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ORIGINAL ARTICLE

Iranian Metal Industries Energy Demand Model: A comparison Between Multi-Layer Perceptron Neural Networks (MLPNN) and Adaptive Network Based Fuzzy Inference System (ANFIS)

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ABSTRACT
According to the increasing demand of energy as a vital input for industrial sector, the assessment of energy demand is necessary for industrial activities in the country. This assessment could be done based on econometric approaches using different models of mathematical demonstration. Because of non-linear behavior of socio-economic indicators, the energy demand could be assessed by the non-linear forms more effectively. In this study Multi-Layer Perceptron Neural Networks (MLPNN) and Adaptive Network Based Fuzzy Inference System (ANFIS) are used to model Iranian Metal Industries Energy Demand (IMIED) based on socio-economic indicators. Number of employees persons, total investments, value added, gas price, and electricity price are used as socio-economic indicators in this study.
Keywords: *Iranian Metal Industry, Multi-Layer Perceptron Neural Networks (MLPNN), Adaptive Network Based Fuzzy Inference System (ANFIS).*

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INTRODUCTION

Developing energy-forecasting models is one of the most important steps in long-term planning for sustainable energy supply toward economic development and social welfare. Nowadays, in addition to the traditional economic aspects of energy, social, political, security and environmental aspects have increased the importance of energy forecasting of studies more than before [1].

Industry is one of the major energy-consuming sectors using energy as a production factor for developing the economy. Forecasting energy consumption in industries requires advanced intelligent tools such as ANNs, ANFIS, etc. In industry, energy is used both in the building components for cooling, heating and lighting, which varies according to the workforce increase, building extension and weather condition, and in the operational process for mechanical and electronic processing [2].

One of the overriding characteristics in the industrial sectors is the heterogeneity of industries, products, equipment, technologies, processes and energy uses. Adding to this heterogeneity is that the industrial sectors include not only manufacturing but also agriculture, mining and construction. These varieties of industries range spread widely from highly energy intensive activities to low energy intensive activities [2].

Several studies are presented to propose some models for energy demand policy management using different techniques. Unler developed PSO (Particle Swarm Optimization) energy demand models to estimate energy demand based on economic indicators in Turkey [3]. Canyurt and Ozturk presented Turkey's fossil fuels demand estimation models by using the structure of the Turkish industry and economic conditions based on GA (Genetic Algorithm) [4]. Toksari developed Ant Colony energy demand estimation models for Turkey [5]. Azadeh et al. presented an ANN for forecasting monthly electrical energy consumption [6]. In a different work, Azadeh et al. compared GA, ANNs and fuzzy regression algorithm to estimate seasonal and monthly changes in electricity consumption in developing countries [7]. Amjadi et al. used PSO and GA to forecast electricity demand of Iran [8]. Zhang et al. applied partial least square regression method to estimate transport energy demand in China [9]. The main objective of

the present study is to forecast energy consumption in Iranian Metal Industries using MLPNN and ANFIS.

METHODS DESCRIPTION

Multi-Layer Perceptron Neural Networks (MLPNN)

MLPs are perhaps the most common type of feed forward networks. Fig.1 shows an MLP which has three layers: an input layer, an output layer and a hidden layer.

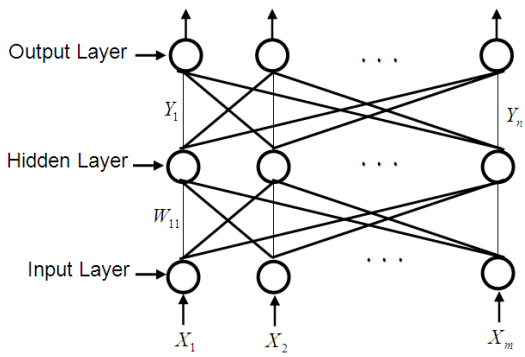

Figure 1. A multi-layer perceptron.

Neurons in input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neurons j (Fig. 2) in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum, viz.

$$y_j = f\left(\sum w_{ji} x_i\right) \tag{1}$$

f can be a simple threshold function or a sigmoidal , hyperbolic tangent or redial basis function [6-9].

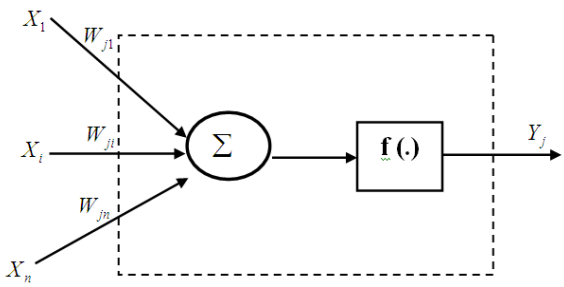

Figure 2.Details of a neuron.

The output of neurons in the output layer is computed similarly the backpropagation algorithm, a gradient the descent algorithm, is the most commonly adopted MLP training algorithm. It gives the change Δw_{ji} the weight of a connection between neurons i and j as follows:

$$\Delta w_{ji} = \eta \delta_j x_i \tag{2}$$

Where η is a parameter called the learning rate and δ_j is a factor depending on whether neuron j is an input neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\left(y_j^{(t)} - y_j\right) \tag{3}$$

And for hidden neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\sum_q w_{qj}\delta_q \tag{4}$$

In Eq.3, net_j is the total weighted sum of input signals to neurons j and $y_j^{(t)}$ is the target output for neuron j.

As there are no target outputs for hidden neurons, in Eq.4, the difference between the target and actual output of a hidden neurons j is replaced by the weighted sum of the δ_q terms already obtained for neurons q connected to the output of j.

Thus, iteratively, beginning with the output layer, the δ term is computed for neurons in all layers and weight updates determined for all connections. The weight updating process can take place after the presentation of each training pattern (pattern-based training) or after the presentation of the whole set of training patterns (batch training). In either case, a training epoch is said to have been completed when all training patterns have been presented once to the MLP.

For all but the most trivial problems, several epochs are required for the MLP to be properly trained.

A commonly adopted method to speed up the training is to add a (momentum) term to Eq.2 which effectively lets the previous weight change influence the new weight change, viz:

$$\Delta w_{ji}(l+1) = \eta \delta_j x_i + \mu \Delta w_{ji}(l) \qquad (5)$$

Where $\Delta w_{ji}(l+1)$ and $\Delta w_{ji}(l)$ are weight changes in epochs $(l+1)$ and (l) respectively and μ is the momentum coefficient [10-16].

Adaptive Network Based Fuzzy Inference System (ANFIS)

The Adaptive Network Based Fuzzy Inference System (ANFIS) integrates the best features of fuzzy systems and neural networks. As a structure; ANFIS is consist of if–else rules and input–output data couples of fuzzy and it uses neural network's learning algorithms for training. ANFIS is a methodology to simulate complex nonlinear mappings utilizing neural network learning and fuzzy inference methodologies. The ANFIS structure is composed of both ANN and fuzzy-logic model and has the ability of working with uncertain noisy and imprecise environments. The ANFIS uses the neural network training process to adjust the membership function and the associated parameter that approaches the desired data sets. It gives more accurate results than mean square error criterion because it has ability to benefit from the expert decisions. The learning algorithm of ANFIS is a hybrid learning algorithm composed of the use of back-propagation learning algorithm and least squares method together. The ANFIS architecture is shown below. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt.

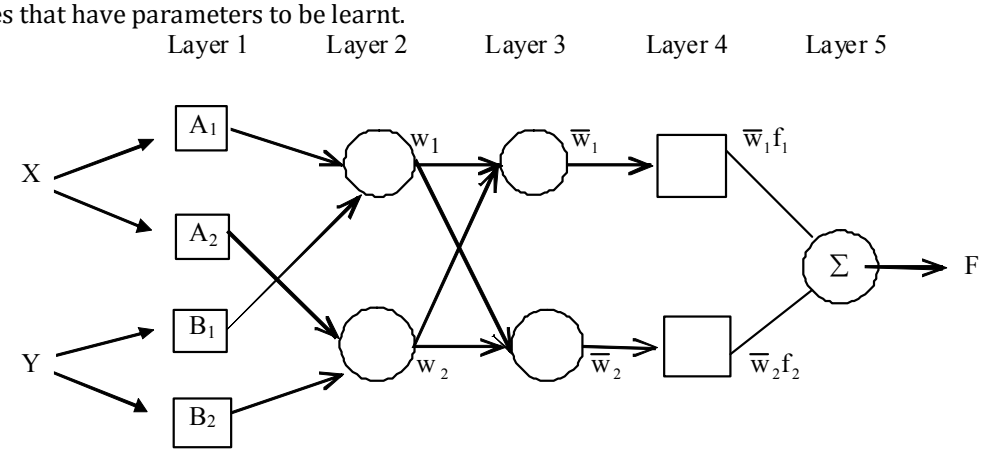

Figure 3. An ANFIS architecture for a two rule Sugeno system

A Two Rule Sugeno ANFIS has rules of the form:

$$If\ x\ is\ A_1\ and\ y\ is\ B_1 \quad THEN\ f_1 = p_1 x + q_1 y + r_1$$

$$If\ x\ is\ A_2\ and\ y\ is\ B_2 \quad THEN\ f_2 = p_2 x + q_2 y + r_2$$

For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to backpropagation.

Layer 1

The output of each node is:

$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2$ and $O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4$

So, the $O_{1,i}(x)$ is essentially the membership grade for x and y.

The membership functions could be anything but for illustration purposes we will use the bell shaped function given by: $\mu_A(x) = \dfrac{1}{1 + \left|\dfrac{x - c_i}{a_i}\right|^{2b_i}}$

where a_i, b_i, c_i are parameters to be learnt. These are the premise parameters.

Layer 2

Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades - for example the product: $O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2$

Layer 3

Layer 3 contains fixed nodes which calculates the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}$$

Layer 4

The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5

There is a single node here that computes the overall output: $O_{5,i} = \sum_i \overline{w_i} f_i = \dfrac{\sum_i w_i f_i}{\sum_i w_i}$

This then is how, typically, the input vector is fed through the network layer by layer. For more details about ANFIS the readers are referred to [17- 20].

PROBLEM DEFINITION AND RESULTS

This study presents application of MLPNN and ANFIS to estimate electricity demand in Iranian Metal Industries. The socio- economic indicators used in this study are number of employees persons, total investments, value added, and gas price. The data related to the design parameters are shown in Figures 4 to 9. The available data is partly used for training (1987-1999), and partly for testing the models (2000–2006).

The following combinations of data are considered for this study:

1. Number of employees persons, total investments, and value added as inputs and electricity consumption as output.
2. Number of employees persons, total investments, value added, and gas price as inputs and electricity consumption as output.
3. Number of employees persons, total investments, value added, gas price and electricity as inputs and electricity consumption as output.

All input and output variables should be normalized in the (0, 1) range.

In order to create both MLPNN and ANFIS models, the Fuzzy logic and Neural Network Toolboxes of MATLAB 2010 (Math Works, Natick, MA) were used. Tables 1 to 3 shows the performance of best trained networks on testing period (i.e. 2000-2006).

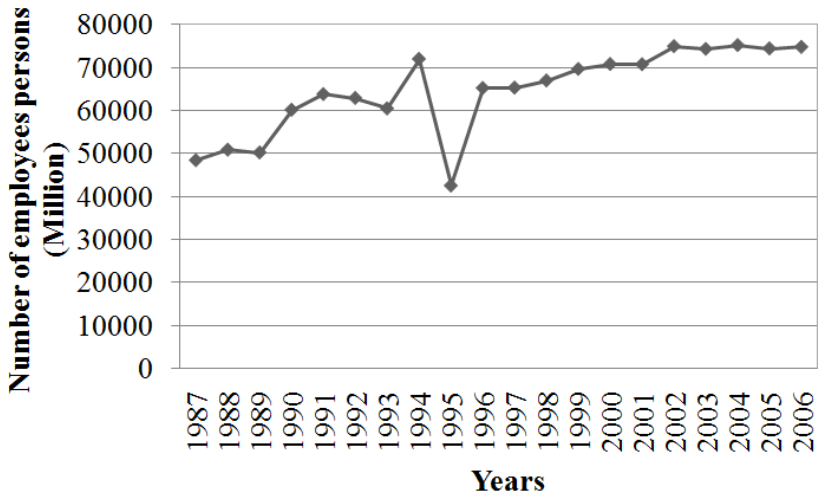

Figure 4. Number of employees persons for Iranian metal industries between 1987 and 2006.

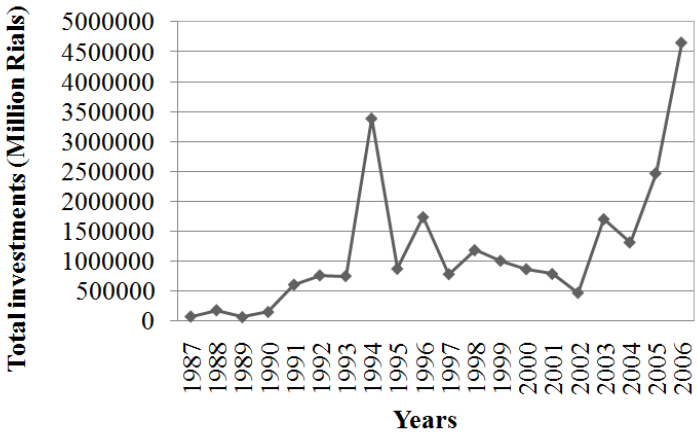

Figure 5. Total investment in Iranian metal industries between 1987 and 2006.

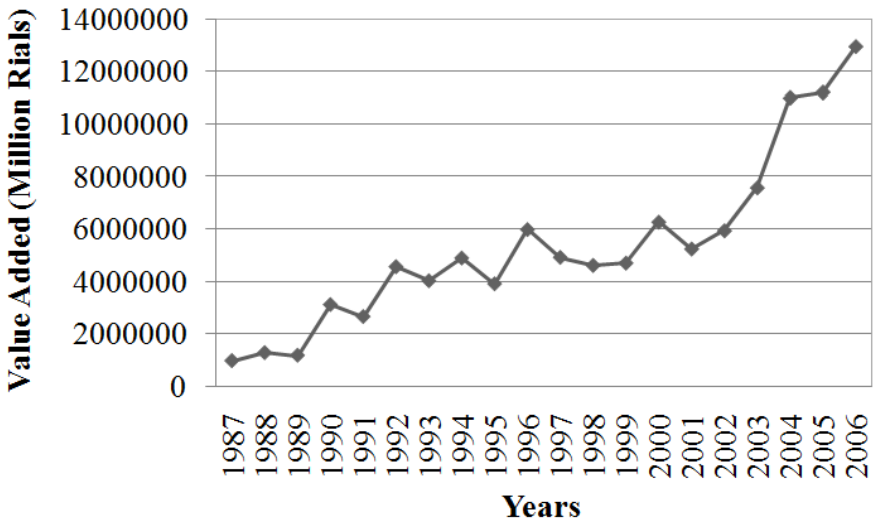

Figure 6. Value added for Iranian metal industries between 1987 and 2006.

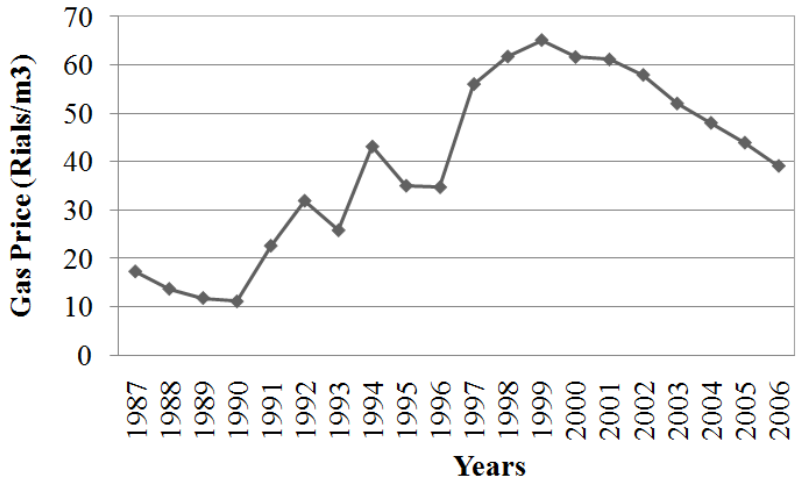

Figure 7. Gas price for Iranian metal industries between 1987 and 2006.

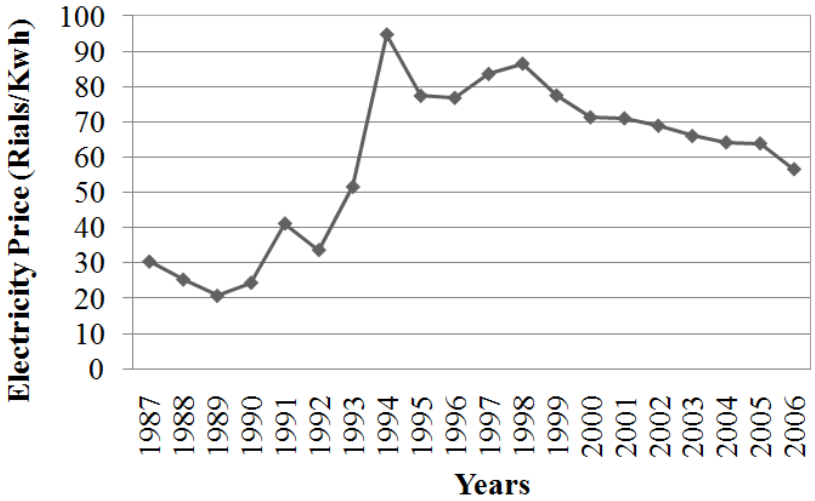

Figure 8. Electricity price for Iranian metal industries between 1987 and 2006.

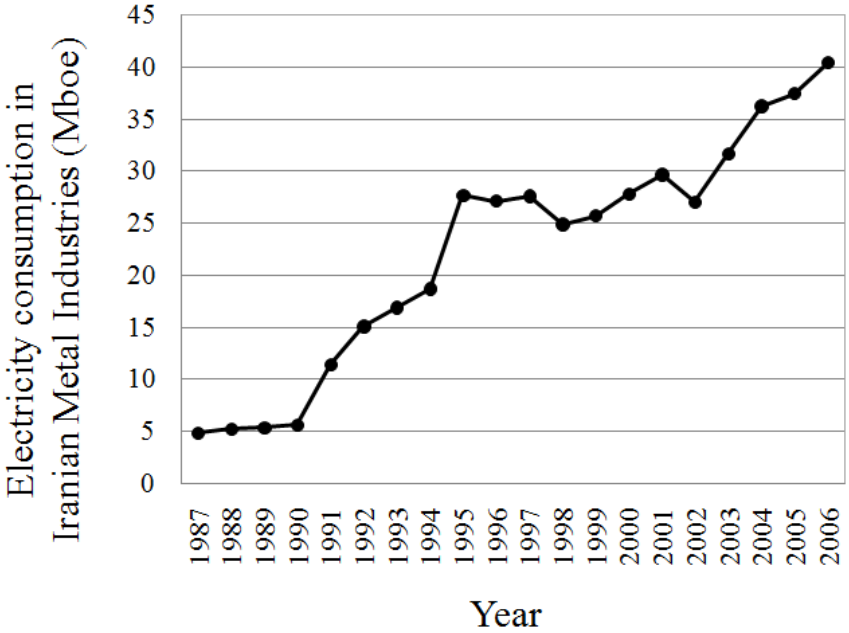

Figure 9. Electricity consumption for Iranian metal industries between 1987 and 2006.

Table 1. Performance of best models for first combination.

Year	Actual data (Mboe)	MLPNN (Mboe)	MAPE (%)	ANFIS (Mboe)	MAPE (%)
2000	27.80	32.12	15.52	23.14	16.78
2001	29.64	33.21	12.05	25.78	13.03
2002	27.04	32.01	18.38	21.67	19.87
2003	31.69	34.01	7.32	29.19	7.91
2004	36.21	37.12	2.51	35.23	2.71
2005	37.41	36.01	-3.75	35.90	4.06
2006	40.40	42.09	4.19	38.57	4.53
Average	-	-	9.10	-	9.84

Table 2. Performance of best models for second combination.

Year	Actual data (Mboe)	MLPNN (Mboe)	MAPE (%)	ANFIS (Mboe)	MAPE (%)
2000	27.80	29.02	4.37	30.84	3.98
2001	29.64	32.54	9.79	30.25	8.91
2002	27.04	30.11	11.36	28.70	10.33
2003	31.69	33.9	6.97	31.85	6.34
2004	36.21	38.01	4.96	35.44	4.52
2005	37.41	39.76	6.27	33.96	5.70
2006	40.40	42.67	5.62	39.94	5.12
Average	-	-	7.05	-	6.41

Table 3. Performance of best models for third combination.

Year	Actual data (Mboe)	MLPNN (Mboe)	MAPE (%)	ANFIS (Mboe)	MAPE (%)
2000	27.80	29.5	6.10	27.37	5.67
2001	29.64	32.11	8.34	30.02	7.76
2002	27.04	30	10.95	27.04	10.18
2003	31.69	33.62	6.09	31.98	5.66
2004	36.21	35.12	-3.02	36.94	2.81
2005	37.41	39.89	6.62	37.31	6.15
2006	40.40	41.32	2.28	41.76	2.12
Average	-	-	6.20	-	5.76

As it can be seen in these tables, the best networks for first, second, and third combinations have Mean Absolute Percentage Errors (MAPE) of 9.10%, 6.41and 5.76% on testing period, respectively.

CONCLUSION

It is concluded that the suggested models are satisfactory tools for successful electricity demand forecasting in Iranian Metal Industries. The results presented here provide helpful insight into energy system modeling. They are also instrumental to scholars and policy makers as a potential tool for developing energy plans.

Future work is focused on comparing the methods presented here with other available tools. Forecasting of electricity demand can also be investigated with Radial Basis Function Neural Networks, Bees Algorithm, Artificial Bee Colony, or other metaheuristic such as tabu search, simulated annealing, etc. The results of the different methods can be compared with the presented methods.

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REFERENCES

1. H. Houri Jafari, A. Baratimalayeri (2008). "The crisis of gasoline consumption in the Iran's transportation sector," Energy Policy, vol. 36pp. 2536– 2543.
2. A.R. Karbassi, M.A. Abduli, F. Mahin Abdollahzadeh, (2007). "Sustainability of energy production and use in Iran," Energy Policy, vol, 35, pp. 5171–5180.
3. A. Unler, (2008). "Improvement of energy demand forecasts using swarm intelligence: The case of Turkey with projections to 2025," Energy Policy, vol. 36. pp. 1937–1944.
4. O.E. Canyurt, H.K. Ozturk, (2008). "Application of genetic algorithm (GA) technique on demand estimation of fossil fuels in Turkey," Energy Policy, vol. 36, pp.2562– 2569.
5. M.D. Toksari, (2007). "Ant colony optimization approach to estimate energy demand in Turkey," Energy Policy, vol. 35. pp.3984–3990.
6. Azadeh A, Ghaderi SF, Sohrabkhani S, (2008). "A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran," Energy Policy, vol. 36. pp.2637– 2644.
7. A. Azadeh, M. Saberi, O. Seraj, (2010). "An integrated fuzzy regression algorithm for energy consumption estimation with non-stationary data: A case study of Iran," Energy, vol. 35, pp.2351–2366.
8. M.H. Amjadi, H. Nezamabadi-pour, M.M. Farsangi, (2010). "Estimation of electricity demand of Iran using two heuristic algorithms," Energy Conversion and Management, vol. 51. pp.493–497.
9. M. Zhang, H. Mu, G. Li, Y. Ning, (2009). "Forecasting the transport energy demand based on PLSR method in China," Energy, vol. 34. pp.1396–1400.
10. Behrang, M.A., Assareh, E., Ghanbarzadeh, A., and Noghrehabadi, A.R. (2010). The potential of different Artificial Neural Network (ANN) techniques in daily global solar radiation modeling based on meteorological data. Solar Energy 84: 1468–1480.
11. Behrang, M.A., Assareh, E., Assari, M.R., Ghanbarzadeh, A., (2011). Using Bees Algorithm and Artificial Neural Network to Forecast World Carbon Dioxide Emission. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects 33:1747–1759.
12. Ghanbarzadeh, A., and Noghrehabadi, Behrang, M.A., Assareh, E., (2009). Wind speed prediction based on simple meteorological data using artificial neural network. 7th IEEE International Conference on Industrial Informatics (INDIN 2009). pp 664-667.
13. Ghanbarzadeh, A., and Noghrehabadi, Assareh, E., Behrang, M.A., (2009). Solar radiation forecasting based on meteorological data using artificial neural networks. 7th IEEE International Conference on Industrial Informatics (INDIN 2009). pp 227-231.
14. Hassan B., H. Haroonabadi, R. Zadehali., (2013a).The Application of a Hybrid Artificial Neural Network and Genetic Algorithm (ANN-GA) to Mapping of Wind Speed Profile for Electrical Energy applications: A Case study for South Coasts of Iran. Bull. Env. Pharmacol. Life Sci., Vol 2 (6) May 2013: 141-147.
15. Hassan B, H. Haroonabadi, R. Zadehali., (2013b). Wind speed forecasting in South Coasts of Iran: An Application of Artificial Neural Networks (ANNs) for Electricity Generation using Renewable Energy. Bull. Env. Pharmacol. Life Sci,. Vol 2 (6): 30-37.
16. Pham, D.T. and Liu, X., (1995). Neural Networks for identification, prediction and control, London: Springer verlag.
17. Jang JSR. ANFIS: adaptive network based fuzzy inference system. IEEE Trans Syst Man Cyb (1993);23(3):665–83.
18. Brown M, Harris C. Neurofuzzy adaptive modeling and control. New Jersey: Prentice Hall; (1994).
19. Mamdani EH, Assilian S. An experiment in linguistic synthesis with a fuzzy logic controller. Int J Man Mach Stud 1975;7(1):1–13.
20. Tsukamoto Y. An approach to fuzzy reasoning method. In: Gupta MM, Ragade RK, Yager RR, editors. (1979).Advances in fuzzy set theory and application. North- Holland, Amsterdam; p. 137–49.

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