AIChE

Longterm Forecasting of Solid Waste Generation by the Artificial Neural Networks

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Published online in Wiley Online Library (wileyonlinelibrary.com). DOI 10.1002/ep.10591

This study presents a new approach—preprocessing for reaching the stationary chain in time series—to unravel the interpolating problem of artificial neural networks (ANN) for long-term prediction of solid waste generation (SWG). To evaluate the accuracy of the prediction by ANN, comparison between the results of the multivariate regression model and ANN is performed. Monthly time series datasets, by the yrs 2000–2010, for the city of Mashhad, are used to simulate the generated solid waste. Different socioeconomic and environmental factors are assessed, and the most effective ones are used as input variables. The projections of these explanatory variables are used in the estimated model to predict the generated solid waste values through the yr 2032. Ultimately, various structures of ANN models are examined to select the best result based on the performance indices criteria. Research findings clearly indicate that such a new approach can be a practical method for long-term prediction by ANNs. Furthermore, it can reduce uncertainties and lead to noticeable increase in the accuracy of the long-term forecasting. Results indicate that multilayer perception approach has more advantages in comparison with traditional methods in predicting the municipal SWG. © 2011 American Institute of Chemical Engineers Environ Prog, 00: 000–000, 2011

Keywords: solid waste generation, artificial neural networks, time series data, Mashhad, Iran

INTRODUCTION

Both planning and design of municipal solid waste management systems (MSWMS) require reliable long-term prediction of solid waste generation (SWG). Yet, achieving the anticipated prediction accuracy with regard to the generation trends is quite challenging. Although in the recent years, there has been much research on the use of ANNs to predict short-term or medium-term, long-term prediction has not been conducted due to the interpolating characteristic of ANNs. To effectively handle this problem, long-term prediction by ANNs, a new analytical approach capable of addressing socioeconomic and environmental situations must be developed and applied for fulfilling the long-term prediction analysis of SWG with reasonable accuracy.

Because of the changing in consumption pattern, quantities and characteristics of municipal solid waste (MSW) vary significantly with time [1]. In addition to population growth and migration, underlying economic development, household size, employment changes, and the impact of waste recycling would influence the SWG significantly. The development of a reliable model for assessing the impact of economic trend, population changes, and weather changes on predicting SWG would be a useful advance in the practice of MSWMS.

Determining the quantities of the generated solid waste provides the opportunity for the waste management organizations to adopt necessary providence for the amount of investment required for machinery, transition stations, disposal capacity, and the amount of required field for sanitary landfills in the future. Traditional forecasting methods for SWG frequently depend on the demographic and socioeconomic factors on a per-capita basis [2]. Solid waste production is influenced by different factors including the economic conditions, population growth, weather conditions, geographical situation, people hobbies, and the household size [3]. McBean and Fortin [4] dealt with certain aspects of MSW management by means of correlations among socioeconomic and solid waste composition and quantities. Dyson and Chang [5] considered the effects of population, income level, and the dwelling unit size in a linear regression model. Beigl et al. [6] estimated a model for the European cities, including the explanatory variables, such as GDP, infant mortality rate, and household size. Benítez et al. [7] predicted the residential solid waste by developing a linear model with the explanatory variables, including education, income per household, and number of residents. Buenrostro et al. [8] and Hockett et al. [2] found that the income is an influential factor on SWG. Dayal et al. [9] assessed the impact of the climatic conditions and socioeconomic status on solid waste characteristics.

Recently, some investigations have been conducted in order to assess the applicability of the artificial neural networks (ANN) in short-term and medium-term forecasting, but not many efforts have been conducted for the long-term forecasting. Zadeh et al. [10] predicted weekly solid waste values, using the ANN. Noori et al. [11] extended the previous study by applying the PCA and Gamma test techniques on the ANN operation for weekly forecasting. Noori et al. [12] evaluated results uncertainty of prediction of SWG by hybrid of wavelet transform-ANFIS and wavelet transform-ANN models. Noori et al. [13] developed an improved SVM model, which combines both the PCA and SVM technique to predict weekly generated solid waste of Mashhad city. Karaca and Özkaya [14] used ANN to control leachate generation rate in landfills. Chen and Chang [15] presented a new theory, gray fuzzy dynamic modeling, for the prediction of waste generation in the urban area based on a set of limited samples.

In the most previous studies on neural network-based forecasting, models have been used which dependent variable (SWG) is taken as an independent variable considering time intervals. By using this procedure, production amount (predicted in previous stages) is used on determining the amount of future production. So, the error increases at each stage and makes these models unable to predict data more than a few time steps. In multivariate models, where SWG is present as a delay of time, delaying parameters have the greatest impact on prediction of waste generation due to the high correlation between dependent variable and intervals of the same variable, which is used as an independent variable in the model. For this reason, the effects of the other variables in predicting future production of solid waste are negligible and cannot model other factors affecting SWG well.

The purpose of this study is to provide a convenient and reliable method for reaching long-term prediction of solid waste while increasing prediction range and decreasing uncertainty.

In the present study, first, the influential variables on SWG whose data are existed are chosen as the input data. The selected variables must have the ability to be forecasted with a relatively high accuracy and a long forecasting horizon. Examples of such factors with high inertias are the population, the household size, or the infant mortality rate [16]. In the next step, the ANN is trained and tested for the observed period, and the most reliable structure is determined based on the performance criteria. Finally, the impact of preprocessing on the data is evaluated. The article concludes by some considerable points that should be noticed for predicting the values of the disposal waste.

METHODOLOGY

To increase the accuracies in forecasting, different kinds of preprocessing are used on data. Although the ANN has been used for short-term forecasting, it has been shown, in this section, that it is an accurate course of action to long-term forecasting of monthly SW generation. In the long-term forecasting, two points should be noticed:

1. Increasing time scope in forecasting (long-term forecasting)
2. Increasing in reliability and accuracy of forecasting

Predicted results with this method are compared to the values predicted using the regression model. For this purpose, after estimating regression model, variables affecting solid waste production are predicted for the desired forecast range and given to the estimated model to obtain the predicted values for SW generation.

Regression Model

To estimate SW generation model, different models as linear and nonlinear are available. The estimated models should be in accordance with the real conditions. The estimating procedure should be corrected, and the model coefficients must be significant. High values of R^2 and proximity of the values of R^2 and R^2adjusted provides the theoretical expectations. *P*-values and *t*-statistics depict the significance of each variable. Autocorrelations are detected through Durbin–Watson test. To avoid the multicollinearity phenomenon, correlation analysis between different pairs of independent variable should be conducted [17, 18]. To assess the cointegration, Augmented Dicky–Fuler unit root test should be applied to the variables and residuals of the estimated model.

The Artificial Neural Network

In the recent years, artificial neural networks (ANNs) have been used in nonlinear system modelling. Generally, ANNs are cellular information processing systems designed and developed on the basis of the perceived notion of the human brain and its neural system [19]. One of the most beneficial and significant factors of ANNs is forecasting because of the ANN's ability to learn and construct a complex nonlinear system through a set of input/output examples. Therefore, the nonlinear structure of SWG makes the ANN an ideal candidate for predicting the estimations.

ANNs include the interconnections of a number of neurons. In the present work, only one kind of network is discussed, which is called the multilayer perception (MLP). This network is considered to be able to approximate every measurable function [20]. In this network, the data flow forward to the output per-

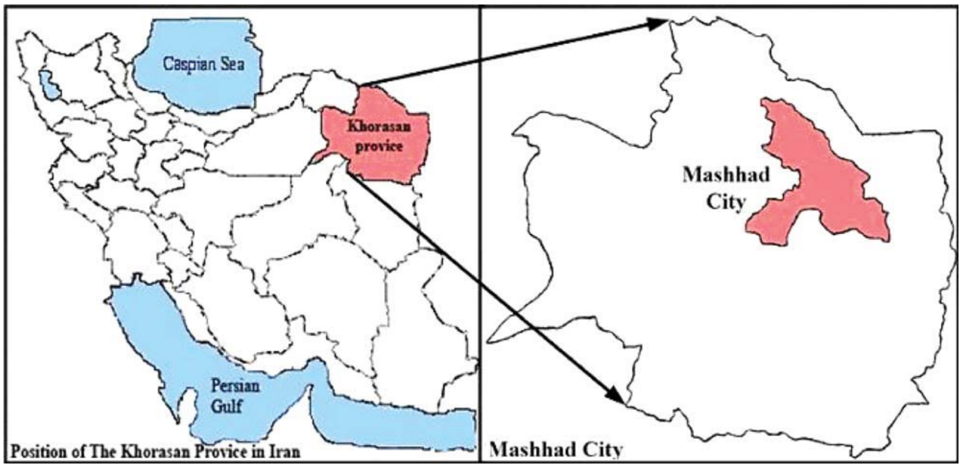

Figure 1. Geographical location of Mashhad in Iran. [Color figure can be viewed in the online issue, which is available at **wileyonlinelibrary.com**.]

sistently. Figure 1 depicts a typical three-layer feed forward model used for predicting the goal. The input nodes are the values of population, the maximum temperature, and the household income, while the output provides the forecast of the future solid waste. The information received by the input nodes is processed in hidden neurons with appropriate nonlinear transfer functions.

The most popular learning rule for MLP is the error back propagation algorithm. This is introduced by Werbos [21]. Therefore, in this part, the delaying variables that decrease the accuracy of forecasting have not been used, because they increase the error in long-term forecasting.

The feed forward back propagated MLP is the default network type for most MLPs. It has multiple layers of neurons with nonlinear transfer functions that allow the network to learn nonlinear and linear relationships between input and output vectors. Different training algorithms can be used in training stage: gradient descent, gradient descent with momentum, gradient descent which has variable learning rate, gradient descent with momentum, which has variable learning rate, and RP are the most famous training functions. Conjugate gradient (CG) algorithms are the other algorithms for training procedure. The standard back propagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient), which the performance function is decreasing most rapidly. In the CG algorithms for faster convergence than steepest descent directions, a search is performed along conjugate directions. Levenberg–Marquardt algorithm is also a training algorithm was designed to approach second-order training speed without having to compute the Hessian matrix [29].

Model Performance

To evaluate the performance of the ANN model, four indices are assessed: root mean square error (MSE) or (MAPE), threshold statistic (Ts), and correlation coefficient (R^2). The accuracy of the model is determined according to these criteria.

In spite of the error indices, TS_x is a criterion that demonstrates the distribution of the errors. So, for evaluating the performance and robustness of the model, it is essential to test the Ts [10, 22]. In this study, the Ts is determined for the error level of 4, 8, and 12%.

Preprocessing of Data

For overcoming the network interpolation problem to use it for long-term prediction, it is necessary to analyze the data. After training the neural network with input and output data for the period of 2001–2010, it is necessary to predict input values (independent variables) for the upcoming 20-yr and use them in the neural network model to obtain future SWG values. Considering the fact that independent variables were highly changed over respect to observed data, and model is trained in the range of observed data, the model is unable to meet these values and then obtain output values corresponding with these independent variables.

Trying to resolve this problem, input and output data in training block are taken to the same scale as input data from prediction period (2011–2032). For achieving this goal, the concept of Stationary Chain in time series is used [23].

A time series variable is called stationary when mean, variance, and correlation coefficients remain constant over time [24]. Time series can be decomposed to trend, seasonal, and irregular component. Trend component changes data series' mean over time, and it is the seasonal part of the time series periodical changes, which repeat on a specific time period. Random component due to the nature of time series is uncertain. The most important step in statistical modeling is the random part of it.

Therefore, predictions based on the random component, which is the term used in most of the time series model, not only increase accuracy of the modeling but also makes the scale of data to be more uniform.

In preparing data series for using in neural network, it is tried to remove certain terms and make data to be

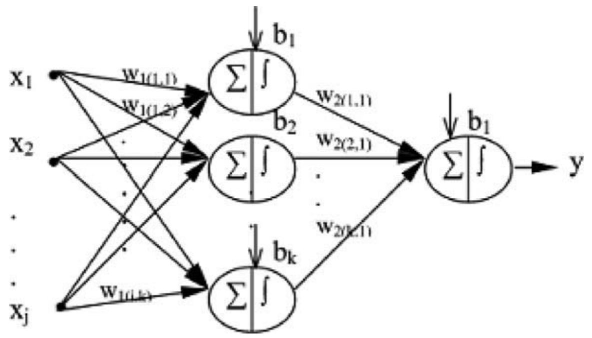

Figure 2. The structure of three layers artificial neural networks.

closer to the stationary chain. For this purpose, the first step is to try all the trend exists in data to be removed, it can make data mean remains constant. Taking logarithm of the variables is another method helps variables to be more static and alter the scale of the data. It also removes collinearity between variables causing an increase in the accuracy of modeling [25]. After forecasting values for future SW generation, the removed terms will be added to them again in order to rescale them and achieve the real results.

To make data values identical and to avoid saturation in neurons, the data should be normalized before training of the neural network [26]. More results from neural network model considering preprocessing will be discussed below and then compared to results obtained from regression models.

RESULTS

Study Area

Mashhad is the second largest city in Iran and one of the holiest cities in the Shia Muslim world. It is located at 850 km east of Tehran, at the capital of the Razavi Khorasan Province. Its population was close to 2.5 million at the 2006 population census. Figure 2 depicts the Geographical location of Mashhad in Iran country.

Data

For developing the forecasting models, a total of 120 monthly records of SWG data were collected from Mashhad Municipality for a period of 10 yrs, starting in 2001. Monthly data for the household income, population, and maximum temperature are provided for the yrs 2001–2010 from the Statistic and Meteorological Organizations of Mashhad. Table 1 indicates the statistical characteristics of the data.

Regression Model

The general form of the SWG model is:

$$\mathrm{SW} = f(I, P, \mathrm{MT}) \tag{1}$$

where SW is SWG in Ton, I is the household income in Rials, P is the number of population, and MT is the average maximum temperature.

The values of the coefficients are obtained through multilinear regression analysis. Two popular functional forms used for estimating the model as follows [27].

Linear model:

$$Y = A1(X1) + A2(X2) + A3(X3) + \cdots + An(Xn) \tag{2}$$

Log–Log model:

$$\begin{aligned}\ln Y =& A1\ \ln(X1) + A2\ \ln(X2) + A3\ \ln(X3) + \cdots \\ &+ An\ \ln(Xn)\end{aligned} \tag{3}$$

SWG models for Mashhad city are estimated using 120 months of data (2001–2010). The ordinary least square (OLS) method is used to estimate the relationship between solid waste and explanatory variables. Two functional forms are used, and the results illustrate that the linear model explains 66% variation in the SWG, whereas the Log–Log model shows 70% variation in solid waste production. Thus, the Log–Log model is selected for forecasting SW generation. Tables 2 and 3 illustrate the results of estimating models with linear and logarithmic forms.

As *t*-statistic indicates, all coefficients are meaningful at the significance level of 5%, and the estimated coefficients are quite matched with theory. The Durbin–Watson statistic shows that there is no correlation between the error sentences. R^2 is located in the desirable level, and closeness of Adjusted-R^2 and R^2 values indicates the absence of additional variables in the models.

Dicky–Fuller unit root test has been applied to all variables and residuals. Results indicate that all the variables are not integrated [18]. Thus, the problem of co-integration does not exist. Autocorrelation is the statistical procedure used to deal with time-series data or data that have auto correlation problems. If a classical linear regression model is found to be subject to autocorrelation problems, the regression coefficient will not be efficient and the R^2 of the linear regression model will also be unreliable. Durbin–Watson statistics depict that the residuals are serially uncorrelated. To avoid heteroskedasticity, the White test is applied to the model, and results indicate that variances are constant [18, 28].

Based on the Log-Log model, long-term SW generation was estimated for period of 2011–2032 using time series data and implementing of Economy Evaluation of OLS method.

Final model, considering maximum mean temperature, household income, and number of population, is illustrated in Tables 2 and 3.

To predict the disposal solid waste up to 2032, prediction of each variable is also required for applying in the simulated model. Although the prediction of the population and the temperature up to 2032 have been conducted for the city of Mashhad by the authorities, there is no available data for the future values of the household income. Thus, based on the information from the Central Bank of Iran, it is hypothesized that the income growth is 5.5% annu-

Table 1. Statistical characteristics of the data.

Variable	Mean	SD	Minimum	Maximum	Units
Population	2346499.24	153690.51	2081527.90	2601407.30	person
Household income	9116.301	857.1304	7192.784	11368.55	Rials
Maximum temperature	22.80	9.49	5.31	38.00	C
Solid waste	45671.59	6116.29	31112.00	60990.00	Ton

Table 2. Results of linear model estimation.

Variable	Coefficient	*t*-Statistic	Standard error	Probability
Population	3.934370	4.255884	0.924454	0.0000
Maximum temperature	269.4627	4.905904	54.92619	0.0000
Household income	1.517384	2.720366	0.557787	0.0056
R-squared	0.660806	Durbin–Watson stat		1.905687
Adjusted *R*-squared	0.645663			

Table 3. Results of Log–Log model estimation.

Variable	Coefficient	*t*-Statistic	Standard error	Probability
LOG (population)	0.626596	15.31322	0.040919	0.0000
LOG (maximum temperature)	0.141462	8.858566	0.015969	0.0000
LOG (income)	0.080403	2.845000	0.043579	0.0501
R^2	0.706904	Durbin–Watson stat		1.919065
Adjusted R^2	0.717322			

ally. By this assumption, the monthly household income is predicted to the yr 2032.

Regression Model Accuracy

To assess the accuracy of the developed model, a comparison between observed and simulated data for the observation period (2001–2010) was conducted. Results indicate that the accuracy of the estimated model is considerable, so that it can be used for forecasting SW generation in the future. Figure 3 depicts the comparison between actual and calculated solid waste data by the estimated model. Results indicate that the model tracks historical developments in SWG patterns fairly well.

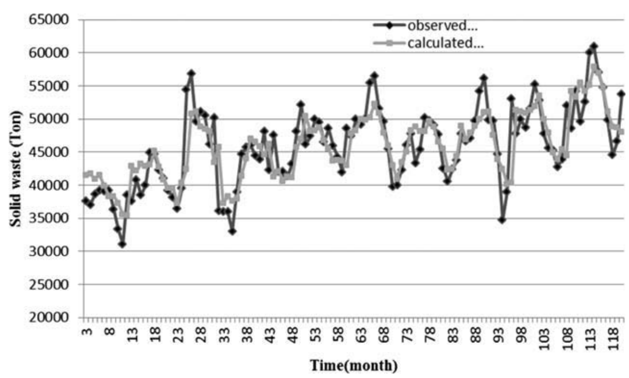

Figure 3. Observed and calculated data with the estimated regression model.

Ann Model

Results of Preprocessing

First Case. Reaching the stationary chain in time series can be implemented by subtracting the trend line from each time series; thus, the fluctuating part of the data can be modeled [23]. Figure 4 illustrates the trend in observed solid waste data. The removed trend of solid waste will be added to the predicted residuals after simulating the model. The trend line formula for the solid waste values is as follows:

$$Sw = 39375 + 104.08t$$

where Sw is solid waste values in Tons and t is time in months ($0 < t < 121$). Figure 5 depicts the residuals that remain from removing the trend from the original data and used in the model simulation.

It should be mentioned that in this section, to compare the results of the regression model and neural network values, the forecasted values of independent variables are used. According to the selection criteria, the

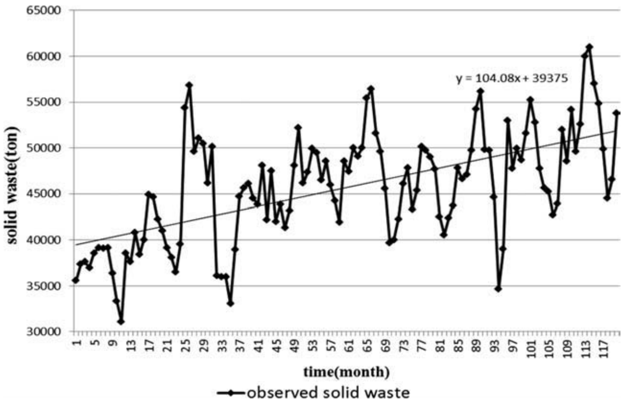

Figure 4. The trend of generated solid waste in the observation period.

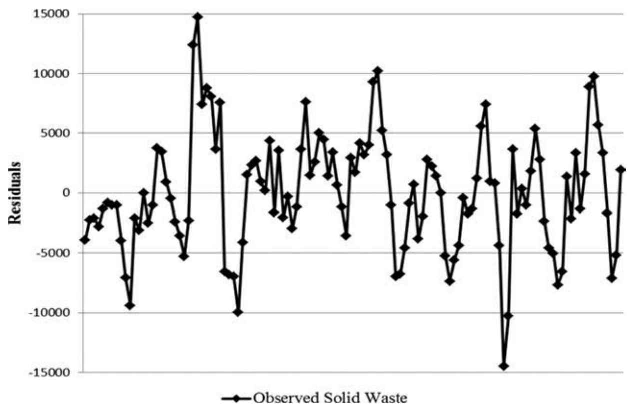

Figure 5. Residuals of the generated solid waste in the observed period.

best neural network model in this section was found. For training the neural network, several training algorithms are assessed, and traincgb algorithm is chosen as it served the best result among the others for our data. The CG backpropagation (traincgb) is a network training function that updates weight and bias values according to the CG back propagation. The gradient descent with momentum weight and bias learning functions (learngdm) is chosen as back propagation weight and bias learning functions. learngdm calculates the weight change for a given neuron from the neuron's input and error [29]. The MSE performance function was chosen as it is the default performance function for most networks. More than 1700 neural networks are tried by changing the number of neurons (4–10 for each layer) and the number of hidden layers (1–2 Layers). Finally, three layers structure was implemented for the network by trial and error respect to best result (Exhaustive Search). The first layer contained nine neurons while the second one had 10 neurons both with TANSIG transfer function. The third one has one neuron (as it should because of one output) with PURELIN transfer function.

The network weights were initialized with values equal to inputs. Input data were separated to three blocks; 70% was used for training, 15% for validation,

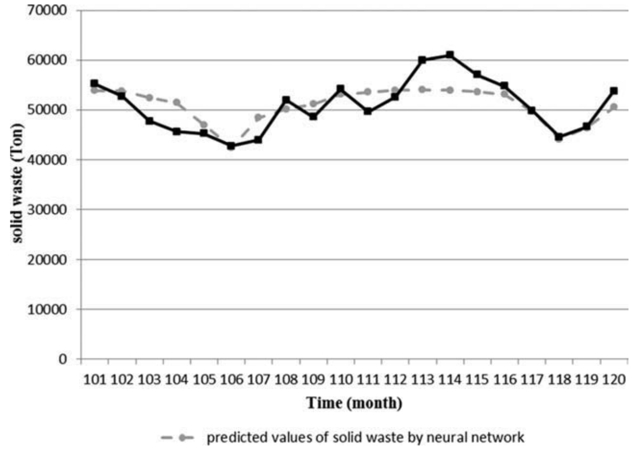

Figure 6. The comparison between observed and predicted solid waste for the test period (20 months).

Table 4. Values of performance indices in the first case.

MSE	MAPE	*R*
0.43	0.05	0.79

and 15% for testing. If the validation error was increased six times sequentially, the training would stop. Training was restarted using network weights, which had been obtained from previous run until we would reach acceptable results on testing block.

According to Figure 6 to evaluate the model, output data from test block were compared precisely with actual values.

According to the Figure 6, ANN model could forecast Sw generation reliably. Also, to assess the accuracy of the model, MAPE and MSE tests and the value of correlation coefficient were used. The values of these statistics are shown in Table 4. Therefore, by determining the model accuracy, the predicted values of independent variables are shown to the neural network as input to obtain the values of waste generation in the future.

After making output data, all the previously removed components should be again added to the time series to rescale data and make them real. Comparing ANN predicted results with predicted values of Sw production obtained from regression model are shown in Figure 7. Based on preprocessing, which was done on input data, the model could follow the general trend in solid waste production up to the 150th month. It also could model the seasonal changes. Because after 150th month, predicted input data are not in the range of data, which network were trained with, it could not model changes well; therefore, the model error increased with increasing values of independent variables, which are increased with time as well.

Second Case. To make the scale of input data values in the prediction phase closer to the data used in the training phase, in this case, first, logarithm is taken from all data, and then the existing trend in time series

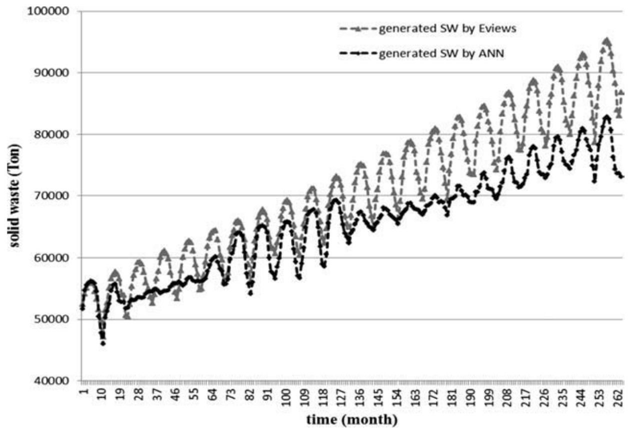

Figure 7. The comparison between predicted solid waste generation by regression model and ANN for the period of 2011–2032 (first case).

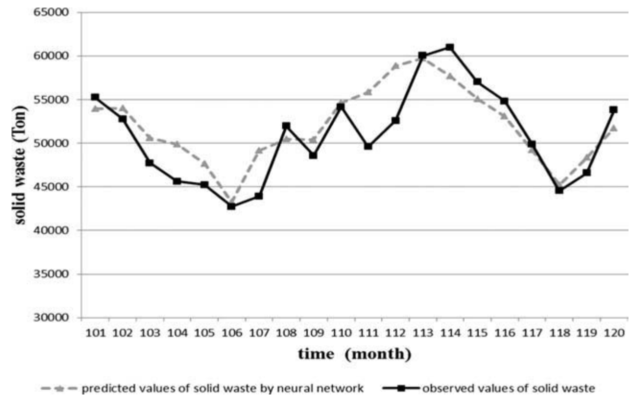

Figure 8. The comparison between observed and predicted values of solid waste the test period (20 months).

Table 5. Values of performance indices in the second case.

MSE	MAPE	*R*
0.26	0.046	0.86

is removed. Taking logarithm makes the data series smoother, while helps a time series to be more stationary and increases modeling accuracy [23, 25].

According to the selection criteria, the best neural network model in this section was found. Gradient descent with adaptive learning rate back propagation function (traingda), and gradient descent weight and bias learning function (learngd) are used in selected neural network with the structure of two middle layers with five neurons on first layer and five neurons on second layer. Both layers have with TANSIG transfer function, and the output layer has one neuron (as it should because of one output) with PURELIN transfer function.

According to the Figure 8, the accuracy of information made in the model test has been compared to actual values.

Also, to assess the accuracy of the model, MAPE and MSE tests were used along with R^2 value. These statistic values are shown in Table 5.

These statistics values indicate that modeling become more precisely. After determining the model accuracy, predicted values of independent variables are put in the model as input data to predict the solid waste production for the future. Then, all the previously removed components should be again added to the forecasted time series to rescale data and make them real. Logarithm transformation should also be reversed. Comparing ANN predicted results with predicted values of SW production obtained from regression model are shown in Figure 9.

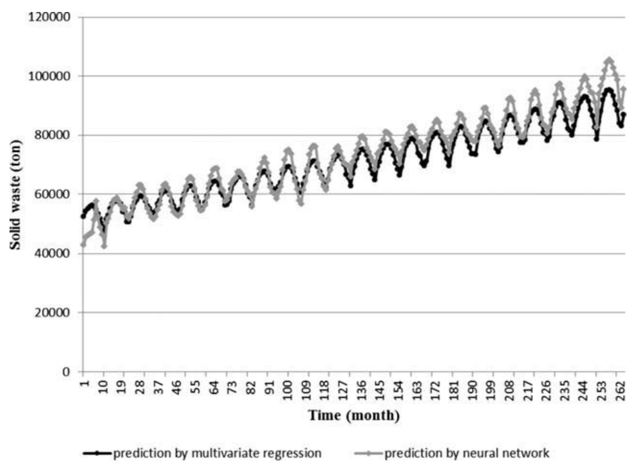

Figure 9. The comparison between predicted solid waste by regression model and ANN for the period of 2011–2032 (second case).

Figure 9 depicts the comparison of ANN predicted results with the predicted solid waste values derived from regression model. Based on the preprocessing, which was implemented on input data, the model could precisely predict the overall trend of the future SWG due to the existing trend in independent variables. Results showed that taking logarithm will increase the accuracy of the prediction. According to Figure 9, research findings indicate that if a time series is modeled with ANN by uncertain components, the results would be more reliable. It is because the data are scaled better, so that the ANN could see a wider range. In the second case, taking logarithms could improve the results of the model.

In Figure 10, the effect of different training algorithms on the *R* and MSE values is illustrated for 3:5:5:1 structure. According to this figure, traingda algorithm makes maximum value of *R* and minimum value for MSE.

Another criterion for selecting the best fitted model is a Ts of the two models. In Figure 11, the cumulative distributions relative errors are depicted, and the different values of Ts for the error level of 4, 8, and 12% are counted in Table 6.

Table 6 and Figure 10 illustrate that by the logarithm transformation of the time series data, 90% of the pre-

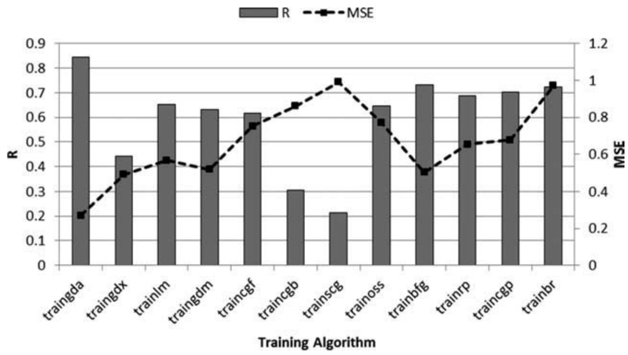

Figure 10. Impact of different training algorithms on the error and correlation coefficient in 3:5:5:1 structure of MLP.

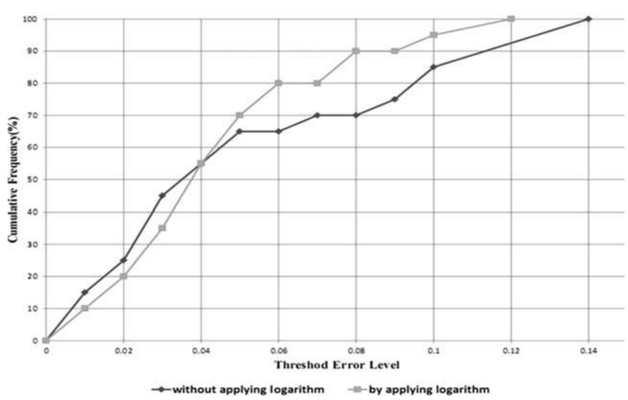

Figure 11. Cumulative distribution of relative errors.

dicted points contain errors less than 8%, whereas without the logarithm transformation, this figure decreases to 70%. Hence, it can be concluded that the logarithm transformation of the time series data helps them reaching more stationary chains and would cause more reliable predictions. Likewise, in stationary conditions, the number of the neurons in hidden layers decreases and leads to have a more elementary network.

Results indicate that MLP approach, similar to the previous studies such as Noori et al. [3], has more advantages in comparison with traditional methods in predicting the municipal SWG.

CONCLUSION

In this study, the capability of the ANNs for modeling long-term SWG time series is evaluated. Population, household income, and maximum temperature are assumed as the effective factors on SWG in Mashhad (regarding the availability and predictability of the dada and having more correlation with solid waste) and considered as the input time series. Forecasting data for maximum temperature values and the number of population have been done by Mashhad authorities. Values of household income are predicted considering the economic growth rate of 5.5% for the period of 2011–2032. To long-term prediction using neural network, a preprocessing should be applied on the data to fix the interpolation issue of models. For this pur-

Table 6. The values of Ts for the two case.

Models	TS 4	TS 8	TS12
First case	55	70	95
Second case	55	90	100

pose, the uncertain component of time series has been used in forecasting process. In the first case, data trend was omitted, and, in the second case, first, logarithm is taken from data and then the trend was removed. With regard to the processed data for the two cases, different structures of neural network were examined, and, by considering performance indices, the best model was chosen in each case, and output parameters are obtained through the selective model. All preprocessing are also reversed in output parameters. To scrutinize the results of modeling with neural network, the MLP applied forecasting results for the next 22 yrs are compared to the results obtained from regression model, and it was determined that whatever data become more stationary, neural network model can follow trends, and fluctuations more accurate.

Based on this investigation, the following conclusions can be made:

First, a stationary condition can provide more reliable and accurate simulation, especially in long-term prediction. Logarithm transformation, removing the trend, and standardizing the residuals can create the stationary conditions.

Second, forecasting the generated solid waste by considering a single explanatory variable is not satisfactory, because the solid waste is heterogeneous and can be affected by numerous factors. Hence, considering more explanatory variables will cause more reliable simulations.

Third, estimation of the future values for valid explanatory variables is a significant issue in forecasting the solid waste. So, the variables should be used in the simulation that can be forecasted with high accuracies for a long forecasting horizon. Apparently, having more accurate data for the household income can lead to a more reliable prediction.

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