

Optimization and forecasting of urban solid waste management by Artificial Neural Networks

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Abstract

Urban solid waste (USW) is the natural result of human activities. USW generation modeling is of major significance in programming and planning solid waste management system. Every year, the municipality spends more than ۷۰% of its budget for collection and transportation of solid waste. Waste disposal is essential and is also very expensive. Due to high fluctuation of the amount of the produced waste in Urmia over time, the use of neural networks is appropriate method to optimize and predict the amount of the produced waste based on non-linear and complex relationships between inputs and outputs. In this study, extra parameters such as number of labor, van and truck (waste collection and transport) were employed to assess their effect in improvement structure of ANN model and training performance of generated model. The monitoring data from summer of ۲۰۱۳ are designed to provide the requirements of training and testing the neural network. Finally, with respect to RMSE and R^2 , suitable models for optimization and forecasting of solid waste were selected for the study. Results point out that artificial neural network model has more advantages in comparison with traditional methods, in optimizing and predicting the municipal solid waste generation.

Keywords: Urban solid waste, artificial neural networks, batch back propagation, solid waste management

Introduction

Solid waste management is an important component in the environmental system, and plays a key role in population health. Furthermore, Municipal Solid Waste Management (MSWM) is one of the critical environmental management challenges which is being faced by many developing countries including Iran due to a rapid urban development.

A suitable management system should be developed for the disposal of MSW to ensure that people's health is not endangered because of environmental pollution. In fact the overall goal of urban solid waste management is to collect, treat and dispose of solid wastes generated by all urban population groups in an environmentally and socially satisfactory manner using the most economical means available.

It's an uphill struggle to implement such a system because of the complicated and wide-ranging nature of the waste. Working out the amount of waste produced is of vital importance to set up a solid waste management system (SWMS).

In developing countries, it is common for municipalities to spend ۲۰-۵۰ percent of their available recurrent budget on solid waste management. Yet, it is also common that ۳۰-۶۰ percent of all the urban solid waste in developing countries is uncollected and less than ۵۰ percent of the population is served. In some cases, as much as ۸۰ percent of the collection and transport equipment is out of service, in need of repair or maintenance. In most developing countries, open dumping with open burning is the norm.

The activities of the municipal solid waste management system can be categorized as six functional elements which are: (i) waste generation; (ii) handling, separation, storage, and processing at the source; (iii) collection; (iv) transfer and transport; (v) separation, processing and transformation; and (vi) disposal (Jafarzadeh et al., ۲۰۱۲b).

The collection and transportation of solid waste in urban areas is a very hard and complicated problem. Collection and transportation of solid waste often accounts for a substantial percentage of the total waste management budget (including labor costs). Therefore, even a small improvement in the collection operation can result to a important saving in the overall cost (Badran et al., ۲۰۰۶; Lopez et al., ۲۰۰۸; Rahman et al., ۲۰۱۴).

There are many ways to assess the waste generation (WG) rates, the most instrumental of which are load-count analysis, weight-volume analysis and materials-balance analysis. In this study, an artificial neural network (ANN) was trained and tested to model waste generation for Urmia city, the capital city of West Azarbaijan province in Iran.

Input data, containing waste generation observation and the numbers of labour, number of trucks and Vans which carry waste were obtained from Urmia Recycling and Material Conversion Organization. The ANN models are basically designed on the perceived working of the human brain. The artificial model of the brain is known as ANN (Jafarzadeh et al., ۲۰۱۲).

For this reason, ANNs have been usefully applied to a wide variety of problems that are convoluted, define, and gauge; for example, in finance, medicine, engineering, etc. Recently, ANNs have been used in the management of MSW such as a proposed model based on ANN to foresee the rate of leachate flow rate in places of solid waste disposal in Istanbul, Turkey (Karaca & Ozkaya, ۲۰۰۶); the prediction of energy content of a Taiwan MSW using multilayer perception neural networks (Shu et al., ۲۰۰۶); HCl emission characteristics and back-propagation prediction by neural networks in MSW/coal co-fired fluidized beds (Chi et al., ۲۰۰۵), recycling strategy and a recyclability assessment model based on an ANN (Liu et al., ۲۰۰۲) and the prediction of heat production from urban solid waste by ANN and multivariable linear regression in the city of Nanjing, China (Dong, et al., ۲۰۰۳), have been evident in current practice.

Also, ANNs have been used in other environmental problems like air pollution and surface water pollution (Sahoo, et al., ۲۰۰۶ ; Shrestha & Kazama, ۲۰۰۷). The results of all these research are evident of the high performance of ANN in prediction of various environmental factors.

Methodology

In this paper, an artificial neural network (ANN) was trained and tested to model waste generation (WG) in Urmia city. Input data consist of waste generation observation and the number of Vans and Trucks which carry waste, number of labor were obtained from Urmia Recycling and Material Conversion Organization.

The monitoring data from Summer of ۲۰۱۳ were designed to provide the requirements for training and testing the neural network.

A multi layer perceptron (MLP) feed-forward neural network which was trained with an error back-propagation algorithm was employed in this work. It consists of an input layer, one or more hidden layers and one output layer. The number of neurons in the input layer and the output layer were determined by the numbers of input and output parameters, respectively. Therefore, the networks with three neurons in the input layer (number of labor, number of van, number of truck) and one neuron in the output layer (carried weight of solid waste) were designed. In order to find the optimal architecture, the number of neurons in the hidden layer had to be determined by developing several networks that varied only with the size of hidden layer and simultaneously observing the change in the root mean squared errors (RMSE). In this study, neurons in the hidden layer are varied from ۱ to ۱۰.

In order to perform a supervised training, a way in which the ANN output error between the actual and the predicted output could be evaluated is therefore required. This is very well suited to the training of the neural network. Decision on the optimum topology and algorithm was based on the minimum error of testing. All topologies were evaluated based on the root mean square error (RMSE) and coefficient of determination (R^2) as a measure of the predictive ability as follows:

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^n (y_i - y_{di})^2 \right)^{\frac{1}{2}} \quad ۳,۱$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - y_{di})^2}{\sum_{i=1}^n (y_{di} - \bar{y})^2} \quad ۳,۲$$

Where 'n' is the number of points, 'y_i' is the predicted value and 'y_{di}' is the actual value. The ANN modelling was done using Neural Power, professional version ۲,۰ (CPC-X Software, Regsoft Inc.) for the current study. This software is a Windows®-based package, which supports several types of training algorithms.

RESULT AND DISCUSSION

In this study, three factors affecting the amount of carried load of solid waste collected. The data were from summer ۲۰۱۳ including the amount of van, lorry and labour and the carried load. Prior to data analysis all data were subjected to normality test using one sample Kolmogorove-Smirnove test. The one sample K-S test, more commonly known as the K-S test, takes the observed cumulative distribution of scores and compares them to the theoretical cumulative distribution of a normally distributed population. Table ۴,۱ is produced which details the normality of solid waste system variables.

The data analysis was done using SPSS ۱۷,۰. The results of this test are given in Table ۴,۱.

۴, ۱ One-Sample Kolmogorov-Smirnov Test

Analysis		labor	van	truck	weight
N		۲۲	۲۲	۲۲	۲۲
Normal Parameters ^{a,b}	Mean	۳۸,۵۹۰.۹	۴,۷۲۷.۳	۲,۳۶۳.۶	۲۶,۵۹,۶۸۱.۸
	Std. Deviation	۸,۹۶۹.۰۴	۲,۲۲۹.۲۸	۱,۲۹۲.۶۷	۹۶۸۷,۲۴۲.۶۳
	Max	۶۰	۱۰	۶	۴۷۲۸۹
	Min	۲۶	۲	۱	۱۲۴۶۸
Kolmogorov-Smirnov Z		.۷۵۷	۱,۴۵۳	.۸۲۰	.۸۷۴
Asymp. Sig. (۲-tailed)		.۶۱۶	.۰۲۹	.۵۱۱	.۴۲۹

a. Test distribution is Normal.

b. Calculated from data.

The first part of the One-Sample Kolmogorov-Smirnov test output table shows N (number of data), Minimum, Maximum, Mean and Standard Deviation. To check the normally distributed of the data, Asymp. Sig. (۲-tailed) values should be > 0.05 to indicate that the observed distribution corresponds to the theoretical distribution. The data is not significantly different to a normal distribution at the $p < 0.05$ level of significance. From the table it can be seen that the variables have Asymp. Sig. (۲-tailed) values > 0.05 , therefore all the variables can be assumed to normally distributed.

Network structure includes ۳ inputs, single hidden layer, and ۱ output. In order to estimate the number of neurons in hidden layer for the best modelling and prediction, a series of topologies (from ۱ to ۱۰ hidden neurons) were examined using batch back propagation (BBP). During learning of a network to avoid the "overfitting" phenomenon, the testing stage was used to control error, and when it increased, the training was stopped. ۱/۴ of the input data were selected as testing data set and the rest of the data (۳/۴) were applied as training data set. Decision on the optimum topology and algorithm was based on the minimum error of testing. All topologies were evaluated based on the root mean square error (RMSE) and coefficient of determination (R^2) as a measure of the predictive ability.

Evaluation results of ANN for batch back propagation (BBP) with different number of neurons in hidden layer is explained as in table ۴,۲.

Table ۴,۲ Statistical measures and performances of the algorithm in testing and training data sets

	structure	Training set		Testing set	
		RMSE	R^2	RMSE	R^2
BBP Algorithms	۳-۵-۱	۱۷۸۱	۰,۹۴۸۹	۱۷۹۳	۰,۹۴۶۶
	۳-۶-۱	۱۷۵۵	۰,۹۴۴۱	۱۷۸۵	۰,۹۴۳۲
	۳-۷-۱	۱۷۱۸	۰,۹۶۰۹	۱۷۷۴	۰,۹۴۲۷
	۳-۸-۱	۱۸۲۲	۰,۹۳۲۰	۱۸۳۶	۰,۸۹۷۵
	۳-۹-۱	۱۸۱۴	۰,۹۲۲۶	۱۸۱۳	۰,۹۱۳۳

based on the lowest prediction error (RMSE) and highest predictive power (R^2), it was found that a network with ۷ neurons in hidden layer had produced the best performance when the BBP algorithm was employed which is used as the best model to predict the carried load in solid waste system.

Figure ۴,۱ and ۴,۲ shows the amount of conformity between actual load and predicted load in testing and training set.

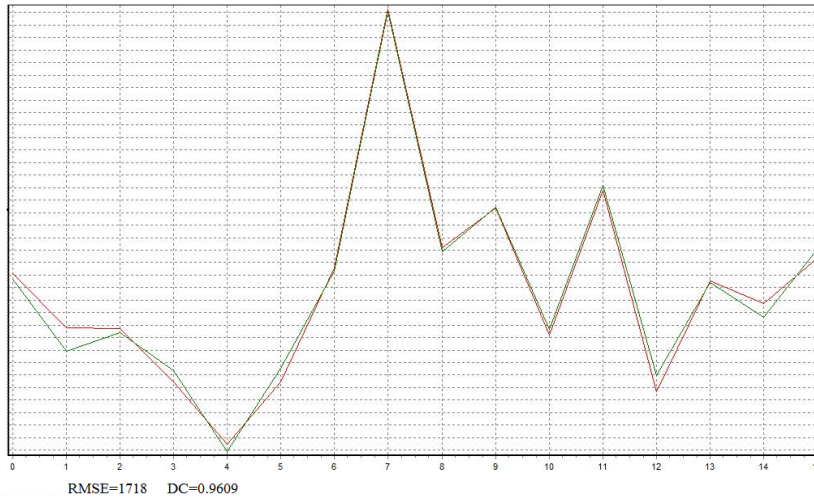


Figure 4,1 Prediction error (RMSE) in testing data set for best model (7 neurons) of BBP algorithm.

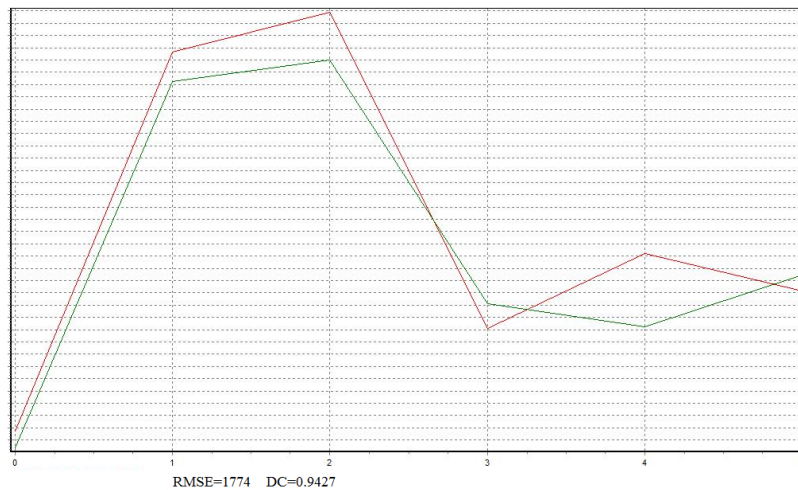


Figure 4,2 Prediction error (RMSE) in testing data set for best model (3 neurons) of BBP algorithm.

Model validation

The predictive ability of the generated model was estimated using the validation data which were excluded from the training. The actual and predicted loads are summarized in Table 4,3. The coefficient of determination (R^2) for the validation data is 0.9063. These results show that the predictive accuracy of the model is high. Therefore, 3-7-1 model in BBP algorithm is a suitable and valid model for prediction. Figure 4,4 shows a comparison between the actual values and the predicted values using the adopted neural network model.

Table ۴,۳ Actual and predicted values for validation data (summer ۲۰۱۳)

labor	van	truck	Actual weight	Predicted weight
۳۶	۲	۴	۲۴۹۱۴	۲۵۳۸۳,۷۶۸
۳۲	۱	۴	۱۹۹۷۵	۱۹۷۴۱,۵۱۵
۲۸	۲	۳	۱۴۴۱۸	۱۵۹۷۸,۶۴۹
۳۰	۱	۴	۱۸۴۹۹	۱۸۲۲۹,۵۳۸
۲۶	۳	۲	۱۱۴۱۵	۱۳۹۸۵,۱۳۱
۲۶	۴	۲	۱۵۴۱۹	۱۴۴۵۵,۲۸۹
۳۱	۴	۲	۱۷۷۲۲	۱۸۷۳۶,۹۹۱
۳۵	۲	۴	۲۲۴۷۰	۲۴۶۳۴,۰۶۴

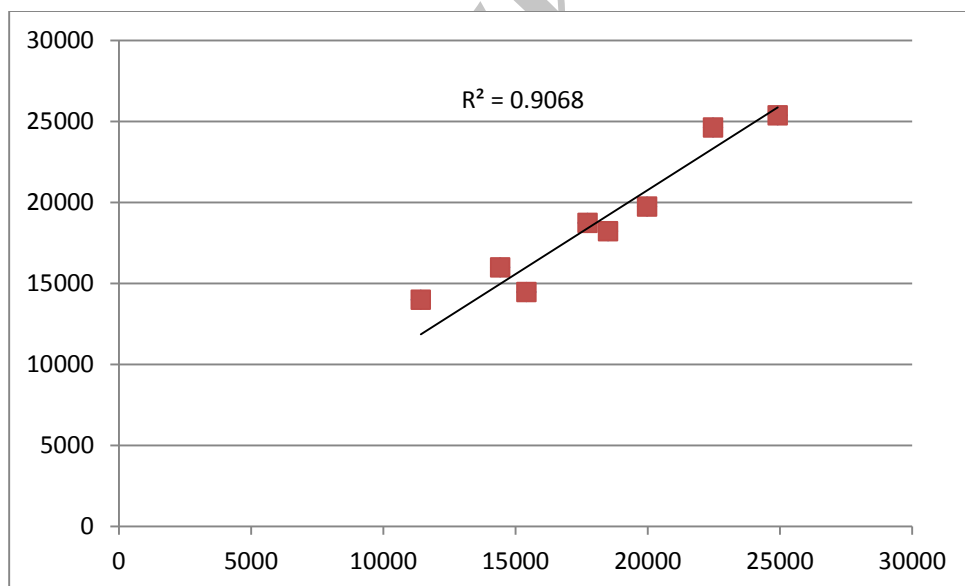


Figure ۴,۴ The scatter plot of ANN predicted load versus the actual load for validating model

Optimization by ANN

Also whit according the most carried loud of solid waste, ANN proposed combination model of impact variables that present in table ۴,۴

Table ۴, ۴ optimum combination of solid waste management system

	Max.- ۱	Max.- ۲	Max.- ۳	Max.- ۴	Max.- ۵
weight	۴۶۴۴۳,۰۶	۴۶۳۷۳,۲۶	۴۶۲۱۲,۲۴	۴۶۲۰۰,۵۵	۴۶۱۰۵,۶۹
A	۶۰	۶۰	۶۰	۶۰	۶۰
B	۱۰	۹,۲	۱۰	۸,۴	۹,۲
C	۶	۶	۵,۵	۶	۵,۵

Conclusion

This study indicated that optimizing and predicting carried weight is possible by using characteristic of artificial neural network (ANN) that reflect the accurate of nonlinear behavior of transportation system demand. The most unique part of this model is that for the first time optimization and prediction of solid waste has been done by the analysis of artificial neural network and combining the amount of generated waste, total of labor and quantity and quality of transport as input data. The results show that ANN is able to optimize and predict of solid waste management system based on maximum efficiency. The methodology or an adapted form of the methodology might also be applied to other fields, subject to the study of requirements in each place.

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