Application of Artificial Neural Network in Prediction of Municipal Solid Waste Generation (Case Study: Saqqez City in Kurdistan Province)

Himan Shahabi, Saeed Khezri, Baharin Bin Ahmad and Hasan Zabihi

Department of Remote sensing, Faculty of Geoinformation and Real Estate, Universiti Teknologi Malaysia (UTM), 81310, UTM Johor Bahru, Johor, Malaysia
Department of Physical Geography, Faculty of Natural resources, University of Kurdistan, Iran
Department of Geoinformatics, Faculty of Geo Information and Real Estate, Universiti Teknologi Malaysia, UTM, 81310 Johor Bahru, Johor, Malaysia

Abstract: Over the years, the management of municipal solid waste (MSW) has been improved to some extent through installation of various schemes, development of new treatment technologies and implementation of economic instruments. Despite such progress, solid waste problems still impose an increasing pressure on cities and remain one of the major challenges in urban environmental management. Although approximating of waste generation in its management is important, the prediction of its production is a difficult job due to the effect of various factors on it. Artificial intelligence is an exciting and relatively new application of computers. It provides new opportunities for harnessing the scarce and often scattered pieces of valuable knowledge and experience in solid waste management which at present is in the possession of the privileged few. While conventional algorithmic programming replaced much of the sophisticated and repetitive analytical work of the solid waste practitioner, artificial intelligence is poised to take over the no-less important tasks of the ill-structured and less-deterministic parts of the planning, design and management processes. In this research with application of feed forward artificial neural network, we proposed an appropriate model to predict weight of waste generation in Saqqez city of Iran. For this purpose, we used time series of generated waste of Saqqez which have been arranged weekly, from 2004 to 2007. After performing of the mentioned model, determination coefficient (R²) and mean absolute relative error (MARE) in neural network for test have been achieved to be equal to 0.648 and 2.17% respectively.

Keywords: Municipal Solid Waste · Artificial Neural Network · Waste Generation · Statistical Indices · Iran

INTRODUCTION

In developing countries, the ever increasing human population and the associated anthropogenic activities have accelerated the phenomenon of urbanization in the past decade. With the rising population and the associated unsustainable practices, there has been an enormous increase in the quantum as well as the diversity of the solid waste being generated [1]. If an appropriate management system is not used for waste disposal, 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 [2]. Being aware of generation quantity can be very effective for estimating the amount of investigation in the field of machinery, on site storage containers, transition stations, disposal capacity and proper organization. There are different ways to estimate the waste generation (WG) rates; the most prominent of
them are load-count analysis, weight-volume analysis and materials-balance analysis [3]. However, although these are the basic methods for estimating the measure of generated waste, 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) [4]. 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 a society and they are computed according to the generation coefficient per person. Since these coefficients change during the time, they are useless devices for dynamics of SWMS. For these reasons, employing new methods and advanced techniques can be useful for computing 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 [5-7].

In this study, artificial neural networks (ANN) was trained and tested to model weekly waste generation (WWG) in the Saqqez city in kurdistan Province of Iran. The input data, consisting of observation of WWG and trucks that carried wastes are obtained from Saqqez waste recycling organization. Artificial Neural Networks (ANNs) are simplified computational models of the brain [8]. They attempt to emulate some of the functions of the brain such as learning from experience and the capability of solving problems by using, modifying and extrapolating acquired knowledge [9, 10]. ANNs are capable of classifying patterns, clustering, approximating functions, forecasting, optimising results and controlling inputs such that a system follows a desired trajectory [11, 12]. An ANN is formed by a large number of processing neurons interconnected by weights, which represent the influence of one neuron on another. ANNs were first introduced in the 1940s [13]. Interest grew in these tools until the 1960s when Minsky and Papert, [14] showed that networks of any practical size could not be trained effectively. It was not until the mid-1980s that ANNs once again became popular with the research community when Rumelhart and McClelland, [15] rediscovered a calibration algorithm that could be used to train networks of sufficient sizes and complexities to be of practical benefit. 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 disposal solid waste site in Istanbul, Turkey [16], prediction for energy content of Taiwan MSW using multilayer perceptron neural networks [17], HCl emission characteristics and back propagation neural networks prediction in MSW. coal co-fired fluidized beds [18], recycling strategy and a recyclability assessment model based on an ANN [19] and prediction of heat production from urban solid waste by ANN and multivariable linear regression in the city of Nanjing, China [20], have been become in current. Also the other environmental issues like air pollution [11, 21, 22], surface water pollution [23, 24], the ANNs have been used. The results of these researches have shown the high performance of ANN in prediction of various environmental subjects like waste production.

**MATERIALS AND METHODS**

**Case Study and Data:** The population of Saqqez in the latest census was estimated about 140000 people. Therefore, this City is selected as the study area. Saqqez county is in the northwest part of Iran with an area of 4911Km² (Fig. 1). In this city, municipality is in charge of collection of MSW. In latest years, increasing of emigration to this city has caused expanding the WG and as a result making problems for the SWMS. According to the Recycling and Material Conversion Organization report, with production of 140 tons of waste in 2006, Saqqez was one of the biggest centers of WG in Kurdistan Province of Iran. On the other hand, the high fluctuation of WG as a result of high numbers of emigrants of marginal villages to the city have made many problems in SWMS.

According to Existing reports the amount of generated waste of Saqqez is between 100 to 140 ton per day. Therefore, employing an appropriate model for the estimation of the quantity of generated waste can be useful for programming and resultant decisions being made by relevant organizations.
Since having seasonal patterns of production waste can have an effective role in its estimation and also fluctuation in this city, a time series model of WG was made for predicting the amount of generated waste in Saqqez (Table 1). 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 has been shown in Fig.2. Another input data, consists the number of trucks which carry waste in week of t (Tr), so composition of waste in Kurdistan Province has been shown in Table 2.

**Models Applied:** 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). A schematic diagram for an artificial neuron model is shown in Fig. 3.

![Study area: Saqqez city in Kurdistan province in Northwest of Iran](image1)

**Fig. 1:** Study area: Saqqez city in Kurdistan province in Northwest of Iran

![Weekly fluctuation of WG in Saqqez](image2)

**Fig. 2:** Weekly fluctuation of WG in Saqqez

![Artificial neuron model](image3)

**Fig. 3:** Artificial neuron model

**Table 1:** Quantity of urban solid waste production and daily in different seasons of Saqqez (2006)

<table>
<thead>
<tr>
<th>Season</th>
<th>Daily amount of generate waste (ton)</th>
<th>Daily production (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spring</td>
<td>140</td>
<td>1.037</td>
</tr>
<tr>
<td>Summer</td>
<td>120</td>
<td>0.889</td>
</tr>
<tr>
<td>Autumn</td>
<td>140</td>
<td>1.037</td>
</tr>
<tr>
<td>Winter</td>
<td>100</td>
<td>0.740</td>
</tr>
</tbody>
</table>
Let $X = (X_1, X_2, \ldots, X_m)$ represent the $m$ input applied to the neuron. Where $W_i$ represent the weight for input $X_i$ and $b$ is a bias then the output of the neuron is given by Eq. (1).

$$u = \sum_{i=1}^{m} x_i w_i - b$$

(1)

The artificial model of neuron consists of three elements as follows:

- A set of synapses or connection links, each of which is characterized by a weight or strength of its own. Specially, a signal $x$ 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.

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

- 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 effect of increasing or lowering the net input of the activation function depending on whether it is positive or negative, respectively. In mathematically, the neuron $k$ will be described by the following equation:

$$w_k = \sum_{j=1}^{m} w_{kj} x_j$$

(2)

where $x_1, x_2, \ldots, x_m$ are the input signals; $w_{1k}, w_{2k}, \ldots, w_{mk}$ are the synaptic weights of neuron $k$. The activation function, denoted by $net$, defines the output of a neuron which considerably.

$$Net = u + b$$

(3)

$$y = f(Net)$$

where $b_i$ is threshold value and is activation function. Three basic types of activation function are generally used in ANN as follows:

- Piecewise-linear function
- Threshold function
- Sigmoid function

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

(4)

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

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

where $a$ is the slope of the activation function. In this paper, neural network is trained and tested.

Using the monitoring data belonging to 2004-2007 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 $[0, 1]$. 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:

$$X_{norm} = 0.8 \left[ \frac{x - x_{min}}{x_{max} - x_{min}} \right] + 0.1$$

(5)
The most popular architecture for a neural network is a multilayer perception [25, 26]. In this study, we used was the feed forward, multilayer perceptron (MLP), which is considered able to approximate every measurable function [27]. 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 under fitting or over fitting [28]. 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 total observation number 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:

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} \left| w_o^i - w_p^i \right| 
\]

\[
MARE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{w_o^i - w_p^i}{w_o^i} \right| 
\]

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (w_o^i - w_p^i)^2} 
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (w_o^i - w_p^i)^2}{\sum_{i=1}^{n} (w_o^i - w_o)^2} 
\]

where \(w_o^i\) is the actual values of \(W_i\) with \(i = 1, 2, ..., n\) weeks observations, \(w_o' \) is the average of \(W_i, n\) is the total observation number and \(w\) is the predicted \(W_i\) value.

**RESULTS AND DISCUSSION**

To achieve the best network structure for estimating generated waste, various structures of feed forward neural networks with three layers (input layer, hidden layer and output layer) and different number of neurons in hidden layer were investigated. Finally, with consideration MAE, MARE, RMSE and \(R^2\) appropriate models were selected. As training and transfer functions, TRAINLM and TANSIG were used respectively. The results of training and testing of network are given in Table 3.

<table>
<thead>
<tr>
<th>ANN Model structure</th>
<th>MAE</th>
<th>MARE%</th>
<th>RMSE</th>
<th>R2</th>
<th>MAE</th>
<th>MARE%</th>
<th>RMSE</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>13-2-1</td>
<td>135</td>
<td>2.10</td>
<td>176</td>
<td>0.265</td>
<td>248</td>
<td>2.87</td>
<td>411</td>
<td>0.666</td>
</tr>
<tr>
<td>13-3-1</td>
<td>146</td>
<td>2.8</td>
<td>286</td>
<td>0.359</td>
<td>295</td>
<td>2.43</td>
<td>383</td>
<td>0.622</td>
</tr>
<tr>
<td>13-4-1</td>
<td>201</td>
<td>2.80</td>
<td>311</td>
<td>0.644</td>
<td>243</td>
<td>2.63</td>
<td>391</td>
<td>0.63</td>
</tr>
<tr>
<td>13-5-1</td>
<td>211</td>
<td>2.74</td>
<td>182</td>
<td>0.389</td>
<td>279</td>
<td>2.77</td>
<td>449</td>
<td>0.632</td>
</tr>
<tr>
<td>13-6-1</td>
<td>123</td>
<td>2.12</td>
<td>193</td>
<td>0.779</td>
<td>287</td>
<td>2.54</td>
<td>410</td>
<td>0.607</td>
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<tr>
<td>13-7-1</td>
<td>177</td>
<td>1.76</td>
<td>198</td>
<td>0.482</td>
<td>309</td>
<td>2.49</td>
<td>394</td>
<td>0.654</td>
</tr>
<tr>
<td>13-8-1</td>
<td>125</td>
<td>2.1</td>
<td>179</td>
<td>0.899</td>
<td>270</td>
<td>2.52</td>
<td>386</td>
<td>0.627</td>
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<tr>
<td>13-9-1</td>
<td>165</td>
<td>1.35</td>
<td>152</td>
<td>0.762</td>
<td>259</td>
<td>2.55</td>
<td>388</td>
<td>0.677</td>
</tr>
<tr>
<td>13-10-1</td>
<td>172</td>
<td>2.50</td>
<td>243</td>
<td>0.73</td>
<td>257</td>
<td>2.25</td>
<td>366</td>
<td>0.64</td>
</tr>
<tr>
<td>13-11-1</td>
<td>170</td>
<td>2.42</td>
<td>238</td>
<td>0.352</td>
<td>298</td>
<td>2.77</td>
<td>364</td>
<td>0.69</td>
</tr>
<tr>
<td>13-12-1</td>
<td>157</td>
<td>1.38</td>
<td>118</td>
<td>0.848</td>
<td>285</td>
<td>2.62</td>
<td>401</td>
<td>0.615</td>
</tr>
<tr>
<td>13-13-1</td>
<td>127</td>
<td>1.27</td>
<td>113</td>
<td>0.728</td>
<td>243</td>
<td>2.33</td>
<td>423</td>
<td>0.67</td>
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<tr>
<td>13-14-1</td>
<td>120</td>
<td>2</td>
<td>174</td>
<td>0.805</td>
<td>267</td>
<td>2.45</td>
<td>384</td>
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<td>13-15-1</td>
<td>117</td>
<td>1.98</td>
<td>127</td>
<td>0.391</td>
<td>257</td>
<td>2.22</td>
<td>456</td>
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<tr>
<td>13-16-1</td>
<td>111</td>
<td>1.93</td>
<td>153</td>
<td>0.798</td>
<td>232</td>
<td>2.17</td>
<td>372</td>
<td>0.648</td>
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<tr>
<td>13-17-1</td>
<td>241</td>
<td>1.85</td>
<td>173</td>
<td>0.295</td>
<td>331</td>
<td>2.46</td>
<td>433</td>
<td>0.655</td>
</tr>
<tr>
<td>13-18-1</td>
<td>122</td>
<td>2.09</td>
<td>195</td>
<td>0.77</td>
<td>278</td>
<td>2.63</td>
<td>396</td>
<td>0.61</td>
</tr>
<tr>
<td>13-19-1</td>
<td>208</td>
<td>2.04</td>
<td>192</td>
<td>0.82</td>
<td>337</td>
<td>3.13</td>
<td>377</td>
<td>0.611</td>
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<tr>
<td>13-20-1</td>
<td>212</td>
<td>2.94</td>
<td>335</td>
<td>0.826</td>
<td>316</td>
<td>3.14</td>
<td>389</td>
<td>0.623</td>
</tr>
<tr>
<td>13-21-1</td>
<td>201</td>
<td>2.83</td>
<td>294</td>
<td>0.183</td>
<td>278</td>
<td>2.56</td>
<td>378</td>
<td>0.625</td>
</tr>
<tr>
<td>13-22-1</td>
<td>119</td>
<td>2.03</td>
<td>185</td>
<td>0.777</td>
<td>278</td>
<td>2.56</td>
<td>378</td>
<td>0.625</td>
</tr>
<tr>
<td>13-23-1</td>
<td>132</td>
<td>2.01</td>
<td>248</td>
<td>0.632</td>
<td>291</td>
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<td>402</td>
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<td>13-24-1</td>
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<td>2.87</td>
<td>311</td>
<td>0.747</td>
<td>319</td>
<td>2.95</td>
<td>400</td>
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<tr>
<td>13-25-1</td>
<td>158</td>
<td>2.49</td>
<td>301</td>
<td>0.286</td>
<td>311</td>
<td>2.89</td>
<td>478</td>
<td>0.618</td>
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<tr>
<td>13-26-1</td>
<td>116</td>
<td>2</td>
<td>176</td>
<td>0.815</td>
<td>362</td>
<td>3.38</td>
<td>499</td>
<td>0.579</td>
</tr>
</tbody>
</table>
Reference to Table 3, the best result is obtained using ANN structure of (13-16-1). These results are shown in figures 4 and 5.

The performance of different architecture are shown as MAE, MARE, RMSE and $R^2$ in table 3. Regarding to this table the architect of (13-16-1) was found to be more efficient in compare to other models (MAE=232 and MARE= 2.17%). The error distribution for this model is shown in Figure 5. The maximum absolute relative error (ARE) for 50% of the predicted $W_{i+1}$ is less than less than 1.59%. In addition, the ARE for 90% of the predicted $W_{i+1}$ in this model is less than 6.69%.

**CONCLUSION**

Major constraint in acceptability of ANN is its ‘Black box’ system approach, unable to explain the weights (parameters) and interreleationship between the inputs and output. As the ANN is an alternate statistical method, the results should be compared in terms of statistical performance criteria. we believe desirable properties of ANN models to include: (1) the ability to coordinate various process control tasks such as prediction, diagnosis and supervisory control, (2) the ability to integrate the solution approaches of data driven, analytical and knowledge-based systems, (3) the ability to coordinate different knowledge representations schemes such as rules, frames, models and cases, (4) the ability to maintain a global database and global management of process knowledge, (5) a hierarchical structure of data models on types of controllers, actuators, logical constraints, process models, faults and processes at various abstraction levels, (6) the ability to adapt to a changing environment. We believe future research on developing ANN models for prediction, diagnosis and Prediction of Municipal Solid Waste Generation should consider including all of the desirable properties. As in MSW management system, the prediction of Waste quantity is an important aspect, therefore the goal of this research was offering of a suitable model to predict this quantity. Three ANN layers were applied and adapted for the prediction of WWG in Saqqez city. At the first stage, we created the models with making changes in neurons of hidden layers. At the second stage, with respect to
the applied index, the optimal number of neurons in the hidden layer was determined. Finally, the best structure includes 16 neurons in the hidden layer were selected for the prediction of $W_{t+1}$ in the area under study.

REFERENCES