ICIC Express Letters
Part B: Applications
Volume **14**, Number **8**, August **2023**

ICIC International ©2023 ISSN 2185-2766
pp. 877–888

PREDICTING DAIRY COW CALVING TIME USING MARKOV MONTE CARLO SIMULATION AND NAÏVE BAYES CLASSIFIER

Thi Thi Zin[1,*], Swe Zar Maw[2], Pyke Tin[1], Yoichiro Horii[3] and Hiromitsu Hama[4]

[1]Graduate School of Engineering
[2]Interdisciplinary Graduate School of Agriculture and Engineering
[3]Center of Animal Disease Control
University of Miyazaki
1-1, Gakuen Kibanadai-Nishi, Miyazaki 889-2192, Japan
{ swezarmaw; pyketin11 }@gmail.com; horii@cc.miyazaki-u.ac.jp
*Corresponding author: thithi@cc.miyazaki-u.ac.jp

[4]Graduate School of Engineering
Osaka Metropolitan University
3-3-138, Sugimoto, Sumiyoshi-ku, Osaka-shi 558-8585, Japan
h21644z@omu.ac.jp

Received January 2023; accepted March 2023

Abstract. *This study proposes an approach that utilizes both Markov Monte Carlo simulation and the Bayesian method to predict the time of calving events in dairy cows. Continuous video surveillance was conducted on 30 individual dairy cows 24 hours before calving. Behaviors such as lying, transition from lying to standing, standing, and transition from standing to lying were annotated for each cow between 72 to 168 hours prior to calving. The probabilities for each behavior were derived and used in Markov Monte Carlo simulations to generate behavior patterns of each cow before calving. Three types of datasets, actual, simulated, and a mixture of the two, were investigated using Naïve Bayes Classifier for prediction. The experimental results showed that the hybrid approach accurately classified the calving event, cent by cent. This approach can assist farmers and veterinarians in making informed decisions and taking appropriate actions before the calving event, ultimately improving the health and welfare of dairy cows.*
Keywords: Calving time prediction model, Markov Monte Carlo, Bayes Theorem, Cow behavior analysis, Video monitoring, Image processing techniques

1. **Introduction.** Calving is a crucial event in precision dairy farming and requires careful monitoring to prevent losses due to a lack of timely humanitarian assistance. Therefore, an accurate prediction of calving time is crucially required. As a consequence, the research concerning calving time prediction has become a demanding research area in dairy science. Recent research topics have indicated that an accurate prediction of the time to calving event is crucial to deciding when a pregnant cow should be moved to maternity pens or when human assistance is necessary, among other factors [1-4]. Farmers and dairy science management experts have recognized that the calving event in dairy cattle is painful and stressful [5,6]. Moreover, prolonged calving, delayed human assistance or severe assisted extraction of the calf at birth may lead to a difficult birth, known as dystocia, resulting in losses in the economy as well as calves or mothers or both [6-8]. Prevention measures can be taken if we can establish a reliable and precise monitoring system to make an accurate prediction for calving time.

Traditionally, the prediction of calving has been done by using manual observation, such as observing breeding records and visual cues. However, the traditional ways of

DOI: 10.24507/icicelb.14.08.877

manual observation are complicated and can result in errors that even experts can miss to make a proper prediction. Moreover, manual prediction is not practical when the farm size is large and will become time-consuming, inefficient, and costly. This problem seems to be taken care of since the number of cattle per farm is increasing every year [9]. In this context, many researchers have attempted to deal with calving time prediction problems by using empirical, clinical, and analytical methods, along with sensor and image processing techniques [1,10-12].

Recently, farmers and researchers observed that the behavior changes around the time of calving could be used as indicators to predict the time of the calving event. Due to advances in image technologies and artificial intelligence, video monitoring systems to investigate the behavior patterns of individual cows have been increasingly utilized [9,13-15]. Consequently, some researchers have shown their eagerness to assess calving behavior for predicting calving time. Such sort of calving time prediction can have advantages to ensure the provision of adequate supervision and timely human intervention when difficulty arises [6,8,16,17]. However, despite a rich literature on this topic, there still remain wide enough research areas needed to be explored, especially methodology aspects.

Therefore, in this paper, we explore and examine an approach that combines vision technology with Markov Monte Carlo simulation and Bayes' Theorem to predict dairy cow calving time based on four types of behaviors of individual pregnant cows around the time of calving. The main contributions of the paper are

(i) To show how this approach can benefit from Markov Monte Carlo simulation and the Bayesian method for the prediction of the calving day and time of cattle.

(ii) To highlight how Naïve Bayes' classifier can accurately predict the remaining multiple of 4 hours before calving time.

(iii) To confirm the proposed method by using real-life experiments conducted on two dairy farms, namely, Farm-A and Farm-B.

The rest of the paper is organized as follows. Section 2 describes the materials and methods followed by the experimental works in Section 3. Section 4 provides statistical analysis and discussions of the experimental results. Finally, Section 5 presents the conclusion and future work.

2. Materials and Methods.

This section details the methodology employed in the study, including data collection and the proposed system architecture.

2.1. Data collection.

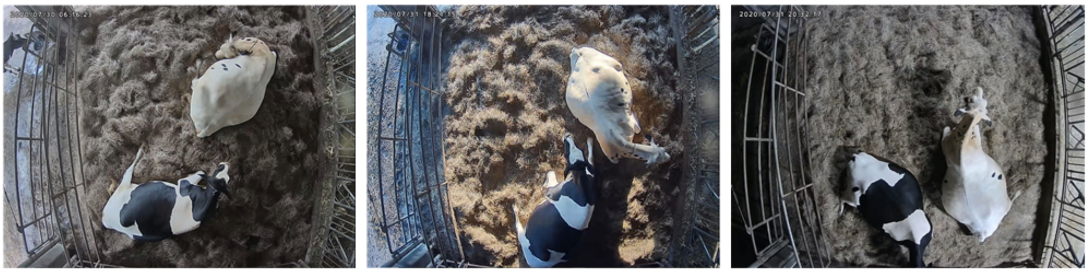
The study aims to predict calving time in dairy cows using a hybrid approach based on Markov Monte Carlo and Bayes Theorem. The analysis utilizes three different datasets: the original dataset, the Markov Monte Carlo simulated dataset, and the hybrid dataset, which combines the original and simulated datasets.

2.1.1. *Original dataset.*

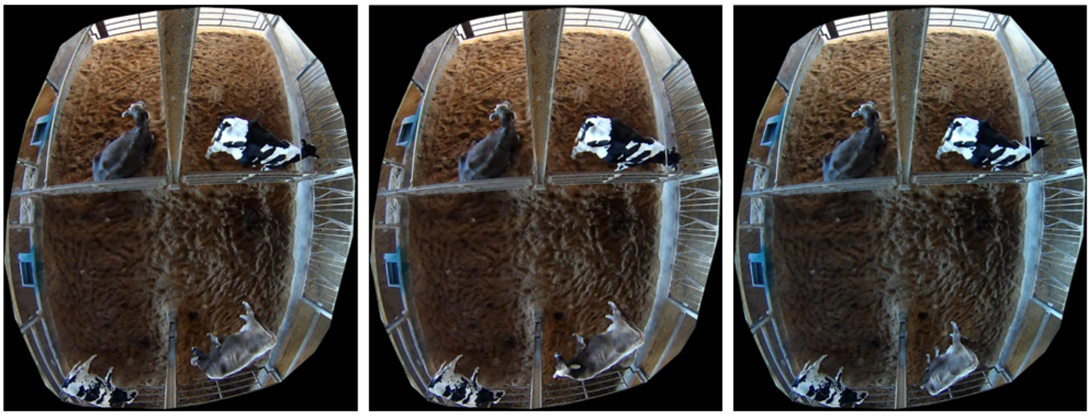
The original dataset was collected by analyzing the behavioral changes of 30 pregnant cows in two farms, Farm-A and Farm-B. Five cows from Farm-A and 25 cows from Farm-B were included in the study. Behavioral changes were analyzed for seven days (168 hours) in Farm-A and three days (72 hours) in Farm-B, up until the cows calved. The dataset includes four types of predictors: lying (L), standing (S), lying to standing (LS) and standing to lying (SL). Each posture takes 5 seconds, each LS takes 15 seconds, and each SL takes 10 seconds. The behavioral changes were counted every hour, with each count representing 5 seconds of one posture or one transition activity. The response variable was either calving or not calving. Table 1 shows the sample behavioral change data for Cow ID 1 from the original dataset. Figure 1 illustrates some sample images taken from the calving pens at the two dairy farms.

Table 1. Sample behavioral changes analysis data of Cow ID 1 (Original dataset)

Time	**Four predictors**				**Two responses**
	No. of L	**No. of S**	**No. of LS**	**No. of SL**	
-168	180	3	537	0	Not calving
-167	0	0	720	0	Not calving
-166	595	3	120	2	Not calving
...	...	...	...	...	...
-4	0	0	720	0	Calving
-3	0	0	720	0	Calving
-2	360	3	355	2	Calving
-1	358	0	360	2	Calving



(a) Farm-A



(b) Farm-B

Figure 1. Sample images from the video sequences taken in the calving pens of two farms

2.1.2. *Markov Monte Carlo simulated dataset.* The Markov Monte Carlo simulated dataset was created through a simulation process that involved estimating transition probabilities between different states using Markov Chain Monte Carlo simulations. This dataset was used to validate the proposed hybrid approach. To generate this simulated dataset, we utilized the Markov Monte Carlo method, which involved several steps. Firstly, we calculated mean values from each column of four predictors, L, S, LS, and SL, from the original dataset, and then normalized each mean value by dividing it by the sum of all mean values. This normalization process allowed us to obtain the probability for each predictor.

The data table for the Monte Carlo simulation is described in Table 2. Next, we calculated the cumulative probabilities for each cow and then generated a random number, R, between 0 and 1.

TABLE 2. Data table for the Monte Carlo simulation

Predictors	**Mean**	**Probability**	**Cumulative probability**
L	119.631	0.166	0.166
LS	0.500	0.001	0.167
S	599.536	0.833	1
SL	0.333	0	1
Sum	720	1	–

The simulation followed a set of rules where, for posture L, we counted it as 1 if ($R < P_1$), otherwise, we counted it as 0. For transition LS, we counted it as 1 if ($R > P_1$ and $R < P_1 + P_2$), otherwise, we counted it as 0. For posture S, we counted it as 1 if ($R > P_1 + P_2$ and $R < P_1 + P_2 + P_3$), otherwise, we counted it as 0. For transition SL, we counted it as 1 if ($R > P_1 + P_2 + P_3$ and $R < 1$), otherwise, we counted it as 0. This process allowed us to obtain new behavioral change data, which we then compared to the original data through 168 iterations. We calculated the new probabilities from the generated data and computed the Euclidean distance between the probabilities of the new and original data. If the original data and generated data were similar, we used them for the prediction process. Table 3 presents a sample behavioral change analysis data of Cow ID 1 from the Markov Monte Carlo simulated dataset.

TABLE 3. Sample behavioral changes analysis data of Cow ID 1 (Markov Monte Carlo simulated dataset)

Time	**Four predictors**				**Two responses**
	No. of *L*	**No. of *S***	**No. of *LS***	**No. of *SL***	
−168	0	0	1	0	Not calving
−167	0	0	1	0	Not calving
−166	1	0	0	0	Not calving
...	...	...	...	...	...
−4	0	0	1	0	Calving
−3	0	0	1	0	Calving
−2	0	0	1	0	Calving
−1	0	0	1	0	Calving

2.1.3. *Hybrid dataset of the original and simulated datasets.* The hybrid dataset was generated by combining the original dataset and the Markov Monte Carlo simulated dataset, which was served as the training set for the proposed hybrid approach. To create the hybrid dataset, we combined the first two-thirds of the original data with the last third of the corresponding simulated data. This combination allowed us to retain the natural variability of the original data while also incorporating the simulated data's modeled behavior changes. Table 4 illustrates a sample behavioral change analysis data of Cow ID 1 from the hybrid dataset. This combined dataset enabled the proposed hybrid approach to learn from both the original and simulated data and make more accurate predictions.

2.2. **Overview of system architecture.** The proposed hybrid approach utilizes a combination of Markov Monte Carlo simulations and Bayes Theorem to predict calving time in dairy cows. The system architecture consists of three main components: data pre-processing, feature extraction, and model training and evaluation. The data pre-processing component involves cleaning and filtering the raw data. The feature extraction component involves extracting relevant features from the pre-processed data. The model training and

Table 4. Sample behavioral changes analysis data of Cow ID 1 (Hybrid dataset)

Time	**Four predictors**				**Two responses**
	No. of *L*	**No. of *S***	**No. of *LS***	**No. of *SL***	
−168	180	3	537	0	Not calving
−167	0	0	720	0	Not calving
−166	595	3	120	2	Not calving
...	...	...	...	...	...
−4	0	0	1	0	Calving
−3	0	0	1	0	Calving
−2	0	0	1	0	Calving
−1	0	0	1	0	Calving

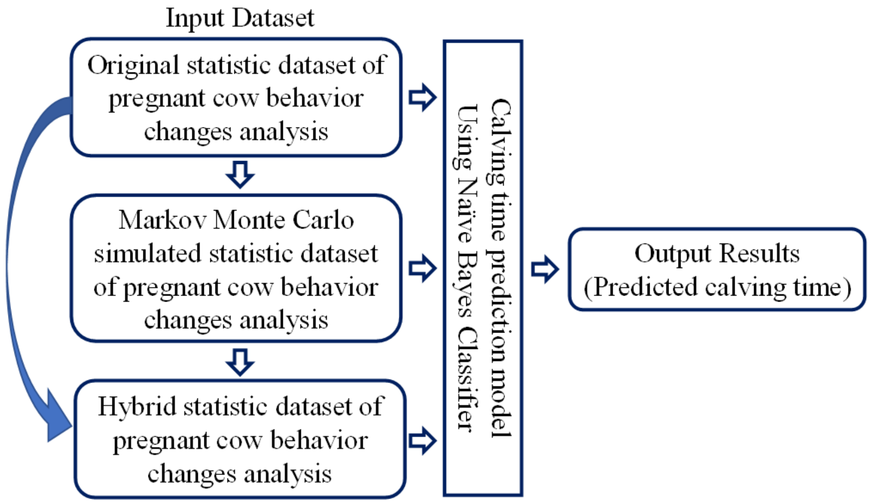


Figure 2. The system architecture of our proposed method

evaluation component involves training the hybrid model using the extracted features and evaluating its performance using various metrics. The proposed hybrid approach outperforms traditional approaches in terms of accuracy and efficiency. Figure 2 illustrates the system architecture of our proposed method. In particular, this section includes three additional subsections that provide a more detailed discussion of the Markov Monte Carlo simulation method used in our research. The new subsections are titled Markov Monte Carlo simulation methodology, Markov Monte Carlo simulation results, and Naïve Bayes Theorem formulation for calving time prediction.

2.2.1. *Markov Monte Carlo simulation methodology.* This subsection provides a detailed description of the Markov Monte Carlo simulation method used in our research. The methodology involves creating a simulated dataset using a Markov chain model with transition probabilities calculated from the collected data. The simulation process involves iterating through the Markov chain model to generate a sequence of predicted outcomes.

The Markov chain model is constructed by dividing the calving process into a sequence of states, each representing a specific stage of the calving event. The transition probabilities between states are calculated based on the collected data, and the initial state is determined by the data from the first day of observation. The simulation process involves iteratively updating the state of the Markov chain model based on the transition probabilities until the final state is reached. The simulated dataset generated by the Markov Monte Carlo simulation method can then be used for further analysis and prediction of the calving time.

2.2.2. *Markov Monte Carlo simulation results.* This subsection presents the results of the Markov Monte Carlo simulation method used in our research. The simulated dataset was generated using the collected data and the Markov chain model with transition probabilities calculated from the data. The results show that the simulated data closely match the actual data, indicating that the Markov Monte Carlo simulation method is an effective approach for predicting the calving time of dairy cows. By using simulated data, it is possible to make accurate predictions with only partial data, rather than collecting data for the entire calving process.

Furthermore, the Markov Monte Carlo simulation method provides a framework for further analysis and prediction of the calving time, allowing for more precise dairy farm management. The results of this simulation method demonstrate the potential for improving the accuracy and efficiency of dairy cow calving prediction.

2.2.3. *Naïve Bayes Theorem formulation for calving time prediction.* To predict the calving time, we generated four types of behavior changes (L, LS, S, SL) in dairy cows as predictor data for 7 days for 5 cows and 3 days for 25 cows prior to the expected calving due date using the Markov Monte Carlo simulation method. We then applied the Naïve Bayes Classifier (NBC) to the original and simulated data.

The Naïve Bayes classifier is a probabilistic algorithm that calculates the conditional probability of an observation X belonging to a class C_k for $k = 1, 2$. In our case, the two possible classes are Calving (C_1) and Not Calving (C_2) for each hour. Observation X corresponds to the four predictors L, LS, S, and SL. The conditional probability is calculated as follows:

$$P(C_k|X) = \frac{P(X|C_k) * P(C_k)}{P(X)} \text{ for } k = 1, 2 \tag{1}$$

where $P(C_k|X) =$ The probability of C_k given observation X, $P(X|C_k) =$ The probability of X given C_k, $P(C_k) =$ The probability of C_k occurring, $P(X) =$ The probability of X occurring.

We can simplify Equation (1) by assuming that the predictors are conditionally independent given the class. This assumption is known as the Naïve Bayes assumption. With this assumption, we can write

$$\frac{P(C_1|X)}{P(C_2|X)} = \frac{P(X|C_1) * P(C_1)}{P(X|C_2) * P(C_2)} = \theta \tag{2}$$

To predict calving time using the Naïve Bayes classifier, we first partitioned the data sequence for each cow into 4-hour intervals. We then calculated the mean and corresponding probabilities for each interval. These probability vectors were used as observation X. Our decision rule was defined as follows: if $P(C_1|X) > P(C_2|X)$, the state is calving; otherwise, the state is not calving.

In summary, our proposed method for predicting calving time involves generating behavior change data using the Markov Monte Carlo simulation method, applying the Naïve Bayes classifier to the data, and using a decision rule to determine the calving state. Our method has the potential to improve the accuracy of calving time prediction, which can lead to better management of dairy cows and increased profitability for farmers.

3. **Experimental Results.** In this study, pregnant dairy cows were housed separately in a calving pen approximately 10 days before the expected calving date. Their behavior was monitored using surveillance cameras until the calving process was complete. Human observers recorded and collected the behavior changes of 5 cows 7 days prior to calving and 25 cows 3 days prior to calving from video recordings. This yielded three types of datasets for cow behavior changes: the original dataset, the Markov Monte Carlo simulated dataset, and the hybrid dataset.

Computational Procedure: To predict the calving time, we used the Naïve Bayes classifier, which involves the following step-by-step computational procedure.

Step 1: For each behavior of (L, LS, S, SL), the means of the first 48 hours, 52 hours, 56 hours, 60 hours, 64 hours, 68 hours, and 72 hours (3 days) and the means of the first 112 hours, 116 hours, 120 hours, 124 hours, 128 hours, 132 hours, 136 hours, 140 hours, 144 hours, 148 hours, 152 hours, 156 hours, 160 hours, 164 hours, and 168 hours (7 days) were computed, starting from 2/3 of 72 hours (48 hours) and 2/3 of 168 hours (112 hours) until calving hours. Table 5 shows a sample calculation for Cow ID 1 from Farm-B.

Table 5. A sample calculation for Cow ID 1 from Farm-B

Time (hours)	**No. of *L***	**No. of *LS***	**No. of *S***	**No. of *SL***	**Sum**	**State**
48	274.500	2.438	441.479	1.583	720	*NC*
52	288.673	2.596	427.039	1.692	720	*NC*
56	293.411	2.625	422.250	1.714	720	*NC*
60	273.850	2.550	441.933	1.667	720	*NC*
64	258.609	2.484	457.281	1.625	720	*NC*
68	249.574	2.603	466.118	1.706	720	*NC*
72	247.798	2.875	467.417	1.917	720	*C*

Step 2: The rows of Table 5 were normalized to derive the corresponding probabilities matrix, which is shown in Table 6.

Table 6. The probability matrix of Cow ID 1 from Farm-B

Time (hours)	**Corresponding probabilities**				**Sum**	**State**
	P_1	P_2	P_3	P_4		
	No. of *L*	**No. of *LS***	**No. of *S***	**No. of *SL***		
48	0.381	0.003	0.613	0.002	1	*NC*
52	0.401	0.004	0.593	0.002	1	*NC*
56	0.408	0.004	0.587	0.002	1	*NC*
60	0.380	0.004	0.614	0.002	1	*NC*
64	0.359	0.004	0.635	0.002	1	*NC*
68	0.347	0.004	0.647	0.002	1	*NC*
72	0.344	0.004	0.649	0.003	1	*C*

Step 3: The probability vector $X = (P_1, P_2, P_3, P_4)$ was defined as an observed feature for the corresponding state. To apply the Bayes rule, two conditional probabilities needed to be computed: $P(X|C)$ and $P(X|NC)$, where C stands for the 'Calving' state and NC stands for the 'Not Calving' state. The following steps were followed to find these conditional probabilities.

(i) The product probability $(P_1 * P_2 * P_3 * P_4)$ was computed for each row.

(ii) Each product was denoted as $p(48), p(52), \ldots, p(72)$.

(iii) The probability of NC in the next time epoch was defined as the ratio of the starting epoch to the current epoch. For example, if the current epoch is 56 and the starting epoch is 46, then the probability of NC, $P(NC)$ at epoch 56 is $(48/56) = 0.857$. Hence, we get the probability of C, $P(C)$ at epoch 56 is $(1 - 0.857) = 0.143$.

(iv) Two conditional probabilities were then calculated as follows:

$P(X|C)$ at the current epoch = The product probability at the current epoch $*$ $P(C)$ at the current epoch.

$P(X|NC)$ at the current epoch = The product probability at the previous epoch $*$ $P(NC)$ at the current epoch.

According to the Bayes rule, if $[P(X|C)/P(X|NC)]$ is less than one, it is an NC state, and otherwise, it is a C state. Table 7 illustrates these computation procedures for Cow ID 1 from Farm-B.

Table 7. Prediction of calving time for Cow ID 1 from Farm-B

Time (hours)	State	Product probability	$P(NC)$	$P(C)$	$P(X\|C)$	$P(X\|NC)$	$P(X\|C)/P(X\|NC)$
48	NC	1.74E-06	–	–	–	–	–
52	NC	2.02E-06	0.923	0.077	1.55E-07	1.61E-06	0.097
56	NC	2.07E-06	0.857	0.143	2.96E-07	1.73E-06	0.172
60	NC	1.91E-06	0.800	0.200	3.83E-07	1.66E-06	0.231
64	NC	1.78E-06	0.750	0.250	4.44E-07	1.44E-06	0.309
68	NC	1.92E-06	0.706	0.294	5.65E-07	1.25E-06	0.451
72	C	2.37E-06	0.500	0.500	1.19E-06	9.61E-07	1.236

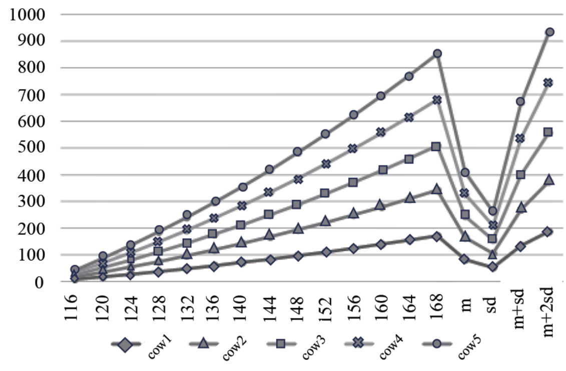
We also used the Bayes Theorem to predict calving time in the Markov Monte Carlo simulated dataset and the hybrid dataset. However, the Markov Monte Carlo dataset contained too many zeros, resulting in zero probability in the observed feature. To avoid this issue, we added 1 to each entry of simulated data before proceeding with the computation procedures used for the original data. The calving time prediction results for each cow are shown in Figure 3.

Based on the computation results in Figure 3, we observed that the value of the last 4 hours before calving occurred is always between the values of one-standard deviation (65) and two-standard deviations (90). This finding can be used to predict the onset of calving in dairy cows, providing important information for farmers to ensure proper management of their herds.

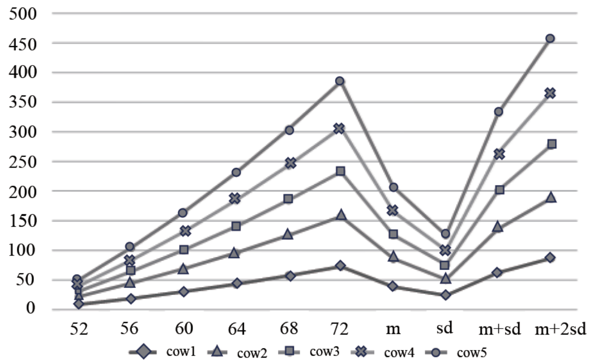
4. **Statistical Analysis and Discussions on Experimental Results.** This section provides an analysis and discussion of the experimental results for the proposed calving time prediction model. The model was tested using video data from 25 pregnant dairy cows collected from the second largest farms located in Oita Prefecture, Japan. Table 8 shows the results for the predicted time and actual calving time, indicating that the predicted times are within a 3-hour range of accuracy compared to the actual calving time. These results demonstrate promising precision for dairy farm management systems, with the ability to accurately predict the calving time of dairy cows.

The hybrid dataset was used to predict the outcomes of the calving day, and the results showed that the prediction time and actual time were almost the same. This finding suggests that using only two days of data and a hybrid dataset can predict the calving time accurately. The Markov Monte Carlo simulated dataset and hybrid dataset were used to create the results. However, the creation of a hybrid dataset had some limitations, with the occurrence of zero probabilities. To address this issue, we augmented a non-zero element and normalized it overall. Further investigation of this issue may be required in future works.

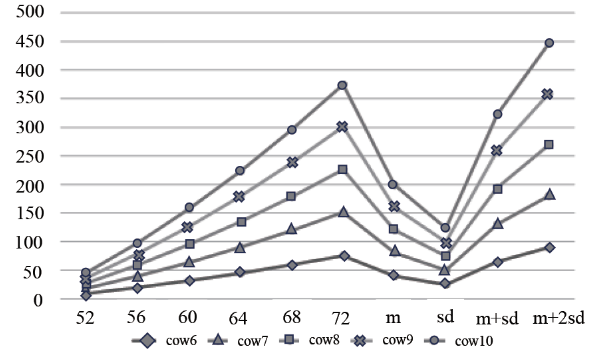
We also compared the statistical items of the generated data based on different numbers of iterations and found no explicit regulation. Additionally, we compared the n-step transition probabilities of the collected data and the simulated data based on the results shown in Table 3 and Table 4, and we found that the simulated hybrid data were very close to the actual data. Thus, it is useful to use the simulated data for further analysis in dairy cow calving prediction. We can make predictions with accuracy using partial data instead of collecting data for the whole process of the calving event. Some sample iteration results are shown in Table 9.



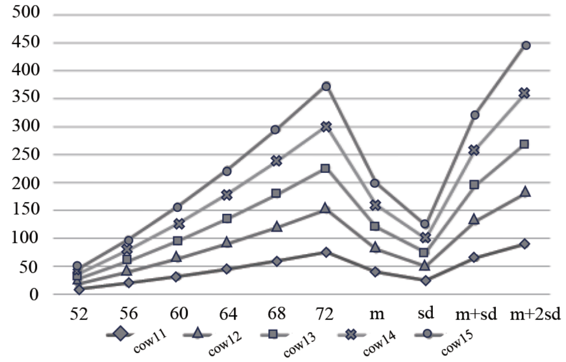
(a) Prediction of calving time for Cow ID 1 to Cow ID 5 from Sumiyoshi Livestock Science Station of the University of Miyazaki, Japan



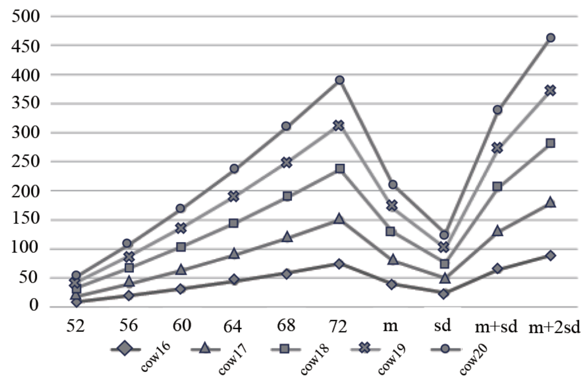
(b) Prediction of calving time for Cow ID 1 to Cow ID 5 from a large-scale dairy farm in Oita Prefecture, Japan



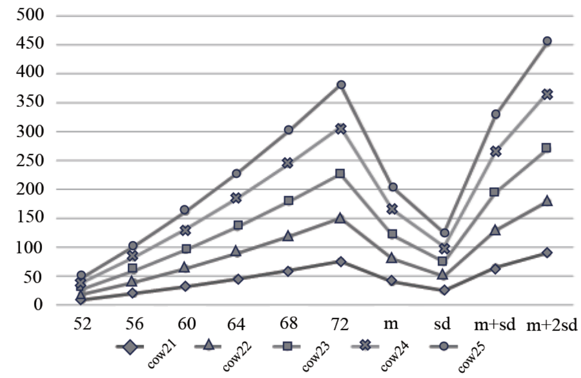
(c) Prediction of calving time for Cow ID 6 to Cow ID 10 from a large-scale dairy farm in Oita Prefecture, Japan



(d) Prediction of calving time for Cow ID 11 to Cow ID 15 from a large-scale dairy farm in Oita Prefecture, Japan



(e) Prediction of calving time for Cow ID 16 to Cow ID 20 from a large-scale dairy farm in Oita Prefecture, Japan



(f) Prediction of calving time for Cow ID 21 to Cow ID 25 from a large-scale dairy farm in Oita Prefecture, Japan

FIGURE 3. Prediction of calving time in 25 dairy cows using Bayes Theorem

Overall, this section provides a thorough analysis and discussion of the experimental results, highlighting key findings and placing them in the broader context of the research topic. The proposed calving time prediction model has demonstrated promising results for precision dairy farm management systems. The use of a hybrid dataset and simulated data has provided accurate predictions for calving times, making it possible to predict the calving time of dairy cows with only two days of data. Further investigations and improvements can be made in future works.

Table 8. Results for predicted time based on original and hybrid datasets

No.	Cow ID	Actual calving date	Actual calving time	Predicted time based on original dataset	Predicted time based on hybrid dataset
1	Cow 2	Dec 02, 2017	12:32	70.723	70.843
2	Cow 3	Nov 29, 2017	17:10	69.874	70.321
3	Cow 4	Nov 29, 2017	19:35	73.765	71.728
4	Cow 5	Dec 07, 2017	10:06	68.942	70.852
5	Cow 6	Dec 03, 2017	15:10	68.128	70.721
6	Cow 7	Dec 03, 2017	21:15	71.568	70.716
7	Cow 8	Dec 07, 2017	10:13	71.993	71.059
8	Cow 9	Dec 07, 2017	16:09	71.298	70.597
9	Cow 10	Dec 06, 2017	20:10	70.734	70.511
10	Cow 11	Dec 14, 2017	05:58	72.338	70.495
11	Cow 12	Dec 08, 2017	03:25	69.541	69.756
12	Cow 13	Dec 15, 2017	04:53	72.013	70.919
13	Cow 14	Dec 10, 2017	17:20	71.310	70.961
14	Cow 15	Dec 16, 2017	21:03	71.297	71.069
15	Cow 16	Dec 19, 2017	21:55	70.229	71.772
16	Cow 17	Dec 17, 2017	17:19	71.969	71.807
17	Cow 18	Dec 20, 2017	06:10	72.420	70.381
18	Cow 19	Dec 17, 2017	16:17	72.455	71.723
19	Cow 20	Dec 20, 2017	09:50	71.346	71.561
20	Cow 21	Dec 18, 2017	01:25	70.435	70.311
21	Cow 22	Dec 20, 2017	12:15	73.081	70.307
22	Cow 26	Dec 12, 2017	17:15	71.274	70.159
23	Cow 27	Dec 04, 2017	10:25	72.592	70.465
24	Cow 29	Dec 06, 2017	02:41	72.405	69.730
25	Cow 30	Dec 02, 2017	00:30	70.889	70.510

Comparisons with some existing methods: After an extensive review of the literature, we have not come across any method similar to our approach. Therefore, we are unable to compare our methodology with existing methods. However, there are some noteworthy existing methods, such as the machine learning approach [13], utilization of online image analysis [1], posture changes indications [3], and investigation of farm devices [2]. Although these methods are appealing, we believe that our approach is simpler to implement and shows promising outcomes.

5. **Conclusions.** In this study, we have proposed a novel hybrid approach that combines Markov Monte Carlo and Naïve Bayes Theorem for calving time prediction. To evaluate the effectiveness of our proposed model, we conducted experiments on three datasets: the original dataset, the simulated dataset, and the hybrid dataset. In addition, we calculated the predicted calving time for 30 dairy cows using their known calving times. Our computational results demonstrate that our proposed method accurately predicts the calving time for all cows in our dataset. The integration of Markov Monte Carlo and Naïve Bayes Theorem enables our model to effectively capture the complex interactions between various factors influencing calving time.

In the future, we plan to expand the scope of our research by applying our proposed method to pregnant dairy cows with unknown calving times. This will allow us to further validate the effectiveness of our model in real-world scenarios.

Table 9. Sample comparison results distance between original and hybrid

(a) For pattern generation

Cow ID	Distance measures	Simulation (n iterations)		
		$n = 3000$	$n = 4000$	$n = 5000$
ID 1	Euclidean	0.0087000	0.0062000	0.0015000
	Cosine	0.0000085	0.0000049	0.0000003
ID 2	Euclidean	0.0507000	0.0092000	0.0476000
	Cosine	0.0003134	0.0000082	0.0002437
ID 3	Euclidean	0.0106000	0.0098000	0.0021000
	Cosine	0.0000136	0.0000094	0.0000005
ID 4	Euclidean	0.0010000	0.0017000	0.0063000
	Cosine	0.0000001	0.0000004	0.0000043
ID 5	Euclidean	0.0050000	0.0054000	0.0024000
	Cosine	0.0000024	0.0000036	0.0000007

(b) For stationary distribution

Cow ID	Distance measures	Simulation (n iterations)		
		$n = 3000$	$n = 4000$	$n = 5000$
ID 1	Euclidean	0.0228	0.0210	0.0147
	Cosine	0.0005	0.0004	0.0010
ID 2	Euclidean	0.0448	0.0180	0.0401
	Cosine	0.0015	0.0002	0.0010
ID 3	Euclidean	0.2675	0.2241	0.2594
	Cosine	0.0518	0.0347	0.0479
ID 4	Euclidean	0.1647	0.1216	0.1570
	Cosine	0.0211	0.0108	0.0187
ID 5	Euclidean	0.0380	0.0814	0.0473
	Cosine	0.0014	0.0063	0.0022

Overall, our proposed approach shows great promise for improving calving management in dairy farming. Accurate prediction of calving time can help dairy farmers plan and prepare for calving, leading to better animal welfare, improved farm efficiency, and increased profitability.

Acknowledgment. We thank K. Honkawa, D.V.M., for giving us every convenience of studying on the ranch and for his valuable advice. We also thank Associate Professor I. Kobayashi, Field Science Center, Faculty of Agriculture, University of Miyazaki, for his valuable advice.

REFERENCES

[1] F. Matamala, A. Strappini and P. Sepúlveda-Varas, Dairy cow behaviour around calving: Its relationship with management practices and environmental conditions, *Austral. J. Vet. Sci.*, vol.53, no.1, pp.9-22, 2021.

[2] Y. Xu, Y. Zhang, H. Liu, Y. Yang and L. Wang, A hybrid method of machine learning and mathematical models for predicting the calving time of dairy cows, *Computers and Electronics in Agriculture*, vol.187, 106255, https://doi.org/10.1016/j.compag.2021.106255, 2021.

[3] S. Higaki, Y. Matsui, Y. Sasaki, K. Takahashi, K. Honkawa, Y. Horii, T. Minamino, T. Suda and K. Yoshioka, Prediction of 24-h and 6-h periods before calving using a multimodal tail-attached device equipped with a thermistor and 3-axis accelerometer through supervised machine learning, *Animals*, vol.12, 2095, https://doi.org/10.3390/ani12162095, 2022.

[4] A. Horváth, L. Lénárt, A. Csepreghy, M. Madar, M. Pálffy and O. Szenci, A field study using different technologies to detect calving at a large-scale Hungarian dairy farm, *Reprod. Dom. Anim.*, vol.56, pp.673-679, https://doi.org/10.1111/rda.13904, 2021.

[5] J. McDonagh, G. Tzimiropoulos, K. R. Slinger, Z. J. Huggett, P. M. Down and M. J. Bell, Detecting dairy cow behavior using vision technology, *Agriculture*, vol.11, no.7, 2021.

[6] A. S. Kecelia, C. Catalb, A. Kayac and B. Tekinerdogand, Development of a recurrent neural networks-based calving prediction model using activity and behavioral data, *Computers and Electronics in Agriculture*, DOI: 10.1016/j.compag.2020.10528, 2020.

[7] M. B. Jensen, Behaviour around the time of calving in dairy cows, *Appl. Anim. Behav. Sci.*, vol.139, nos.3-4, pp.195-202, 2012.

[8] M. Speroni, M. Malacarne, F. Righi, P. Franceschi and A. Summer, Increasing of posture changes as indicator of imminent calving in dairy cows, *Agriculture*, vol.8, no.11, 2018.

[9] M. R. Borchers, Y. M. Chang, K. L. Proudfoot, B. A. Wadsworth, A. E. Stone and J. M. Bewley, Machine-learning-based calving prediction from activity, lying, and ruminating behaviors in dairy cattle, *Journal of Dairy Science*, vol.100, no.7, pp.5664-5674, 2017.

[10] A. C. Barrier, M. J. Haskell, A. I. Macrae and C. M. Dwyer, Parturition progress and behaviours in dairy cows with calving difficulty, *Appl. Anim. Behav. Sci.*, vol.139, nos.3-4, pp.209-217, 2012.

[11] V. Ouellet, E. Vasseur, W. Heuwieser, O. Burfeind, X. Maldague and É. Charbonneau, Evaluation of calving indicators measured by automated monitoring devices to predict the onset of calving in Holstein dairy cows, *J. Dairy Sci.*, vol.99, no.2, pp.1539-1548, 2016.

[12] N. Zehner, J. J. Niederhauser, M. Schick and C. Umstatter, Development and validation of a predictive model for calving time based on sensor measurements of ingestive behavior in dairy cows, *Comput. Electron. Agric.*, vol.161, pp.62-71, 2019.

[13] M. V. Robichaud, A. M. de Passillé, D. L. Pearl, S. J. LeBlanc, S. M. Godden, D. Pellerin, E. Vasseur, J. Rushen and D. B. Haley, Calving management practices on Canadian dairy farms: Prevalence of practices, *J. Dairy Sci.*, vol.99, no.3, pp.2391-2404, 2016.

[14] S. Z. Maw, T. T. Zin, P. Tin, I. Kobayashi and Y. Horii, An absorbing Markov chain model to predict dairy cow calving time, *Sensors*, vol.21, no.19, https://doi.org/10.3390/s21196490, 2021.

[15] T. C. Lwin, T. T. Zin and P. Tin, Predicting calving time of dairy cows by exponential smoothing models, *2020 IEEE 9th Global Conference on Consumer Electronics (GCCE)*, Kobe, Japan, pp.322-323, DOI: 10.1109/GCCE50665.2020.9291903, 2020.

[16] C. Fenlon, L. O'Grady, J. F. Mee, S. T. Butler, M. L. Doherty and J. Dunnion, A comparison of 4 predictive models of calving assistance and difficulty in dairy heifers and cows, *J. Dairy Sci.*, vol.100, no.12, pp.9746-9758, 2017.

[17] K. Sumi, S. Z. Maw, T. T. Zin, P. Tin, I. Kobayashi and Y. Horii, Activity-integrated hidden Markov model to predict calving time, *Animals*, vol.11, no.2, 2021.