Trop Anim Health Prod (2010) 42:639–644
DOI 10.1007/s11250-009-9468-7

Use of test-day records to predict first lactation 305-day milk yield using artificial neural network in Kenyan Holstein–Friesian dairy cows

D. M. Njubi · J. W. Wakhungu · M. S. Badamana

Accepted: 22 September 2009 / Published online: 10 October 2009

Abstract The study is focused on the capability of artificial neural networks (ANNs) to predict next month and first lactation 305-day milk yields (FLMY305) of Kenyan Holstein–Friesian (KHF) dairy cows based on a few available test days (TD) records in early lactation. The developed model was compared with multiple linear regressions (MLR). A total of 39,034 first parity TD records of KHF dairy cows collected over 102 herds were analyzed. Different ANNs were modeled and the best performing number of hidden layers and neurons and training algorithms retained. The best ANN model had one hidden layer of logistic transfer function for all models, but hidden nodes varied from 2 to 7. The R^2 value for ANNs for training, validation, and test data were consistently high showing that the models captured the features accurately. The R^2, r, and root mean square were consistently superior for ANN than MLR but significantly different ($p>0.05$). The prediction equation with four variables, i.e., first, second, third, and fourth TD milk yield, gave adequate accuracy (79.0%) in estimating the FLMY305 from TD yield. It emerges from this study that the ANN model can be an alternative for prediction of FLMY305 and monthly TD in KHF.

Keywords Artificial neural networks · Back propagation · Dairy cows · Milk-yield prediction

Abbreviations

ANN	Artificial neural network
DRSK	Dairy recording services of Kenya
MLP	Multilayer perceptron
NN	Neural network
SAS	Statistical analysis software
MATLAB	Matrix Laboratory

Introduction

There is a strong evidence (Schaeffer et al. 2000; Jensen 2001; Ferreira et al. 2002; Mostert et al. 2006) that dairy cattle evaluation using test-day milk yield (TDMY) has significant advantages over the 305-day milk yield: (a) The use of TDMY allows a more accurate definition of contemporary groups and associated environmental effects, thus offering a more specific definition of the effects of the lactation stage and reproduction of dairy cows; (b) characteristics associated with TDMY include the use of additional information on a single animal during genetic evaluations; (c) a better adjustment for lactation of different durations and the possibility of adjusting for

D. M. Njubi · J. W. Wakhungu · M. S. Badamana
Department of Animal Production, University of Nairobi,
P.O. Box 29053-00625, Nairobi, Kenya

D. M. Njubi (✉)
National Council for Science and Technology,
P.O. Box 30623-00100, Nairobi, Kenya
e-mail: davidnjubi@yahoo.com

individual differences in the shape of a lactation curve; and (d) use of TDMY makes possible to assess animals with lactations in progress, allowing for more frequent assessments and thus a reduction in the generation interval (Swalve 1998 and 2000; Jensen 2002).

The correlation between lactation and test-day (TD) milk yields is high (El Faro and de Albuquerque 2003; Ilatsia et al. 2006). Some studies have shown minimal change in ranking of sires and cows (Swalve 1995; Meyer et al. 1989; Kaya et al. 2003).

In developing countries, there is limited level of milk recording, and use of TD models would result in reduced cost of recording as we could have longer intervals between milk recording and less frequent collection of milk samples. In this way, the amount of information that can accrue from incorporating the majority of smallholders who have small herd sizes would be large.

In Kenya, official milk recording schemes in cattle for smallholders is non-existent. A majority of dairy farmers are smallholder producing some 56% of total milk and 80% of the total marketed milk nationally (Omore et al. 1999) based on small herd sizes of two to three animals in about 1 ha land size. The dairy industry is a significant source of employment in Kenya.

With a suitable policy framework, for example, subsidies and economic incentives coupled with suitable TD models, the level of milk recorded will increase, which is crucial for any meaningful accurate genetic evaluation.

Increased genetic gain and improved profits can accrue from using TDMY on dairy heifer at early stage of lactation, unproductive cows would be culled early, and there will be decreased generation interval.

In Kenya, we are yet to embrace the use of TD observations instead of aggregated 305-day production records despite several studies having shown advantages (Ilatsia et al. 2006; Mostert et al. 2006). If adopted, the country stand to gain in that ranking of animals could change significantly as observed in other countries (Schaeffer et al. 2000).

Breeding programs in Kenya are based primarily on milk production, and therefore, accurate measurement or prediction of milk yield is essential for proving bull faster and eventually high genetic gain.

Dairy yield prediction is a current challenge, which has been improved using different statistical methods. Recently, artificial neural networks (ANNs) have been employed as an alternative method of milk yield prediction.

Artificial neural network

ANN is a system loosely modeled based on the human brain.

ANNs offer a completely different approach to problem solving, and they are sometimes called the sixth generation of computing.

NNs are powerful techniques to solve many real world problems (El Emary 2006; Huang Mei et al. 2006). They have the ability to learn from experience in order to improve their performance and to adapt themselves to changes in the environment.

From the point of view of statistics or econometrics, NN models are a particular class of nonlinear input–output models. NNs have been established to be superior to the conventional models of linear kind (including regression, univariate time series models, and multivariate time series transfer function models) and some other non-linear kind. Application of NN does not require the data to meet the assumptions that must otherwise be met in a regression model.

ANN adapts to learn the relationship or mapping between input and outputs during the training process. During supervised training, which is used in this study, pairs of input and target data are used. An input is propagated through the ANN, the model output is compared with the target output, and the weights between nodes are updated to minimize the error between simulated and target output.

The design of NN architecture (topology) and methods of training, testing, evaluating, and implementing the network is very important. The design of NN architecture consists of the choice of the NN algorithm, the structure (number of layers, and number of neurons in the layers), the input and output functions, and the learning parameters.

This research focuses on the back propagation algorithm learning method. The back propagation algorithm seeks to minimize the error term between the output of the neural net and the actual desired output value. The error term is calculated by comparing the net output to the desired output and is then fed back through the network, causing the synaptic weights to be changed in an effort to minimize error. The process is repeated until the error reaches a minimum value (Haykin 1994).

ANNs are used in various fields such as financial market forecasts but currently are increasingly being applied in bioinformatics and genetic analysis. ANN is

Table 1 Days in milk (DIM), number of records (N), mean and standard deviation (SD) for milk yield

DIM	N	Mean	SD
305-day	3,137	4,360.60	1,628.52
TD1	3,582	15.34	5.73
TD2	3,547	16.79	6.21
TD3	3,644	16.32	6.38
TD4	3,619	15.85	6.41
TD5	3,686	15.24	6.30
TD6	3,698	14.61	6.20
TD7	3,680	14.04	6.07
TD8	3,651	13.41	5.99
TD9	3,610	12.50	5.79
TD10	3,826	11.67	5.83
Overall test-day milk yield	36,543	4,371.22	1,631.63

increasingly being applied in the fields of agriculture (Bertis et al. 2001; Cunningham and Holmes 2001) and livestock (Wade and Lacroix 1994; Salehi et al. 1998; Kominaks et al. 2002; López-Benavides et al. 2003).

Thus, the objective of the present study was to assess the predictive power of ANN as compared to linear regressions in predicting first lactation 305-day and monthly milk yields using TD records.

Materials and methods

Data comprised TD records of first lactation Holstein–Friesian cows calving from1985 through 2005. The records were obtained from the Dairy Recording Services of Kenya, the organization responsible for the official milk recording in Kenya.

Evaluation of dairy cattle for milk yield has generally been done for 305-day lactation yield, which was obtained by summing up to ten TD records taken approximately at monthly intervals.

The Holstein–Friesian cattle data were used because they comprise a high proportion of the exotic dairy animals raised in Kenya in both large- and medium-scale farms. The breed is evenly distributed in the country.

Data

In this study, 39,034 daily yield records from the first lactation of 3,693 cows were used for prediction. The number of TD records per cow averaged 9.98. First, TD comprised daily yield records sampled between days 5 and 15 postpartum, while the second TD comprised daily yield sampled between days 16 and 31. Successive tests were approximately 30-day intervals. Cows with at least the first five TD were included. Table 1 shows the characteristic of the data used. Descriptive analyses were done using Statistical Analysis Software (SAS 2003).

Each record contained the following information: herd identification, individual cow identification, cows date of birth (day–month–year), cows calving dates (day–month–year), lactation milk yield (kg), lactation length (days), parity, sire, and dam.

The data were preprocessed with all the inconsistency removed, e.g., animal without known sire and dam, daughters of sires with less than eight daughters

Table 2 The best fitness for different models

Model	Architecture	Bestfitness	Correlation	R^2
TD1 vs TD2	4-6-1	0.328	0.751	0.564
TD1 vs TD3	4-5-1	0.300	0.703	0.495
TD1 vs TD4	4-4-1	0.302	0.666	0.444
TD2 vs TD3	4-2-1	0.402	0.816	0.666
TD2 vs TD4	4-2-1	0.373	0.775	0.600
TD3 vs TD4	4-5-1	0.399	0.839	0.703
TD1-TD4 vs FLMY305	7-4-1	0.002232	0.890	0.790
TD1 vs FLMY305	4-5-1	0.00140	0.746	0.553
TD2 vs FLMY305	4-8-1	0.00180	0.843	0.711
TD3 vs FLMY305	4-4-1	0.302	0.666	0.444
TD4 vs FLMY305	4-2-1	0.402	0.816	0.666

Table 3 ANN (above diagonal) and MLR (below diagonal) correlations between test-day (TD) yield and 305-day yield for the test set

TD1	TD2	TD3	TD4	305-day
TD1	0.751	0.703	0.666	0.746
TD2	0.696	0.816	0.775	0.843
TD3	0.613	0.603	0.839	0.666
TD4	0.556	0.555	0.545	0.816
305-d	0.627	0.634	0.633	0.632

per class of H-Y-M TD, cows older than 48 months of calving, and lactation less than 150 days. The age of cows at first calving was grouped into four classes: 20–24, 25–29, 30–34, and 35–48 months. Season of calving were also grouped into four: dry (January to March), long rains (April to June), intermediate rains (July to September), and short rains (October to December).

Model

Each cow had at least eight TD records for milk production trait. The data was split into three: an estimation data set, consisting of the first 68% of TD, used for training and a validation data set (VDS), consisting of the next 16% of TD, and the rest for testing records (16% of TD).

The network architecture was optimized by selecting the best number of hidden layers and nodes per layer. Several models were analyzed with varying number of hidden layers and nodes per layer ranging from 1 to 10. Multilayer perceptrons (MLP) with one hidden layer was shown to model the first 305-day lactation (FLMY305) and monthly TD (MTD) milk yields resulting with the best accuracy. It has been demonstrated that at most two hidden layers are sufficient to solve any problem (Haykin 1999). Among the training algorithms (conjugate gradient descent algorithm, quasi-Newton and Levenberg–Marquardt), the former had more accuracy, so only this one will be described here.

Table 4 The correlation, RMS, and R^2 between first four test days and 305-day yields for the test set

	ANN	MLR
Correlation	0.916	0.822
RMS	423.3	575.0
R^2	0.839	0.676

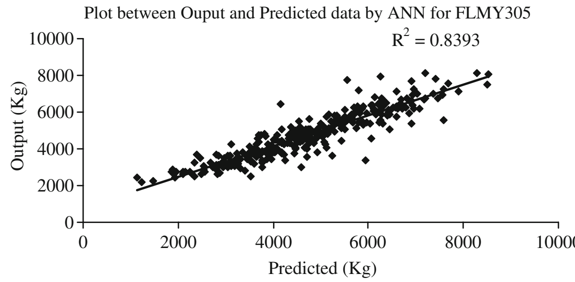

Fig. 1 Plot between output and predicted data by ANN for FLMY305

The back propagation training algorithm was employed to predict the FLMY305 and MTD. MLP, a layered feed-forward network typically trained with back propagation, have been proven to be universal approximators (Reed and Marks 1998) and capable of implementing any given function through the use of various non-linear transfer functions. The common activation functions, which also happened to be used by the network tested during this research, are the logistic or sigmoid function $\mathrm{f}(x) = 1/(1+\exp(-X))$.

For the first two set of models, the input variables for FLMY305 consisted of the nodes corresponding to the following variables: individual TDs or the first four TDs, mean herd production, number of days in milk, and month of calving. The inputs were introduced to the three NN layers of input, hidden, and output.

For the second set of models, the input variables for MTD consisted of TD1 to TD4 and mean herd production, number of days in milk, and month of calving. The inputs were introduced to the three NN layers of input, hidden, and output.

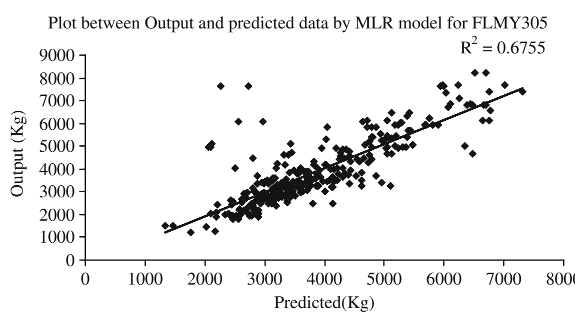

Fig. 2 Plot between output and predicted data by MLR for FLMY305

In all instances, model construction used the NN toolbox (MATLAB 2002).

Results and discussion

Unlike the conventional statistical models, soft computing methods like back propagation NN are useful when a model is unknown because they can ‘learn’ from the data. All the network designs used in this study consisted of one hidden layer with nonlinear activation function logistic and a logistic output layer; this give the best accuracy. It has been demonstrated that at most two hidden layers are sufficient to solve any problem (Haykin 1999).

The architectures with the best fitness for the three models varied from [7-4-1] to [4-2-1] (Tables 2). The R^2 value for training, validation, and test data sets for the ANN was relatively high (44.5% to 79.0%), which showed that the model has captured the features accurately.

For the monthly model the correlations (r) and accuracy of prediction (R^2) of daily yields between consecutive TDs were high but decreased down for the most distant TDs. The r and R^2 were highest (70.3%) for TD3 and TD4, consistent with peaking of milk for exotic breeds of between third to fourth lactation months. The correlation for FLMY305 with TDs was highest between FMLY305 and TD2 (71.1%) and lowest for FLMY305 and TD3 (44.4%). This is not consistent with the expectation of lactation milk yield peaking around the third month. The R^2 followed the same trend as the correlation.

The prediction equation with four variables, i.e., first, second, third, and fourth TD milk yield, gave adequate accuracy (79.0%) in estimating the FLMY305 from TD yield in Holstein–Friesian cows. These results show that the models captured the features accurately.

Table 3 shows the correlation within and between TDs and FLMY305 for ANN and multiple linear regression (MLR) methods. The correlation between pairs of TDs was highest for adjacent TDs but declined subsequently in both methods, but ANN was consistently higher than MLR.

The ANN was superior than MLR as also highlighted in the overall prediction of FLMY305 using the first four TDs (Table 4). ANN method has higher r, R^2, and lower RMS than MLR. This implies that we can predict monthly as well as FLMY305 with accuracy using the early TD records.

These results are consistent with several other studies (Schaeffer et al. 2000; Jensen 2001; Ferreira et al. 2002; Mostert et al. 2006). The use of TD model appears to be a better alternate of the 305-day lactation model because early selection on the basis of TDs could reduce generation interval (Swalve 1998, 2000; Jensen 2002), and therefore, improve accuracy of evaluation and at farm level culling of unproductive animals would improve overall farm profitability. This method becomes even more important in Kenya where we have many small herd sizes and without well-established milk recording schemes.

Figures 1 and 2 show a plot between experimental and computed data by ANN and computed data by MLR model for prediction of FLMY305 using first four TDs. These results prove that the proposed ANN can be used successfully for the prediction of 305-day lactation and monthly milk yields.

Conclusion

It is clear from the model accuracy that ANNs can accurately predict next month’s and FLMY305 milk yields. This is welcome particularly in developed countries, which have poor infrastructure for proper milk recording, as only few data points would be recorded per lactation. When compared to regression analysis, ANNs are a better tool for prediction for they are significantly more accurate than (MLR) analysis as observed in this study. In addition, if the models are to be incorporated in a decision support system, then ANNs are more suitable than the MLR; as for the latter, the user must have a deeper understanding of statistics.

Acknowledgment Appreciation is expressed to the Dairy Recording Services of Kenya for providing data.

References

Bertis B, Johnston WL, Lovell A, Olson S, Steed S., Cross M (2001) Data mining in U.S. corn fields. Proc. First SIAM International Conference on Data Mining, Chicago, 3 IL, USA.

Cunningham, S. J. and Holmes, G. 2001. Developing innovative applications in agriculture using data mining. Department of Computer Science, University of Waikato, Hamilton, New Zealand.

El Emary I. M. M. 2006. On the Application of Artificial Neural Networks in Analyzing and Classifying the Human Chromosomes. Journal of Computer Science 2 (1): 72-75.

El Faro, L. and de Albuquerque, L.G., 2003. Estimation of genetic parameters for the lactation test-day records and total milk yield for Caracu cows. Rev. Bras. De Zootecn., 32: 284-294.

Ferreira, W.J., Teixeira, N.M., Torres, R.A. and Silva, M.V.G.B. 2002. Utilizao da produo de leite no dia do controle na avaliao genetica em gado de leite - Uma reviso. Archivos Latinoamericanos de Produccion Animal 10:46-53.

Haykin, S. 1994, Neural Networks: A Comprehensive Foundation, Macmillan, New York, 1994.

Haykin, S. 1999. Neural Networks: A Comprehensive Foundation. Prentice Hall, Upper Saddle River.

Huang Mei, G.P., Zhang J. and Zhang, S. 2006. Application of artificial neural networks to the prediction of dust storms in Northwest China. Global and Planetary Change 52:216–224.

Ilatsia, E.D., Muasya, T.K., Muhuyi, W.B. and Kahi, A.K. 2006. Use of test day milk yield records for genetic evaluation in Sahiwal cattle. Proceedings of the 8th World Congress on Genetics Applied to Livestock Production, Belo Horizonte, Minas Gerais, Brazil.

Jensen, J. 2001. Genetic evaluation of dairy cattle using test-day models. Journal of Dairy Science 84:2803-2812.

Jensen, J. 2002. Genetic evaluation of dairy cattle using test-day models. Journal of Dairy Science 84, 2803-2812.

Kaya, I., Akbap, Y. and Uzmay, C. 2003. Estimation of Breeding Values for Dairy Cattle Using Test- Day Milk Yields. Turk. J. Vet. Anim. Sci., 27: 459-464.

Kominaks, A.P., Abas Z., Maltaris, I. and Rogdakis, E. 2002. A preliminary study of the application of artificial neural networks to prediction of milk yield in dairy sheep. Computers and Electronics in Agriculture, v.35, p. 35-48.

López-Benavides M.G., Samarasinghe S. and Hickford J.G.H. 2003. The use of artificial neural networks to diagnose mastitis in dairy cattle. Proceedings of the International Joint Conference on Neural Networks (IJCNN)

MATLAB 2002. Matlab 6.5 (Release 13), The Language of Technical Computing, The MathWorks, Natick.

Meyer, K., Graser, H.U. and Hammond, K. 1989. Estimates of genetic parameters for first lactation test day production of Australian black and white cows. Livest. Prod. Sci., 21: 177-199.

Mostert, B.E., Theron, H.E., Kanfer, F.H.J. and van Marle-Köster, E. 2006. Comparison of breeding values and genetic trends for production traits estimated by a Lactation Model and a Fixed Regression Test-day Model. S. Afr. J. Anim. Sci. 36, 36, 71-78

Omore, A., Muriuki, H., Kenyanjui, M., Owango, M and Staal, S. 1999. The Kenya dairy sub-sector: A rapid appraisal. Smallholder Dairy (Research & Development). http://www.smallholderdairy.org/milk%20cons%20and%20marketing.htm

Reed, R.D. and Marks, R. J. 1998. Neural smithing: Supervised learning in feedforward artificial neural networks. Cambridge: MIT Press.

SAS 2003 Procedures guide for personal computers (version 9 edition). SAS Institute Inc, Cary.

Salehi, F., Lacroix, R. and Wade, K.M. 1998. Improving dairy yield predictions through combined records classifiers and specialized artificial neural network. Computers and Electronics Agriculture, v.20, p. 199-213.

Schaeffer, L.R., Jamrozik, J., Kistemaker, G.J. and Van Doornmaal, B.J. 2000. Experience with a test-day model. J. Dairy Sci. 83, 1135-1144.

Swalve, H.H. 1995. The effect of Test Day Models on the Estimation of Genetic parameters and Breeding Values for Dairy Yields Traits. J. Dairy Sci., 78: 929-938.

Swalve, H.H. 1998. Use of test day records for genetic evaluation. In Proceedings of the sixth world congress of genetics applied to livestock production, Armidale, Australia. CD-ROM.

Swalve, H.H. 2000. Theoretical basis and computational for different test-day genetic evaluation methods. Journal of Dairy Science 83, 1115-1124.

Wade, K.M. and Lacroix, R. 1994. The Role of Artificial Neural Networks in Animal Breeding, Proceedings of the 5th World Congress on Genetics Applied to Livestock Production, Guelph, Canada, v.22, pp. 31–34.