Turkish Journal of Veterinary and Animal Sciences

http://journals.tubitak.gov.tr/veterinary/

Research Article

Turk J Vet Anim Sci
(2022) 46: 165-169
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doi:10.3906/vet-2112-33

Estimation of the factors affecting lactation milk yield of Holstein cattle by the adaptive neuro-fuzzy inference system

Aycan Mutlu YAĞANOĞLU*
Department of Animal Science, Agriculture Faculty, Atatürk University, Erzurum, Turkey

Received: 14.12.2021 • **Accepted/Published Online:** 24.01.2022 • **Final Version:** 23.02.2022

Abstract: The aim of this study is to estimate lactation milk yield of Holstein cattle using first calving age, lactation period, and service period with (ANFIS) adaptive neuro-fuzzy inference system. The input variables for the system in the study were first calving age, lactation period, and service period. The output variable from the system was lactation milk yield. Predicted values obtained from the ANFIS were compared with the observed values. Twenty-seven rule functions are used to obtain the best model and 1000 epochs are used to estimate the accuracy of the training and testing error. The relations between the output and input variables are shown with 3D graphics. R^2, RMSE, and MAPE evaluation criteria were used to check the accuracy of the system's estimations. As a result, ANFIS estimates of lactation milk yield were quite close to the observed values and a positive correlation (r: 0.848) was found between them. The results showed that ANFIS can be successfully applied to estimate the lactation milk yield.

Key words: ANFIS, Dairy cattle, Holstein, milk yield, lactation period

1. Introduction

As in the world, cattle breeding comes to the fore in animal production in Turkey and it is seen as a necessity to increase the productivity per animal in closing the production gaps. In order to increase animal production, increasing the number of animals was considered as a way out before, but because the desired result could not be achieved, other approaches and studies were intensified. In this sense, it has been seen that it is a more realistic approach to increase the yield per animal instead of increasing the number of animals in order to increase production [1].

In order to increase lactation milk yield in cattle, optimizing fertility characteristics is important in terms of the economy of the enterprise and selection. The fact that the fertility is not at the desired level is expected to adversely affect the lactation milk yield throughout the cattle productive life. Since lactation milk yield is associated with many fertility traits, the more traits are studied, the more success can be achieved in estimating lactation milk yield [2].

The relationship between fertility characteristics and lactation milk yield differs according to the farm and breed. Whether there is a relationship between the features and the direction of the relationship is controlled by the correlation coefficient. Lactation milk yield (LMY) and fertility characteristics as age at first breeding (AFB), first calving age (FCA), lactation period (LP), gestation period (GS), calving interval (CI), service period (SP). The relationships between birth weights (BW) have been a matter of curiosity for researchers and they have obtained significant results in their studies [3].

To establish a relation between scattered data points, different methods are applicable, regression methods (including linear, polynomial and logistic), artificial neural networks (ANN), fuzzy inference system (FIS), and a combination of fuzzy and neural networks which are called adaptive-network-based fuzzy inference system [4]. Therefore, the aim of this study is to determine the best model for lactation milk yield- lactation period, first calving age, and service period using adaptive-network-based fuzzy inference system.

2. Materıal and methods

2.1. Materials

Data for this study were recorded on 212 Holstein cattle maintained in Atatürk University, food and livestock research and application center. Lactation milk yield, lactation period, first calving age, and service period were determined from records.

2.2. Methods

As mentioned in the introduction, the smart technique to implement is an ANFIS, which combines two smart

* Correspondence: myagan@atauni.edu.tr

techniques, neural network, and fuzzy logic, to gain strengths and overcome the weaknesses of each. Figure 1 shows the structure of an ANFIS consisting of 3 inputs x_1, x_2, and x_3 with three membership functions that convert the input values to values between 0 and 1 to create sentences or fuzzy rules of diffuse logic. Equation 1 represents the output between three membership functions where μ is the membership function [5]. In the study, 3 input variables (first calving age, lactation period, and service period) and 1 output variable (lactation milk yield) were included in the model. A total of $3^3 = 27$ pieces of IF-THEN rules have been established.

$$w_i = \mu_{Ai}(x_1) * \mu_{Bi}(x_2), \qquad i = 1,2. \tag{1}$$

Layer 3 consists of normalizing these forces. Layer 4 contains certain parameters known as "results" that allow "defuzzification" to produce results within the original output range. Finally, Layer 5 results in an average of all the outputs of Layer 4 to find a single output result described by equation 2; where fi corresponds to the combination of the result parameters and the input values of Layer 4.

$$\text{Total output} = \frac{\sum_i w_{i\, f_i}}{\sum_i w_i} \tag{2}$$

For the descent of the gradient, equation 3 shows the so-called cost function described through the difference between the estimated value $T_{m,p}$ and the real value $O_{m,p}$ also known as the error E_p between both signals. The descent of the gradient contemplates partial derivatives concerning α (generic parameter of the system) as shown by equation 4 and this, in turn, is based on equation 5 which applies the learning ratio represented by η [6].

$$\sum_{m=1}^{L} (T_{m,p} - O^{L}_{m,p}) \tag{3}$$

$$\frac{\partial E_p}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E_p}{\partial \alpha} \tag{4}$$

$$\Delta\alpha = -\eta \frac{\partial E_p}{\partial \alpha} \tag{5}$$

ANFIS's general architecture is shown on a simple Sugeno FIS with three inputs and one output (Figure 1). In Sugeno FIS, the conclusion of IF-THEN rules-namely the next section of THEN can be a linear equation of input variables or a fixed value [7,8]. The rule structure used in this study was a linear equation of input variables. The generated IF-THEN rules structure was as follows:

Rule 1: IF a is X_1 and b is Y_1 and c is Z_1 THEN $f_1 = p_1$a + q_1b + r_1c + s_1

Rule 2: IF a is X_2 and b is Y_2 and c is Z_2 THEN $f_2 = p_2$a + q_2b + r_2c + s_2

Rule 3: IF a is X_3 and b is Y_3 and c is Z_3 THEN $f_3 = p_3$a + q_3b + r_3c + s_3

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Rule 27: IF a is X_{27} and b is Y_{27} and c is Z_{27} THEN f_{27} = p_{27}a + q_{27}b + r_{27}c + s_{27}

Upper side can be written as;

For i = 1 to 27

Rule i: IF a is X_i and b is Y_i and c is Z_i THEN $f_i = p_i$a + q_ib + r_ic + s_i

Next i

Where a, b, and c are input variables; p, q, r, and s are the parameters of the results; *X*, *Y*, and *Z* are membership functions and *f* is the output function [9,10].

3. Results

In this part of the study, an ANFIS model was performed on lactation milk yield based on FCA (first calving age), LP (lactation period), and SP (service period) variables.

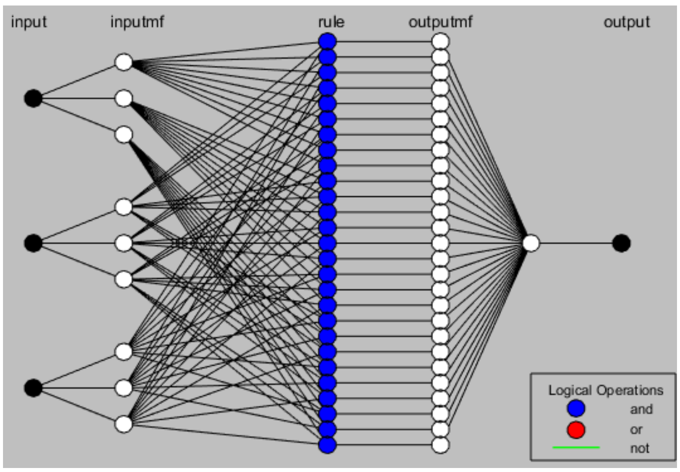

Figure 1. The structure of ANFIS for the predicted lactation milk yield.

The ANFIS model, which is the main subject of our study, was used to predict lactation milk yield in Holstein cattle Table. Various membership functions such as Triangular, Trapezoid, Gaussian bell, and Gaussian have been applied to obtain the best result. As a result of the study, the Triangular membership function gave better results than the other (Trapezoid, Gaussian bell, and Gaussian) membership functions. Twenty-seven rule functions are used to obtain the best model. Accordingly, the three input membership functions for the models are specified as 3, 3, 3. In addition, a hybrid learning algorithm was used to estimate the relationship between input and output variables. The training error of this model which includes 1000 epochs is shown in Figure 2.

Before training, network data were for training and testing in ANFIS. A total of 212 cattle data were randomized such as 70% of the data (148 cattle) training data and 30% (64 cattle) testing data.

As shown in Figure 2 the training error value is changed between 91.21 and 106.22 for 1000 epochs. The training error is regarding a constant value of nearly 850 to 1000 epochs.

Performance parameters show that the proposed model has a determination coefficient (R^2) of 0.848, mean relative error (RMSE) 0.361, and mean absolute percent error (MAPE) 1.132 to predict performance more accurately and with less error rate. A comparison between actual and predicted values of lactation milk yield after training by ANFIS is shown in Figure 3; this means that the system is well trained to model its output based on real data.

Figure 4 shows the control level of lactation milk yield from ANFIS. The effect of lactation period-first calving age change on lactation milk yield is shown in Figure 4A. Lactation milk yield is shown on the vertical axis. As seen in the figure, the decrease in the first calving age values up to a certain interval causes the lactation milk yield value to decrease nonlinearly, as the lactation period increases and the first calving age value decreases, lactation milk yield decreases. Figure 4B shows the relationship between service period and first calving age on lactation milk yield. The figure shows that the increase in the service period and first calving age values increase the lactation milk yield value. According to Figure 4C, the correlation between the two parameters is nonuniform, and the lactation period and service period is an irregular surface, that is, increasing the lactation period and service period increases the lactation milk yield up to a certain point, then decreases after leaving this point. It can be deduced from the figure that the two input parameters (lactation period and service period) have almost the same effect on the output value (lactation milk yield).

4. Discussion

Sitkowska et al. [11] supported the effect of first calving age on milk yield of cattle, as in this study. RMSE, RoM, and R^2 values were used as a goodness of criteria to

Table. The characteristics of the best structure of ANFIS architecture.

	Type of MF		Number of MF		Learning method	R^2	RMSE	MAPE (%)
	Input	Output	Input	Epoch				
ANFIS	Triangular	Linear	3 3 3	1000	Hybrid	**0.848**	**0.361**	**1.132**
	Trapezoid					0.707	0.575	2.016
	Gaussian					0.735	0.512	1.874
	Gaussian bell					0.635	0.591	2.534

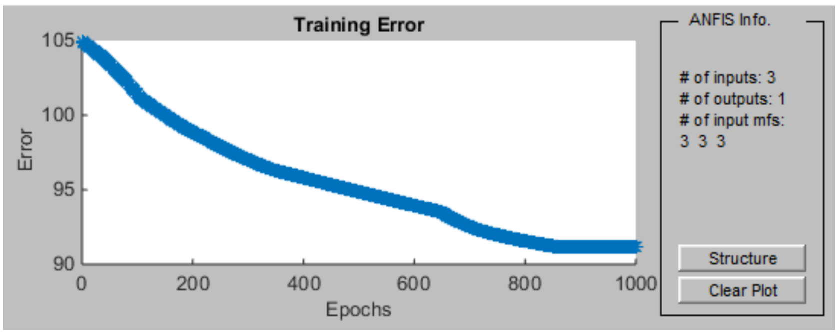

Figure 2. Number of epochs for testing the training error.

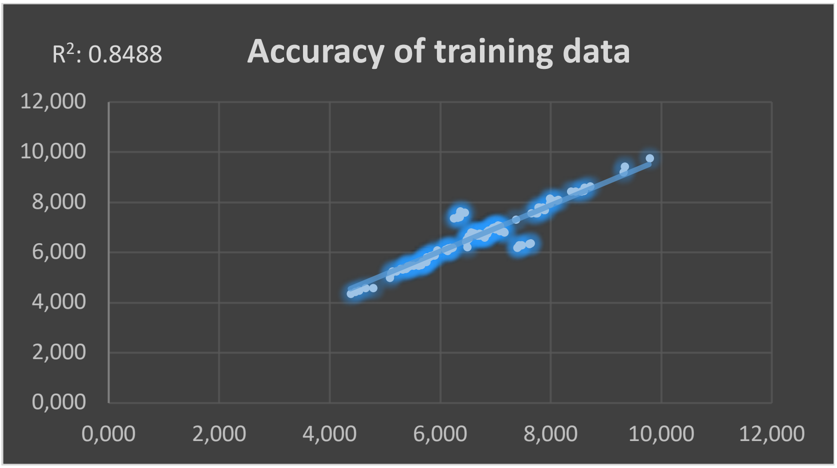

Figure 3. Accuracy of training data.

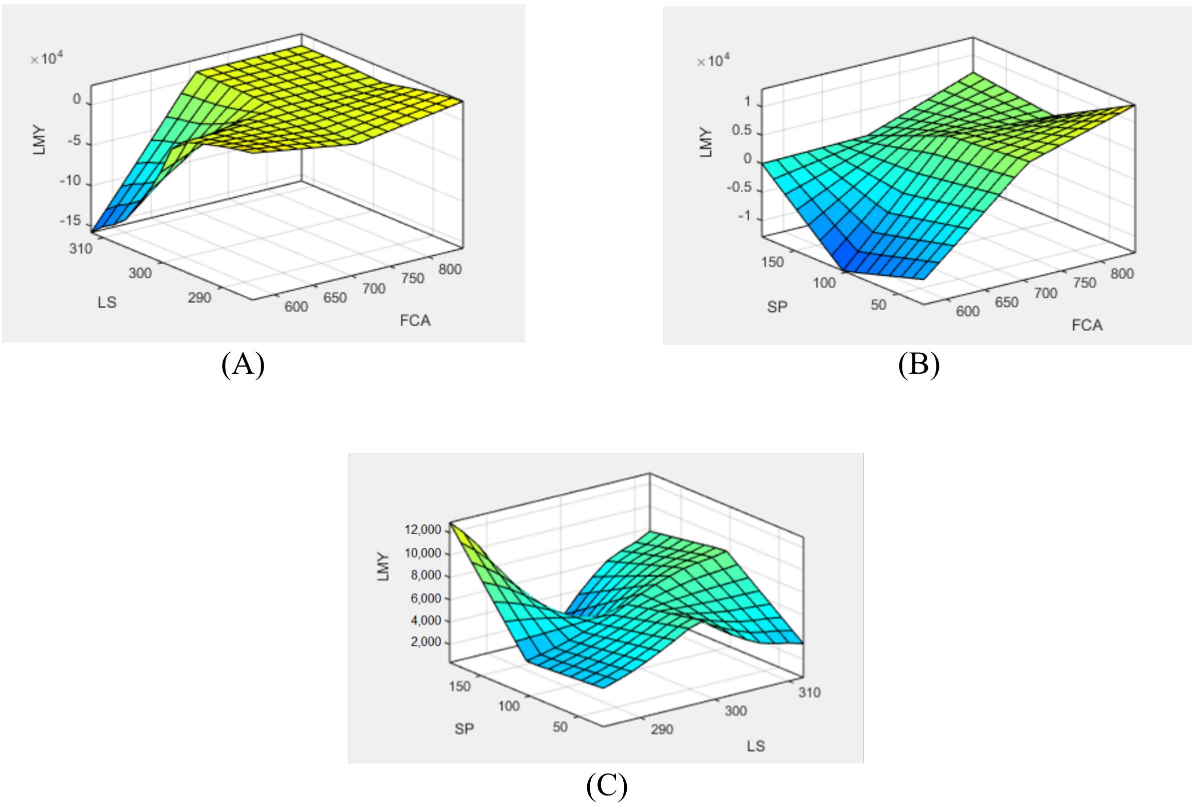

Figure 4. The obtained images from the controlling rule surfaces of lactation milk yield, the lactation period-first calving age (A), the service period-first calving age (B), and service period-lactation period (C).

evaluate the prediction accuracy of the studied algorithm [12]. The coefficient of determination (R^2) value for training data was 0.848 and Olori et al. [13] reported that $R^2 \geq 0.70$ mentioned a very good fit for a model. A positive correlation was found between the number of lactations and 305-day milk yield, and a very high correlation between 305-day milk yield and animal age [14]. Considering only the first lactation period, it has been reported that there is a positive relationship between AFC and milk yield in animals with higher age at first calving [15,16].

Bayram et al. [17], Salazar-Carranza et al. [18], and Hutchison et al. [19] reported first lactation milk yield to increase by around 1000 kg when the age of first calving was increased from 21 to 32 months. RMSE value of training data was 0.361. This value is better than several other studies [20,21,22].

As a result; in this study, the first calving age, lactation period, and service period were used to predict lactation milk yield by the ANFIS method. The ANFIS method, which does not require any assumptions and gives much more sensitive results than other estimation methods and this model can be used as an alternative method for estimating milk yield.

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