ventilation (with roll up facility), height of the side vent (30 cm from ground), double doors, fogger for maintaining humidity, drip irrigation, proper installation of shade nets (outside polyhouse), proper selection of the crop variety and the technical knowledge of growing vegetables inside polyhouses.

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2. http://hpagriculture.com/
3. http://hpagrisnet.gov.in/hpagris/Horticulture/Default.aspx?SiteID=5&PageId=1033
4. http://admis.hp.nic.in/himachal/economics/REPORTS/BriefFacts-2013_14_A1b.pdf

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Comparative study of feed-forward neuro-computing with multiple linear regression model for milk yield prediction in dairy cattle

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The main objective of this work is to compare the accuracy of artificial neural networks (ANNs) and multiple linear regression (MLR) model for prediction of first lactation 305-day milk yield (FL305DMY) using monthly test-day milk yield records of 443 Frieswal cows. We have compared four versions of feed-forward algorithm with conventional statistical model. The performancre of ANN is found to be better than the MLR model for milk yield prediction. The Bayesian regularization neural network model was able to predict milk yield with 85.07% accuracy as early as 126th day of lactation. It has been found that R^2 value of the models increases with increase in the number of test-day milk yield records.

Keywords: Artificial neural network, dairy cattle, milk yielded, multiple linear regression.

INDIA is the largest producer of milk in the world and it also has the world's largest dairy herd animals. The Indian dairy sector is now changing from traditional to well-organized dairies. The application of information technology-based services at all levels in this sector will improve planning and management of milk production in India. Milk production in India was around 133 million metric tonnes (MMT) in 2012–13, and it accounts for more than 13% of total milk production in the world[1,2]. The average milk yield per lactation is only 1214 kg as against the world average of 2104 kg (ref. 3). This indicates that there is a need to improve the productivity of the animals.

The analysis of first lactation 305-day milk yield is important. It is helpful to select genetically superior bulls[4,5]. Genetically superior bull identification is dependent on the high yielding ability of cows. If accurate milk yield prediction before the completion of lactation is done, it will speed up the bull identification process and lead to greater progress[6,7]. Milk yield prediction also helps in the selection of animals, which leads to optimal breeding strategies and increased annual genetic progress[8]. It also helps farmers plan the feed and fodder requirement and to sort non-productive animals from the herd. The present study has been made to predict first lactation 305-day milk yield (FL305DMY) using monthly test-day milk yield records of 443 Frieswal cows, a crossbred of indigenous Sahiwal cattle with the exotic Holstein–Friesian breed[9]. The breed is expected to produce around 4000 kg of milk in a lactation under good management practices[10].

It is well known fact that the milk yield which is normally represented in the form of lactation milk yield curve (Figure 1) follows a nonlinear pattern of milk production. Therefore, the nonlinear function should be used for the prediction of lactation milk yield[6]. The traditional multiple linear regression (MLR) does not consider nonlinearity for prediction. It also fails to address the interdependency of independent variables. Therefore, 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[11]. In this study, monthly test-day milk yield was used as an input variable (Table 1) in ANN to

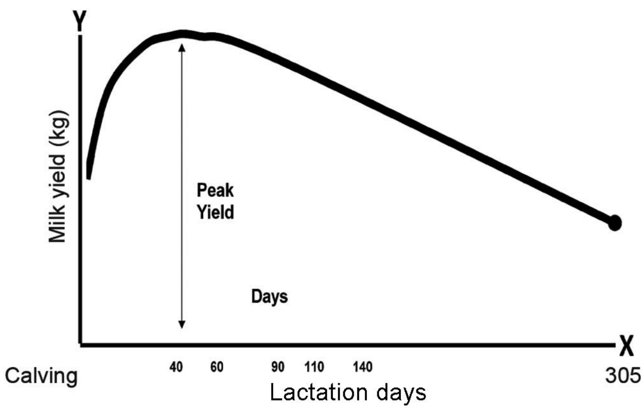

Figure 1. Standard lactation curve.

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train data using four variants of the feed-forward algorithms.

1. Bayesian regularization (BR): This algorithm is considered as one of the best approaches to prevent overfitting tendencies and improve their prediction accuracies. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well[12–14].

2. Scaled conjugate gradient (SCG): The SCG algorithm developed by Moller helps avoid time-consuming line search[15]. Thus it significantly reduces the number of computations performed in each iteration[14]. This algorithm also has relatively modest memory requirements[15].

3. Levenberg–Marquardt (LM method): LM is a variation of Newton's method. It has better convergence properties than the conventional back-propagation method. However, it requires more memory and more computation time. This is the fastest and default training function for feedforward network. LM performs better on nonlinear regression problems[16,17].

4. Broyden–Fletcher–Golfarb–Shanno quasi-Newton algorithm. The BFGS algorithm is one of the most popular of the quasi-Newton algorithms. This method often converges faster than conjugate gradient methods, but it is complex and expensive to compute the Hessian matrix for feed-forward neural networks[14,18].

There has been relatively modest research in the application of ANNs in the dairy sector in and outside India for prediction and forecasting of milk yield. Researchers have found that ANN performs better than MLR in FL305DMY[5,19–21] as well as in lifetime milk yield[22,23] in different breeds. Some researchers found that prediction of milk yield by the ANN model was more accurate than Wood's model[24,25], as well as by linear regression method[26]. Hence it has potential as an alternative to the MLR model[7,27]. As earlier study[6] has used 2, 3, 5, 7 and 8 monthly test-day milk yield records for the first lactation milk yield in Sahiwal cattle. The suggested model was able to predict with 93.18% accuracy. Further, when the model was compared with MLR, there was no significant difference between ANN and MLR. ANN and neuro-fuzzy system (NFS) have been used to estimate breeding value of Iranian cows. Very little difference was found between ANN and NFS, but there was more predictive ability in NFS than in ANN[28]. Dongre and Gandhi compared three lactation curve models for prediction of the first lactation milk yield, and found inverse polynomial function to be the highest coefficient of determination with least root mean square error.

Data on 4873 monthly test-day milk yield records of first lactation pertaining to 443 Frieswal cows maintained at the Military Dairy Farm, Pimpri-Chinchwad, Pune, India over a period of five years (2007–2012) were used to predict FL305DMY. Data were collected from the history sheets and daily milk record registers. The data collected pertain to animal number, date of calving, lactation number, total milk yield (kg), 305-day milk yield and monthly test-day milk yield (kg). A total of 11 test-day records were collected at 30 days interval starting from the sixth day of lactation. The incomplete records were retrieved by the missing plot technique[30].

The input variables considered were the first five monthly test-day (TD) milk yield data, which were derived by MLR. Table 1 provides details of input and output variables used. These input variables were again divided into three subsets. Table 2 provides details of input variable subsets.

Table 1. Input and output variables

Input variable	Days of lactation	Output variable
TD1	6th day of lactation	First lactation
TD2	36th day of lactation	305-day milk yield
TD3	66th day of lactation	
TD4	96th day of lactation	
TD5	126th day of lactation	

Table 2. Input variable subset

Subset	Test days included
1	TD1, TD2 and TD3
2	TD1, TD2, TD3 and TD4
3	TD1, TD2, TD3, TD4 and TD5

Table 3. Data partitioning schemes used

Subclass		Division of data	No. of records
A	Training	66.67	3249
	Test	33.33	1624
B	Training	75	3654
	Test	25	1219
C	Training	80	3898
	Test	20	975
D	Training	90	4386
	Test	10	487
E	Training	95	4629
	Test	5	244

Table 4. Comparison of R^2 and RMSE values of different variants of back-propagation algorithm

Algorithm	R^2 value	RMSE value
BR	85.07	0.827
LM	84.39	0.012
BFG	84.15	0.013
SCG	83.78	0.012

Bayesian Regularization (BR), Levenberg Marquardt (LM), Broyden–Fletcher–Golfarb–Shanno (BFG), Scaled Conjugate Gradient (SCG).

Table 5. Comparison of R^2 and RMSE values of ANN and MLR with all types of subclass

		R^2 value		RMSE	
Subclass	Training–test data (%)	MLR (%)	ANN (%)	MLR (%)	ANN (%)
A	66.67–33.33	74.41	79.92	831.62	0.794
B	75–25	76.21	81.96	801.87	0.803
C	80–20	76.06	81.69	802.28	0.808
D	90–10	84.60	85.07	637.79	0.827
E	95–5	81.95	83.50	752.94	0.855

ANN, Artificial neural network; MLR, Multiple linear regression.

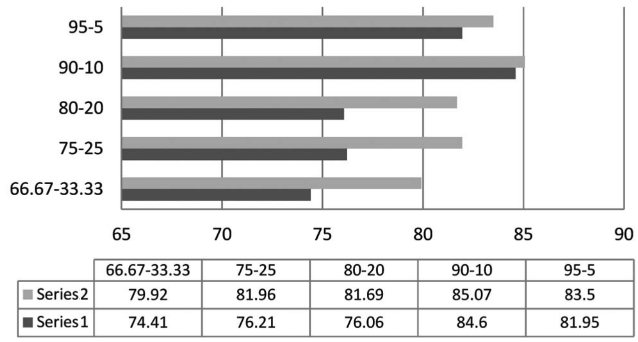

Figure 2. Comparison of R^2 between MLR and ANN.

All the subsets were divided into training and testing datasets and partitioned into five subclasses. Table 3 provides details of the data partitioning scheme.

Backward elimination MLR algorithm of ANN was implemented on input variables. Using all data partitioning schemes, the ANN model was tested on each subset of input variables. The best prediction equation was decided on the basis of highest coefficient of determination (R^2 value).

A multilayer feed-forward neural network with back propagation of error learning mechanism was developed using Neural Network Toolbox (NNT) of MATLAB 7.8 to predict FL305DMY. The network was trained and simulated in supervisory mode using four different variants of feed-forward algorithms up to 4000 epochs or till the algorithms were truly trained. The R^2 and RMSE values were used to evaluate the efficiency of the network.

The network was tested with one hidden layer with 3, 5, 7 and 10 neurons and two hidden layers with 3 : 5, 3 : 7, 5 : 5 and 5 : 10 neurons. Initial weights and bias matrix were randomly initialized between –1 and +1. A nonlinear activation (transformation) function, i.e. tangent sigmoid[31] was used to compute the output from summation of weighted inputs of neurons in each hidden layer. The pure linear transformation function was used as activation function in output layers for obtaining the network response.

The performance of all the algorithms was compared with each other. It was found that the performance of the BR model was superior to the other models (Table 4).

Further, the BR model was also compared with the MLR model. Table 5 shows a comparison between R^2 and RMSE values of MLR and ANN for all the subclasses, i.e. subclasses A–E (Table 3). It is observed that R^2 increases as the number of training datasets increases in MLR as well as in ANN. The R^2 value of MLR is comparatively less in case of subclasses A–C and E, but we could not get significant difference in case of subclass D. Figure 2 is a graphical presentation of R^2 values between MLR and ANN. Series 1 in Figure 3 shows R^2 values obtained by MLR and series 2 shows R^2 values by BR model.

$$\hat{Y} = 82.18 + (84.63 * \mathrm{TD1}) + (24.30 * \mathrm{TD2}) + (21.99 * \mathrm{TD3}) - (36.01 * \mathrm{TD4}) + (152.11 * \mathrm{TD5}). \quad (1)$$

Equation (1) is the best prediction equation with R^2 value 85.07 and RMSE value 0.827.

The designed network was trained in supervisory mode. The best strategy has been found to be '90–10%' division of data with five input variables, two hidden layers having five neurons in the first layer and five neurons in the second layer (Figure 3). Equation (1) gives an accuracy of prediction value of 85.07%. Therefore BR is considered as the best algorithm for milk yield prediction in Frieswal cows. The best ANN algorithm achieved 85.07% accuracy of prediction for optimum model, whereas MLR explained 84.60% accuracy of prediction of FL305DMY in Frieswal cows. The prediction accuracy from all the models increased with the addition of test day milk yields as input variables[6]. Figure 4 shows the regression line of actual verses the best ANN model predicting the 305-days milk yield.

The two hidden layers model with five input variables, five neuron in first and five neurons in second hidden layer using Bayesian regularization algorithm was found to be most accurate for prediction of FL305DMY. It can be inferred from the present study that the coefficient of determination value increases with addition of test-day milk yield records up to 90–10% dataset only. The

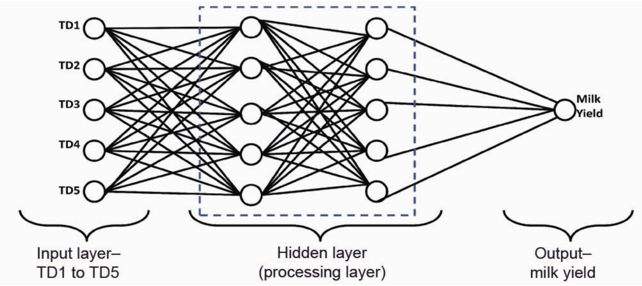

Figure 3. Architecture of two hidden layers ANN model having five nodes in the first and second layer.

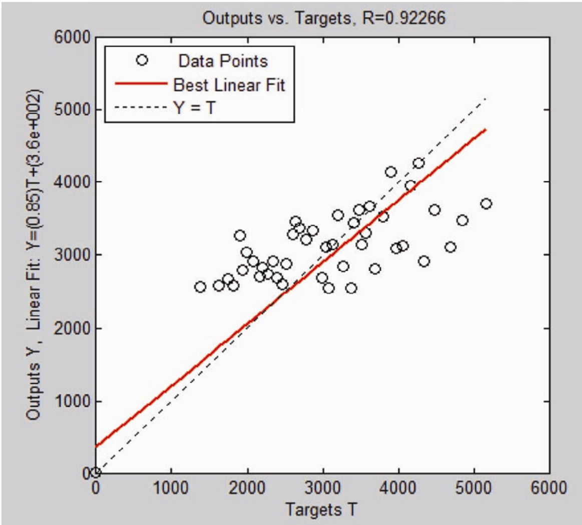

Figure 4. Actual versus predicted milk yield.

present study shows that FL305DMY could be predicted with 85.07% accuracy in ANN and 84.60% accuracy in MLR, if the first five monthly test-day milk yield data are available in Frieswal cows. However, this accuracy was found with comparatively less data size from previous studies. The coefficient of determination obtained by ANN was significantly different from MLR with 66.67–33.33%, 75–25%, 80–20% and 95–5% division of data. There is no significant difference in 90–10% division of data for prediction of FL305DMY using monthly test-day milk records in Frieswal cows. ANN is found to be the potential tool for milk yield prediction and to analyse animal productivity with available milk yield information from the farmers.

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Occurrence of unusual quartz xenocryst-laden dykes in the Chhota Udaipur alkaline–carbonatite sub-province, Deccan Igneous Province, India

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Occurrence of unusual basaltic dykes laden with a dense population of quartz xenocrysts within the Chhota Udaipur alkaline–carbonatitic sub-province of the Deccan Igneous Province is reported here. These dykes occur near Rorda (22°07.890′N; 74°04.267′E) and Samalavat (22°05.586′N; 74°07.261′E). The xenocrysts vary in size and shape and show effects of corrosion and partial assimilation by the host magma. These dykes have been affected by the carbonatitic fluids which commonly attack quartz xenocrysts, resulting in the formation of a complex growth pattern between quartz and carbonates. Mineralogical study confirms the presence of plagioclase, magnetite, ilmenite, rutile, chlorite, apatite, barytes and hydrated Fe-oxides. Original basaltic texture (sub-ophitic) and mineralogy (plagioclase, magnetite, ilmenite) is preserved, though pyroxenes are converted to chlorite; hematite, ilmenite, calcite and altered glassy material occur profusely in the groundmass. Basaltic dykes of such description have not so far been reported from the Deccan Igneous Province, although there are few references to the occurrence of quartz xenocrysts within basaltic dykes. It appears prima facie that quartzite xenoliths were selectively escalated by the basaltic magma at depth at the time of crustal extension leading to formation of Narmada rift; roughly coinciding with the emplacement of alkaline–carbonatite magma.

Keywords: Basalt, carbonatite, quartz, xenocrysts.

THE Chhota Udaipur alkaline–carbonatite complex, famous for Amba Dongar carbonatite ring dyke and alkaline magmatism was first discovered in 1963 (ref. 1). Subsequently the complex has been studied by several workers[2–6]. It comprises various intrusive rocks in the form of dykes, sills, plugs and veins of variable sizes intruding the country rock mainly Upper Cretaceous to Eocene Deccan Trap basaltic lava flows, Cretaceous Bagh sediments (sandstones and limestones) and the Archaean–Proterozoic Aravalli granites and metasediments (granitic gneisses, phyllites, schists and quartzites). All the intrusives can be grouped into the following categories:

1. Carbonatites and carbonatite breccia: occurring as almost complete ring dyke at Amba Dongar, ~11 km long sill of carbonatite breccias at Siriwasan and several plugs and dykes at Panwad–Kawant and other places[3,7,8].
2. Alkaline rocks: nephelinite, phonolite, ijolite, tinguiates, pseudoleucite tinguites, camptonites and monchiquites[2–4].
3. Tholeiitic rocks: gabbros, dolerites and picrobasalts[3,9–11].
4. Layered gabbro-anorthosite–granophyre: The Phenai Mata layered igneous complex hosts cumulate gabbro, anorthosite, granophyre with intrusive dolerite and lamprophyre dykes[3,11,12].
5. Trachytes and trachytic rocks: several dykes of trachytes occur profusely between Dugdha and Naswadi areas[3,13].
6. Calcareo-siliceous rocks: calcareo-siliceous dykes, small veins of calcite and quartz[9,14,15].

However, the dykes being reported here (Figure 1) differ considerably from the intrusive rocks mentioned above, and has not been reported so far from the Chhota Udaipur sub-province. Such outcrops were considered to be carbonatite breccias (see figure 1 of Gwalani *et al.*[3]). The texture of this dyke can be easily confused with either carbonatite breccias[3,4,8] or with giant plagioclase basalts (GPB)[9], both of which occur profusely in and around this area.

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