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Landfill area estimation based on integrated waste disposal options and solid waste forecasting using modified ANFIS model

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ABSTRACT

Solid waste prediction is crucial for sustainable solid waste management. The collection of accurate waste data records is challenging in developing countries. Solid waste generation is usually correlated with economic, demographic and social factors. However, these factors are not constant due to population and economic growth. The objective of this research is to minimize the land requirements for solid waste disposal for implementation of the Malaysian vision of waste disposal options. This goal has been previously achieved by integrating the solid waste forecasting model, waste composition and the Malaysian vision. The modified adaptive neural fuzzy inference system (MANFIS) was employed to develop a solid waste prediction model and search for the optimum input factors. The performance of the model was evaluated using the root mean square error (RMSE) and the coefficient of determination (R^2). The model validation results are as follows: RMSE for training = 0.2678, RMSE for testing = 3.9860 and R^2 = 0.99. Implementation of the Malaysian vision for waste disposal options can minimize the land requirements for waste disposal by up to 43%.

1. Introduction

Proper solid waste management is important for protecting both human health and the environment (Koroneos and Nanaki, 2012). The quantity and quality of solid waste changes with time due to variable lifestyles and consumption behaviors (Rimaitytė et al., 2012; Unnikrishnan and Singh, 2010). Municipal solid waste prediction is essential for sustainable waste management and the planning and selection of handling, treatment and disposal options (Cho et al., 2012). However, solid waste forecasting is a complex task due to the influence of multiple factors that are not constant over time (Younes et al., 2013). In Malaysia, solid waste generation has rapidly increased in recent years as a result of urbanization, increasing per capita income and consumption behaviors (Akil and Ho, 2014).

Forecasting is divided into two areas: (i) qualitative techniques based on expert opinion and/or personal judgment and (ii) quantitative techniques based on mathematical models that are objective in nature. Quantitative forecasting is developed using time series or causal variables. Time series forecasting employs historical data to predict the targeted future, whereas causal variable forecasting finds the relationship between the input and output variables and then implements this relationship to predict the future (Makridakis et al., 2008). Implementation time series forecasting does not require significant data, and it can assess the data fluctuations. However, the lack of empirical justifications is the main disadvantage of time series forecasting (Chung, 2010).

Causal forecasting requires the determination of the model structure, the model type, and the input variables based on the forecast goal and model developer. Although solid waste prediction models are highly diverse, they address the same issue (Beigl et al., 2008). Solid waste prediction using a data intensive forecasting approach is limited by the availability of the required data. An increase in the number of modeling variables requires additional effort to collect, organize and correlate the data and reduces the ability to guarantee the data reliability and quality. However, the consideration of all solid waste generation influencing factors is impossible.

In developing countries, where reliable data are not extensively available or are inaccurate, the estimation of solid waste generation is usually performed by load-count, materials-balance, or volume/

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weight analyses (Shahabi et al., 2012). However, the majority of these methods are insufficient for properly determining the solid waste generation. For instance, a load-count analysis reflects the rate of waste collection. However, the actual rate of waste generation is not determined. Implementation of the materials-balance approach is complex and requires accurate records and massive efforts for large cities and communities. Consequently, the need to employ dynamic nonlinear and data-driven techniques, such as the artificial intelligence model, is evident (Abbasi et al., 2012).

The adaptive neural fuzzy inference system (ANFIS) is a dynamic data-driven model that employs a feed-forward network to search for a fuzzy membership function between inputs and outputs (El-Shafie et al., 2011). It benefits from the powers of fuzzy logic and neural networks (Noori et al., 2009) and can be implemented for short-, medium- and long-term predictions (Mordjaoui and Boudjema, 2011). The fuzzy inference system involves five functional blocks: (i) a rule base that contains if-then rules, (ii) a database; (iii) decision-making; (iv) fuzzification, which determines the degree of matching; and (v) defuzzification, which transforms the fuzzy results into crisps (Subasi, 2007; Tahmasebi and Hezarkhani, 2010). A fuzzy inference system employs historical input data to tune and develop the final shape of the membership function using either a backpropagation algorithm or a least squares method (Al-Ghandoor et al., 2012).

The popularity of ANFIS recently increased due to its efficiency and its potential to capture a large amount of nonlinear and noisy data. For example, it has been utilized to predict the industrial solid waste in Durg-Bhilai Twin City (DBTC) using population number, percentage of urban population, and gross domestic product (GDP) as input variables (Tiwari et al., 2012). The integrated wavelet and ANFIS model have been employed to forecast flood frequency, where the wavelet model was employed in preprocessing to eliminate the noise in the data (Sehgal et al., 2014). It has been used to determine the most effective variables in determining the dissolved oxygen concentration in river water (Najah et al., 2014). In addition, ANFIS has been utilized to model solar radiation based on metrological variables (Piri and Kisi, 2015).

However, the ANFIS model has one limitation: the complexity of the model topology can be increased by increasing the number of input variables, as the rules are generated using all possible combinations of premises, which is a function of the number of variables. The number of generated rules N for a system with n inputs and P premises is ($N = P^n$). Therefore, the use of ANFIS may be unfeasible for problems with several variables. Although the utilization of human expertise for determining an ANFIS structure is preferable, this solution is not viable. For example, the structure of an ANFIS model with eight inputs and two membership functions will produce a large number of rules ($2^8 = 256$ rules), with a significant increase in the total number of parameters and computing time.

To overcome this limitation, a modified ANFIS (MANFIS) is suggested and employed in this study. The system includes several steps: (i) optimizing the number of rules (Khatibinia et al., 2012) by optimizing the inputs and search for the optimal number of membership functions; (ii) searching for the best input combinations that minimize the model error and (iii) determining the best membership function performance by altering the function usage. To evaluate the appropriate input selections and model performance and the ability to produce precise forecasts, the root mean square error (RMSE) (Lin et al., 2013) and the coefficient of determination (R^2) were employed (Abushammala et al., 2014; El-Shafie et al., 2011).

1.1. Landfill in Selangor State

Landfills are the ultimate solid waste disposal method in the world (Alslaibi et al., 2011) as well as in Malaysia and Selangor State. According to the Ministry of Urban Wellbeing Housing and Local Government (MUHLG) (2014), 301 landfill sites exist in peninsular Malaysia and Malaysian Borneo, including 161 in-operation landfills; and approximately 60% of the working landfills are open dumps lacking pollution control facilities or daily coverings (Manaf et al., 2009). A summary of the characteristics of active landfills in Selangor State is presented in Table 1. Six landfills are open dumps, and all landfills, with the exception of Bukit Tagar, will attain their maximum capacity within the next decade, which indicates an urgent demand for new landfill construction and/or the development of other disposal options.

This study proposes a model structuring process to forecast the annual solid waste generation rate (kg/capita year) in Malaysia. It applies a systematic search algorithm to select the best available representative variables that affect solid waste generation, such as population age groups, GDP, power demand per capita, and employment and unemployment numbers. The selection of these variables is based on the results of a literature review and the availability of records. A MANFIS model is then built to predict the waste generation. The model is employed to predict the future amount of solid waste and estimate the required landfill area for Selangor State. To obtain reliable results, the future solid waste disposal options suggested in the Malaysia Vision (2020) have been integrated in the landfill area estimation. This approach aims to minimize the modeling complexity and provides effective tools for simulating environmental applications. In addition, the results can help decision makers properly establish sustainable waste management plans.

2. Methodology

2.1. Study area and data collection

Malaysia is located in Southeast Asia with population around 29 million, its climate is tropical with uniform temperature (between 22 and 32 °C) and high humidity. Malaysia is newly industrialized country and classified as upper middle income with economy growth rate is about 5.7% (CIA, 2015). Selangor State is the most populated state in Malaysia. Selangor State, Putrajaya and Kuala Lumpur, are responsible for approximately 30% of the total solid waste generation in Malaysia. The annual solid waste generation is expected to increase by a factor of 1.7 within the forecast period (441 kg/capita year). The total waste generation within the next twenty-five years is approximately 92.38 million tons, with an

Table 1
Summary of the operating landfill in Selangor (Department of Solid Waste, 2014).

No.	Landfill name	Class	Daily capacity (ton)	Area (hectare)	Start year	Planned end year
1	Sg Sabai Kalumpang	Open dump	50–100	8.08	2001	2021
2	Bukit Beruntung	Open dump	150	8	1998	2021
3	Panchang Bedena	Open dump	60	4.04	1983	2007
4	Kuang[a]	Open dump	50	10.92	2007	2032
5	Dengkil[a]	Open dump	200	58.68	2004	2029
6	Sg Kertas[a]	Open dump	3	5.74	2011	2036
7	Bukit Tagar	Sanitary	1950	700	2005	2045
8	Jeram	Sanitary	2066	80.9	2007	2027
9	Mukim Tanjung	Sanitary	300	64.7	2010	2030

[a] Inert landfill.