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Modeling Energy Use in Dairy Cattle Farms by Applying Multi-Layered Adaptive Neuro-Fuzzy Inference System (MLANFIS)

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ABSTRACT

This study focused on the capability of two artificial intelligent approaches, including Artificial Neural Networks (ANNs) and Multi-Layered Adaptive Neural Fuzzy Inference System (MLANFIS), as a prediction tool to model and forecast milk yield on the basis of energy consumption in dairy cattle farms of Iran. For this purpose, data was collected from 50 farms in Tehran province, Iran. For the purpose of gaining the best accurate ANFIS model, five energy inputs were clustered into two groups based on their energy share in total energy consumption and an ANFIS network was trained for each cluster. The results of statistical parameter evaluation showed that ANFIS 1 and ANFIS 2 from layer one were not as accurate as ANFIS 3 network (layer two) whereas, coefficient of determination (R^2), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values were 0.75, 1256.72 and 0.129 for ANFIS 1 and 0.65, 1409.43 and 0.144 for ANFIS 2 and 0.93, 681.85 and 0.063 for ANFIS 3 network, respectively. These results were considerably better than ANNs model with R^2, RMSE and MAPE calculated as 0.85, 1052.413 and 0.0702, respectively. Eventually, the outcomes revealed that multi-layered ANFIS contrasted to ANNs modeling could successfully predict the milk yield level accurately. Hence, it is recommended that the multi-layered ANFIS can potentially be applied as an alternative approach.

Key words: Adaptive neuro-fuzzy inference system, energy use, milk production, dairy farm, modeling

INTRODUCTION

Milk as a rich resource of animal protein is known as the first edible food for the human beings and likewise it is strongly recommended by scientists as a nutrient in food composition. Regarding this fact, safe production of milk is an increasing issue for producers and consumers over the last decade. On the other hand, economics of dairy production systems is under pressure mainly due to decreasing milk prices and increasing production costs especially cows' feed.

Today dairy farming and milk collection posts are huge energy consumers, because of several operations such as milking machines, water heaters, milk coolers, vacuum pumps, lighting, etc. (Rodrigues *et al*., 2011). In Iran, considering to the high energy costs in comparison with low yield and farmers' income, amount of energy expenditure is befit of attention. Generally, modern farming has become very energy intensive and dependent on energy sources, especially fossil fuels. Meanwhile, the intensified and mechanized livestock farming management has its own side effects. With implementing a high level of farm management strategies, conventional dairy farming would be highly productive preventing improper allocation of natural resources. At the present time, world population and energy use growth brings the necessity to seek for energy conserving agricultural production systems in the light of meeting population nutrition demand (Koknaroglu, 2010).

Energy is considered as an important production factor in many systems and therefore it should be managed in parallel to other main production resources including land, labor and capital. Since, energy resources are limited and depleting, the outlook of energy consumption needs optimizing decisions. So that, improving energy use management is becoming increasingly important for combating rising energy costs, depletion of natural resources and environmental deterioration (Dovi *et al*., 2009). The pattern of energy input-output use with various inputs and contribution of each energy input vary based on agricultural production systems and other related conditions such as management qualifications, government policies, etc. Thus, paying attention to the relationship of energy inputs and yield, using functional forms is very important.

Traditionally, mathematical methods such as regression analysis have been the most popular modeling technique in finding the relationships between inputs and outputs of a production process (Flores *et al*., 2004; Al-Ghandoor *et al*., 2008). Recently, fuzzy logic, Artificial Intelligence (AI) methods such as Artificial Neural Networks (ANNs) and newly forms such as Adaptive Neural Fuzzy Inference System (ANFIS), derived from the term adaptive network were tailored to allow if-then rules and membership function to be constructed for data mining. This is believed that fuzzy logic allows us to solve many problems which are not well defined and for which it is difficult or even impossible to find a solution (Guillaume, 2001).

ANNs has been a tool for energy consumption prediction in various studies. Grzesiak *et al*. (2006) applied the ANNs model to predict the milk yield of dairy cattle farming in Canada. Also, an ANNs approach for forecasting world green energy consumption to the year 2050 was presented and the equations for consumption of different energy sources were obtained. Also, an integrated Genetic Algorithm (GA) and Artificial Neural Networks (ANNs) approach was presented for analyzing global electricity consumption by Assareh *et al*. (2011).

Recently, with the rapid development of data modeling, alternative approaches such as neural networks and neuro-fuzzy methods have become of particular importance and easier to operate in different areas such as agricultural production systems. The ANFIS technique was applied to yield modeling by Arkhipov *et al*. (2008). Fahimifard *et al*. (2009) implemented ANFIS to predict the poultry retail price. Pan and Yang (2006) analyzed livestock farm odor using a neuro-fuzzy approach. They came to the conclusion that ANFIS is effective in comparison to neural networks. Despite such literature review, this method has been rarely explored in energy analysis and prediction applications. Two techniques, for modeling electricity consumption of the Jordanian industrial sector, including multivariate linear regression and neuro-fuzzy models were presented in the study done by Al-Ghandoor and Samhouri (2009). The advantages of applying these approaches are generally the same and they are tools for energy management and planning strategies as the first step for massive cases such as a regional or national energy management programs. Naderloo *et al*. (2012) employed ANFIS to predict the grain yield of irrigated wheat on the basis of different energy inputs in Iran. In their study, a multi-layered ANFIS showed that the first ANFIS network (including diesel, fertilizer and electricity energy inputs) had a greater impact on grain yield and the combined network (ANFIS 3) could predict the grain yield with good accuracy. Recently, Khoshnevisan *et al*. (2014a) prophesied yield based on energy use of potato crop in Iran using the same methodology. In another similar study, strawberry yield was predicted in 33 greenhouses in Guilan province, Iran using multi-layered ANFIS and ANNs model in which MLANFIS was found to be slightly superior to ANNs model. The models were validated using some statistical parameters. Eight energy inputs and one output were selected for modeling; hence in this study strawberry yield was predicted based on energy use, as well (Khoshnevisan *et al*., 2014b).

In this study, we will propose an approach to the problem of the energy modeling, i.e., by using the multi-layered adaptive network fuzzy inference system approach. The main objective of this study is to evaluate ANFIS application for modeling and predicting milk yield of dairy farms in Tehran province, Iran. To compare with ANFIS modeling results, ANN models were also developed to model milk yield. The following section of this paper will discuss the data collection and preparation. Then in this section, we will introduce the basic architecture of ANNs and ANFIS and the results will be discussed in section 3. In section 4, the possible suggestion will be proposed on the basis of the derived results.

MATERIALS AND METHODS

Data collection and preparation: The study area included an industrial complex for dairy cattle farming in Tehran province of Iran. Tehran province is located within 35°34' and 35°50' N latitude and 51°02' and 51°36' E longitude. This province with 4,443 industrial dairy and beef cattle farms plays an important role in producing milk and meat for the population of Iran. The milk yield for the first three months of 2010 was announced as 265,501 t yielded from 1,897 dairy cow farm units (Anonymous, 2010). “Dam-Gostar Dairy Cattle Farms Complex” was established in this province for the purpose of drawing dairy farms off the residential areas inside the city. Currently, there are about 200 industrial and semi-industrial dairy farms producing milk in this complex. This survey was made in 2011-2012 by interviewing the dairy cattle farmer of 50 units. The sample size was determined by using the random sampling method (Cochran technique) (Cochran, 1977). Some assumptions were made essentially in order to have a much more precise computation such as the period for which energy consumption was estimated for. A lactation period of a cow is approximately 305 days and cows are dry in about 60 days. Therefore, input consumptions assigned to a production year were considered. More specific characteristics of the target farms and cows are given in Table 1.

The culled data was transformed into energy equivalents. To achieve this, gained energy coefficients from various references (Table 2) were applied. The references of each energy coefficient have also been cited in third column. These energy coefficients were multiplied by the inputs consumption quantities to compute the energy use equivalents.

Table 1: Characteristics of the dairy cattle farms and cows of the studied area

Races	Holstein
Lactation period (days)	305
Dry period (days)	60
Average milk yield (kg day^{-1} cow^{-1})	26.5
No. of lactations (times per day)	3
Milk protein (%)	3.5
Milk fat (%)	4
Barn	Semi open

*Dry matter

Table 2: Energy equivalent coefficients of inputs and outputs

Inputs (unit)	Energy coefficient (MJ unit^{-1})	References
Inputs		
Tractor and self-propelled (kg a*)	9-10	Kitani (1999)
Stationary equipment (kg a*)	8-10	Kitani (1999)
Implement and machinery (kg a*)	6-8	Kitani (1999)
Fossil fuels		
Diesel (L)	47.8	Kitani (1999)
Gasoline (L)	46.3	Kitani (1999)
Kerosene (L)	36.7	Kitani (1999)
Natural gas (m^3)	49.5	Kitani (1999)
Electricity (kWh)	11.93	Ozkan *et al.* (2004)
Human labor (h)	1.96	Kitani (1999)
Feed		
Concentrate (kg)	6.3	Meul *et al.* (2007)
Silage (kg)	2.2	Wells (2001)
Alfalfa (kg)	1.5	Sainz (2003)
Outputs		
(a) Milk (kg)	7.14	Coley *et al.* (1998)
(b) Cow manure (kg dry matter)	0.3	Singh and Mittal (1992)

a*: Economic life of machine (year)

Based on the energy equivalent computation results, various energy indices including Energy Use Efficiency (EUE) or Energy Ratio (ER), Energy Productivity (EP), Specific Energy (SE) and Net Energy Gain (NEG) were estimated as follows (Eq. 1-4) (Pishgar-Komleh *et al.*, 2011):

$$\text{Energy use efficiency} = \frac{\text{Energy output (MJ cow}^{-1})}{\text{Energy input (MJ cow}^{-1})} \tag{1}$$

$$\text{Energy productivity} = \frac{\text{Egg yield (MJ cow}^{-1})}{\text{Energy input (MJ cow}^{-1})} \tag{2}$$

$$\text{Specifc energy} = \frac{\text{Energy input (MJ cow}^{-1})}{\text{Egg yield (MJ cow}^{-1})} \tag{3}$$

$$\text{Net energy gain} = \text{Energy output (MJ cow}^{-1})\text{-Energy input (MJ cow}^{-1}) \tag{4}$$

Artificial neural networks model: The acronym ANNs which stands for artificial neural networks, is an information processor with identical characteristics as biological and behavioral neural networks of human brain (Movagharnejad and Nikzad, 2007). Multi-Layer Perceptron (MLP) is a widely used ANNs architecture. It consists of one input layer, one or more hidden layers and one output layer and each layer employs several neurons. To run the model, data was divided into three groups. One of these groups was used for training (training set) and the other was used for testing (testing set) of the network and the third is for validation measuring network generalization. The artificial neural network model with back propagation is the most widely used multi-layered prediction model.

In this study, in order to forecast milk yield in the studied region, five energy inputs were chosen as input parameters to the ANNs model. Milk yield of the target farms was selected as output variable. Different hidden layers and different number of neurons in each hidden layer were examined to determine the best topology of the network. Networks with different activation functions were also developed to attain the best results. To perform ANN models, MATLAB M-le environment version 7.1 (R2012a) was employed. Moreover, various required modifications were applied to the program. These modifications included number of hidden layers, number of neurons in each hidden layer. After making each modification, the model was run for forty iterations.

Adaptive neuro-fuzzy inference system: A Fuzzy Inference System (FIS) forms a useful computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning. The ANFIS is a FIS implemented in the framework of an adaptive fuzzy neural network. This is a rule-based system with three components: membership functions of input-output variables, fuzzy rules and output characteristics and system results. A Neuro-fuzzy network is the combination of neural networks with the fuzzy logic; this combination has the explicit knowledge representation of a FIS with the learning power of ANNs. The ANFIS is capable of simulating and analyzing the mapping relation between the input and output data through a hybrid learning to determine the optimal distribution of membership function. It is mainly based on the fuzzy "if-then" rules from the Takagi and Sugeno type (Jang *et al*., 1997).

In general, the algorithm first requires the establishment of fuzzy sets and rules over the number of inputs (N). By defining appropriate membership functions the input data would change from crispy into the non-crispy manner through a process called fuzzification. Then, the non-crispy data were analyzed in the fuzzy inference engine based on the pre-defined if-then rules, before being converted back to the crispy output through the defuzzification process. the basic block diagram of the fuzzy system is illustrated in Fig. 1 (Hou and O'Brien, 2006).

The FIS, whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method (hybrid), is applied to a given input/output data set. This allows the fuzzy systems to learn from the data they are modeling. The ANFIS uses either back propagation or a combination of least squares estimation and back propagation (hybrid) for membership function parameter estimation. In some cases, data is collected using noisy measurements and the training data cannot be representative of all the features of the data that will be presented to the model. This is where model validation comes into play.

In order to create ANFIS models, MATLAB M-file environment version 7.1 (R2012a) was utilized. In running the ANFIS models, we faced two major constraints. One was the number of input parameters and other the number of units (fifty dairy cattle farms). The total number of inputs was five including: diesel fuel, electricity, machinery, human labor and feed supply energy equivalents. The milk yield was regarded as the output of the model. When the number of ANFIS inputs exceeds 5, increased computational time and rule numbers cause ANFIS to run out of analysis (Naderloo *et al*., 2012). To overcome this constraint, input clustering was performed so that they were classified into two clusters based on their share in energy consumption. Correspondingly,

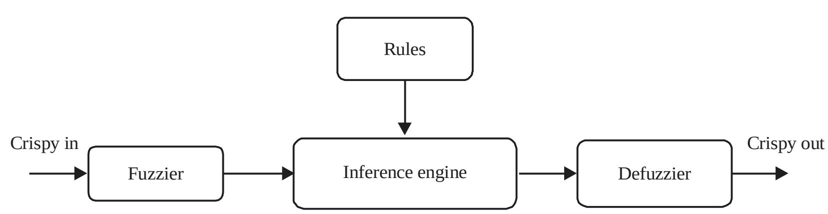

Fig. 1: Fuzzy block diagram

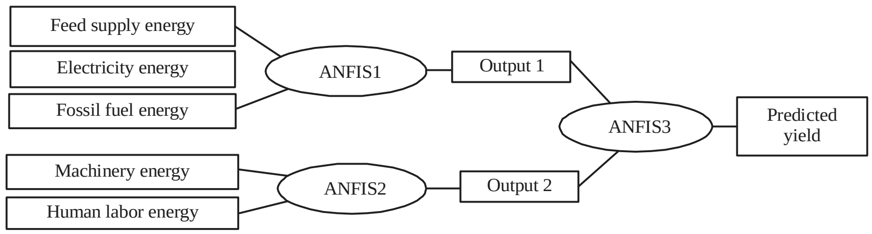

Fig. 2: ANFIS network diagram

three ANFIS sub-networks were developed (Fig. 2). Hence, an individual ANFIS network was employed for each category and two predicted values were used as inputs to ANFIS 3. Eventually the output of the last model was milk yield. Applying this procedure the problem of limited number of samples (dairy cattle farms) was also solved and the total number of parameters did not exceed the number of training data pairs.

Moreover, in order to achieve the best and effective model with minimum errors, five significant and important adjustments were made in the structure of ANFIS network. These settings include types of membership function (mf) (including triangular, trapezoidal, bell-shaped, Gaussian and sigmoid), the number of membership functions, the number of epochs, types of output membership function (constant or linear) and optimization methods (hybrid or back propagation). The ANFIS performance was validated using some statistic parameters such as the coefficient of determination (R^2), the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) (Eq. 5-7):

$$R^2 = \frac{\left[\sum_{i=1}^{n} (x_i - \bar{x})(x_i - \bar{x})\right]^2}{\left[\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (x_i - \bar{x})^2\right]} \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \hat{x}_i)^2} \tag{6}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{x_i - \hat{x}_i}{x_i}\right| \tag{7}$$

where, x_i is the observed value, $\hat{x}$ is the predicted value, $\bar{x}$ is the mean of each observed or predicted values and n is the number of samples (Khoshnevisan *et al*., 2014a). Therefore, these parameters indicate the agreement between the actual and forecast values and are used as evaluation criteria for comparing this model with others.

RESULTS AND DISCUSSION

Energy consumption estimation: Energy input-output analysis was carried out in order that we could model the energy use pattern in milk production process. In Table 3, the energy equivalents of inputs and output, their contribution in total energy consumption and some of the energy indices are presented. Based on the findings, feed supply, fossil fuel and electricity energy

Table 3: Energy inputs and output equivalents for studied dairy cattle farms

Energy (MJ cow^{-1})	Values	Percentage
Inputs		
Human labor	406.94	0.77
Machinery	524.40	0.99
Fossil fuels	8655.82	16.30
Electricity	1699.21	3.20
Feed intake	41548.76	78.24
Total energy input	5310.98	-
Output		
Milk	57756.33	-
ER	1.16	-
EP (kg MJ^{-1})	0.16	-
NEG	5480.22	-

NEG: Net energy gain, EP: Energy productivity, ER: Energy ratio

inputs had highly contributed in total energy consumption as 41548.7 (78.24%), 8655.8 (16.3%) and 1699.2 (3.2%) MJ cow^{-1} in a production period (365 days), respectively. The shares for human labor and machinery energy in total energy input was less than 1% indicating their less importance in energy optimization programs. It should be noted here that electricity energy was observed to be highly applied for operating dairy farming equipment. Based on the results, energy is used efficiently to produce milk in the studied region while, this index is used to measure the system efficiency. Energy productivity index was calculated as 0.16. In other words, to produce 8089.12 kg cow^{-1} milk per year, 0.16 MJ cow^{-1} energy is consumed.

Development of ANNs model: The program written in MATLAB environment was modified from different viewpoints. Different number of hidden layers, number of neurons, activation functions and training algorithms were attempted to obtain the best network topology. Finally, the best ANNs architecture was 5-18-16-1 which composed of one input layer with five input variables, two hidden layers each consists of eighteen and sixteen neurons and one output layer with one parameter. The abovementioned structure gained the best statistical parameters, too. The coefficient of determination (R^2) between the observed and predicted milk yield was estimated 0.85. The RMSE and MAPE were calculated as 1052.413 and 0.0702, respectively. The relatively high correlation between measured and predicted yield for testing data set indicated that the developed ANNs model can accurately predict milk yield amount of studied farms on the basis of energy inputs (Fig. 3).

Khoshnevisan *et al*. (2014b) reported the best prediction of the ANNs network with 11-30-2-1 structure that consisted of an input layer with eleven parameters, two hidden layers each one consisted of 30 and 2 neurons, respectively and one output layer including one output variable (potato yield). In another study by Sharma *et al*. (2007), an Artificial Neural Network (ANNs) model is proposed to predict the first lactation 305-day milk yield. several training algorithms such as gradient descent algorithm with adaptive learning rate, Fletcher-Reeves conjugate gradient algorithm, Polak-Ribiére conjugate gradient algorithm, Powell-Beale conjugate gradient algorithm, Quasi-Newton algorithm with Broyden, Fletcher, Goldfarb and Shanno (BFGS) update and Levenberg-Marquardt algorithm with Bayesian regularization along with various network architectural parameters, i.e., data partitioning strategy, initial synaptic weights, number of hidden layers, number of neurons in each hidden layer, activation functions, regularization factor, etc., were experimentally investigated to arrive at the best model for modeling and predicting the milk yield. The results of this study emerged that the performance of ANNs model seems to be slightly superior to that of the conventional regression model.

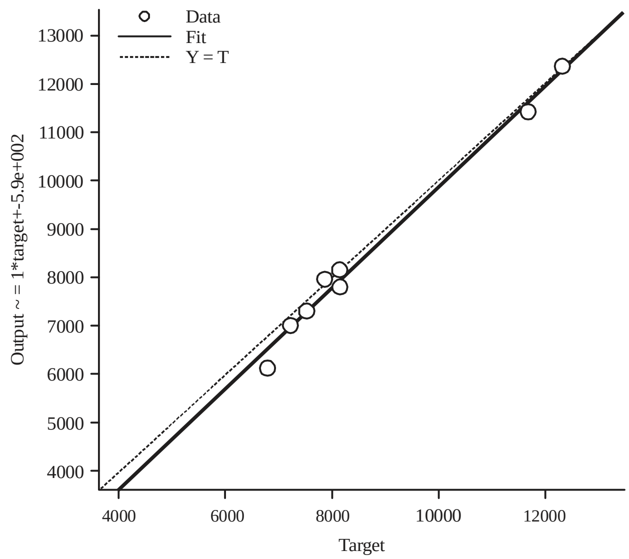

Fig. 3: Correlation plot between actual and predicted values of milk yield for the testing data

Assessment of ANFIS modeling: In situations that there is uncertainty about data for approximation problems, fuzzy logic is a proper tool to apply modeling and predicting techniques such as ANFIS in imprecision environment. As, it is mentioned in previous section and depicted in Fig. 2, inputs were divided into two clusters based on their energy share. This classification was undertaken to overcome constraints on the number of input parameters (five energy input elements) and simultaneously number of samples in each variable (fifty dairy cattle farms). Therefore, feed supply of cows, electricity and fossil fuel energies were considered as input parameters to ANFIS 1 network; while machinery and human labor energy inputs were considered as inputs to ANFIS 2. Accordingly, three ANFIS networks were developed to predict and model milk yield in dairy cattle farms. In ANFIS editor, there are different input membership functions including triangular, trapezoidal, generalized bell, Gaussian curve, Gaussian combination, q-shaped, difference between two sigmoid functions and product of two sigmoid functions. The best results were derived from triangular membership function. It is worth nothing that, in this study, three membership functions were applied to each input variable. The type of output membership function was considered to be linear. In Fig. 4, the structure of the ANFIS 2 network with two input parameters and also the number of fuzzy rules are illustrated.

The number of epochs was another modification to the written program. One to forty epochs were tested in training step and the results of their variation against the number of epochs for ANFIS 1 and ANFIS 2 are depicted in Fig. 5. As it can be observed, the amount of error is diminishing by increasing the number of epochs. The same trend was observed for ANFIS 3 network.

Some statistical parameters were calculated for the purpose of best model validation including R^2, RMSE and MAPE. The validation results are given in Table 4. As, it is presented in Table 4, the correlation coefficient (R^2) of ANFIS 1 and ANFIS 2 were 0.75 and 0.65, respectively; while it has improved to 0.93 for ANFIS 3 network. So, it can be concluded that the MLANFIS model was able to predict and model the milk yield successfully based on the energy use. The correlation results of each three ANFIS networks in contrast with ANNs model is presented in Fig. 6.

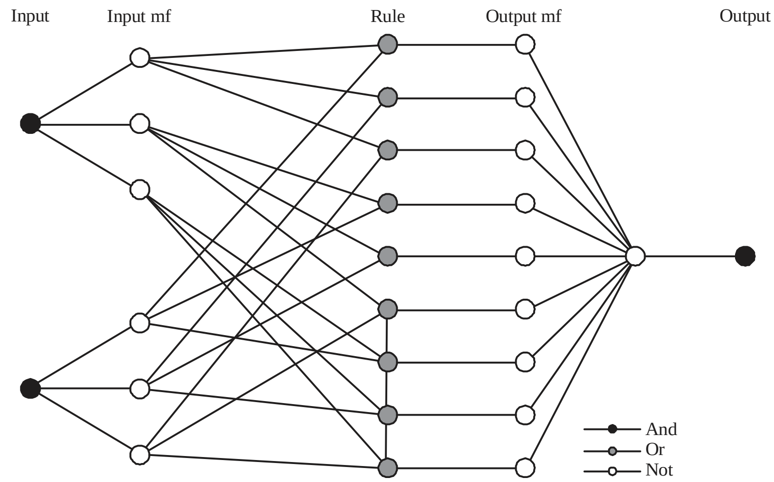

Fig. 4: General structure of the ANFIS 2 network

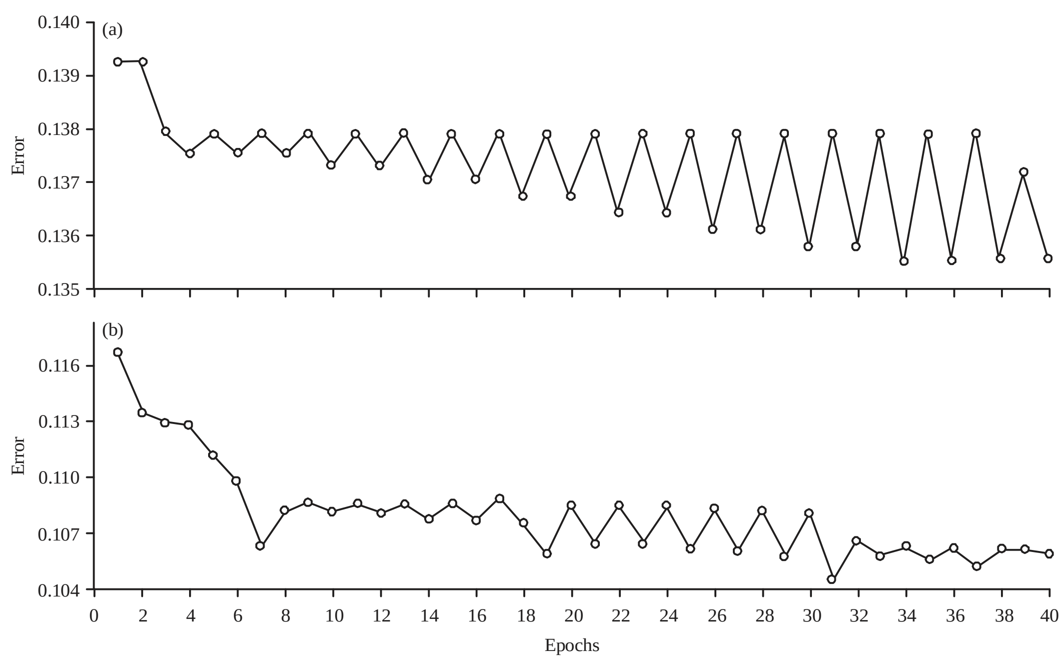

Fig. 5(a-b): Relation between training error and the number of epochs in (a) ANFIS 1 and (b) ANFIS 2

Table 4: Characteristics of the best structure

	Type of mf		No. of mf					
Parameters	Input	Output	Input	Epoch	Learning method	RMSE	MAPE	R^2
ANFIS 1	Trimf	Linear	3	40	Hybrid	1256.72	0.130	0.75
ANFIS 2	Trimf	Linear	3	40	Hybrid	1409.43	0.144	0.655
ANFIS 3	Trimf	Linear	3	40	Hybrid	681.85	0.063	0.931

mf: Membership function, RMSE: Root mean square error, MAPE: Mean absolute percentage error, R2: Correlation co-efficient and ANFIS: Adaptive neuro-fuzzy inference system, Trimf: Triangular membership function

Due to the lack of similar studies to our research criteria (use of MLANFIS in modeling milk yield based on energy use), the results of this study are compared with other agricultural fields but

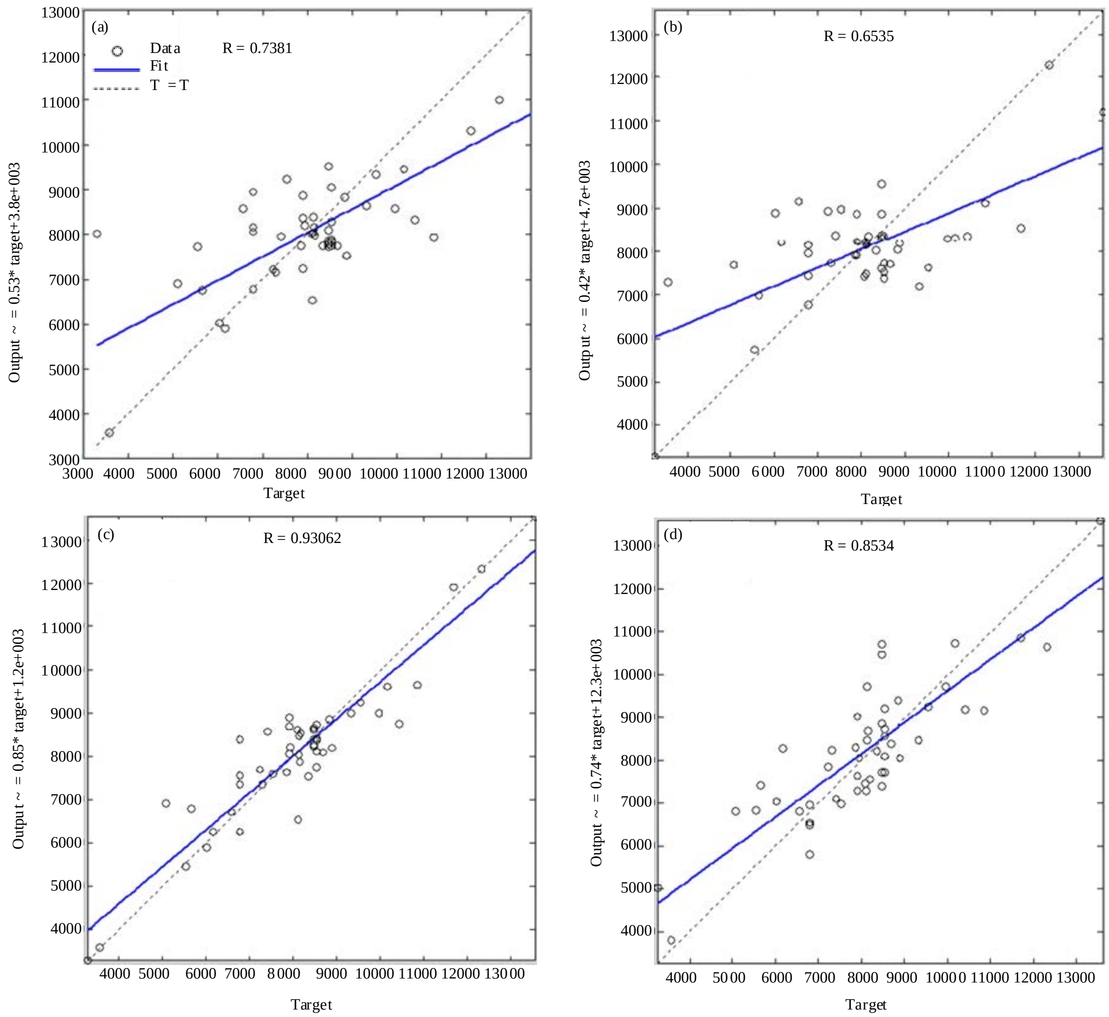

Fig. 6(a-d): Correlation between predicted and observed milk yield for (a) ANFIS 1, (b) ANFIS 2, (c) ANFIS 3 and (d) ANN models

in similar geographical zone. Naderloo *et al*. (2012) developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the grain yield of irrigated wheat in Abyek town of Ghazvin province, Iran. The R^2 and RMSE values were found 0.996 and 0.013 for ANFIS 1 and 0.992 and 0.018 for ANFIS 2, respectively. Hence, this emerged the fact that ANFIS 1 and ANFIS 2 could well predict the yield based on energy use pattern. Also, the R^2 and RMSE values for ANFIS 3 were 0.013 and 0.996, respectively. These results showed that the final network (ANFIS 3) could predict the grain yield with good accuracy. Khoshnevisan *et al*. (2014a) found ANFIS technique with multiple layers more precise than artificial neural network in predicting potato yield on the basis of energy inputs in Isfahan province of Iran. According to their results, the best ANNs model had a topology with 11-30-2-1 structure. In their study labor, machinery, diesel fuel, seeds, biocides, chemical fertilizers (N, P_2O_5), farmyard manure, irrigation water and electricity were energy variables and potato yield was considered as output parameter. Correlation coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for the best ANNs model were 0.925, 0.071 and 0.5, respectively while, the corresponding R, RMSE and MAPE values for the best ANFIS topology were reported as 0.987, 0.029 and 0.2, respectively. Finally, it was concluded that MLANFIS model gives better results than does ANNs model in imprecise and fuzzy conditions.

Finally, there would be one more query on why the proposed ANFIS model was developed by clustering input variables to two groups based on their energy share. As the first step, we examined various networks using logical relationships between inputs and the MATLAB written program was run. For instance, electricity and fossil fuel were considered as a cluster and the model was tested. Correspondingly, the gained results were not effective on the final ANFIS network performance. Therefore, based on energy use analysis, clustering was performed using the share for each input variable in total energy use of studied dairy cattle farms. In addition, Khoshnevisan *et al.* (2014b) expressed identical findings.

CONCLUSION

In this study, artificial intelligent techniques including Multi-Layered Adaptive Neural Fuzzy Inference System (MLANFIS) and Artificial Neural Network (ANNs) were employed to model and predict the milk yield of some dairy cattle farms based on energy consumption in Tehran province, Iran. Using the input use amounts and their related energy coefficients, energy equivalents of inputs were computed. Also, energy indices in the studied region were estimated. Total energy use was calculated as 5310.98 MJ cow^{-1} and among all inputs, cows' feed with 41548.76 MJ cow^{-1} (78.24%) of total energy use had the highest share; moreover fossil fuels and electricity energy with 8655.82 MJ cow^{-1} (16.3%) and 1699.21 MJ cow^{-1} (3.2%) shares were in the second and third rank, respectively. The average total milk yield of the target production process was about 8089.12 kg cow^{-1} during one production year. The ANNs model with two hidden layers based on energy inputs was applied to model milk yield. The best ANNs model was 5-18-16-1. Furthermore, ANFIS model was developed and in order to have an accurate ANFIS model performance and to overcome the constraints of this method (number of input variables and samples for each variable), inputs were divided into two clusters based on their energy share in total energy input and the output for each cluster (ANFIS 1 and 2) was assumed as the input to the final ANFIS network (ANFIS 3). The outcomes of these two methods were compared in this study. Firstly, R^2 value of ANFIS 1 (0.75), ANFIS 2 (0.65) and ANFIS 3 (0.93) networks indicated that input clustering had been effective in the ANFIS performance as data were not crisp and precise. Secondly, results revealed that MLANFIS model was relatively better in prediction capability of milk yield rather than ANNs model and it is suggested to be considered as an alternative technique in the same situations for other future studies. Indeed it is simple for programming though it seems extremely complicated. To extend this model for further studies, it is recommended to assess other production factors in dairy farms like socio-economic conditions, economical productivity and other management parameters to investigate their effects on milk yield. Moreover, researchers can develop this model with more layers and draw a comparison between its outcomes and the results of this study.

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