Predicting Calving Time of Dairy Cows by Time Series Model

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Tunn Cho Lwin[a], Thi Thi Zin[b], Mitsuhiro Yokota[b]

Abstract

Calving time prediction is an important factor in dairy farming. The careful monitoring of cows can help to decrease the loss of calf rates during the calving time; moreover, to know the exact time of birth is crucial to make sure timely assistance. However, direct visual observation is time-wasting, and the continuous presence of observers during calving time may disturb cows. Therefore, in this study, the recording from video cameras and counting the number of standing to lying and lying to standing transitions of 25 cows before 72 hours of calving time are used. The time series approaches namely the exponential distribution probability and autoregressive integrated moving average (*ARIMA*) model are applied to predict the calving time and the root mean square error (*RMSE*) is used to check the accuracy and error value of the experiment. By these methods, the calving time is predicted with exact time interval by using exponential probability. Moreover, the *ARIMA* model is better accuracies in predicting calving time than autoregressive (*AR*) and moving average (*MA*) models.

Keywords: Calving time, Prediction, Exponential Distribution Probability, *ARIMA* Modeling

1. INTRODUCTION

Among agricultural sectors, dairy farming is one of the most important segments all over the world as dairy products are necessary nutrients of humans, and it can also be expressed as vital earning of farmers who are majorities in most of the countries. For dairy farming, most relevant and efficient forms of livestock are dairy cows, which can also be called as dairy cattle. Mostly, the United States, the United Kingdom, Australia and New Zealand are progressing dairy farming as agriculture practices mainly. In United States, during 2010, 2.3 million of calf death cases occurred. On modern dairy farms, calf loss rates are also rising recently in many countries[1].

Most of the calf loss cases can be assumed with the cause of perinatal mortality, which is known as death of perinate within 48 hours of calving, and at least 260 days of gestation periods are also included. Therefore, difficulties of calving had become a concern of all cattlemen as it can cause calf deaths and cause rebreeding failures of the second time in reducing calf crop rates. That is, the highest possible of calving difficulties can have lower fertility at rebreeding significantly[2]. For calving, 75% of calf died within an hour of calving, 10% were in the pre-calving stage and post-partum death was 15%[3].

Compare to beef cattle, dairy cows can have more difficulties in calving[4]. Those difficulties which are the major causes of perinatal mortality can usually find as dystocia, anoxia, infections, congenital defects, and other problems. By describing those causes, parturient traumatic injuries are reasons for these situations.

All mammals, also cows have calving or maternal behavior expressions due to a series of hormonal changes that can produce physiological, physical adjustments, and metabolic phenomena as preparation[4,5]. Calving can also be assumed as a major impact of dairy farming routines and it can also be a high effective on the physiological state of dairy cows[6]. Cattle express lesser pain and injury than humans. A cow can be known that it is a compromised welfare state or in the inability to behave naturally with the presence of stereotypic behaviors. Waiting can only cause loss of time which can threaten the lives of calves. Therefore, calf loss rates should be recognized as a preventable welfare problem.

To monitor those difficulties in calving, calving time should be predicted accurately. The prediction of calving time can help to alert human to assist birth and safeguard of calf and cows' health, especially from the cases of perinatal mortality, dystocia and also to know when to move a cow to the maternity pen. Even normal calving is needed to be recognized importantly to know when abnormal behavior occurs and can get assistance for secure calving. Those cows' difficult behaviors can sometimes also be related to the behavior of cow handler, welfare, and performance. Positive behavior of cow handler can produce a relaxed cow and negative behavior can lead to being a more fearful and more difficult situation for calving.

Behavioral changes of dairy cows before, during, and after the calving have already been described in several studies. The only possibility to deal with those problems is to recognize early signs of dystocia to determine when the help of the professional is needed[2]. Assisting in calving can help appropriately with a significant decrease in calf mortality,

a) Master DDP Student, Energy and Electronics Course, Graduate School of Engineering, University of Miyazaki (Master Student, University of Yangon, Myanmar)
b) Professor, Department of Electrical and Systems Engineering, Faculty of Engineering, University of Miyazaki

post-partum uterine infections, and placental retention and together with a shorter duration of calving. Later, dairy producers tried to use breeding records as visual cues to predict calving time. However, even experienced professionals could not succeed to detect all calving accurately yet because every cow can have perceptible physiological and behavioral changes across calving[7].

Therefore, to prevent perinatal mortality, researchers tried to predict calving stages with different approaches. Automated devices were used to predict calving time by measuring tail raising, lying time, uterine contractions, measuring vaginal temperature[8]. Before the calving period, the number of standing positions between lying rest moments is increased with discomforts. Moreover, time spending by standing positions is also increasing. During 72 hours before calving time, numerous numbers of clinical signs can be observed which are hormonal changes. Furthermore, behavioral changes can be observed directly which can be seen several days before parturition, sometimes, those can be observed 4 to 10 days before calving and sometimes, only on the actual day of calving[9].

In this paper, the behaviors of dairy cows will be observed starting from 72 hours before calving time. And, the number of transitions: standing-to-lying and lying-to-standing observed hourly three days before calving time are used to produce the accurate prediction for calving time by using exponential distribution probability and Autoregressive Integrated Moving Average (*ARIMA*) model.

2. LITERATURE REVIEW

In these day's organizations, which are subject to abrupt and large changes that affect even the foremost established structures and where all requirements of sector need accurate and practical reading into the future, the predictions have become vital because they are the sign of survival within the world. A prediction may be a science of estimating the longer-term level of some variables. Prediction is that the operation of constructing an assumption about the future values of studied variables.

A time series is nothing but observations per the chronological order of time[10]. Time series forecasting models use mathematical techniques that are supported by historical data to forecast demand. It is founded on the hypothesis that future is an expansion of the past; therefore, we can exactly use historical data to forecast the future demand.

Many studies about forecasting by time series analysis are wiped out in several sectors. By time series analysis, the forecasting accuracies rely on the characteristic of time series. If the transition curves show stability and periodicity, we will reach high forecasting accuracies, whereas we cannot hope high accuracies if the curves contain highly irregular patterns[11].

In dairy farming, forecasting calving time is among the most crucial issues in the factor of profitability and animal welfare to reduce the loss of calf rates. The continuous monitoring systems can test the behavioral changes occurring on the day of calving, most of them being accentuated within a previous couple of hours before delivery, standing/lying transitions, tail raising, and feeding time. Applying these behavioral changes has the potential to improve the management of calving.

There are some methods and experiments have been evaluated to predict calving time by analyzing behavioral changes, considered individually or in combination. Here are some methods that researchers used to predict calving time in cattle: (a) using Rumi-watch sensor; which can be used to monitor the animal for recording behavioral changes and potentially generating calving alerts 10 days before calving time; (b) using the IceQube to collect the number of steps, number of standing to lying and lying to standing transitions 14 days before calving time; (c) using electronic data loggers to detect behavioral activities 4 days before calving time.

In the fieldwork of the American Dairy Science Association for predicting parturition, the electronic data loggers were used to show behavioral activities changes within 24 hours before parturition wit increased numbers of step and lying bouts (*LB*) with decrease standing time. In the related literature[12], the real-time ultrasound, changes in body temperature, and relaxation of the pelvic ligament, and video monitoring of cows were used before calving.

In a machine-learning-based calving prediction system[13], the researcher collected data from 20 primiparous and 33 of multiparous dairy cattle. In addition, they used the *HR* tag, which collects neck activity and rumination data in 2-hour increments, and IceQube which collects the number of steps, lying, and standing times. The machine-learning method was effective in performing the retrospective calving prediction. By monitoring the activities and standing-lying behaviors could accurately predict the calving day 8 hours before calving time.

The sensor data of a novel monitoring device was used for ingesting behaviors of 35 dairy cows[6]. In the use of sensor data: the RumiWatch noseband sensor, Ettenhausen, and Agroscope are included for predicting the calving time. Evaluating the detection model for 168 hours before calving that was used for sensitivity and specificity values and it also uses true positive predictive values and the false positive alerts qualifications are considered as well. Moreover, the approach of modeling the Naïve Bayes classifier is also suitable for comparably small samples and training datasets.

3. PROPOSED METHODS

Among different time series techniques, these are impossible to know which one will be the best for a dataset. It is customary to undertake out several different techniques and choose the one that seems to be the best. In this study, the exponential distribution probability, the unit root testing, *ARIMA* modeling, and the root mean square error (*RMSE*) that are the most widely used time series techniques. The major workflow for ARIMA modeling is illustrated in Figure 1, and the methods for each module are described in following.

3.1 Exponential Distribution Probability

The exponential distribution probability is a type of continuous probability distribution that can take random values on the interval [0, +∞]. It is one of the widely used continuous distributions to model the time elapsed between events.

The probability density function[14] for an exponentially distribution is given by Eq. 1,

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Equivalently, its distribution function is given by Eq. 2,

$$F(x) = \begin{cases} 1\text{-}e^{-\lambda x} & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where λ is the parameter of exponential distribution and x is continuous nonnegative random variable.

3.2 Autoregressive Integrated Moving Average

To model the time series, we will work with the normal statistical models including moving average, exponential smoothing, and *ARIMA*. These models are linear since the forecasted values are disturbed to be linear functions of past data. The *ARIMA* modeling approach becomes restricted, and in many cases, it is impossible to see a model, when seasonal adjustment of order is high, or its diagnostics fail to point out that time series is stationary after adjustment.

The autoregressive integrated moving average (*ARIMA*) is the combination of autoregressive (*AR*) term and moving average (*MA*) term. It is the most widely used model for forecasting in time series (Box and Jenkins). An *ARIMA* model is characterized as an *ARIMA*(p, d, q), wherein: p is the number of autoregressive terms, d is the number of differencing required to make stationary, and q is the number of moving average terms.

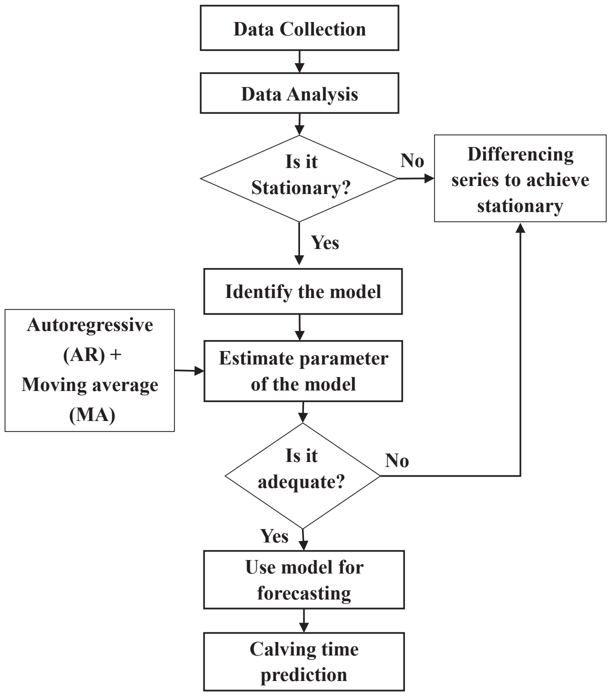


Fig. 1. Flowchart of ARIMA Modeling.

3.2.1 The Autoregressive Process

Autoregressive models assume that Y_t is a linear function of the preceding values and is given by Eq. 3.

$$Y_t = \alpha + \varphi_1 Y_{t\text{-}1} + \varepsilon_t \tag{3}$$

where Y_t , Y_{t-1} are the observed data at time t and t-1, respectively, α is constant, ε_t is error term, and φ_1 is the parameter to be determined. Literally, each observation consists a random component and a linear combination of the previous observations.

3.2.2 The Integrated Process

The behavior of the time series could also be stricken by the cumulative effect of some process. A time series confirmed by the cumulative effect of activity belongs to the category of the integrated process. Whether or not the behavior of a series is erratic, the 1st order of differences from one observation to the following are needed to determine. If the results are still going to be non-stationary, we have to make 2nd order differencing. The stationary of the series of differences for an integrated process could be a vital characteristic. Integrated processes are for the type of nonstationary series. A 1st order differencing means that the difference between two successive values of observed series is constant. An integrated process is defined by Eq. 4.

$$Y_t = Y_{t-1} + \varepsilon_t \tag{4}$$

where Y_t , Y_{t-1} are the observed data at time t and t-1, respectively, and ε_t is error term.

Before analyzing the time series, the observed data that are stationary in each series must be satisfied. The stationary means that statistical properties like mean, variance observation do not change throughout the time period. The unit root must be processed before implementing it.

To examine the stationary properties of the observation series in the first step, researchers used the Augmented Dickey-Fuller (*ADF*) [15] and unit roots with constant to present the series properties which can be written as Eq.5:

$$\Delta Y_t = \alpha + \beta_1 Y_{t-1} + \delta T + \varepsilon_t \quad (5)$$

where Δ represents the differencing order, Y_t means the observed data, α means the constant term, and T represents the time trend effect. ε_t represents the error, δ and β_1 denote the parameters to be determined.

The null and alternative hypotheses for the existence of a unit root in variable Y_t are:

H_0: $\beta_1 = 0$, the series has a unit root,

H_1: $\beta_1 < 0$, the series does not have a unit root. The series is stationary.

If the statistical result for any variable cannot refuse the hypothesis, then the data must be made the first order difference, I (1), for stationary.

3.2.3 The Moving Average Process

The current value of the moving average process is a linear combination of the current disturbance with one or more previous error terms. The moving average order shows the number of previous periods hidden in the current value. A moving average is defined by Eq.6.

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} \quad (6)$$

where Y_t , Y_{t-1} are the observed data at time t and t-1, respectively, ε_t is error terms and θ_1 is parameter to be determined.

The *ARIMA* model principle consists of three iterative steps by summarizing Figure 1 of the flowchart. They are model identification, parameter estimation, and diagnostic checking steps. The principle rule to identify the model is that if a time series is received from an *ARIMA* process, it should have some theoretical properties. Box and Jenkins proposed to use the autocorrelation function (*ACF*) and the partial autocorrelation function (*PACF*) of the sample data as the basic tools to identify the order of the *ARIMA* model.

After the identification step is finished, we should make a stationary time series, which is a mandatory condition to search out the *ARIMA* model. The statistical characteristics of a stationary time series such as the mean value and the autocorrelation structure are constant over time. We usually have to use differencing to the observed data to get rid of the trend and stabilize the variance before the *ARIMA* model may be fitted. After that, we must estimate the parameter of the fitted model.

Finally, the diagnostic checking of model adequacy is required. During this step, the diagnostic statistics and plots of residuals can be applied to assess the adequacy of future values of observed data. If the model is not adequate, we have to check the stationarity and another parameter estimation.

3.3. Root Mean Square Error (RMSE)

The mean square error is an accuracy measurement computed by squaring the individual error for individually in a dataset and then finding the average or mean value of the sum of those squares are expressed in Eq. 7 and 8,

$$MSE = \sum_{t=1}^{n} \frac{\left(Y_t - \overline{Y_t}\right)^2}{n} \quad (7)$$

$$RMSE = \sqrt{MSE} \quad (8)$$

where Y_t and $\overline{Y_t}$ are the actual values and forecasted values, respectively.

It gives greater weight to large errors than to smaller ones because errors are squared before being summed.

4. EXPERIMENTS AND DISCUSSION

In this study, the predicting of the calving time of the cows is conducted based on the real data and the accuracy and characteristics are studied. This study examines the effectiveness of calving time forecasting in dairy cattle.

4.1 Dataset

The data in this study are hourly time series of the number of transitions from standing-to-lying and lying-to-standing over the period of 72 hours before calving time. These data are from total 25 cows of Oita branch and collected them by using the videos taken by camera 360. The collected data are as shown in Table 1 with 4 hours interval. By using the standing-to-lying and lying-to-standing data between 68 hours before calving event occurs are used to predict the last 4 hours of calving time as shown in Figure 2.

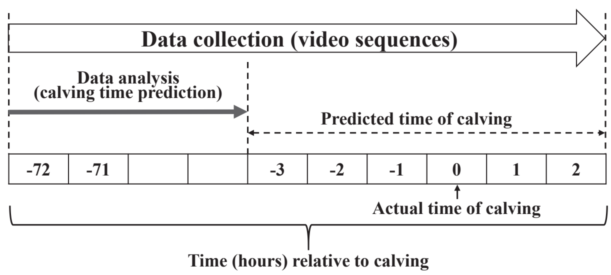


Fig 2. Time frames of data collection and analysis.

Table 1. Transition from standing-to-lying and lying-to-standing of cows' data.

Before Calving time (h)	Number of Standing-to-Lying and Lying-to-Standing Transitions							
	Cow 1	Cow 2	Cow 3	Cow 4	- - -	Cow 23	Cow 24	Cow 25
-72	15	1	7	2		13	5	4
-68	4	3	6	2		3	5	1
-64	6	6	5	2		5	3	5
-60	7	2	1	0		7	1	1
-56	1	5	7	2		0	2	3
-52	5	3	0	0		4	5	3
-48	11	2	5	1		11	4	3
-44	4	4	4	1		3	3	3
-40	6	5	5	0	- - -	7	4	7
-36	8	1	2	0		7	4	2
-32	1	1	4	0		2	0	3
-28	9	5	0	2		7	6	3
-24	12	2	2	0		12	4	4
-20	8	4	2	0		5	4	1
-16	4	10	2	1		2	1	6
-12	4	2	0	1		8	3	2
-8	12	7	0	2		11	4	8
-4	22	13	7	3		21	20	14

4.2 Exponential Probability

The exponential probability is the continuously increasing function. We can use this method when the observed data have significant growth per time. The data in Table 2 are the 72 hours before the calving time with four hours' time interval. Clearly, the probability of birth is increased as time is nearer. This means the cow will birth in the next interval of time.

Table 2. The experimental result of using exponential probability of a dairy cow.

Before Calving Time (h)	Standing/Lying Transition Counts	λ	λt	Probability
-72	3	0.25	18	0.1993
-68	4	0.25	17	0.2097
-64	4	0.25	16	0.2212
-60	3	0.25	15	0.2341
-56	2	0.25	14	0.2485
-52	4	0.25	13	0.2649
-48	0	0.25	12	0.2835
-44	7	0.25	11	0.3049
-40	3	0.25	10	0.3297
-36	4	0.25	9	0.3588
-32	5	0.25	8	0.3935
-28	8	0.25	7	0.4353
-24	2	0.25	6	0.4866
-20	1	0.25	5	0.5507
-16	7	0.25	4	0.6321
-12	5	0.25	3	0.7364
-8	4	0.25	2	0.8647
-4	6	0.25	1	0.98187

4.3 ARIMA Modeling

Based on the Box-Jenkins approach, our study will be carried out in three parts: identification, parameter estimation, and verification.

For the identification of the model, we start with the initial preprocessing of the data to check the stationary and make it stationary and then we choose possible values for p and q. For stationary, the series are shown in Figure 3 and 4, respectively, fluctuates around an average value and its *ACF* decays to zero rapidly which proves the stationary of the time series. Moreover, to assess whether the data come from a stationary process we can perform the unit root test: Augmented Dickey-Fuller (*ADF*) test for stationary. After carrying out the test on R software, the results are grouped in Table 3 and 4, respectively. Table 3 results are the non-stationary data before differencing, that printed as p-value. Since the calculated p-value of some data set of cows is larger than the threshold significance level $p = 0.05$, the null hypothesis H_0 cannot be rejected. Table 4 represents the series after 1st order differencing printed as τ-value and become the series stationary.

Table 3. *ADF* test result.

Cow ID	Lag	p-value	Condition
Cow 1	2	0.69	Non-stationary
Cow 2	2	0.99	Non-stationary
Cow 7	2	0.05	Non-stationary
Cow 9	3	0.95	Non-stationary
Cow 12	3	0.24	Non-stationary
Cow 14	2	0.29	Non-stationary

Table 4. *ADF* test result after first order differencing.

Cow ID	Lag	τ-value	Condition
ΔCow 1	2	0.02*	Stationary
ΔCow 2	2	0.03*	Stationary
ΔCow 7	2	0.01*	Stationary
ΔCow 9	2	0.01*	Stationary
ΔCow 12	2	0.01*	Stationary
ΔCow 14	2	0.01*	Stationary

Δ and * denote the different orders and rejection of the hypothesis at $p<0.05$, respectively.

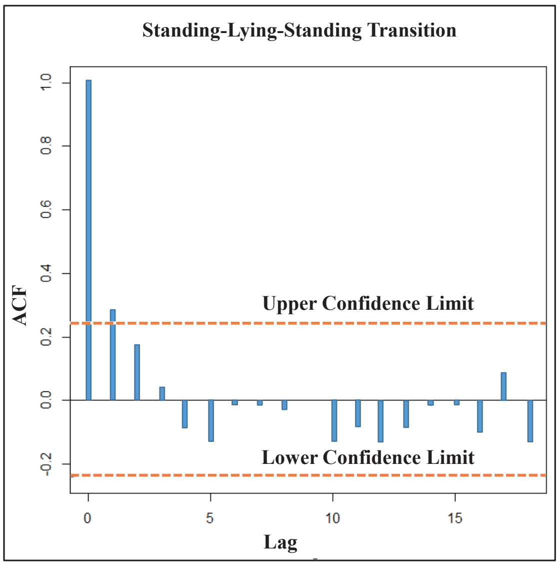
Table 5. Coefficients of different models.

Models / Characteristics		*ARIMA* (1,0,0)	*ARIMA* (0,0,1)	*ARIMA* (1,0,1)	*ARIMA* (2,0,1)	*ARIMA* (2,0,2)	*ARIMA* (2,0,1) without constant
AR (1)	φ_1	0.1322	-	-0.4465	0.2027	-1.0826	0.2749
MA (1)	θ_1	-	0.2146	0.6646	0.2122	1.4496	0.2547
AR (2)	φ_2	-	-	-	-0.1214	-0.8088	0.0419
MA (2)	θ_2	-	-	-	-	0.1546	-
Constant	α	1.548	1.1159	0.8985	0.7021	0.1909	-
AICc		172.53	171.89	172.13	169.25	178.2	173.54
Log likelihood		-83.27	-82.94	-82.07	-82.67	-78.1	-84.21

AICc: Akaike Information Criterion, *ARIMA*: autoregressive integrated moving average, *AR*: autoregressive, *MA*: moving average.

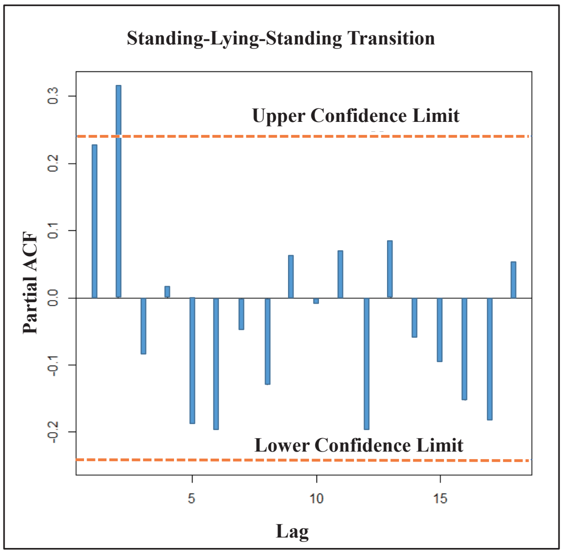
According to the Box-Jenkins principle, after verification of the stationary of the series, we noted that the *ACF* and *PACF* correlograms of our model is not only pure for AR but also for *MA*. Therefore, we tested several models to identify the most suitable one for calving time prediction.

In order to identify the model, the best model is as simple as possible and minimizes the certain criteria *AICc*, log-likelihood[16)]. Table 5 summarizes the values of the different models' parameters calculated by the method of moments and proves the selected of the model on which we will base our predictions. The chosen model is that of *ARIMA* (2, 0, 1). For the other models, one of the values of the minimization criteria is bigger than that obtained for the *ARIMA* model (2, 0, 1) with the constant value. In addition, *ARIMA* (2,0,1) model without constant has larger *AICc* values than with constant value. Clearly, Table 5 shows that *ARIMA* (2, 0, 1) is selected because every coefficient is different from 0 with an acceptable level of adjustment.



ACF: autocorrelation function

Fig. 3. *ACF* correlograms of the Standing/lying Transition of series.



PACF: partial autocorrelation function

Fig. 4. *PACF* correlograms of the Standing/lying Transition of series.

The chosen parameters are grouped in Table 6. The developed model is given by Eq. 9.

$$\bar{Y}_t = \alpha + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \varepsilon_t - \theta_1 \varepsilon_{t-1} \qquad (9)$$

where $\bar{Y}_t$ is the forecasted standing/lying data at period t, Y_{t-1} and Y_{t-2} are the observed standing/lying transitions of period t-1, and t-2, respectively. ε_t and ε_{t-1} are the residuals of period t and t-1. φ and θ represent the coefficient of autoregressive and moving average process, respectively.

From Table 6, we can select the coefficients of autoregressive and moving average processes. Therefore, Eq. 10 becomes:

$$\bar{Y}_t = 0.7 + 0.2Y_{t-1} - 0.1Y_{t-2} + \varepsilon_t - 0.2\varepsilon_{t-1} \qquad (10)$$

After we defined the most appropriate model for predicting calving time, we must make the forecasting. Figure 5 represents the results of calving time prediction that we received by applying the selected model *ARIMA* (2, 0, 1). The accuracy of the developed model was evaluated by comparing the experimental results of the *AR* (2) model and *MA* (1) model. Figure 6 clearly shows that the *ARIMA* model gives more accurate values in most of the series.

We can clearly see that the chosen model can be used for forecasting the calving time of dairy cows, but each time we need to feed the past data with the new data to improve the new model and forecasting. We tested whether the cow would birth or not in our estimated time interval by using the sum of mean and standard deviation of observed values lines. If the data passes through that line, we can get the information that the cow will calve. That will help us to take the right decisions related to the calving time of dairy cows.

Figure 6 shows that the *MA* (1) model has the largest error values among testing 7 cows data series. *AR* (2) model is also acceptable in training data, however, it has greater weight when compare with the *ARIMA* model. According to the *RMSE* values, it is also shown that *ARIMA* (2, 0, 1) is the most suitable model in this study.

Table 6. ARIMA model parameter.

Transitions from standing-to-lying and lying-to-standing of cow series			Estimate	Standard Error
Constant			0.7	0.024
AR	Lag 2	φ_1	0.2	0.047
		φ_2	-0.1	0.0125
MA	Lag 1	θ_1	0.2	0.144

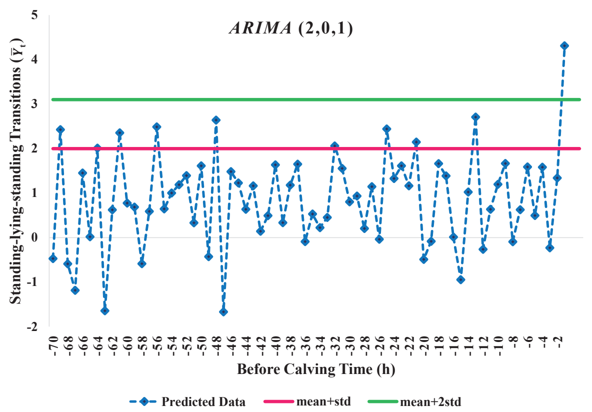


Fig. 5. Predicted values by *ARIMA* (2, 0, 1) model.

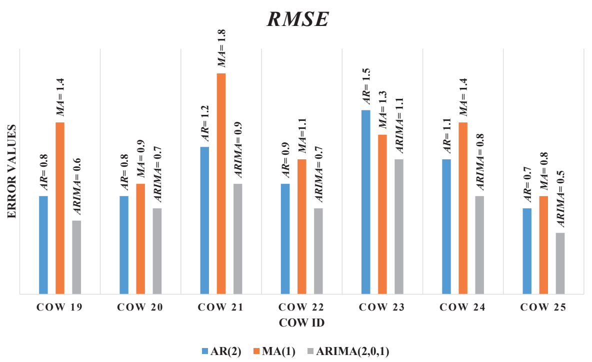


Fig. 6. *RMSE* values of *AR*, *MA*, and *ARIMA* models.

5. CONCLUSION

In this paper, we implemented the exponential distribution probability and *ARIMA* modeling. In ARIMA modeling, we developed a model to perform the calving time prediction of dairy cattle by using the Box-Jenkins time series approach. The 25 series of standing/lying transitions of cows were used to develop several models and the adequate one was selected according to the criteria: *AICc* and log-likelihood and root mean square error. The model that was selected and which minimizes the previous criteria is *ARIMA* (2, 0, 1). The analysis results might be summarized as: (i) we can estimate the calving time with the exact time interval by using the exponential distribution probability, and (ii) in *ARIMA* modeling, the developed model can be used for modeling and forecasting the calving time of dairy cows.

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