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Modeling Output Energy and Green House Gas Emissions of Dairy Farms using Neural Networks

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ABSTRACT: The aim of this study is to determine the amount of consumable energy and its index, the amount of greenhouse gas emissions resulting from energy consumption and choose the best model energy output and green house gas emissions using the model with neural network in dairy farms in Qazvin city of Iran. The results of this study showed; average energy input in dairy farms is 147659.442 MJ per head of cow. Instead this amount of energy input, 23642.25 MJ of energy been produced per head of cow that 91% of it has been related to the milk. An analysis of greenhouse gas emissions showed that for each lactation period, 5393.492kg of greenhouse gas emissions per head of a cow to be released in one year that methane from enteric fermentation has most roles in greenhouse gas emissions in dairy farms. In this study, multi-layer neural networks based on the back propagation algorithm and sigmoid learning function was used for training artificial neural network based on data collected from dairy farms. The artificial neural network model with (5-17-2) structure was the best model for predicting the amount of energy output (milk) and the amount of greenhouse gas emissions. In the best topology, the (R) was calculated as 0.999 and 0.968 for train and test, respectively.

Keywords: Energy, Emission, Artificial neural network, Dairy Farm

I. INTRODUCTION

As an agricultural product, milk is extracted from mammals during or soon after pregnancy and is used as food for humans. Worldwide, dairy farms produced about 730 million tons of milk in 2011 (FAO, 2012). Throughout the world, there are more than six billion consumers of milk and milk products) Hemme and Otte, 2010). Milk is one of the major sources of calcium and protein for human requirements from past until now. According to this fact and increasing urbanization, the global demand has increased for milk and this trend will have a greater growth in the coming decades. Considering to the high demand and lack of accountability traditional system of milk production to this demand, for increase the amount of performance is requiring the use of industrial equipment instead of using traditional methods and human force. More utilization of fossil fuels and electricity is for represents a direct dependence on the manufactured product into energy on factory farms. Therefore, the efficient utilization of energy makes achieving increased productivity and it will help to the economy and stable competition of rural communities (Canakci *et al.*, 2005). Thus, the calculation of energy efficiency is one of the key indicators the development of sustainable agriculture and livestock farm. The efficient use of energy can be achieved by identifying production methods that increases energy efficiency and reduce greenhouse gas emissions (GHG) (Tzilivakis *et al.*, 2005). To identify the production of best method is the first step in determining and analyzes the consumable energy that it besides give stability to the produced system can as well be considered as a tool for the assessment of environmental pollution. Abundant research conducted for the calculated energy of inputs and outputs and optimization of energy consumption is reflects the importance of this subject in the agricultural sectors and its subset, according to the sustainable agriculture strategy and reduces the economic and environmental problems (Streimikiene *et al*., 2007). On the other hand, create a model between input energy and energy output will give useful information from the impact of each of the inputs into performance the products (Mousavi-Avval *et al*., 2011).

Modeling cycle of energy and GHG can reform the consumption pattern and increase the production of clean products. So far, various methods for modeling of energy were used. For example, the use of regression analysis has been very important for researchers in concerned with modeling of energy. But today, the use of artificial intelligence for modeling a variety of fields, including energy and the environment is growing. Modeling with artificial neural network is one of the useful methods that for solving a variety of complex problems, Non-understandable or require very high resources in comparison with the old computational methods has been shown quite useful (Ceylan, 2002).

The main reason to consider this method is utilization of the previous information to for modeling of difficult nonlinear systems (Safa and Samarasinghe, 2011). Because easier use and the flexibility to use this method than older methods and the lack of accurate data on agriculture and livestock farms, using from this type of method for modeling the fields listed is growing.

In order to determine the energy indicators and energy modeling is needed to energy analysis in the produced system. The number of study sample in relation to energy analysis in the livestock farms mentioned.

Research has shown in dairy farms in Austria, electricity and fuel were devoted to their most energy consumption in section direct energy at all phases of production from production of feed until production of milk in herd different sizes (Moitz *et al*., 2010). About determination of the consumable energy in the cattle farms in one of the provinces of Canada, the consumable electric energy was reported much higher than other inputs of energy inputs (Basarir and Gillespie, 2003). The evaluation of dairy farms in the Flemish Belgium province at various intervals has shown that straight energy consumption (gas, oil and electricity) versus indirect energy (machinery, equipment, labor and feed inputs for production) highly has been significant. The fuel of consumption has the greater share of the energy input (Meul *et al*., 2007). The total energy input to the dairy farm system has been calculated per head of cow 53102 MJ in Tehran province of Iran. Feed with mean energy 41549 (MJ. Cow^{-1}) has the greatest amount of energy input (Sefeedpari *et al*., 2012). The studies have been done on modeling for livestock farms, too. Using from artificial neural networks (ANN) to predict of milk yield in dairy farms in Canada has shown that with the use of ANN can be estimated for milk yield in exchange for specific consumption energy with a high percentage easily and reliability (Grzesiak *et al*., 2006).

In addition, this technique has been used for energy analysis and modeling at different agricultural products.Rahman and Bala (2010) employed ANN to estimate jute production in Bangladesh. In their study an ANN model with six input variables including Julian day, solar radiation, maximum temperature, minimum temperature, rainfall, and type of biomass was applied to predict the desired variable (plant dry matter). Pahlavan *et al*. (2012) developed a network to predict greenhouse basil production. Khoshnevisan *et al*. (2013) predicted yield and GHG emissions of wheat production using ANN.ANN model with eleven input and two output variables was applied to predict the desired variables (yield and GHG emissions). Nabavi-Pelesaraei *et al*. (2014a) studied the energy consumption and CO_2 emission of watermelon production in three different farm sizes in the Guilan province of Iran. Despite the importance of energy, in this study has been investigated analysis and modeling of energy production and consumption and also determined and modeling of GHG against energy consumption in industrial and semi-industrial dairy farms discussed in the Qazvin city of Iran.

MATERIALS AND METHODS

A. Collecting data and assumptions

Qazvin city is located between 48° 85´ to 50° 51´east longitude Greenwich meridian and 36° 7´ and 36° 48´ minutes north latitude and the equator. According to the official announcement in 2014, the capacity of dairy farms in Qazvin city has been estimated 8844 head of cow (Anonymous, 2014). The data used in this study were obtained with using direct interviews and with ranchersby using random sampling. Sample size to obtain information using the random sampling method has been calculated and determined (Cochran, 1997).

$$n=\frac{\frac{z^2pq}{d^2}}{1+\frac{1}{N}\left[\frac{z^2pq}{d^2}-1\right]} \qquad \ldots(1)$$

Where 'N' is the size of population, 'n' is sample size, 'p' amount the ratio of the trait in the population, if not available, can be considered 0.5. In this case amount, variance reaches its maximum, 'q' is the percentage of those who are lacking in character (q = 1-p), 'd' is the amount allowable error and 'Z' amount of the standard normal variable, at the 95 percent confidence level is 1.96. The sample size was calculated at 95% and 5% error has been made.

According to the official announcement (Anonymous, 2014) the total number of dairy farms were 111 units in area that by using the Cochrane formula, 50 units were selected for review as the sample. (Three of the units did not have complete data and were excluded from the analysis). The general characteristics of dairy farms and cow in the study area has been shown in Table 1.

Table 1: The general characteristics of dairy farms.

Specifications Units	Amount
Average No. of cows per farms (head)	153.53
During the lactation period (days)	305
During the drying period (days)	60
Average milk yield (kg . day^{-1} cow^{-1})	21.92
Average feed intake (kg . day^{-1} cow^{-1}) (DMa)	34.584

B. Energy analysis

To convert the input used in dairy farms to equivalent energy have been used from the coefficient of energy that value of these coefficients has been shown in Table 2. In dairy farm, fossil fuels, machinery, equipment, electricity, feed intake and labor were inputs and manure, milk and meat were considered as output. Energy of equivalent was obtained from the multiplication the amount consumption of inputs and production of output in the equivalent energy content. For the estimate energy equivalent of machinery and equipment was used from the Equation 2:

$$ME = \frac{G \times M_P \times t}{T} \quad \ldots(2)$$

Where the 'ME' is same energy machinery and equipment, 'MP' is equivalent to the energy production process, 't' is time machine in any of the 'T' is at the useful life of the machine. After determining the amount of consumable energy and produced energy, Analysis was performed in relation to the energy cycle of dairy farms that for the analysis of the energy indicator was used (Nabavi-Pelesaraei *et al*., 2013) as follows:

$$E.R = \frac{E_{out}}{E_{in}} \quad \ldots(3)$$

$$NEG = E_{out} - E_{in} \quad \ldots(4)$$

$$EP = \frac{Y}{E_{in}} \quad \ldots(5)$$

$$SE = \frac{E_{in}}{Y} \quad \ldots(6)$$

Where, 'E.R' is energy; 'NEG' is net surplus energy (MJ per head of cow), 'EP' is energy efficiency (kg. MJ-1), 'SE' is specific energy (MJ. Kg^{-1}), 'E in' is energy input of the system (MJ per head of cow), 'E out' is energy output of the system (MJ per head of cow) and 'Y' is the yield (kilograms of product per head of cow).

Table 2: The energy content of the inputs and outputs of dairy farm.

Item	Energy content (MJ / Unit)	References
A. Inputs		
Tractor (kg a *)	9-10	(Kitani, 1999)
Equipment and machinery (kg a)	6-8	(Kitani, 1999)
Fossil fuels		
Diesel (l)	47.8	(Kitani, 1999)
Gasoline (l)	46.3	(Kitani, 1999)
Oil (l)	36.7	(Kitani, 1999)
Natural gas (m^3)	49.5	(Kitani, 1999)
Electricity (KWh)	11.93	(Ozkan *et al.*, 2004)
Labor (h)	1.96	(Kitani, 1999)
****Feed**		
(a) Concentrate(kg)	13.6	(Frorip *et al.*, 2012)
(b) Silage (kg)	10.41	(NRC, 2001)
(c) Alfalfa (kg)	10.92	(NRC, 2001)
B. Outputs		
****Milk (kg)**	2.7	(NCR, 2001)
****Meat(kg)**	9.22	(Frorip *et al.*, 2012)
Cow manure (kg dry matter)	0.3	(Singh and Mittal,1997)
*: Economic life of machine, **: Metabolizable energy		

C. Green house gas emissions

The attention to GHG and the need to reduce its production the reason is that mean global temperature has risen during the last 100 years and concern is about increasing its severity. Since the energy consumption in industrial manufacturing systems is more than natural systems, lack management of energy consumption will have irreversible effects for the environment. For estimating the amount of GHG dairy farms; the amount of inputs consumed that they are effective in the production GHG (fuel, electricity, machinery) was multiplied in the corresponding diffusion coefficients that have been shown in Table 3.

Table 3: GHG factor inputs in dairy farms.

Item	unit	GHG factor	References
Machinery	MJ	0.071	Nabavi-Pelesaraei *et al.*, 2014a
Diesel	l	2.76	(Sabzevari *et al.*, 2015)
Gasoline	kg	0.85	(Lal, 2004), (Khoshnevisan *et al.*, 2013)
Natural gas	m^3	0.6	(Lal, 2004), (Khoshnevisan *et al.*, 2013)
Electricity	KW h	0.608	(Nabavi-Pelesaraei *et al.*, 2014b)

Also part of GHG produced in dairy farms units are for their livestock that includes greenhouse gases released from microbial fermentation of feed in the rumen cow and as well the amount greenhouse gases released from manure produced by cow. According to the IPCC commented (2007) cattle farms are one of the most important producers of methane gas. Measurement of methane from enteric fermentation cattle has been done in several cases that were time consuming and very costly. For this reason, tendency is towards estimation of methane from enteric fermentation the by using parameters that are related to livestock weight and feed (Mc Court *et al*, 2006). Accordingly, estimates and equations have been done in this context that results obtained from some sample is mentioned in following. In researchin China, amount output methane from enteric fermentation beef and dairy cow in several age ranges was calculated using the IPCC guidelines that for dairy cow was calculated 100with first instructions and using second instruction was estimated at 102.2 kg for each year (Xue *et al*., 2014). In Australia for dairy cow was estimated 80-175 kg inthe year (Gollnow *et al*., 2014). In Table 4 has been shown examples of equations derived for estimating methane output of dairy cattle.

Table 4. Estimates equations of the methane output of cow

Equation predicting output methane	References
26.49 DMI +1.64 0.26 LW + 52.76	(Mc Court *et al.*, 2006)
6.14 $e^{0.0049Lw}$ 22.1 DMI + 9.6	(Jiao *et al.*, 2014)

LW: Live weight of cow
DMI: weight of intake

The most important greenhouse gas released from manure is nitrous oxide. Livestock waste are included a lot of nitrogen that after the chemical conversion were released form of nitrogen oxides. In this study, the amount of nitrogen was calculated using Equation 7 (Hollmann *et al*., 2003).

$$N_E = DMI \times dietaryCP \times 84.1 + BW \times 0.196 \quad \ldots(7)$$

'DMI' is weight of intake (kg), 'dietary CP' is a dietary protein. 'BW' is weight of the cow (kg). Nitrogen oxide levels are made from accumulation of manure nitrogen is 2% amount of nitrogen excretion (IPCC, 2003).Moreover, manure from sources of methane in dairy farms units. If to the manure is allowed to remain on the ground, it dried quickly and methane emissions to be minimized. However, if manure accumulated and stored, methane emissions will increase (Wuebbles *et al*., 2002). Due to compression and accumulation of manure in industrial dairy farms units, methane emission is greater compared to traditional units.

Methane emission from manure is 0.03 amount of methane emission from enteric fermentation per head of cattle (Herrero *et al*., 2008).

D. Artificial neural networks

Artificial neural networks are computational models that have been simulation from real biological networks and composed of nerve cells. (Topuz, 2010). Each network trained with examples and the neural network be trained can predict the proportional output with the new set of data (Dayhoff, 1990). Multi-layer neural networks based on the back propagation algorithm is the most common artificial neural networks that are composed from several layers of simple processing elements that called neurons (Cakmak *et al*., 2011). The overall structure of artificial neural network is composed of a layer of input neurons and a layer of output neurons and one or more hidden layers (Khoshnevisan *et al*., 2013). Input and output layers are connected by a hidden layer. The structure of the multi-layer perceptron has been shown in Fig. 1.

One of the problems that may occur when the neural network training is over training. This means that during training the error reaches to acceptable level but when evaluating, the network error is more than the training data error (Hernandez-Perez *et al*., 2004). There are two ways for avoid of over-training: stop training quickly and select the minimum number of neurons in the hidden layer as possible (Erenturk *et al*, 2007). In this research for solve this problem was used of second method.

For learning network, data were divided into three parts randomly, 70% of the data for training, 15% for testing and 15% for validation were divided. The learning function was sigmoid and learning algorithm was selected multi-layer neural networks based on the back propagation too.

For making neural networks of required was used from the MATLAB version 7.1 (R2013a). The number of neurons from 1 to 20 and the number of hidden layers from 1 to 2 layer changed and the best model was extracted, finally. The amount of energy equivalent to fossil fuels, labor, electricity, machinery and equipment and feed were as input parameters and the energy equivalent of milkand greenhouse gases were considered as output parameters.

To determine the best model derived from between models made with artificial neural networks were used from various statistical indicators, such as RMSE, MAPE and R2. The following is provided equations related to the statistical indicators (Nabavi-Pelesaraei *et al*., 2014b).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)}{n}} \quad \ldots(8)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}(\frac{|O_i - P_i|}{O_i}.100) \quad \ldots(9)$$

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - O_{ave})(P_i - P_{ave})}{\sqrt{\sum_{i=1}^{n}(O_i - O_{ave})\sum_{i=1}^{n}(P_i - P_{ave})}} \quad \ldots(10)$$

Where 'Oi' is measured data, 'Pi' is predictive data; 'Oave'is mean data measured, 'Pave' is average data-anticipated and 'n' is the number of data.

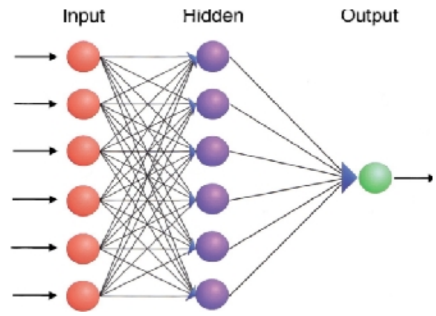

Fig. 1. The structure of a perceptron with one hidden layer.

RESULTS AND DISCUSSION

A. Energy analysis

In order to analyze the energy input and energy output and modeling energy cycle of dairy farms, were examined data obtained from the questionnaires and the amount of energy input and output energy were calculated for each head cow.

Table 5. The amount of energy input and energy output in dairy farms with different levels.

Items	Farm size groups			Average (MJ. cow^{-1})	(%)
	Small (<50)	Medium (50-150)	Large (>150)		
A. Inputs					
Tractor and implement and machinery	730.2175	546.4153	708.5812	606.9124	1
Fossil fuels	12929.61	9611.49	7844.835	9405.2336	6
Electricity (kWh)	3385.131	1959.699	1871.159	2056.52248	1
Human labor (h)	653.5122	528.4058	428.6398	511.4583	0
Feed	129854.3	133297.8	140798.2	135079.3155	92
B. Outputs					
Milk (Kg)	16899.17	21426.28	23449.48	21600.60494	91
Meat (Kg)	1354.375	1320.553	1337.383	1328.08631	6
Cow manure (kg dry matter)	606.7039	667.9459	851.6922	713.5572	3

The results was obtained in three levels. First level was related to small units with less than 50 heads, the second level related to medium units with 50 to 150 heads and the third level related to large units with more than 150 head. The results of each group has been shown in Table 5. The amount of energy input to dairy farm was calculated 147659.4424 MJ per head of cow. Feed with an average energy 135079.3155 MJ per head of cow and 92% of total consumable energy the highest energy consumption was accounted to the self. Fuel was placed the second order with an average energy 9405.2336 MJ per head of cow.

The percent of the energy input during the period has been shown in Fig. 2. The amount of output energy was calculated 23642.24849 MJ per head of cow that 91% of the energy of production was related to milk , 6% was related to meat and 3% was related to manure of production by cow.

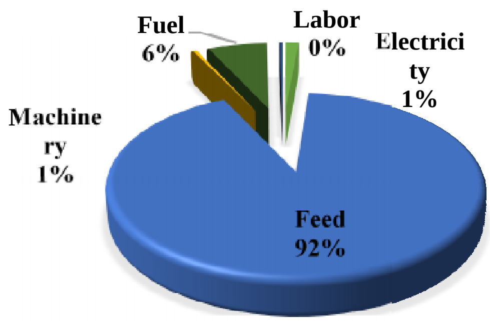

Fig. 2. The percentage of each of the energy input in dairy farms.

Analysis of energy has been shown energy efficiency 0.16 in the dairy farms. This amount is represented the less energy efficiency in these units. Of course nature of some products as livestock product is negative net energy in production especially. It appeared that the animals can convert only 14-16% of the feed input energy to usable product (milk and meat energy) (Frorip *et al*., 2012). However, it should try to improve its amount. The results showed, for production per kilogram of milk is required to consumption 18.45 MJ of energy. As well as large units (more than 150 heads) were more efficient in energy consumption while they have more energy consumption. Other indicators of energy has been shown in Table 6.

Table 6. Energy indicators in dairy farms at different levels.

Items		Farm size groups			Average (MJ.cow^{-1})	(%)
		Small (<50)	Medium (50-150)	Large (>150)		
Energy efficiency	–	0.12782	0.159515	0.1690	0.16	-
Energy productivity (milk)	Kg. MJ $^{-1}$	0.0424	0.0540	0.0572	0.0541	-
Specific energy(milk)	MJ. Kg $^{-1}$	23.57	18.49	17.46	18.45	-
Net energy gain	MJ. cow^{-1}	-128692	-123372	-123372	-124017.19	-
Direct energy	MJ. cow^{-1}	16968.25	12099.59	10144.63	11973.21	8.11
Indirect energy	MJ. cow^{-1}	130584.5	134687.4	141506.8	135686.23	91.89
Renewable energy	MJ. cow^{-1}	130507.8	133826.2	141226.9	135590.77	91.82
Non-renewable energy	MJ. cow^{-1}	17044.95	12960.81	10424.57	12068.66	8.18
Total energy input	MJ. cow^{-1}	147552.7	146787	151651.4	147659.44	100

B. Greenhouse gas emissions

Determination of GHG from the dairy farm has been done in two parts. In the first part was determined the amount of GHG resulting from energy consumption (fuel, electricity and machinery and equipment) and in the second part of GHG from biological activity dairy cow was studied.

(Emission of greenhouse gases resulting from pesticides used per head of cow was negligible).

The amount of greenhouse gases released in first section was calculated per head of cow to the lactation period of one year 561.2012 kg CO_2eq.

In the present study for the estimate the amount of methane from enteric fermentation, average number derived from different equations presented in Table 4 as output methane was considered. Given that the greenhouse effect of methane and nitrogen oxides are 25 and 300 times the greenhouse effect of carbon dioxide (IPCC, 2007).

Finally, the results of the analysis of GHG showed in one year 5393.492 kilograms of carbon dioxide against consumable energy per head of cow were released.

Table 7. Amount of GHG from dairy farm at different levels

Items		Farm size groups			Average	(%)
		Small (<50)	Medium (50-150)	Large (>150)		
Fossil Fuels	Kg CO_2eq	720.8693	424.3077	287.9709	414.7376	7
Electricity	Kg CO_2eq	170.1564	98.05994	94.83644	103.3728	2
Machinery	Kg CO_2eq	51.84544	39.4083	49.68565	43.09078	1
Manure	Kg CO_2eq	451.0557	465.6586	485.6018	469.5077	9
Enteric fermentation	Kg CO_2eq	4206.85	4330.255	4498.791	4362.783	81
Total	Kg CO_2eq	5600.777	5357.69	5416.886	5393.492	100

The amount of GHG from per head of cow in three levels have been shown in the Table 7 and Fig. 3. The results have shown in medium levels, less greenhouse gas been produced.

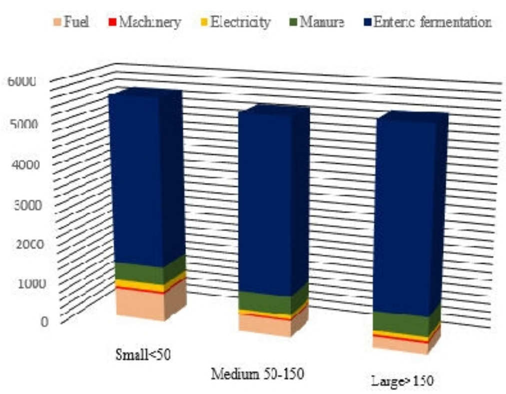

Fig. 3. Amount of GHG from dairy farm at different levels.

C. Evaluation of artificial neural network

For find the best model with the maximum R2 and minimum error, various networks with different changes were made and have been examined. These changes include the change in the number of hidden layers change in the number of neurons and changes in learning parameters and network architecture. The selected artificial neural network has been structured with an input layer with 5 neurons, a hidden layer with 17 neurons and an output layer with two neurons (5-17-2), eventually. The plots the output from the software have been shown in Fig. 4.

Charts show that R obtained for modeling with the chosen network for all data and data that have been used for network training is 0.99 that indicates the high ensure of the network was established. The results indicated, structure with one hidden layer and fewer neurons shows better results. Statistical indicators were computed for modeling with artificial neural networks for the amount of energy output and amount of GHG has been shown in Table 8 that show modeling with neural network selected for predict the amount of energy output (milk) and amount of greenhouse gas emissions is acceptable amount according to the amount of R2.

The results this study and other research that have been done related to the modeling of artificial neural networks in the process production of crops and livestock have shown that the modeling by artificial neural networks for these products is ideal. Because it is lack of a clear relationship between the inputs and outputs in agriculture and livestock. For example, for predict the yield performance of hemp, the structure with input layer (six neurons), two hidden layers (9 and 5 neurons) and an output layer (a neuron) (Rahman and Bala, 2010) and structure 1.20-20-7 to anticipated yield of basil (Pahlavan *et al.*, 2012) were used that had good results. In another study, the best model for prediction of environmental indices of watermelon production in the Guilan province of Iran was reported being an ANN model with (11-10-2) structure (Nabavi-Pelesaraei *et al.*, 2014a).

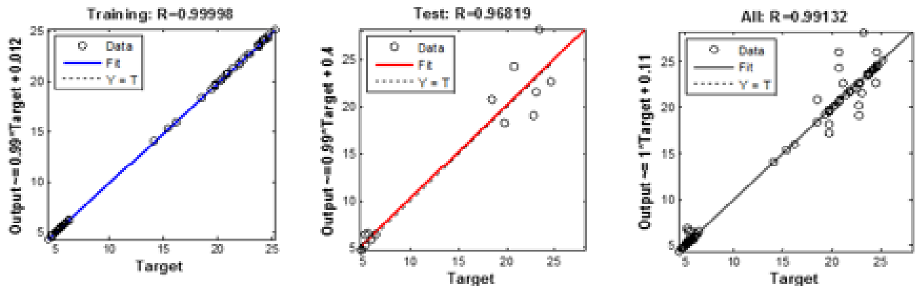

Fig. 4. The most appropriate topology for communication between actual data and predicted data with the selected artificial neural networks.

Table 8. Statistical indices calculated for modeling with artificial neural networks.

Item	RMSE	R^2	MAPE (%)
Output Energy	1.5184	0.7191	3.56
Output GHG	0.3634	0.7909	1.6972

In Fig 5 and 6 have been shown the relationship between the amount of energy output (milk) and the GHG predicted using artificial neural network model against actual amount.

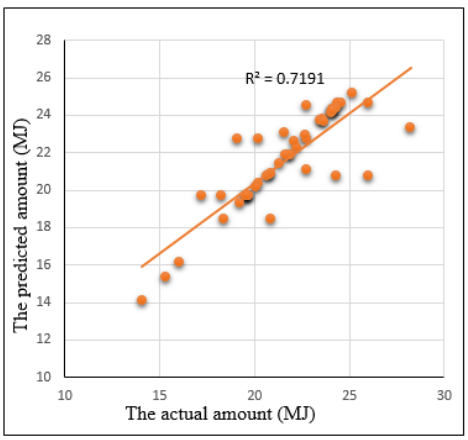

Fig. 5. The relationship between predicted using neural networks and actual of energy output (milk).

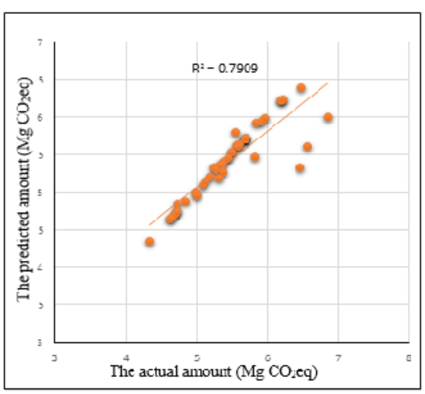

Fig. 6. The relationship between predicted using neural networks and actual of GHG.

CONCLUSION

The mean energy input was calculated in dairy farms 147659.4424 MJ per head of cow that the feed intake with 92% of the maximum amount of energy consumption to be allocated that dairy farms with more than 150 head of cow have assigned to themselves the most amount of the energy consumption. The mean energy output from units was calculated 23642.25MJ per head of cow that 91 % related to milk. The results showed energy efficiency 0.16 and the special energy for produce one kilogram of milk obtained 18.45 MJ in dairy farms. Share of renewable energy has been 91.82 % and share of non- renewable energy has been 8.18 %. Analysis of greenhouse gas emissions showed that 5393.4919 kilograms of greenhouse gas were released into the atmosphere during the period one year that it is equal to 0.7 kg per kilogram of milk. The ANN model with (5-17-2) structure was the best model energy output and the GHG in dairy farms. In the best model, R2 was 0.7191 and 0.7909, RMSE was 1.5184 and 0.3634, MAPE was 3.56 and 1.69 for energy output and GHG, respectively.

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