Waste Management 121 (2021) 206–214

Contents lists available at ScienceDirect

Waste Management

journal homepage: www.elsevier.com/locate/wasman

Forecasting of municipal solid waste generation using non-linear autoregressive (NAR) neural models

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ARTICLE INFO

Article history:
Received 23 May 2020
Revised 8 December 2020
Accepted 9 December 2020
Available online 25 December 2020

Keywords:
Solid waste generation
Forecasting
Time series model
Non-linear autoregressive neural models
Feedback delays

ABSTRACT

Municipal solid waste (MSW) generation is a multi-variable dependent process and hence its quantification is relatively not easy. The estimations for monthly MSW generation are required to provide theoretical guidelines for understanding and designing the disposal system. These estimations help in budgetary planning for the handling of future waste with optimized waste management system. This study forecasts the monthly MSW generation in Nagpur (India) for the year 2023 using non-linear autoregressive (NAR) models. The classical multiplicative decomposition model with simple linear regression in time series was constructed with maximum absolute error of 6.34% to overcome the problem of data availability. It was observed that NAR neural models were able to predict short-term monthly MSW generation with absolute maximum error of 6.45% (Model A) and 3.05% (Model B) for the observation period. It was also concluded that the variation in MSW generation was best captured when yearly lagged values were used for the construction of NAR model and coefficient of efficiency (E) was 0.99 and 0.97 during testing and validation, respectively. It was found that in the year 2023, the city will record minimum waste generation in the month of February and maximum in the month of December. For the year 2023, it had been estimated that the maximum 48504 ± 1569 tons of waste in December and minimum 39682 ± 471 tons in February will be generated. It had also been estimated that the minimum waste generation from the year 2017 to 2023 will increase by approximately 5345 tons.

1. Introduction

Municipal solid waste (MSW) generation in any city is directly proportional to the population of the city. In cities with higher standard of living, more commercial activities, and more population i.e. in metro cities, per capita MSW generation is more compared to small towns (Sharholy et al., 2008). India with a population of 1.37 billion in 2019 is the second most populated country in the world after China constituting about 18% of total global population (World Population Prospects, 2019; United Nations, 2019). With a huge inhabitance, it becomes imperative from solid waste management prospective to estimate and forecast reliable MSW generation for the present and future. This is important to manage waste and environmental systems as failure to accurate prediction might lead to problems like over or under estimated capacity of MSW treatment facilities and increased environmental impacts (Intharathirat et al., 2015). For different Indian cities, the existing MSW generation has been reported based on the quantification exercise practiced by municipalities (Kumar et al., 2009). MSW generation quantification has intricate relationships among various demographic and socio-economic factors which are variable over a period of time and hence projections are quite challenging (Srivastava and Nema, 2008, Ali Abdoli et al., 2011; Kumar and Samadder, 2017). MSW composition and generation with respect to socio-economic factors like different income groups, number of people employed etc. has been studied earlier to relate the dynamics of society with waste generation (Bandara et al., 2007, Wu et al., 2020). As waste generation is a highly interrelated process, it is difficult to get reliable historical data for MSW characteristics (Rimaityte et al., 2011, Wu et al.,2020) in developing countries and thus in such a scenario, modeling is of particular importance (Beigl et al., 2008, Abbasi and El Hanandeh, 2016, Kannangara et al., 2018) with limited data available so as to have a theoretical base for the future scenario.

In the last one decade, the prediction of MSW generation using artificial intelligence and machine-based models has gained momentum (Vu et al., 2019, Wu et al., 2020) because these models are able to capture the non-linear dynamics of any system (Shahabi

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https://doi.org/10.1016/j.wasman.2020.12.011
0956-053X/

et al., 2012) and solid waste generation is one such system. Researchers have used Artificial Neural Networks (ANNs) for predicting MSW generation in different countries (Shahabi et al, 2012, Singh and Satija, 2016, Noori et al., 2010) with component prediction (Ribic et al., 2019) and by logistics of transportation (Jalili Ghazizade and Noori, 2008). These models are widely used because of the capability of self-learning (i.e. capturing trends and fluctuations) for new situations compared to other traditional models (Ordonez-Ponce et al., 2004; Thanh et al., 2010, Azadi and Karimi-Jashni, 2015). The ANN models have also been compared with other intelligent models like Adaptive neuro-fuzzy interference system (ANFIS), Support Vector Machine (SVM) for waste prediction (Abbasi and El Hanandeh, 2016) but the efficiency of ANN models as a whole was better while others were outperforming at certain conditions like peaks or average of quantities. For MSW generation prediction, researchers have used feedforward backpropagated neural models, generalized regression neural networks (Antanasijevic et al., 2013), principal component analysis combined with Gamma test for ANN (Noori et al., 2010), hybrid model (Noori et al. 2009), etc. The studies in the last decade for MSW prediction used variables of economy, population, employment (Younes et al., 2015) using non-linear autoregressive (NAR) network, weekly waste prediction (Jalili Ghazizade and Noori, 2008). Using neural model, other intelligent models like SVM, ANFIS, fuzzy logic have also been used (Kolekar et al., 2016). Waste generation is a complex non-linear process which has multiple independent variables linked to its estimation and inventory of all is time consuming and costly. Therefore, data driven models with fewer independent variables are needed (Noori et al., 2009). The major advantage that ANNs have over other traditional models is their ability to self-learning through input/output examples and grouped variables like monthly or weekly waste generation can be used to understand the dynamics (Ali Abdoli et al., 2011, Batinic et al., 2011, Jalili Ghazizade and Noori, 2008). The neural models are data driven models and require significant relevant parameters to attain the desired results. Therefore, in cases where data is limited or knowledge of significant variables is missing, it is difficult to achieve the best results. The extrapolation of results in neural model is better when done within trained data range and therefore efforts for outward range of data prediction is the future of a new research in different fields (Abiodun et al., 2018). From the above literature, it has been observed that feedforward backpropagated neural models have performed well in understanding the dynamics of waste management and therefore NAR neural model was used. Since the availability of data in waste generation for different places is difficult and hence self-lagged neural model was constructed with only one variable of monthly waste generation compared to other models like multilayer perceptron, NAR models with exogenous inputs (NARX) requiring more variables (Cadenas et al., 2015). The NAR models developed have also been tested for autocorrelation (AC) and partial autocorrelation (PAC) (Adhikari and Agrawal, 2013). NAR Neural Models in this study forecast monthly MSW generation for Nagpur, India till the year 2023.

2. Methodology and study area

In this study, neural models had been used for forecasting short-term monthly MSW generation for Nagpur, India till the year 2023 because it has been identified that combined detrending and deseasonalizing data as a preprocess in neural model is the most effective approach (Bărbulescu, 2018; Gheyas and Smith, 2011; Zhang and Qi, 2005). For detrending and deseasonalizing classical decomposition, multiplicative model has been used and then forecasting has been done. National Environmental Engineering Research Institute (NEERI), India conducted a feasibility study with Arcadis GmbH Germany for solid waste management for Nagpur, India and detailed waste characterization was done for the city. The study reported that MSW collected from different zones of Nagpur, India is finally dumped at Bhandewadi dumpsite which is approximately 10 km from the city (Arcadis GmbH report, 2017) (Fig. S1). Monthly MSW dumped at the site was observed during the year 2015 to 2017 which was used as observation period in the study (Fig. S2). The data of observation period was used for constructing time series regression model and were validated using the same period. To avoid the problem of data availability, the results were used in neural models for independent monthly MSW generation forecasting till the year 2023. The Nonlinear Autoregressive (NAR) neural model for predicting the monthly MSW generation was also constructed on the basis of delays and self-lagged inputs.

2.1. Regression modeling

For estimating solid waste generation, different linear and nonlinear models can be constructed to do predictive modeling. The constructed models are used to understand the relationships among different variables or variables solely on time-scale (Pavlas et al., 2017). The choice of time scale is empirical and depends upon the availability of data and sensitivity to time of the variable investigated. The model statistics are then used to assess the performance of model. High values of coefficient of determination in the first step are indicative of good performance of model. A good model will have values closer to the exact values and it can be said that model is able to capture the variations of condition being investigated.

For time series forecasting, it is important first to check the stationarity of the series (Ali Abdoli et al., 2011). This step helps in extrapolating the behavior of variable much easier in future. The series which are non-stationary i.e. if mean and variance changes significantly over a period of time and there is no autocorrelation, extrapolations in such cases will result in the values far from the actual values. Durbin-Watson test is done to detect autocorrelations (Ali Abdoli et al., 2011). Durbin Watson test cannot be used in series when lagged dependent variable is used in the regression model (https://towardsdatascience.com, 2019). In the present study, moving averages (MA) and central moving averages (CMA) were obtained to use classical decomposition multiplicative model which is represented in Eq. (1) (Adhikari and Agrawal, 2013)

$$Y(t) = T(t) \times S(t) \times C(t) \times I(t) \quad (1)$$

Where Y(t) is observation, S(t) is Seasonality, C(t) is Cyclical and I(t) is irregular variance at time t. After deseasonalizing and detrending, a simple linear regression was constructed to obtain MSW generation till the year 2023 using Eq. (2)

$$MSW(t) = 34332.79 + 305.9 \times t \quad (2)$$

Where MSW(t) is municipal solid waste generated in month 't'. The results were validated using observation period and mean absolute percentage error (MAPE) of 2.38% was obtained.

2.2. Artificial neural network (ANN)

Using Artificial Neural Network (ANN) in developing computational models under the concept of employing artificial intelligence derives its origin from analogy of the working and design of brain and central nervous system (Maier and Dandy, 2001). The use of ANN includes the characteristics of brain, such as massive parallelism, distributed representation and computation, learning ability, generalization ability, adaptivity, inherent contextual information processing, fault tolerance, and low energy consumption (Jain et al., 1996). ANN works like a parallel computer, consisting of number of processing elements (PEs) which are interconnected. In feed-forward networks, the PEs are arranged in layers i.e., an input layer, one or more hidden layers, and an output layer. The input from each PE in the previous layer is multiplied by adjustable connection weights. As these connection weights are adjustable, they may be linked to the coefficients in statistical models. At each PE, the weighted input signals are summed up and a threshold value is added. This combined input is then passed through a non-linear transfer activation function to produce the output of the PE. The pictorial representation for working principle of a single layered neural model is presented in Fig. S3.

2.2.1. Neural architecture and algorithm

Neural architecture broadly can be grouped under two categories feed forward and feedback neural networks. Feed forward networks are mostly used to model many complex problems and are trained using algorithm like gradient descent, gradient descent with variable learning rate and momentum constant, conjugate gradient etc. are used (Ali Abdoli et al., 2011). The choice of neural model depends upon the process to be modeled. The neural networks are constructed for static as well as dynamic processes as a function of time. In this study, NAR neural models had been used to predict monthly MSW generation for Nagpur, India. The models were constructed on MATLAB 2012b platform for the study.

2.2.2. NAR neural network

The prediction of solid waste generation has complex dependencies on many factors (Arcadis GmbH report, 2017). Hence, in this study, NAR model with different lagged inputs has been used to predict the future values of MSW generation by populating data with time series regression model. The NAR model can be understood as given in Eq. (3) (Sarkar et al, 2019)

$$w(t) = f(w(t-1), w(t-2), w(t-3)\ldots w(t-d) + \varepsilon(t) \quad (3)$$

Where, w is MSW generation data series over time, d is the input delay or lagged inputs used and f is the activation function used in the neural model. The function is constructed by training of neural models under different lags. The lags were estimated by calculating auto-correlation and partial auto-correlation. In this study, NAR model with input and output layers and with single hidden layer was constructed and neurons were varied as discussed under 3.3.1. The neural models were trained using Levenberg-Marquardt (LM) algorithm and log-sigmoid transfer function was used between input and hidden layers and linear activation function between hidden and output layers. The NAR models were trained, validated and tested in open loop mode and for prediction close loop model was used as shown in Fig. 1.

2.3. Data used and preprocessing

In this study, the values of actual monthly MSW generation for Nagpur, India were available from April 2015 to March 2017. Using classical simple linear regression (SLR) approach, the values were populated till the year 2023. The values thus obtained were then fed to the neural network model. This has been done to overcome from lack of historical data availability. NAR models were trained, validated and tested on data from April 2015 to December 2022. The whole data was divided randomly in training, validation and testing. During this process, the neural model was operated in open loop mode and then for the year 2023, the monthly MSW generation was predicted in close loop.

2.3.1. Data used

Training data was 70% of the total 93 values and validation and testing data were 15% of 93 values. When delay or lag of 1 was incorporated, the data set for training had 64 values, validation and testing has 14 values. For delay of 12, training data had 57 values, validation and testing data had 12 values each. The incorporation of delay in the NAR model thus changes the distribution of different data sets. The training phase imparts learning to the neural model based on input and output combinations. Validation of model was carried out to generalize the performance of neural model and testing was done to evaluate the model performance during training (Singh and Satija, 2016).

2.3.2. Data preprocessing

In construction of neural models, the raw data was not used directly because of the topology of ANN. The time series data had to be arranged based on chronological order and no randomization was done while doing dynamic modeling. The data was then normalized using formula given in Eq. (4) (Shahabi et al., 2012). The value of 'a' and 'b' was taken as 0.1 and 0.9, respectively.

$$W_{norm} = a + (b-a)\left[\frac{w - w_{min}}{w_{max} - w_{min}}\right] \quad (4)$$

The normalized values were then fed to neural model and the obtained values were denormalized to the original values. This step puts the variable on uniform scale so that the sensitivity of individual variable does not affect the results. Once the model is trained on input and output combinations, it is required to do short-term prediction for MSW generation for the upcoming years. Then, the neural models were used to predict monthly MSW generation till the year 2023.

3. Results

In this section, the existing scenario of MSW generation in Nagpur, India has been discussed along with outcomes of time series regression modeling. Once data is populated, NAR neural models were used to forecast monthly MSW generation till the year 2023.

3.1. Existing MSW scenario

From the monthly variation of MSW generation, it was concluded that solid waste dumped every month in the city follows seasonality and trend round the year. It has been observed for the year 2015 that May has the least amount of MSW generation with 31,103 tons, August and September had approximately the same order of MSW generation with 32,330 and 32,255 tons, respectively. December had the highest MSW generation with 36,448 tons. This variation in MSW generation in different places is owing to the factors like population density, average household size, unemployed rates etc. (Adamović et al., 2016) and is also based on climatic factors like temperature and rainfall (Keser et al., 2012). Therefore, it was well concluded that for Nagpur, India, MSW generation is also very dynamic across months and years as well. The variation in other cities in Indian context can also be attributed to various factors which could be socio-economic, seasonal or floating population etc. (Keser et al. 2012). As MSW generation was varying across months and hence planners can use such models to optimize the waste collection across months so that the efficiency in waste management can be achieved on monthly basis and negative environmental impacts can also be reduced. The physical characteristics of MSW Nagpur, India for observation period can be referred in Table S1 a & b.

3.2. Time series regression modeling and performance of a model

The monthly MSW generation data during April 2015 to March 2017 was used for forecasting the short-term MSW generation. The data for the available period was checked for stationarity and was

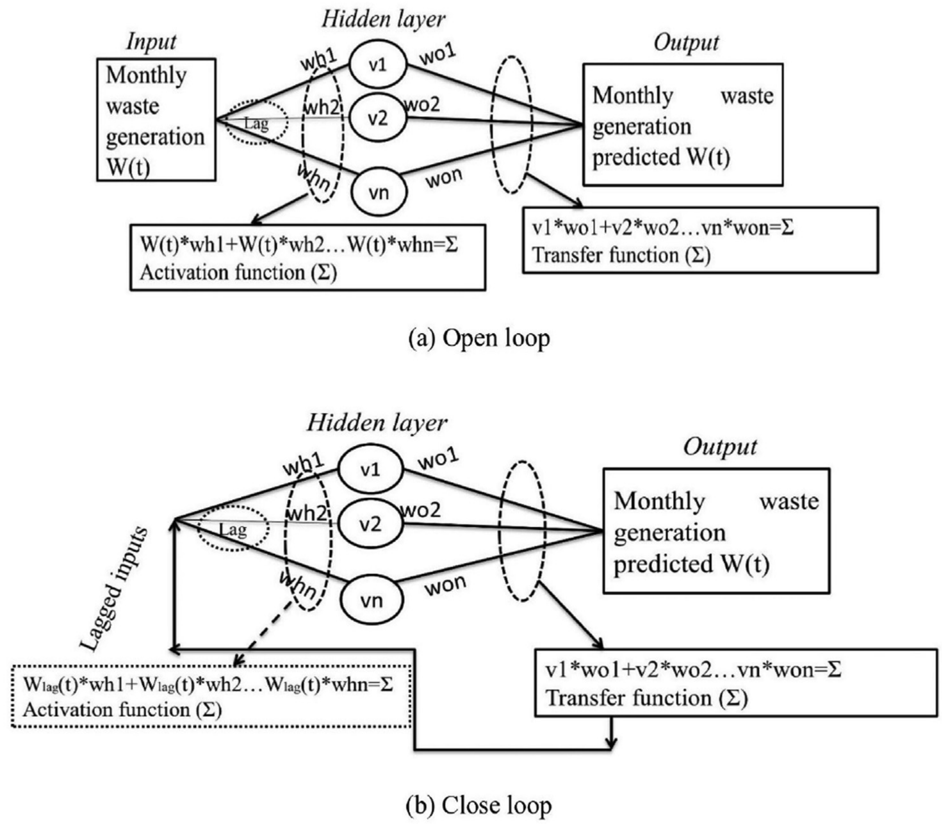

Fig. 1. NAR architecture (a) Open loop (b) Close loop.

found to be stationary with constant mean and variance over a period of time. The seasonality and trend were extracted using classical multiplicative decomposition model and then simple linear regression (SLR) was used to prepare time series values for the years ahead till the year 2023. Further, for assessing the performance of developed time series regression model, comparison between actual and observed values from the model was done for the year 2015 to 2017 (Fig. 2).

From Fig. 2, it was observed that time series model was able to capture the monthly MSW generation variation for Nagpur, India. The model predicted values closer to the actual values from June 2015 to March 2017. It was also observed that for the month of April 2015, the result was under predicted and for May 2015, it was over predicted. For the year 2016 and 2017, the model was able to capture the monthly variations of MSW generation very closely. The performance of this model was also assessed based on evaluation metrics for which different errors and parameters were identified. In this study, mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage Error (MAPE) were estimated as given in Eq. (5) to Eq. (7).

$$MAE = \frac{\sum_{k=1}^{N} |W_a - W_p|}{N} \tag{5}$$

$$RMSE = \left[\frac{\sum_{k=1}^{N} (W_a - W_p)^2}{N}\right]^{1/2} \tag{6}$$

$$MAPE = \frac{100}{N} \sum_{k=1}^{N} \left|\frac{W_a - W_p}{W_a}\right| \tag{7}$$

Where W_a is actual value of waste dumped monthly (tons) and W_p is predicted value of waste dumped monthly (tons) and N is total number of observations. The performance of time series model based on the evaluation metrics is presented in Table 1 and the bias of the model revealed that it was predicting value above the actual value because bias has negative value.

3.3. NAR architecture

The NAR models basically predict a time series from the past values of the same series and hence were used for forecasting short-term monthly waste generation for Nagpur city till the year 2023. For making time series predictions, it is important to first construct and derive the best architecture of neural model. Therefore, NAR models were constructed by varying the neurons in hidden layer from 2 to 15 and performance parameters were estimated. The topology of neural network that has least MSE was fixed as optimum structure and predictions were made using that model. Apart from fixing the neurons in hidden layer in autoregressive series, it is also important to decide the delays for the best model.

In NAR model, as there was a single variable used, it had to be tested for autocorrelation so that the feedback delay for the NAR model can be adjusted. The monthly waste generation was used to understand the auto-correlation. For short-term forecasting of monthly MSW generation, the time series populated data was fed to neural model and NAR model was evaluated independently based on forecasting done till the year 2023. Hence, two different approaches were used first to decide the delays in this study.

Model A was constructed based on autocorrelation for adjusting the delays and it was found that at lag one, high correlation was observed. For yearly pattern of waste generation, partial autocorrelation was also calculated. It was observed that at lag of 12, the values were above confidence bounds and close to 1. Therefore, other

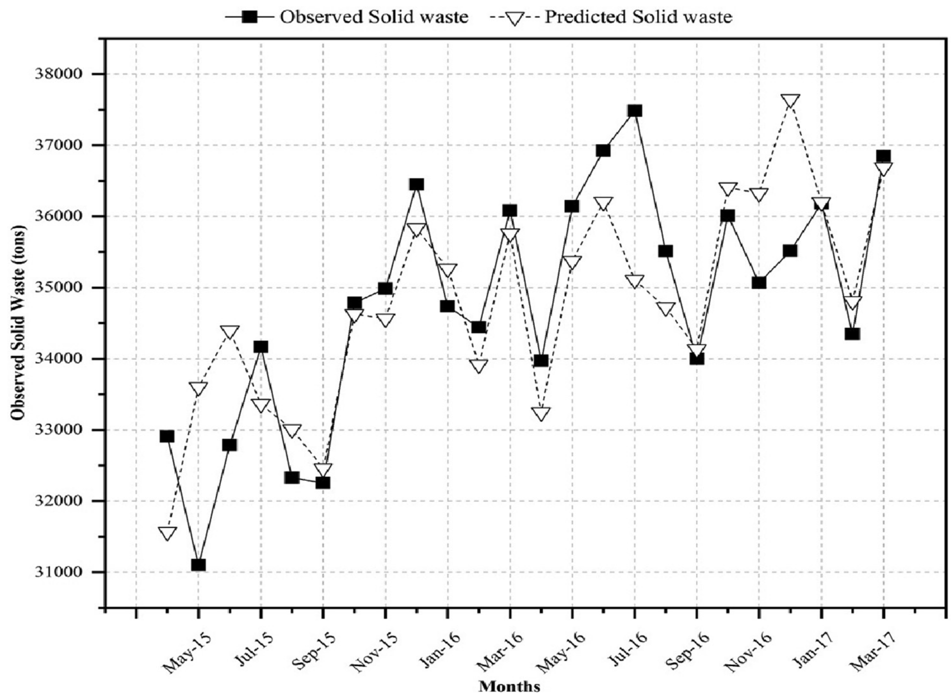

Fig. 2. Observed and Predicted results using time series regression model.

Table 1
Performance of time series model.

Error Type	Value
MAE	818.16
RMSE	1069.4
MAPE	2.37

sets of neural models were constructed by changing the delays in model B.

3.3.1. Selection of neurons

For the best topology of NAR models (Model A and Model B), neurons in hidden layer were varied. The MSE variation for Model A and Model B at different neurons is shown in Fig. 3. From Fig. 3, the number of neurons in hidden layer for both the models was decided and it was found that model A was performing well with 8 neurons in hidden layer, and with 13 neurons in hidden layer, model B was better. The selection of neurons in hidden layer is the first step for constructing any neural model. In Fig. 3, it can be seen that MSE during training, validation and testing phase has converged at neuron 8 with minimum values in all the three phases for Model A. For Model B, it was observed that error during testing and validation phase showed huge variation and at neuron 13, the testing error converged with the minimum value and corresponding training and validation error was also less. Therefore, this criterion was used to decide the topology of NAR model (Model A: 1–8-1 and Model B: 1–13-1).

3.3.2. Performance of neural models

Both the NAR models constructed were feed-forward and back propagated neural model and were trained using Levenberg-Marquardt (LM) algorithm. The log-sig activation function was used between input and hidden layers and the linear activation functions between hidden and output layers. The neural models were constructed by the forecasted values of monthly MSW generation obtained from time series model and the matrix obtained was used for training, testing and validation of neural models. The performance of model A and model B during training, validation and testing is shown in Fig. 4.

It should be noted that Model A and Model B were trained on MSW generation values from the year 2015 to 2022 with random division. From Fig. 4, it can be seen that both Model A and Model B performed well during testing phase and predicted closer values for every randomly selected month across different years. Model A gave closer results during testing while Model B gave better results during validation. For overall better performance of both the models, predictive performance was assessed.

After getting closely related results during the testing phase, NAR model was used for short-term MSW generation prediction for the year 2023. The performance of neural model (Model A and Model B) was assessed using parameters like MSE, Correlation Factor (CF), Correlation coefficient (r) and Coefficient of Efficiency (E) which are calculated as per Eq. (8) to Eq. (11) and presented in Table 2.

$$MSE = \left[\frac{\sum_{i=1}^{N}\left(W_a - W_p\right)^2}{N}\right] \tag{8}$$

$$CF = 1 - \left[\frac{\sum_{i=1}^{N}\left(W_a - W_p\right)^2}{\sum_{i=1}^{N}\left(W_a\right)^2}\right] \tag{9}$$

$$r = \frac{\sum_{i=1}^{N}(W_p - \bar{W}_p)(W_a - \bar{W}_a)}{\sqrt{\sum_{i=1}^{N}\left(W_p - \bar{W}_p\right)^2}\sqrt{\sum_{i=1}^{N}\left(W_a - \bar{W}_a\right)^2}} \tag{10}$$

$$E = 1 - \frac{\sum_{i=1}^{N}\left(W_a - W_p\right)^2}{\sum_{i=1}^{N}\left(W_a - \bar{W}_p\right)^2} \tag{11}$$

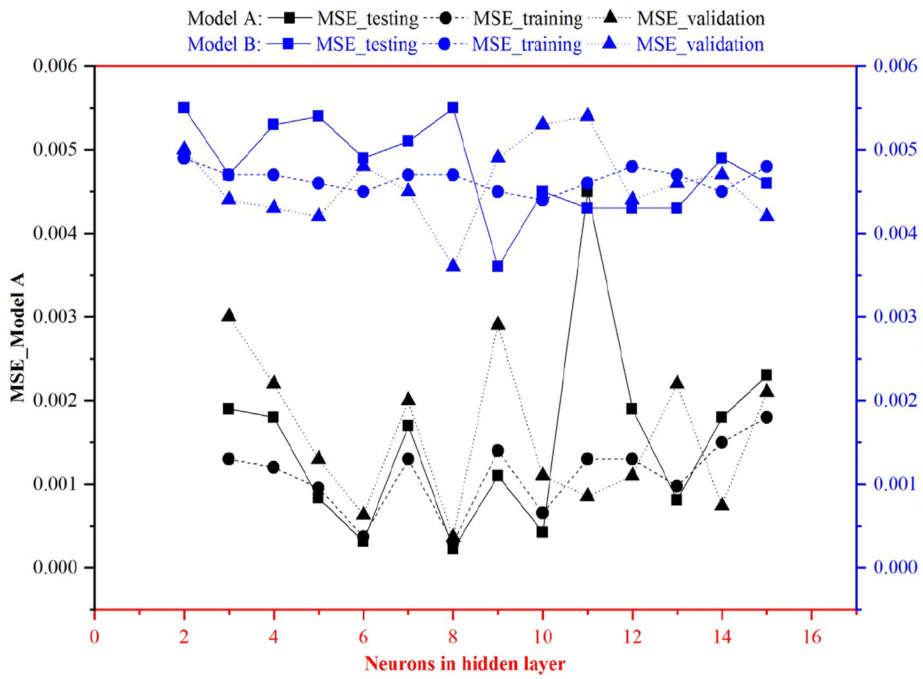

Fig. 3. Variation of MSE with changes in neurons for Model A and Model B.

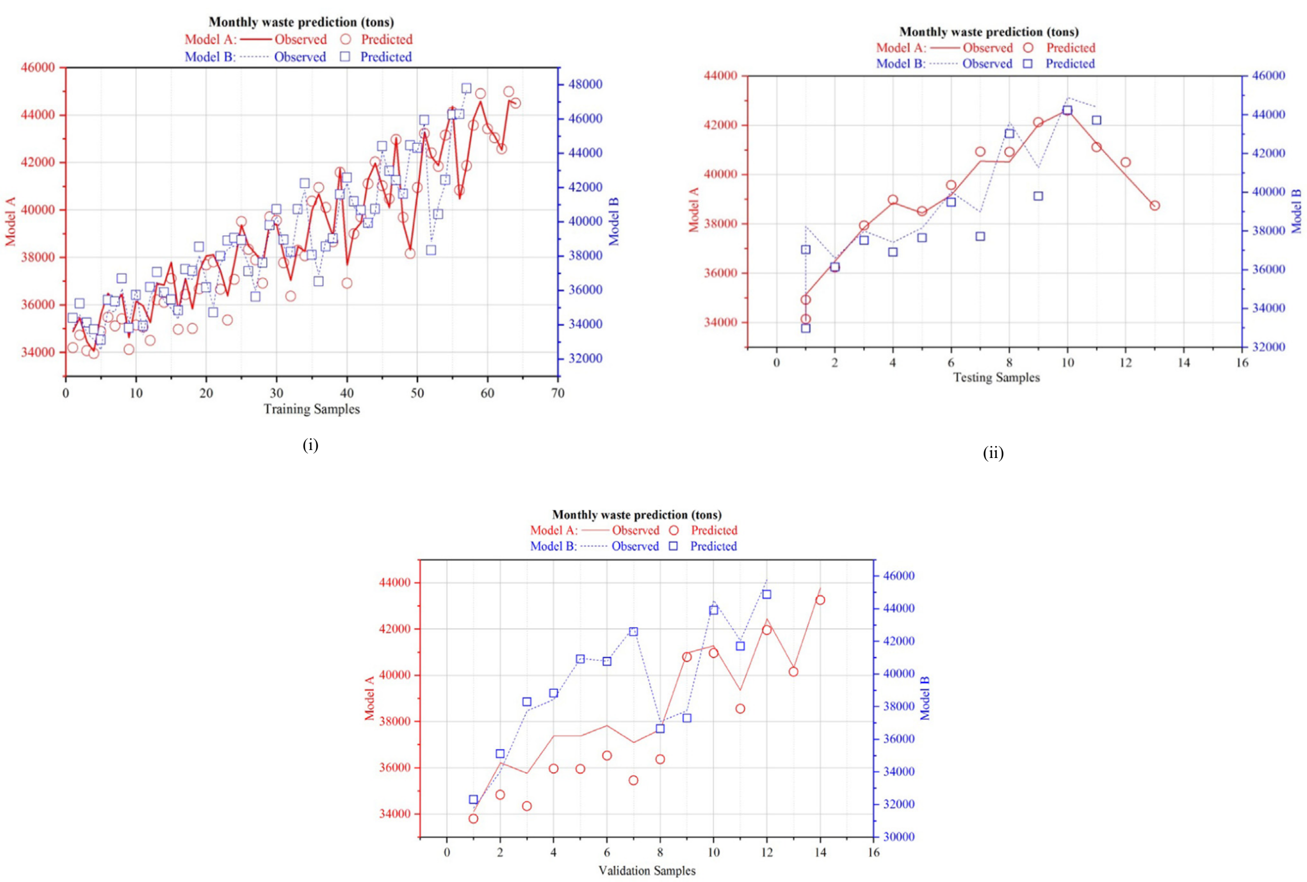

Fig. 4. Predicted and Observed monthly MSW generation during (i) training (ii) testing (iii) validation for Model A and Model B.

Table 2
Performance statistics for Model A and Model B.

	MSE	CF	r	E
Model A				
Training	0.0009	0.9970	0.9863	0.9514
Testing	0.0008	0.9980	0.9983	0.9912
Validation	0.0022	0.9932	0.9948	0.9757
Model B				
Training	0.0006	0.9954	0.9952	0.9708
Testing	0.0004	0.9966	0.9992	0.9959
Validation	0.0011	0.9875	0.9969	0.9889

From Table 2, it is clear that Model B has better correlation coefficient (r) values between actual and predicted waste generation compared to the values of Model A. Therefore, Model B has overall better performance parameters when compared to Model A.

3.4. Forecast performance of NAR models for observation period and the year 2023

In this section, the performance of neural models during observation period compared with the actual values has been discussed. The neural models forecasting short-term MSW generation were compared with the results from time series model. After these two comparisons, monthly MSW generation in the year 2023 for Nagpur city was obtained in tons. The comparison of Model A for the observation period is shown in Fig. 5. From Fig. 5, it was concluded that Model A performed better than time series model as the values of MSW generation during the observation period were closer to the actual values. Model A performed better for the months of May and June 2015 which were not captured properly by the time series model. The model A captured the combined trend of time series model and the actual values from October 2015 to March 2017 very closely and the values for some months were almost same to the actual values. Therefore, it was concluded that neural models independently were able to predict MSW generation for Nagpur, India and hence formed the basis for estimations for the year 2023.

The performance of Model A and Model B during the observation period showed that Model B performed better than Model A in terms of capturing the trend of monthly MSW generation for Nagpur, India. The performance of model B also shows that the partial autocorrelation should also be checked to understand the seasonal or yearly lags that might exist in behavior of any time dependent process.

The short-term prediction for MSW generation using model A i.e. for the year 2023 was done and shown in Fig. 6. From Fig. 6, it was observed that Model A when compared for its short-term prediction accuracy for monthly MSW generation, the absolute maximum error was 12.29% and minimum absolute error was 2.36%. The maximum error was obtained for the month of December 2023 and the minimum was obtained for March 2023. It was observed that for the year 2023 using Model B, the absolute maximum error in prediction was 3.9% and minimum error was 2.10%. The Model A on the contrary has higher errors for short-term prediction with maximum as 18.62% and minimum as −8.08% for December 2023 and February 2023, respectively. Therefore, it was concluded that Model B with yearly lagged values had better forecast potential for the year 2023 and hence can be used for monthly MSW generation in future. Based on Model B forecasts, it was observed that December of every year had highest waste generation and October and November across different years record the closer values. The increase in MSW generation was in the months of May and June and then remains almost constant from July to September.

The predictive performance of NAR model is independent of geographical location and time period because it was constructed using the monthly MSW generation values. Therefore, it has wider applicability and requires only the incorporation of time dependent variables.

4. Conclusions

In this study, the forecast for monthly MSW generation for Nagpur, India was undertaken. It was found that the proper extraction of trend and seasonal variation serves the basis for extrapolation of future values. The time series model constructed in this study was able to capture the trend of monthly MSW generation for Nagpur,

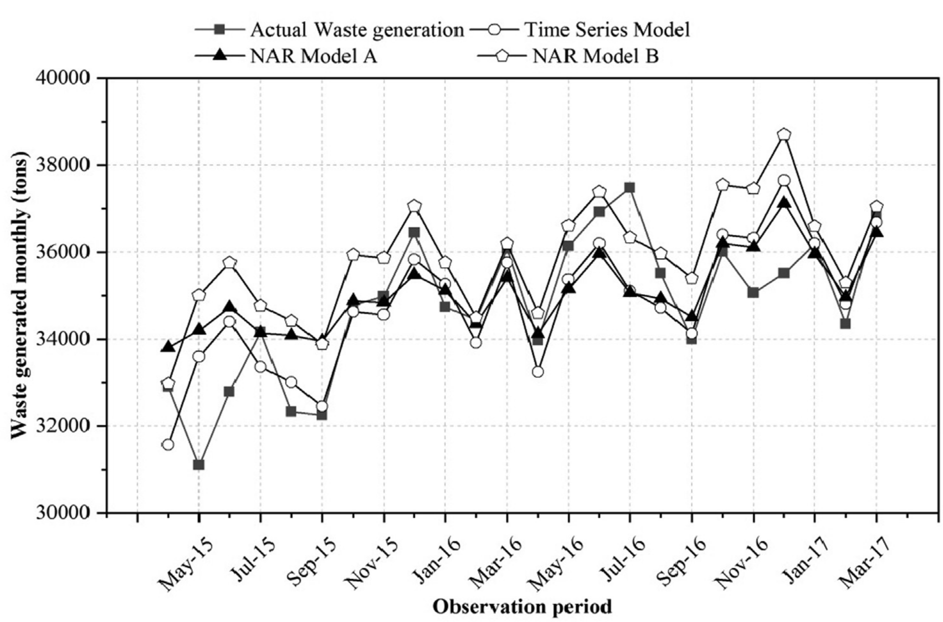

Fig. 5. Performance of time series model and NAR model for observation period.

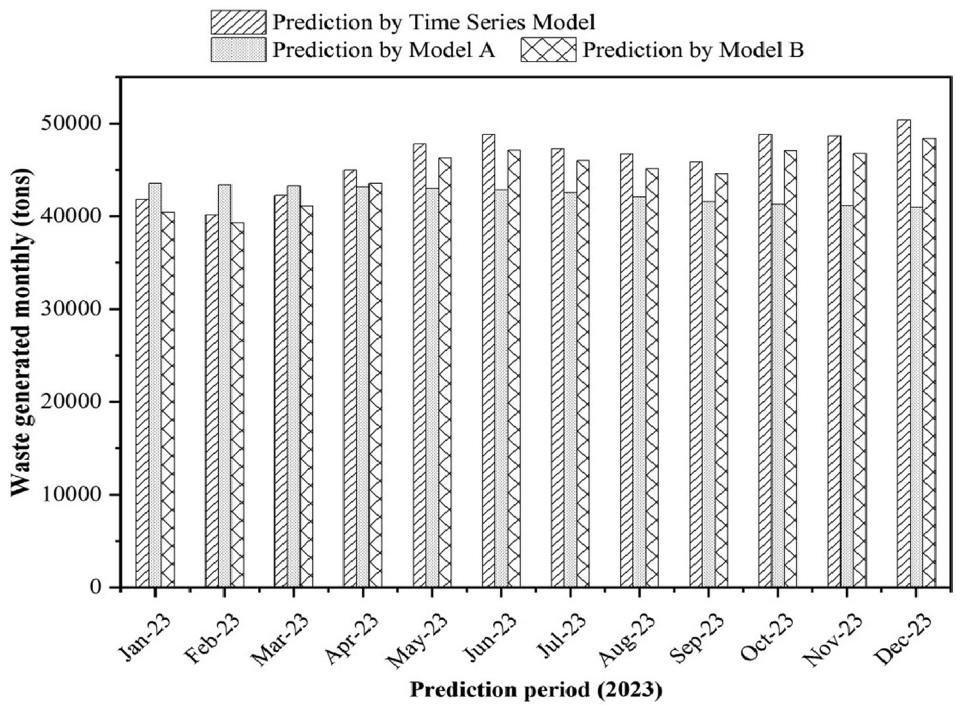

Fig. 6. Comparison of performances of NAR model for year 2023.

India with the value of R^2 as 0.8896. The results of NAR (Model B) showed that with yearly lagged values decided for delays based on partial-autocorrelation, forecasts value was closer to the actual values of monthly MSW generation. This study highlights that NAR models with self-lagged monthly MSW generation values can forecast future MSW generation for any city. These models are very simple because only monthly MSW generation estimates were required to construct the model and are geographically independent. Therefore, for developing countries where availability of historical data on waste logistics is difficult, this model can be used to do the forecasting. This study highlighted that deseasonalizing and detrending NAR can be used to do better future forecasting compared to traditional statistical models. This study aimed at forecasting of MSW generation with less intensive data requirement primarily and it was found that the theoretical estimates for the total MSW generation can be done if the estimates from municipality at common dumpsite are available. The developed model can be used at any geographical locations provided there are no parallel modes of disposal existing and if available, it needs to be combined before using. The future research on waste generation using logistics of waste collection, transfer and disposal is needed so as to have better inventory of the available historical data and models that can reveal more information on waste management. The use of AI based models in such non-linear dynamic process of waste generation helps in projections when it is difficult to carry out the inventory due to budget constraints faced by the municipality.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2020.12.011.

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