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COMBINING ARTIFICIAL NEURAL NETWORK- GENETIC ALGORITHM AND RESPONSE SURFACE METHOD TO PREDICT WASTE GENERATION AND OPTIMIZE COST OF SOLID WASTE COLLECTION AND TRANSPORTATION PROCESS IN LANGKAWI ISLAND, MALAYSIA

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ABSTRACT Solid waste management is an important component in the environmental management system. Due to high fluctuations of the amount of the produced waste in langkawi because of tourism in area, the use of neural networks is appropriate method to predict the amount of the produced waste based on non-linear and complex relationships between inputs and outputs. Collection and transportation of solid waste devote most part of municipality budget about 60% in area. The purposes of this research are to develop a model to predict the generation of solid waste and to reduce the cost of collection and transportation for solid waste management. This research has used the artificial neural network (ANN) and response surface model (RSM) to predict solid waste generation and to optimize the cost of waste collection and transportation. The authors believe that this approach will assist the authorities to determine the amount or quantity of solid waste generated over time. It will also assist the authorities to optimize cost, design appropriate and cost effective measures to collect and transport solid waste. This will improve environmental conditions and the cost saved could be used to provide other important services. We used time-series data with multiple input variables to perform the analyses. The results showed that use of variety of inputs data decreased the number neurons in hidden layer, which reduced the calculations performance and point of dimensionality, and increased accuracy in prediction the amount of produced waste; and whereas there is an increase in solid waste generation from 7825.7 tons (T) in 2009 to 8030.68 T in 2011; cost reduction amount is 10.64%. The methodology or an adapted form of the methodology can be applied to other fields, subject to a study of the requirements in each place.

(**Keywords**: Solid Waste Management- ANN-GA - RSM- Langkawi Island)

INTRODUCTION

The generation and management of municipal solid waste (MSW) are global issues, which are considered as socio-environmental problems resulting from consumption and production cycles. All mass-produced, commercialized and used products are finally transformed into waste in this way; fully or partially. Because consumption is increasing rapidly, waste production is increasingly posing a serious threat to achieving the goals of sustainable development [1]. In Langkawi Island, the issue of municipal solid waste (MSW) generation is a cause for concern.

Booming economy, growing population levels, the rise in standards of community living and fast urbanization have significantly accelerated the generation of MSW in developing countries [2]. Generally, urban municipalities face the challenge to develop an efficient and effective system for waste management. Nevertheless, municipal authorities are not able to tackle the problem primarily due to lack of financial resources, organization, multi dimensionality and complexity of the management system [3, 4, and 5].

The increasing amounts of MSW per year in a number of industrialized countries raises much concern about the environmental acceptability and economic feasibility of the present waste-disposal methodologies. To achieve an effective solid waste management necessitates designing efficient and reliable modeling techniques to forecast effectively the quantity of MSW generation and cost optimization. And these techniques will assist waste management policy makers in selecting and applying the most suitable treatment methods [6].

Generally the accurate forecasting of the quantity of solid waste generated is a significant step toward identifying the proper line of action to take to manage municipal solid waste [7, 8]. For that reason, knowledge about the accurate amount of solid waste generation is very significant for future planning in the Langkawi Island. This knowledge will assist the authorities in estimating the number of machinery, containers, and the capacity of disposal site required. Moreover, some amount of the expenses or costs for collecting and transporting waste to landfill site when optimized can be allocated to the provision of other essential social amenities for people in Langkawi Island.

More than 70% of the total waste management budget may be accounted for by the collection of solid waste [9]. In Langkawi Island, collection and transportation of solid waste take the highest share of the total municipality budget; about 60% (according to personal interview with the mayor). Based on the United Nations Development Programme survey on 151 city mayors around the world, insufficient solid waste management is considered as the second most serious problem confronting city residents after unemployment [10]. It is against this backdrop that this research has combined Artificial Neural Network (ANN) and Response Surface Method (RSM) with more input variables or parameters to predict or forecast solid waste generation and optimize the cost of waste collection and transportation in Langkawi Island. The knowledge of the amount or quantity of solid waste generated over time, and how to optimize the related cost will assist the authorities to design appropriate and cost effective measures to collect and transport solid waste in general and in Langkawi in particular. This will, in turn, improve environmental and personal health conditions.

BACKGROUND

The review of literature focuses on the number of parameters or input variables used and the results obtained by using ANN and RSM to forecast solid waste generation and to optimize cost of collection and transportation. The review begins with ANN and followed by RSM. The methods used to measure the rates of waste generation (WG) are diverse. And the most commonly used methods are load-count analysis, weight-volume analysis, and materials-balance analysis. Moreover, there are various statistical techniques used to calculate the quantity of waste generation. Nevertheless, some of them have inadequacies. For example, the method of load-count analysis states only the collection cost, but not the production rate [11]. The technique of material’s balance analysis has faults if the WG source is a massive area such as a city or region.

A waste generation sub-model was built, as part of the generic solid waste management model by Chang at 1991. The model utilized an econometric analysis to predict the quantity of waste generated within 20 years, which differentiated the total area into districts and projected the waste of each district “as a linear function of residence units, per capita income, and inhabitants”. The significance of the method is the use of income as a determining factor of waste generation. However, Chang did not differentiate waste by subdivision [12].

Mathematical model was created to forecast the generation of residential solid waste per capita by using the variables of education, income per family and population of urban residents in Mexico. The findings showed the greatest linear relation and greater association between the variables. Finally, a general mathematical model was used to forecast the generation of residential waste in which 51% of the outcomes showed a relationship between the selected variables [13].

The generation of municipal solid waste was predicted by using neural network in Mashhad on a time series data on waste generation from 2004 to 2007. The objective of the study was to identify the impact of each input data on waste generation. The input variables used were the amount of waste generation and number of trucks. The results of training and testing ANN showed that the model structure of 13-10-1 and 13-16-1 were the best obtained results. Correlation coefficient (R2) for training was 82% and R2 for testing was 74.96%. The mean absolute error (MAE), mean absolute relative error (MARE), and R2 structure with 16 neurons in hidden layer were selected to forecast solid waste generation [14].

The neural network and principal component regression analysis were combined to forecast the generation of solid waste in Tehran. The methods used were multivariate linear regression (MLR) and ANN. In the model, only the weight of waste and the number of trucks were used as input data. The results showed R2 for structure of 13-22-1 neurons, and were chosen as the best network architecture. The R2 for training ANN was 46.9% and R2 for testing ANN was 92.5 %. And ANN model showed better result in comparison with MLR model [7, 8]. Prediction of MSW in Kaunas, Lithuania was undertaken. Time series data and regression techniques were used in LCA-IWM model to predict the weekly waste generation, and the mean absolute percentage error was equaled to 6.5 [15].

ANN and principal component analysis (PCA) model were used to predict the amount of waste generation in Mashhad with data from 2004 to 2007. They used ANN 13 original variables and 13 principal components (PCs); first 8 PCs were applied for network inputs. Subsequently two models of ANN and PCA-ANN were compared to each other. Architecture with 16 neurons in hidden layer was chosen, R2 training for 13-16-1 ANN was 89.9 % and for testing it was 74.6%; R2 for 8PCs-ANN 8-3-1 in training obtained 78.6 % and for testing it was 77.6 %. The results showed that input variables pre-processing contains a definitive effect on ANN action and PCA-ANN showed that the network structure designed with the number of neurons in hidden layer reduced from 16 to 3 than in the ANN model [57].

ANN was used to identify the important parameters to forecast the amount of waste generation in Chile. The parameters included the population of urban residents, level of education, number of libraries and poor people (to explain the socio-economic condition) in waste generation. The variables were classified into three groups to measure the amount of waste generation. The best scenario indicated 67.3% based on all the selected variables or parameters [16].

The use of RSM as optimization tool seeks to supply the 'best' organization pattern, principles and operating policy variables in order to achieve maximum system efficiency. Optimization method as an organizational operations technique has become increasingly important as a model to achieve effective solutions [17, 18, and 19]. The idea to economically optimize the solid waste management system was first recommended by Anderson in the 1960s [20]. Afterward, much of waste-related planning model emphasized the minimization of cost in the provision of technology, location of landfill, timing and sizing related to facilities of waste management [20, 21, and 22]. Several surveys have been conducted on solid waste management optimization [23, 24], which showed that the supply of MSW services is an expensive operation, and poses a huge financial challenge to the local authorities around the world [25]. To reduce the cost of solid waste management, many researchers [26, 27] used operational research methods and separated event imitations.

Growth in urban consumption in the developing industries, and rapid population growth lead to increased consumable materials which result in an increasing rate of solid waste being produced [28]. The classical method of the optimization involved changing one variable at a time while keeping the others at fixed levels [29]. While such experiments are simple to plan and execute, they are inefficient and fail to detect any interaction amongst the independent variables. Furthermore, it will require more experimentation than an experimental design using the factorial approach. And there is no assurance that it will produce correct result [30, 31]. Thus, to overcome such disadvantage, the technique of Response Surface Model (RSM) is being progressively employed for modeling, interaction study and optimizing any processes or experiments.

Optimization in the management of solid waste system was performed in Niš, Serbia. The selected optimal method by analytic hierarchy process was carried out to determine the efficiency of the maximal system and the happiness of the service consumers. Clarke-Wright savings algorithm and the Geographical Information System (GIS) were also used to develop the mathematical models. The parameters used were the number of containers; their locations and vehicle movement way for collection of waste. The results declared that route reduction had impact on costs of vehicle movement and ecological effects on the environment [32].

Municipal solid waste collection routes optimization with Arc GIS network analysis was undertaken by Ashtashil at Nagpur, Maharashtra in 2011. With the GIS technique, optimum route was identified which was found to be cost effective and less time consuming when compared with the existing run route. The results showed 5.1 km route length reduction, time reduction of 8hr. 35 min, and a cost reduction of up to 14 % per month [33].

A study to improve solid waste collection was conducted through optimization technique. The study sought to identify the most cost effective system and optimal routes because about 60-80% of the total amount of municipality money is spent on the collection. Therefore, a small fraction in improvement in the collection process can result in a considerable reduction of total costs. The variables used were waste bins location, waste collection program, road network and population density. The first experiments have shown that applying the optimization technique in the collection of urban solid waste can greatly minimize the collection tour length and eventually the total cost in time and money. And as per the locations and collection schedule, it is possible to collect 100% of waste generated. The per capita collection charges can be reduced in this area up to 135 Rs. [34].

Municipal solid waste is a worldwide problem and its management causes dilemma for many societies [35, 36]. For small islands this is a major problem due to the limited options for waste management systems and the large number of tourist arrivals. This scenario leads to higher waste generation [35]. Therefore, it is significant that both the ANN and RSM have been used in this study to predict the quantity of solid waste generation and to simultaneously optimize the cost of solid waste collection and transportation in Langkawi Island.

MATERIAL AND METHOD

Materials

The materials used include the following variables or parameters: (i) Fuel consumption; (ii) 4-ton truck; (iii) 10-ton truck; (iv) Number of trips made by the trucks to the landfill; (v) Number of times the personnel entered into the landfill; (vi) Number of tourists; (vii) Salary per worker per day.

Study Location

Langkawi is the first global Geopark in Malaysia and Southeast Asia. This Geopark comprises 99 islands of Langkawi in the Kedah State, Malaysia. The total area of Langkawi consists of six sub-districts. The islands have a total land area of about 47,848 hectares, and the main island of Langkawi has a total area of about 32,000 hectares [37].

Langkawi is located in the Andaman Sea, which is about 30 km away from the mainland coast of north-western Malaysia. The largest island is the eponymous Pulau Langkawi, which had a population of 96,726 in 2007. Langkawi Island has sunny, hot, humid, and tropical climate with an average annual temperature of about 32 degrees Celsius where the amount of annual rain is about 2500 mm. The rainy season is during August/September. Currently, the population is approximately 99,000 (2010 statistics). An economy based largely on cultivation of paddy, rubber and fisheries is quickly being overtaken by a tourism-based economy due to the ecological beauty of the island coupled with the public sector support.

The landfill in Langkawi Island is located at Kampung Belanga Pecah, Jalan Air Hangat, Kuah. It covers a total area of 20 hectares and from the time it was operational, 12 personnel have been working there and three machines are installed and operational. The disposal method used here is land filling. In year 2000, the average daily load was 80 ton of waste. This particular landfill has a lifespan of about 10 years. While the latest statistics have not been available, it is expected that the daily load of waste transported to this landfill would have increased significantly as Langkawi Island is a major Malaysian tourist destination and additional waste generated by the tourists would account for the expected increase.

Methods

Calculating the amount of waste produced is vital to setting up a sustainable waste management system (SWMS) [38]. Defining the amount of SW produced can simplify assessment of total investment for appropriate organization of machinery, containers and capacity of disposal. Traditional methods are used to estimate solid waste production rate, and factors such as population and socio-economic parameters are computed based on the generation of SW per person. Since these coefficients change over time, they are not effective tools for the dynamics of SWMS.

Furthermore, in tourist locations such as Langkawi, there are seasonal variations due to the population of tourists who travel to the area . Therefore, there is a considerable variation in WG and the exact amount of waste generated cannot be predicted [39]. One of the main methodological approaches used in the prediction of MSW generation is the time series approach, i.e., to use past data and their generalization to predict the future waste tendency. Based on this method, time is employed as a predictor variable. In this analysis, yearly, monthly and daily data were used. The advantage of using time-series analysis concerns its flexibility that needs only small amount of data [40].

Artificial Neural Network

Splitting the data is a significant issue in the development of artificial intelligence. It is a common technique to separate the available data into three divisions including the training, validation and testing set [41]. Data normalization in ANN is valuable for model application when normally the input data are on a varying scale. It can also accelerate the required time of training through the procedure of training for all characteristics within the equal level [42, 43]. In the process of data arrangement, the weekly data were prepared in Excel and transferred to MATLAB. In MATLAB, the matrixes were changed to vector shape.

This research used Artificial Neural Network (ANN), training and testing for weekly waste generation modeling (WWG) in Langkawi Island. Input data consisted of WWG observation and the number of trucks, which carry waste from the entrance to landfill (i.e., from waste generation source to disposal site), number of personnel (that is, the persons working in the collection and transportation of solid waste), number of tourists visiting the Island, and fuel cost (used by trucks during collection and transportation of solid waste). These data were selected since they have direct influence on the amount of solid waste generated and collected. The raw data were obtained from (Majlis Perbandaran) municipality of Langkawi. The monitoring data from 2004 to 2009 were planned to supply the training and testing process necessary for the neural network. In the next step, to find the best train function, several tests of learning function between 'traingdx'; 'trainbr'; 'traincgb'; 'traincgf'; 'traincgp'; 'traingd'; 'traingda'; 'traingdm'; 'trainbfg'; 'trainlm'; 'trainoss'; 'trainrp'; 'trainscg' were undertaken and then the best function was selected. To find the best test function, the more accurate functions with the highest score were selected one more time.

In this study, the data used in ANN method are separated into three fractions. The first part is relevant to training of network, the second fraction is applied to discontinue estimation when the integrity error begins to rise, and the last part is applied to the testing of network (integrity purpose). In the final step of ANN modeling, the Genetic algorithm was used to optimize the number of hidden layers.

Genetic algorithm recommends a more intelligent methodology to search for the best possible pattern of ANN parameters when evaluated, and to fully investigate all the parameter patterns (Goldberg 1988). Genetic Algorithms (GA) mimic the theory of natural selection, which is considered as the survival of fittest [44]. GA is made up of three fundamental parts including selection, crossover and mutation. The algorithm begins by providing a set of solutions to the problem under assessment. The solution set (indicated by chromosomes in GA) is named the population. Crossover operation is done to achieve an original explanation through merging dissimilar chromosomes to produce improved offspring. In addition, a new solution is developed by changing the existing population element called mutation [45].

Selection of function among the feed forward net, feed net and cascade forward net for training and testing was performed based on MAE, MSE, RMSE, MARE, MSRE, RMSRE and R2.

To assess the ANN model and examine its performance, four statistical indexes were used: the Mean Absolute Error (MAE), the Mean Absolute Relative Error (MARE), the Root Mean Square Error (RMSE), and correlation coefficient (R2) values that are derived from statistical calculations of observation in the model output predictions [46, 47, 48, 49, 7, 8, 50, and 51].

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

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

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

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

The neuron model can also include an externally applied bias, which is shown as bk. The bias, either 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 [52, 53, 7, and 8]. In this study, the artificial model of neurons was made of these factors including a set of synapses that are characterized by weight of each synapse. The synaptic weight of an artificial neuron may be in negative and positive value range. An adder for summing the input signals which are weighted by the respective synapses of the neuron. Activation f unctions or transfer functions limited the output amplitude of a neuron [52, 53].

$$w = \sum wx \tag{5}$$

$$uk = \sum_{j=1}^{m} WkjXj \tag{6}$$

$$Net = u_k + b_k \tag{7}$$

$$Y_{K=}f\,(\text{net}) \tag{8}$$

The Piece-wise Linear function:

$$f(v) = \begin{cases} 1 & v \geq 1 \quad 2 \\ v & -1 < v < 1 \\ 0 & v \leq -1 \quad 2 \end{cases} \tag{9}$$

The Threshold function:

$$f(v) = \begin{cases} 1 & v \geq 0 \\ 0 & v \leq 0 \end{cases} \tag{10}$$

The Sigmoid function:

$$f(v) = \frac{1}{1+\exp(-av)} \tag{11}$$

Data and Materials for ANN

Calculation and prediction of the quantity of solid waste generation depend on several factors; for instance, ecological situation, period of the year, frequency of collection processes, and people living in the area, financial situation, laws and the cultural conditions. Therefore, the significant process to realize an effective forecasting of the accurate quantity of SW production should incorporate such factors as 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, number of tourists visiting the area, and average number of personnel working in collection and transportation of SW per week. These are shown in the appendixes.

Response Surface Model

The weakness of single element optimization procedure can be reduced by applying several methods, such as response surface methodology (RSM), which is used to give more details regarding the joint outcomes of all the parameters involved in the procedure, experimental strategies collection, and methods of mathematic and statistical inference [54, 55]. RSM can be utilized to estimate the relevant importance of various influential elements even in the presence of complex interactions [56, 57]. The main general approach in controlling the fundamental condition for any response is investigated by the standard one-variable-at-a-time process. The standard approach for the optimization includes shifting one variable at a time while keeping the other alternative at fixed stages [58, 59]. Four main steps identified by Erin in 2005 as essential in RSM include the experimental setup, experimental design, statistical analysis, and model selection.

RSM presents important statistical tools and models to guide the design of procedures. RSM plays a crucial role in providing precise maps for effective experiments, which are based on mathematical patterns. RSM makes it possible for researchers to analyze the likely associations among variables or responses via sophisticated optimization approaches. This is known to have facilitated the meeting of all specifications at minimal cost in most experiments. The data used for RSM related to solid wastes generated per three months from 2004 to 2009. Analysis of information was performed using such variables as salary per worker per day, which is equivalent to 10 US dollars (i.e., salary of personnel for collection and transportation of MSW), per fuel liter equal to 63 cents in Malaysia. Fuel consumption for 4-ton truck is 30 Liter (L) and for 10-ton truck is 40 L in Langkawi, Malaysia. Framework of methodology for this research is shown on Figure 1.

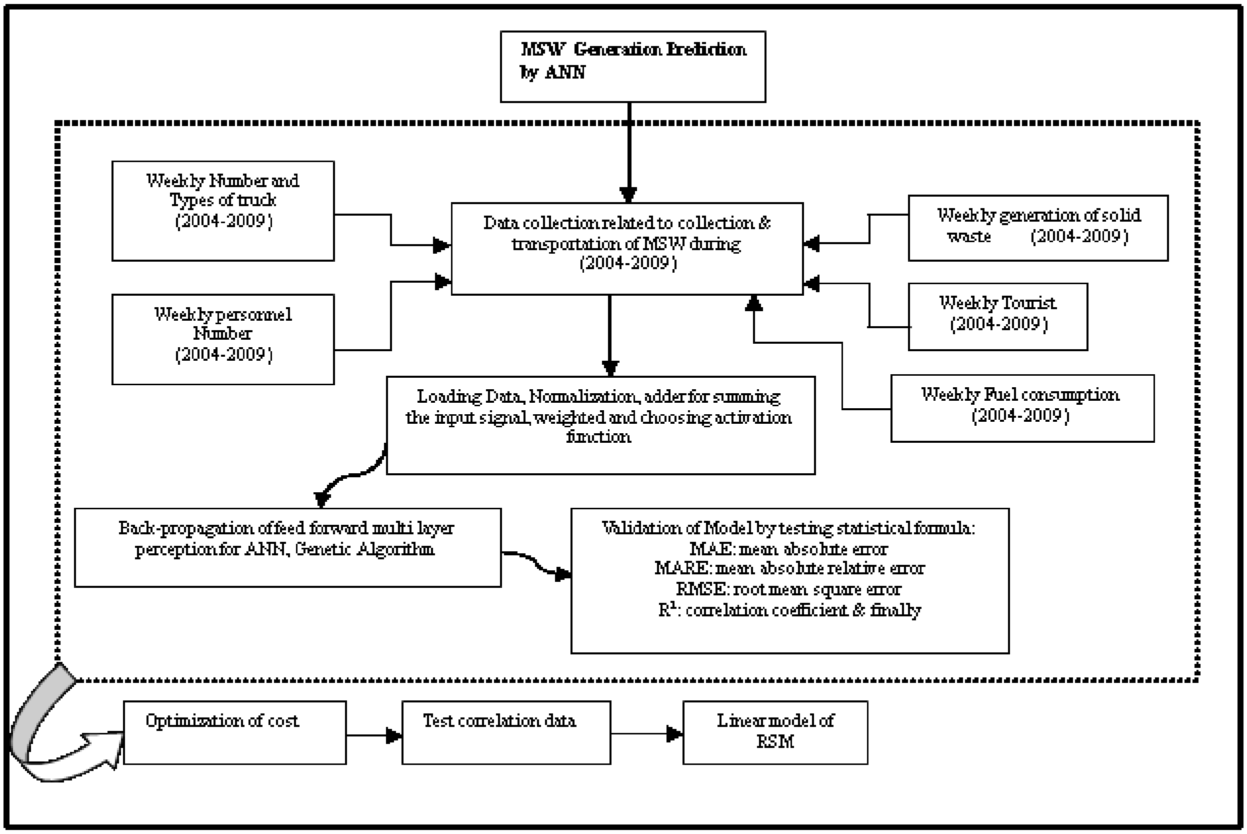

Figure 1. Methodology framework for this study

The first approach in the RSM is to estimate the parameters of the model using the least-squares regression, and to determine the fitness of these parameters in an analysis of variance (ANOVA). The surface estimated is usually curved with a “hill” having peaks that appear at the exclusive estimated point of maximum response, and a “valley,” or a “saddle-surface” without any exclusive minimum or maximum response [58].

Numerous RSMs encouraged transforming the normal variables to coded variables x1, x2, x3,..., xk, which are usually defined to be dimensionless with signifying zero and the same standard deviation. In terms of the coded variables, the response function was presented by Mirhosseini et al. in 2007 as follows:

$$Y=f(x1, x2, x3,..., xk) \tag{12}$$

$$Y=\beta0+\beta1x1+\beta2x2 \tag{13}$$

The form of the first-order model is usually referred to as the most significant effect model, due to the fact that it incorporates only the major effects of the two variables x1 and x2. For instance, if a response variable y is measured, values are combinations of two factor variables, x1 and x2. If there is an interaction between these variables, it can be easily added to the model as follow:

$$Y= \beta0+ \beta1x1+ \beta2x2+\beta\ 2x2 + \beta12x1x2 \tag{14}$$

RESULTS AND DISCUSSION

The statistical analysis of waste materials in Langkawi Island in different months from 2004-2009 is presented in appendixes. Since the values of average and median are close, the amount of waste generation demonstrates a standard distribution in the seasons and weeks. Due to the high number of tourists during the peak season, the rate of WG increases rapidly. Various structures of feed forward ANN through three layers organization with several neurons quantity in the hidden layer were considered in this research to obtain the most excellent structure of ANN for calculating the waste generated.

With reference to Levenberg-Marquadte [60] as a training function and testing as a weekly average SW produced, we used the weekly fuel consumption, weekly number and types of truck used for collection and transportation of the SW produced, weekly average number of personnel involved in the collection and transportation of SW, and weekly number of tourists were used in this analysis. And by applying MAE, MARE, RMSE, TS and R2, appropriate types of model were chosen in this study.

At first, the data were recorded in Excel, then transformed to MATLAB and normalization analysis was performed in equation (15). In the next step, sensitivity analysis was used to select the effective factors. In fact, sensitivity analysis attempts to find the existing relationship among the data.

$$\text{Normalization Analysis} = (x - \text{Min}X) / (\text{Max}X - \text{Min}X) * 2 - 1 \tag{15}$$

The sensitivity analysis in Figure 2 showed that the impact of peak seasons on the prediction of solid waste depends on generation of solid waste in the 26th, 39th and 52nd weeks prior to the peak seasons. To forecast the waste generated in the n-th week, waste generated in the previous 13 weeks (N-1 to N-13), the said weeks based on the findings of sensitivity analysis, average number of trucks, number of tourists who visited the area, fuel consumed and the number of personnel in those weeks were used as input variables to ANN with the structure of feed forward. The network training was performed according to the back propagation algorithm using the tangent hyperbolic function.

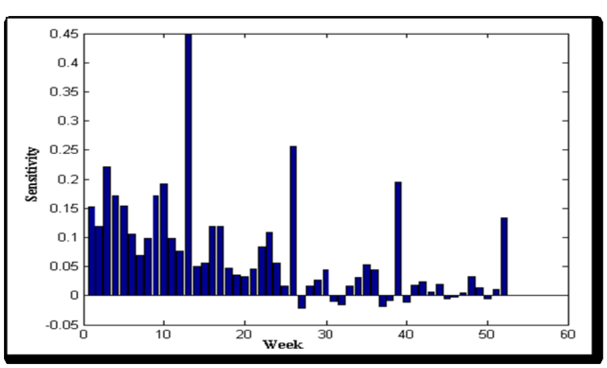

Figure 2. Sensitivity analysis of average weekly solid waste in Langkawi Island (2004-2009)

To obtain the best results, the genetic algorithm was used for network training and testing to optimize the number of hidden layers, to predict the amount of waste generated with 20 input layers (waste generation during the previous 13 weeks); amount of waste generated during the 26th, 39th, and 52nd previous weeks, average number of personnel, tourists, types of truck and fuel consumption (based on the type of truck). In this step, the data were prepared to determine the effective elements considering the information obtained. The matrix in MATLAB included 20 columns and 260 rows. In the next step, validation assessment was made; quarter of the input data was chosen as testing data set (random) and the remainder was used as training data set (i.e., 200 for training and 60 for testing, 52 in the sensitivity analysis). Finally, normalization of the data was performed. Afterward, the networks were arranged using feed forward net, fit net and cascade forward net to assess the network based on the three functions applied to the following errors; i.e., MAE (mean absolute error), MSE (mean squared error), RMSE (root mean squared error), MARE (mean absolute relative error), MSRE (mean squared relative error), RMSRE (root mean squared relative error) and R^2. Based on the findings of the errors and R^2, the feed forward net was selected for Langkawi Island. The results are shown in the Tables 1,2,3 and 4. In Table 1 amounts of all errors are less in feed forward net and amount of R^2 is bigger than the other function in training data. According to amount of errors in feed forward net for testing data and R^2 it is better function for training. Amount of R^2 in 'trainbr' function is higher than the others based on Table 2.

Table 1. Rate of errors on the training data for various functions of Feed forward net, fit net and cascade forward net (for selection of the best function of train)

	MAE	MSE	RMSE	MARE	MSRE	RMSRE	R^2
feedforwardnet	**0.1327**	**0.0367**	**0.1916**	**1.6604**	**8.1811**	**2.8603**	**0.5091**
Fitnet	0.1358	0.0374	0.1933	2.9881	215.3317	14.6742	0.5048
cascadeforwardnet	0.1869	0.0564	0.2375	35.0650	192976.91	439.2914	0.4947

Table 2. Rate of errors on the testing data for various functions of Feed forward net, fit net and cascade forward net (for selection of the best function of train)

	MAE	MSE	RMSE	MARE	MSRE	RMSRE	R^2
feedforwardnet	**0.140**	**0.049**	**0.2227**	**2.2002**	**27.83**	**5.2757**	**0.599**
Fitnet	0.1957	0.074	0.2715	3.9544	217.37	14.744	0.255
cascadeforwardnet	0.2467	0.145	0.3804	2.9933	65.866	8.1158	-0.067

Table 3. The Results of The errors for the training data in different functions due to select the best function

	MAE	MSE	RMSE	MARE	MSRE	RMSRE	R^2
'traingdx'	0.1462	0.0466	0.2159	5.3915	414.8412	20.3677	0.2390
'trainbr'	**0.0316**	**0.0119**	**0.1090**	**0.2775**	**2.5797**	**1.6061**	**0.8824**
'traincgb'	0.1018	0.0184	0.1356	5.7717	825.7565	28.736	0.7939
'traincgf'	0.1018	0.0184	0.1356	5.7717	825.7565	28.736	0.7939
'traincgp'	0.1098	0.0210	0.1451	3.0847	133.9714	11.5746	0.7575
'traingd'	0.1263	0.0322	0.1794	4.7661	642.8201	25.3539	0.5945
'traingda'	0.1358	0.0385	0.1961	15.6596	13324.0274	115.4298	0.4912
'traingdm'	0.1360	0.0468	0.2164	5.6301	306.8240	17.5164	0.2506
'trainbfg'	0.1125	0.0253	0.1590	2.0103	18.3127	4.2793	0.6991
'trainlm'	0.116	0.029	0.170	1.1677	3.6818	1.9188	0.6427
'trainoss'	0.1055	0.0182	0.1347	75.1768	1068795.0679	1033.8255	0.7951
'trainrp'	0.1100	0.0232	0.1524	6.2791	1522.7902	39.0229	0.7291
'trainscg'	0.1250	0.0359	0.1894	2.6634	41.8603	6.4700	0.5758

Table 4.The Results of The errors for the testing data in different functions due to select the best function

	MAE	MSE	RMSE	MARE	MSRE	RMSRE	R^2
'traingdx'	0.1695	0.0711	0.2666	21.2919	11041.0390	105.0763	0.0993
'trainbr'	0.2389	**0.2023**	0.4498	**1.3296**	**14.6369**	**3.8258**	0.1820
'traincgb'	**0.1186**	0.0284	0.1686	5.4059	146.9237	12.1212	0.7896
'traincgf'	0.1363	0.0355	0.1884	7.2226	543.0691	23.3038	0.7282
'traincgp'	0.1746	0.0621	0.2492	3.2423	46.0640	6.7870	0.3661
'traingd'	0.1560	0.0464	0.2153	2.8233	26.8270	5.1795	0.5989
'traingda'	0.1644	0.0705	0.2654	15.5982	3285.9326	57.3231	0.1983
'traingdm'	0.1685	0.0881	0.2969	5.9469	144.5886	12.0245	-0.3257
'trainbfg'	**0.1165**	0.0269	**0.1639**	2.2092	25.3664	5.0365	0.7931
'trainlm'	0.1766	0.0614	0.2479	2.9017	25.6682	5.0664	0.3922
'trainoss'	0.1235	0.0260	**0.1612**	2.9811	55.7531	7.4668	**0.7968**
'trainrp'	0.1327	0.0350	0.1872	17.8676	8576.8258	92.6112	0.7439
'trainscg'	0.1453	0.0560	0.2367	3.2156	40.1210	6.3341	0.5565

The next step was the selection of the best training function among the 13 functions in ANN.

Functions of 'trainbr'و 'trainbfg'و'trainoss' had the best answer; these functions were reassessed to obtain the best answer with more accuracy. Table 5 showed errors during training and Table 6 illustrated errors for testing data.

Table 5. The errors on the training data for different functions due to select the most accurate function

	MAE	MSE	RMSE	MARE	MSRE	RMSRE	R^2
'trainbr'	**0.0314**	**0.0191**	**0.1382**	**2.3294**	841.8276	29.0143	**0.8502**
trainbfg	0.1077	0.0223	0.1492	10.8239	11825.3410	108.7444	0.7422
'trainoss'	0.1280	0.0299	0.1731	2.5434	**112.9518**	**10.6279**	0.6861

Table 6. The errors on the testing data for different functions due to select the most accurate function

	MAE	MSE	RMSE	MARE	MSRE	RMSRE	R^2
'trainbr'	**0.2425**	0.1278	0.3575	**1.5873**	**6.3330**	**2.5165**	0.2807
trainbfg	0.1376	**0.0325**	**0.1802**	7.0152	894.3073	29.9050	**0.7469**
'trainoss'	0.1517	0.0358	0.1891	3.4834	72.1797	8.4959	**0.7526**

Function of feed forward net with training function of trainbr were the best functions for modeling in Langkawi, which resulted from the optimization of number of hidden layers with genetic algorithm. Number of layers between 1- 4 tested and the number of neurons between 1- 32 were calculated and the best answer was selected among a variety of shapes. The binary genetic algorithm was used with the single point of crossover. The initial population was 20, with maturation rate of 15%, selection rate of 0.5 and bit number of (4) per chromosome. The selection mode was based on the random design between 0 and 1 (binary).The cost function (neuron numbers) per layer was equal to R2 minus one (1- R2). The primary selection was based on the direct random method from the population based on the lower cost (or higher R2). It was repeated 200 times and per time data was selected based on the best result. Finally, 3 hidden layers were selected in this model, and the number of neurons were (31, 14, 24) and (9, 5, 11). If the number of neurons in the layers were more, the final answer would be deficient. The best answer of the ANN model is shown in the Figures 3, 4, 5 and 6.

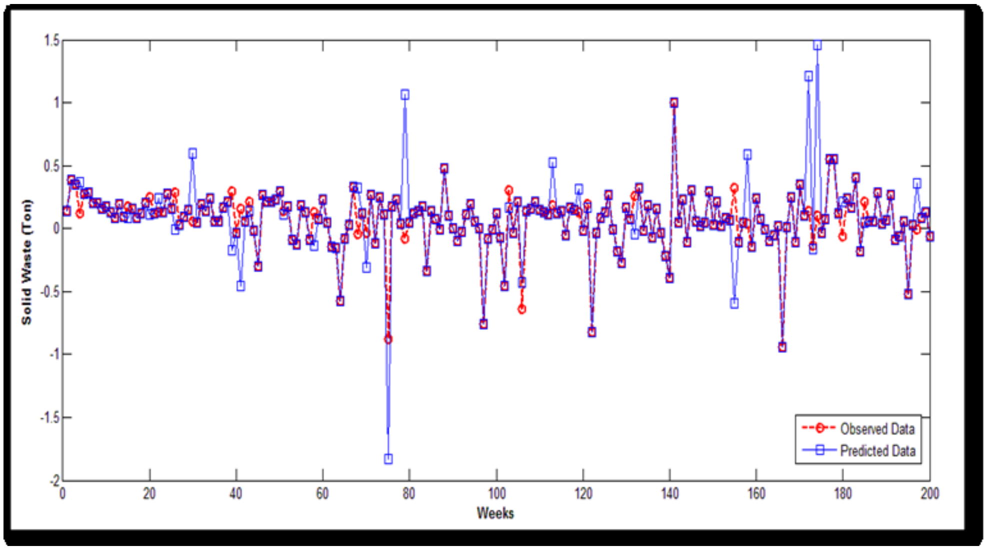

Figure 3. The observed amount of solid waste and the predicted output of ANN model with three neurons in the hidden layer for training data set in Langkawi Island (2004-2009).

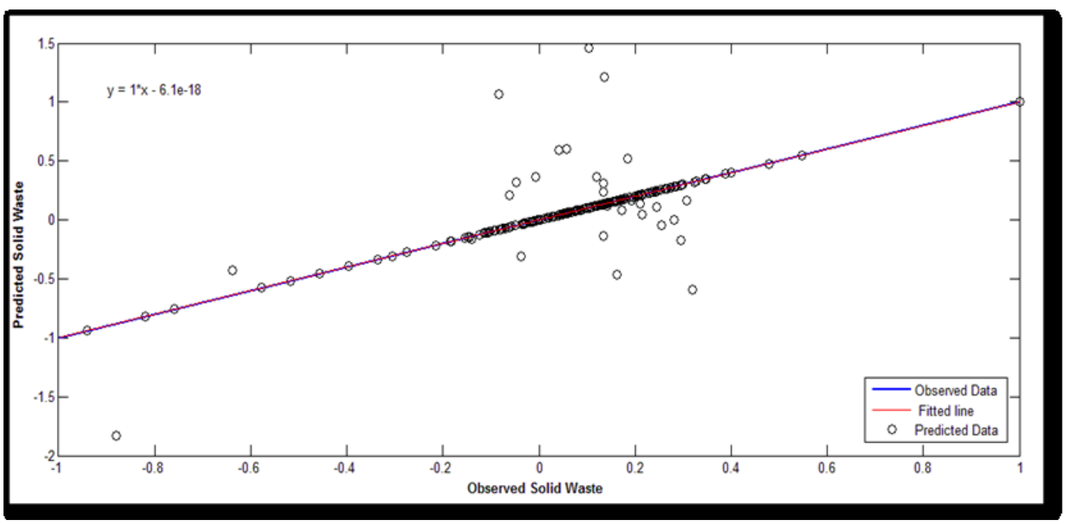

Figure 4. The scatter plot of predicted output of ANN model with three neurons in the hidden layer for training data set versus the observed amount of solid waste in Langkawi Island (2004-2009).

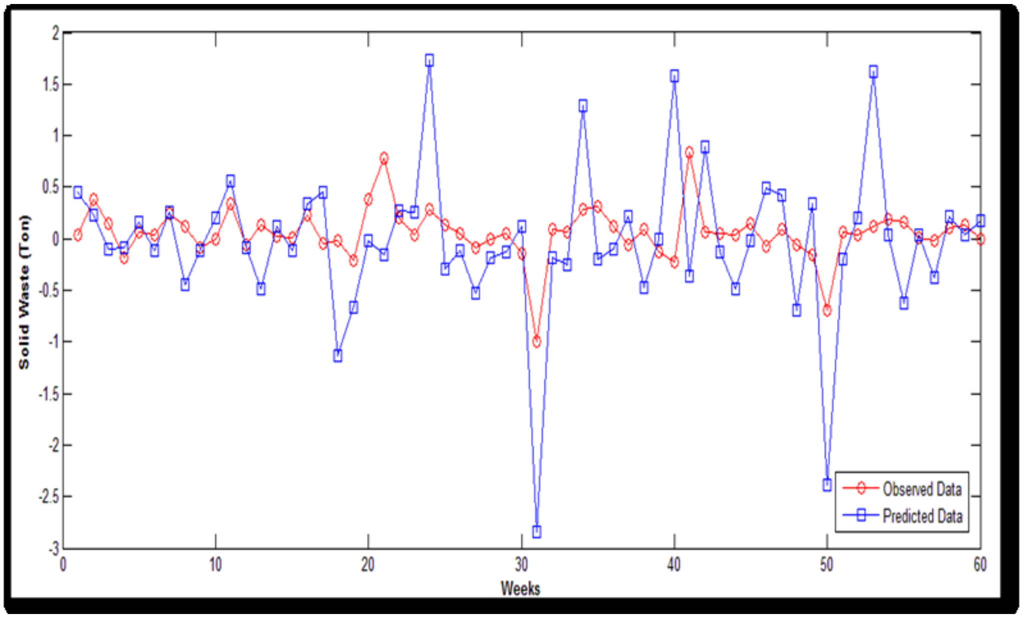

Figure 5. The observed amount of solid waste and the predicted output of ANN Model with three neurons in the hidden layer for testing data set in Langkawi Island (2004-2009).

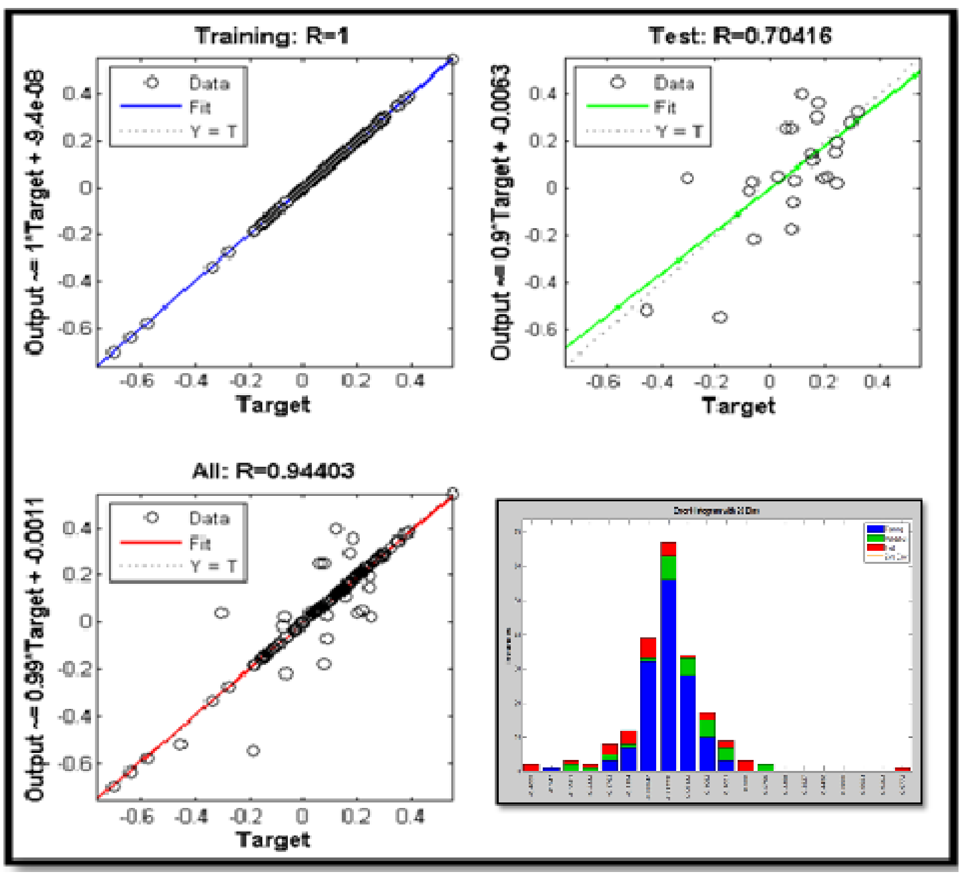

Figure 6. The scatter plot of predicted output of ANN model with three neurons in the hidden layer for testing data set versus the observed amount of solid waste (2004-2009).

The final result of ANN model with optimization by genetic algorithm is shown in the Table 7. The validations of model and error histogram are shown in the Figure 7; moreover Residuals versus based on observation order is in Figure 8. The validations of ANN for test and training are 94%.

Table 7. The calculated errors for ANNs with three neurons in the hidden Layers (based on the genetic algorithm) applied in training and testing data sets for Langkawi Island (2004-2009).

	MAE	MSE	RMSE	MARE	MSRE	RMSRE	R^2
Train	0.0847	**0.0119**	0.1093	5.1472	1226.79364	35.0256	**0.87229**
Test	0.1426	**0.03587**	0.1894	2.67084	31.6998	5.6302	**0.711169**

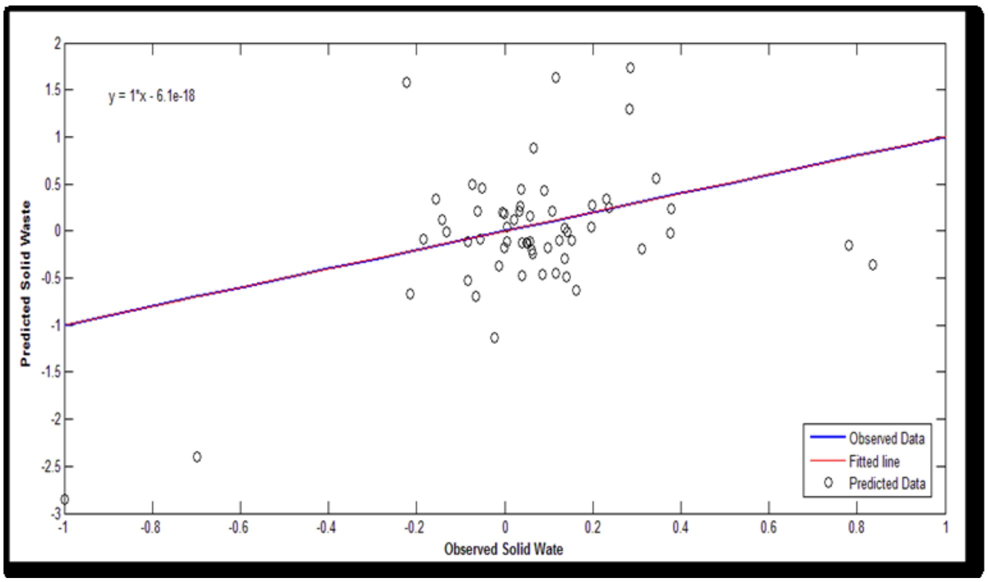

Figure 7. Validation of modeling with three neurons in the hidden layer,Validation of the ANN model in Langkawi.

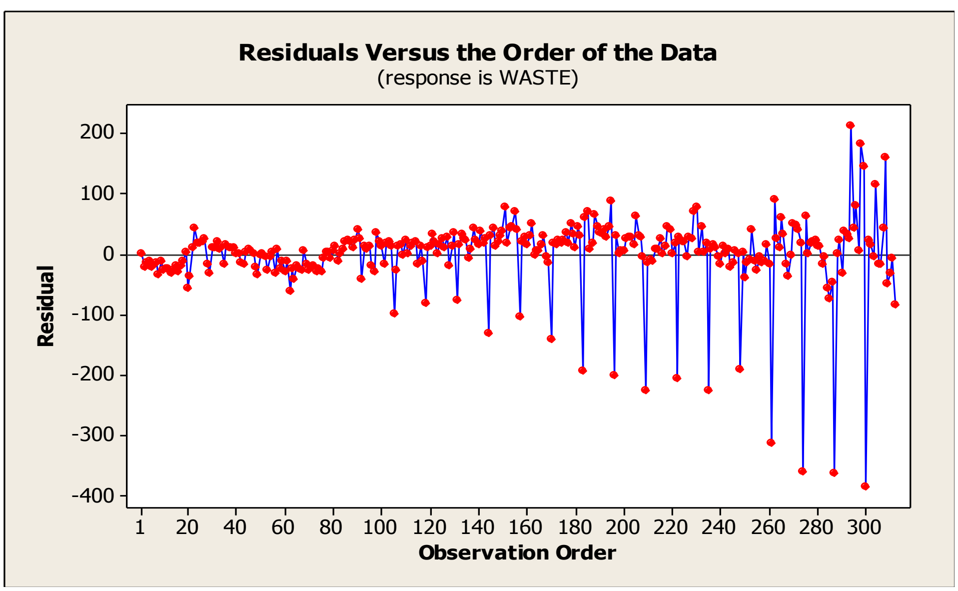

Figure 8. Residuals versus the order of the data based on observation and residual by response of weekly previous waste generated in Langkawi Island

One of the most significant ANN characteristics is the number of neurons in the hidden layer. With an increase of the neurons in the hidden layer, the error was higher than the selected number of neurons in this study. However, the inadequate number of neurons applied to the network was not able to completely model the data.

In this study, the response surface analysis was performed, and the aim was to optimize the cost of collecting SW. Afterward, the relations between the independent variables and response variables were examined. The experimental data is presented in Table 8. The response surface analysis allowed an empirical relationship progress, where every response variable (Y1, Y2 and Y3) was measured as a function of X1 (number of personnel), X2 (number of trucks), and X3 (amount of fuel consumption), forecasted as the sum of constant (β0), four first-order consequence (Linear Model terms in X1, X2, X3 and interaction effects among them. The final outcome was investigated by using ANOVA to calculate the ‘‘goodness of fit’’. The conditions found to be statistically significant ($p < 0.05$) were considered in the model. As shown in the following equation, the result and model for forecasting the response variables demonstrated the most important relationship and interaction between the variables. Table 9 and 10 presents the approximated regression coefficients of the polynomial response surface models with the corresponding R^2 values and lack of fit tests. The significance of every element was specified by the F-ratio and p-value as presented in Tables 11 and 12. The values of "Prob > F" were less than 0.05 and the value indicating model terms was significant. Before using the model, it is important to ensure the normality of the data. Therefore, the NPar-test was used through IBM SPSS 19 and the result indicated that all the data met the normality requirement (Table 9 and 10). Table 11 explained model based on response cost. Table 13 demonstrated the characteristic of model, and Table 14 showed lower and upper limitation of identified variables based on the expert’s ideas for planning during collection and transportation of solid waste in Langkawi Island. Expert Design of research is showed in Figure 9; in addition validation of RSM model illustrated in Figure 10.

Table 8. Central composite design independent (Xi) and response variables (Yj), Langkawi Island (2010)

Treatment Run	Personnel Number (X_1)	Fuel Liter (X_2)	Lorry Number 10-ton (X_3)	Lorry Number 4-ton (X_4)	Solid Waste Ton (Y)
1	13708	22867.5	2700	1454	6932.3
2	14634	24409.5	2885	1547	7452.8
3	15694	26189.1	3083	1681	8032.3
4	14578	24457.8	2739	1811	7691.2
5	14500	24503.7	2556	2138	7780.4
6	14542	24489	2645	1981	7676.6
7	13850	23162.1	2673	1579	7558.9
8	13852	23237.3	2605	1716	7587.1
9	12832	21548.4	2392	1632	7172.9
10	12784	21371.3	2475	1442	7162.5
11	13446	22570.5	2515	1693	7669.9
12	13404	22462.4	2543	1616	7793.8
13	12346	20767.4	2268	1637	7185.8
14	12674	21399.2	2252	1833	7599.8
15	12836	21613.7	2337	1744	7871.2
16	12532	21060.5	2321	1624	7341.7
17	11754	19725.6	2203	1471	6862
18	11954	20046	2255	1467	7122
19	11718	19600.4	2258	1343	6586.6
20	12068	20258.7	2256	1522	6786.5
21	12972	20240.6	2523	1440	7300.7
22	13930	23196.6	2783	1399	7150.7
23	15000	24982.4	2993	1514	8399.1
24	15666	25470	3165	1503	7825.7

Table 9. Correlation matrix of factors [Pearson's r]

	A	**B**	**A^2**	**B^2**	**AB**
A	1.000				
B	0.965	1.000			
A^2	0.734	0.657	1.000		
B^2	0.953	0.988	0.740	1.000	
AB	0.968	0.931	0.872	0.958	1.000

Table 10. Analysis of linear model in Langkawi

Std. Dev	**279.95**
Mean	7439.27
C.V.	3.76
PRESS	2.246
R-Squared	0. 6315

Table 11. Sequential model sum of squares based on the response cost

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Mean	1.170E+010	1	1.170E+010	3.973E+006	< 0.0001	
Linear	9.554E+007	3	3.185E+007	6.93	0.0030	Suggested
2FI	88.23	3	29.41	0.86	0.4855	Suggested
Quadratic	11.20	3	3.73	19.89	0.0009	Aliased
Cubic	58.68	8	7.34			
Residual	2.21	6	0.37			
Total	1.179E+010	24	4.914E+008			

Table 12. Analysis of variance table [Partial sum of squares]

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Model	9.554E+007	6	1.592E+007	3.755E+006	< 0.0001	significant
A	1.896E+005	1	1.896E+005	44711.88	< 0.0001	
B	3.279E+005	1	3.279E+005	77319.14	< 0.0001	
C	22.04	1	22.04	5.20	0.0358	
AB	39.26	1	39.26	9.26	0.0074	
AC	34.80	1	34.80	8.21	0.0107	
BC	23.74	1	23.74	5.60	0.0301	
Residual	72.09	17	4.24			
Cor Total	9.554E+007	23				

Table 13. The model characteristics

Std. Dev	2.06
Mean	22076.46
C.V.	9.328
PRESS	10919.74
Pred R-Square	0.9999
Adeq Prediction	6218.082

Table 14. Constraints of planing for collection and transportation of solid waste in langkawi Island, lower and upper limit are identified based on the experts ideas and suggestions

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight
Personnel	is in a range	10000	16000	1	1
Fuel	is in a range	19725	25000	1	1
Total Truck	is in a range	1300	5000	1	1
Solid Waste	is in a range	7986.6	8399.1	1	1
Cost	minimize	19193.7	26110.4	1	1

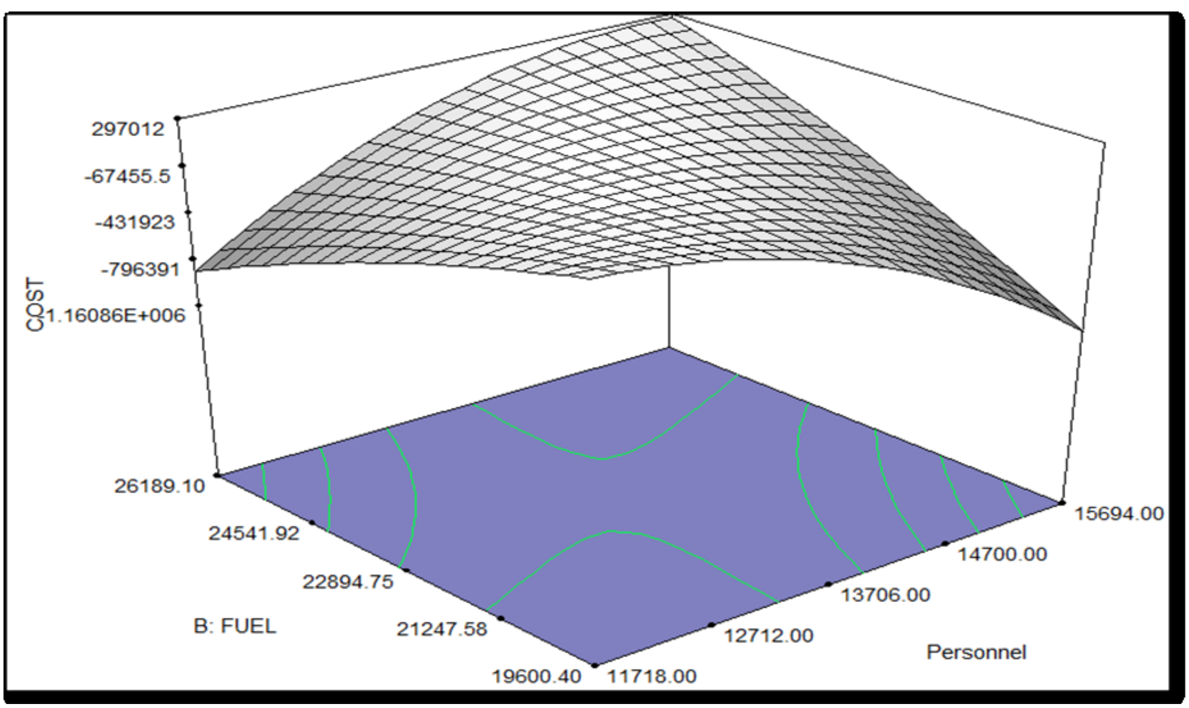

Figure 9. Design expert plot cost in Langkawi

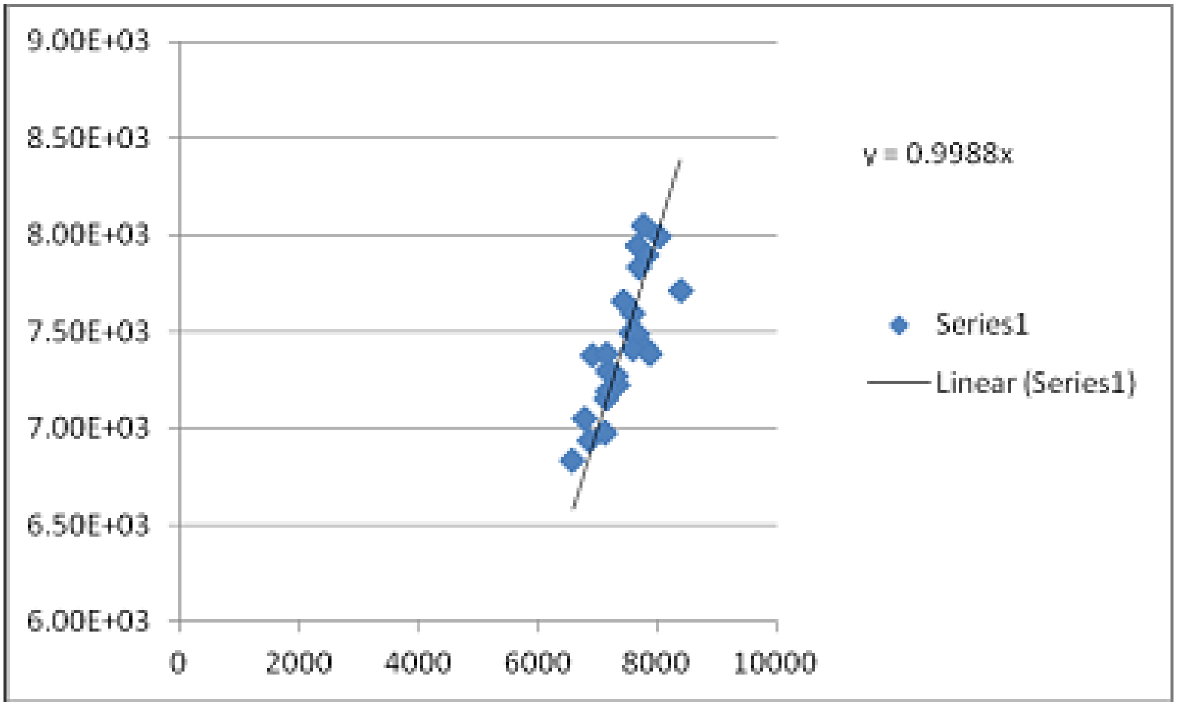

Figure10. Validation of RSM model for SW response by excel in Langkawi Island

Final Equation in Terms of Coded Factors:

(Solid Waste) = 3163.084-0.053088 * Personnel +1.49818* Total truck - 0.056234*fuel (16)

This study used a linear response surface. The full quadratic response surface is shown to be the most efficient approximation to fit the finite element model.

Based on the existing facilities and other parameters as well as the linear model, the best use of machinery and labor, and the minimum cost in the collection and transportation of waste are presented in Table 14, and Figure 9. Table 15 shows scenario according to interview with the experts.

Table 15. Number optimization-set goals for each response

No.	Personnel	Fuel	Total Truck	Solid Waste	Cost	Desirability	
1	10488.57	17358.13	4278.20	8039.68	14873.6	1.000	Selected
2	11677	17566.6	4321.32	8029.46	17540.6	1.000	
3	10470.8	22727.76	4572.16	8281.53	14156.2	1.000	
4	12177.42	18636.55	4591.83	8348	18079.5	0.999	

The 3D response surfaces model in linear form showed the best significant relationship ($p < 0.05$). The interaction effects of the independent variables were plotted based on the cost optimization related to the solid waste collection and transportation. The plots are drawn as function of four factors at the same time, holding the fifth factor at fixed levels (at the mid level). The plots are helpful to understand both the main and the interaction effects of these four factors. Table 16 summarized SW cost estimation in Langkawi Island.

Table 16. Prediction and estimation of solid waste management cost in Langkawi Island

Factors	Autumn 2009	Spring 2011	Unit cost RM	Sum cost Aut 2009	Sum cost Spr 2011
Solid waste	7825.7 (ton)	8039.68 (ton)	-	-	-
Personnel	15666 (person)	10488.57 (person)	3.75	58747.5	39332.14
Total fuel consumption	171690 (liter)	157353.1 (liter)	1.9	326211	298970.8
Total Truck (maintenance,repair and rent)	4668 (number)	4278.20 (number)	60,40	250020	229142.2
Total cost	-			634978.5	567445.1

Notes : 15666 trips made by individual worker within three months

The total cost of collection and transportation of solid waste in Langkawi Island in 2009 reached RM 67533.4; therefore,

634978.5 - 567445.1= 67533.4

67533.4*100/634978.5= 10.63554 %

This means that in spite of the increase in population and generation of solid waste in 2011, the use of RSM showed 10.63 percent reduction in cost in Langkawi Island.

The first step was to set up a design and then arrange the data collected from 2004 to 2009 in form of per three months, and the second step was to prepare the model based on the experimental settings. The third step was to apply ANOVA to fit the model and calculate the fitting model and error. The last step was the verification and validation of the model by statistical analysis. From the findings, the use of the linear function of the response surface model appeared to be effective in the Island.

In the autumn season of 2009, the amount of solid waste generated in Langkawi Island was 7825.7 tons and it took 15666 trips per person into the landfill, 171690 liters of fuel and 4668 total trips made by the trucks to transport this amount of waste to the landfill. In spring 2011, the amount of solid waste generated increased to 8039.68 tons, while based on the linear RSM model, number of times that personnel entered the landfill to work on solid waste decreased to 10488.57 times, fuel consumption for carrying this amount of waste decreased to 157353.1 liters and the number of trips made by the trucks decreased to 4278.20 times. The analysis was undertaken using the primary data collected through interview with experts in the Municipality regarding daily wages per person (i.e., salary of person for collection and transportation of MSW) which is equivalent to 10 dollars; per fuel liter is equivalent to 63 cents; Fuel consumption for 4-ton truck is 30 L and for 10-ton truck is 40 L in Langkawi, Malaysia.

Also, the cost of maintenance related to repair and rent of trucks was computed. In 2011, a total of 4278.20 trips were made to the landfill, i.e., 1378 times by the 4-ton trucks and 2900 times by the 10-ton trucks. The total cost incurred during the autumn season in 2009 was RM 634978.5, which reduced to RM 567445.1 in spring in 2011.

CONCLUSION

This research has combined ANN and RSM with more input variables to predict or forecast solid waste generation and optimize the cost of waste collection and transportation in Langkawi Island. The objective in combing the two models was to provide knowledge about the amount or quantity of solid waste generated over time and how to optimize the related cost, which the authors believe will assist the authorities who are in-charge of solid waste management to design appropriate and cost effective measures to collect and transport solid waste in general and in Langkawi in particular.

Based on the findings of the current study, the following policy recommendations are proposed to facilitate achieving the objectives of solid waste management, particularly in Langkawi, Malaysia. The use of ANN model showed increasing amount of solid waste generation in relation to the increasing number of tourists. Therefore, the activities of the Environment *Idaman Sdn Bhd*, a local waste management company which is involved in solid waste management in Kedah, should be fully supported financially and technically. This is because the cost involved in the programs to minimize solid waste generation will be lower than the solid waste collection, transportation and treatment at the landfills. For that reason, more private companies should be enticed by the Malaysia Government into the business of solid waste management, particularly in activities focusing on minimizing solid waste generation.

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