Comparison of Artificial Neural Network (ANN) and Multiple Regression Analysis for Predicting the Amount of Solid Waste Generation in a Tourist and Tropical Area—Langkawi Island

Elmira Shamshiry, Mazlin Bin Mokhtar, and Abdul-Mumin Abdulai

Abstract**—** Prediction of the accurate amount of solid waste is difficult work because several parameters affect it. There is a high degree of fluctuation in the prediction of amount of solid waste generation. Therefore, applying neural network as intelligent system can be a good option. In a tourist area such as Langkawi Island, protection of the area and pollution control are important issues; also it is significant for planning managers to obtain accurate forecasting of the quantities of solid waste generated. In this paper, weekly data of solid waste generation, types of trucks and their trips, number of personnel in per trips (entrance to landfill) during 2004-2009 have been used as variables, through feed forward back propagation, in the testing and training processes. In the last step, the best model for forecasting waste generation in Langkawi Island was selected based on mean absolute error, mean absolute relative error, correlation coefficient and threshold statistics. Validation of model is calculated for different hidden layer. Comparison between final result of ANN and Multiple Regression Analysis (MRA) showed the result of ANN is better than MRA, which suggests that ANN is a better modeling tool. Therefore, in terms of predictive accuracy test, the ANN has a higher accuracy than regression analysis.

Keywords**—**Prediction of Solid Waste Generation, Langkawi Island, Artificial Neural Network, Multiple Regression Analysis, comparison

I. Introduction

SOLID waste management is an important component in the environmental management system, and it plays a key role in the caring for human health. Although urbanization is a global phenomenon, its ramifications and challenges in terms of issues such as solid waste management are more pronounced in the developing countries. Municipal solid waste management (MSWM) is one of the critical environmental challenges of quick urban development facing the developing countries [34]. One of the most complicated problems of human society is the production of solid waste materials in different quantities and of different kinds.

Elmira Shamshiry*, Institute for Environment and Development (LESTARI), Universiti Kebangsaan Malaysia (UKM). 006-0172884912 Email id : ele_shame19@yahoo.com.

Mazlin Bin Mokhtar, Institute for Environment and Development (LESTARI), Universiti Kebangsaan Malaysia (UKM). Email Id: mazlin@ukm.my.

Abdul-Mumin Abdulai. Institute for Environment and Development (LESTARI), Universiti Kebangsaan Malaysia (UKM). Email id: mumins2003@yahoo.com

Establishing a management system of collecting and disposing of solid waste materials is important for the purpose of controlling production, consumption and the process of garbage collection and disposal. Furthermore, this, in turn, leads to the preservation of the environment, promotion of health in the society, and saving costs. In order to provide a comprehensive management system related to solid waste materials, six relevant factors of production, collection, transportation, saving, processing, recycling, and disposal need to be given attention [1], [2]. It has become very difficult to manage and organize environmentally sound solutions with the rising amount of waste generated by commercial, industrial, household and other human activities. Waste and its disposal are the inherent result of human life, and the dangers of mismanagement of the disposal are a serious problem in the world. Unfortunately, huge volumes of solid waste are generated nationwide, and as the population and economic activity increase, waste generation increases too. The outcomes of irregular solid waste dumping are causing some sort of crisis in many countries. There are many studies that have unfolded the effects of this crisis in terms of economic, social and environmental problems [3]. Besides the challenges that these problems have brought for governments, the irregular growth of population and development of cities have also increased the complexity of the problem [4]. Knowledge about the amount of SW produced can simplify assessment of investment total for appropriate organization of machinery, containers and capacity of disposal. Surveys about artificial neural networks normally connect 'neural networks' to the human brain, but the human brain calculates in a totally dissimilar technique from the usual digital computer. The brain is a very comprehensive, non-linear and equal computer (system of information processing). It has the ability to manage its structural components, accepted as neurons, and to present confident calculations several times more rapidly in comparison with the best digital computer these days. Human idea is a processing information mission. It is the visual system whose purpose is to supply an environment icon near us, and it is significant to provide the required information to interconnect with the environment [6]. The ANN approach is a branch of artificial intelligence [6], [7], [8], [9]. The brain's capabilities are able to learn, preserve the information and make it public [10], [11]. ANN is a software and model based on the system of human neurology. It is created from necessary input and calculates elements (nodes) interconnected with each other through strands of weighted communication [6], [9]. The source nodes (in the network input layer) offer respective aspects of the activation design (input vector) organize the input practical to the neurons in the second layer. In the brain, there are both small-scale and large scale descriptive organizations and different functions take place at lower and higher levels [7].

II. Materials And Methods

A. Study Area

The first global Geopark in Malaysia and Southeast Asia, Langkawi Geopark comprises 99 islands of Langkawi of the Kedah State, Malaysia. The total area of Langkawi consists of six sub-districts. Population in Langkawi's island has been reported about 98,000. The Majlis Perbandaran Langkawi (MPL) is responsible for MSW collection. A wide range of population and tourism in this Island in recent years has increased WG accordingly; it has created a problem for the SWMS. The establishment of Langkawi Geopark was initiated by the Malaysian Geological Heritage Group (MGHG), which since 2001 has identified the potential of Langkawi Islands as a world class Geopark [12], [13].

B. Methods

Furthermore, in a tourist area such as Langkawi there is a seasonal variation because of the in-out travelling of tourists and the increasing rate of the local population. Therefore, there is an important variation in WG and the exact amount of waste generated cannot be forecast [19]. So, employing new technique can be positive to calculate the dynamics of waste structure. In this research, the prediction of MSW generation has been investigated by using time series data, that is. Based on this method, "time" is employed as a forecaster variable, that is, that yearly, monthly, weekly and daily have been used in the analysis. The benefit of using time-series analysis is its flexibility, which needs just a few categories of statistics [20]. This research applied Artificial Neural Network (ANN), training and testing for modeling weekly waste generation (WWG) in Langkawi Island in Malaysia. Input data consist of WWG observation and the trucks, their kinds, and the number of trips that the trucks carry waste from waste generation source to disposal site (i.e., enter landfill), personnel number (just personnel work in collection and transportation of solid waste) and fuel cost (used by trucks during collection and transport of solid waste). The data were selected because they are directly involved in the amount of solid waste generated; the raw data were obtained from *Majlis Perbandaran Langkawi*. The monitoring data from 2004 to 2009 were used in the training and testing process, which is necessary in the neural network. In this model, the weight of waste in t+1 week (Wt+1), is a function of waste quantity in t (Wt), t-1 (Wt-1)… t-11 (Wt-11) weeks. Another input data, consist of the number of trucks which carry waste in the week of t (Trt), number of personnel (Pr) and fuel cost (Fu). This research used tangent Hyperbolic function for output layers and input layers used function Y=X. For prediction of solid waste amount, training and testing, the MATLAB R2009a software and neural network were applied [21], [22], [15], [16], [24], [25]. This study has chosen the activation functions of the hyperbolic tangent (that function was within the hidden layers). In this study, the artificial model of neurons are made of these factors that include a set of synapses that can be characterized by a weight of each synapse, the synaptic weight of an artificial neuron may be in a negative and positive values range. An adder for summing the input signals which are weighted by the respective synapses of the neuron. Activation functions or transfer functions which limit the output amplitude of a neuron [7]. The neuron model can also include an externally applied bias, which is shown by *bk*. The bias, positive or negative, may increase or decrease the net input of the activation function. Mathematically, the neuron k will be described by the following equations [7], [15], [16]:

$$\mathrm{w} = \sum wx$$

$$uk = \sum_{j=1}^{m} WkjXj$$

In this study, the data used in ANN method are separated into three fractions. The first part of them is relevant to training of network, the second fraction is applied for discontinue estimate when the integrity error begins to rise, and the last part is applied for the testing of network (integrity purpose). To examine the performance of the ANN model, four statistical indexes 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 from statistical calculations of observation in the model output predictions [28], [29], [31] [32], [15], [16], [35], [33].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|W0 - Wp| \tag{1}$$

$$MARE = \frac{1}{n}\sum_{i=1}^{n}\frac{|W0-Wp|}{W0} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(W0 - Wp)^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(W0-Wp)^2}{\sum_{i=1}^{n}(W0-W/p)^2} \tag{4}$$

In order to test the relationship between variables multiple regression equation is proposed for this prediction also.

III. Results And Discussion

Average weekly SW production, average weekly fuel consumption for SW collection and transportation, average weekly numbers and types of trucks that collect, carry and transport SW and the average number of personnel working in part of collection and transportation of SW per week are used in this research. The average and median amounts of waste generation are close together. According to the raw data, the amount of waste generation demonstrates a standard distribution among the seasons and the weeks. However, there is a fluctuation of SW generation in peak season.

The increasing number of people or tourists, climatic and economic conditions play important role in WG rate, thereby producing more solid waste. Various structures of feed-forward ANN through three layers organization with several neurons quantity in the hidden layer were considered in this research. This is to get the most excellent structure of ANN for calculating waste generation. In conclusion, by applying MAE, MARE, RMSE, TS and R2, the appropriate type of model was chosen in this study. To forecast the waste generated in the n-th week, waste generated in 12 previous weeks (N-1 to N-12), types and number of trucks used, fuel consumed and number of personnel in the previous 12 weeks were applied as 16-input to ANN with a structure of feed-forward. The network training was carried out according to the back propagation algorithm, and by employing the tangent hyperbolic function. To achieve the best results, 10-20 neurons in the hidden layer for network training were used to predict the amount of waste generation with 4 variables (i.e., personnel, types and number of truck and fuel consumption based on truck),which produced the greatest outcome. Also, 10–15 previous weeks were tested. Again, the testing process using 16 layers, which contain 12 layers of the previous week related to waste generation with four layers of the personnel, fuel consumption, types and number of machinery (trucks), produced the best results. For that reason, the structure of the network includes the 16-input layers, 1 hidden layer and 1-output. With the aim of estimating the neurons number in the hidden layer for better forecasting, hidden layers from 1-10 neurons were tested and the results are shown in Table 1. The result obtained stated that if the number of neurons in the layers is more than 10 neurons, the final answer will be deficient in correctness.

In the next step, validation assessment was done; therefore, ¼ of input data was chosen as testing data set and the remainder of them used as training data set. Based on the outcome, ANN structure with four neurons in the hidden layers was chosen as a best possible result which could decrease the computation issues and high accuracy. Nevertheless, ANN with one and four neurons in hidden layers could be utilized as the most favorable organization.

In the first step, a neural network with one neuron in the hidden layer was applied. Training and testing data sets were applied to the ANN. Predicted results are presented in Figures 1 and 2. The results indicate high accuracy in prediction. The relative errors are presented in Table 1.

In this step, a neural network with four neurons in hidden layer was applied. The correlation coefficient (R^2) of training and testing set increased 0.97888 and 0.98014, respectively. Training and testing data sets were applied to the ANN. Predicted results are presented in Figures 3 and 4. The results indicate high accuracy in prediction. The relative errors are presented in Table 1.

TABLE 1
CALCULATED ERRORS FOR ANNS WITH DIFFERENT NEURONS IN HIDDEN LAYERS APPLIED IN TRAINING AND TESTING DATA SETS FOR LANGKAWI ISLAND (2004-2009)

	Training set				Testing Set			
NO	MAE	MARE%	RSME	R^2	MAE	MARE%	RSME	R^2
16-1-1	91.25	0.0096	109.2	0.98	119.2	0.049	148.6	0.98
16-2-1	96.17	0.0099	111.6	0.97	107.2	0.037	145.8	0.95
16-3-1	101.7	0.0111	123.9	0.96	111.6	0.041	161.3	0.92
16-4-1	198.02	0.0201	241.5	0.98	131.9	0.048	179.4	0.98
16-5-1	176.1	0.0182	202.1	0.97	149.7	0.036	196.9	0.92
16-6-1	102.11	0.0117	123.5	0.96	137.5	0.046	181.2	0.95
16-7-1	108.04	0.0121	129.7	0.97	168.4	0.049	217.8	0.92
16-8-1	163.9	0.0184	201.1	0.96	159.4	0.061	207.9	0.97
16-9-1	106.1	0.0127	141.5	0.97	198.5	0.056	224.1	0.93
16-10-1	98.23	0.0107	119.7	0.97	185.6	0.041	229.7	0.96

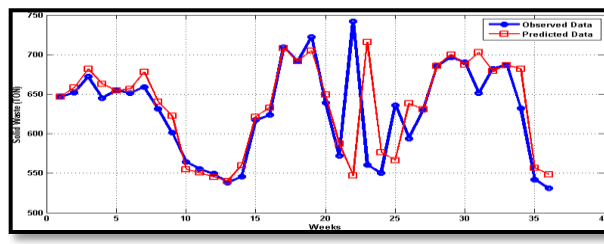


Fig. 1 Observed amount of solid waste and predicted output of ANN Model with one neuron in hidden layer for testing data set, Langkawi Island (2004-2009).

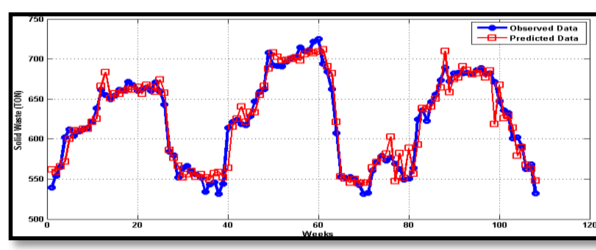


Fig. 2 Observed amount of solid waste and predicted output of ANN Model with one neuron in hidden layer for training data set, Langkawi Island (2004-2009).

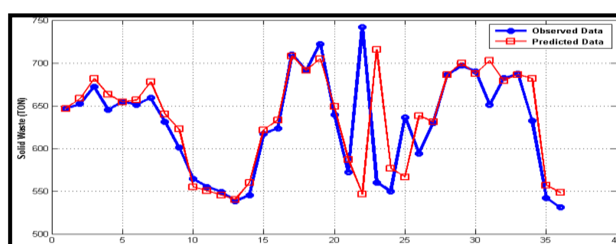


Fig. 3 Observed amount of solid waste and predicted output of ANN Model with four neurons in hidden layer for testing data set, Langkawi Island (2004-2009).

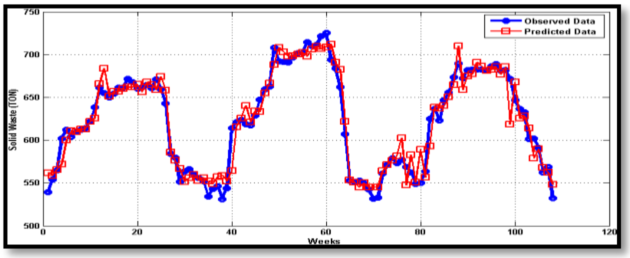
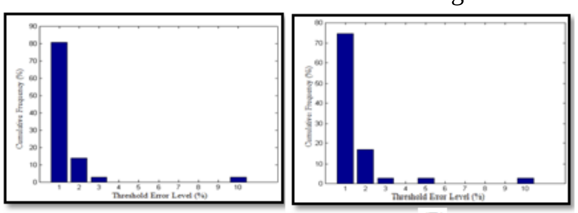


Fig. 4 Observed amount of solid waste and predicted output of ANN Model with four neurons in hidden layer for training data set, Langkawi Island (2004-2009).

Based on MAE and MARE, the model (16-4-1) gives better results than the model (16-1-1). While the R2 index is the same for these two models, the RMSE index for the second model produces better results than the first model. The results of model showed (16-4-1) and (16-1-1) had approximately similar answer based on MAE, MARE, RMSE and R^2 indexes. Since criteria explain the error average in model and they do not provide information regarding the error distribution, therefore, to test the model robustness by applying threshold statistics (TS) to estimate efficiency of criteria [37], [19]. According to Figure 5 (A) and (B) , absolute relative error (ARE) maximum for ninety four percent of the amount of waste generation predicted in the model of 16-1-1 was less than 2.99 % , and ARE for eighty eight percent related to predicted waste generation in model of 16-4-1 was less than 2.99 %. So the model with the structure of 16-1-1 had better results in comparison with the other model 16-4-1 in Langkawi Island.



(A) (B)

Fig. 5 (A) Absolute relative error for the structure of 16-1-1 and (B) 16-4-1 in the testing step of artificial neural network.

Multiple regression analysis using the stepwise method was used to find the important characters contributing to waste generation. For this purpose, all the variables used in the study were subjected to linear multiple regression analysis. Waste was used as a dependent variable and all the other variables were used as independent variables. Among the parameters studied, personnel showed no significant relation with waste, and it could not be considered as a proper variable for waste. In contrast, fuel and truck appeared to play an important role in waste generation.

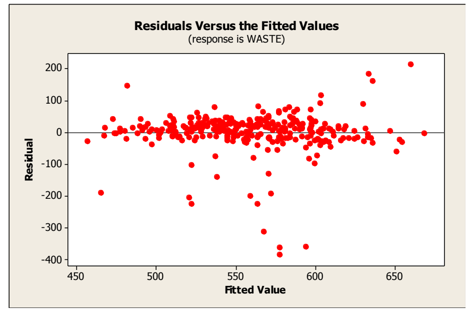


Fig. 6 Residuals versus the fitted values by response of waste in Langkawi Island

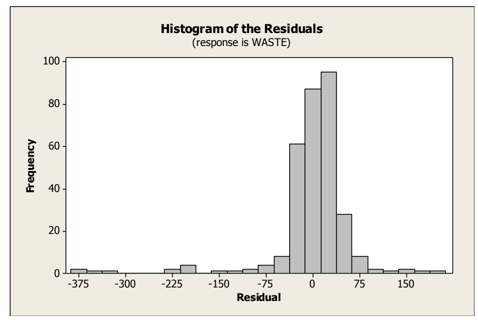


Fig. 7 Residuals histogram and frequency by response of waste in Langkawi Island

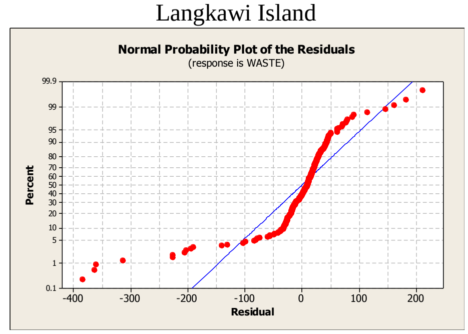


Fig. 8 Normal probability plot of the residuals percent by response of waste in Langkawi Island

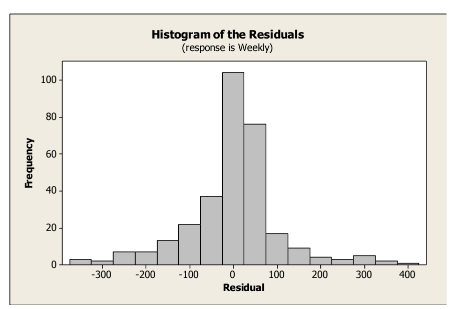


Fig. 9 Residuals histogram and frequency by response of weekly previous waste generated in Langkawi Island

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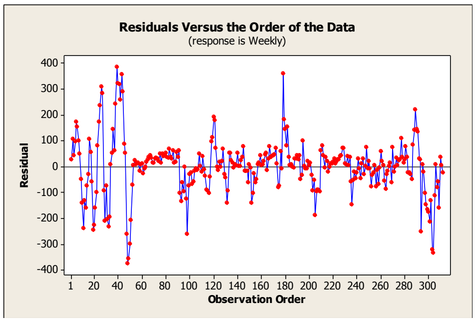

Fig. 10 Residuals versus the order of the data based on observation and residual by response of weekly previous waste generated in Langkawi Island

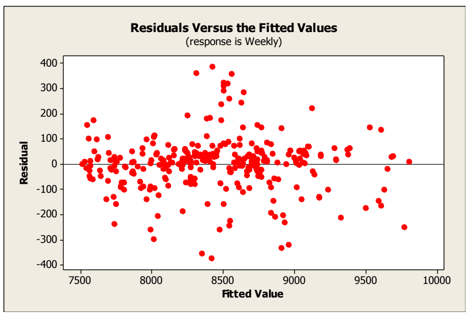

Fig. 11 Residuals versus the fitted values based on fitted value and residual by response of weekly previous waste generated in Langkawi Island

Using the number of trips that a truck makes as variable (that is, entering and leaving the landfill) has shown no strong correlation with solid waste generation. This is probably due to the different sizes of the trucks used to collect the wastes, that is, (the 2 kinds of truck). This means that larger truck needs lesser number of trips to finish the same volume of wastes than the medium to smaller trucks. However, there has been strong correlation between the independent variables (that is, truck, fuel and personnel) used in the prediction by ANN.

VI. Conclusion

Due to high fluctuations of the amount of the waste produced in Langkawi Island, especially in the peak seasons, the use of neural networks is appropriate method in comparison with regression to predict the amount of the waste produced based on non-linear and complex relationships between inputs and outputs. In other studies, only the amount of waste produced has been used for training in a model based on artificial neural network. In this study, extra parameters such as fuel consumption, types and numbers of trucks and number of personnel involved in waste collection and transport were used to assess their effect in attempts to improve the structure of ANN model, and the training performance of model generated. The new models with different parameters ranging from 2004 to 2009 were used as input variables. Structure with 1 and 4 neuron in hidden layer were chosen as appropriate model; although according to the absolute relative error, the model with the structure of 16-1-1 had the best results for forecasting waste generation in Langkawi Island. The final results by using ANN model are better than the result of multiple linear regression models, and also the correlation between the selected parameters is nonlinear. ANN model with the above stated parameters in Langkawi Island can be applied as effective tools in municipality systems; moreover the local decision makers and stakeholders concerning environmental issues to make better planning decisions in future. Also, controlling the amount of the solid waste generated supplies the opportunity for the decision makers to adopt essential actions and decisions for future investment in field of machinery, disposal capacity of landfill and preparing sanitary landfill according to appropriate place situations. From the multivariate regression results, the influence factors are personnel, fuel, and truck. The determination coefficient R^2 is around 0.80. However, we applied the same data to the back-propagation neural network with different neurons, including testing and training, cross validation and testing ratios as listed in Table 1. From the study of the generation of solid waste training results show that the analysis by using neural network yielded better results than the regression method. Furthermore, in the area of predictive accuracy test, the ANN has a higher accuracy than regression analysis.

V. Recommendation

It is recommended that it will be beneficial to apply methods such as public education for waste separation at source, increasing the efficiency of source separation methods with ANN model (before waste is disposed in landfills); these methods will reduce the amount of leachate produced in the Island. However, leachate that originates from solid waste has very high potential of contaminating the environment of Langkawi Geopark. So in order to prevent its environmental impact it is important to apply effective management techniques to reduce the volume of leachate produced.

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References

[1] Tchobanoglous, G., Thiesen. H. & Vigil S. A. 1993. Integrated solid waste management, engineering principles and management issues. New York: Mc Graw-Hill.

[2] Leao, S., Bishop, I. & Evans, D. 2001. Assessing the demand of solid waste disposal in urban region by urban dynamics modeling in a GIS environment. Resources, Conservation and Recycling. 33, 289-313. http://dx.doi.org/10.1016/S0921-3449(01)00090-8

[3] Kontos, D. T., Komilis, D. P., & Halvadakis, C. P. 2005. Siting MSW landfills with a spatial multiple criteria analysis methodology. Waste Management, 25(8): 818-832. http://dx.doi.org/10.1016/j.wasman.2005.04.002

[4] Lebensministerium. 2006. "Lebensmittelbericht Österreich 2006. Wertschöpfungskette Agrarerzeugnisse – Lebensmittel und Getränke" ["Austrian food report 2006. Value added chain of farm produce – food and drinks"]. (Online) www.lebensministerium.at/filemanager/download/18886/.

[5] Jain, A. K., Mao, J. & Mohiuddin, K. M. 1996. Artificial neural networks - a tutorial. Computer March, 29(3)31-44.

http://dx.doi.org/10.1109/2.485891
[6] Haykin, S. 1994. Neural networks: A comprehensive foundation (2nded.). New York: Macmillan.
[7] Simon Haykin. 2009. Neural network and learning machines-3rd ed. (Pearson Prentice Hall,)
[8] Ogwueleka, TC. 2009. Municipal solid waste characteristics and management in Nigeria. Iranian Journal of Environmental Health Science and Engineering 6(3): 173-180.
[9] Ogwueleka, T. Ch. & Ogwueleka, F. N. 2010. Modeling energy content of municipal solid waste using artificial neural network. Iran J.Environ. Health. Sci. Eng. 7 (3): 259-266.
[10] Andries, E. 2002. Computational Intelligence. An Introduction: John Wiley & Sons.
[11] Andries P. Engelbrecht. 2007. Computational Intelligence. Second edition: John wiley & Sons. Ltd. Francisco J. Uhia and Jame sieres and Antonio Campo, 2007. A general review of the Wilson plot and its modifications to determine convection coefficients in heat exchange devices. Applied Thermal Engineering pp: 2745 2727.
[12] Ibrahim Komoo. 2004. Geoheritage Conservation and Its Potential for Geopark Development in Asia-Oceania. Dalam Warisan Geologi Malaysia. Mohd Shafeea Leman & Ibrahim Komoo. (eds.). Bangi: LESTARI UKM.
[13] Mohd Shafeea Leman, Kamarulzaman Abdul Ghani, Ibrahim Komoo, Norhayati Ahmad (ed). 2007. Langkawi Geopark. Institute for Environment and development (LESTARI) and Langkawi Development Authority (LADA).
[14] Noori, R., Khakpour, A., Omidvar, B., & Farokhnia, A. 2010. Comparison of ANN and principal component analysis-multivariate linear regression models for predicting the river flow based on developed discrepancy ratio statistic. Expert Systems with Applications 37 (8) 5856–5862.
http://dx.doi.org/10.1016/j.eswa.2010.02.020
[15] Noori, R., Abdoli , M. A., Ameri, A., & Jalili-Ghazizade, M. 2009. "Prediction of Municipal Solid Waste Generation with Combination of Support Vector Machine and Principal Component Analysis: A Case Study of Mashhad". Environmental Progress & Sustainable Energy 28 (2): 249-258.
http://dx.doi.org/10.1002/ep.10317
[16] Noori, R., Abdoli, M.A., Jalili Ghazizade, M. & Samieifard, R. 2009. Comparison of Neural Network and Principal Component-Regression Analysis to Predict the Solid Waste Generation inTehran. Iranian J Publ Health 38 (1):74-84.
[17] Liwei Ning, 2009, Artificial neural network prediction of glass transition temperature of fluorine-containing polybenzoxazoles, J Mater Sci 44:3156–3164
http://dx.doi.org/10.1007/s10853-009-3420-0
[18] Sadugh, M.B., Jalili Ghazizadeh, M., Pezeshk, H., & Jalili Ghazizadeh, V. 2009. Evaluating the Recovery Potential of Solid Wastes. International Journal of Environmental Research 3 (4): 681-690.
[19] Jalili Ghazi Zade, M. & Noori, R. Winter 2008. Prediction of Municipal Solid Waste Generation by Use of Artificial Neural Network: A Case Study of Mashhad. Int. J. Environ. Res. 2(1):13-22. ISSN: 1735-6865.
[20] Chung, Shan Shan. 2010. Projecting municipal solid waste: The case of Hong Kong SAR, Resources, Conservation and Recycling 54(11) 759–768
http://dx.doi.org/10.1016/j.resconrec.2009.11.012
[21] Deng, Shuo., Hu, Jianming., Wang, Yin., & Zhang, Yi. 2009. Urban Road Network Modeling and Real-Time Prediction Based on Householder Transformation and Adjacent Vector. ISNN, Part III, LNCS 5553, pp. 899–908.
[22] Erdik, Tarkan. 2009. Discussion on ''Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neuro-fuzzy inference system'' Environ Geol 57(3):715.
http://dx.doi.org/10.1007/s00254-008-1321-1
[23] Hsiao-Tien Pao. 2008. A comparison of neural network and multiple regression analysis in modeling capital structure. Expert Systems with Applications 35, 720–727
http://dx.doi.org/10.1016/j.eswa.2007.07.018
[24] Rajdev, P., Ward, M.P., Rickus, J., Worth, R., & Irazoqui, P.P. 2010. Real-time seizure prediction from local field potentials using an adaptive Wiener algorithm. Computers in Biology and Medicine 40(1) 97–108.
http://dx.doi.org/10.1016/j.compbiomed.2009.11.006
[25] Wiederkehr, T., Klusemann, B., Müller, H., Svendsen, B. 2011. Fast, curvature-based prediction of rolling forces for porous media based on a series of detailed simulations, Advances in Engineering Software 42(4) 142–150.
http://dx.doi.org/10.1016/j.advengsoft.2011.01.001
[26] mathcentre January 9, 2006, http://www.mathcentre.ac.uk/resources/workbooks/mathcentre/hyperbolicfunctions.pdf
[27] ActiveMath. , 11 Aug 2012 http://demo.activemath.org/ActiveMath2/main/view.cmd;jsessionid=FDB7622F9240E21BE23DAD0BCA468631?book=edin_maths_for_inf&page=40
[28] Twomey, Janet. M. & Smith, Alice E. 1996. Validation and Verification. Kartam ,NAbil, Flood, Ian & Garret, James H Jr, (eds.) artificial neural networks for civil engineers: fundamentals and applicatons. New York: ASCE, 44-46.
[29] Yang, J., Greenwood, D.J., Rowell, D.L., Wadsworth, G.A., & Burns, I.G. 2000. Statistical methods for evaluating a crop nitrogen simulation model. N_ABLE, Agricultural Systems 64(1) 37-53. http://dx.doi.org/10.1016/S0308-521X(00)00010-X
[30] Muhammad A. Razi, Kuriakose Athappilly. 2005. A comparative predictive analysis of neural networks (NNs), nonlinear regression and classification and regression tree (CART) models. Expert Systems with Applications 29 , 65–74.
http://dx.doi.org/10.1016/j.eswa.2005.01.006
[31] Yorucu, Vedat. 2003. The Analysis of Forecasting Performance by Using Time Series Data for Two Mediterranean Islands, Review of Social. Economic & Business Studies 2175-196.
[32] Department Of Treasury. 2008. Forecasting Accuracy of the Act Budget Estimates, Forecasting Accuracy Comparison, May. (online) (http://www.treasury.act.gov.au/documents/Forecasting%20Accuracy%20-%20ACT%20Budget.pdf) (20 December 2011)
[33] CarmeliaM. Dragomir,WimKlaassen, Mirela Voiculescu, Lucian P. Georgescu, & Sander van der Laan. 2012. Estimating Annual CO2 Flux for Lutjewad Station Using Three Different Gap-Filling Techniques, The ScientificWorld Journal,vol. 2012. (online) http://www.tswj.com/2012/842893/ (31 August 2012)
[34] Alamgir, M., McDonald, C., Roehl, K. E., Ahsan, A., Eds.,(2005). Integrated Management and Safe Disposal of Municipal Solid Waste in Least Developed Asian Countries. Final Report of 'WasteSafe', a feasibility project under the Asia Pro Eco Programme of the EC, Department of Civil Engineering, Khulna University of Engineering and Technology, Bangladesh.
[35] Kumar, Jha Dilip., Sabesan, M., Das, Anup., Vinithkumar, N.V., & Kirubagaran, R. 2011. Evaluation of Interpolation Technique for Air Quality Parameters in Port Blair. India. Universal Journal of Environmental Research and Technology 1 (3): 301-310.
[36] Elmira Shamshiry. 2013. solid waste management sub-models for sustainable regional development: case studies of Langkawi (Malaysia) and Mashhad (Iran). PhD thesis , University KEbangsaan Malaysia.
[37] Jain, A. and Indurthy, S. K. V. P., (2003). Comparative analysis of event based rainfall-runoff modeling techniques-deterministic, statistical, and artificial neural networks. J. Hydro. Eng. ASCE., 8 (2), 93-98.
http://dx.doi.org/10.1061/(ASCE)1084-0699(2003)8:2(93)

Elmira Shamshiry was born in Iran. Her bachelor was in natural resource engineering- environment in Shahid Chamran University- Ahvaz-Iran, 1380. Her master was finished in 2009, University Putra Malaysia and PhD in 2013 at National University of Malaysia (UKM). She is post doctoral researcher at Institute of Environment and Development (LESTARI), UKM. And the first Author is Membership for Scientific Committees and Editorial Review Boards from 2013.