ORIGINAL ARTICLE

Forecasting Municipal Solid Waste (MSW) generation in Klang, Selangor using Artificial Neural Network (ANN)

Nur Atikah Jannah Mohamad [1], Siti Rohana Mohd Yatim[1], Samsuri Abdullah[2], Mohamad Tarmizi Azmin[3], Norliana Alwi[4]

[1] Centre of Environmental Health and Safety, Faculty of Health Sciences, Universiti Teknologi MARA Selangor,Cawangan Selangor, 42300 Puncak Alam Selangor, Malaysia
[2] Fakulti Teknologi Kejuruteraan Kelautan & Informatik, Universiti Malaysia Terengganu, 21030, Kuala Nerus, Terengganu
[3] Jabatan Perkhidmatan Persekitaran Majlis Perbandaran Klang, Jalan Lembaga Bandaran off Jalan tepi sungai 41000 klang Selangor, Malaysia
[4] KDEB Waste Management Sdn Bhd, 10th floor Menara Serba Dinamik, Lot 3,4 Persiaran Perbandaran Sek.14, 40000 Shah Alam, Selangor Malaysia

ABSTRACT

Introduction: Municipal solid waste (MSW) generation involves complex mechanisms. Prediction of future MSW amount can help the authority to comprehend and produce guidelines towards disposal system. In this study, we aimed to develop non-linear model for MSW prediction in Klang, Selangor on monthly basis. **Methods:** Data of MSW were acquired from Klang Municipal Council, composed of monthly MSW collection from the year 2017 to 2021. Non-linear autoregressive (NAR) models using artificial neural network (ANN) were developed using MATLAB software, and the best-fitted model for MSW prediction is assessed via coefficient of determination (R^2). **Results:** We found a fluctuating trend of MSW generated between months and years. MSW has statistically significant difference on monthly basis ($p < 0.05$), with 17 273 kg produced in January, and interestingly MSW has no statistically significant difference ($p > 0.05$) across the years, the highest was 21 7310.4 kg in the year 2021. The best architecture for the NAR models based on neurons testing ranges from 1 to 15 is 1-1-1, 1-2-1, 1-3-1,1-4-1, 1-5-1, 1-7-1, 1-8-1, 1-9-1, 1-10-1, 1-12-1 and 1-14-1 with R2 > 0.90. **Conclusion:** The developed models can be used for MSW prediction for MSW management by other municipalities.
Malaysian Journal of Medicine and Health Sciences (2022) 18(8):151-158. doi:10.47836/mjmhs18.8.21

Keywords: Artificial neural network, Municipal solid waste, Non-linear autoregressive, Prediction

Corresponding Author:
Siti Rohana Mohd Yatim , PhD
Email: sitirohana@uitm.edu.my
Tel: +603-32584446

INTRODUCTION

The human population has been expanding rapidly in recent decades along with economic development, resulting in an exponential increase in municipal solid waste generation. Municipal solid waste (MSW) is an obligatory result of daily human activities' by-products generated from residential, industrial, commercial, institutional, municipal, and construction that produces paper, food waste, plastic, metal, and glass (1,2). Plastic is the most abundant element in solid trash, and it has been estimated that about 400 million tonnes of plastic are created each year (3). MSW consists of different groups of waste including biodegradable waste, recyclable waste, inert waste, composite waste, and medical waste (4). Fauziah & Agamuthu predicted the total MSW generation in the municipal area of Kuala Lumpur by 2023 will reach about 4419.77 tonnes/day from the residential area, 2209.88 tonnes/day from commercial activity, and 368.31 tonnes/day from industrial sectors (5).

Malaysia reported a 27% increase in waste output during the COVID-19 pandemic, primarily due to the use of personal protective equipment (PPE) like gloves, masks, and coats, with an estimated 35.41 tonnes being disposed of daily (6,7). Additionally, this epidemic increased demand for online grocery shopping and food delivery services, which contributed significantly to the 44.8% increase in plastics and paper used as packing materials (8).

The growth of the MSW generation had driven the government of Malaysia to introduce the National Solid Waste Management Plan which acts as a guideline in assisting and improving MSW minimization through the concept of sustainable development. The waste minimization relies on the 3R concept of 'Reduce, Reuse, and Recycle' which have been highlighted as the main policy (9). The solid Waste and Public Cleansing Management Corporation Act has also been gazetted. However, a study has revealed that the policy is not being supported which can be seen through actual practices by the public; therefore, a more strategic monitoring approach is necessary to ensure public compliance towards the policy (10). The approach to improve the efficacy of solid waste management is crucial to make sure that operations involved in the management do not contribute any problem to human health and welfare, and it should focus on the goal of improving life quality (11).

The countless generation and continuous disposal of MSW have become an issue to MSW management since it can contribute to adverse effects to humans and environmental problems (12). The common and the most practical method for disposal of MSW in Malaysia is landfill. Landfill usually consists of different levels consisting of controlled dumping sites and sanitary landfills (13). Unfortunately, the MSW generation, collection, and waste processing are becoming an environmental problem as MSW highly contributes to the pollution of air, soil, and water.

The majority of landfill and dumping areas with uncontrolled gas recovery systems pollute the environment by producing unpleasant odours and emission of greenhouse gasses including ammonia (NH3), dihydrogen sulphide (H2S), carbon dioxide (CO2), and ammonium (CH4) which lead to climate changes and later contribute to the occurrence of extreme weather (14). Increasing emission of greenhouse gases including CH4 and CO2 is one of the major environmental problems that arise from waste disposal sites that have led to climate change affecting Malaysia's extreme weather conditions and rising sea level (15).

Additionally, soil and water will get the impact from improper management of solid waste as heavy chemicals from leachate will pollute the soil and water bodies (16). Previous studies regarding community perception of odour pollution from landfills found that the odour problem arising from solid waste had affected public life wellbeing due to daily exposure to foul smell, which caused people to experience nausea, headache, and vomiting (17). Unmanageable MSW might also cause the spreading of vector-borne diseases like dengue and Zika fever, and zoonotic diseases like rabies and leptospirosis (18).

Due to urbanization and rising population, MSW management requires adequate and effective planning that can be implemented based on the anticipated generation of MSW in the coming years. Failure to do so may result in problems for MSW treatment facilities if the amount is underestimated, as well as contribute to the growth of environmental problems (19). Computer-based models have been proven to be powerful tools addressing a variety of environmental issues, and computers have numerous advantages over traditional methods. Thus, this research was conducted to forecast MSW generation in the town of Klang, Selangor, Malaysia by developing a time series analysis of the nonlinear autoregressive (NAR) model using artificial neural network (ANN) for prediction.

Artificial neural network (ANN) is the forecasting method that is frequently used by many researchers in predicting MSW generation in different countries, since ANN is most effective in determining waste amount and its application in foreseeing the quantity of solid waste generated in the future is interesting (20). The predicted amount of MSW will result in a substantial contribution to the local authority, as it will allow for better planning and management of MSW in the coming years. Consequently, damaging effects that might happen from unmanageable MSW can be prevented, hence the goal towards sustainable cities and communities can be achieved.

Additionally, following the countless MSW generated in approaching years, the prediction might raise awareness to Klang residents and drive them to change their lifestyle habits. Therefore, this research aimed to determine the current trend of domestic waste generation and to develop an ANN prediction model for MSW in Klang as well as to identify the trend of waste production based on the prediction made.

MATERIALS AND METHODS

Study Location and Data Collection

This study was conducted in Klang, Selangor, Malaysia based on MSW data collection on monthly basis from 2017 to 2021. The data on amount of domestic waste collection was obtained from the local authority of the area, namely Klang Municipal Council. Klang is a district with a 573 km^2 area, occupied by 879 867 populations and located in the urban area of Selangor (Fig. 1). Klang is well-known as a major industrial area with growing economic activities, which influences the amount of waste generated to be among the highest in Selangor and serves as the primary reason it was chosen as a study location for developing a forecasting generation model using time series analysis.

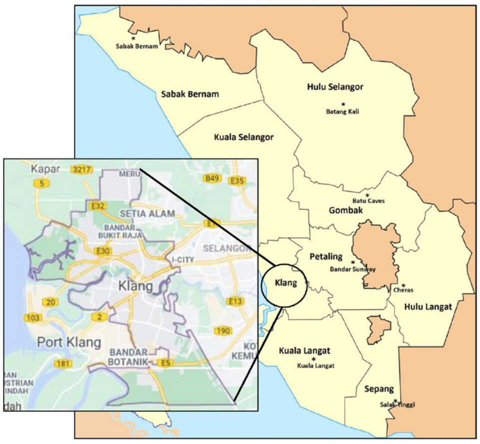

Fig 1: Study Location

The flow chart in Fig. 2 depicts the MSW forecasting process used in this study. The waste generation rate in the city is anticipated to be between 1.0 and 1.2 kg per occupant, and it is expected to rise year after year.

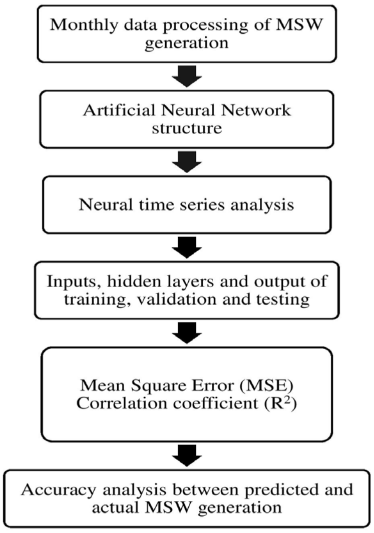

Fig 2: Flowchart of MSW forecasting

Model Applied

Artificial neural network (ANN) is a neural model that is mainly based on the perceived work of human intelligence – which makes it known as the artificial model of the brain (21). ANN models are particularly beneficial for forecasting the future using historical data. ANN models are capable of mapping between input and output. This network is a data-driven mathematical tool and is composed of neurons that are organised in layers, capable of learning from its situation and making up the association of a process's input and output (22). The set of input and output will assist in constructing a complex non-linear structure of MSW generation. The accuracy of this model can be assessed by evaluating its criteria including mean square error (MSE) and correlation coefficient (R^2).

In this study, a non-linear autoregressive (NAR) model with an input of monthly MSW amount has been developed in predicting the future amount of MSW generation by filling data with time series regression model. NAR models were then tested on monthly data from January 2017 to October 2021 while the missing data of November 2021 and December 2021 were excluded in this study. The missing data refers to the non-availability of MSW weight records for November 2021 and December 2021. A total of 58 datasets were used and during the testing process, the models were operated in the close loop and open loop.

The neural models were used in forecasting the monthly generation of MSW until the year 2023. The dataset was divided into three sections: training (70%) involving 40 target timesteps, validation (15%) involving 9 target timesteps, and testing (15%) involving 9 target timesteps. Each year of MSW data was optimized using the training algorithm of Levenberg-Marquardt (LM), a type of training that automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. The best models for each year of the MSW dataset were selected based on their correlation coefficient (R2). A value close to one indicates a close relationship and the model is suitable for forecasting MSW generation.

The NAR mod model is given as in Equation 1 where *y(t)* is the output at time *t* and *b* is the coefficient.

$$y(t) = b_0 + b_1\, y(t\text{-}1) + b_2 y(t\text{-}2) + \ldots + \; b_n y(t\text{-}n) \qquad (1)$$

The diagram of NAR neural network used in this study is shown in Fig. 3.

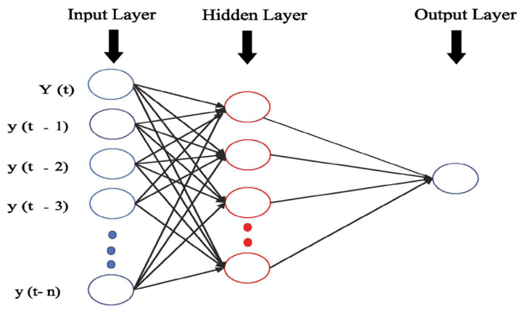

Fig 3: The NAR neural network

RESULT

The outcomes of this investigation were simulated using an ANN time series tool (MATLAB 2021 software). By adjusting the number of hidden layer neurons, the best ANN time series model was discovered. Various ANN structures were identified during the iteration process. To evaluate the optimised network structure, the minimum value of mean square error (MSE) and the maximum value of R were measured as performance indices. The trend of MSW from 2017 to 2021 that shows a progressive growth of production was identified.

The total amount of waste in Klang showed a sharp increase from year to year. On average, the monthly amount of waste during 2017 was 15 989.63 kg/month, in 2021 was 21 731.04 kg/month, and will reach 27 706.49 kg/month in 2023.

The generation of MSW has statistically significant difference on monthly basis ($p < 0.05$), with 17 273 kg produced in January, and interestingly MSW has no statistically significant difference ($p > 0.05$) across the years, the highest was 21 7310.4 kg in the year 2021. The total amount of MSW in Klang during 2023 is predicted to rise to 33 2477.93 kg.

This increasing waste generation is worrying and might lead to detrimental effects to the environment and public health if efficient management is not being implemented by the local authority of Klang. Fig. 4 shows the fluctuation pattern of MSW generation (actual and predicted) in Klang.

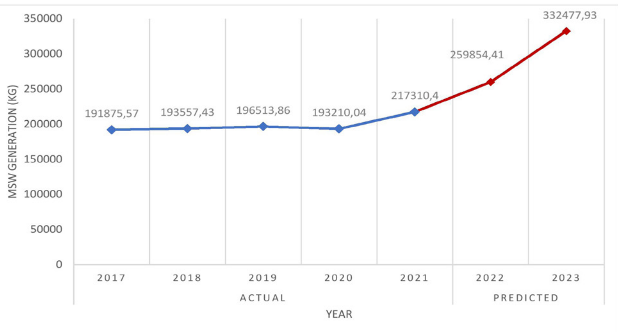

Fig 4: Trend of MSW from 2017 to 2023

For this study, the calculation of the MSW generations outputs in 2022 and 2023 was carried out based on the equations in the best neurons number. The equations used to obtain the output of MSW amount in every predicted month were based on the highest R^2 value of neurons during testing.

NAR model development is directed through the error and trial method where a number of neurons are added one after another. To accomplish the best network structure, the neurons' testing process is conducted from 1 to 15 and trained with three layers of an input layer, an output layer, and hidden layer. Selection of the best and optimized network structures are measured based on the maximum value of the coefficient of determination (R2) during testing which is closest to 1 and mean square error (MSE) value which is closest to 0.

The ANN structures 'learned' from past target data and undergo the testing process. The 70% that represents 40 datasets indicates the highest values of forecasting and the highest fluctuation pattern of MSW can be seen during 2017. 15% of data represents 9 datasets are taken for testing where the data was optimized as evaluation as the best forecasting model.

Overall, the testing of best neurons from 1 to 15 for predicted times of January 2022 to December 2023 showed the range of R^2 value between 0.86749 to 0.990881, which indicates high accuracy of forecasting and is highly relevant to be used for the prediction of MSW in the future. The target for the first 12 months was taken based on actual value from MSW data obtained while the target for January 2023 to December 2023 were taken based on last value predicted in December 2022. The overall regression performance of training, validation and testing for 2022 and 2023 are depicted in Fig. 5 and Fig. 6.

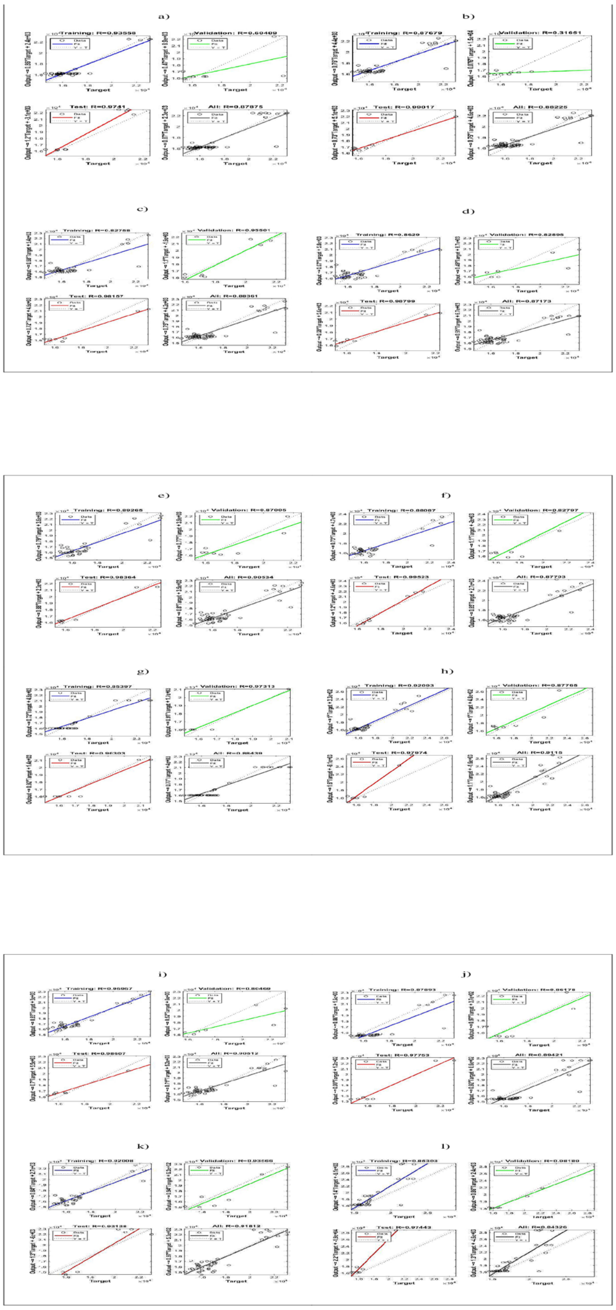

Fig 5: Regression curve between the monthly estimated and predicted ; a)January, b)February, c)March, d)April, e)May, f)June, g)July, h)August, i)September, j)October, k) November, l)December 2022

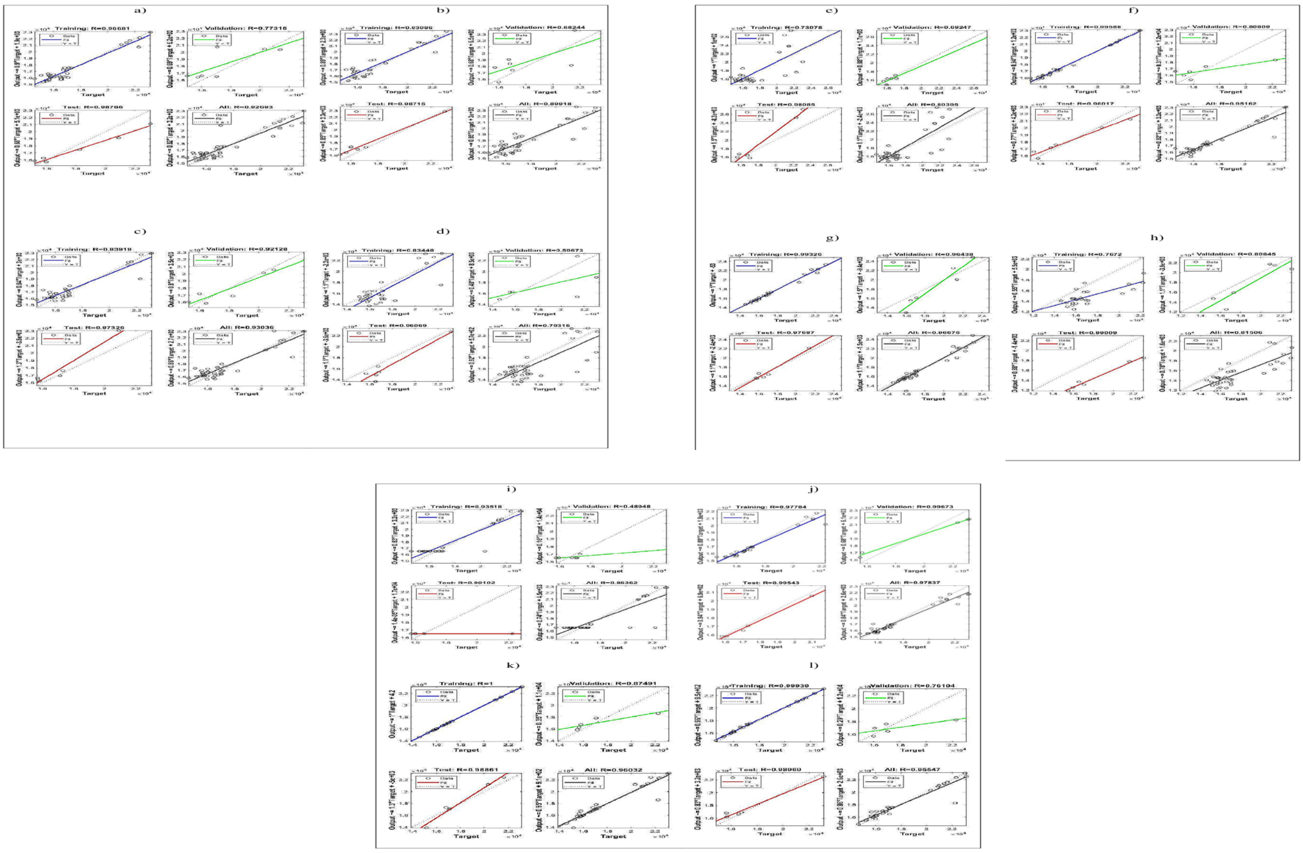

Fig 6: Regression curve between the monthly estimated and predicted ; a)January, b)February, c)March, d)April, e)May, f)June, g)July,]h) August, i)September, j)October, k) November, l)December 2023

The result of R^2 values selected based on optimum neuron for training, validation, and testing and their ANN time series model architectures of neuron 1 to 15 for 24 predicted months are listed in Table I. The predicted MSW amount for each month was generated from the chosen equation.

Table I: R^2 values, predicted MSW amount and MSE values for the testing of neuron 1 to 15

Pre-dicted times	Opti-mum neuron	ANN archi-tecture	Predicted Equation	Predicted MSW amount (kg)	R^2 values			MSE value
					Training	Validation	Testing	
Jan-22	6	1-6-1	y= 1.2(21367.08) + -3.1e+03	22540.5	0.87531	0.364925	0.948871	1191816.88
Feb-22	3	1-3-1	y= 0.73(21367.08) + 5.1e+03	20697.97	0.768761	0.100179	0.980437	716788.65
Mar-22	3	1-3-1	y = 0.72(21367.08) + 4.6e+03	15388.93	0.684889	0.912044	0.96348	930056.70
Apr-22	2	1-2-1	y = 0.69(21367.08) +5.6e+03	20343.29	0.744596	0.687158	0.976124	868682.35
May-22	4	1-4-1	y = 0.88(21367.08) +2.3e+03	21103.03	0.796824	0.756987	0.967548	319312.14
Jun-22	10	1-10-1	y= 1.2(21367.08) + -4.6e+03	21040.5	0.775932	0.685534	0.990483	347934.89
Jul-22	1	1-1-1	y = 0.92(21367.08) +1.4e+03	21057.71	0.729265	0.946982	0.927427	399622.41
Aug-22	9	1-9-1	y = 1.6(21367.08) + -9.1e+03	25087.33	0.848112	0.77027	0.95989	4479995.73
Sep-22	5	1-5-1	y = 0.7(21367.08) + 5.5e+03	20456.96	0.920775	0.647526	0.972334	609380.22
Oct-22	2	1-2-1	y = 0.99(21367.08) +1.2e+03	22353.41	0.772518	0.742665	0.955565	453225.93
Nov-22	4	1-4-1	y= 1.3(21367.08) + -6e+03	21777.2	0.846547	0.87546	0.867469	2657540.13
Dec-22	2	1-2-1	y = 2.2(21367.08) + -1.9e+04	28007.58	0.72766	0.964108	0.949514	9933080.41

CONTINUE

Table 1: R^2 values, predicted MSW amount and MSE values for the testing of neuron 1 to 15 (CONT.)

Predicted times	Optimum neuron	ANN architecture	Predicted Equation	Predicted MSW amount (kg)	R^2 values			MSE value
					Training	Validation	Testing	
Jan-23	10	1-10-1	y= 0.68(28007.58) +5.1e+03	24145.15	0.934722	0.597776	0.975472	1173794.80
Feb-23	9	1-9-1	y = 0.85(28007.58) +3.3e+03	27106.44	0.8665	0.465724	0.974465	727823.32
Mar-23	9	1-9-1	y = 1.3(28007.58) + -3.8e+03	32609.85	0.882078	0.848757	0.947235	1066415.90
Apr-23	9	1-9-1	y= 1.1(28007.58) + -3.6e+03	27208.34	0.696357	0.356087	0.922925	2371876.81
May-23	7	1-7-1	y = 1.8(28007.58) + -8.3e+03	42113.64	0.534039	0.479515	0.962067	458745.90
Jun-23	14	1-14-1	y= 0.77(28007.58) + 4.2e+03	25765.84	0.991737	0.653009	0.960733	481204.12
Jul-23	12	1-12-1	y = 1.1(28007.58) + -2.4e+03	28408.34	0.986565	0.930029	0.954275	317292.44
Aug-23	14	1-14-1	y = 0.88(28007.58) + -1.4e+03	23246.67	0.588596	0.807212	0.980278	13973591.24
Sep-23	1	1-1-1	y = 1.4e-05(28007.58) + 1.7e+04	17000.39	0.874562	0.239591	0.982121	5650000.24
Oct-23	3	1-3-1	y = 0.94(28007.58) + 6.9e+02	27017.13	0.956171	0.993471	0.990881	114000.41
Nov-23	7	1-7-1	y = 1.3(28007.58) + -5e+03	31409.85	1	0.765468	0.97735	702875.63
Dec-23	8	1-8-1	y= 0.83(28007.58) +3.2e+03	26446.29	0.99878	0.579182	0.979486	402293.23

DISCUSSION

The trend of MSW generation from 2017 to 2021 shows an increasing trend and will continue to grow progressively based on the prediction made where a total of 332 477.93 kg of MSW is expected to be generated during 2023. As stated by Asante-Darko et al. (23) and Vivekananda & Nema (24), the reasons why the MSW generation rate keeps increasing are related to influencing factors of higher living standard, rapid urbanization, economic expansions, increasing the demands of goods by the public, income of families, and level of education in a population. Klang population is currently nearing a million and the population growth rate will surely increase in future years.

Based on the prediction model developed, the forecast amount of waste during 2022 and 2023 shows an increasing generation of 16.37% and 21.84%, respectively. According to Mian et al. (25) and Hoornweg & Bhada-Tata (26), by 2025, the MSW is probably increasing to 2.2 billion tonnes per year and generated about 1.42 kg per capita per day, produced from an estimated 4.3 billion urban residents. It was also calculated that about 6.9 million tonnes of CO2 were emitted in 2016 from solid waste disposal sites and about to increase to 10 million tonnes of CO_2 in 2030 (27).

In Malaysia, MSW mismanagement has become a critical environmental issue. Aside from the growing population, waste mismanagement is compounded by rapid industry, urbanization, a lack of public awareness about waste generation, public lifestyles, geographic conditions, and poor planning. The effects of this waste mismanagement have a negative impact on our health. The management of MSW continuously becomes a major environmental concern as it causes global restriction for green growth (28). MSW constantly becomes a challenge especially in developing countries and contribute to numerous serious environmental issues driven by factors of the economic growth, inadequate fund, lack of expertise, shortage of manpower, insufficient technology, and poor facilities (29-31).

The forecasting of solid waste generations has become a necessity for the policymaking and planning to MSW management (12). The MSW management by Klang Municipal Council might become critical if the quantities of waste generated in Klang are wrongly estimated. Therefore, the prediction made by using the NAR model on the amount of waste produced till 2023 will help the authorities to improve or add more of the required facilities, particularly for collection and disposal. In consequence, the issues of uncontrollable waste management due to operational inefficiency, insufficient service coverage, and shortage of landfill disposal area can be prevented, and in the meantime, the health and welfare of the public can be protected.

NAR model is a great model since it can capture and process non-linear and complex data as established in past studies. Its application has been applied widely to different study fields like environment, medicine, and engineering. This model is capable of self-learning in determining the trend of MSW and have received favourable responses due to its ability in capturing non-linear dynamics and high accuracy in a specific study location.

The present study shows that the time series NAR model developed based on 60 months data were relevant to be used for forecasting trends of MSW generation in approaching years. The trial-and-error step applied during the identification of the best neuron number in the hidden layer in this study is also important to prevent less or overfitting in the NAR model. The determination of the optimum NAR model through the implementation of the LM algorithm is crucial to reduce any bias during the training, testing and validation model. The fluctuation amount of municipal solid waste generated in Klang is one of the contributing reasons for the various results of R^2 values testing.

A similar study conducted in India by Ali & Ahmad (32) shows that the monthly waste generation amount in Kalkota was successfully predicted for 2030 by using ANN structure and time series analysis with high accuracy of R^2. Also, this time series forecasting model used is flexible since it does not involve much data and capable of gathering fluctuations. Thus, these ANN times series models are highly applicable for the long-term prediction of solid waste generation.

CONCLUSION

The NAR model established in this study is well constructed for the prediction of MSW amount in Klang in 2022 and 2023. The prediction shows that by 2023, the total amount of MSW produced in Klang reach up to 332 477.93 kg. Hence, better strategies and extra allocation are necessary for Klang Municipal Council in managing the additional waste which expands from year to year. The non-linear autoregressive (NAR) Neural Network of time series analysis prediction model that was used in capturing non-linearity of MSW generation data is suitable for adoption by other local authorities as a driven tool for more sustainable management of solid waste produced, particularly in the urban area. The result could be enhanced by using weekly MSW data and other variables such as population, per capita income, and migrations of individual as input parameters for the prediction purpose in future.

ACKNOWLEDGEMENTS

The author wishes to express the gratitude and appreciation to Klang Municipal Council for granting the permission to carry out this research.

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