Journal of Entomology and Zoology Studies

Available online at www.entomoljournal.com

E-ISSN: 2320-7078
P-ISSN: 2349-6800
www.entomoljournal.com
JEZS 2020; 8(5): 516-520

Received: 28-07-2020
Accepted: 30-08-2020

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Comparative study of artificial neural network algorithms performance for prediction of FL305DMY in crossbred cattle

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Abstract
In the current investigation, records of 1092 crossbred cattle (Vrindavani) were collected at Indian Veterinary Research Institute, Izatnagar. Crossbred cattle's First Lactation 305-Day Milk Yield (FL305DMY) was predicted using three separate Artificial Neural Network (ANN) algorithms, and their performance was evaluated. Each algorithm's efficiency was measured and evaluated on the basis of the coefficient of determination and Root Mean Square Error (RMSE). Two different set of inputs were used in the analysis to predict the yield of milk. The first set of inputs comprised of a record of test day milk yields together with age at first calving (AFC) and peak yield (PY) and a second set comprised of monthly milk yield records, AFC and PY. Three ANN algorithms used for training were Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG). Every algorithm was evaluated using four separate data sets for the training test (66.66:33.33, 75:25, 80:20, and 90:10). BR reached 79.89% best accuracy with 16.89% lowest RMSE value for first input set and 82.67% accuracy with 14.45% RMSE value for second input set-2. Therefore, BR algorithm can be used to predict FL305DMY in Crossbred cattle as it demonstrates higher accuracy over LM and SCG algorithm.

Keywords: Levenberg-marquardt, scaled conjugate gradient, test day milk yields, Vrindavani

Introduction
Milk yield and its composition are the main source of incomes for the farmer. The accurate prediction or measurement of milk yield thus becomes essential for farmers economy (Fernandez *et al*., 2007) [1]. For dairy production, prediction of milk yield is very important, as much of the selection of genetically superior bulls is based on their ability to produce high-yielding daughters. Therefore, the sooner these bulls can be identified, the sooner the collection of semen can commence and insemination of cows can proceed (Sharma *et al*., 2007) [2]. It can help to reduce the generation interval and thus create greater genetic progress.

Conventional models (Pindyick *et al*., 1991) [3] have been widely used as prediction tools for various real-life problems. However, these mathematical models have some inherent drawbacks (Kominakis *et al*., 2002) [4] such as: (a) they impose restrictions on the number of input data (limited to a few inputs among various available); (b) the hypothesis that only one dependency function over the whole dataset is assumed; and (c) other hypotheses imposed by their underlying theories (normality, linearity, data independence, etc.). These hypotheses are sometimes overlooked for the operational purpose of a method or diluted with the help of assumptions.

Artificial neural networks (ANNs) are computational techniques and mathematical models that belong to the field of machine learning (Kelleher *et al*., 2015) [5]. Machine learning involves adaptive mechanisms which enables the computers to learn by example, learn from experience, and learn by analogy. The ANN consists of main basic units, called as neurons, whose design is suggested by their biological counterparts. These artificial neurons have input paths just like biological neurons have dendrites; they have output paths just like biological neurons have axons (Sharma *et al*., 2004) [6]. Artificial and biological neurons both have predispositions (biases) that affect the strength of their output. The neuron combines the inputs, incorporates the effect of the predisposition, and outputs signals. In both real and artificial neurons, learning occurs and alters the strength of connections between the neurons and the biases.

The 'learning by example' replaces the traditional 'programming' in solving the problems which makes the ANN models appealing in application domains even if researcher has little or incomplete knowledge about the underlying problem. The true power and best advantage of artificial neural networks lies in their ability to represent both linear and non-linear relationships in the data and in their ability to learn these relationships directly from the data which is being modelled. Traditional conventional linear models are simply inadequate when it comes to modelling data which consist of non-linear characteristics.

In India, however, there is very limited research relating to the application of ANN in the field of animal science, and in particular in dairy farming. Consequently, the latest research was conducted in crossbred cattle for comparative study of artificial neural network algorithms performance for FL305DMY prediction.

Materials and Methods

Data collection: Vindavani cattle is a synthetic strain of crossbred cattle with exotic ancestry of Holstein-Friesian, Brown Swiss, Jersey and indigenous ancestry of Hariana cattle produced at the Indian Veterinary Research Institute (IVRI), Izatnagar, Bareilly, India (Singh *et al*., 2011) [7]. At Livestock Production Management Section, Indian Veterinary Research Institute I.V.R.I, Izatnagar, first lactation records of 1092 crossbred cattle were gathered from maintained database. The data were obtained from the Vrindavani cattle history cum pedigree papers, calving notes, health records, auction papers, and daily milk yield records held at the Cattle and Buffalo farm of the IVRI, Izatnagar. A total of 1092 first lactation records of crossbred cattle consisting of first four monthly milk yield, four test day milk yields, peak yield and age at first calving of each crossbred cattle in the research were collected. The input variable used for FL305DMY prediction comprised TD1, TD2, TD3, TD4, M1, M2, M3, M4, first calving age (AFC) and peak yield (PY), respectively (Table 1). In order to predict FL305DMY, those input variables were further classified into two input sets (Table 2). Additionally, the total data was split into 4 major training: test subsets as subset-A (66.67:33.33), subset-B (75:25), subset-C (80:20) and subset-D (90:10).

Artificial Neural Network (ANN)*:* ANN model is essentially an intelligent computing system which automatically learns the predictive ability from the data set presented during network training. Different ANN models are available for data processing but the widely used form is multilayered feed forward network. In the back propagation process, the input variables and corresponding target data are used to train the network before it can approximate a prediction function (Fausett, 1994) [8].

A multilayer feed forward neural network with back propagation of the error learning process was developed using the MATLAB 7.8.0 (MATLAB Users' Guide, R2009a) Neural Network Toolbox (NNT) for milk yield prediction in this analysis. Network testing and training was performed using three different algorithms. The Bayesian regularisation (BR) scaled conjugate gradient (SCG) and Levenberg-Marquardt (LM) algorithms are used. Total 6000 epochs, or before the converged algorithm was set. To minimise the error, the standardisation and pre encoding of input and output data was performed using the prestd feature available in NNT. The setting parameters are momentum (0.05), error target (0) and learning rate (0.01) other parameters have been held at the default parameters as defined in NNT within MATLAB.

Bayesian regularisation (BR) is a mathematical approach that transforms a nonlinear regression in the manner of a ridge regression into a "well-positioned" statistical problem. The benefit of Bayesian regularized artificial neural systems (BRANNs) is that the models are stable, and the validation mechanism which in standard regression approaches, such as back propagation, scales like O(N2) is unnecessary. Scaled conjugate slope (SCG) produces super linear convergence for a directed learning algorithm. SCG is a variation of a hybrid slope technique that stays away from line-search by learning repetition and using a Levenberg-Marquardt method to measure the size of progression. This technique evades a repetitive line-search learning iteration by using a stage size scaling portion. SCG network training method changes weight and bias according to the scaled technique of the conjugate slope. Calculation of Levenberg – Marquardt (LM), better known as the Damped Less Squares (DLS) technique, is used to resolve problems with non-linear least - square. These problems of minimization arise particularly in the bend fitting of least squares. The LMA interjects the equation between the Gauss – Newton (GNA) and the gradient descent technique.

Performance evaluation of network: To compare and verify of algorithm's accuracy, the test data was based on determination coefficient (R2-value) and root mean square error (RMSE) values. The determination coefficient, predicted error, and RMSE values in algorithms were determined using the equations below:

$$R^2 = \frac{TSS-ESS}{TSS} * 100$$

Where *TSS* is total sum of squares and *ESS* is error sum of squares

$$Predicted\ error = \frac{predicted\ yield - actual\ yield}{actual\ yield} \times 100$$

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(Predicted\ error)^2}{N}}$$

The network monitoring was further conducted using 1 and 2 secret layers keeping the number of neurons increasing until the best outcome was achieved. Initial weights and matrix of bias were initialised uniformly between -1 and 1. Function tangent sigmoid was used for activation to evaluate the output. On the output layer a pure linear activation function was used for network reply. In equations the tangent sigmoid and pure linear functions used here are given:

$$f(x) = \frac{\exp(2x)-1}{\exp(2x)+1}$$

$$f(x) = x$$

Where x denotes weighted sum of the inputs.

Results

Highest coefficient of determination observed for all three respective algorithms BR, LM and SCG were 79.89, 73.65

and 74.65%, respectively of input set-1, all observed in subset-D (Table 3 and 4). And in input set-2 the highest coefficient of determination observed for all three respective algorithms BR, LM and SCG were 82.67, 74.22 and 76.69% respectively, all observed in subset-D (Table 3 and 4). And consequently, the lowest RMSE values found were 16.89, 20.52 and 20.45 percent for all three algorithms BR, LM and SCG, respectively in the input set-1 subset-D (Table 3 and 4). And the lowest measured RMSE value in input set-2 was 14.45, 17.45 and 16.56 percent respectively in subset D (Table 3 and 4).

In both the input set-1 and 2 irrespective of the algorithms BR, LM and SCG, best result were observed in subset-D for First Lactation 305-Day Milk Yield prediction, the accuracy recorded was more than 70% (Table 3 and 4). As well as the lowest RMSE values in both the input sets were also recorded in subset-D. But in all subsets A, B , C and D for input set-1 and 2 it was shown that the accuracy was lower for the algorithms LM and SCG where the accuracy was just marginally higher than 54 percent whereas it was higher than 70 percent for subset-D. A regular increasing trend is observed when the training–test data was changed from 66.67:33.33 to 90:10 ratios. It was clearly observed that the R2-values kept on increasing with increase in training data i.e. from 66.77 to 90% (Table 3 and 4). Generally it was found that the accuracy was higher for all subsets of both the data set when using a single hidden layer, by using 2 hidden layers the accuracy was diminished.

Discussion

In general, the best findings were discovered in the sub-set-D in which training-test data was acquired at 90:10, similar results were reported by Dongre *et al*. (2012) [11]. This must have been due to more data in training. It was also shown in the present study that the coefficient of determination for the input set-2 was greater than that of the input set-1. That specifically shows that the input set-2 is best for predicting the First Lactation Milk Yield in crossbred cattle. In both input sets, Bayesian Regularisation algorithm performance was found better in all subsets with greater accuracy and lower RMSE values. In our analysis, the Bayesian regularisation algorithm undoubtedly outperforms other two LM and SGG algorithms. Bhosale and Singh (2015) [9], Mundhe *et al*. (2015) [10] reported similar results in Frieswal and Sahiwal cattle respectively while Dongre *et al*. (2012) [11] findings in Sahiwal cattle were not similar, he found out SCG as the best algorithm.

Table 1: Description of variables used in the study.

Input variables		Output variable
TD1	6th day of lactation	First lactation 305 day milk yield (FL305DMY)
TD2	36th day of lactation	
TD3	66th day of lactation	
TD4	96th day of lactation	
M1	1st month yield of lactation	
M2	2nd month yield of lactation	
M3	3rd month yield of lactation	
M4	4th month yield of lactation	
AFC	Age at first calving	
PY	Peak yield	

Table 2: Description of input set.

Input set	Input variables
Set-1	TD1, TD2, TD3, TD4, AFC and PY
Set-2	M1, M2, M3, M4, AFC and PY

Table 3: Assessment of different algorithm based on R^2 and RMSE values for input set-1.

Input Set-1								
Algorithm								
			BR		LM		SCG	
Subset	Hidden layer	Neurons	R^2 (%)	RMSE (%)	R^2 (%)	RMSE (%)	R^2 (%)	RMSE (%)
Subset-A (66.67:33.33)	1	2	76.14	20.17	69.33	22.85	69.03	23.80
	1	4	76.56	20.10	68.44	23.69	70.73	22.10
	1	5	76.17	20.25	69.66	24.56	70.51	22.26
	1	8	76.50	20.14	71.33	24.56	68.36	23.56
	2	3:3	76.24	20.24	72.96	21.21	66.42	24.31
	2	5:3	76.58	20.63	70.43	20.65	63.48	25.96
	2	5:7	76.19	20.15	66.45	23.65	63.26	24.71
	2	10:3	77.19	19.54	67.62	22.56	63.63	25.96
Subset-B (75:25)	1	4	76.38	20.92	72.15	20.56	72.67	20.29
	1	6	75.86	21.51	73.46	20.21	70.72	22.62
	1	8	75.69	21.39	73.88	20.28	71.32	20.72
	1	10	75.39	21.23	70.95	22.14	69.23	21.63
	2	2:8	76.10	20.33	72.61	19.92	69.53	23.20
	2	3:3	75.23	21.20	71.48	20.56	71.85	21.03
	2	3:6	75.82	21.54	71.61	20.21	68.62	23.63
	2	3:8	75.34	21.62	71.66	19.65	69.20	23.02
Subset-C (80:20)	1	4	75.47	21.90	71.76	20.12	71.88	19.70
	1	6	75.94	21.56	71.82	19.98	71.89	20.55
	1	5	76.44	20.79	72.95	20.58	71.69	19.86
	1	8	76.50	20.25	72.46	20.65	71.95	20.23
	2	3:4	75.73	21.83	72.76	19.56	71.03	20.43
	2	5:6	76.67	20.52	72.86	20.85	72.50	19.96
	2	5:7	75.51	21.38	72.92	20.82	71.25	20.82
	2	10:3	75.82	21.43	71.75	22.56	71.23	20.26
Subset-D (90:10)	1	2	78.67	17.28	73.56	20.56	70.27	22.47
	1	4	78.06	17.63	73.65	20.52	70.74	22.55

	1	6	78.29	17.74	73.46	22.53	74.65	20.45
	1	8	79.89	16.89	72.36	22.89	71.54	21.23
	2	3:6	78.28	17.96	72.99	23.36	72.22	20.38
	2	5:4	78.34	17.60	72.76	23.58	72.25	20.56
	2	5:7	78.26	17.64	72.49	22.45	72.65	21.45
	2	10:3	78.64	17.43	72.65	23.54	72.56	20.69

Table 4: Assessment of different algorithm based on R^2 and RMSE values for input set-2.

Input Set-2								
Algorithm								
			BR		**LM**		**SCG**	
Subset	**Hidden layer**	**Neurons**	**R^2 (%)**	**RMSE (%)**	**R^2 (%)**	**RMSE (%)**	**R^2 (%)**	**RMSE (%)**
Subset-A (66.67:33.33)	1	2	74.84	22.77	57.03	19.80	64.17	20.75
	1	4	74.68	23.75	57.73	20.10	66.25	18.56
	1	5	75.36	22.85	54.51	27.26	68.42	18.25
	1	8	75.43	23.79	54.36	21.56	66.52	19.56
	2	3:3	75.87	22.86	58.42	20.31	65.45	19.86
	2	5:3	76.23	22.49	56.48	20.96	64.89	20.98
	2	5:7	74.43	24.30	54.26	22.21	65.59	19.45
	2	10:3	74.65	23.77	57.63	18.96	65.75	19.86
Subset-B (75:25)	1	4	78.46	20.39	72.67	18.29	69.60	18.89
	1	6	78.38	20.18	69.72	19.62	70.45	20.25
	1	8	78.49	20.74	70.32	19.72	69.85	20.75
	1	10	78.95	20.35	69.23	20.63	69.25	20.56
	2	2:8	78.02	20.41	70.53	18.20	66.25	20.65
	2	3:3	77.84	20.56	70.85	18.03	69.56	20.56
	2	3:6	78.51	19.97	70.62	18.63	69.58	21.25
	2	3:8	78.31	19.96	71.20	19.02	68.58	20.25
Subset-C (80:20)	1	4	76.46	22.86	72.88	22.70	71.44	16.67
	1	6	76.77	22.91	73.89	22.55	72.56	17.64
	1	5	75.87	22.17	73.69	22.86	72.24	17.92
	1	8	75.20	23.23	72.95	22.23	73.32	16.72
	2	3:4	75.60	23.41	72.03	21.43	72.36	18.55
	2	5:6	74.98	22.72	71.5	21.96	71.98	18.56
	2	5:7	74.20	22.75	71.25	22.82	72.65	17.14
	2	10:3	74.21	22.25	72.23	22.26	72.69	17.25
Subset-D (90:10)	1	2	82.30	16.94	71.27	17.47	76.23	16.59
	1	4	82.67	14.45	72.74	19.55	76.69	16.56
	1	6	82.00	14.68	70.58	19.26	74.69	17.58
	1	8	82.29	15.90	74.22	17.45	74.23	17.23
	2	3:6	81.91	15.64	72.22	18.38	71.93	18.91
	2	5:4	80.42	16.12	72.25	18.56	70.63	19.36
	2	5:7	81.50	16.26	71.65	19.25	71.96	18.69
	2	10:3	80.61	16.04	72.56	17.69	72.25	18.12

Conclusion

When analyzing all three results of algorithms it was shown that Bayesian regularisation was better achieved, followed by Scaled Conjugate Gradient and Levenberg-Marquardt. BR algorithm has the highest statistical performance for First Lactation 305 Day Milk Yield i.e. 82.67%. Thus we can tell from this present research that the Bayesian regularisation algorithm can be used to predict milk yield in crossbred cattle. With more than 80% precision we can pronounce on this system that prediction by this model is very reliable. In future with addition of more input variables the models accuracy can be increased.

References

1. Fernandez C, Soria E, Sanchez-Seiquer P, Gómez-Chova L, Magdalena R, Martín-Guerrero JD *et al*. Weekly milk prediction on dairy goats using neural networks. Neural. Comput. Appl. 2007; 16(4-5):373-381.
2. Sharma AK, Sharma RK, Kasana HS. Prediction of first lactation 305-day milk yield in Karan Fries dairy cattle using ANN modelling. Appl. Soft Comput. 2007; 7:1112-1120.
3. Pindyck RS, Rubinfeld DL. Econometric Models and Economic Forecasts McGraw-Hill. Inc. USA. 1991.
4. Kominakis AP, Abas Z, Maltaris I, Rogdakis E. A preliminary study of the application of artificial neural networks to prediction of milk yield in dairy sheep. Comput. Electron. Agric. 2002; 35(1):35-48.
5. Kelleher JD, Mac Namee B, D'arcy A. Fundamentals of machine learning for predictive data analytics: algorithms, worked examples, and case studies. MIT Press. 2015.
6. Sharma RK, Sharma AK. Neuro-computing paradigms with application to dairy production, in: Ashwini Sharma (Ed.), Lecture Compendium, National Training Programme on Information Resources on Genetics and Documentation Techniques for Livestock Improvement, Centre for Advanced Studies-AG&B, Dairy Cattle Breeding Division, NDRI, Karnal, India, 2004, 173-178.
7. Singh RR, Dutt T, Kumar A, Tomar AKS, Singh M. On-farm characterization of Vrindavani cattle in India. Indian J Anim. Sci. 2011; 81(3):267-271.

8. Fausett LV. Fundamentals of neural networks: architectures, algorithms, and applications Englewood Cliffs: prentice-Hall. 1994, 3.
9. Bhosale MD, Singh TP. Comparative study of feed-forward neuro-computing with multiple linear regression model for milk yield prediction in dairy cattle. Curr. Sci. 2015; 108(12):2257-2260.
10. Mundhe UT, Gandhi RS, Das DN, Dongre VB, Gupta A. Genetic and non-genetic factors affecting monthly part lactation milk yields in Sahiwal cattle. Indian J Anim. Sci. 2015; 85(5):517-518.
11. Dongre VB, Gandhi RS, Singh A, Ruhil AP. Comparative efficiency of artificial neural networks and multiple linear regression analysis for prediction of first lactation 305-day milk yield in Sahiwal cattle. Livest. Sci. 2012; 147(1-3):192-197.