Research Article

Forecasting MSW generation using artificial neural network time series model: a study from metropolitan city

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Abstract

Forecasting the quantity of municipal solid waste generation is an essential task for sustainable solid waste management and strategy implementation. The estimation of future waste generation rates can help to motivate for analyzing gaps in existing waste management and better planning strategies. Improper management and unsafe disposal of solid waste create a threat to the environment and human health. Hence, a sound forecasting of solid waste generation is very crucial for planning and management accordingly. Artificial intelligence is an excellent and new application of soft computing which is used as a forecasting tool. The main objective of this study is to apply ANN time series model along with autoregressive technique to forecast the monthly solid waste generation in Kolkata. For the same, data related to the monthly solid waste generation was gathered from 2010 to 2017. Total data of 96 months were divided into three categories, i.e., 70%, 15%, and 15% for training, validation, and testing, respectively. The model was evaluated based on performance value of mean square error, root mean square error, and regression coefficient. The ANN structure of 1-19-1 was considered as optimized model for solid waste forecasting because it has the lowest mean square error and the highest regression coefficient. The applied time series model forecasts that Kolkata will generate about 5205 MT/day municipal solid waste in 2030 which will add more than 1000 MT/day waste with the existing rate of generation. The present study helps in estimating and allocating essential resources that need in future for sound solid waste management and preparing alternative strategies to reach the sustainable goals.

Keywords Municipal solid waste · Waste quantity · Artificial neural network · Evaluation metrics · Waste forecasting

1 Introduction

Every step of human activities is directly or indirectly related to waste generation. But the unawareness propensities toward environment create serious problems with increasing population and standardization of living status. Sustainable management of municipal solid waste (MSW) is now becoming a critical task for any municipal body due to changing characteristics and compositions of MSW day by day. Actual records of solid waste generation are essential to avoid environmental pollution, better management, and planning [1]. Present day, in the era of urbanization and social transformation, not only the quality of MSW has changed but the quantity has also increased. Excessive generation of solid waste and improper management severely affects environmental and human health [2–6]. Hence, sound planning and waste management are required for a healthy environment especially in highly urbanized and highly populated areas. But the successful planning of an efficient waste management system largely depends on accurate projection and forecast of municipal solid waste quantities, because future estimations of MSW generation serve as a basis in the development of the existing waste management infrastructures, optimization, and sustainable development. Imprecise forecasts may lead to several problems, like inadequate

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infrastructure to the collection, transportation, landfilling, or processing [7, 8].

Among many environmental challenges that most urban areas are faced today is the management of solid waste. This is because of an aggregation of the human population that has the potential to generate a large amount of waste. Solid waste is a global environmental problem, especially in developing countries. Growing population, gradual economic development, and the rise in community living standards accelerate solid waste generation [9]. The major problems of inappropriate disposal of solid waste can cause environmental contamination. Generated wastes extensively thrown here and there resulted in aesthetic problems, nuisance, and pollution of land and water bodies of an area [10]. As a whole, untreated waste causes several problems in situ. Thus, planning and management of generated waste including storage, collection, transfer, and disposal are essential to any nation for environmental safety and social wellbeing. But the gap is always seen in any place because the existing management never reaches a desired level of managemental strategies that are recommended and guided by the environmental ministry. Among different stages of waste managemental, waste forecasting and prediction is very significant because based on waste quantification the best strategies depend on it [11]. Literature proves different algorithm-based studies on forecasting of MSW which can be classified into five categories [8]. These are statistical analysis [9]; regression analysis [12]; material flow analysis [13, 14]; time series analysis [15, 16]; and artificial intelligence [8, 17–19]. However, these all different models and analyses have their own weaknesses and strengths in comparison to others. But the artificial intelligence model of forecasting MSW generation has been gaining more popularity because of their high flexibility and proven prediction abilities in comparison to conventional and descriptive statistical methods, regression analysis, material flow model, and time series analysis [20–23].

Artificial neural networks are usually structured into layers of processing units. These units are similar in the sense that they all have the same activation dynamics and output function. The connections are either in a feed-forward or feedback manner [24]. Perceptron learning law can be used for the purpose. The objective of the perceptron learning is to systematically adjust the weights for each presentation of an input vector belonging to its class identification [25]. In the present study, the artificial neural network was trained and tested to model monthly waste generation (MWG) in a metropolitan city, i.e., Kolkata. The concept of an artificial neural network is closely associated with our brain that helps in the decision-making process [26]. The structures of the biological neural network (BNN) are recognized as the artificial neural network's structure and function. An ANN comprises a set of processing units, and when it is assembled in a closely consistent input network, it offers a remarkably rich structure revealing some features of the BNN. Functionally, it receives 'N' input values, weights each value, and offers output value by computing weighted sum [24]. ANNs can deal with data that are not only noisy but also fuzzy, inconsistent, and probabilistic. All this is due to the associative and dispersed nature of the stored information and the redundancy in the information storage due to the large size of the network [27, 28].

With such advantages, the ANNs have been successfully applied to different fields of studies and problems that are very difficult to identify, understand, and define including environment, medicine, and engineering. Recently, the application of artificial neural networks in predicting the generation and modeling of solid waste has become an interesting task. The artificial neural network has been evidenced much-weighted method than the other practiced traditional methods for long-term prediction of the generated solid waste [22]. Different studies throughout the earth have been carried out in the field of forecasting. ANN-based model was utilized to forecast the rate of leachate flow in solid waste disposal site of Istanbul, Turkey [29]. Training and testing of neural networks using backpropagation method are highly useful in the prediction of municipal solid waste [30]. ANN is not only used in the forecasting of waste generation but also applicable in recycling strategy and a recyclability assessment model [31]. Combining ANN and multivariable linear regression analysis was applied to the prediction of heat production from urban solid waste [32]. ANNs can also successfully apply in other environmental issues including air pollution [33, 34], water pollution [35, 36], emission characteristics [30], flash flood [35], and many other types of researches which have shown the high performance of the artificial neural network in the prediction of various environmental disciplines [37].

Literature proved the need for forecasting the generation of MSW quantity and rate for the efficient waste management system. There are several studies tried to forecast the quantity of MSW generation using different techniques. Recently, artificial intelligence model and machine learning as a part of soft computing have been gaining popularity due to flexibility and applicability. Different methods of artificial intelligence include support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), and artificial neural network (ANN). The present study highlighted the application of ANN model for forecasting municipal solid waste generation. ANN model has been widely used in different researches as a prediction algorithm. A synoptic view of the literature survey regarding the application of ANN model is highlighted in Table 1.

Looking toward the previous result and review, the effort was made to use the ANN time series tool to predict the rate and quantity of solid waste generation based on the past data. Kolkata is one of the fastest-growing metropolitan and capital city of West Bengal, India. Here, the quantity of waste generation and composition is high and diversified. For successful planning of efficient waste management system, the present study aimed to forecast the future waste generation by applying artificial neural networks. In this study, with the application of feed-forward artificial neural network, a suitable model was suggested to predict the future quantity of waste generation.

2 Materials and methods

2.1 The case study area for model application

The nature of generated waste, quantity, and rate of waste generation is high and quite different when compared to the other urban and rural areas. That is why a metropolitan city from eastern India was selected for applying the ANN time series model. Kolkata is one of the four growing metropolitan cities in India. It is the capital city of the state West Bengal. It is located on the eastern bank of the river Hooghly (Fig. 1). Kolkata is typically a deltaic plain. Kolkata is fallen under the tropical wet and dry climate which is symbolized as 'Aw' after Kopen's climatic classification. The annual mean temperature over Kolkata is 26.8 °C and the annual rainfall is near about 1600 mm. Kolkata Municipal Corporation (KMC) is the largest municipal body in the state. By areal extension, KMC has a very little area (only 200.07 Sq.km) in comparison to other districts in W.B. But it has the largest population (about 4.5 billion).

Table 1 Literatures showed the application of ANNs model in different fields of study

Sl. no.	Study area	Method applied	Field of application	References
1.	Logan city, southeast Queensland, Australia	ANFIS, SVM, ANN, and kNN	Forecasting municipal solid waste generation	Abbasi and El Hanandeh [8]
2.	Iasi, Romania	Prognostic tools and regression analysis	Forecasting municipal solid waste generation	Ghinea et al. [38]
3.	Faridabad city, Haryana, India	Artificial neural network and time series model	Prediction of municipal solid waste generation	Singh and Satija [39]
4.	For developing countries	ANFIS modeling	Solid waste forecasting	Younes et al. [40]
5.	Malaysia	Nonlinear autoregressive network	Prediction of municipal solid waste generation	Younes et al. [41]
6.	Kuala Langat, Selangor, Malaysia	Artificial neural network	Modeling of methane oxidation in landfill cover soil	Abushammala et al. [42]
7.	Hashemite Kingdom of Jordan	ANN and generalized regression neural network	Predicting the effects of medical waste	Al-Shayea and El-Refea [43]
8.	Madras, India	Artificial neural network	Forecasting the tropospheric ozone	Kandya et al. [44]
9.	Saqqez city, Kurdistan province	Artificial neural network	Prediction of municipal solid waste generation	Shahabi et al. [37]
10.	Lower Mahanadi River basin, eastern India	Neural network and adaptive neuro-fuzzy inference systems	River flow prediction	Pramanik and Panda [45]
11.	Three gasifier well in Sieved, Beijing, and Hongkong	Artificial neural network	Estimation gasification characteristics of MSW	Xiao et al. [46]
12.	Istanbul Odayeri sanitary landfill	NN-LEAP: a neural network-based model	Controlling leachate flow rate in a MSW landfill site	Karaca and Ozkaya [29]
13.	Taiwan	Multilayer perceptron neural networks	Prediction for energy content of MSW	Shu et al. [47]
14.	The name of treatment plant was not disclosed due to confidentiality	Artificial neural network (ANN) with a backpropagation algorithm	To determine the relationship between sewage odor and BOD	Onkal-Engin et al. [48]
15.	Grand Traverse Bay Watershed, Michigan	Neural networks and GIS	To forecast land use changes	Pijanowski et al. [49]

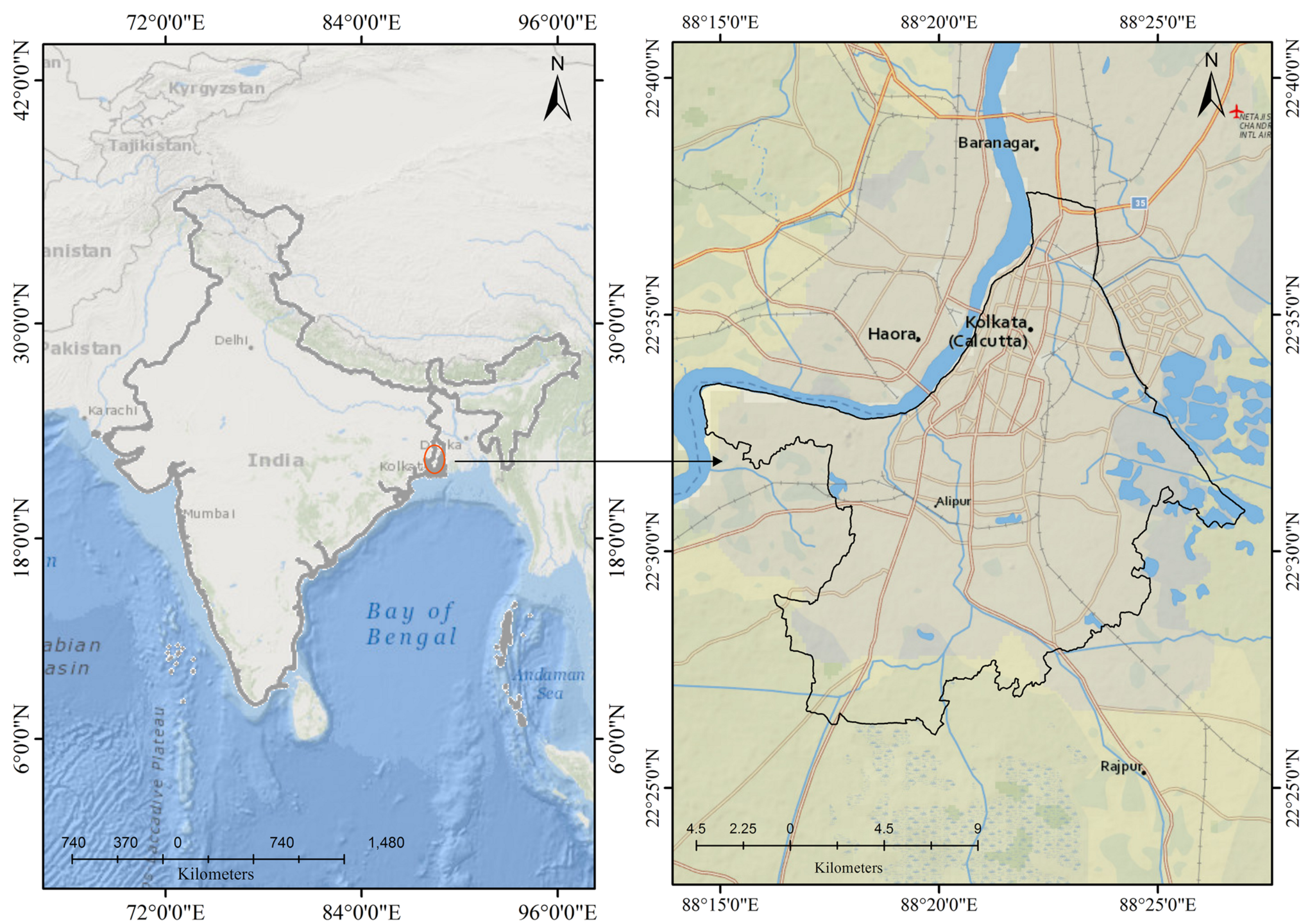


Fig. 1 Location of the case study area, Kolkata is a metropolitan city of Eastern India in the state of West Bengal

Nearly about 90 lakhs floating population daily visit the city for many purposes. According to the latest census, the city has a population density of 24,306 persons/km^2 and household density is estimated as 755–23,237 household/km^2. It is the third-rank metropolitan city in terms of the population in India just after Mumbai and Delhi. These all factors including high residential population, high floating population, small area, and lack of suitable site create many challenges with municipal solid waste management for KMC. Therefore, looking toward these all factors, KMC was chosen to apply such a model for predicting or proper forecasting of the future amount of waste generation for better planning and management in the city.

2.2 Data source

The accurate measurement of solid waste is really a challenging task for any governing body and authority. Therefore, the actual data availability on solid waste generation and management system is really protracted. In the present study, an initial survey was carried out to collect solid waste generated data from Dhapa landfill site Kolkata, West Bengal. The quantity of waste generation is measured based on the average capacity and the number of trips of different types of waste transporting vehicles meet to landfill site daily. It was seen that the waste generation rate in KMC varies from 500 to 700 g per capita per day (0.500–0.700 kg/c/d). The seasonal occasion, festivals, and migration of people to the capital city tremendously affect the seasonal deviation in a waste generation (Fig. 2). Figure 2 highlights the seasonal and monthly fluctuations of waste generation in Kolkata. It was recorded from the survey that large quantities of garbage generated during rainy season followed by autumn, summer, and winter. As per authority's records, throughout the city, about 80–90% of waste is collected. Due to this seasonal variation, time series model with artificial neural networks was applied for the prediction of solid waste generation. In the present study, 96 months data (January 2010 to December 2017) were gathered and arranged through tabulation to predict the waste generation in KMC.

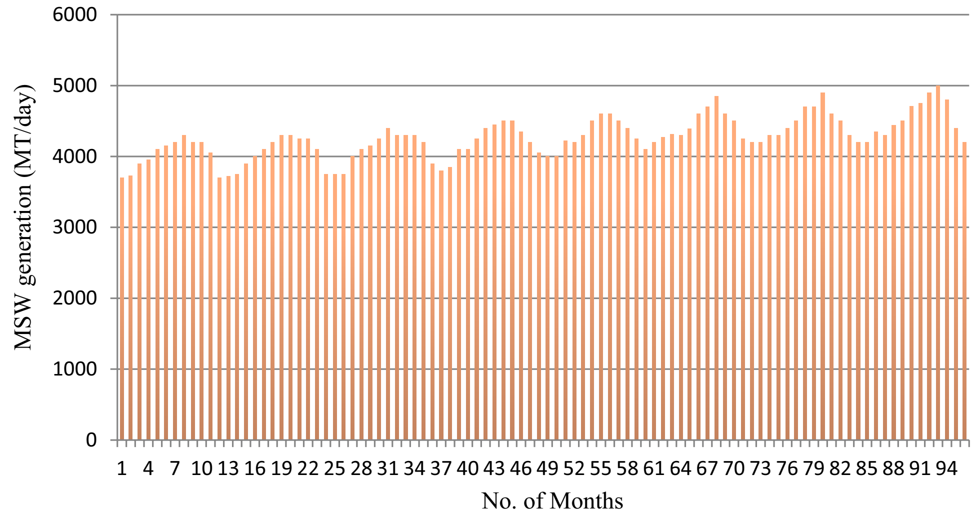


Fig. 2 Seasonal and monthly variations of waste generation in KMC. *Note* 1 means January and 12 means December, 1–12 is the whole months in a year. Ninety-six months data are presented here between the years 2010–2017

Table 2 Quantity of municipal solid waste generation in different seasons in KMC. *Source*: KMC

Season	Daily amount of generated waste (MT)	Daily generation (pc/d)
Summer	4400	0.5500 kg
Rainy	4800	0.7000 kg
Autumn	4500	0.6000 kg
Winter	4200	0.5000 kg

The summer season extends from the first week of March to June, the rainy season stretches from July to the end of September, autumn season is experienced in West Bengal for a very short period, from the beginning of October to the middle of November, and winter season is experienced in the state from mid-November to February

Table 3 Waste composition—Dhapa disposal site, KMC. *Source*: KMC

Types of waste	Composition in %
Food waste	20
Garden waste	6
Paper	4
Textiles	4
Wood	3
Plastic	25
Construction and demolition waste	15
Metals	2
Glass and ceramics	1
Others	20
Total	100

Organic fraction (wet basis) 63.01% and organic fraction (dry basis) 25.9%

2.3 Existing MSW generation

The KMC comprises 16 boroughs and 144 electoral wards. The municipal solid waste (MSW) related issue and disposal of waste in the city are governed by the Department of Solid Waste Management (D/SWM), KMC. Due to the high density of population and excessive pressure of the floating population, large quantities of waste are generated in the city. According to D/SWM, KMC, 4000–4500 MT waste generation was reported daily for the year 2017. It was 3600–3900 MT during the year 2010, it means, during a 7-year interval, about 400–600 MT has been increased. The generated MSW varies with sessional changes (Table 2). Table 2 illustrates the seasonal variation in collected solid waste data. It is found that the highest and lowest waste generation sessions are rainy and winter, respectively. During a rainy session, waste generation rate is higher due to the wet weight of waste and the reverse case happened during winter. The waste composition data was collected from Dhapa landfill site, and average approximation data was recorded (Table 3). Plastic and food waste have the highest proportion of the generated waste. Although the actual generated waste is estimated, their characteristics and compositions are a very difficult task because of the lack of availability of accurate data. Based on the data provided in D/SWM, a detail of recent wards-wise MSW generation quantity has been shown here (Fig. 3).

The huge quantity of MSW generation in KMC has become a great challenge [50]. The urban local bodies (ULBs) committed their best services, but finding this issue difficult to manage properly due to the growing magnitude of problems [51]. About 70% of the KMC budget on solid waste management is reserved for the collection of waste, and yet the results are not seen satisfactorily. The waste collection efficacy is still adequate where 100%

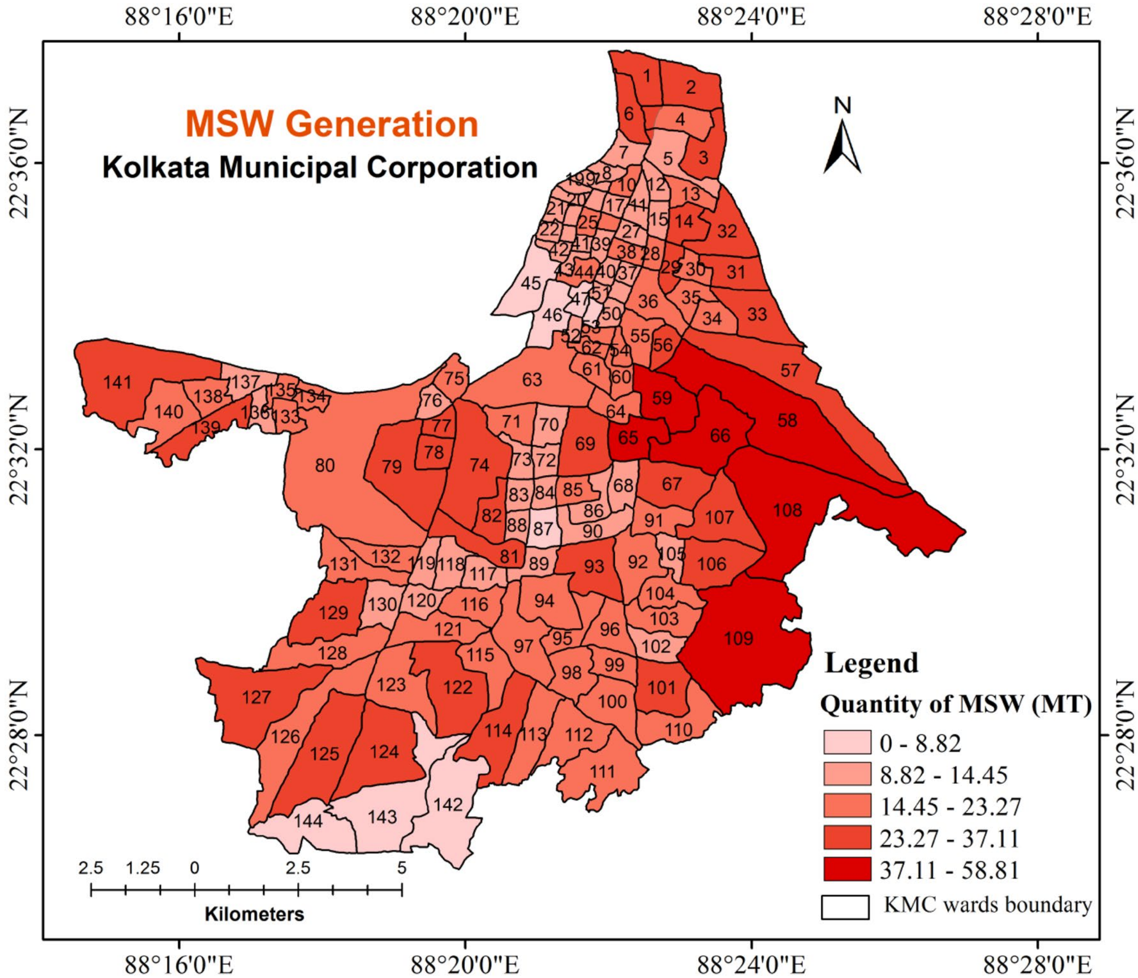


Fig. 3 Current wards-wise quantity of MSW generation in KMC

collection is not practiced in the registered residents and less than 20% is covered in unregistered residents like slum inhabitants. The total container or storage capacity is also found adequate and their locations are not appropriate which results frequently in overflow of waste storage bins [52]. Thus, proper MSW prediction is required to handle these all arisen issues and manage properly by implementing proper strategies.

2.4 Study plan

The prediction of municipal solid waste generation quantity in Kolkata Municipal Corporation was performed based on a specific algorithm, i.e., artificial neural network. MSW prediction using ANN is a multistage process (Fig. 4). Figure 4 presents the detail procedures carried out in the present study. First of all, year-wise monthly waste generation data was arranged sequentially. These data were further rearranged looking toward cell and row matrix of MATLAB environment. Suitable network architecture is essential to get accuracy in the result. Therefore, neural net time series (ntstool) was chosen which consists of three sequential layers including training, validation, and testing the result. The collected MSW data was utilized to train, validate, and test to forecast MSW generation in Kolkata. The acceptable proportion of dataset was considered to train the model using the Levenberg–Marquardt algorithm. Globally used statistical techniques for evaluating forecast/prediction result, i.e., mean square error (MSE), root mean square error (RMSE), and regression coefficient (R), were measured for performance, final decision, and best model structure.

2.5 Model applied

Artificial neural network (ANN) as a forecasting model was applied in the present study. Neural network is more or less similar to a biological neural system. It is a set of processing units when assumed in a closely associated and interconnected network, deals with a rich structure

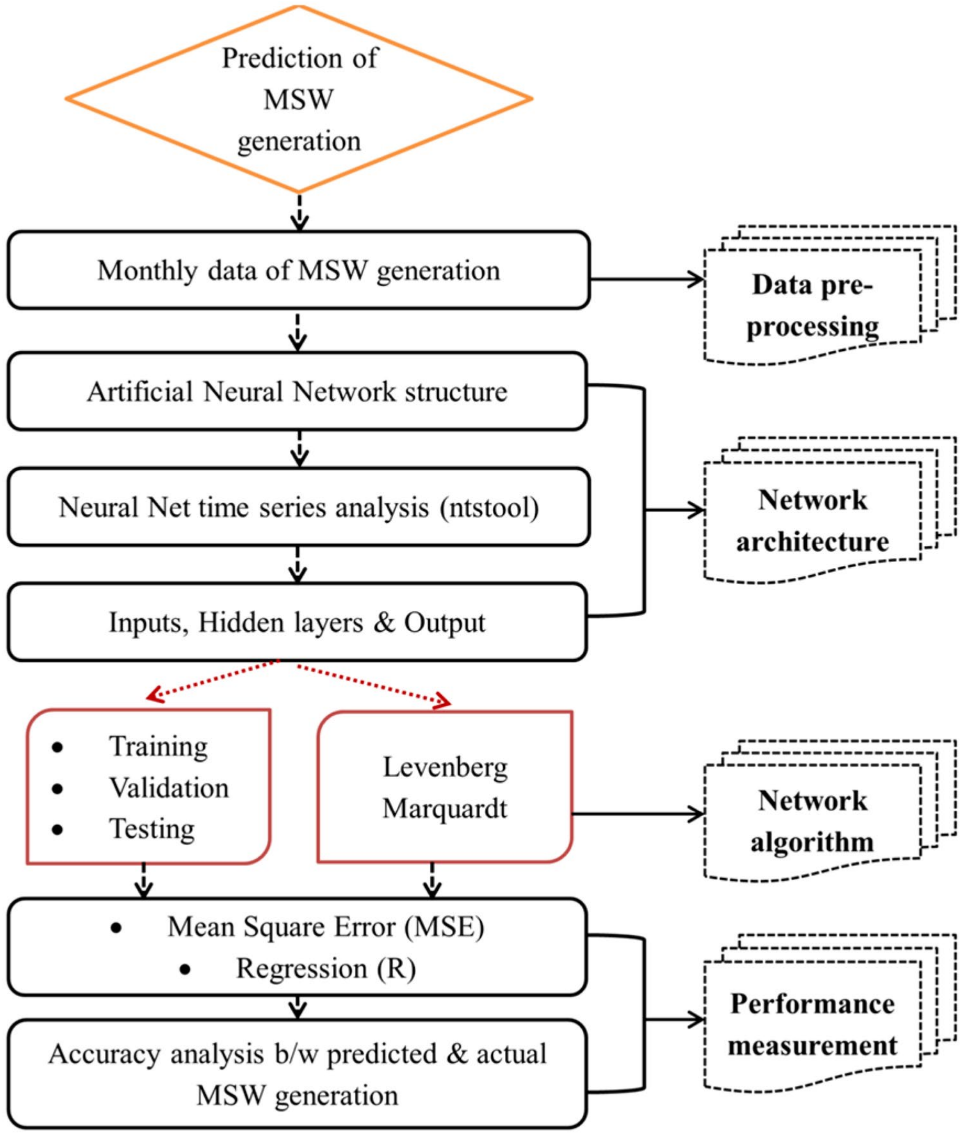


Fig. 4 Methodological flowchart showing detail procedure that adopted and used to carry out the study

exhibiting some features of biological neural network. Like regression, neural networks were designed for capturing the relationship between inputs and output variables using the cross-sectional data. The wide application of ANNs is for predicting through time series analysis (numerical or binary). ANN models are very suitable to predict the future based on the previous data [39]. ANN models have the ability to plot input and output. It works like multiprocessor, parallel processor as well as a distributed system when the weights, as well as inputs, pass through appropriate neurons.

Figure 5 illustrates a simple neural network model. It comprises three elements comprising a set of connection link, i.e., synapses which passes inputs 'x' connected to the neuron that is multiplied by the weight '$w_i x_i$', summing part and activation function f(.) for restraining amplitude of the output of a neuron. The neuron model can also include an applied bias value, denoted as b_k. In Fig. 5, $x_1, x_2, \ldots x_n$ are the set of inputs and $w_1, w_2, \ldots w_n$ are the set of weights. Actually, the weights are the strengths of inputs. If the strength of input is high, the weight will carry a high value; concomitantly, if the strength of input is low, then the weight will be low. So these weights are multiplied with their corresponding inputs $x_1, x_2, \ldots x_n$. It is expressed as

$$S = w_1 x_1 + w_2 x_2 + \ldots \text{next}, \quad = \Sigma w_i x_i$$

$$S = \sum_{i=1}^{n} \left(w_i x_i - \theta \right)$$

$$S = f(x) = x$$

$$\delta = b - s = b - x$$

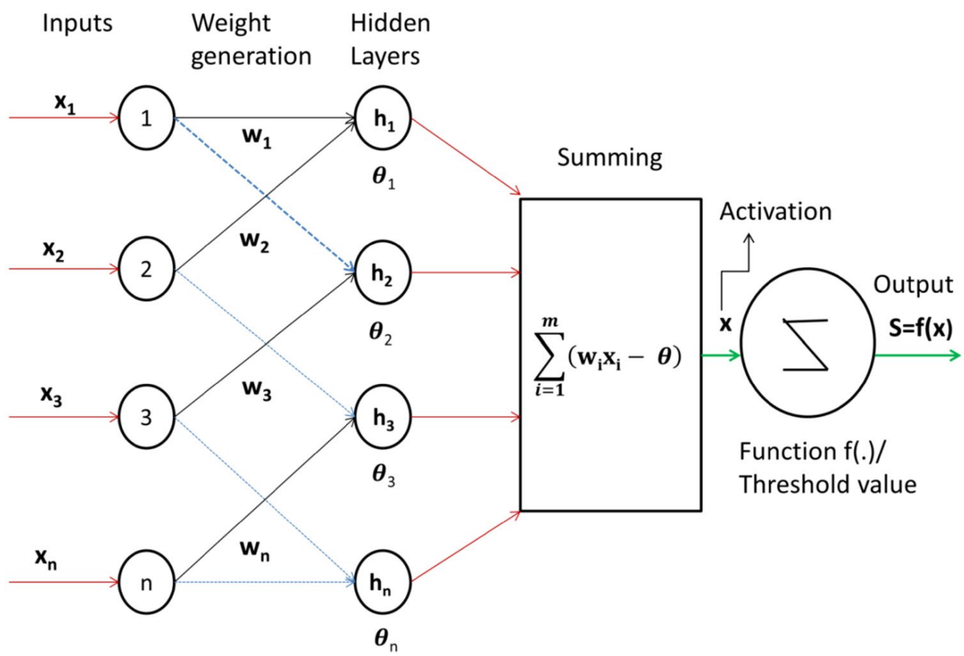


Fig. 5 A simplified neural network model consists of three layers including input, hidden, and output

where $x_1, \ldots x_n$ = inputs to neuron, $w_1, \ldots. w_n$ = weight, $i = 1, 2, \ldots.. n$, θ = bias term, S = summing function, and x = activation function.

This summing value in the above equation is essential to measure the threshold value. Because of a single input and a single output, neuron with proper weight and threshold value give a unit time output. The threshold function is required for comparing the difference between input and output. If the weight of output sum S ($f(x)$) is greater than this threshold value, then the output will be 1 otherwise 0. It can be written as

$$f(x) = 1, \quad x > 0$$

$$f(x) = 0, \quad x \leq 0$$

There is generally three widely used threshold function, i.e., sigmoid function, signum function, piecewise linear function, or hyperbolic tangent function [53]. In the present study, tangent sigmoid function was used between input and hidden layer neurons and linear transfer function was used between hidden and output layer neurons (Fig. 6). This is mathematically equivalent to tanh (N). This function has a good adjustment for neural networks, where speed is significant and the exact figure of the transfer function is consistent [54].

The most popular and commonly used design for a neural network is a multilayer perceptron, i.e., MLPs [55]. MLP network could help in structuring the future intelligence with learning and perception capability. In present work, multilayer feed-forward neural network structure was applied along with nonlinear autoregressive technique. MATLAB R2015a version of MathWorks software with network toolbox 8.3 (ntstool) was used for the same.

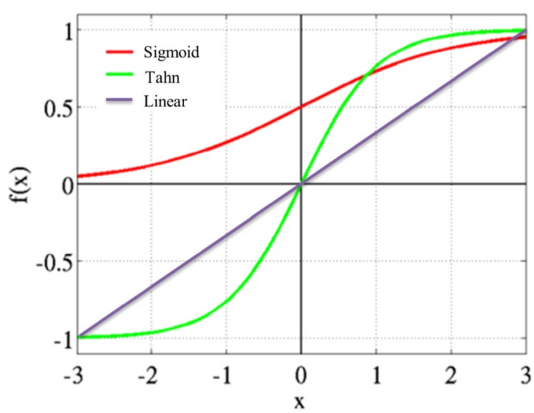


Fig. 6 Activation transfer function which is used between input, hidden, and output neurons layer

Prediction is a kind of dynamic filtering in which past values of one or more time series are used to predict the future values. A neural network includes tapped delay lines for nonlinear filtering and prediction. MATLAB R2015a version provides three types of time series problems in ntstool, i.e., nonlinear autoregressive with external (exogenous) input (NARX), nonlinear autoregressive (NAR), and nonlinear input–output. NAR was applied in the present study. It predicts series $y(t)$ given the past value of $y(t)$. Mathematically, it can be expressed by

$$yt = f(y(t-1) + y(t-2))$$

$$yt = f(y(t-1) + y(t-2) + y(t-3)$$

$$yt = f(y(t-1) + y(t-2) + y(t-3) + y(t-m))$$

To train and test for predicting MSW generation for KMC, 96-month data on total waste generation (MT/day) were arranged. Multilayer perceptron (MLP) model was used, but the major issue in using MLP is either overfitting or underfitting like the other flexible nonlinear estimation methods. As a result, error appears between input and output layers. To reduce such error, stop training approach (STA) has been adopted. The entire gathered data on SW generation are randomly divided into three parts, i.e., training data, validating data, and testing data.

The target time series dataset was selected to define the desired output $y(t)$. In time step, cell column as time series row matrix was chosen, because target dataset 'waste generation' is an 'x' cell array of 'x' matrix, representing dynamic data 'x' time steps of 1 element. 70% data of 96 months is taken as the training data. This means that 68 SW/day time series data is divided in the form of 1×68 cell array of 1×1 matrices. Here, training is connected with the learning process of the network. 15% data of 96 months is taken for both the validation and testing. This implies that 14 SW/day time series data is divided in the form of 1×14 cell array of 1×1 matrix for both. One can change the ratio of selection by either increasing or decreasing the value of validation and testing between 5 and 35%; this will automatically result in increasing or decreasing the value of training. But 70:15:15% is the best selection and default. The selection of the hidden layer is also a vital task which affects the accuracy result in output. 1–25 hidden layers were chosen here.

2.6 Evaluation metrics

There are many standard techniques that can be used to evaluate the performances of the forecasting result. In this regard, to evaluating the performance of the ANN model, three statistical indices, i.e., mean square error (MAE), root mean square error (RMSE), and regression coefficient (R) has been used. Levenberg–Marquardt as a training algorithm was utilized to train, validate, and test the dataset. MSE is the average squared difference between the targets and output. MSE is the most commonly used error metric which appears larger error because of the squaring number. The MSE is the sum of the squared error divided by the number of observations. Root mean square error (RMSE) is the square root of MSE. Mathematically, MSE and RMSE are expressed as

$$\mathrm{MSE} = \frac{\sum_{t=1}^{n} (\mathrm{At} - \mathrm{Ft})^2}{n}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (\mathrm{At} - \mathrm{Ft})^2}{n}}$$

where t = time, n = total number of observations, At = actual dataset, and Ft = forecast dataset.

For mean square error, lower values are more preferable and better, 0 means no error. Concomitantly, R-value measures the correlation between the targets and output. An R-value of 1 means a close relationship and 0 means random relationship. These all calculations were run and performed on Windows 64 bit operating system and MATLAB (Version R2015a, MathWork Inc.).

3 Results

By changing the neurons of hidden layers, different ANN structures have been verified during training, testing, and validating processes. The ANN structure *1-19-1* was considered as the best structure because of the least value of mean square error (MSE) and the high value of regression coefficient (R). Minimum value of MSE and maximum value of R acquaint with the best ANN structure in which the weights were improved. The recommended model has been found applicable to the forecasting of MSW in the future. To attain most suitable and best network structure for predicting the generated MSW, different structures of feed-forward neural networks with three layers (i.e., input layer, hidden layer, and output layer) and a different number of neurons in hidden layer were considered. As a final point, consideration was made with MSE, RMSE, and R to select the appropriate models. The minimum value of mean square error (i.e., 0 means no error) and maximum value of regression (i.e., 1 means close relationship) is measured as performance keys to estimate and select the optimized network structure. The whole efforts have been carried out by using artificial neural network time series tool (ntstool) in MATLAB Environment (R2015a_8.3). Table 4 shows the numerous ANN time series model structures in which the test was done with a different number of hidden layer neurons varied from 1 to 25. But in stated table, performance metrics of structures with neuron 10–25 are included and 1–10 are excluded from the table due to out of range value of MSE and regression coefficient R. The model structure with 19 hidden layer neurons is considered as the best neural network structure due to the lowest value of MSE 0.00047 (very close to 0) and the highest value of regression coefficient R as 0.9267 (Fig. 7). The R-value is considered for accuracy assessment of the trained model. If R-value is close to 1, it means that the model prediction is very close to the actual dataset and reverse case occurred if R-value is 0. In the present study, the R-value of the trained model always ranges between 0.86 and 0.94, indicates a high accuracy of prediction.

The comparison between observed and predicted municipal solid waste generations per day (MT/day) during

Table 4 Performance matrix of training, validation, and testing process in ANN time series model

ANN model structure with hidden layers	MSE	RMSE	Regression R			
			Training	Validation	Testing	All
1-10-1	0.0011	0.03162	0.9055	0.9104	0.9414	0.9191
1-11-1	0.0010	0.03256	0.9330	0.9147	0.9272	0.9249
1-12-1	0.0011	0.03317	0.8275	0.8586	0.8591	0.8484
1-13-1	0.0057	0.07550	0.9235	0.9190	0.9392	0.9272
1-14-1	0.0040	0.06325	0.9222	0.8840	0.9402	0.9154
1-15-1	0.0027	0.05196	0.0930	0.8252	0.8810	0.5997
1-16-1	0.0081	0.09000	0.9329	0.9460	0.8899	0.9229
1-17-1	0.0069	0.08307	0.9437	0.9058	0.7639	0.8711
1-18-1	0.0059	0.07681	0.9438	0.8958	0.8910	0.9102
1-19-1*	0.0004	0.02168	0.9404	0.9397	0.8643	0.9267
1-20-1	0.0054	0.07348	0.9536	0.8922	0.8995	0.9151
1-21-1	0.0058	0.07616	0.9440	0.9022	0.8068	0.8843
1-22-1	0.0056	0.07483	0.9259	0.8263	0.9458	0.8993
1-23-1	0.0026	0.05099	0.8720	0.9487	0.8608	0.8938
1-24-1	0.0007	0.02646	0.9245	0.9179	0.9102	0.9175
1-25-1	0.0042	0.06481	0.9400	0.9407	0.8416	0.9074

* is considered as the best neural network structure for MSW prediction

the training of the neural network is shown in Fig. 8. During the training process, the structure gets learned from the previous target data points which will be further generalized and tested. Out of the total data, 70% was taken for testing. It indicates that in maximum cases the values of predicted and actual MSW were not much fluctuated except in the 60th number of the month. Figure 9 reveals the comparison between the observed and predicted municipal solid waste generations per day (MT/day) during the validation of the neural network. During the validation process, weights were optimized to evaluate the best predictive model. The best performance of the same structure was considered here. Here, 15% of the data was taken for validation. The same figure shows that in some cases the values of the predicted and actual MSW were a little much fluctuated. But the overall result may consider as consistent.

The association between the observed and predicted municipal solid waste generations per day (MT/day) during the testing of time series model is illustrated in Fig. 10. The best performance of the same structure as chosen for training and validation was also considered for testing. Out of the total data, 15% was taken for testing. The result shows that in some cases the values of predicted and actual MSW were closed and similar. Thus, the overall result may be considered as significant. The mean value of the predicted MSW generation per day has been estimated as 4369.55 MT/day and the mean value of the observed MSW generation per day has been estimated as 4351.30 MT/day. Therefore, mean absolute deviation (MAD) derived from ANN 1-19-1 model is 0.19009 MT/day with MSE 0.00047, which may also be considered as a significant model for the prediction of MSW. The histogram error of the same structure was drawn to estimate the error among training, validation, and testing the targets and output (Fig. 11). It reveals that the data fitting errors were distributed within a reasonably good range between −0.25 and 0.20.

Based on the applied time series model and optimized ANN structure, the monthly waste generation rate was estimated. As a metropolitan city, the solid waste generation rate in Kolkata Municipal Corporation has been increasing day by day. The prediction result reveals that the monthly average waste generation rate in the study area was 1,08,900 (about 3630 MT/day) during 2010, which is now about 1,35,000 (about 4500 MT/day) and will reach 1,56,160 MT (about 5205 MT/day) in the year of 2030 (Fig. 12). The increasing trend of waste generation is an alarming threat to both the environment and public health if proper management and strategies not follow. The result further shows that the highest and lowest waste generation month is August and December, respectively. In August, the waste generation rate is higher due to the wet weight of waste and reverse case happened during December.

4 Discussion

The design and operation of a waste management system become critical with maximum quantities of waste produced from different sources in any region. Accurate estimation of maximum waste produced in any city

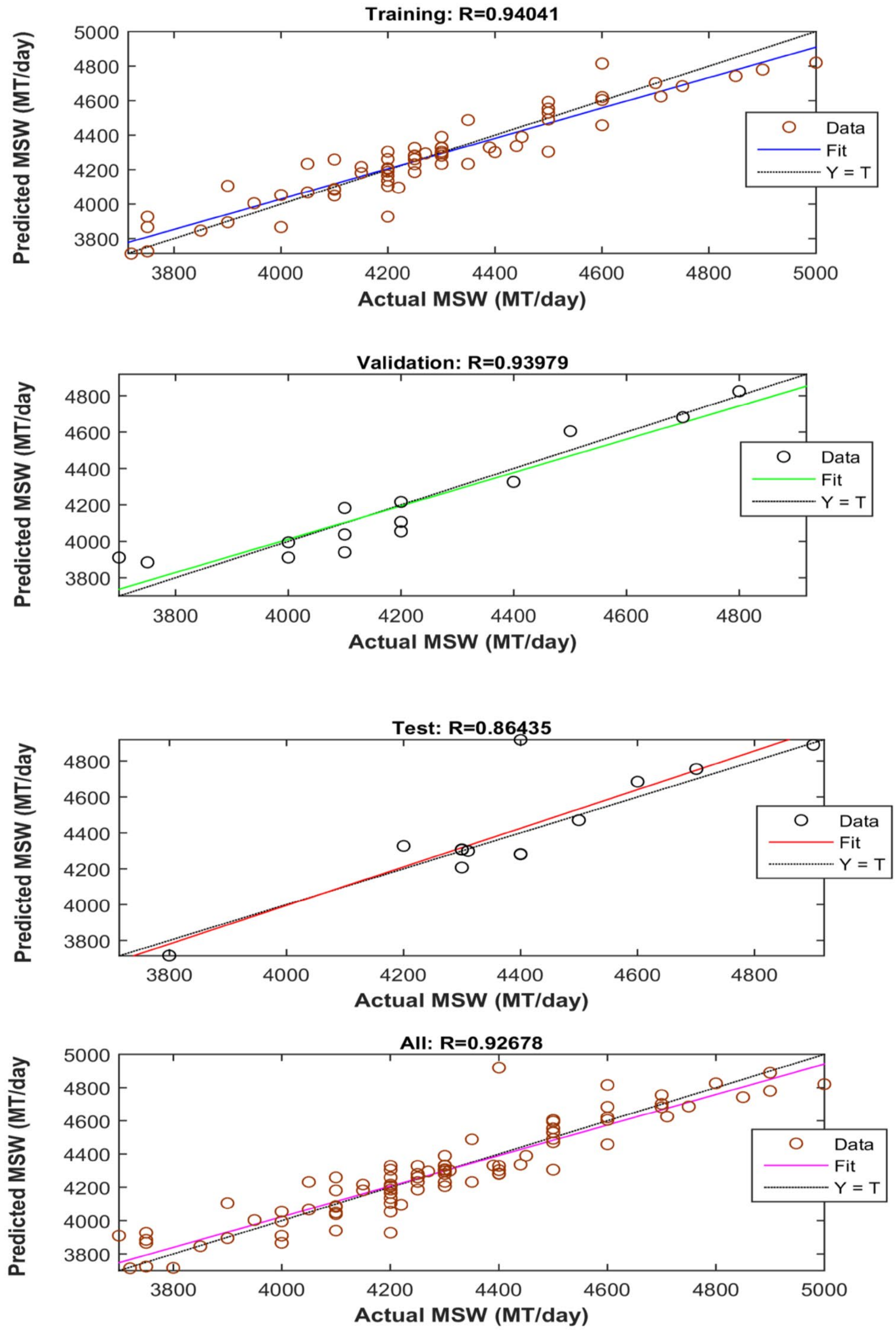


Fig. 7 Value of regression coefficient (*R*) of best model structure with 19 hidden layer neurons during training, validation, and testing

allows the authorities and managers to understand the required facilities related to waste collection and disposal. Moreover, the daily operation of waste management system largely depends on estimating an average quantity of generation in a year. The present study used ANN time series model in which waste generation data of 96 months were considered for forecasting future trends of waste generation. Methodologically, the result of the present study more or less similar to the other studies although the variables of forecasting are different. Like the present study, different types of socio-economic variables like population, Schedule cast, Tribe population, lifestyle of population, quality of built-up environment, municipal services, and geographic variables like latitude and longitude can be used for long-term solid waste prediction using artificial neural networks and

Fig. 8 Contrast between observed and predicted municipal solid waste generations (MT/day) during training (model structure with hidden layer 1-19-1)

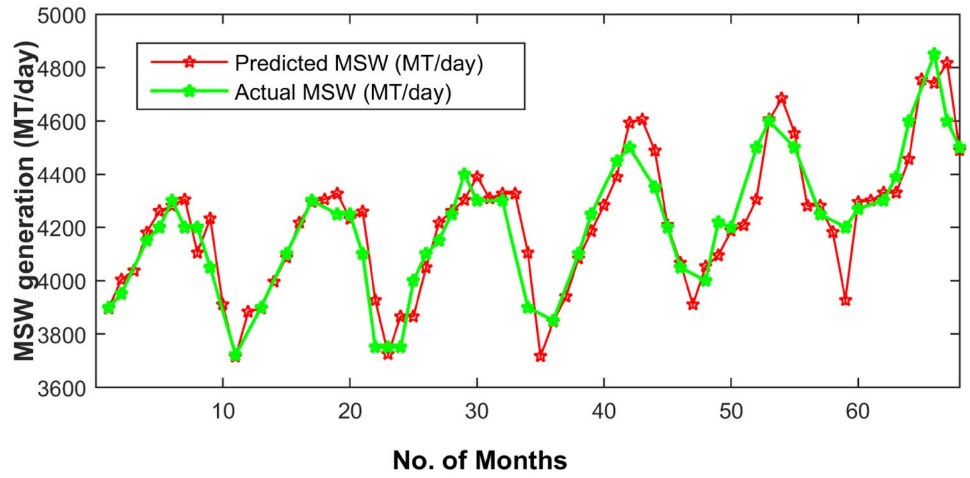


Fig. 9 Comparison between observed and predicted municipal solid waste generations (MT/day) during validation (model structure with hidden layer 1-19-1)

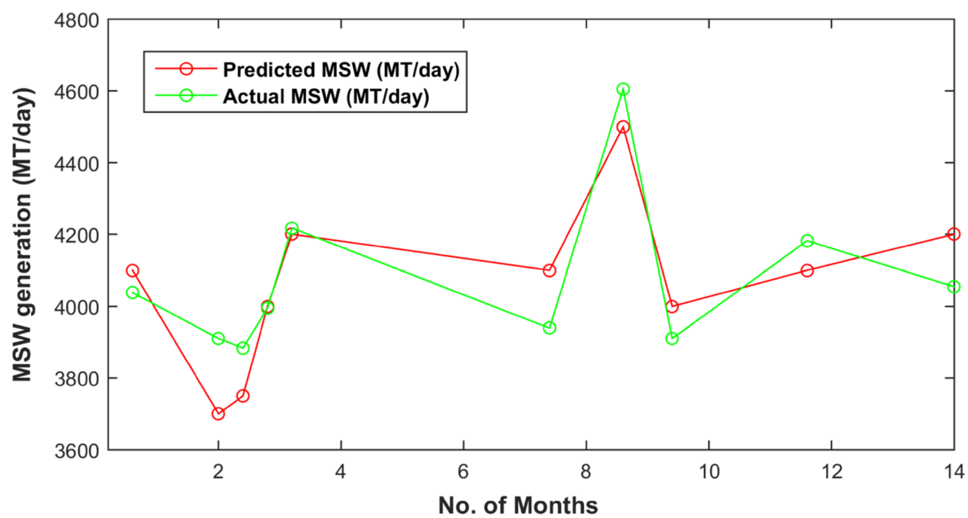
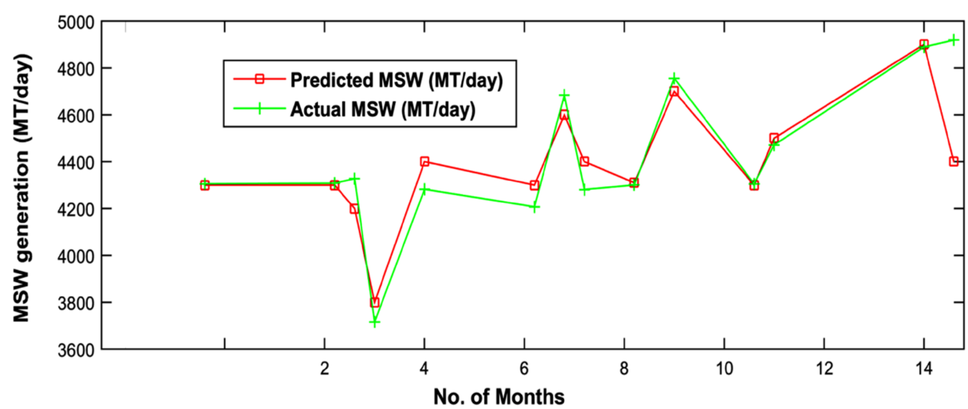


Fig. 10 Comparison between observed and predicted municipal solid waste generations (MT/day) during testing (model structure with hidden layer 1-19-1)



percentage prediction errors of performance index can be calculated to validate the output waste generated data [56]. Same as the present study, the ANN time series autoregressive approach was used by Singh and Satija for forecasting the monthly basis municipal solid waste generation in Faridabad city of Haryana, India and found accurate results [39]. Not only the quantity of waste generation but also the waste composition characteristics can be analyzed using an artificial neural network approach by considering per capita income, level of education, the average age of the population, and rural and urban area population as input criteria [57].

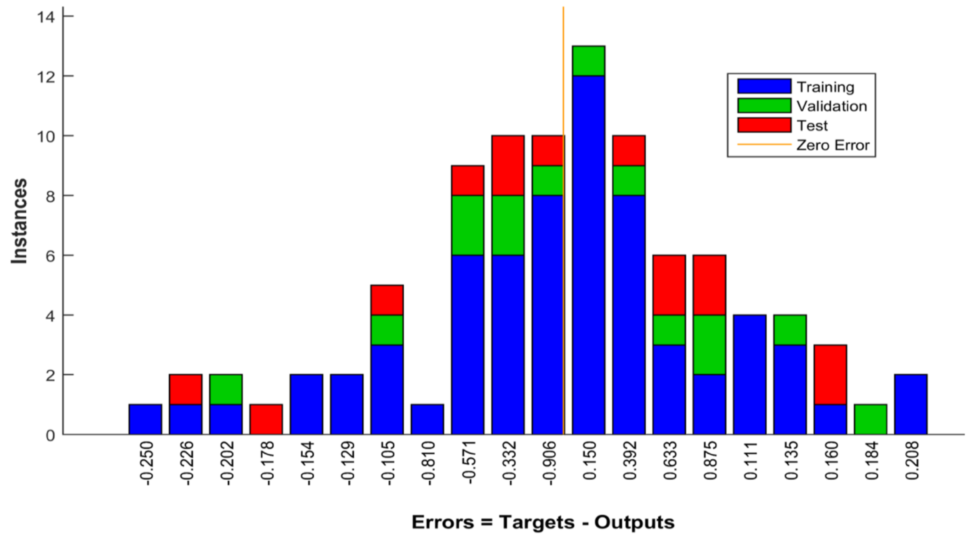


Fig. 11 Histogram error to estimate the error among training, validation, and testing the targets and output

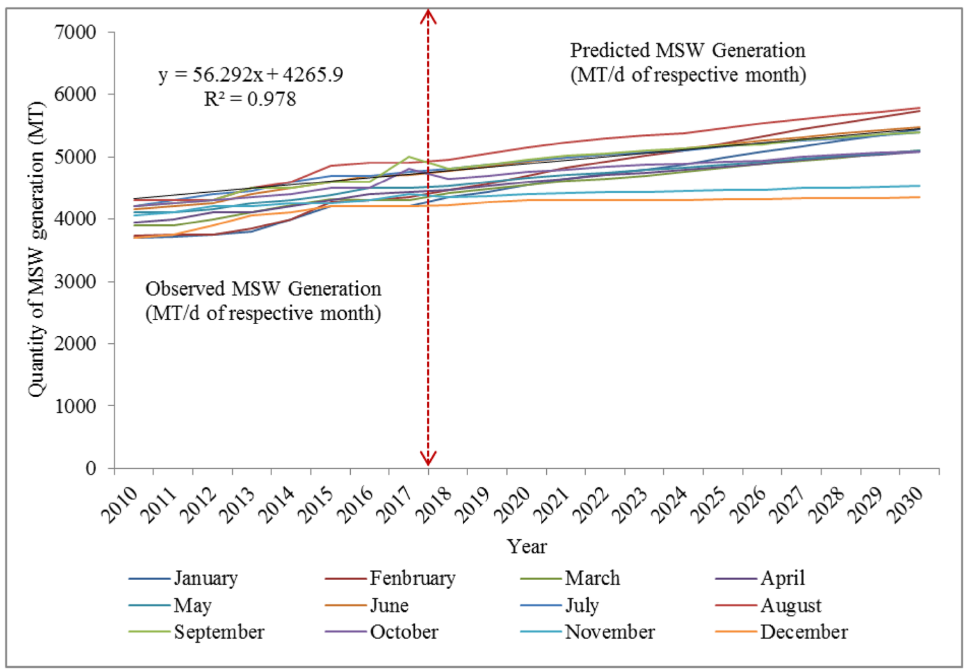


Fig. 12 Monthly MSW generation predicted using time series model

The time series forecast uses past data to predict the future, while causal variables forecasting tries to find the relationship between the input and the output variables [58]. Time series forecasting is a flexible method, where its application does not require much data. Additionally, it is capable of gathering the fluctuations. A cohesive time series model combining ANN, principle component analysis, and gamma test was implemented to forecast the weekly solid waste generation [59]. ANN approach is much better than any traditional methods for long-term prediction for solid waste generation [8, 19, 22]. Stop training performance can be useful to resolve the problem of variation in errors between the training and testing solid waste data in ANN models [37]. Thus, in the present study, the time series forecasting model was used looking toward its flexibility and good result.

5 Conclusion

Growing population, urban expansion, and changing human lifestyle are directly or indirectly responsible for altering the quantity of waste generation. Day by day, the properties and composition of generated waste have also been varying from least to large extent. Thus, the implementation of suitable technology and sustainable managemental strategies is essential for decreasing the burden of adverse impacts of solid waste management from the environment and public health. These could be possible by designing suitable model and operational framework. Accurate waste prediction is one of the aspects of operational framework. In case of Kolkata Municipal Corporation, about 3500 MT/day waste had been generated throughout the city before a decade ago, but presently, this quantity reaches a range of 4200–4500 MT/day with seasonal changes. The municipal authority along with private agencies doing their best from the collection and storage to final disposal, but still deficiency remains in the term of scientific treatment. To allocate proper resources in terms of waste collection and storage, it is essential to estimate future waste generation quantity. The prediction or forecasting of waste quantity is really an essential phase of sustainable waste management. The present study proposed the suitable artificial neural network time series model using the nonlinear autoregressive technique for forecasting the quantity of MSW for KMC. The present model would be applicable for predicting MSW for the coming year. The available data on solid waste generation in KMC reveals that the city has collected and disposed an averagely 4043, 4129, 4245, 4278, and 4351 MT/day waste for the year 2013, 2014, 2015, 2016, and 2017, respectively. The average solid waste growth has been computed as 89, 86, 116, 33, and 73 MT/day, respectively, for the same year. Based on these available data, the ANN time series model has applied to estimate the future trend of solid waste for coming year. The result reveals that Kolkata will generate about 5205 MT/day municipal solid waste in 2030 which will add more than 1000 MT/day waste with the existing rate of generation.

Therefore, the proper strategies and allocation of more useful resources are required to manage the extra waste that adds every year. Every city, especially in developing countries, has been facing problems to ensure suitable MSW management. To resolve the problem permanently, planning should be addressed from roots. Forecasting of MSW generation is considered as an essential step for better operation and planning. Thus, it is compulsory for MSW administrators and decision makers to improve a tool for exact forecasting of solid waste quantities. In this regard, the applied methodology can help the local authorities and governing bodies in estimating possible rate of future waste generation and in making actionable strategies for coming year in Kolkata Municipal Corporation. This methodology can also be applied in other parts of developing countries to forecast waste generation rate. This study would be a source of research in the field of not only waste forecasting but also other aspects of forecast to those who desire the same.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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