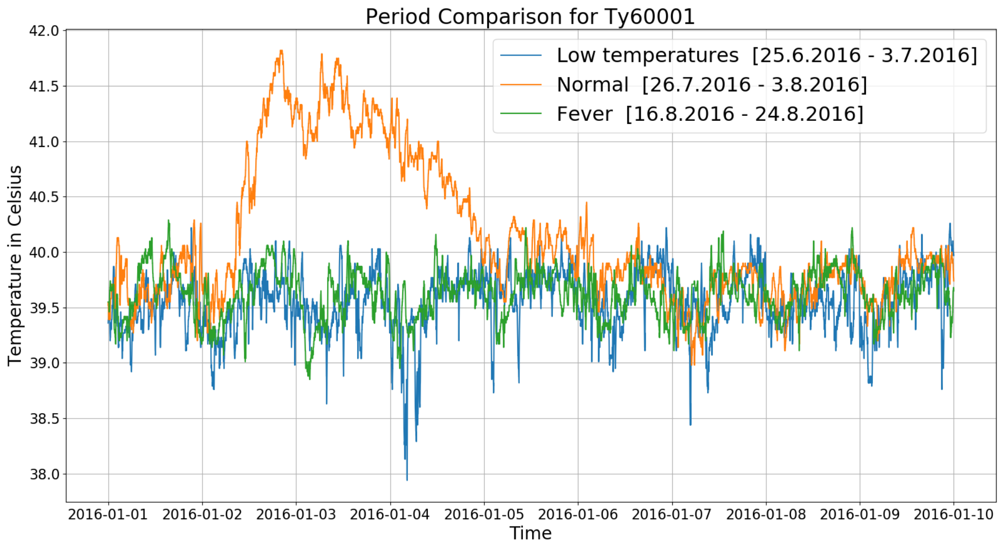

Figure 5.17: Comparisons of different periods for Ty60001

Comparison between 3 different time periods for the individual Ty60001. It contains one period, in which there were fever, one normal period, and a period, in which there were several occasions of abnormally low temperatures. The labels on the time axis does not show the actual date of the recordings, but is related to the amount of time after the first record in each of the time periods.

5.7 Individual Analysis of Sheep Ti60097

We wanted to take a deeper look at some of the individuals in order to see if we found interesting data that would have been lost in our previous analyses as we used the average values for several individuals.

Different illnesses might have different temporal finger prints. These would be difficult to see if we are just looking at average illness periods. Looking at individual cases of fever can therefore give us greater understanding in how illness periods differ.

The individual sheep we found the most interesting was Ti60097, as this was the only sheep to die of other causes than slaughter, more specifically the cause of death was coccidiosis [3]. As we want to be able to detect illness, and first and foremost serious illnesses, finding the symptoms of such a serious decease is for us very important.

5.7.1 Method

In Figure 5.18 we have depicted the temporal history of Ti60097 from the sensor insertion to the death of the animal. We have in this figure also depicted some lines representing the fever threshold, a base temperature, and a lower threshold for what we consider normal temperatures. The fever threshold was chosen considering the works of Grøva et.al.[15]. The base temperature was chosen based on what we had seen in Chapter 5.2.5; the temperature was often oscillating around a temperature around 39.5°C. The lower threshold was chosen to be 38.5°C, as the normal range of temperature is above 38.5°C, as discussed in Chapter 3.2.

5.7.2 Discussion

The first aspect that strikes us as strange about the temporal history of this sheep is that it has barely had fever, however as cossidiosis have few clinical signs this might be expected, see Chapter 3.1. The temperature reaches temperatures above the fever threshold only for a short time, not more than 2 days before it's death. After it reaches the threshold the temperature quickly starts to decline steadily to around 38.5 °C where it, after some time, suddenly drops, indicating death. The temperature drops sometimes under the lower threshold for short periods of time, but the temperatures we see are in no way extreme, and there is nothing that immediately indicates illness.

We noted that the temperature seems a bit low; for most of the time the temperature is below the base temperature. Not including periods of illness, this lamb had an average temperature of 39.34°C and a standard deviation of 0.27°C. The average temperature if all sheep, except this individual and not including illness periods, is 39.53°C with a standard deviation of 0.17°C, giving us a range of [39.36°C , 39.70°C]. From Chapter 5.2.5, looking only at the Tingvoll herd we get an average temperature of 39.46°C with a standard deviation of 0.13°C, giving us a range of [39.33°C , 39.59°C]. We see that the average temperature of this individual is barely within the standard range of average temperatures for the Tingvoll herd and falls just short for the range of both herds combined.

During the last week we also see that there is little oscillation, and the changes doesn't seem to fit any pattern. It seems that the natural circadian rhythm had broken down. We know from Chapter 3.1 that low temperatures could be a sign of very serious illness, as this could be an indication of failing circulation. During the last 4 days we also see some very sudden changes in temperatures. The temperature jumps with almost 1 degree in a short amount of time. We are also quite certain that these jumps are not due to measuring errors as the temperature stays at the new temperature for a while. This coincides with what we read about illness in human infants [23], where they stated that they were able to see differences in the circadian rhythm days before illness occurred, without the observed temperatures to be outside the normal range. In that paper it was also stated that similar disturbances had been observed in relation to sudden infant death.

One would naturally assume that very high temperature would be what we were looking for in order to see if a sheep is seriously ill. However we see that several sheep get temperatures above 42°C, as we can see in figure 5.16, and they all survive the season, although several of them receive treatment. For the lamb at Tingvoll, these illness periods are caused by TBF [4] [5]. These results show that not all serious illnesses has fever as a symptom, and in order to detect illnesses like that one would need to detect small changes and abnormalities.

5.8 Comparison to Journal

As we had access to the journal of the follow-up of the lamb at Tingvoll, we thought it would be interesting to compare the observations with the temporal data. In this part of the analysis we chose some individuals we that had interesting observations, and compared these observations with the temporal data of that sheep in the time frame of the observations.

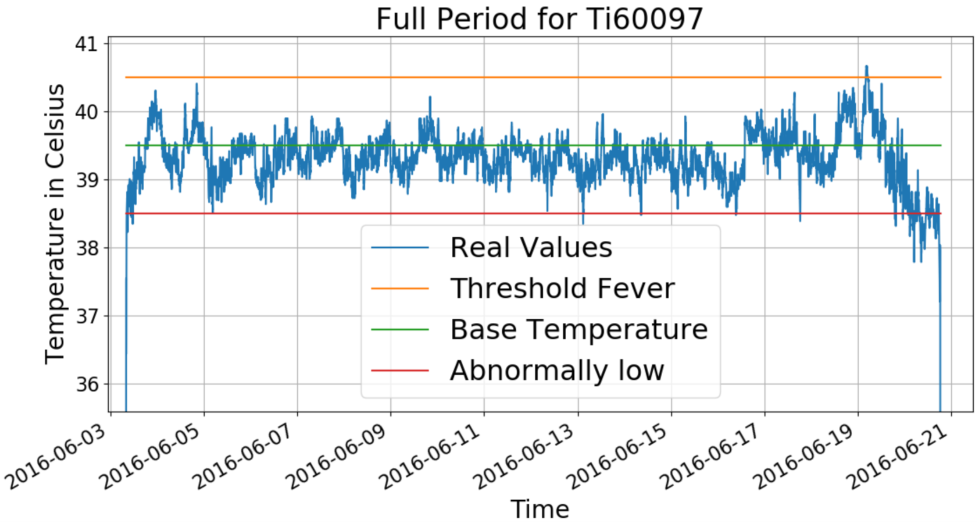

Figure 5.18: Entire period for Ti60097

Shows all the temporal records for Ti60097. Included are lines for the thresholds for fever, at 40.5°C, a base temperature, at 39.5 °C, and threshold for abnormally low temperatures, at 38.5°C.

5.8.1 Comparison for Ti60026

We started our analysis with the individual "Ti60026" as it had some minor symptoms according to the journal, and we wanted to see how these symptoms would be reflected in the temperature of the sheep. Figure 5.19 depicts the temporal data for this individual in the time frame of [11.06.2016 − 23.06.2016], and the observations that were noted in the journal, [33], during this period.

The first symptom that was noted in the journal during this period, was a small swelling around the wound where the temperature sensor was implanted. This was treated with penovet [33]. In the figure we see that 2 days before this swelling was discovered the temperature had been above 40.5°C, and around the time of discovery we see that the temperatures are somewhat high. After the treatment there are signs that the temperature is lowering, except for a peak a day later, which was almost 40.5°C. Shortly after this peek we see some low temperatures, followed by a period with fever.

The period with fever was first noticed when the temperature already had started to decrease, where it was noted that the sheep was "a bit slow". The sheep was at this time treated with Terramycin [33], and later that same day the sheep seemed normal again. It seems a bit odd that the sheep first seemed tired or slow after the peak temperature of the fever period, however it could

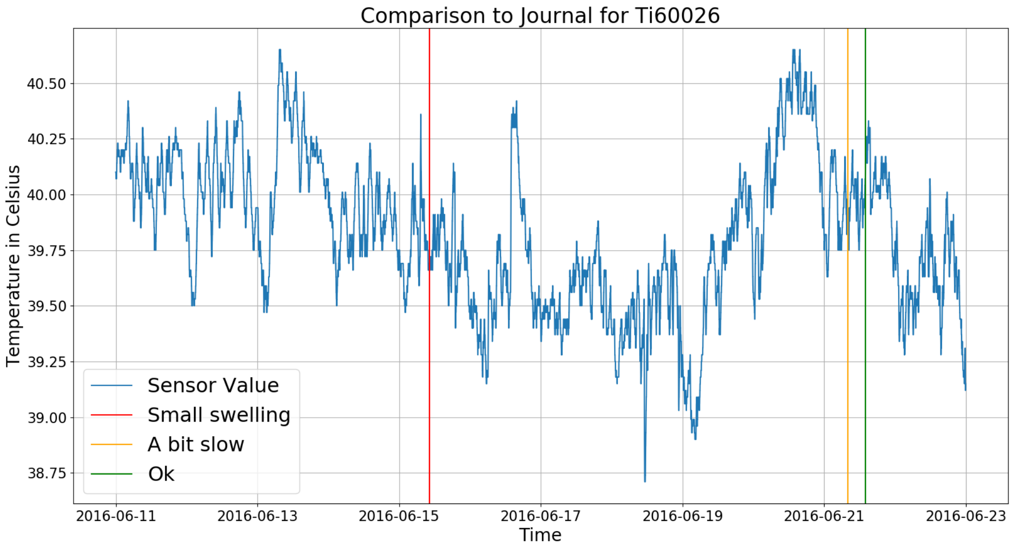

Figure 5.19: Comparison to journal data for Ti60026

Shows the temporal data for Ti60026, during the period $[11.06.2016 - 23.06.2016]$. Clinical observations that were done, regarding the health of this individual, is represented by vertical lines, and placed at the time of the observations. The observations are differentiated with colors.

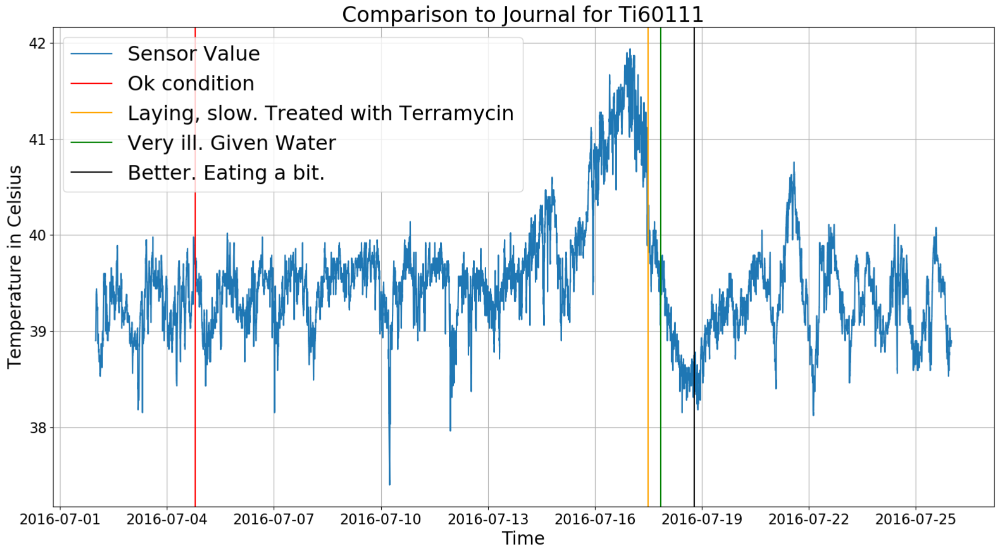

Figure 5.20: Comparison to journal data for Ti60111

Shows the temporal data for Ti60111, during the period [02.07.2016 − 26.07.2016]. Clinical observations that were done, regarding the health of this individual, is represented by vertical lines, and placed at the time of the observations. The observations are differentiated with colors.

suggest that the tiredness is not directly a symptom of illness, but rather exhaustion from the body fighting the infection. What's more is that the sheep seemed fine shortly after being treated, even though the temperature is still quite high.

5.8.2 Comparison for Ti60111

Figure 5.20 shows the registration of symptoms related to the core temperature of the individual "Ti60111". In the beginning of this period it is noted that the lamb seems fine. In the temporal data we see nothing to contradict this. The temperature seems to oscillate evenly from day to day, and the temperatures seems to be well within a normal range. Two days later we see that the temperature oscillation begins to be uneven, and we get some very low temperatures ($< 38°C$) at times. The temperature then transcends into a fever period.

During the fever period the lamb almost reaches 42°C at the peak. However, it is first after the peak, when the temperature is decreasing, that the first symptoms are noted. Here it is noted that the lamb was laying, and moving slowly. It was at this point treated with Terramycin [33]. Later the same day the lamb was noted to be rather ill, and had to be given water. At this time the temperature is still dropping.

The temperature continues to drop for another day, where the next follow-up occurred. It was at this time noted that the lamb was better and now eating a bit. This observation happened at around 7 o'clock in the afternoon, during this time, the temperature of the lamb was of a local minimum, something which is quite strange as, from our other analyses, the temperature normally peaks sometime in the afternoon. It is clear that this lamb has been quite sick, so it shouldn't be surprising that the temperature is abnormal, however it is worth noting as it seems like the circadian rhythm had completely broken down during this period of illness. If the lamb had stopped eating as a result of the illness, that could also have affected the temperature [22]. After the lamb starts eating, the temperature rises and we see temperatures above the fever threshold ($> 40.5°C$) 3 days later. We see that the lamb regains a circadian rhythm, and the temperature is within the normal range again. Although it seems healthy at this point, we see that the curve looks different after the illness than a week before the illness occurred. This can indicate either that the lamb still hadn't recovered fully, or that the incubation period can be very long.

5.8.3 Comparison for Ti60097

To get a deeper understanding of what happened to Ti60097, the lamb that died, we decided to compare its core temperature to the observations that were noted in the journal. Figure 5.21 depicts the results from this analysis.

During the beginning of the depicted period, the lamb is noted to seem fine. From the figure we can see that the temperatures are well within a normal range and there are no clear indications that something is wrong. We note that there are not much oscillation, something that, at least in human infants, can be part of the incubation phase of illness [23]. About a day later we see a sudden increase in temperature. This new temperature is not alarmingly high, however we once again see little oscillation over the next days.

During the next increase in temperature it is noted that the lamb seems a bit tired. Shortly after the temperature reaches it peek, at just above 40.5°C, it starts to steadily decline. During this decline the lamb is observed again, and it seems to be doing fine, this is just hours after the peak. Less than two days later the lamb dies.

Both in regards to the journal and the temporal data, there are few signs that the lamb is ill, however considering the illness it was suffering from, cocciosis, symptoms are often not present as discussed in Chapter 3.1. It is

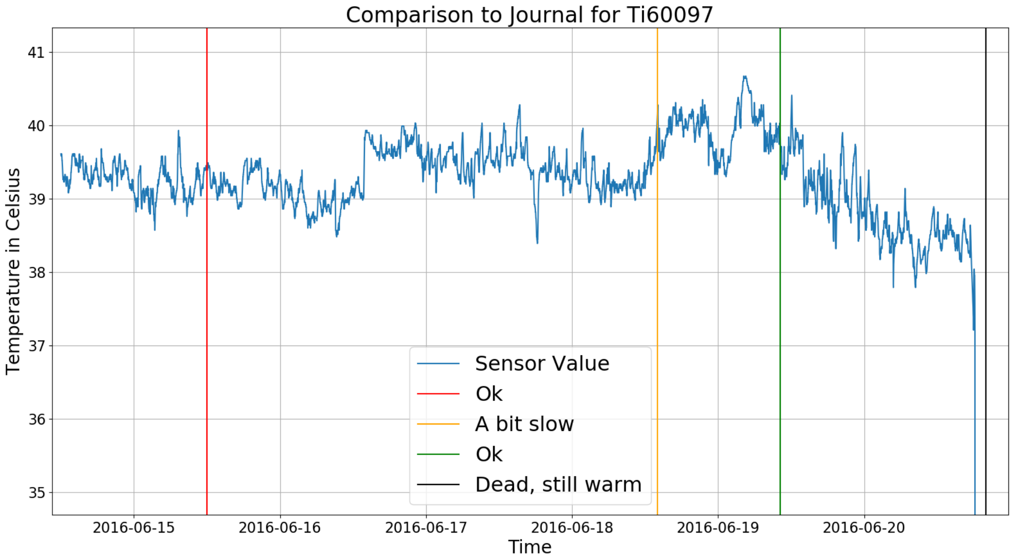

Figure 5.21: Comparison to journal data for Ti60097

Shows the temporal data for Ti60097, during the period [14.06.2016 − 22.06.2016]. Clinical observations that were done, regarding the health of this individual, is represented by vertical lines, and placed at the time of the observations. The observations are differentiated with colors.

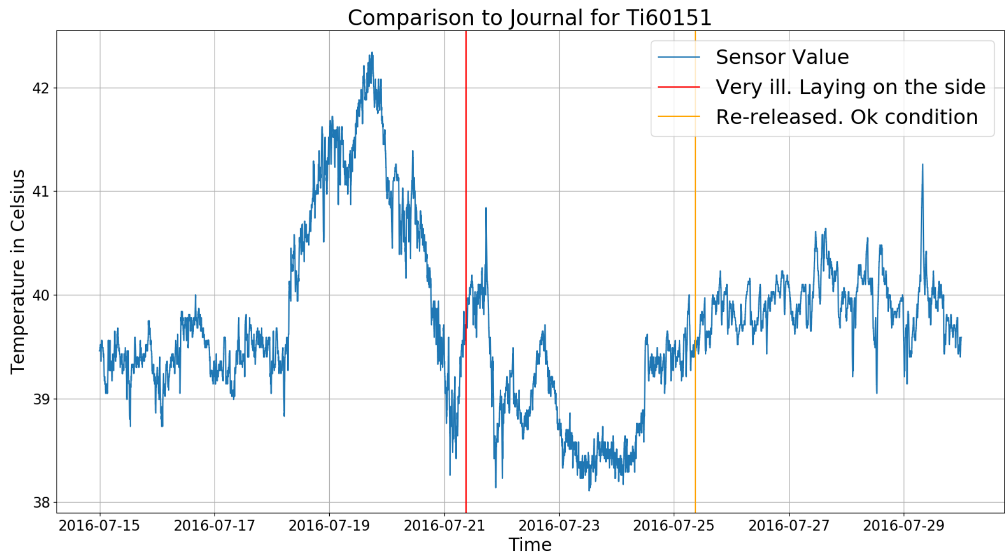

Figure 5.22: Comparison to journal data for Ti60151

Shows the temporal data for Ti60151, during the period [15.07.2016 − 30.07.2016]. Clinical observations that were done, regarding the health of this individual, is represented by vertical lines, and placed at the time of the observations. The observations are differentiated with colors.

therefore not surprising that we don't find obvious signs, such as very high fever for instance. If we would be able to detect illnesses like this, by using sensors and temporal data, we would have been able to provide a very useful service as this would drastically improve the detection rate and ability.

5.8.4 Comparison for Ti60151

While on pasture the individual Ti60151 became very ill, in fact so ill that it had to be taken in and treated. Signs of illness were discovered the 21.07.2016 [33]. The lamb survived, and was after some days re-released to the pasture. In Figure 5.22 we have depicted the temporal data of the period of which we speak, and the documented observations of the lamb.

The figure shows that the lamb had very high fever ($> 42°C$), that developed quickly. Signs of illness was first discovered later than the peak, at which time the lamb was in a poor condition. The lamb had a heavy, quick, and irregular breath, and had dark red mucous. At this time it was so ill that it was just laying on its side. It was treated with Tribrissen and Terramycin [33].

Shortly after the sheep was taken inn and treated, the temperature drops.

At first the temperature drops to a normal level, where it stays for about a day, and then it drops again to subnormal levels (~ 38.5°C). The lamb has this low temperature even during the day, where the daily maximum is supposed to occur. This doesn't seem to be a good sign, and is probably a sign that the sheep was near death. As discussed in Chapter 3.2, low temperatures can indicate circulation failure.

The temperature increases again, and reaches normal levels. At this time the lamb seems to be in good condition, and is released to the pasture again. After the lamb is released to the pasture the temperature increases a bit, and its oscillation seems a bit off. Four days after being released on pasture the temperature reaches a temperature above 41°C, however this is only for a short amount of time. It's strange that these abnormalities occur after the sheep has been treated and seems to have recovered. The abnormal temperature after the sheep is released on the pasture again could be caused by stress from transportation, acclimatization, reduced health after illness, or other causes. It might also be that the sheep quickly became ill after returning to the pasture as the immune system probably wasn't in a good condition at this point.

5.8.5 Comparison for Ti60080

The individual Ti60080 was the 7th of August recorded to have been very ill, laying down, and not eating, and was at this point treated with Terramycin [33]. We wanted to see how the temperature had been around the time of this observation, to look for patterns in very ill sheep.

In the days before the observation, the temperature seems to be oscillating normally, however the temperatures are generally low. The daily maximum is under 39.5°C, so the maximum is lower than the daily average of a healthy sheep. During the night, the temperature falls well below 38.5°C, which is unusual for a healthy lamb.

The day after the lamb is treated we see a large range in temperature. The temperature varies with approximately 2°C. This large variance is also very unusual, however it could have been caused by the medicine that was administered it. We are unsure if this is a sign of the medication starting to work, and therefore a good sign, or not.

Two days after the the treatment, the temperature has decreased to around 38°C, and at times going below 37°C. This is, from what we have seen, very low temperatures, that are seldom present in the data we have. Why the temperatures are this low is hard to say. This could be an effect of the treatment that was received, however it could also be an indication that the health of the lamb was very poor. It was noted that the lamb was not

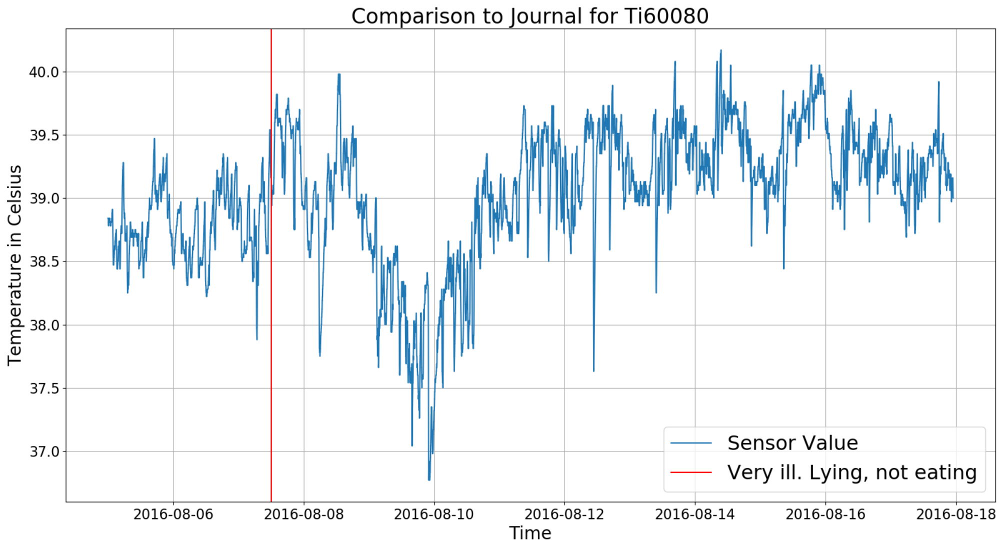

Figure 5.23: Comparison to journal data for Ti60080

Shows the temporal data for Ti60080, during the period $[05.08.2016 - 18.08.2016]$. Clinical observations that were done, regarding the health of this individual, is represented by vertical lines, and placed at the time of the observations. The observations are differentiated with colors.

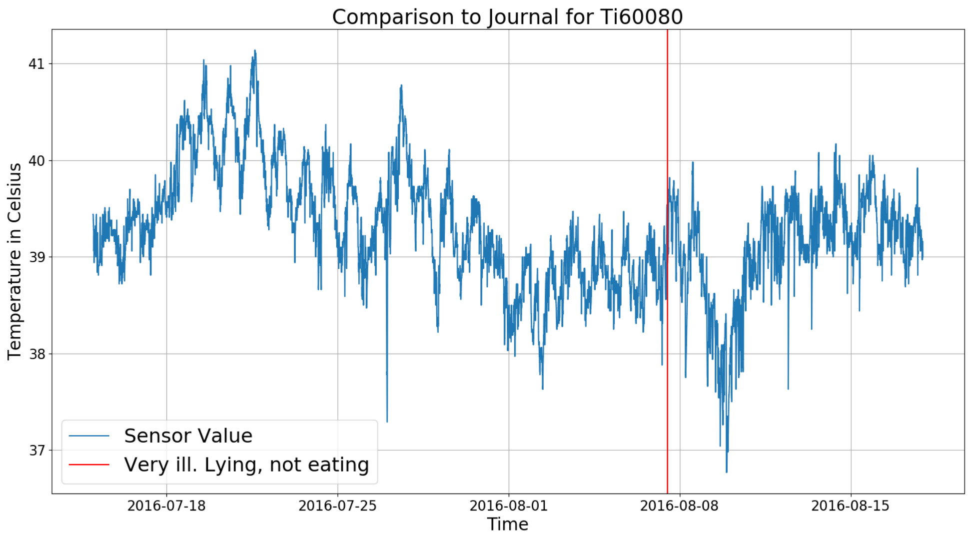

Figure 5.24: Comparison to journal data for Ti60080 during a longer period

Shows the temporal data for Ti60080, during the period [15.07.2016 – 12.08.2016]. Clinical observations that were done, regarding the health of this individual, is represented by vertical lines, and placed at the time of the observations. The observations are differentiated with colors.

eating at the time of treatment, so if the lamb still had not started eating sufficiently, this lowered temperature could be due to starvation, which can cause hypothermia [22] .

After the period of low temperatures, the temperature of the sheep starts to slowly increase. This process takes days, but it reaches a normal range of temperature, and the circadian rhythm starts to return to normal. At this point, the lamb has probably recovered, or at the very least is getting better. We don't in this case have other records of the health of the lamb shortly before and after the treatment.

In Figure 5.24 we have once again depicted the analysis for the individual Ti60080, however this time we extended the amount of time before the observation we included in the graph. Before the period of low temperatures in Ti60080, there was a period of illness/fever. The fever period had ended more than a week prior to the observation, however we see that after the illness period, the temperature drops, and it doesn't recover until the lamb has been treated. This can indicate that the illness was still present even though the temperature was lowered. It seems therefore likely that the illness had been a direct cause for this period of lowered temperature.

5.8.6 Comparison and Discussion of Results

In the periods and individuals, that we chose for these analyses, there are differences in the temperature, and in the situations that occurred. However we still do see some patterns. In the cases of fever, clinical signs were first discovered relatively late after the peak temperature, and the sheep were considered to be in good shape already before abnormalities in the core temperature disappeared.

The fever periods for individuals Ti60111 and Ti60151 seem quite similar. Both fever periods develop quickly, and after the peak both of them drop to subnormal temperatures. Both sheep were described to be quite ill when they were diagnosed to be ill. Had these not received treatment it is likely that they could have died. We can see that if we had warned as soon as the temperature get above 40.5 °C for both of these, we would have been able to detect the illness approximately 3 days before illness was clinically discovered.

In the case of the individual Ti60080, we see that the temperature was very low during the time of the observed illness. This shows us that we must consider the abnormally low temperatures as well as the abnormally high. Arguably if the fever, that precedes the period of low temperatures in this individual, was detected and treated, the lamb may not have become so ill that the temperature dropped so significantly.

What seems to be in common for these, is that the circadian rhythm breaks down during time of illness, which can be an important aspect to take in consideration when predicting illness. Especially in the case of Ti60097, and to some degree also for Ti60026, as its temperature was, for most of the time during the period with illness, under 40.5°C.

In the beginning the sheep were kept in a fenced in pasture, receiving regular care and were observed regularly, as discussed in Chapter 4.2. After the sheep were moved to the free-range pasture they were observed for only 2-3 times a week. This must be taken into consideration when discussing how early the signs of illness were observed. Most of the cases we have depicted here are in the beginning of the season, and we see that the sheep have been regularly observed. However the illness incidence of Ti60080 occurred late in the season. It might seem unfair to compare this to the other periods as they were less looked after, however this serves to prove a point; when the sheep are at free-range pasture, signs of illness are harder to observe and our system would be even more useful.

During the first weeks, the lamb were kept in a fenced in pasture and received systematic inspections twice a day. When the sheep were moved to the free-range pasture they were looked after at a normal rate, 2-3 times a

Tingvoll	
Mean Amount of Moderate Fever	2.19
Mean Amount of High Fever	2.75
Mean Amount of Fever	4.94
Tynset	
Mean Amount of Moderate Fever	1.67
Mean Amount of High Fever	0.533
Mean Amount of Fever	2.20

Table 5.1: Comparison of amount of fever periods

week, and not as throughout as previously. This change in how they were looked after, likely is the reason illnesses were earlier detected late in the season compared to early in the season. This shows how much harder it is to detect illness in sheep at free-range pastures.

5.9 Fever Periods and Sick Time

The sheep of the different herds likely suffered from different illnesses, and for a different amount of time. To investigate this we visually inspected our data for fever periods. We classified the fever periods in two groups, namely moderate- and high fever. Moderate fever was fever periods that had low fever temperatures [40.5°C $-$41°C], and high fever were fever periods where the temperature was above 41°C.

Results from this analysis presented in Table 5.1. The mean amount of fever periods in the Tynset herd is less than half that of the mean amount of fever periods for the Tingvoll herd. The biggest difference between the herds is the mean amount of periods of high fever. This result indicates, not only that the herds were differently exposed to illness, but also that they were likely exposed to different illnesses. Lamb in Tingvoll were expected to suffer more from TBF, which is characterized by high fever temperatures [15], this difference is visible in our results.

These results are merely indicative, and was quickly visually analyzed. The reader should therefore take these results with some skepticism.

In the analyses of Kjell Bratbergsengen, [34], a clear difference between the herds emerge with regards to the amount of time the sheep are ill. In these analyses, the sheep of the herd at Tingvoll are ill between 10% and 20% of the recorded time with few exceptions. The herd at Tynset is ill between 0% and 3% of the recorded time. This difference is quite significant. A consequence of this difference is that we have less reliable data for the herd at Tingvoll, and there are more uncertainties with regards to the results of our analyses for this herd.

5.10 Summary of Analysis

From these analyses we find there is a clear presence of a circadian rhythm in sheep, and that illnesses can have a huge impact on the temperature, and circadian rhythm of sheep. We have found there to be a lot of variance, not only between individuals, but also between herds, gender, season, and age groups. We have also found there to be indications that disturbances in the circadian rhythm can be a sign of illness, or predicate illness in sheep. There are also indications that clinical signs off illness in sheep, usually is first visible after the peak temperature of a fever period, in other words relatively late in the illness period.

We find these results promising. It seems that the ability to detect fever alone could improve detection rates, and ensure that illness is detected at an earlier stage than what is possible at the time being. Deviation from the circadian rhythm also seems like a useful metric for detecting illness, however deciding what is a normal rhythm, and what is within the normal deviation is still difficult to determine. If we are to make a model that is based on the circadian rhythm, we might need to individually fit the model. The model would also likely need to be relatively complex, however such a model seem to hold the most potential regarding finding all different types of illness, and regarding predicting illness at a stage as early as possible.

Chapter 6

Developing Software for Illness Detection

In this Chapter we develop models for detection of sheep illness. We base our models on what we found out through our analyses. We will not program sensors, but make programs to run as computer simulations. As we are only in an initial stage, and we want to be able to easily test our models.

6.1 Methods

To make software, we used Python[31] as a programming language. We would likely not make the software to be run on actual sensors in Python, however Python is perfectly adequate for our use, developing and testing models locally on our computer. This first development is for investigating what model works, and have an idea of the possible results, we are not to actually program sensors at this point. Another important point for our choice regarding the programming language is that it is easy to use, and we are comfortable using this. Python also has good possibilities for illustrating results, and using machine learning plugins if that would be necessary.

For simulations and testing of our software we will use the full data set, which was also used for our analyses. The results from the simulations will be compared to hand-picked, abnormal periods, and to periods that are picked out by the machine. Sadly we do not have knowledge about which periods that are actually times of illness, part of the incubation period, or in other ways differ from the norm. We will therefore do our best to correctly identify illness periods by ourselves. This becomes another source of errors, as there will likely be errors in our marking of the data. We do have a log of clinical signs of illness in the lambs, however this is only for the lambs at Tingvoll, and mostly for the first weeks post implantation. It is highly likely that not all signs of illness had been detected.

6.2 Constraints

In the imagined complete product, these models would run on sensors. The sensors would have limited computing power, and preferably use little power for the battery to last as long as possible. This means that the models for detecting illness can't be too complex, and when developing our models we have to consider the constraints the hardware imposes.

We will not perform complexity tests and comparisons, or check how much power each model uses, however we will prefer the simplest models. More complex models will naturally be considered and developed, as we want to see the performance difference between a complex and a simple model. A complex model could be preferred over a simpler, if the increased performance outweighs the increased cost.

6.3 Problems that Need to be Solved

There are a lot of problems we have to attempt to solve in order to make a good model. As we could see in Chapter 5, there are significant differences based on individuals and age groups. Our first problem then arises; is it possible to make a general model that fit all individuals? If this is not possible, we have to find a way to fit the model to the individual without the software becoming overly complicated.

From our analysis we also see that not all periods of illness are characterized by a very high temperature. In some cases some lamb are seriously ill, while their core temperature is within a normal temperature range. There are some signs that it could still be possible to detect illness based on

Even if we manage to make a general model that works, we might need to change it with time, as the circadian rhythm changes with age. If we have a model that fits itself to the individual it's certain that we have to change the model while it's running. For these changes it will be very important to know what we have to tweak, how we should tweak it, how often we should tweak it, and how periods of fever and abnormal periods are to be handled considering this adaption. We can see from the data that some individuals have had fever and abnormal periods for large parts of the measured time period.

Sensitivity could also be a problem we might need to work on. We do not want the model to be too sensitive, such that it warns about illness too often. If it warn about illness to often, and when there is no illness in the lamb, it will cause distrust to the system, and its users will likely stop caring about and believing in the warnings from the sensors. While we don't want the sensors to be too sensitive, we don't want them to be too insensitive either. If they are too insensitive they might not warn about important signs of illness, that can in worst case be fatal illnesses.

6.4 Simple Threshold Model

We start by making a very simple model that is based on a threshold value. This model would consider temperatures above the threshold as a sign of illness. In order to filter out measurement errors and sudden spikes in the temperature, we introduced a counter. With the counter the temperature would have to be above the threshold for a certain amount of time.

The counter would store an integer value in the range [0 - X], where X is the number of minutes required for the model to consider the deviation to be a sign of illness. For each measurement that was above the threshold value, the counter would increase with one until X was reached. Measurements under the threshold value would decrease the counter, until 0 was reached. Once the counter would reach X, the sheep would be classified as ill, and it would not be classified as healthy before the counter had reached 0 again. By using a counter like this, we avoid the problem of sudden measurements that are above/under the threshold changing the status.

In Figures 6.1, 6.2, and 6.3 we show the results for a simulation run, using this model, for the individuals respectively Ty60001, Ti60097, and Ti60007. In these simulations we used 40.5°C as the threshold value, and we set X equals 30. This means that the temperature had to be above 40.5°C for at least 30 minutes for the model to consider the lamb ill.

We did a quick test of the model, where we compared the warnings issued by the model with the periods that we have previously marked as abnormal. For this model, with the parameters as discussed over, we usually got an accuracy in the range $[70\% - 75\%]$. It should also be noted that the periods, that we had hand-picked as abnormal, can by no means be considered a perfect benchmark, however we will use these periods as a benchmark for now.

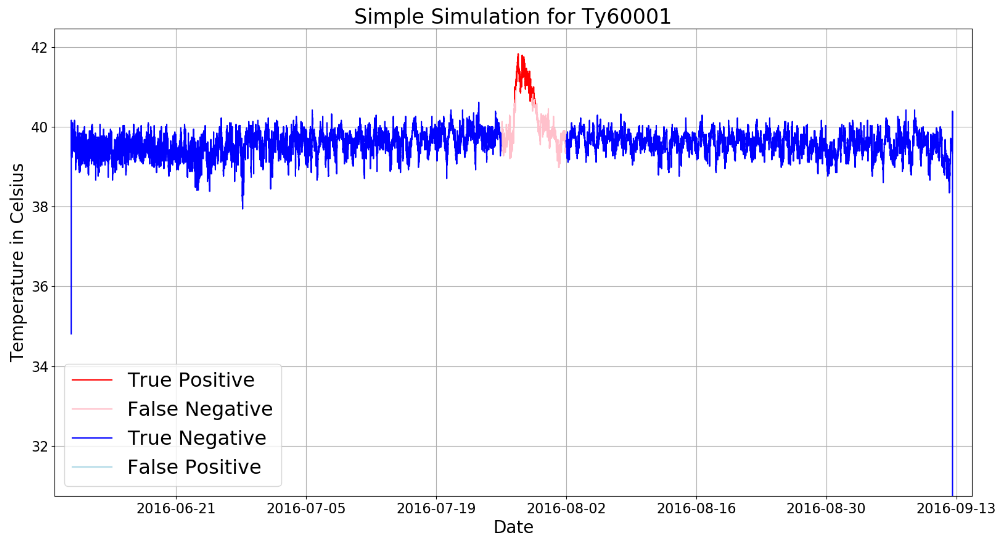

Figure 6.1: Results of the Simple Threshold Model for Ty60001

Simulation for the individual Ty60001 by using the Simple Threshold Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model compared to our benchmark.
Periods that are marked dark red are true positives, meaning that the lamb is ill both according to the model and the benchmark. Dark blue are true negatives, meaning that both the model and benchmark consider the lamb healthy. False negative is when the model think the lamb is healthy, but the benchmark thinks it's ill. False positive is opposite of false negative.

6.4.1 Simulation for Ty60001

In Figure 6.1 we see the results for the simulation for the individual Ty60001. This individual had one fever period, which was quite distinct in the dataset, and is easily visible by eye. The model did detect this fever period, however we see that the temperature rises quickly, even during the night, before it reaches fever temperature. This sign of illness appear approximately a day before the fever threshold is reached.

We do not have any journal data for this individual, however one trend we saw when comparing the journal data to the temporal data, was that clinical signs of illness usually was first visible when the fever was decreasing. Here we are able to detect illness even when the temperature is rising, so this seems like quite the improvement, as we will be able to detect illness days in advance.

6.4.2 Simulation for Ti60097

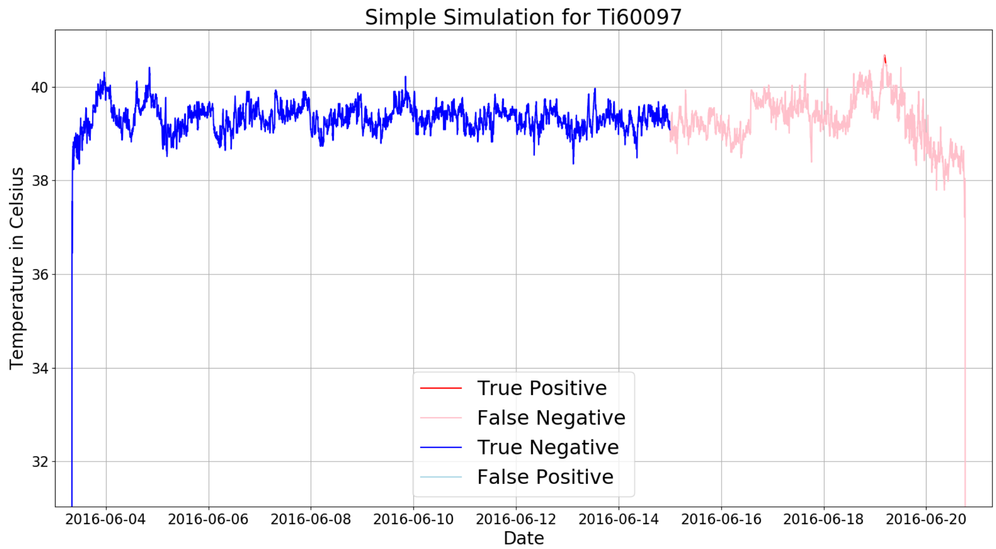

Figure 6.2: Results of the Simple Threshold Model for Ti60097

Simulation for the individual Ti60097 by using the Simple Threshold Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model compared to our benchmark.
Periods that are marked dark red are true positives, meaning that the lamb is ill both according to the model and the benchmark. Dark blue are true negatives, meaning that both the model and benchmark consider the lamb healthy. False negative is when the model think the lamb is healthy, but the benchmark thinks it's ill. False positive is opposite of false negative.

In the simulation for the individual Ti60097, shown in Figure 6.2 , we see that the fever has barely been registered by our model. The problem with this individual, or rather the illness it was suffering from, is that it shows few symptoms. While we can see that there are some disturbances in the circadian rhythm, our model is not able to detect the illness, as the temperature, for most of the time, is within a normal range.

We see that the model detects fever, however this is just barely and occurs near the end of the life of the lamb. Cocciosis, which the lamb in this case suffered from, needs to be treated early, so despite the fever was detected as we see here, it could already be too late for treatment.

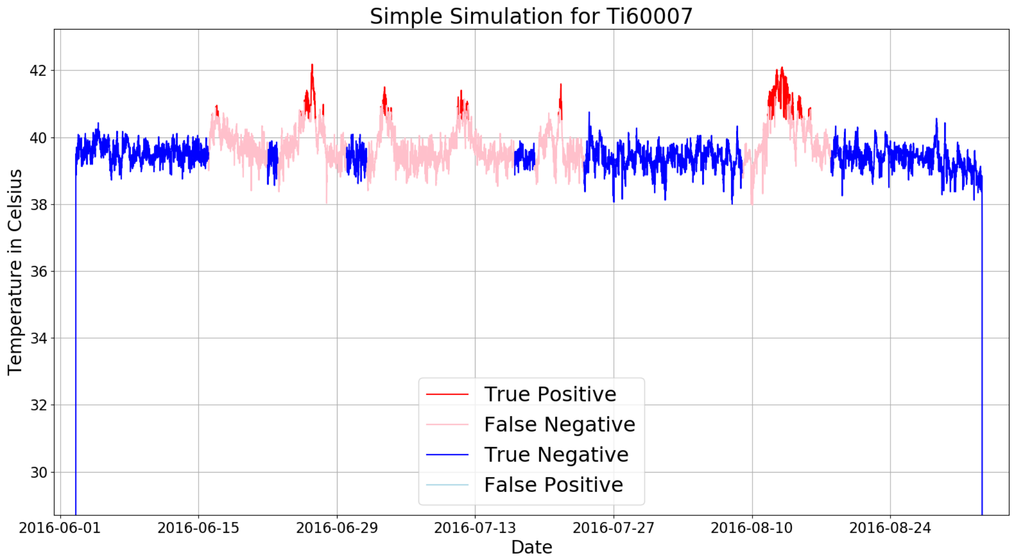

Figure 6.3: Results of the Simple Threshold Model for Ti60007

Simulation for the individual Ti60007 by using the Simple Threshold Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model compared to our benchmark.
Periods that are marked dark red are true positives, meaning that the lamb is ill both according to the model and the benchmark. Dark blue are true negatives, meaning that both the model and benchmark consider the lamb healthy. False negative is when the model think the lamb is healthy, but the benchmark thinks it's ill. False positive is opposite of false negative.

6.4.3 Simulation for Ti60007

The results from the simulation for individual Ti60007, as shown in Figure 6.3, is somewhat similar to that of the results for individual Ti60001, see Figure 6.1. The fever periods are detected, however there are visible signs of illness before the model are able to detect the illnesses.

We also see that the first fever period of individual Ti60007, while it is detected it seems to barely have been so. This indicates that illnesses that have a fever around the threshold value will be more difficult to detect for this model. Due to measurement errors, or other causes, the temperature can suddenly drop repeatedly below the threshold, leading to an increment in the number of minutes the temperature needs to be above the threshold for illness to be detected.

6.4.4 Thoughts on Performance

All in all we think this model seem to work surprisingly well despite its simplicity. It is able to detect most cases of fever, however we see that cases of low fever can be difficult for the model to detect, and might possibly go undetected. The threshold and counter can be adjusted as to detect more cases of illness, however this can lead to an increased number of false positives.

We also see that disturbances in the circadian rhythm, which can be important for illness detection, is not addressed by the model. In case of illnesses as cocciocis, as we see in Ti60097, we saw that the model barely discovered the decease. A positive aspect of this model is that we seem to have few false positives.

6.5 Simple Cosine Model

As we had discovered, the core temperature of sheep follows a circadian rhythm, and some illnesses creates disturbances in this rhythm. For this reason we wanted to make a model that takes this rhythm into consideration, and that would be able to detect these disturbances. This model will be a general model, and not fitted to each individual.

We based our model on a cosine function, that would try to emulate the circadian rhythm. The model would calculate what would be an expected temperature, given the time of day, and deviation over a margin of error would be considered sign of illness. We used a counter, that demanded deviation from the norm for a certain amount of time, as we did in the Simple Threshold Model.

The function we used to calculate the expected temperature is depicted in Equation 6.1. The **mesor** is the base temperature, around which the temperature would oscillate. **A** is the amplitude, and **X** was the number of minutes passed since the start of the phase. The **X** value would be initialized for each individual based on the time of insertion. At the end of each phase, **X** would be set to 0 again. In this model we assume 24-hour cycles, where the maximum and minimum are 12 hours apart.

In these simulations we used the parameters given in Table 6.1.

$$temperature = mesor + A \cdot \cos{(2\pi \cdot \frac{X}{24 \cdot 60})} \tag{6.1}$$

In simulations using this model, we did also use the hand-picked, abnormal periods as a benchmark. To easier compare the performance here we

Parameters	
Base Temperature	39.5
Amplitude	0.4
Counter	180
Error Margin	0.4
Start of Phase	22.30

Table 6.1: Parameters for the Simple Cosine Model

decided to showcase the same individuals we showed for the Simple Threshold Model. A general thing we see is that this model manages to detect the abnormal periods at an earlier stage than the Simple Threshold Model, however this comes at the cost of a very high number of false positives, which is unfortunate.

6.5.1 Simulation for Ty60001

Figure 6.4 shows the simulation for individual Ty60001. We see that the abnormal/fever period is well detected, however there is a lot of false positives. We see a lot of false positives especially during the first two weeks, which could be an indication that the insertion of the sensors had a relatively long lasting effect on the circadian rhythm. We also note that the temperatures are somewhat low during this period. This might be an indication that the lamb was actually ill during this period. In the days leading up to the fever period, we also see a large number of false positives. This could indicate disturbances in the circadian rhythm during the incubation period of the illness. These positives could also just be caused by the model not fitting the rhythm well, or that it is overly sensitive.

6.5.2 Simulation for Ti60097

The simulation of individual Ti60097 is depicted in Figure 6.5. Compared to the Simple Threshold Method, this model is much better at detecting illness in individual Ti60097, however we do also see that there is a high number of false positives. These false positives could be caused by actual disturbances caused by insertion of sensors, or illness. We know that this lamb was suffering from cocciosis, of which it died, so it is not unthinkable that it was ill, and affected, for a longer time than the period we had marked as abnormal.

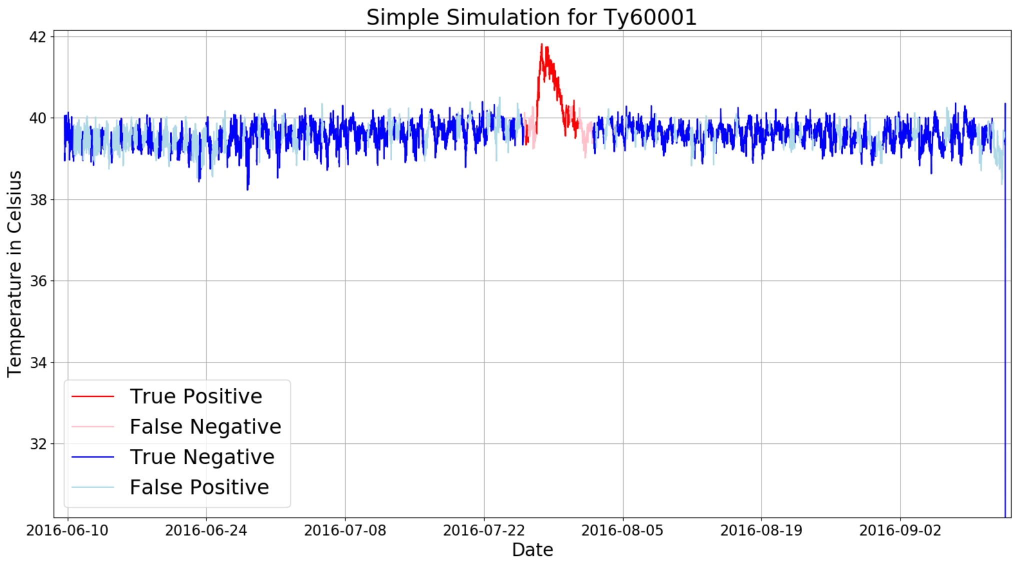

Figure 6.4: Results of the Simple Cosine Model for Ty60001

Simulation for the individual Ty60001 by using the Simple Cosine Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model compared to our benchmark.
Periods that are marked dark red are true positives, meaning that the lamb is ill both according to the model and the benchmark. Dark blue are true negatives, meaning that both the model and benchmark consider the lamb healthy. False negative is when the model think the lamb is healthy, but the benchmark thinks it's ill. False positive is opposite of false negative.

6.5.3 Simulation for Ti60007

In the simulation for individual Ti60007 we see the same as we do for the two previous simulations. This model is better at detecting the periods of illness than the Simple Threshold Model, however at the cost of many false positives. This simulation gives us far more false positives than the simulation for Ty60001, but this individual is also much more sick than Ty60001. We don't know enough about the effects that illness can have on the circadian rhythm, and for how long before and after a period of illness the circadian rhythm will be affected. Previously we have seen that there are huge individual differences, the increased number of false positives for Ti60007, compared to Ty60001, could be due to the model fitting the individual rhythm of Ty60001 better than that of Ti60007.

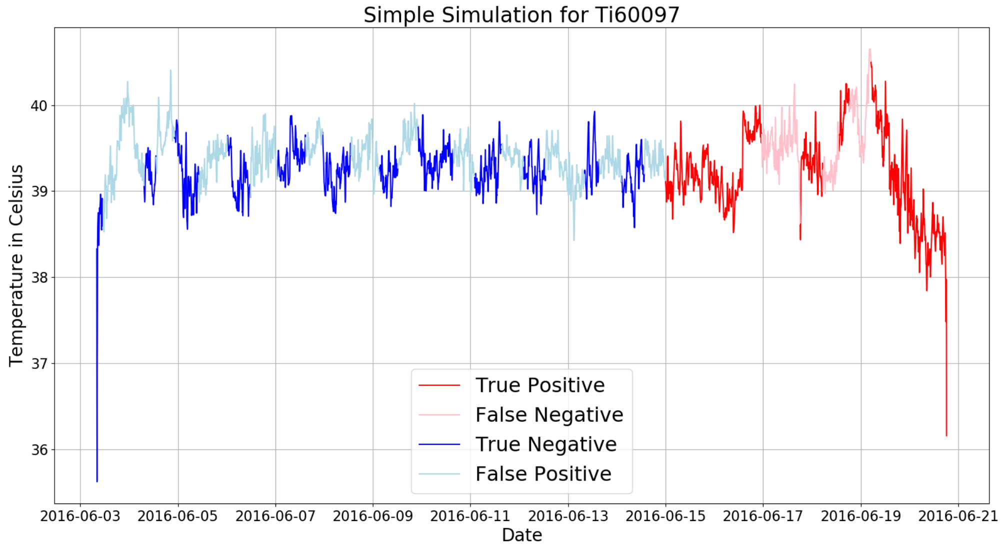

Figure 6.5: Results of the Simple Cosine Model for Ti60097

Simulation for the individual Ti60097 by using the Simple Cosine Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model compared to our benchmark.
Periods that are marked dark red are true positives, meaning that the lamb is ill both according to the model and the benchmark. Dark blue are true negatives, meaning that both the model and benchmark consider the lamb healthy. False negative is when the model think the lamb is healthy, but the benchmark thinks it's ill. False positive is opposite of false negative.

6.5.4 Thoughts on Performance

Based on our simulations of this model, we see that this is not usable, at least not with the configurations that we have used here. There are simply far too many false positives for this model to work in a "real" scenario. This model do however seem promising, as it seems to be better at finding the illnesses than the Simple Threshold Model, also when the temperature is within a normal range.

6.6 Complex Cosine Model

The Simple Cosine Model did not very accurately simulate the actual temperature oscillation. We therefore made a new model, which is a bit more complex, however still based on a cosine function. The new model would change with time. The changes would be a phase shift, increased amplitude,

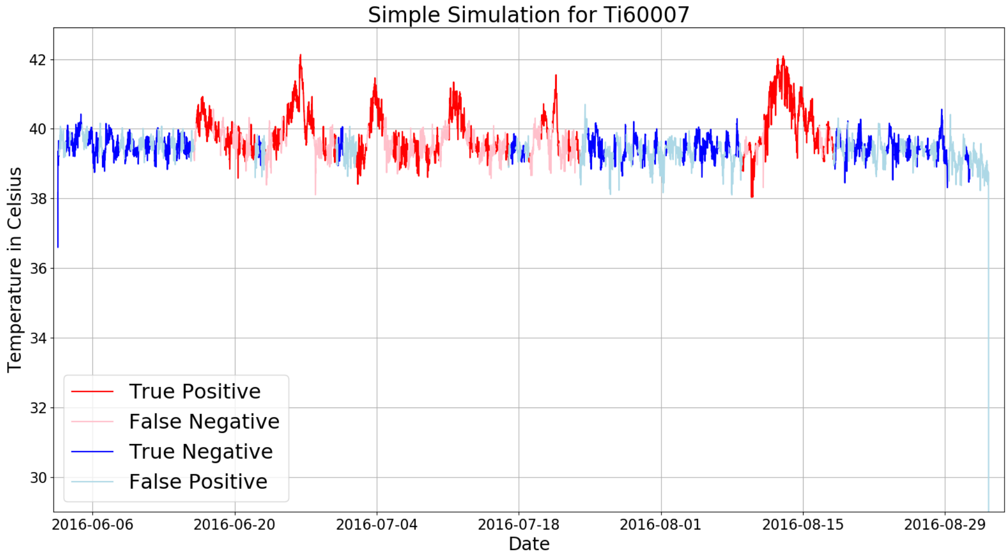

Figure 6.6: Results of the Simple Cosine Model for Ti60007

Simulation for the individual Ti60007 by using the Simple Cosine Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model compared to our benchmark.
Periods that are marked dark red are true positives, meaning that the lamb is ill both according to the model and the benchmark. Dark blue are true negatives, meaning that both the model and benchmark consider the lamb healthy. False negative is when the model think the lamb is healthy, but the benchmark thinks it's ill. False positive is opposite of false negative.

and decreased base temperature. We changed these aspects of the model based on what we learned through our analyses.

In this model we change some parameters with regards to the age of the sheep based on the changes with age we saw in Chapter 5.3. We do not know if these changes are caused by age necessarily, however these changes correlates at least to some degree with the age. Age was therefore used as an approximate metric for these changes.

For determining the expected temperature we still use the Equation 6.1, however we will now change the variables **mesor**, **A**, and **X**, on a weekly basis. Equation 6.2 shows our method for the weekly change in amplitude, where **A** stands for amplitude, and **weeks** is the age of the sheep in number of weeks. We decided to let the amplitude gradually increase until an adult amplitude would be reached, which it would at 13 weeks of age in this model.

The **mesor** would also change on a weekly basis, and the method for

Parameters	
Start Amplitude (**A**)	0.15
Margin of Error	0.35
Counter	180
Start Base Temperature (**mesor**)	39.65
Start Phase Start	03.30

Table 6.2: Parameters for the Complex Cosine Model

changing it is shown in Equation 6.3. This method simply lower the **mesor** by a small value each week. We have not set an age limit for the change of this value. Thus the longer the sheep lives, the lower the value would be. For our case, and in testing on our individual lamb, this works well. However we assume that the base temperature would not be forever decreasing and it's lowering should probably have a lower limit. It might even be the case that we would need to increase and decrease the base temperature for different times of year.

The period was shifted using the method as seen in Equation 6.4. The variable **X** defines the number of minutes passed since the start of the last cycle. We changed the model by adding 60 minutes to the counter. In that way we shifted the phase. Our model would change the phase until the sheep had reached 13 weeks of age, at which point they would be assumed to have adopted an adult rhythm.

This model takes into consideration the change in temperature, and temperature oscillation, with age. However, it doesn't take into consideration the change caused by season, individual differences, and other causes. It is therefore also just a simple approximation of the circadian rhythm of sheep.

In the following simulations we used the parameters given in Table 6.2. After the lamb had reached an age of 13 weeks the amplitude would have risen from 0.15 to 0.35. The phase start would have been shifted to 22.30. The base temperature would have been lowered to approximately 39.59. We see that the parameters grow closer to what we used for the Simple Cosine Model, as seen in Table 6.1.

$$A = A + change \cdot min(\frac{weeks - 3}{10}, 1) \tag{6.2}$$

$$mesor = mesor - 0.01 \tag{6.3}$$

$$X = X + 60 \tag{6.4}$$

6.6.1 Simulation for Ty60001

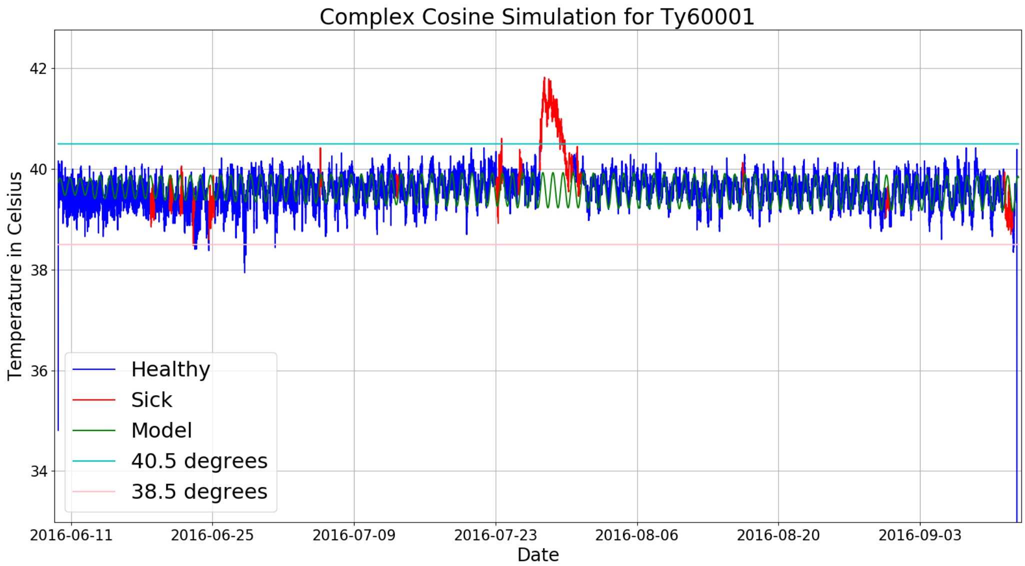

Figure 6.7: Results of the Complex Cosine Model for Ty60001

Simulation for the individual Ty60001 by using the Complex Cosine Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model.
Periods that are marked red are periods where the model deem the individual to be ill, and blue periods are periods where the individual is deemed to be healthy. The green curve depicts the expected temperature of the model. The light blue line has the value of 40.5, which is our threshold for fever. The light red line has the value 38.5, and is a temperature we consider abnormally low.

When simulating this model for the individual Ty60001, the results is depicted in Figure 6.7. We see that the model is able to detect the clear fever period and even warns about the health of the individual several days before the fever starts. Compared to the simulation using the Simple Cosine Model for the same individual, as depicted in Figure 6.4, we see that there are fewer warnings about the health of the individual. This can be considered as a good thing, as there were a lot of false positives using the Simple Cosine Model.

In the beginning of the simulation we see that this model consider the individual ill in a period that we have previously considered normal. Upon closer inspection we noticed that there are some disturbances to the circadian rhythm during this period, and the temperatures are lower than normal. It might very well be that this individual was ill during this period, just that it wasn't easy to detect as the temperature is within the normal range. We have already seen in the case of Ti60097, that a sheep can be very ill and yet show little indications of this except disturbances in the circadian rhythm.

6.6.2 Simulation for Ty60021

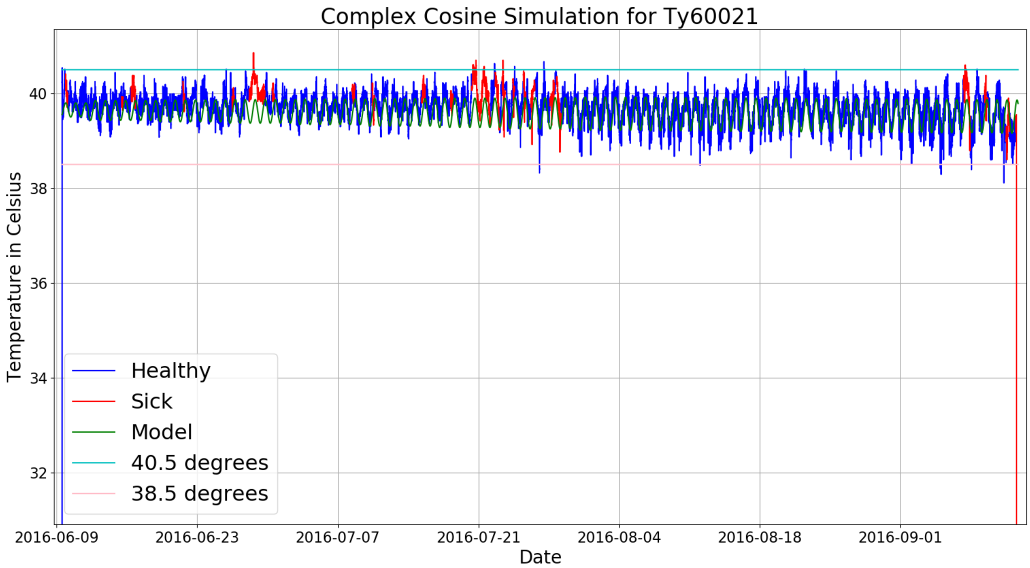

Figure 6.8: Results of the Complex Cosine Model for Ty60021

Simulation for the individual Ti60097 by using the Complex Cosine Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model.
Periods that are marked red are periods where the model deem the individual to be ill, and blue periods are periods where the individual is deemed to be healthy. The green curve depicts the expected temperature of the model. The light blue line has the value of 40.5, which is our threshold for fever. The light red line has the value 38.5, and is a temperature we consider abnormally low.

Looking at the temporal data of the individual Ty60021, we see that it has several periods of moderate fever. In these periods the fever doesn't last long, and it could possibly have been caused by other factors such as activity, however as the temperature seems somewhat abnormal around these peeks, and that these peeks sometimes occurs within a short time period, we believe these peeks are caused by illness. The temporal data, as well as the simulation using this model, can be seen in Figure 6.8.

This model is able to detect these periods of moderate fever, something we doubt the Simple Threshold Model would be able to do. We do see some warnings from the model in periods where the temperature is within the normal range, however it is hard to say if these are signs of illness that we don't see, or if they are false positives.

6.6.3 Simulation for Ti60007

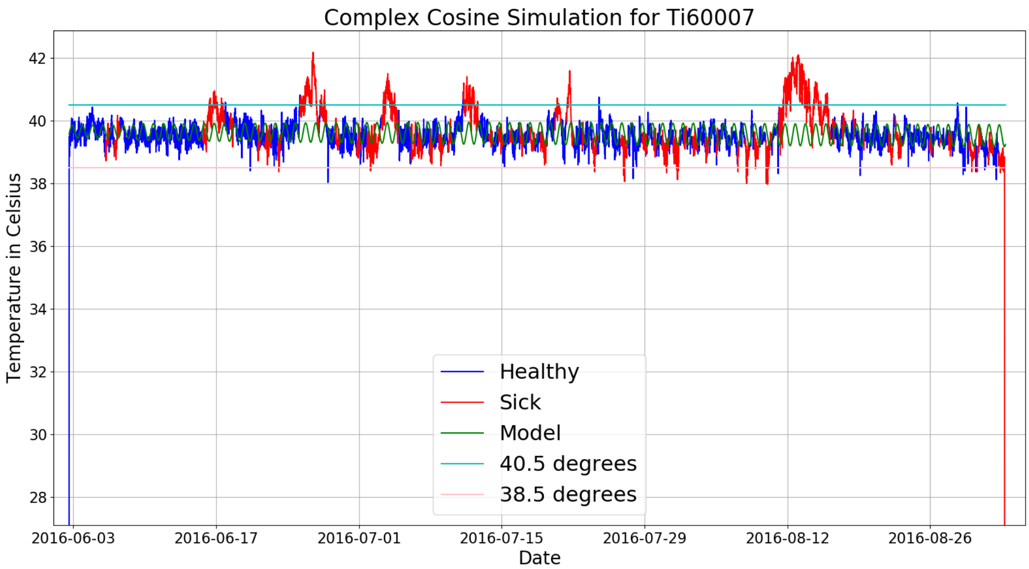

Figure 6.9: Results of the Complex Cosine Model for Ti60007

Simulation for the individual Ti60007 by using the Complex Cosine Method. The graph shows the actual core temperature of the lamb at the given time, and the colors show the result of the model.
Periods that are marked red are periods where the model deem the individual to be ill, and blue periods are periods where the individual is deemed to be healthy. The green curve depicts the expected temperature of the model. The light blue line has the value of 40.5, which is our threshold for fever. The light red line has the value 38.5, and is a temperature we consider abnormally low.

When we compare the results of simulating for individual Ti60007 by using this model, as shown in Figure 6.9, and the Simple Cosine Model, as shown in Figure 6.6, we notice there are differences. We haven't presented the results in the same way for both simulations, however we are still able to compare them. This model seem to have far fewer false positives than the Simple Cosine Model, and is still able to detect all periods of illness, of which there are many for this individual. Still we see a lot of periods of illness according to this model.

What remains up for discussion is what is, and what is not an abnormal period, and for how long before and after a period of illness can we expect to see disturbances in the temperature and the circadian rhythm. It might be that some of the cases of false positives actually are early signs of illness, or effects of a previous illness. There is also a chance that some of the periods we consider abnormal, and a sign of illness, is simply an abnormality and has nothing to do with illness at all.

6.6.4 Evaluation of Performance

The few cases we have depicted here of the performance of this model is promising. This model seem to detect periods that are abnormal with ease. It seems to be better in detecting periods of illness than the Simple Threshold Model, and seem to have a better accuracy than the Simple Cosine Model. Here we have only shown tentative results, and it is not possible to make a great conclusion based on these alone. We will have to do more analyses on the performance of this model, and experiment with different parameters to see how this affects the performance of this model.

6.7 Evaluation Model for Solutions

The only benchmark we had so far was the hand-picked abnormalities. We wanted to develop a program that would mark periods as abnormal to ensure objectivity, and to judge all periods by the same standards. These machine picked periods would still be influenced by our choices as of what is abnormal, how long these abnormalities would have to be present, and other parameters and their values set by us.

Our model for classifying periods would operate with 4 different type of periods, namely normal-, incubation-, illness-, and post-illness periods. Normal periods are periods where we assume the individual is healthy. The incubation periods are periods where we assume early signs of illness appear, and is therefore tied to the illness periods. Illness periods are periods in which we assume the individual is ill. Post-illness periods are periods in which we assume abnormalities are to be expected, however the illness is considered ended.

If the sensor-models during testing warns about an illness in a normal period we would view this as a false positive. Warnings that occur either during the incubation period or the illness period would be considered as successful warnings of an illness. During post-illness periods we didn't care whether the sensors warned of illness or not as we assumed this stage would be too late for treatment. We were not interested in false negatives, however we would record the number of illness periods that were not detected.

In order for the false positives not to simply be the number of minutes that the sensor warned about illness outside of the selected periods, we used an error margin. A new false positive would only be counted if it was further from the last recording of a false positive than the error margin. If however the last recording is within the margin of error, we would update the time of the last recording to the current time and consider it part of the same "illness" period.

For detecting the illness periods we operated with a base temperature and deviation from this above a margin of error would constitute an incidence of illness. This illness would last until the temperature was within the margin of error. After detection all such incidences we would aggregate our list of illnesses, where periods that happened within the time of incubation would be joined to one incidence lasting from the earliest to the latest date of the dates of these periods. After we had aggregated the illness periods we added the incubation periods and the post-illness periods. The normal periods would then simply be the periods that are not present in the incubation-, illness-, or post-illness periods.

This model would take in some parameters so that we could alter the way this method selected the periods. We had parameters for the base temperature, the margin of error, the number of days prior to an illness we expect early signs, and the days after an illness we would expect there to be disturbances.

This way of categorizing the illness periods gives us an uniform way of evaluating the models on different individuals and takes into consideration both abnormally high and abnormally low temperatures. What this method does not take into consideration is the circadian rhythm. We have earlier discussed the effects illness might have on the circadian rhythm, and tried to model with regards to the circadian rhythm, however we still don't know enough to use this to create a benchmark for evaluating our models.

Figure 6.10 depicts how this program would partition the temporal data into the categories, and how we would evaluate the our models to these machine picked periods. In this example we have used 4 day long incubation periods, and 2 day long post-illness periods. We used 39.5 degrees as a basis, and allowed 1.0 degree deviation. The model we evaluate here is the Complex Cosine Model with the same parameters as we used for this earlier in Chapter 6.6.

We see that the machine found 3 periods of illness, out of which all were detected. The model had 2 false positives, where one was just before an incubation period.

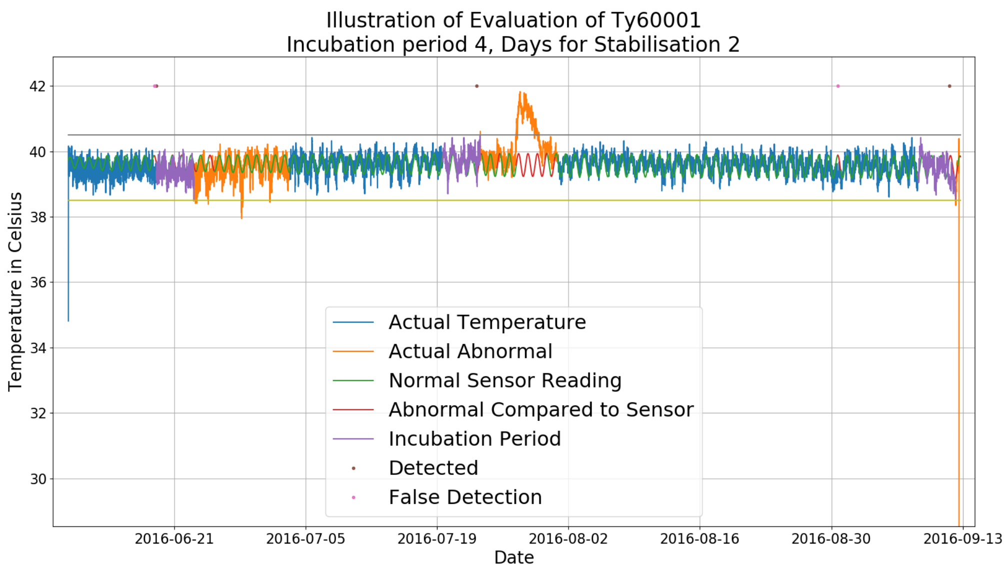

Figure 6.10: Test and evaluation of the Complex Cosine Model on Ty60001

This is an illustration of how our program for period classification work, and how we would compare the results from our simulations to these periods.
The blue, purple, and yellow parts show the actual temperature of the individual. The blue are normal periods, the purple is the incubation periods for the illnesses, and the yellow show the illness periods, including the post-illness periods. The green and red are the expected temperatures according to our model, where green are when the model consider the individual healthy, and red when the model consider the individual ill. Brown dots are when the model detects an illness for the first time, and light purple dots are false positives. The two horizontal lines depicts the lower- and upper thresholds for our categorization.

Chapter 7

Results

While we in the previous chapter briefly looked at the performance of the different models, more systematic testing needs to be done, and we cannot look at this on an individual level. We also need to tweak our parameters to see what works best, and try to optimize our models with regards to our benchmarks.

For comparing the different models and different set-ups, we measure the mean detection rate, number of false positives, number of true positives, and the percentage of the the healthy periods that are mislabeled. The detection rate is the percentage of the illness periods that were detected. True positives might seem redundant given that the detection rate is given, however to same number of true positives can give different detection rates, and vice verso.

The number of false negatives can be misleading in that we measure periods of illness according to the sensor and not the time it indicates wrongly. The healthy periods are measured from the time we start evaluating the sensor readings until an illness is detected.

In all the following tests we use the parameters shown in Table 7.1 for the machine picked benchmark.

Good results would be to have a high detection rate (**Mean Detection Rate %**) and few false positives as well as a low percentage of mislabeled healthy periods (**Mean False Illness %**). Results showing a high detection rate shows that most of the illness periods were detected, while few false positives and a low percentage of mislabeled healthy periods imply that the model seldom is wrong.

Machine Benchmark Parameters	
Days Prior	4
Days After	2
Error Margin	1

Table 7.1: Parameters for the machine picked benchmark

7.1 Results from Simple Thresh Method

The first of our models we decided to test was the Simple Threshold Model. The results for this model would then act as sort of a benchmark for the other models. For us to consider the other models better, they would need to perform considerably better than this model to compensate for their increased complexity.

Our earlier test simulations with this model indicated that it was the model with the lowest number of false positives, which is an important point for us. In our tests of this model we have tweaked which base temperature to use and the error margin in order to see what combination would give the best results.

The Simple Threshold Model is tested with regards to both the hand picked benchmark and the machine picked benchmark. In both cases the counter was set to 30 minutes.

7.1.1 Results Compared to Machine Picked Periods

Results for the tests of the Simple Threshold Model to the machine picked benchmark can be seen in Table 7.2. The mean detection percentage stayed relatively stable in the range [83% , 85%] for all iterations. The mean number of true positives also stayed stable at approximately 5. The mean number of false positives and the percentage of mislabeled healthy periods were changing the most when adjusting the variables.

This model works much in the same way as the software for picking illness periods, the difference is that this model needs to observe temperatures outside the normal range for an extended period of time. The margins of error we have used in testing this model is approximately half of what the machine picked benchmark use.

The smallest number of false positives and percentage of wrongful fever periods were observed when using a base temperature of 39.55 and an error margin of 0.54.

Generally for all the base temperatures the lowest number of false positives were observed with a high margin of error, and the highest detection

Base Temperature/Error Margin		0.54	0.5	0.44	0.38	0.32
39.65	Mean Detection %	83	84	84	85	85
	Mean False Positives	14	17	22	26	31
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	4.9	7.9	12	19	29
39.6	Mean Detection %	83	83	84	85	85
	Mean False Positives	13	16	22	26	30
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	3.9	6.5	11	18	27
39.55	Mean Detection %	83	83	85	85	85
	Mean False Positives	12	17	22	26	30
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	3.4	6.0	11	17	26
39.5	Mean Detection %	83	84	84	85	85
	Mean False Positives	14	18	22	27	31
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	3.9	6.5	11	18	27
39.45	Mean Detection %	84	84	85	85	85
	Mean False Positives	15	19	24	28	31
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	4.8	8.2	13	20	29

Table 7.2: Comparison of different temperature and error margin combinations with the Simple Threshold Model and machine picked benchmarks

Dark green- and red fields mark respectively the best- and worst results for the given metric. Light green- and light red fields mark respectively the best- and worst results for the given base temperature. The number of true positives are not marked, as this didn't change for the different configurations.

rates were observed when a small margin of error was used. This is not very surprising as a smaller margin of error would result in more of the temperatures to be marked as illness and then it follows that both the chance of detecting illness, and false positives increase.

The best results were observed with a base temperature of 39.55. It is close to the mean temperature, see Chapter 5.2.5, and might therefore work well. Having a base temperature close to the mean temperature might make it is able to equally well detect abnormally high and low temperatures. Another reason is that if it is too high, the threshold for detecting abnormally high temperatures would be elevated and the threshold for abnormally low temperatures would similarly set too low. When the base temperature is set too low the opposite would happen.

7.1.2 Results Compared to Hand Picked Periods

Base Temperature/Error Margin		0.56	0.5	0.44	0.38	0.32
39.65	Mean Detection %	97	97	97	97	97
	Mean False Positives	28	32	38	43	48
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	13	17	22	28	38
39.6	Mean Detection %	97	97	97	97	97
	Mean False Positives	27	31	38	43	47
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	12	15	21	28	36
39.55	Mean Detection %	97	97	97	97	97
	Mean False Positives	26	32	38	43	48
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	10	14	20	26	35
39.5	Mean Detection %	97	97	97	97	97
	Mean False Positives	27	33	38	44	48
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	11	14	19	27	35
39.45	Mean Detection %	97	97	97	97	97
	Mean False Positives	28	34	40	44	48
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	11	15	21	28	36

Table 7.3: Comparison of different temperature and error margin combinations with the Simple Threshold Model and hand picked benchmarks

Dark green- and red fields mark respectively the best- and worst results for the given metric. Light green- and light red fields mark respectively the best- and worst results for the given base temperature. The detection rate and the number of true positives are not marked as they did not change for the different configurations.

Compared to the results using the machine picked benchmark, see Table 7.2, results using the hand picked benchmark, see Table 7.3, has a much better detection rate. However, healthy periods are mislabeled for a higher percentage of the time than when we use the machine picked benchmark.

Similarly to the previous results, the model performs best with a high margin of error, and a base temperature of 39.55. The results might have changed if we changed the counter, or if we used substantially different values for the amplitude and error margin than we have here. However, as with the previous test, we see that the number of false positives and percentage of mislabeled healthy periods increase both when we increase the base temperature, and decrease the base temperature with regards to a base temperature of 39.55. This is further indication that this model works best with a base temperature close to the mean temperature.

7.2 Results from Experimenting with Different Error Margins and Amplitudes for the Simple Cosine Model

The Simple Cosine Model was also tested against both the benchmarks. In all tests we use 39.65 as a base temperature, and 180 minutes for the counter. The counter is much larger than what we use for the Simple Threshold Model, this is due our experiences from earlier test runs.

7.2.1 Results Compared to Machine Picked Periods

In the results, see Table 7.4, the detection rate stayed quite stable for the different configurations, however there were some changes. A lower margin of error usually results in a higher detection rate, however also results in a higher number of false positives. This coincides with the results for the Simple Threshold Model.

Best results, in regards to false positives, are seen when using a small amplitude. This is both surprising and disappointing, as we had hoped emulating the circadian rhythm would yield better results. The lowest number of false positives for this model is high compared to the Simple Threshold Model, and has a worse detection rate.

From the results it might seem as the results gets better the closer it gets the Simple Threshold Model, as the most reliable results are obtained with a low amplitude. However, comparing the combination of an amplitude of 0.35 and an error margin of 0.56 to an amplitude of 0.25 and an error margin of 0.44, the detection rates are the same, but the configuration with the highest amplitude is more reliable. This indicates that the emulation of the circadian rhythm might have some benefit.

The poor results can be a consequence of how the machine picked benchmark is picked, and it might favor a threshold model over this type of model.

Amplitude/Error Margin		0.56	0.50	0.44	0.38	0.32
0.45	Mean Detection %	85	85	85	85	85
	Mean False Positives	26	31	33	34	35
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	24	32	41	51	64
0.40	Mean Detection %	85	85	85	85	85
	Mean False Positives	23	28	31	34	35
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	20	28	36	46	58
0.35	Mean Detection %	85	85	85	85	85
	Mean False Positives	20	24	28	32	34
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	17	23	31	41	52
0.30	Mean Detection %	83	85	85	85	85
	Mean False Positives	17	21	25	30	33
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	13	19	26	36	47
0.25	Mean Detection %	81	84	85	85	85
	Mean False Positives	13	18	22	27	31
	Mean True Positives	5	5	5	5	5
	Mean False Ilness %	10	15	22	30	42

Table 7.4: Comparison of different results with different start amplitudes and error margins with the Simple Cosine Model and machine picked benchmarks

Dark green- and red fields mark respectively the best- and worst results for the given metric. Light green- and light red fields mark respectively the best- and worst results for the given start amplitude. The number of true positives are not marked as they did not change for the different configurations.

In these results, the base temperature was unchanged, as was the counter. There might be better configurations than those we have tested here. Further testing would be needed to discover the best combinations, however these results give some insight on the performance of this model.

7.2.2 Results Compared to Hand Picked Periods

As for the Simple Threshold Model, the results compared to the hand picked benchmark, as seen in Table 7.5, shows a higher detection rate. However, the number of false positives and the percentage of mislabeled healthy periods are also significantly higher.

Amplitude/Error Margin		0.56	0.5	0.44	0.38	0.32
0.45	Mean Detection %	97	97	97	97	97
	Mean False Positives	43	48	50	52	53
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	31	38	46	55	66
0.40	Mean Detection %	97	97	97	97	97
	Mean False Positives	38	44	48	51	52
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	27	34	42	51	62
0.35	Mean Detection %	97	97	97	97	97
	Mean False Positives	35	40	46	49	51
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	24	30	38	47	57
0.30	Mean Detection %	97	97	97	97	97
	Mean False Positives	30	36	42	47	50
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	21	27	34	43	53
0.25	Mean Detection %	97	97	97	97	97
	Mean False Positives	26	32	37	44	48
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	18	24	31	39	49

Table 7.5: Comparison of different results with different start amplitudes and error margins with the Simple Cosine Model and hand picked benchmarks

Dark green- and red fields mark respectively the best- and worst results for the given metric. Light green- and light red fields mark respectively the best- and worst results for the given start amplitude. The detection rates and number of true positives are not marked as they didn't change for the different configurations.

Best results were achieved by using a small amplitude and a high margin of error, as it was when using the machine picked benchmark. It might be caused, as previously discussed, by the benchmarks favoring a threshold model, or that the benchmarks does not take into consideration signs of illness that this model is able to detect, but get counted as a false positive.

When decreasing the amplitude, this model gets closer and closer to the Simple Threshold Model. An amplitude of 0.0 (zero) would give us a flat line, just as the base temperature of the Simple Threshold Model. However, as we use a base temperature of 39.65 for this model, an amplitude of zero would make this model similar to the worst configuration for the Simple Threshold

Model that we tested, with the exception of the counter, which is 6 times as long.

7.3 Results from Experimenting with Different Error Margins and Amplitudes for the Complex Cosine Model

For all the following tests of the Complex Cosine Model, we use a base temperature of 39.65 and a counter of 180 minutes, as we did for the Simple Cosine Model. The base temperature will however, in difference to the Simple Cosine Model, change with time, so even though this might start with the same base temperature as the Simple Cosine Model, at the end of the simulation the base temperatures would differ.

The start amplitudes might seem low compared to the amplitudes used for the Simple Cosine Model. However, as stated in Chapter 6.6, the amplitude increase by age. I case of a start amplitude of 0.0 the amplitude end up at 0.20. Considering this change, the amplitudes used here are not that far of the ones used for the Simple Cosine Model.

7.3.1 Results Compared to Machine Picked Periods

The results for the Complex Cosine Model, as seen in Table 7.6, is better than any of the results we have seen so far with regards to having few false positives. The downside is that the detection rate is lower than that of the previously tested models against the machine picked benchmark. This number of false positives, and percentage of mislabeled healthy periods, is half that of the best results we have for the Simple Threshold Model, which is very promising results in terms of accuracy.

The highest detection rate we get with this model, against the machine picked benchmark is 84% . The lowest number of false positives we get, while having a detection percentage of 84% , is 16. The Simple Threshold Model get 18 false positives with a detection rate of 84% with the machine picked benchmark. The amount of the healthy periods that are mislabeled for this model is 20% , for the Simple Threshold Model we get 8.2% . Even though this model had fewer false positives, the false warnings lasted for much longer. In this regard, this model is outperformed by the Simple Threshold Model for this detection rate.

The range of the detection rates is [70%, 84%], which is a far bigger range than we have previously seen. This model is more vulnerable to changes in

Start Amplitude/Error Margin		0.56	0.50	0.44	0.38	0.32
0.0	Mean Detection %	71	74	77	81	82
	Mean False Positives	2.6	4.5	6.9	10	15
	Mean True Positives	4.2	4.4	4.5	4.8	4.9
	Mean False Ilness %	1.5	3.3	6.6	11	19
0.04	Mean Detection %	70	76	78	81	84
	Mean False Positives	3.3	5.2	7.7	11	16
	Mean True Positives	4.1	4.4	4.6	4.8	5.0
	Mean False Ilness %	1.9	3.8	7.0	12	20
0.08	Mean Detection %	73	77	79	81	84
	Mean False Positives	4.1	5.9	8.9	13	17
	Mean True Positives	4.3	4.5	4.7	4.8	5.0
	Mean False Ilness %	2.4	4.5	8.2	14	22
0.12	Mean Detection %	73	78	80	82	84
	Mean False Positives	4.7	7.1	10	14	19
	Mean True Positives	4.4	4.6	4.7	4.9	5.0
	Mean False Ilness %	3.1	5.5	9.3	15	25
0.16	Mean Detection %	76	79	81	83	84
	Mean False Positives	5.7	8.5	12	16	22
	Mean True Positives	4.5	4.7	4.8	4.9	5.0
	Mean False Ilness %	3.8	6.8	11	18	28

Table 7.6: Comparison of different results with different start amplitudes and error margins with the Complex Cosine Model and machine picked benchmarks

Dark green- and red fields mark respectively the best- and worst results for the given metric. Light green- and light red fields mark respectively the best- and worst results for the given start amplitude.

the parameters than the two other models. This can be both good and bad. This allows us to tweak the performance to larger degree. However, wrong parameters will also have a greater effect.

7.3.2 Results Compared to Hand Picked Periods

As for the previous models, the detection rate and number of true positives are remarkably stable when comparing to the hand-picked benchmark. This model performs rather well in terms of number of false positives and percentage of healthy periods that are mislabeled compared to the other models.

When we compare the results seen here compared to the results to the

Start Amplitude/Error Margin		0.56	0.50	0.44	0.38	0.32
0.0	Mean Detection %	95	95	97	97	97
	Mean False Positives	10	13	18	23	29
	Mean True Positives	2.4	2.4	2.5	2.5	2.5
	Mean False Ilness %	8.0	11	17	23	32
0.04	Mean Detection %	95	96	97	97	97
	Mean False Positives	11	14	19	24	30
	Mean True Positives	2.4	2.5	2.5	2.5	2.5
	Mean False Ilness %	8.5	12	17	24	33
0.08	Mean Detection %	96	97	97	97	97
	Mean False Positives	12	16	21	26	33
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	9.1	13	19	26	36
0.12	Mean Detection %	97	97	97	97	97
	Mean False Positives	13	18	23	28	35
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	10	14	20	27	38
0.16	Mean Detection %	97	97	97	97	97
	Mean False Positives	15	20	25	31	38
	Mean True Positives	2.5	2.5	2.5	2.5	2.5
	Mean False Ilness %	11	16	21	29	40

Table 7.7: Comparison of different results with different start amplitudes and error margins with the Complex Cosine Model and hand picked benchmarks

Dark green- and red fields mark respectively the best- and worst results for the given metric. Light green- and light red fields mark respectively the best- and worst results for the given start amplitude. The number of true positives are not marked as they had almost no change for the different configurations.

machine picked benchmark, we see the same pattern as with the previous models. The detection rate goes up together with the number of false positives and the percentage of healthy periods mislabeled.

7.4 Comparison on Model Effectiveness between the Herds

In Chapter 5 we saw that the herds had relatively large differences in the core temperature and its oscillation. We wanted therefore to see if there were large performance differences between the herds. We do the comparisons for all

Parameters - Simple Threshold Model	
Base Temperature	39.55
Error Margin	0.56
Counter	30

Table 7.8: Parameters for the Simple Threshold Model when comparing performance on herds

Tingvoll - Machine Picked		Tingvoll- Hand Picked	
Mean Detection %	88	Mean Detection %	95
Mean False Positives	6.9	Mean False Positives	18
Mean True Positives	5.8	Mean True Positives	3.6
Mean False Ilness %	3.5	Mean False Ilness %	14
Tynset - Machine Picked		**Tynset - Hand Picked**	
Mean Detection %	78	Mean Detection %	100
Mean False Positives	18	Mean False Positives	35
Mean True Positives	4.1	Mean True Positives	1.3
Mean False Ilness %	3.4	Mean False Ilness %	6.7

Table 7.9: Herd comparison on the Simple Threshold Model to the machine picked benchmark

Comparison of the Simple Threshold Models performance on the herds. Results from sensor is compared to both the benchmarks.
Green- and red fields mark respectively the best and worst results. Light green- and light red fields mark respectively the best and worst results in regards to its benchmark.

the models and using both benchmarks.

For generating the machine picked benchmarks we use the same parameters as used previously, shown in Table 7.1.

In the results of these tests we will include the number of true positives. This metric informs us of how many periods are detected. This is not a metric for comparison as we have seen that the different benchmarks have a different amount of illness periods and in Chapter 5.9 we saw that the different herds have a different number of illness periods. Although we cannot compare this metric, we still think it provides the reader useful information.

7.4.1 Comparison on the Simple Threshold Model

When comparing the performance of our Simple Threshold Model we used the parameters shown in Table 7.8. These parameters were chosen as they

Parameters - Simple Cosine Model	
Base Temperature	39.65
Error Margin	0.56
Counter	180
Amplitude	0.25

Table 7.10: Parameters for the Simple Cosine Model when comparing performance on herds

had previously given us the best results.

Table 7.9 contains the results of our comparison for the Simple Threshold Model. We see here that there are clear differences. For both herds we see that results for the machine picked benchmark has a lower detection rate than for the hand picked benchmark. This coincides with previous results. Similarly to previous results, we see that testing in regards to the machine picked benchmark gives us a lower amount of false positives than the hand-picked benchmark.

Interestingly we see that when testing to the machine picked benchmark, the Tingvoll herd has the highest detection rate, while when we test to the hand picked benchmark it is the Tynset herd that has the highest detection rate.

For both the benchmarks we see that the herd at Tynset gets a higher amount of false positives, however has a lower percentage of healthy periods that are mislabeled as illness. In Chapter 5.9 we saw that the herds have differences in the number of illness periods, this is supported in these results, where we see that for both benchmarks the herd at Tynset has far fewer true positives i.e. number of detected illness periods. This explains how the herd at Tynset can have a higher number of false positives and at the same time have a smaller amount of the healthy periods mislabeled.

7.4.2 Comparison on the Simple Cosine Model

For the comparison of the herds we used the parameters given in Table 7.10 for the Simple Cosine Model for both the benchmarks. These parameters were chosen based on our previous results.

The results of this comparison is given in Table 7.11. The results are quite similar to what we got for the Simple Threshold Model, given in Table 7.9, although generally with slightly worse detection rates and higher numbers of false positives. We see that this model performs worse in all aspects compared to the Simple Threshold Model for both the herds and with both the benchmarks.

Tingvoll - Machine Picked	
Mean Detection %	87
Mean False Positives	10
Mean True Positives	6.0
Mean False Illness %	13

Tingvoll - Hand Picked	
Mean Detection %	95
Mean False Positives	21
Mean True Positives	3.6
Mean False Illness %	26

Tynset - Machine Picked	
Mean Detection %	74
Mean False Positives	17
Mean True Positives	3.9
Mean False Illness %	7.4

Tynset - Hand Picked	
Mean Detection %	100
Mean False Positives	31
Mean True Positives	1.3
Mean False Illness %	11

Table 7.11: Herd comparison on the Simple Cosine Model

Comparison of the Simple Cosine Models performance on the herds. Results from sensor is compared to both the benchmarks.
Green- and red fields mark respectively the best and worst results. Light green- and light red fields mark respectively the best and worst results in regards to its benchmark.

Parameters - Complex Cosine Model	
Start Base Temperature	39.65
Error Margin	0.56
Counter	180
Start Amplitude	0.0

Table 7.12: Parameters for the Complex Cosine Model when comparing performance on herds

7.4.3 Comparison on the Complex Cosine Model

For these comparisons we used the parameters given in Table 7.12 for the Complex Cosine Model. These parameters were chosen based on our previous results, as this combination gives us the lowest number of false positives of all the combinations we have tested.

The results for this comparison, given in Table 7.13, is rather different from the results for the two other models, however some trends remains. As for the previous results, we see that the herd at Tingvoll has the best detection rate when using the machine picked benchmark, and when using the hand picked benchmark the herd at Tynset has the best detection rate.

A difference from the previous comparisons is that the herdt at Tynset has a lower number of false positives than the herd at Tingvoll when using the hand picked benchmark. This is interesting as it differs from the previous

Tingvoll - Machine Picked		Tingvoll - Hand-Picked	
Mean Detection %	81	Mean Detection %	93
Mean False Positives	2.3	Mean False Positives	11
Mean True Positives	5.3	Mean True Positives	3.5
Mean False Illness %	2.0	Mean False Illness %	12
Tynset - Machine Picked		**Tynset - Hand-Picked**	
Mean Detection %	59	Mean Detection %	97
Mean False Positives	2.7	Mean False Positives	9.5
Mean True Positives	2.9	Mean True Positives	1.3
Mean False Illness %	0.94	Mean False Illness %	3.9

Table 7.13: Herd comparison on the Complex Cosine Model

Comparison of the Complex Cosine Models performance on the herds. Results from sensor is compared to both the benchmarks.
Green- and red fields mark respectively the best and worst results. Light green- and light red fields mark respectively the best and worst results in regards to its benchmark.

results.

Generally we see that this model has worse detection rates for both herds, and both benchmarks than both the other models. When using the hand picked benchmark, the difference is not great. However, when using the machine picked benchmark we see bigger differences. For the Tingvoll herd the Simple Threshold Model and the Simple Cosine model have detection rates of 88% and 87% respectively, while this only detect 81% . For the Tynset herd, the Simple Threshold Model and the Simple Cosine Model have detection rates of 78% and 74% respectively, while this model has a detection rate of 59% . This might be a good thing. As we have discussed, the software for picking illness periods might be too sensitive. Using this model we get a mean number of 2.9 true positives, i.e. detected periods. Looking at our analysis in Chapter 5.9 we have found the mean number of fever periods to be 2.2 for the Tynset Herd. This might be an indication that this model is more accurate than the others.

From these results we see that this model outperforms the other models in regards to the mean number of false positives and percentage of healthy periods that are mislabeled. Now this might be because we accidentally found the ideal parameters for this model, and for the other models used less than ideal parameters.

Chapter 8

Discussion

In our analysis we see clear indications of a circadian rhythm in sheep. We do also see indications of individual differences, and changes with time. There are also strong indications that disturbances of the circadian rhythm can indicate illness in sheep, and that periods with fever has a core temperature elevated far over the normal range of temperature.

Temporal signs of illness also seem to appear at an earlier stage than clinical signs appear. It seems very likely that it is possible to develop models based on temperature that detect illnesses before one is able to do so manually. We see also that when sheep are at free-range pastures, it is increasingly difficult to inspect and detect illness manually, increasing the usefulness of our proposed system.

As we have seen in Chapter 5, the circadian rhythm is clearly present in sheep, and illnesses can cause abnormalities in this rhythm. The results of our analyses seem therefore positive to the possibility of creating a model for detection sheep illness based on the temperature.

There are however also indications that approximating the circadian rhythm can be more difficult than expected. There are huge individual variations, and we see changes with time. There is some doubt whether these changes are caused by aging, seasonal changes, both, or other unknown causes. These uncertainties can also have affected our results from our analyses.

Our data set consisted of 31 individuals in total. These individuals were from two different herds, at two different locations. Approximately half of the individuals were males, and the other half females. All together we have approximately 4.3 million records. Although there seem to be a lot of data, which it was, it might not have been enough. Some of the individuals were sick for a quarter of the time, creating either a lack of data, or a lot of abnormalities for our analyses.

As all our data is from lambs, we have no data to say anything about adult sheep. We can neither compare the daily oscillation and temperature in general between lambs and adult sheep. The change with time in the lambs might have impacted our results, and we cannot compare these data with the data of adult sheep. This makes it more difficult to make decisions based on our data.

From the journal data we have regarding signs of illness in sheep, we see that detection of clinical signs of illness can be difficult, and clinical signs of illness usually appear later than temporal signs. When the sheep are at free-range pastures, observing clinical signs of illness is extremely difficult. We see this in part in the journal data, as there are fever records of illness in the journal, however we see in the temporal data that there has been a clear presence of illness also when the sheep were free-range grazing. This implies that the current way of detecting illness in sheep in free-range pastures is inefficient and inaccurate.

Our results from testing our models are promising. They detect most of the illness periods, however not all of them are detected. This might be due to the benchmarks marking healthy periods as illness periods, or other mislabeling. We see that for some of the models and configurations, a relatively high amount of the healthy periods are mislabeled as illness periods. An example is seen in the results of the simulations of the Simple Cosine Model to the hand picked benchmark, seen in Table 7.5. The worst configuration mislabel 66% of the healthy periods as illness. This is far too much mislabeling, and this model with this configuration could not work in a real world scenario. On the other hand, some of the models show very low amount of mislabeled periods. The Complex Cosine Model mislabel only 1.5% of the healthy periods when comparing to the machine picked benchmark, as seen in Table 7.6.

False positives would be a problem if there are many of them. A high number of false positives could force the farmer to check in on healthy sheep more than needed, and thus cause an unnecessary amount of extra work for the farmers. If the farmers are forced to check in on healthy animals too often, this might cause distrust in the system, leading the farmers to stop controlling the sheep in case of warnings, or stop using the system all together.

The results surprise us a bit, as we thought that the handpicked periods would be harder to detect than the machine picked. However, in the results we see that the opposite is true. We see that the mean number of true positives, i.e. the number of detected illness periods is higher for the machine picked threshold than for the hand picked benchmark, despite the higher detection rate on the hand picked benchmark. This shows that the machine picked benchmark has far more illness periods than the hand picked benchmark.

This rather large difference between the benchmarks might explain the differences we see between the performance to the benchmarks. As the hand picked benchmark might include mainly illness periods that are easy to detect, leading to a high detection rate, however at the same time leading to a high number of false positives as there are illness periods that are not marked in the benchmark so detection of these result in false positives. Another possibility is that the software for detecting illnesses is too sensitive and includes periods deviating from the base temperature that are not caused by illness.

We saw in the analyses that the periods of illness looked different. We also saw that in some cases, where the sheep had been very ill, that the temperature was abnormally low right after a fever period. Some illnesses were characterized by disturbances in the daily oscillation alone, and did not have elevated temperature. This indicates that different illnesses can cause different footprints on the temperature and its oscillation, and on the seriousness of the illness. However, we do not have information about which illness the sheep suffer from in each case of illness, so it is not possible for us to state anything specifically about this based on our analyses and our knowledge at this point. However it seems like it would be possible to predict, if not the specific illness, at least a group of illnesses, and possibly an approximate severity level of the illness based on temperature alone.

The Simple Threshold Model seem to catch most of the illness periods, and seemingly at an earlier stage than clinical signs start to appear. This is a simple model, and should be easy to implement in sensors. It does however not take into consideration disturbances in the circadian rhythm, and as we have seen in our analyses, deadly deceases can have seemingly normal temperatures, however with disturbed rhythms. We have also seen that it can have trouble detecting light fever, which is just around the threshold temperature. This model seem to have a low number of false positives, making it a very trustful method.

The Simple Cosine Model tried to emulate the circadian rhythm, without taking into consideration the changes over time. We thought this would be better at detecting illnesses than the Simple Threshold Model, however it was worse at detecting illnesses and had a far higher number of false positives. This model did not work well, and it worked best, the closer it got to the Simple Threshold Model.

Our last model, namely the Complex Cosine Model, is based on emulating the circadian rhythm. However, it was not a constant model as the Simple Cosine Model, but changed to accommodate the changes we observed in the temperature and circadian rhythm as seen in Chapter 5. This model had a worse detection rate than both the previous models, something that surprised us a bit, however it fared way better in terms of low amount of false positives than both the previous models. Although we haven't tested all possible configurations for our models, and there are some uncertainties in regards to our benchmarks, this model seem to be working rather well.

The Complex Cosine Model changed as the lamb aged. This was due to our findings of change that coincided with the aging of the lamb. This change seemed to be working well, judged by our results. However, as we have previously discussed, we do not know the reason for the change, as there are many possible causes for the change. In this case it do work, however it is not certain that it would work as well for other herds or for adult sheep.

Professor Emeiritus Kjell Bratbergengen shared with us a model he had developed [34]. This model would be tweaked based on the sensor readings and deviations, and would in that way over time be fitted to the individual. This has several benefits as it solves the problem of individual differences, and we don't need to know what causes change over time, it would change with the changes. Using this model, we would not have to use calibrated sensors, as it is the relative temperature that is important in this case. The problem arises when dealing with large differences, if one should adjust the model also when the difference is large or not. Large differences can be signs of illness, so if we adjust for them, it might make the model inaccurate. However, if we do not adjust for large differences we have a problem if the starting point is far of the individual's values.

Kjell's model, [34], have good results, and seem to be a step in the right direction. One would have to address how to deal with large deviations and needs to be tested. However, its results are promising, and the individually adapting nature of the model might solve many of the problems we uncovered in Chapter 5.

For evaluation of our models, we had both hand-picked abnormal periods, and used a program that would select abnormal periods. This was done as we didn't have a blueprint telling us when the illness periods started, how long they lasted, and for how long time the temperature and the temperature oscillation was affected. We might have wrongfully marked periods as abnormal and normal. It is therefore not certain that all our results depict the true performance of our models. It might be that they perform worse or better than what we have recorded.

Sheep are a relatively low cost livestock. Margins for profit for each individual sheep are therefore slim. As the herds often are of considerable size, and there is a trend of an increasing livestock size per farmer [3] the sensors and the insertion needs to be cheap and efficient. The insertion of the sensors took around 15 minutes and a team of trained veterinarians were needed. While this might seem like a short time for a surgical process, this is not possible to do on a large scale [3] . The sensors would also be too expensive. The majority of the sheep do survive, however illness might slow growth, and loss in revenue must also consider this lost weight at slaughter. At the moment, this process would be too costly, however it could possibly be used in other livestock that have a higher value, but then new analyses for these animals would be needed. It could also be possible to use different sensors, that have a lower cost, and that are easier to install. With time it is not unthinkable that new, cheaper sensors will be available, that can be more easily inserted in the sheep.

Chapter 9

Conclusion

While there are a lot of uncertainties concerning our results, we are confident that our work support some hypotheses. We have found clear support for a circadian rhythm in sheep, and that illness often impact the temperature and its oscillation. Our results also seem to support the theses that the temperature and its oscillation changes with time, however the cause is not clear. We found that aging in our lamb was related to changes, however we cannot say if this is caused by aging or if it just coincides with aging. There are many factors that might affect the temperature of sheep and its oscillation, and it is known that the temperature and circadian rhythm of animals have seasonal changes.

Our simple threshold model will be able to detect illness at a far better rate than what is today possible, and it could help save both income for the farmer and lives of sheep. Although this method has its drawbacks, it would improve detection of illness in sheep on free-range pastures drastically compared to the situation of today.

Our Simple Cosine Model was not very successful. However, it serves to prove that when making models that try to emulate the circadian rhythm, one needs to take the changes that occur into consideration. The circadian rhythm change with time and if one does not take these changes into consideration, one's model will become unreliable.

Our results indicates that the Complex Cosine Model is a good choice for a detection model. It has a low number of false positives and has a decent detection rate. It is far from certain that this model would work on other herds, if it was implemented at a different time, etc. However, it shows that a model that emulates the circadian rhythm, and that changes accordingly to the changes that is expected of the circadian rhythm will be of great utility.

Based on our results, we are convinced it is possible to detect illness in sheep, by looking at the temperature only. We are also convinced that a model based on the circadian rhythm, that takes changes of the rhythm into consideration would be a good model for detecting sheep illness. As we do not fully understand the causes for the change we saw, we think an approach like that of Kjell's model, [34], is the way to go.

As of right now, we don't think our proposed system would be feasible to develop. The components would be too expensive, and the implantation to complicated, costly, and time consuming. For this system to be feasible, we would need to look at alternative methods of measuring the core temperature, or an approximate of it. We strongly believe that sensor technology will evolve such that sensors will become cheap enough, and possible to install with ease, so that this system will be feasible to develop in the future.

Chapter 10

Future Work

There is still a lot of work that needs to be done before it will be possible to develop our proposed system. We need to do more analyses, like we have done here, with more sheep to verify our results. We would also prefer to do the same analyses with more animals to see if this changes the results. Further more, it would be very useful to analyze the circadian rhythm of adult sheep, and measure the temperature for a longer time period to better understand how the temperature and its oscillation changes with age, and the season. It would also be interesting to investigate the impact climate and weather can have on the sheep, and if there are differences between different breeds of sheep.

We should analyze whether it is possible to differentiate different illnesses, and its severity, by the temperature alone. Illnesses should be analyzed from a temperature point of view, and the different phases of the illness should be compared to the temporal data, in order to learn the affects of different phases of the illnesses have on the temperature, and if it is possible to find a pattern that indicates a illness ”fingermark” on the temperature.

There are similar products available for other types of livestock, such as FEVERTAGS [35]. We should compare our results with existing solutions and how well these work. We could use this information to aid decisions on our product, draw inspirations, and discover what can be improved.

More development and testing is needed for the models for detecting illness in sheep, in order to make them more reliable and accurate. When a reliable and accurate model is found, it should be tested in real-life on sensors in living sheep over an extended time period. Preferably one would be able to equip some of the sheep in an area with these sensors, and see whether there are significant differences between these and the unequipped sheep. Differences that might be interesting to look at are mortality rate, weight at slaughter, and quality of the meat.

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Prediction of Illness in Sheep on Body Temperature

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