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Prediction of Municipal Solid Waste Generation by Use of Artificial Neural Network: A Case Study of Mashhad

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ABSTRACT: Accurate prediction of municipal solid waste's quality and quantity is crucial for designing and programming municipal solid waste management system. But predicting the amount of generated waste is difficult task because various parameters affect it and its fluctuation is high. In this research with application of feed forward artificial neural network, an appropriate model for predicting the weight of waste generation in Mashhad, was proposed. For this purpose, a time series of Mashhad's generated waste which have been arranged weekly, from 2004 to 2007, was used. Also, for recognizing the effect of each input data on the waste generation sensitive analysis was performed. Finally, different structures of artificial network were investigated and then the best model for predicting Mashhad's waste generation was chosen based on mean absolute error (MAE), mean absolute relative error (MARE), root mean square error (RMSE), correlation coefficient (R^2) and threshold statistics (TS) indexes. After performing of the mentioned model, correlation coefficient (R^2) and mean absolute relative error (MARE) in neural network for test have been achieved equal to 0.746 and 3.18% respectively. Results point that artificial neural network model has more advantages in comparison with traditional methods in predicting the municipal solid waste generation.

Key Words: Waste Generation, Artificial Neural Network, Sensitive Analysis, Mashhad.

INTRODUCTION

Municipal solid waste (MSW) is the result of human activities. If an appropriate management system isn't used for this problem, it may lead to environmental pollution and jeopardize the mankind's health. But it is too difficult to design such system because the nature of waste is quite complicated and heterogeneous. Recognizing the quantity of generated waste is one of the most important factors for operating the solid waste management system (SWMS), correctly. Being aware of generation quantity can be very effective for estimating the amount of investigation in the field of machinery, onsite storage containers, transition stations, disposal capacity and proper organization. There are different ways to estimate the waste generation (WG) rates, which the most prominent of them are load-count analysis, weight-volume analysis and materials-balance analysis. However, these are the basic methods for estimating the measure of generated waste, but they have some disadvantages. For example load-count analysis method determines the rate of collection, not the rate of production. Materials-balance analysis method also suffers from many errors if the source of WG were in a giant size (like a city). On the other part, traditional methods for estimating the amount of generated solid waste are established, mostly, on the basis of some elements such as population and social-economic factors of one society and they are computed according to generation coefficient per person. Since these coefficients change during the time, so they are useless devices for one dynamics SWMS. Beside in touristy cities like Mashhad, where fluctuation of population and as its result, fluctuation of WG is significant, they can't predict the amount of generated waste, accurately. For these reasons, employing new methods and advanced techniques can be useful for computing

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by means of this dynamic and non-linear system. These methods mostly consist of some models, classic statistics methods and many new techniques like time series methods and artificial neural networks.

In this study, Artificial Neural Network (ANN) was trained and tested to model weekly waste generation (WWG) in Mashhad city of Iran. Input data, consist of WWG observation and the number of trucks which carry waste, were obtained from Mashhad's Recycling and Material Conversion Organization. The ANN models are basically based on the perceived work of the human brain. The artificial model of the brain is known as ANN (Sahin, *et al.,* 2005). ANNs were first introduced in the 1940s (McCulloch & Pitts, 1943). Interest grew in these tools until the 1960s when Minsky and Papert showed that networks of any practical size could not be trained effectively (Minsky & Papert, 1969). It was not until the mid-1980s that ANNs once again became popular with the research community when Rumelhart and McClelland rediscovered a calibration algorithm that could be used to train networks of sufficient sizes and complexities to be of practical benefit (Rumelhart & McClelland, 1986). Since that time research into ANNs has expanded and a number of different network types, training algorithms and tools have evolved. Given sufficient data and complexity, ANNs can be trained to model any relationship between a series of independent and dependent variables (inputs and outputs to the network respectively). For this reason, ANNs have been usefully applied to a wide variety of problems that are difficult to understand, define, and quantify; for example, in finance, medicine, engineering, etc. Recently, use of ANNs in management of MSW like a proposed model based on ANN to predict rate of leachate flow rate in place of disposal solid wastes in Istanbul, Turkey (Karaca & Ozkaya, 2006), prediction for energy content of Taiwan MSW using multilayer perceptron neural networks (Shu *et al.,* 2006), HCl emission characteristics and back propagation neural networks prediction in MSW/coal co-fired fluidized beds (Chi *et al.,* 2005), recycling strategy and a recyclability assessment model based on an ANN (Liu et al., 2002) and prediction of heat production from urban solid waste by ANN and multivariable linear regression in the city of Nanjing, China (Dong, *et al.,* 2003), have been become in current.

Also in the other environmental problems like air pollution (Sahin, *et al.,* 2005 ; Lu, *et al.,* 2004 ; Lu, *et al.,* 2006), surface water pollution (Sahoo, *et al.,* 2006 ; Shrestha & Kazama, 2007), the ANNs have been used. The results of these researches have shown the high performance of ANN in prediction of various environmental parameters like production.

MATERIALS & METHODS

According to final received reports, Mashhad's population is about 3 million. In this city, municipal ministry is charged with the duty of MSW collection. In latest years, increasing of emigration to this city has been caused in expanding the WG and as a result making a problem for the SWMS. According to the Recycling and Material Conversion Organization report, with production of 0.5 million tons waste in 2006, Mashhad was one of the biggest centers of WG in Iran. In the other hand, the significant fluctuations of WG as a result of high number of emigrants in this city have made many problems for SWMS. According to Existed reports the amount of generated waste in Mashhad is between 1200 to 1900 ton/day, thus offering an appropriate model for estimating the quantity of generated waste and its fluctuation can be useful for true programming and deciding which is made by related organizations.

Effective factors in the amount of generated wastes are: geographical situation, seasons, collection frequency, onsite process, people's food habits, economic condition, recovery and reuse boundaries, existed law and people's cultural conditions. Since having seasonal patterns of generated waste can have an effective role for estimating the generated waste and its fluctuation in one city (especially in touristy city like Mashhad), so a time series model of WG has been made for predicting the amount of generated waste in Mashhad. In this model weight of waste in t+1 week (W_{t+1}), is a function of waste quantity in t (W_t), t-1 (W_{t-1}), …, t-11 (W_{t-11}) weeks. The weekly fluctuation of WG in Mashhad has been shown in Figure 1. Another input data, consist the number of trucks which carry waste in week of t (Tr_t).

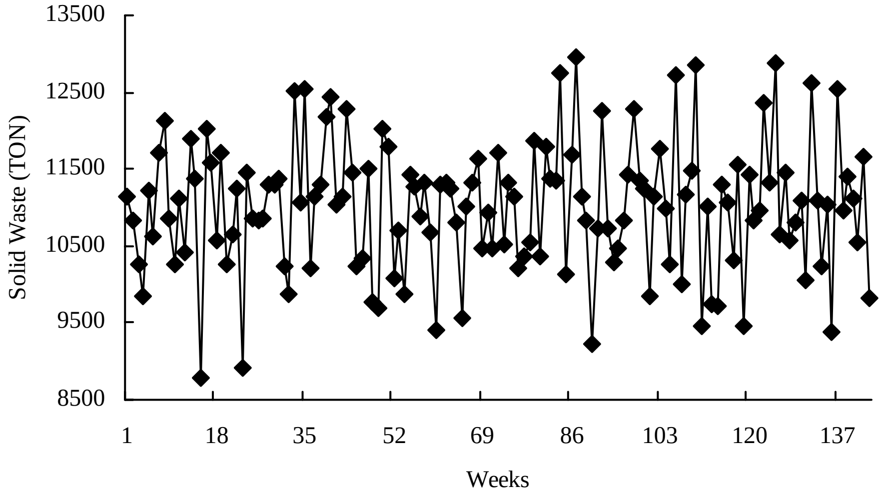

Fig. 1. Weekly fluctuation of waste generation in Mashhad

The neural models are basically based on the perceived work of the human brain. The artificial model of the brain is known as Artificial Neural Network (ANN) or simply Neural Networks (NN). Neural Networks have many applications. Generally, however, the ANNs are a cellular information processing system designed and developed on the basis of the perceived notion of the human brain and its neural system. Rapid, efficient propagation of electrical and chemical impulses is the distinctive characteristic of neurons and the nervous system in general. The neurons operate collectively and simultaneously on most for all data and inputs, which performs as summing and nonlinear mapping junctions. In some cases they can be considered as threshold units that fire when total input exceeds certain bias level. Neurons usually operate in parallel and are configured in regular architectures. They are often organized in layers, and feedback connections both within the layer and toward adjacent layers are allowed. Strength of each connection is expressed by a numerical value called a weight that can be updated. Also they are characterized by their time domain behavior, which is often referred as dynamics. In general, the neuron could be modeled as a nonlinear activated function of which the total potential inputs into synaptic weights are applied. It is assumed that synapses can impose excitation or inhibition but not both on the receptive neuron. The artificial model of neuron consists of three elements. These are:

1. A set of synapses or connection links, each of which is characterized by a weight or strength of its own. Specially, a signal x_j at the input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj} . Unlike a synapse in the brain, the synaptic weight of an artificial neuron may lie in a range that includes negative as well as positive values.

2. An adder for summing the input signals, weighted by the respective synapses of the neuron.

3. An activation function or transfer functions for limiting the amplitude of the output of a neuron.

The neuron model can also include an externally applied bias, denoted by b_k . The bias has the effect of increasing or lowering the net input of the activation function depending on whether it is positive or negative, respectively. Mathematically, the neuron k will be described by the following equations:

$$w_k = \sum_{j}^{m} w_{kj} . x_j \qquad (1)$$

Where are the input signals; are the synaptic weights of neuron. The activation function, denoted by, defines the output of a neuron which considerably. Influences the behavior of the network,

$$net = u_k + b_k \qquad (2)$$

$$y_k = f\left(net\right) \qquad (3)$$

Where is threshold value and is activation function. Three basic types of activation function are generally used in ANN. These are:

Piecewise-linear function

$$f(v)=\begin{cases}1, & v\geq\frac{1}{2}\\ v, & \frac{-1}{2}<v<\frac{1}{2}\\ 0, & v\leq\frac{-1}{2}\end{cases}\qquad(4)$$

Threshold function

$$f(v)=\begin{cases}0, & v\geq 0\\ 1, & v<0\end{cases}\qquad(5)$$

Sigmoid function

$$f(v)=\frac{1}{1+e^{-av}}\qquad(6)$$

where is the slope of the activation function. In this paper, neural network is trained and tested using MATLAB 7.2. A three-layer neural networks that consist of an input layer, output layer and one hidden layer is used and structure of this network is presented in Fig. 2.

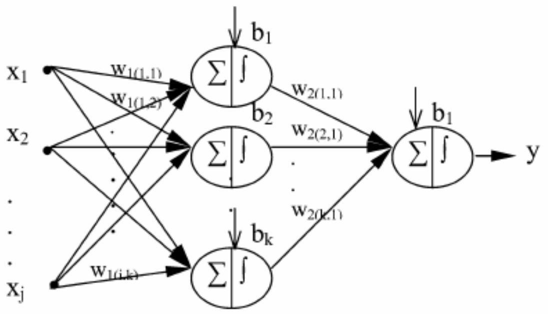

Fig. 2. Structure of the three layers artificial neural network

In this Fig., the ellipse-shape processing units in all the layers represent artificial neurons. The monitoring data belonging to 2003-2007 years is designed to meet the requirements of training and testing the neural network. Various ANN models are tested changing the number of neurons in the hidden layer between 4 and 26. All the data are normalized into the range $\{0.1, 0.9\}$. This is carried out by determining the maximum and minimum values of each variable over the whole data period and calculating normalized variables using equation (7).

$$X_{norm}=0.8\left[\frac{(X-X_{\min})}{(X_{\max}-X_{\min})}\right]+0.1\qquad(7)$$

The most popular architecture for a neural network is a multilayer perceptron (Bishop, 1995; Jain, *et al.*, 2006). In this study, we used was the feed forward, multilayer perceptron (MLP), which is considered able to approximate every measurable function (Gardner and Dorling, 1998). The main issue in training MLP for prediction is the generalization performance. MLP, like other flexible nonlinear estimation methods such as kernel regression, smoothing splines, can suffer from either underfitting or overfitting (Coulibaly, *et al.*, 2000). In this situation error between training and testing results start to increase. For solving this problem, Stop Training Approach (STA) has been used. Data are divided into 3 parts in this method. First part is related to network training, second part for stopping calculations when error of integrity start to increase and the third part that is used for integrity of network.

In order to evaluate the performance of the ANN model four statistical indices are used: the Mean Absolute Error (MAE), the Mean Absolute Relative Error (MARE), the Root Mean Square Error (RMSE) and correlation coefficient (R^2) values that are derived in statistical calculation of observation in model output predictions, defined as:

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|w_o-w_p\right|\qquad(8)$$

$$MARE=\frac{1}{n}\sum_{i=1}^{n}\frac{\left|w_o-w_p\right|}{w_o}\qquad(9)$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(w_o-w_p)^2}\qquad(10)$$

$$R^2=1-\frac{\sum_{i=1}^{n}(w_o-w_p)^2}{\sum_{i=1}^{n}(w_o-w_o^{'})^2}\qquad(11)$$

Where w_o is the actual values of W_{t+1} with $\{i=1,2,...,n\ weeks\}$ observations, $w_o^{'}$ is the average of W_{t+1}, n is the total observation number and w_p is the predicted W_{t+1} value.

RESULTS & DISCUSSION

Mashhad's Statistics Analysis of waste, during the different seasons between "2004-2007", is given in Table 1. Since the amount of average and median is close to each other, so waste generation in Mashhad has normal distribution among the different seasons. Also significant amount of Standard deviation shows that generation fluctuation in different seasons of year. To know the percentage of every independent variable's impact on generated MSW, the sensitivity analysis was performed. Its results are shown in Fig. 3. According to Fig. 3, the generated waste in each week got the most effect from W_t , W_{t-3} and W_{t-6}.

This can be the result of people's hobbies and economic conditions. To achieve the best ANN structure for estimating generated waste, various structures of feed forward ANN with three layers and different number of neurons in hidden layer was investigated. In this investigation, Levenberg-Marquadte as a training function and Tansig as a transfer function were used. Finally, with consideration on MAE, MARE, RMSE and R^2 appropriate models were selected. The results of training and testing of ANN are given in Table 2. According to Table 2 the best results were obtained of (13-10-1) and (13-16-1) structures. These results are shown in Figs. 4 to 11.

Table 1. Statistics analysis of waste generation in Mashhad (Ton)

parameter	Win.2004	Spr.2004	Sum.2004	Aut.2004	Win.2005	Spr.2005
Average	9980.799	10959.57	10870.12	11234.99	10997.52	11281.54
St.dev.[a]	606.9078	724.0159	334.9799	293.3581	721.8998	634.3071
Median	10109.39	10923.17	10840.24	11234.99	10997.52	11281.54
Max	10563.04	12398.09	11378.81	12014.95	12116.64	12251.74
Min	8468.545	9857.88	10255.82	10820.54	9398.16	10223.86
	Sum.2005	**Aut.2005**	**Win.2006**	**Spr.2006**	**Sum.2006**	**Aut.2006**
Average	11836.57	11986.04	9791.232	10453.8	10729.67	11052.47
St.dev.[a]	885.1061	500.7468	529.9601	578.5291	614.1047	556.3639
Median	11783.52	11954.51	9686.935	10486.47	10729.67	11177.34
Max	12902.26	12784.45	10425.01	11535.43	11575.03	11599.42
Min	10647.67	11141.24	8822.945	9469.42	9570.22	9810.25

[a] Standard Deviation

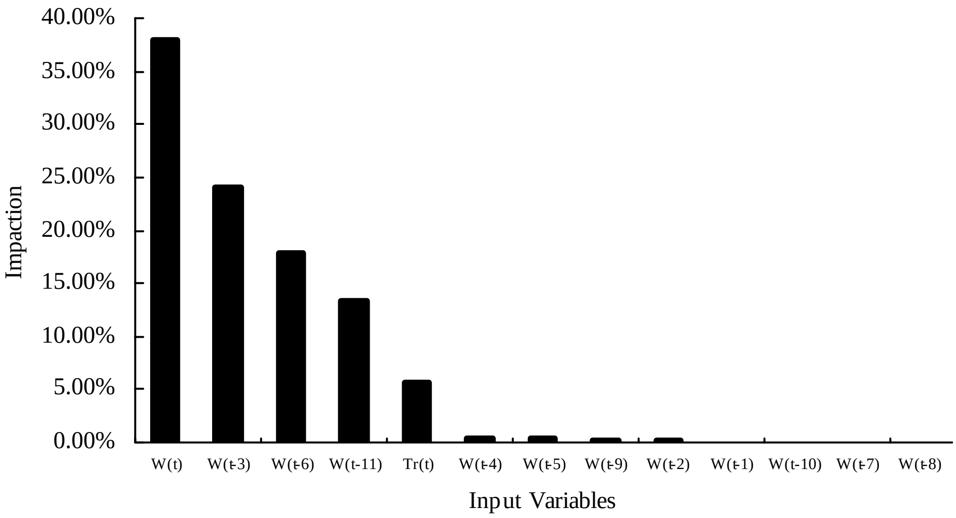

Fig. 3. Percentage of every input variables' impact on generated municipal solid waste

Table 2. Results of training and testing steps of ANN

ANN model structure	TRAINING				TESTING			
	MAE	MARE %	RMSE	R^2	MAE	MARE %	RMSE	R^2
13-4-1	302	2.83	411	0.748	388	3.64	494	0.73
13-6-1	224	2.03	290	0.877	387	3.54	508	0.707
13-8-1	228	2.1	276	0.901	380	3.51	487	0.729
13-10-1	283	2.59	350	0.83	358	3.29	467	0.75
13-12-1	163	1.48	210	0.938	395	3.63	502	0.716
13-14-1	221	2	273	0.905	377	3.46	485	0.74
13-16-1	212	1.94	262	0.899	342	3.18	470	0.746
13-18-1	224	2.07	296	0.87	386	3.64	497	0.715
13-20-1	324	2.96	434	0.727	399	3.62	499	0.721
13-22-1	220	2.04	286	0.879	378	3.57	479	0.735
13-24-1	308	2.84	411	0.748	419	3.91	501	0.708
13-26-1	216	2	271	0.915	462	4.39	598	0.681

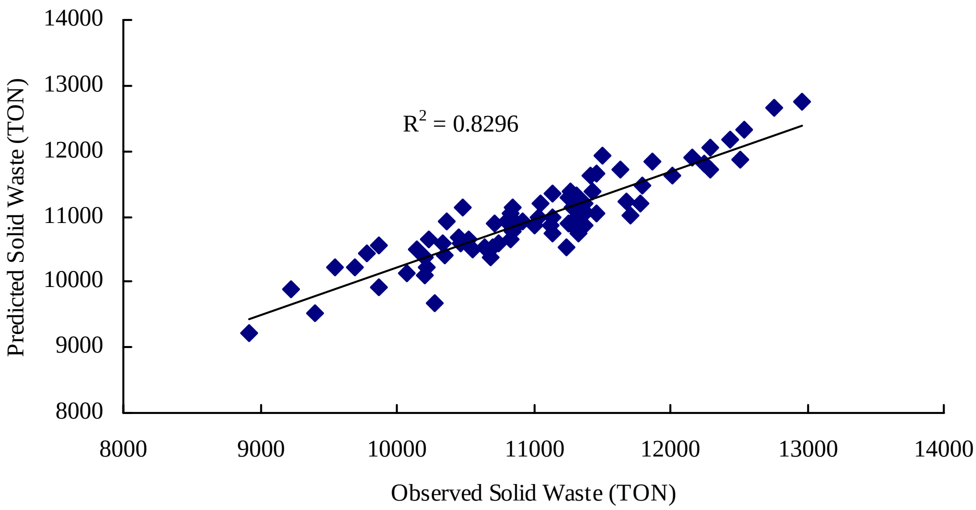

Fig. 4. Scatter plot of observed and predicted solid waste from training of ANN model with structure (13-10-1)

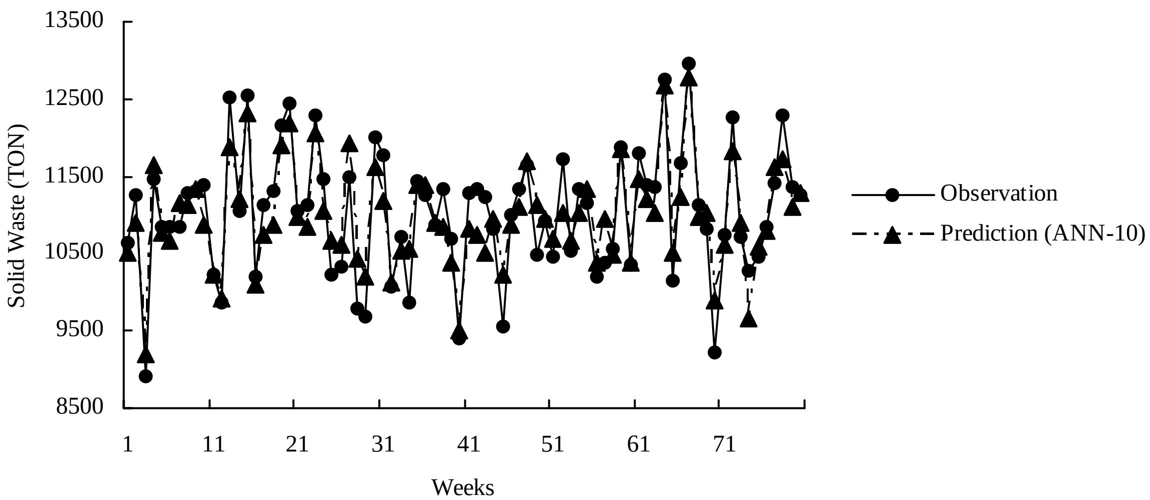

Fig. 5. Observed and predicted solid waste from training of ANN Model with structure (13-10-1)

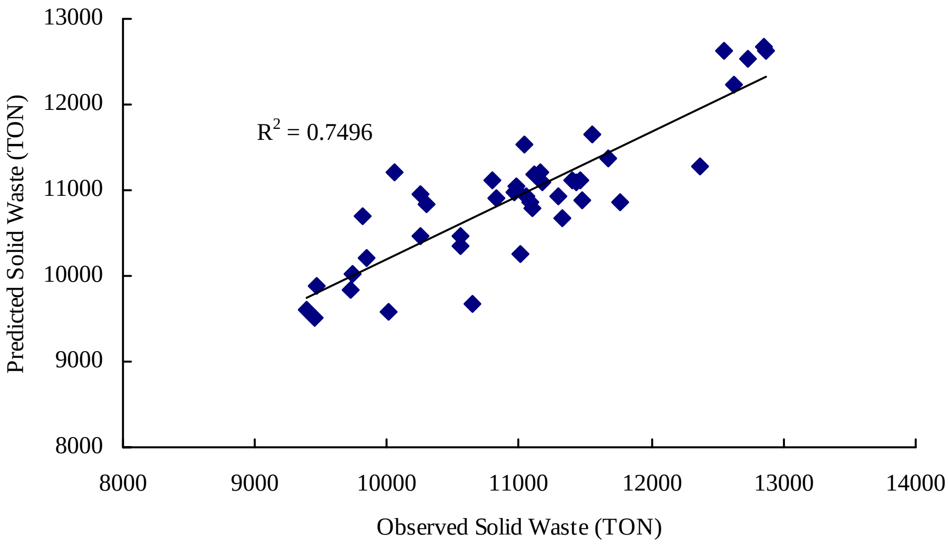

Fig. 6. Scatter plot of observed and predicted solid waste from testing of ANN model with structure (13-10-1)

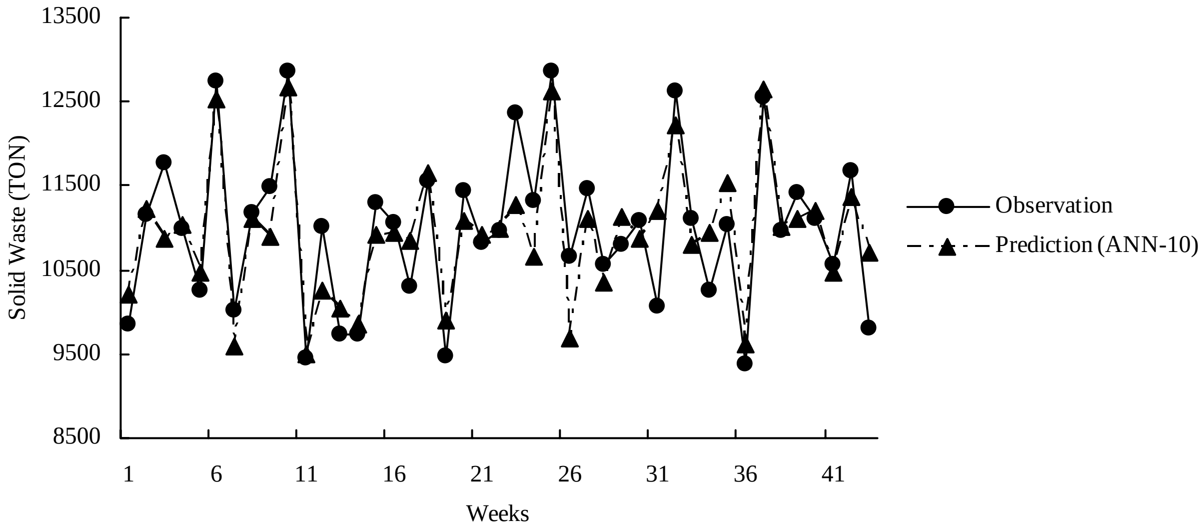

Fig. 7. Observed and predicted solid waste from testing of ANN Model with structure (13-10-1)

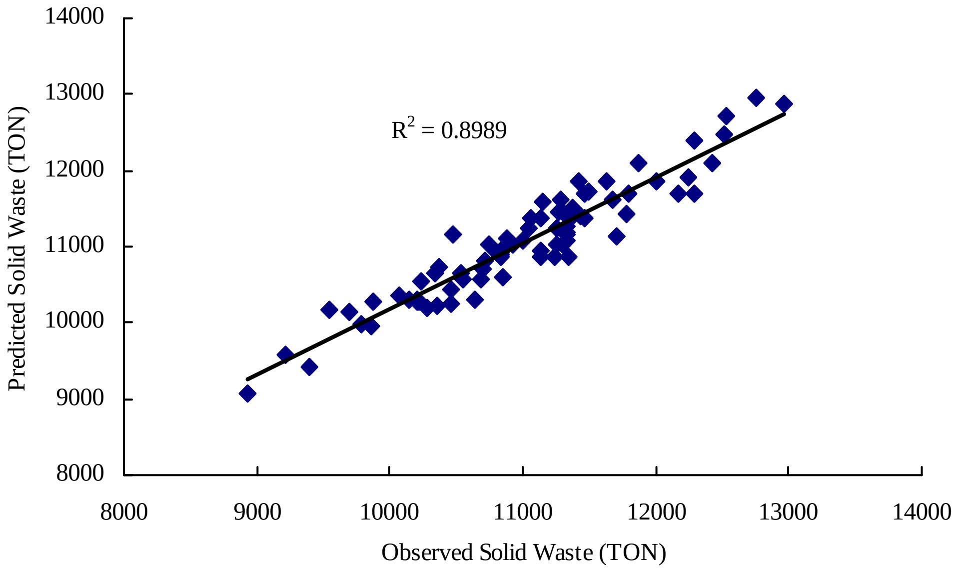

Fig. 8. Scatter plot of observed and predicted solid waste from training of ANN model with structure (13-16-1)

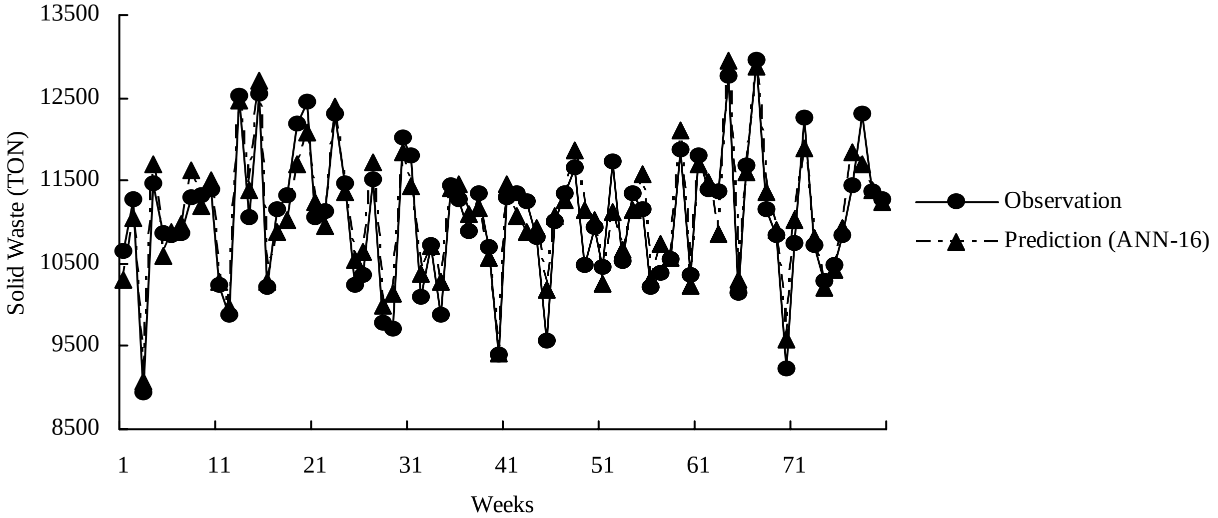

Fig. 9. Observed and predicted solid waste from training of ANN Model with structure (13-16-1)

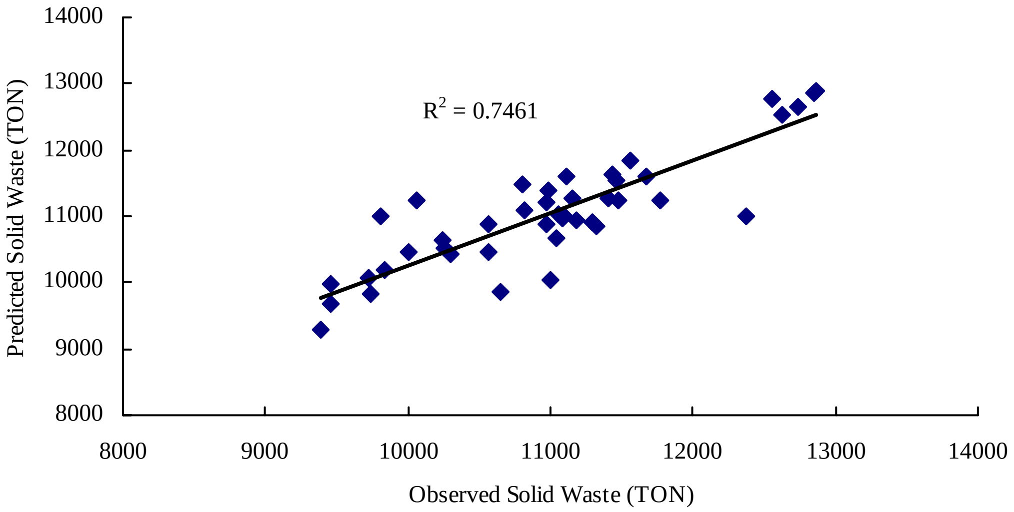

Fig. 10. Scatter plot of observed and predicted solid waste from testing of ANN model with structure (13-16-1)

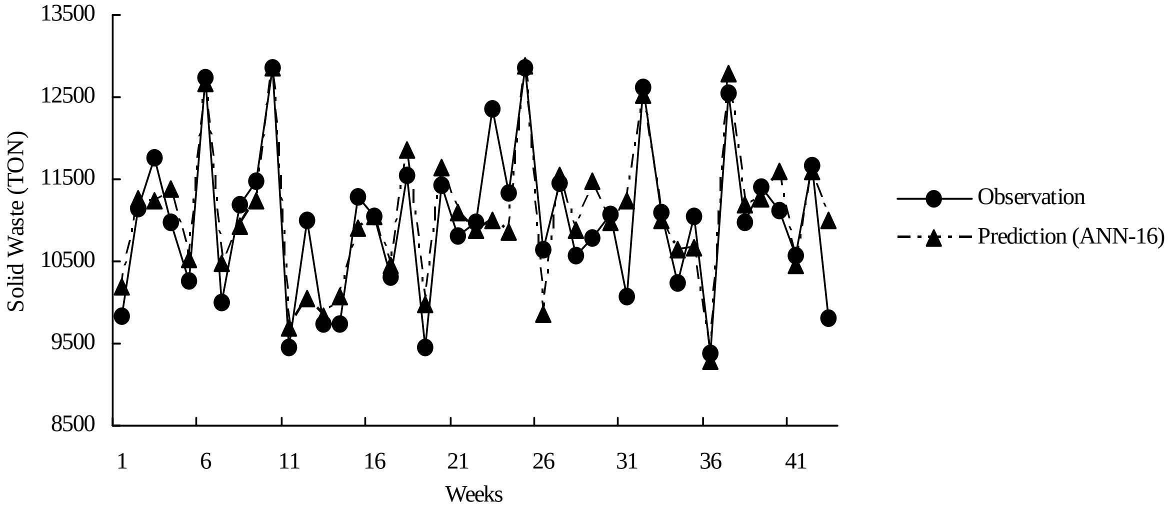

Fig. 11. Observed and predicted solid waste from testing of ANN Model with structure (13-16-1)

As mentioned before, on the base of examined criteria (MAE, MARE, RMSE and R^2), models with the structures of (13-16-1) and (13-10-1), have better results in comparison with other models.

The first model (13-10-1) shows the better results than the second model (13-16-1) based on MAE and MARE. The R^2 index is same for these models, but RMSE index for the second model shows better results in comparison with the first model.

Since these criteria show the average of error in model and don't give any information about the error distribution, so to test the robustness of the ANN model, it is important to test the model using some other performance evaluation criterion such as threshold statistics (TS) (Jain and Indurthy, 2003). The TS not only give the performance index in terms of predicting WG but also the distribution of the prediction errors. The TS for a level of x% is a measure of the consistency in forecasting errors from a particular model. The TS are represented as TS_x and expressed as a percentage. This criterion can be expressed for different levels of absolute relative error from the model. It is computed for the x% level (TL) as:

$$TS_x = \frac{Y_x}{n}100 \qquad (12)$$

Where in equation (12), Y_x is the number of computed WG (out of n total computed) for which absolute relative error is less than x% from the model. Fig. 12 shows the distribution of errors at different threshold levels for first and second models.

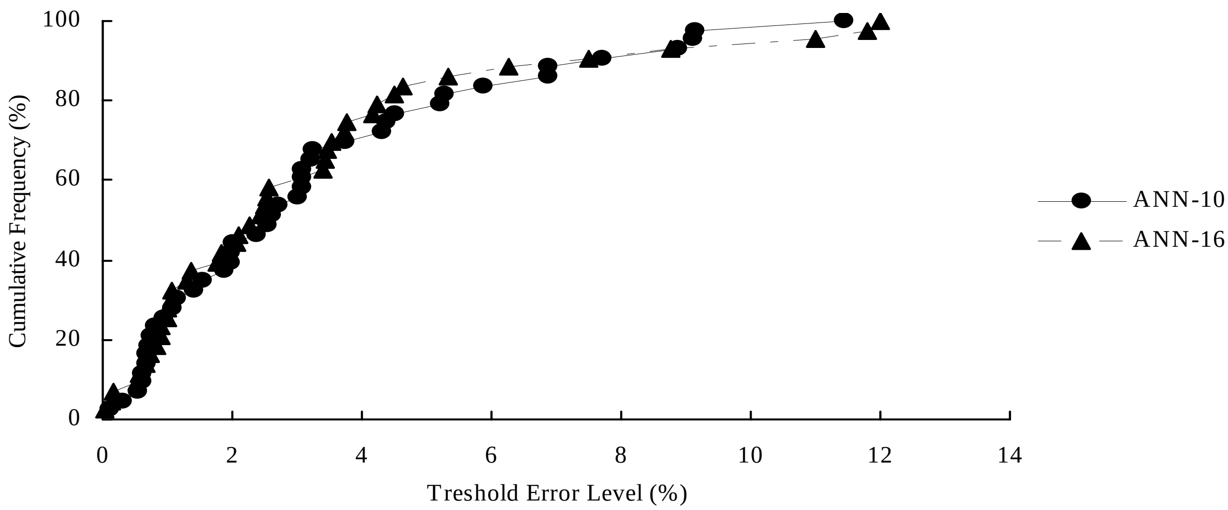

Fig. 12. Absolute relative error for the structures (13-10-1) and (13-16-1) in the testing step of artificial neural network

According to Figure 12, the maximum of absolute relative error (ARE) for fifty percentage of predicted W_{t+1} in the first model is less than 2.59%, however it is less than 2.45% for the second model. The ARE for ninety percentage of predicted Wt+1 in the first model is less than 7.69%, but for the second model this value is less than 7.51%. So the model with the structure of (13-16-1) has better results in comparison with the other model (13-10-1).

CONCLUSION

Accurate prediction of WG plays an important rule in the MSWMS. Therefore the goal of this research is offering a suitable model to predict this quantity. In this paper was used the feed-forward artificial neural network for the prediction of weekly waste generation of Mashhad city. At the first, by using of ANN with the one hidden layer and changing the number of neurons of the layer, different models were created and tested. Then according to applied index in this paper (MAE, MARE, RMSE and R^2), structures with 10 and 16 neurons in the hidden layer, were selected as the suitable models. Finally, based on TS index, structure with 16 neurons in the hidden layer was chosen for the prediction of waste generation in Mashhad.

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