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Predictions of 305-day milk yield in Iranian Dairy cattle using test-day records by artificial neural network

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ABSTRACT

Artificial neural network was used as non-linear models to predict 305-day milk production using test-day records. Test-day records (32475) belong to five recording period, of the first lactation were used in analyses. A total of 75% of records were used for training of back propagation artificial neural network system. The ANN system in this study had 3 layers of input, hidden and output each with 11, 30 and 1 neurons, respectively. The results showed that there was no significant difference between observed and predicted data. R^2 values ranged from 77% in period 1 to 92% in period 5 when 100 records were used in the analysis. The error coefficients of I^2_o, I^2_B and I^2_E resulted from inadequacy in flexibility and insufficient convergency between direction of changes in the observed and predicted data were reduced as period number was increased. Our results showed that ANN system have ability for reasonable prediction of 305-day milk yield from small number of test–day records in early stages of milk production.

Key words: Artificial neural network**,** Dairy cattle**,** Milk yield**,** Test-day record

Milk yield, and milk fat and protein percentages are important in Iranian dairy cattle industry (Edriss *et al*. 2008). Selection of genetically superior bulls is mostly based on their ability to paramount daughters for their milk production. Therefore, earlier collection of semen would result in better profit (Salehi *et al.* 2000). In dairy cattle, any approach which lead to an accurate prediction of milk yield before the end of a lactation period, could expedite selection of superior bulls, decrease the genetic interval and increase the genetic progress (Salehi *et al.* 1998). Current mathematical models used for prediction of milk yield have some substantial limitations (Kominakis *et al.* 2002).

In addition to mathematical functions and current models, neuro-computing paradigm, is gaining momentum as plausible alternatives for solving real-life problems (Fang *et al*. 2000). Artificial neural network (ANN) proposes a completely different approach compared to conventional methods. It solves particular problems through a learning system by typical inputs and specific desired outputs (Grazesiak *et al.* 2006). ANN is made of a set of neurons. These neurons process the presented input and matching output in a supervised manner and extract linear and non-linear relationship between the inputs and outputs (Edriss *et al*. 2008). The ANN is a form of simulated human central nervous system (Wildberger 1990, Adamczyk *et al*. 2005). Network learning ability is more dependent on its presented learning example and patterns (Dayhoff 1990). However, divergence in performance was often reported in array of agriculture, due to over modification of the net structure (Yang *et al*. 1999). ANN is mainly used in engineering, economic, or medicine, and also in recent years has come in agricultural field (Paquet *et al*. 2000) or livestock management (Suchorski-Temblay *et al.* 2001). The ANN can successfully be used in prediction of 305-day milk production (Edriss *et al*. 2008).The aim of this study was to investigate the use of ANN as a predictor of total milk yield in dairy cattle using small number of early TD records at the beginning of the lactation period.

MATERIALS AND METHODS

Test-day records (32475) of period 1 to 5, for milk yield from 16 herds of Iranian Holstein cows collected between year 1999–2004, were used in this study. For each test day period several subsets of 100, 500, 1000, 2000 and 5000 records were randomly extracted from edited data and used in the analyses (Fig. 1). The cumulative, monthly and 305-day milk yields were calculated using the actual test-day data. The randomly selected records were restricted to cows which had complete pedigree and production records for all test-

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Table 1. Input and output variables for ANN models

Input variable	Output variable
Cows registration number	Total milk yield (kg)***
Purity*	
Herd	
Sire	
dam	
Birth year (BY)	
Birth month (BM)	
Calving year (CY)	
Test-day milk	
Partial milk yield	
cumulative milk yield**	

*% of Holstein blood, was 88.86±9.67 in the sample; **, this variable haven't attended in TD1 period; ***, Obtained from partial milk yield for 10 TD period

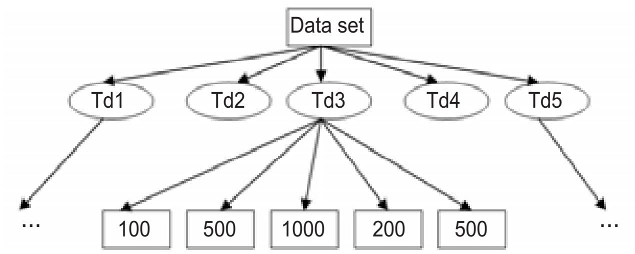

Fig 1. Flowchart of record data sets and subset in every data set include 100, 500, 1000, 2000 and 5000 number of record

day periods of 1 to 5. The following variables were fitted in the models of analysis: purity (Holstein blood % which was 88.86±9.67 in the sample), herd, sire, dam, birth year (BY), birth month (BM), calving year (CY), test-day milk, partial milk yield, cumulative milk yield, and total milk yield (obtained from partial milk yield for 10 TD period). These variables were utilized in the ANN as inputs and outputs (Table1). Each category in data set was used by its corresponding ANN system.

ANN model

The ANN toolbox in Matlab software (Matlab 2006) was used to analyze the data in prediction section of the program. The back propagation neural network (bpANN) is a form of ANN, used in this study. To build an ANN model, number of input, hidden and output layers and number of neurons in the layers need to be determined. The bpANN consists of three layers of input, hidden and output each with 11, 50 and 1 neurons, respectively. However, the number of input layer for TD1 in ANN model was 10 neurons. Fig. 2 shows that how neurons in different layers connect together. The tangent hyperbolic transfer function was applied for input and hidden layers and purline transfer function was used for the output layer (Matlab 2006).The type of learning algorithm was "trainlm". The learning function, update weights and bias values were conformable to levenberd-marquerdt

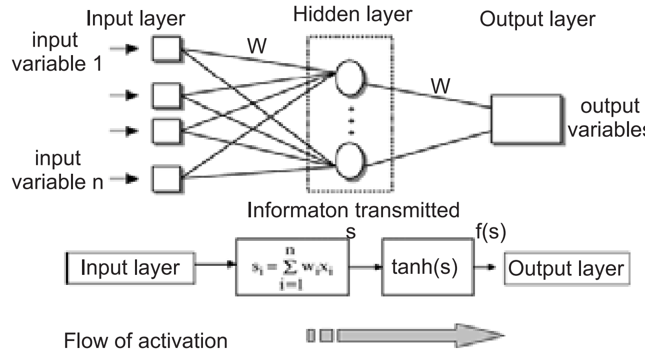

Fig 2. Neuron connection in systematic ANN

optimization algorithm (Hagan and Menhaj 1994). In composing an ANN model, it is very important to have training and testing data sets as confidence against over estimating (Leahy 1994). Each data set was divided into training, testing and verification data sub-sets, i.e.%75 of data allocated to training, and for each of testing and verification sub-sets%12.5 of data was allocated. The training set was used to obtain and modify the weights and bias by ANN. Verification set was used to control the size of network error during the training step. The testing set was employed to assess prediction ability of the ANN for production. ANN system was trained in 100 000 cycles of element processing in which the followings were included: epoch=23, goal= 1E-10, MSE 0.103071 and gradient 4401.75/1e–010;
where; epoch is a single pass through the sequence of all input vectors; goal is to minimize the performance to the goal parameter; MSE is mean square error of the performances; and gradient is a back propagation algorithm which adjusts weights in the steepest descent direction (negative of the gradients).

Network performance evaluation

The criteria used for evaluation of ANN anticipation with the actual observed data were: (i) Pearson's coefficient of correlation between observed and predicted data, (ii) adjusted coefficient of determination, (iii) root mean square error, (iv) SD ratio, (v) relative mean error of prediction, and (vi) Theil's inequality coefficient.

$$r_p = \delta_{ip} / \delta_i \delta_p \tag{1}$$

where, r_p , Pearson's correlation coefficient between observed and predicted values; δ_{ip}, covariance between observed and predicted values; δ_i, standard deviation of observed values; and δ_p, standard deviation of predicted values.

$$R_A^2 = 1 - \frac{n-1}{n-k} \times \left(1 - R^2\right) \tag{2}$$

where, R_A^2 , adjusted coefficient of determination; n, number of records; k, number of prediction variables; and R^2, coefficient of determination.

$$RMSE = \sqrt{\frac{\sum_{i}^{n}\left(y_i - \hat{y}\right)^2}{n}} \tag{3}$$

where, RMSE, root mean square error; n, number of records; y_i, observed value; $\hat{y}$, estimated value by ANN.

$$SD_{ratio} = \sqrt{\frac{\sum_{i=1}^{n}\left(e_i - \bar{e}\right)^2}{\sum_{i=1}^{n}\left(y_{i-}\hat{y}\right)^2}} \tag{4}$$

where, SD_{ratio}, Ratio of error standard deviation to the total standard deviation;e_i, individual error; $\bar{e}$, mean of errors; y_i, observed value; and $\bar{y}$, mean of observed values.

$$\psi = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}}{y_i}\right| * 100\% \tag{5}$$

where, ψ is the relative mean error of prediction and the other symbols are the same as for the previous formulas.

$$I^2 = \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}\right)^2}{\sum_{i=1}^{n} y_i^2} \tag{6}$$

where, ψ^2 is Theil's inequality coefficient (Theil, 1979) and the other symbols are the same as for the previous formulas. The last coefficient (ψ^2) is the sum of three other models' inequality coefficients:

$$I^2 = I_O^2 + I_B^2 + I_E^2 \tag{7}$$

The components of Eq. 7 are as follows:

$$I_o^2 = \frac{\left(\bar{y}_i - \hat{y}_m\right)^2}{\left(1/n\right)\sum_{i=1}^{n} y_i^2} \tag{8}$$

where, I^2, prediction bias; $\hat{y}_i$, mean of observed values; $\hat{y}_m$, mean of predicted values;

$$I_B^2 = \frac{\left(\delta_i - \delta_p\right)^2}{\left(1/n\right)\sum_{i=1}^{n} y_i^2} \tag{9}$$

Where, I^2_B represent the error resulting from predictions inadequate flexibility.

$$I_E^2 = \frac{2\delta_i\delta_p\left(1 - r_p\right)}{\left(1/n\right)\sum_{i=1}^{n} y_i^2} \tag{10}$$

where, I^2_E represents the error resulting from insufficient convergencey between direction of changes in the observed values and changes in the predicted values.

RESULTS AND DISCUSSION

Observed and predicted statistics: Statistical parameters for observed and predicted data are showed in Table 2. In comparison with observed data, in most predicted data by ANN the minimum and maximum values for milk production were over estimated and under estimated, respectively. For the validation of mean of predicted data, the actual measured values for the milk yield were compared to the corresponding values predicted by the relevant ANN model. The comparisons were made using the paired t-test. In all cases, no significant differences were detected between the mean of observed and predicted values, except for TD1-5000 data subset (P> 0.05). In general, the data sets predicted by ANN had less variation than the actual values. This might be the result of the method used by ANN for updating the data. The data structure predicted by ANN in this study were similar to others reported in the literature (Kominakis *et al*. 2002,

Table 2. Statistical summary of observed and ANN predicted values

Dataset	Subset	Min	Max	Mean	SD	t-value
OBS	100	2514	10550	7335	1749	
	500	2267	11697	7203	1724	
	1000	2051	11697	7319	1661	
	2000	1903	12937	7310	1608	
	5000	1291	12937	7381	1616	
TD1	100	2744	11544	7348	1892	–0.43ns
	500	3152	10659	7334	1372	–1.32ns
	1000	2703	1186	7384	1284	–0.98ns
	2000	2335	10920	7348	1173	–0.85ns
	5000	1512	13020	7577	1142	–7.02**
TD2	100	1845	10941	7321	2032	0.05ns
	500	2550	11577	7403	1511	–1.95ns
	1000	1305	12421	7348	1485	–0.92ns
	2000	2180	11408	7325	1214	–0.35ns
	5000	2066	141853	7339	1220	1.45ns
TD3	100	2375	11141	7225	1914	0.42ns
	500	2422	11514	7181	1540	0.22ns
	1000	2287	11027	7308	1417	0.15ns
	2000	1637	12205	7325	1273	–0.34ns
	5000	1745	11421	7338	1225	–0.27ns
TD4	100	3324	10501	7331	1876	0.01ns
	500	2615	11651	7271	1532	–0.66ns
	1000	2179	11258	7325	1389	–0.08ns
	2000	2190	10853	7327	1285	–0.37ns
	5000	1962	11914	7374	1293	0.23ns
TD5	100	3152	10719	7455	1749	–0.49ns
	500	2736	10635	7247	1495	–01.43ns
	1000	2338	11130	7409	1441	-41.29ns
	2000	2444	11174	7290	1337	0.43ns
	5000	1770	11350	7387	1272	0.09ns

**P<0.041; ns, non significant (P>0.05); OBS, observed value TD1-5, predicted value in first test-day period to 5 period. t-value, mean difference between the observed and predicted data of the same category.

Grazesiak *et al*. 2006). However, input variables and size of data sets could affect the predictions made by ANN.

Quality evaluation of ANN predictions: Factors indicating quality evaluation of ANN predictions are shown in Table 3. Decreasing the number of input data from 5000 to 100 resulted in better predictions of all statistical parameters examined. Modification of learning or training parameters and the method of data presentation can considerably influence the network performance (Salehi *et al.* 1998). However, performance of ANN model could become better with higher number of input vectors (Kominakis *et al.* 2002), but in some cases would lead to increasing oscillation in training network phase (Lacroixe *et al.* 1997). The value of neural network SD_{ratio} was varied between 0.39 for TD1-5000 data subset and 0.81 for TD3-100 data subset, and in all sets this index slake from 5000 data toward 100 data. Also, SD_{ratio} decreased with the increase of TD period number. The correlations between actual and predicted values decreased by increasing size of data sets. These values tend to be higher in later test-day periods compared with ones belong to early stage of the milk production. The correlation between actual and predicted data sets ranged between 0.59 (data sub-set 5000) and 0.92 (data sub-set 100). Grezesiak *et al.* (2006) used this parameter for decision making to choose the best ANN model for prediction. The SD_{ratio} parameter of less than 0.4 indicated acceptable quality of ANN system. However, SD_{ratio} of greater than 0.7 indicated that ANN is not ideal for prediction. In other words, the index of lower than 0.1 means that the ANN has a very good quality and would be almost ideal (Statistical neural network 1998). The SD_{ratio} could be used as a criterion to test the adequacy of the network training. The high variation in the input data which introduced to ANN model as training data might also be another reason for the weak prediction made by the system in the cases of the larger data sets.

Higher adjusted coefficient of determination (R^2_A) and lower root mean square error (RMSE) for ANN models could be considered as indications of having a higher accuracy of prediction. The best result observed in TD5 subset. Olori *et al.* (1999) stated that the R^2 values of higher than 0.7 indicate the model prediction is reliable. By increasing the period number of TD the value for RMSE decreased. This implies the network detection of the indexes in the data training. Feeding the network with input variables such as test-day records increased the overall accuracy of prediction (Lacroix *et al*. 1995). The TD5 had more useful information compared with the previous test-day periods (including cumulative milk yield). As an example, prediction accuracy was higher in TD5 data compared with one of TD1 data set. This may cause a better trend, proper update weight and less bias in the network system; and as a result, to higher coefficient of correlation between predicted values and observed values.

Table 3. Statistics of quality parameters for prediction of ANN

Dataset	Subset	r_p	R^2	RMSE	RMSE%	SD_{ratio}
TD1	100	0.88	0.77	915	12	0.52
	500	0.73	0.53	1186	16	0.68
	1000	0.65	0.42	1274	17	0.77
	2000	0.63	0.40	1239	17	0.77
	5000	0.59	0.35	1329	18	0.81
TD2	100	0.82	0.67	1162	16	0.67
	500	0.76	0.58	1155	16	0.66
	1000	0.73	0.53	1163	16	0.70
	2000	0.72	0.52	1122	15	0.70
	5000	0.70	0.49	1156	16	0.72
TD3	100	0.87	0.76	985	13	0.55
	500	0.83	0.70	959	13	0.56
	1000	0.80	0.64	988	13	0.60
	2000	0.77	0.60	1020	14	0.63
	5000	0.75	0.56	1062	14	0.66
TD4	100	0.89	0.79	875	12	0.49
	500	0.86	0.74	864	12	0.50
	1000	0.83	0.70	915	12	0.55
	2000	0.80	0.64	936	13	0.60
	5000	0.78	0.61	1009	14	0.63
TD5	100	0.92	0.85	692	9	0.39
	500	0.88	0.77	816	11	0.47
	1000	0.86	0.74	836	11	0.50
	2000	0.83	0.70	898	12	0.56
	5000	0.82	0.68	927	13	0.57

%RMSE: RMSE divided by the mean of performance

Table 4. Statistics of progenostic evaluation of ANN

Dataset	Subset	ψ	I^2	I^2_o	I^2_B	I^2_E
TD1	100	7.55	0.014523	0.000186	0.000360	0.013977
	500	14.73	0.071610	0.000861	0.006264	0.064665
	1000	15.87	0.042298	0.000109	0.003663	0.038526
	2000	15.26	0.028333	0.000026	0.003386	0.024921
	5000	16.41	0.030535	0.000677	0.003930	0.025928
TD2	100	10.62	0.025729	0.000005	0.002769	0.023018
	500	14.50	0.041462	0.000727	0.000827	0.039908
	1000	13.52	0.041814	0.000057	0.000545	0.041212
	2000	13.59	0.036524	0.000005	0.002769	0.033480
	5000	13.86	0.038012	0.000030	0.002750	0.03523
TD3	100	7.2	0.016370	0.000208	0.000841	0.015321
	500	11.24	0.0170.91	0.000009	0.000615	0.016476
	1000	11.68	0.017785	0.000002	0.001055	0.016728
	2000	12.36	0.018862	0.000004	0.002007	0.016815
	5000	12.74	0.020023	0.000001	0.002674	0.017348
TD4	100	7.4	0.012996	0.000000	0.000287	0.012709
	500	9.9	0.014243	0.000033	0.000673	0.013487
	1000	10.83	0.015250	0.000001	0.001318	0.013931
	2000	11.48	0.016631	0.000005	0.001859	0.014767
	5000	11.94	0.017939	0.000001	0.001819	0.016119
TD5	100	6.3	0.008862	0.000255	0.000000	0.008607
	500	9.6	0.012273	0.000035	0.000959	0.011279
	1000	9.8	0.011208	0.000143	0.000860	0.010205
	2000	10.7	0.014407	0.000008	0.000953	0.013446
	5000	10.8	0.015039	0.000000	0.002071	0.012968

The quality evaluation statistics such as R^2, revealed that increasing the number of records reduced the performance of ANN significantly. It seems that, the above facts have a correlation between the structure of network for instance: epoch, goal, hidden layer,… and the numbers which were used for feeding to the network. This view could be identified by comparison of the quality evaluation and prognostic evaluation statistics of the model.

Prognostic evaluation of the model: The mean relative prediction error (Ø) and Theil's inequality coefficient (I^2) are better quality control parameters for network evaluation. They are good indices for understanding the manner of shakeup in ANN processing phase. TD5 Data set showed the best result compared with other data sets. When smaller data sets was used in the ANN as input vector, for instance 100 data, the system produced smaller values for the quality control parameters of Ø, I^2 (Table 4). TD1 produced the weakest result. Perhaps this is because of insufficient weight change due to small value of learning rate.

Dayhoff (1990) stated that the general network error (I^2) of lower than 0.1 means that the network is well trained. Also Skapura (1996) suggested that if I^2 errors in a network is lower than 0.2 for, it has a sufficient training. The good results from feeding small data sets to ANN model as input vectors suggest that the process of the network learning and demonstration of the data parameters by the system are adequately done. Conversely, weak results were produced when large data sets feed to the system. This is due to the lack of converged predicted value to the actual value.

According to Table 4, I_E has a major role in the value of Theils' coefficient. This represents the error resulting from lack of full convergencey in the direction of change between observed and predicted values. However, I_B and I_O represent the errors resulting from inadequate flexibility and bias in predictions, respectively (Theil 1979). The ANN tended to have negative oscillation in prediction ability when larger number of input vectors (large dataset) was fed to the system. This will result into a drop in total network performance.

The information of Tables 3 and 4 indicated that larger data sets produce higher oscillation in the system. However, increasing period number of test-day within the same parity caused a better performance and more accurate predictions by ANN system.

The major use of any predictive system is to support accurate decision makings which are dependent on prior knowledge of the possible outcomes. Our result study showed that in some cases, neural networks have ability to predict milk yield and milk fat percentage with high accuracy. The efficiency of ANNs would be more improved when samples and variables which are more related to the output variables are used. The results also showed that, using ANN, early test-day records can be used in prediction of 305-day milk yield with high correlations between predicted and observed data. It could be concluded that ANN has a well potential to be used in prediction of subsequent records of dairy cows and to be used as a management tool at herd level. ANN could also be used in setting up selection programs in order to increase the production potential of the herd. It is a good support system for dairyman for decision making.

The flexibility of ANN system allows us to use it in other aspects of dairy industry such as health, fertility, lifetime and other economical traits. This study showed that size of data set and stage of milk production are important factors in ANN performance. Furthermore, choosing appropriate learning algorithm for the system has a major role in accuracy of the predictions. In some cases, the learning rate value I^2 tend to become too small in the iteration. Therefore, inadequate weight correction of changes between observed and predicted values was occurred. More studies need to be down to find out the reason why some time the optimum learning rate value and adequate weight correction can not be reached at the same time.

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