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Development of lifetime milk yield equation using artificial neural network in Holstein Friesian crossbred dairy cattle and comparison with multiple linear regression model

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The scope of this study was to develop lifetime milk yield (LTMY) prediction equation using different economical traits. The traits used were first lactation length, first peak yield, first lactation total milk yield, and total of three lactation milk yield of 1210 Holstein Friesian crossbred dairy cattle in India. Four variants of feed-forward back propagation algorithms were compared with the multiple linear regression model. The performance of Bayesian regularization (BR) algorithm was found to be better than the other algorithms for LTMY prediction. The BR neural network model was able to predict milk yield with 71.18% R^2.

Keywords: Artificial neural network, cows, lifetime milk yield, multiple linear regression.

ACCORDING to the National Dairy Development Board, India will need around 220 MMT milk by 2022. To achieve this target, we will need to improve productivity of our existing population of cows, as it is difficult to increase the number of animals due to shortage of land, feed and fodders[1]. In the last two decades migration of population towards urban areas has increased several fold in search of livelihood. So it is expected that the number of farmers will decrease and the number of animals per farmer will increase. In this situation, if a farmer could know how much milk his cow can produce in a lifetime, it will be the most important factor for further planning and management[2,3]. The analysis of lifetime milk yield (LTMY) is important for various reasons. It is helpful to select genetically superior bulls[4,5]. Milk yield prediction also helps in the selection of animals, which leads to optimal breeding strategies and increased annual genetic progress[6].

The objective of this study was to develop the LTMY prediction equation for dairy cattle. The cow starts giving milk after the birth of its calf; this is called the lactation period. Scientifically it should be 305 days to maintain the productivity of the animal. Standard lactation curve (Figure 1) follows a nonlinear pattern of milk production. Therefore, a nonlinear function should be used for the prediction of milk yield[7]. The traditional multiple linear regressions (MLRs) do not consider multicollinearity for

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prediction. They also fail to address the interdependency of independent variables. An artificial neural network (ANN) approach is used for prediction of milk yield. ANN has the ability to learn from experience to improve performance and adapt to changes in the environment[8].

In this study, ANN was used to train data using four variants of the feed-forward back-propagation (FFBP) algorithms that are Bayesian regularization (BR), scaled conjugate gradient (SCG), Levenberg–Marquardt (LM) and Broyden–Fletcher–Goldfarb–Shanno algorithm quasi-Newton (BFG) algorithm.

BR prevents over-fitting tendencies and improves prediction accuracies. It minimizes combination of squared errors, and weights, and determines the correct combination to produce a generalized network[9–11]. SCG avoids time-consuming line search. It significantly reduces the number of computations performed in each iteration. It has relatively modest memory requirement[10,12]. LM has better convergence properties; however, it requires more memory as well as computation time. LM performs better on nonlinear regression problems[13,14]. BFG converges faster than conjugate gradient methods, but it is complex and expensive to compute the Hessian matrix for feed-forward neural networks[10,15].

There has been relatively less research in the application of ANNs in the dairy sector for prediction and forecasting of milk yield. Few studies focus on the capability of ANN to predict LTMY, first lactation 305-day milk yield (FL305DMY), fat and protein concentration of milk, etc.[4–6,8,16–19]. Some studies showed that prediction of milk yield by using ANN model was more accurate than Wood's model[16,20] as well as by the MLR method[17–19,21]. Hence it has potential as an alternative to the MLR model in different breeds[17,22–24]. Gandhi *et al.*[17,18] have developed the optimum equation incorporating three variables, namely age at first calving (AFC), FL305DMY and first lactation length (FLL). They found the ANN was more accurate than MLR for prediction of LTMY on the basis of early lactation traits in Sahiwal cattle. Sanzogni and Kerr[8] compared MLR and ANN models for prediction of total annual farm milk production from nutritional inputs. They found that ANN gave better results than MLR.

This study was carried out on 1210 Holstein Friesian crossbred dairy cattle maintained at different organized dairy farms in Pune, India, over a period of six years (2006–12). The cows completing first three parities were considered for the study. Various economic traits of each cow considered were AFC, average body weight (ABW), calving interval (CI), first service period (FSP), FLL, total milk yield of first lactation (FMY), first lactation peak yield (FPY) and total of three LTMYs. Exploratory data analysis was first conducted to identify the outliers, find trends and validate assumptions like normality of dependent variable LTMY and linearity assumption between LTMY and various traits like AFC, FPY, CI, FSP, ABW, FLL and FMY. Bivariate analysis was conducted using Statistical Analysis Software (SAS 9.3) to identify the strength and direction of the relationship between each trait with LTMY. Stepwise forward regression method in MLR technique was used to decide the best traits impacting LTMY among AFC, FPY, CI, FSP, ABW, FLL and FMY. FLL, FPY and FMY turned out to be the best predictors ($P < 0.05$) of LTMY (Table 1).

Around 2% of the data was imputed for missing values or outlier treatment by taking an average of all respective variables to avoid loss of information[25]. For example; cows having FLL more than 400 or less than 120 were imputed to their average figure. The data were then divided randomly into two groups, namely training and testing. The model was built on the training dataset and test dataset was used to validate the estimated regression parameters. Various partitioning schemes were used to test the robustness of the developed model (Table 2).

A supervised multilayer feed-forward neural network with back-propagation of error learning mechanism was developed using neural network toolbox of MATLAB 7.8

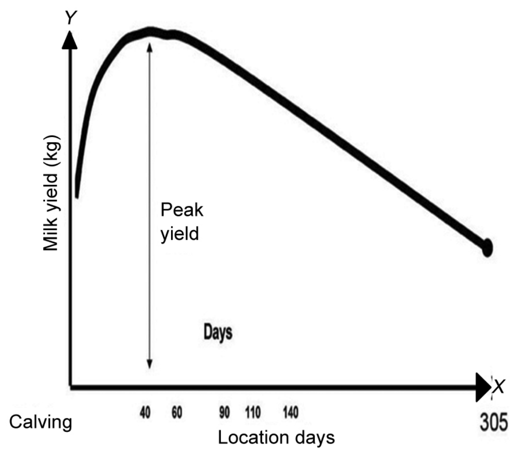

Figure 1. Standard lactation curve.

Table 1. Input and output variables

Input variable	Description	Output variable
FLL	First lactation length	LTMY (lifetime milk yield)
FPY	First peak yield	
FMY	First lactation total milk yield	

Table 2. Data partitioning scheme used

Data partition (%)	Training	Testing
66.67–33.33	807	403
75–25	908	302
80–20	968	242
90–10	1089	121
95–5	1149	61

for the LTMY prediction equation. The multilayer network was divided into three layers: input layer which receives input, 1–2 hidden layers, and one output layer which gives output[26]. Back-propagation indicates the neurons are organized in layers, and send their signals 'forward', and then the errors are propagated backwards. In supervised learning the algorithm is provided with the inputs and outputs we want the network to compute, and then the error, i.e. the difference between actual and expected results is calculated. The training begins with random weights, and the goal is to adjust them so that the error will be minimal[27].

As explained earlier, the network was trained and simulated using BR, LM, SCG and BFGS algorithms up to 4000 epochs or till the algorithm was trained. Initial weight and bias matrix were randomly initialized between –1 and +1. The nonlinear activation function tangent sigmoid was used to compute the output from summation of weighted inputs of neurons in each hidden layer[28]. The pure linear transformation function was used as the activation function in output layers for obtaining the network response. Each neural network model was trained with different neural network design schemes such as single hidden layer and two hidden layers with different number of neurons in the hidden layers (Table 3) with five combinations of data partition strategy (Table 2). The R^2 and RMSE values were used to evaluate the efficiency of the network.

The designed network was trained in supervisory mode. The best strategy was found to be '95–5%' division of data with three input variables – FLL, FPY, FMY, and two hidden layers having five neurons in both the layers and one output variable, i.e. LTMY (Figure 2).

The main aim of the dairy industry is to draw maximum benefits from a cow in terms of LTMY. In this study we have predicted LTMY of cows using different economic traits of first lactation, like CI, ABW, AFC, FSP, FLL, FPY and FMY. The influence of these factors on total milk yield was analysed by various statistical methods. We also studied the effect of one trait on another with the help of regression. The Pearson correlation matrix was tested for all the traits to check the association among them (Table 4).

The results revealed that FPY and FMY had the highest association with LTMY, while ABW and AFC were not significantly associated with it. Among the various first lactation economic traits, we found that FLL, FPY and FMY had the most significant effect on the LTMY prediction model. Therefore, these three traits were considered as input variables and LTMY as output variable in this study (Table 1). The descriptive statistics in Table 5 shows the mean, standard deviation and coefficient of variation for all the traits. For example, the data reveal that average LTMY is 9510 with ± 3205 kg, average FLL is 260 with ± 65 days, etc.

As discussed earlier, the model was simulated with four variants of FFBP algorithm with different data partition strategies (Table 2). In this study a total of 32 neural network models with each data partition scheme have been evaluated (Table 2). The trial and error approach of using different data partition schemes helps improve the prediction accuracy in all the variants. The best data partition strategy was found to be 95% records used as training and 5% records used to test the model performance. Performance of all the four variants was compared. It was found that the BR model (eq. (1)) was superior to the other three variants. This model was able to attain 71.18% R^2, i.e. 71.18% variation in the milk yield prediction was explained by this model with prediction accuracy measured by RMSE value of 0.527 (Table 6). Further, the performance of the BR model (eq. (1)) was compared with the MLR model (eq. (2)). The R^2 value in MLR was 53.03% and RMSE was 10.13, both comparatively less than the BR model.

$$\hat{Y} = 2951.82 + (2.42 * \text{FLL}) + (76.30 * \text{FPY}) + (1.72 * \text{FMY}), \quad (1)$$

$$\hat{Y} = 2358.65 + (3.358 * \text{FLL}) + (98.3 * \text{FPY}) + (1.73 * \text{FMY}), \quad (2)$$

where $\hat{Y}$ is the predicted LTMY.

From eq. (1) we can deduce the following:

- For each cattle, minimum of 2951.82 liters of milk is predicted.
- For each additional day, FLL is predicted to give additional 2.42 kg of milk.
- With each additional 1 kg milk, FPY is predicted to give additional 76.3 kg of milk.

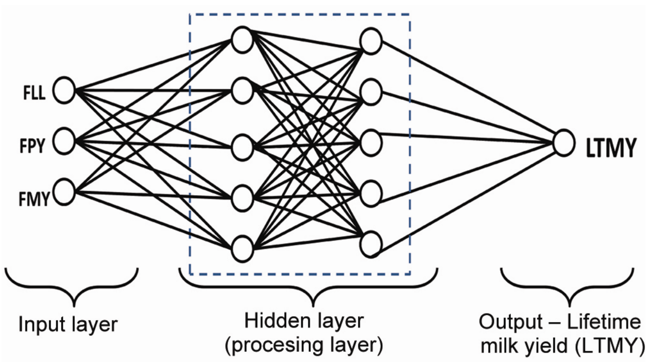

Figure 2. Architecture of two hidden layers artificial neural network model having five nodes in the first and second layers.

Table 3. Neural network design used in this study

Layer	No. of neurons used
1	3, 5, 7, 10
2	{3,5}, {3,7}, {5,5}, {5,10}

Table 4. Pearson correlation coefficients

	AFC	FLL	FSP	CI	ABW	FPY	FMY	LTMY
AFC		0.066	0.150	0.118	–0.006	0.021	0.063	0.044
FLL			0.192	0.223	0.026	0.013	0.265	0.079
FSP				0.611	–0.048	0.020	0.259	0.150
CI					–0.050	0.014	0.232	0.176
ABW						0.010	0.012	0.002
FPY							0.304	0.471
FMY								0.631
LTMY								

AFC, Age at first calving; FLL, First lactation length; FSP, First service period; CI, Calving interval; ABW, Average body weight; FPY, First peak yield; FMY, First milk yield and LTMY, Life time milk yield.

Table 5. Descriptive statistics

Traits	Mean	SD	CV
AFC	1024	425	41.5
FLL	260	65	25.0
FSP	120	97	81.1
CI	413	94	22.8
ABW	473	61	12.9
FPY	20	5.7	27.8
FMY	2843	1353	47.6
LTMY	9510	3205	33.7

SD, Standard deviation; CV, Coefficient of variation.

Table 6. Results of Bayesian regularization (BR), Levenberg Marquardt (LM), scaled conjugate gradient (SCG) and Broyden–Fletcher–Goldfarb–Shanno (BFGS) on 95–5% dataset

Algorithm	Layer	Neurons	R^2	RMSE
BR	2	5, 5	71.18	0.527
LM	2	3, 5	68.95	0.035
SCG	2	5, 5	68.43	0.033
BFG	2	3, 5	70.48	0.027

- Cows with additional 1 kg FMY are predicted to give additional 1.72 liters of milk.
- Equation (2) corresponds to MLR with similar description.

The ANN model has been proposed to predict LTMY in Holstein Friesian crossbred dairy cattle. Economic traits used in this study are FLL, FPY, FMY and LTMY. In the development of this model four variants (BR, LM, SCG and BFG) of FFBP were used for network optimization. We have tried various combinations of architectural parameters like different data partitioning strategy, 1–2 hidden layers, various combinations of number of neurons in each layer, learning rate, activation functions, performance goal, and epochs for enhancement of the neural network. From this study it can be concluded that the nonlinear function should be used for prediction of milk yield. MLR does not consider nonlinearity for prediction. It also fails to address the interdependency of independent variables. This study shows that ANN can be used as a potential tool for the prediction of LTMY in Holstein Friesian crossbred dairy cattle.

The prediction equation developed in this study can be used as a decision support model to analyse animal productivity with available milk yield information from individual dairy farmers is having less than 10 cattles, or organized dairy farms having more than 10 cattle. Use of least variables helps make the model more generic, as the farmer has to provide minimum information. It shows that the three traits considered in the study have the maximum influence on LTMY while selecting any cow. It also helps farmers plan the feed and fodder requirement and discard non-productive animals from the herd.

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Pliocene Indonesian Throughflow change and planktic foraminiferal diversity in the eastern subtropical Indian Ocean

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The opening and closing of seaways due to plate tectonic movement strongly influenced the past oceanic circulation patterns which have their influence on the past climate and faunal record. The considerable restructuring of one such seaway, Indonesian seaway, took place during Pliocene (4–3 Ma). This would have changed the source of Indonesian Throughflow (ITF) from warm and saline south Pacific waters to the north Pacific cool and relatively fresh waters. In the present study, three indices of diversity (Shannon-Wiener Index; $H(S)$, equitability; E' and alpha index; α) at ODP sites 762B and 763A in the eastern subtropical Indian Ocean are calculated to better understand the role of ITF on Pliocene surface hydrography and planktic foraminiferal diversity. A major interval of early Pliocene demonstrates more diverse fauna and low abundance of fertile taxa along with increased planktic Mg/Ca ratios. Strong influence of warm ITF waters due to broad and open seaway until the end of early Pliocene, increased the sea surface temperature (SST) and depth of thermocline in the Leeuwin current area of eastern subtropical Indian Ocean. This would have been responsible for more vertical niche partitioning of surface water and thus, higher planktic foraminiferal diversity. The significant decline in faunal diversity between critical interval of ~3.5 and 3 Ma (beginning of Late Pliocene) is suggested to be the response of fall in SST and increase in surface water productivity possibly due to relatively less influence of ITF waters in the eastern Indian Ocean as a consequence of significant constriction of Indonesian Seaway.

Keywords: Diversity, Indian Ocean, Indonesian Throughflow, Pliocene, planktic foraminifera.

THE climatic systems during most of the Cenozoic are significantly influenced by opening and closing of various seaways due to the drifting of continents[1]. Significant changes in the circulation during the Pliocene as a result of several tectonic rearrangements in the tropics are believed to be the major causal mechanism for plunging the world into an ice age with well-known northern

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