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APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR SOLID WASTE PROJECTION AND ENERGY CONTENT EVALUATION

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Abstract: Forecasts of the heterogeneous municipal solid waste (MSW) generation are vital for sustainable MSW management. Artificial neural network (ANN) models have been successfully demonstrated to predict complex MSW trends, but the negligence of the MSW's heterogeneous characteristics hinders the further application of the predictions. This study aims to adopt robust ANN models coupling Bayesian hyperparameter optimization and uncertainty analysis to forecast the heterogeneous MSW generation in a country with further application in energy content evaluation. The impact of the hyperparameter optimization is illustrated by comparing the forecast uncertainties of ANN models using the Bayesian-optimized hyperparameters and default hyperparameters using ensemble forecasts. The relative standard deviations of the ensemble forecasts show that overfitting is more susceptible in the default models (11.1% – 44,400%) than in the Bayesian-optimized models (3.64% – 27.7%). By using the Bayesian-optimized models, Malaysia's heterogeneous MSW generation is projected individually based on its physical composition. The total MSW generation in Malaysia is expected to grow by 12% from 2020 to 2030, with food waste as the dominant composition (44%). The energy content of the overall MSW is evaluated based on the lower calorific value of the forecasted MSW. The forecasted increase in food waste generation reduces the lower caloric value of Malaysia's MSW below the lower limit to burn without supporting fuel (i.e., 6.5 MJ/kg). An alternative scenario where food waste is segregated from the overall MSW shows an increase in the lower calorific value from 5.874 MJ/kg to 10.31 MJ/kg. Without food waste segregation, the development of organic waste treatment facilities in Malaysia should be emphasized instead of incinerators. This study not only offers useful information for capacity planning of MSW treatment facilities using a data-driven approach, but it also broadens the scope for future related research by examining the application of the forecasted outcomes using ANN models.

Keywords: ensemble forecast, heterogeneous composition, lower calorific value, uncertainty analysis, waste segregation

Introduction

Global municipal solid waste (MSW) generation has grown with the changes in production and consumption patterns as a consequence of urbanization and population growth (Gómez-Sanabria *et al.*, 2022). On current trends, the World Bank projects the global waste generation to double from 2×10^9 t in 2016 to 3.4×10^9 t in 2030 (Kaza *et al.*, 2018). The absence of proper waste treatment

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facilities to cope with the surging MSW jeopardizes the environment and human health, especially in developing countries (Bui *et al.*, 2020). Projections of MSW generation are vital to assist policymakers in resolving data scarcity to conduct localized studies for the planning of a sustainable MSW management system (Abbasi & El Hanandeh, 2016). However, the MSW issues are challenging to model due to their heterogeneous characteristics, non-linearities, temporal fluctuations, and influences by socioeconomic factors (Abdallah *et al.*, 2020).

Artificial intelligence techniques emerge as solutions to unraveling the complexity of the MSW issues with satisfactory performance (Vitorino de Souza Melaré *et al.*, 2017). Amidst the artificial intelligence techniques, artificial neural network (ANN) models can be used to handle big data for prediction without an explicit relationship or equation (Singh, 2019). Ayeleru *et al.* (2021) developed an ANN model to forecast annual MSW generation in Johannesburg with a high determination coefficient of 99.9%. Hoque and Rahman (2020) forecasted MSW generation at a landfill site via an ANN model and estimated its remaining landfill area. Wu *et al.* (2020) predicted the MSW generation in China using regional models with determination coefficients ranging from 0.943 to 0.968. These studies demonstrated precise forecasts of MSW generation using ANN models, but forecasts of MSW generation as a whole hamper further economic and environmental assessment due to the negligence of the MSW's heterogeneous characteristics. Understanding the MSW's heterogeneous characteristics is imperative as there is no single dominant treatment method (e.g., material recycling, incinerating, and composting) that is suitable to treat all types of MSW (Ooi *et al.*, 2021).

ANN models are described as black-box functions where accurate predictions can be generated but with no knowledge of their internal workings to the users (Yao *et al.*, 2017). This makes them prone to overfitting where they try to memorize too many details and the noises from the training data. Consequently, the ANN models may perform poorly on unseen datasets. To maximize the reliability and validity of the forecasts, hyperparameter optimization and uncertainty analysis are encouraged during the ANN development (Abiodun *et al.*, 2018). A recent review of ANN studies on MSW-related issues by Xu *et al.* (2021) found only 31% of the 177 reviewed studies involved hyperparameter optimization and only four studies involved uncertainty analysis. Bayesian optimization is a probability-based global optimization algorithm capable of concurrently optimizing multiple hyperparameters, reducing computational cost without compromising its effectiveness (Baptista & Poloczek, 2018). As opposed to a local optimization which searches for the optimum of a function within a specific search space, a global optimization searches for the optimum among all possible solutions (Sergeyev *et al.*, 2018). The superior performance of the Bayesian optimization in neural networks is evidenced by the application of forecasting microalgae-based biodiesel yield (Sultana *et al.*, 2022), forecasting electric power load (Jin *et al.*, 2021), and forecasting electricity price for energy exchange (Cheng *et al.*, 2019). Here, we aim to develop an ANN framework integrating Bayesian optimization and ensemble uncertainty analysis for the heterogeneous MSW projection and energy content evaluation.

Materials and Methods

The methodological framework is divided into three phases, as shown in Figure 1. This study provides a country case study analysis. The methodological framework is applied to Malaysia to forecast its heterogeneous MSW generation and evaluate the energy content of the forecasted MSW.

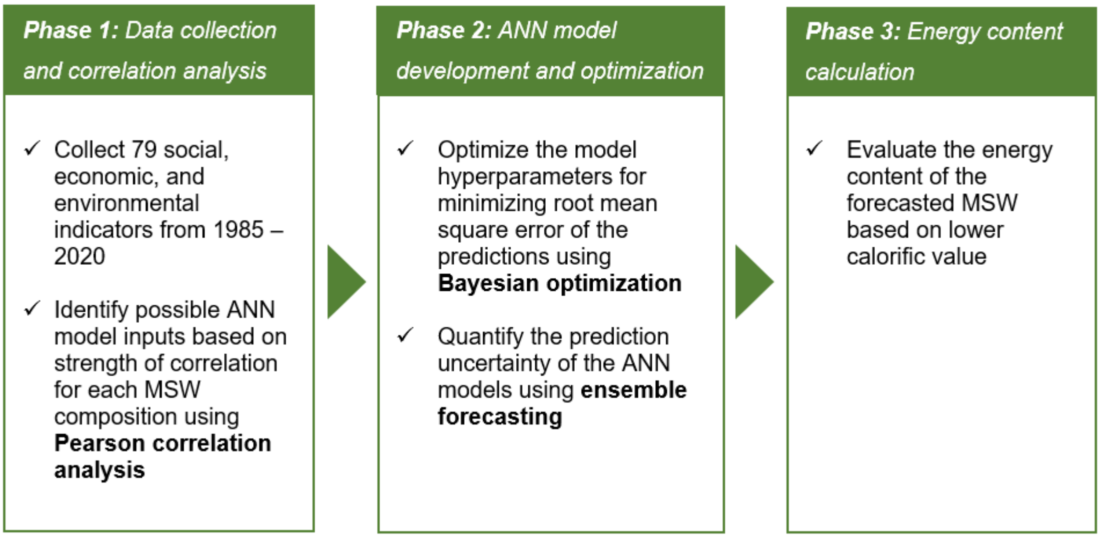

Figure 1. The methodological framework of research

Data collection and correlation analysis

The country-level data used in this study are mainly collected from past studies, the Malaysia Department of Statistics, and the World Bank Database. The input data consists of 79 types of social, economic, and environmental indicators (e.g., population, gross domestic product, and electricity consumption) from 1985 to 2020. The national MSW data are collected based on eight physical compositions which are food, garden, paper, plastic, glass, textile, metal, and others.

Pearson correlation analysis is performed to select the ANN model inputs based on the strength of correlation with the MSW data. The thresholds of high and low correlations are at > 0.7 (+, −) and < 0.5 (+, −) respectively (Jaadi, 2019). For each MSW physical composition, four indicators are selected as possible inputs based on the highest correlation coefficient regardless of the sign of the number.

ANN model development and optimization

Eight individual ANN models are developed for each MSW physical composition according to their respective highest correlated indicators. The ANN models identify arbitrary non-linear functions based on the intrinsic relationship between the correlated indicators and the MSW physical composition data. The ANN models are implemented in MATLAB R2021 while integrating Bayesian optimization and ensemble forecast. The Bayesian optimization simultaneously optimizes the number of neurons in the hidden layer, learning rate, and input combination among the four highest correlated indicators. It employs prior knowledge to calculate posterior probabilities to narrow down the optimal search space using Bayes' rule of conditional probability (Eq. 1). The probabilistic approach of the hyperparameter optimization hastens the convergence of the function; in other words, approximating the function to a state which predicts the MSW generation with the minimum objective function (i.e., error). The objective function of the optimization is configured to minimize the root mean square error of the predictions.

$$P(X|Y) = P(Y|X)P(X)/P(Y) \tag{1}$$

Where X is an unobserved quantity, $P(X|Y)$ is the posterior distribution, $P(Y|X)$ is the likelihood, and $P(X)$ is the prior distribution. $P(Y)$ is the normalizing value that can be removed by describing $P(X|Y)$ as a proportional quantity.

An ensemble forecast is performed for 10 trials to indicate the model stability from the range of possible forecasts. The forecasted MSW generations via the Bayesian-optimized models and the default model are compared based on their relative standard deviation (Eq. 2). The default model has 10 neurons in the hidden layer and a learning rate of 0.01 (MathWorks, 2021a, 2021b).

$$RSD = \sigma/\mu \tag{2}$$

Where RSD = relative standard deviation, σ = standard deviation of forecasted values, and μ = mean of forecasted values.

Energy content calculation

The projected MSW generation after 10 trials of the ensemble is averaged for the energy content calculation. The energy content of the overall MSW is calculated based on the lower calorific value (LCV) of the individual physical composition (e.g., food, garden, and paper) (Eq. 3). In the case study, the localized individual LCV are extracted from Malaysia’s National Solid Waste Management Department (JPSPN, 2016).

$$LCV_{overall} = \sum LCV_i \times \%composition_i \tag{3}$$

Where $LCV_{overall}$ = LCV of the overall MSW, LCV_i = LCV of the individual physical composition, and $\% \ composition_i$ = forecasted percent composition of the individual physical composition i.

Results and Discussion

To evaluate the performance improvement between the Bayesian-optimized and default models, the eight MSW physical compositions are forecasted up to the year 2030 with ensembles of 10 trials. The relative standard deviations of the forecasts are summarized in Table 1. The Bayesian-optimized models forecast with smaller relative standard deviations ranging from 3.64% – 27.7% compared to the default models with 11.1% – 44,400%. This improvement is contributed by the lesser likelihood of the Bayesian-optimized models to overfit. The reduced relative standard deviation of the Bayesian-optimized models significantly improves the forecast reliability.

Table 1. Relative standard deviations of forecasted waste in 2030 using the Bayesian-optimized and default model at ensembles of 10 trials

Waste type	Forecasted waste in 2030, relative standard deviation (%)	
	Bayesian optimized model	Default model
Food	7.91 – 9.01	11.7 – 305
Garden	5.28 – 7.06	253 – 741
Paper	17.5 – 22.0	39.8 – 1,450
Plastic	3.64 – 5.81	11.1 – 1,860
Glass	16.9 – 20.6	542 – 10,950
Textile	7.01 – 9.16	227 – 879
Metal	23.0 – 27.7	191 – 44,400
Others	13.0 – 14.9	26.3 – 243
Overall range	3.64 – 27.7	11.1 – 44,400

Table 2 shows the forecasted MSW generation, percent composition, and LCV of the forecasted MSW. Malaysia's MSW generation is expected to grow by 12% from 2020 to 2030, reaching 42,873 t/d in 2030. Food waste still constitutes the largest portion of the MSW physical composition at 44% in 2030. The immense increase in food waste is likely contributed by the booming population, putting pressure on food security, ultimately causing an increase in food loss and waste (Mattar *et al.*, 2018). The LCV of Malaysia's overall MSW in 2012, 2020, and 2030 are 6.371, 6.034, and 5.874 MJ/kg, respectively.

Table 2. The LCV of Malaysia's MSW in 2012, 2020, and 2030

	2012			2020			2030		
	MSW generation (t/d)	Percent composition (%)	LCV (MJ/kg) [1]	MSW generation (t/d)	Percent composition (%)	LCV (MJ/kg)	MSW generation (t/d)	Percent composition (%)	LCV (MJ/kg)
Food	14,743	44.5	0.102	17,041	44.5	0.102	18,865	44.0	0.101
Garden	2,365	7.1	0.811	2,719	7.1	0.806	3,783	8.8	1.002
Paper	2,816	8.5	0.679	3,255	8.5	0.679	3,655	8.5	0.681
Plastic	4,890	14.8	3.936	4,978	13.0	3.466	4,996	11.7	3.107
Glass	1,100	3.3	- [2]	1,149	3.0	-	986	2.3	-
Textile	1,014	3.1	0.217	1,187	3.1	0.219	1,589	3.7	0.262
Metal	1,073	3.2	- [3]	766	2.0	-	1,370	3.2	-
Others	5,129	15.5	0.627	7,199	18.8	0.761	7,629	17.8	0.720
Total	33,130	100	6.371	38,294	100	6.034	42,873	100	5.874

[1] The LCV based on MSW compositions is calculated from the LCV provided in JPSPN (2016).

[2, 3] The LCV of glass and metal waste are omitted as they are categorized as non-combustible materials (National Research Council, 2000).

Mass development of incinerators was within the Malaysian government's strategy in tackling the evergrowing MSW issue (Malay Mail, 2018). The suitability and efficiency of incinerating MSW are highly dependent on its calorific value (Kumar & Ankaram, 2019). Figure 2 compares the LCV trend with the combustible MSW (i.e., excluding glass and metal waste) generation from 2012 to 2030. The LCV of Malaysia's overall MSW is mainly contributed by its plastic waste composition, followed by its garden, other, and paper waste composition. Despite their steady increment in the generation amount, food waste still dominates the overall MSW composition. The slower increment rate of plastic waste decreases its share in the overall MSW composition from 14.8% in 2012 to 11.7% in 2030. The forecasted increase in the dominating food waste generation is expected to further reduce the LCV of Malaysia's overall MSW to 5.874 MJ/kg in 2030. Due to the food waste's high moisture content, the LCV of Malaysia's overall MSW is below the lower limit (i.e., 6.5 MJ/kg) at which the waste can burn with no supporting fuel at start-up (World Bank, 1999).

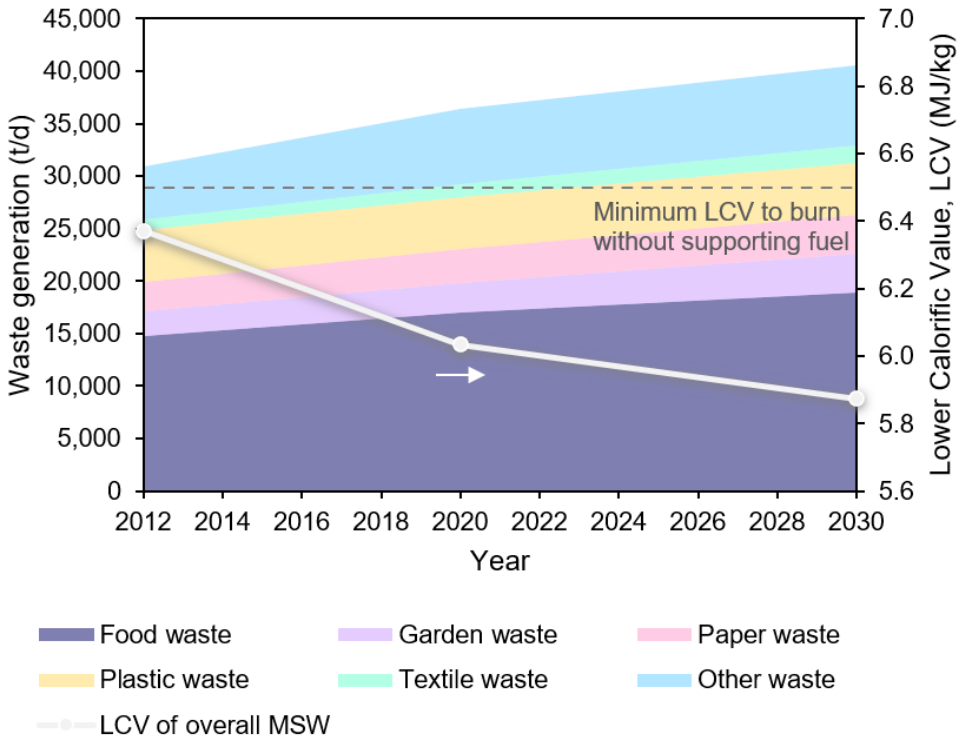

Figure 2. Changes in Malaysia's combustible MSW generations from 2012 to 2030 and their effects on the LCV of overall MSW. Glass and metal waste are omitted as they are non-combustible materials.

The Twelfth Malaysian Plan emphasized the enforcement of the Solid Waste and Public Cleansing Management Regulations 2018 to ensure all waste is separated at source for proper treatment, recycling, and disposal (Prime Minister's Department of Malaysia, 2022). Figure 3 illustrates an alternative scenario of the LCV of Malaysia's overall MSW increasing above the threshold after segregating the food waste. The LCV is increased to 10.31 MJ/kg when food waste is segregated from the overall MSW. However, the LCV after food waste segregation still follows a downward trend due to the decreasing percent composition of plastic waste. These outcomes show the apparent necessity of segregating food waste that has high moisture content to effectively treat the MSW using incineration. Otherwise, the development of organic waste treatment facilities such as anaerobic digestion or composting should be emphasized as they are more effective in treating the growing food waste with high moisture content.

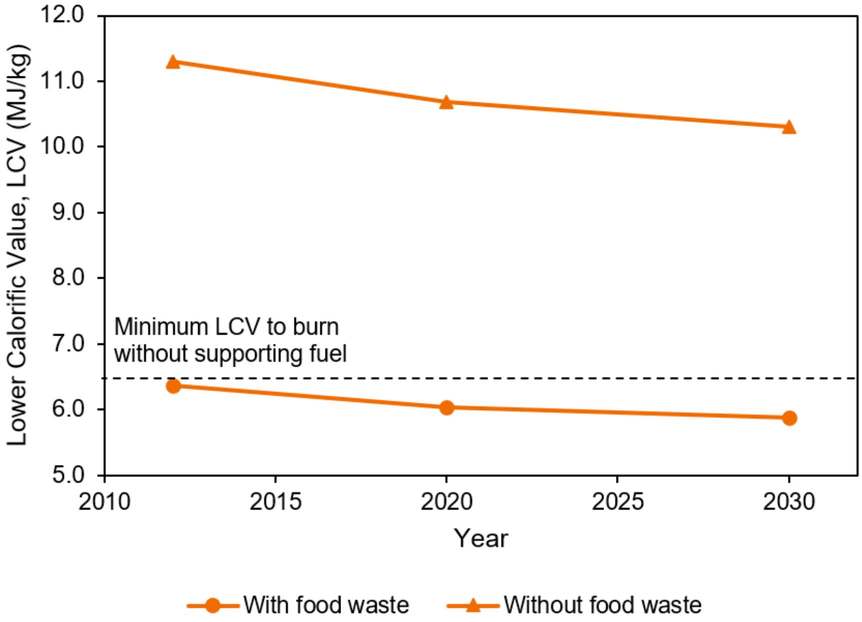

Figure 3. The LCV of Malaysia's overall MSW with and without food waste

Conclusion

The developed ANN models coupling Bayesian optimization and uncertainty analysis forecast MSW generation with high reliability. Ensemble forecasts of the Bayesian-optimized models highlight the significantly reduced forecast uncertainties in terms of relative standard deviation (3.64 % – 27.7 %) compared to the default models (11.1 % – 44,400 %). Based on the Bayesian-optimized models, Malaysia's waste generation is expected to increase by 12% from 2020 to 2030, constituting 44% of food waste. The increase in food waste generation further reduces the LCV of the overall MSW to 5.874 MJ/kg, which is below the lower limit at which the MSW can burn without supporting fuel. The alternative scenario where food waste is segregated shows an increase in the LCV to 10.31 MJ/kg. Without food waste segregation, organic waste treatment facilities should be emphasized instead of incinerators. The outcomes are vital to support policymakers in planning the waste treatment capacity based on a data-driven approach. Future studies could explore the generalization ability of ensemble forecast integrating with other optimization algorithms when dealing with MSW-related issues.

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Declaration of Interest Statement

The authors declare that they have no conflict of interest.

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