Artificial Neural Network Based Optimum Scheduling and Management of Forecasting Municipal Solid Waste Generation – Case Study: Greater Noida in Uttar Pradesh (India)

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Abstract. Precise forecast of municipal strong waste era has a critical part in future arranging and squander management framework. The attributes of the created strong waste are distinctive at better places (region to district or nation to nation). The precise forecast of municipal solid waste (MSW) era turns into an essential errand in present day period. Its prediction requires accurate MSW data. The point of the present review is to outline the time series model for foreseeing month to month based strong waste production in Greater Noida city of Uttar Pradesh State (India) utilizing artificial neural network (ANN) with time series autoregressive method. The gathered municipal waste perceptions have been organized month to month from 2012 to 2016. The 60 months data set has been classified into 42 training data sets, 9 testing data sets and 9 validating data sets. An assortment of models of ANN has been examined by altering the number of hidden layer neurons. Ultimately, paramount enhanced architecture of neural network is established. The least value of performance parameters is validated in the proposed model as mean square error 0.0004, root mean square error 0.0203 and the high value of the coefficient of regression 0.8123. On the premise of these execution parameters it is reasoned that the ANN model provides precise prescient outcomes.

1. Introduction
In the race of crowded nation India is second in the world after China. Each individual around us is a latent producer of the ravage (waste). Consequently, these 1.31 billion individuals are latent producer of the ravage. For the Indian society central environmental issue is the municipal solid waste management (MSWM). Other than this developing populace the major factors responsible for waste blunder is the quickly expanding industrialization, urbanization, absence of mindfulness among individuals for waste era, open way of life, sustenance propensities, temperature, yearly normal precipitation, geographic conditions, absence of sanitation assets, sanitation vehicles, deficient number of sanitation specialists and inappropriate arranging.

The outcomes of this fumble of waste influence our wellbeing. The unlawful blazing of waste produces air contamination. After leakage contaminated surface water along with solid waste plunder the ground water. Harmful waste riches soil fruitlessness.

Henceforth strong waste era radically influences the ecological manageability. Consequently better arranging and waste management is basic for the general public particularly in profoundly urbanized, very populated regions. Greater Noida region is one of such quickest developing, mechanical domain in Greater Noida State, India. For solid waste prediction in Greater Noida a time series autoregressive model has been applied. The anticipated strong waste relies on different financial variables. Previous studies motivated to forecast an autoregressive time series model.

Before continuing to next area taking after systems have been uncovered from the past reviews which are given below. Input variables used in the multiple regression models [1] with twofold record structure in which number of excursions to the dumpsite, number of times waste gathered, the number
of waste holders, the number of years spent in vehicles have given streamlined outcomes for the prescience of strong waste accumulation. Using artificial neural network (ANN) approach [2] analyzed waste composition characteristics with the help of per capita profits, standard age of populace, height of schooling and rural and urban area populace.

The financial variables as populace, schedule cast, schedule tribe populace, income gathered by means of expense for metropolitan administrations, longitude, scope can be utilized for long term solid waste forecast progressively utilizing ANN. [3] predicted the percentage errors in validating the output generated waste data by using performance index. Owing to altering seasonal conditions [4] the produced strong waste shifts from week to week and months to months. [5] Proved that ANN approach is superior to conventional methods for elongated forecast for produced solid waste. [6] Applied to quite preparing a strategy to persistence the trouble of uniqueness of mistakes flanked via preparing and testing strong squandered information that focuses on ANN models.

By utilizing edge insights as a measure of presentation list [7] the most ideal ANN model can be demonstrated. To see the effort of autocorrelation in the time arrangement models Durban–Watson test can be applied [8]. By applying 4R principals [9] the strong defile generation can be decreased.

2. Material And Methods

The present research has been completed in Greater Noida, the quickest developing city of tourism in Greater Noida state, India. Greater Noida district bounded on the northwest, across which lie the districts of Ghaziabad and Hapur. It is surrounded on the north by Delhi, on the east by Bulandshaher district. More prominent Noida City is a city with a populace more than 100,000, situated in the Gautam Budh Nagar region of the Indian province of Uttar Pradesh. The city was made under the UP Industrial Area Development Act, 1976.

It is a division of the National Capital Region of India. According to the temporary information of the 2011 census, it had a population of 107,676, with 58,662 males and 49,014 females. Waste generation in this city is about 0.6 kg per day per capita. Nearly, 900 tons per day waste is produced. It has an average effective literacy rate of 90.43 percent, as compared to the national average of 74.04 %.

The male education rate is 95.41 percent and the female proficiency rate is 85.08 %. The municipal corporation unit of Greater Noida (MCU) is responsible for administering the loss from its initiation to the closing dumping in the city. Supervision rising waste is an imperative environmental issue for MCU. Subsequently, fitting organizing is required for waste generation, gathering transportation and in its last move. The achievement of organizing depends on the exact prediction of generated strong waste. We have used a nonlinear auto backward approach with ANN methodology for the better desire for generated strong waste. In the following subsection, we will dismember the month clever made solid waste information.

The Accessibility of precise data is a challenging task which plays an indispensable role in waste management system. In this study the MSW produced data has been composed from the landfill in Kasna village, Greater Noida. It was observed that 350 to 500 g per capita waste has been produced in the city. Be that as it may, just 60–70 % waste is gathered in the city. The regular conditions, celebrations and movement of individuals for occupation definitely impact the occasional variety in waste era. Because of this regular variety time series model will be demonstrated the best model for expectation. To advance our outcome we have joined ANN approach with this time series model. The 60 months information (September 2015 to September 2019) has been organized as time ventures of time series model. Fig. 1 shows the regular variety of gathered strong waste information.
The artificial neural network (ANN) models are essentially indistinguishable from our biological neural system. There exists a message-passing structure between natural neurons. While in ANN models the information is passed inside artificial neurons, ANN models are amazingly useful in anticipating the future in perspective on the previous history. ANN models have the ability to manage data and yield. ANN shows works like multiprocessor, parallel processor and furthermore circled structure when the loads and extra data sources experience neurons. The streamlined model of ANN architecture is appeared in Fig. 2.

Here considering \( \{x_1, x_2 \ldots x_n\} \) as the arrangement plan of data sources and \( \{w_1, w_2 \ldots w_n\} \) as the course of action of loads. Basically the loads are the characteristics of information sources. If the nature of a flag is high weight will be high. If the nature of a flag is low then the weight will pass on low regard. So these loads are copied with their relating inputs. By then, this total is traded as far as possible units. In this unit, there will be an assessment between data weight complete and a point of confinement regard \( h \). Threshold work is basically used to consider this qualification. On the occasion that weight input item whole \( S \) (state) is more unmistakable than this farthest point regard at that point yield will be 1 by and large 0. There is an alternate edge work to be specific, sigmoid function, piecewise linear function or hyperbolic tangent function [10]. Here, we are tangent sigmoid function joined by information and hidden layer neurons and linear transfer function joined by hidden and yield layer neurons.
Here, autoregressive technique with Multilayer feed forward neural network structure has been applied. Non linear auto regressive technique has been combined with the above neural network model. The sequence of observations \{x_1, x_2 \ldots x_n\} may be considered by time series method. Assume \( a_0 \) be the normal estimation of the time arrangement model and \( a_1, a_2 \ldots a_n \) are the like to the slopes to the \( x_{t-1}, x_{t-2} \ldots x_{t-n} \) planes. In the autoregressive model consider the value \( x_t \) of the time series model to be expressed in terms of its last one going before values \( x_{t-1} \). By then this model will be called an autoregressive model of order 1.

\[
x_t = a_0 + a_1 x_{t-1} \\
(1)
\]

\[
x_t = a_0 + a_1 x_{t-1} + a_2 x_{t-2} \\
(2)
\]

The (3) shows the autoregressive model of order \( n \) with the value of \( x_t \).

\[
x_t = a_0 + a_1 x_{t-1} + a_2 x_{t-2} + \ldots a_n x_{t-n} \\
(3)
\]

In (3) nonlinear function \( F (x_{t-1}, x_{t-2} \ldots x_{t-n}) \) is added. Joined by input neurons and yield neurons \( h \) quantities of hidden layer neurons have been presented. Presently, in general, non-direct autoregressive neural network time series model (NAR) can be appeared as

\[
x_t = a_0 + a_1 x_{t-1} + a_2 x_{t-2} + \ldots a_n x_{t-n} + U \\
(4)
\]

where,

\[
U = F(x_{t-1}, a_2 x_{t-2} \ldots x_{t-n}) \\
F(x_{t-1}, a_2 x_{t-2} \ldots x_{t-n}) = A \\
(5)
\]

where,

\[
A = \sum_{j=1}^h \phi \gamma_{0j} + \sum_{i=1}^n \gamma_{ij} x_{t-i} \beta_j + \varepsilon_t
\]

In (5) inclination factor is shown by \( \gamma_{0j} \) which is presented among info and hidden layer neurons and loads are shown by \( \gamma_{ij} \) which is presented among information and hidden layer neurons close to loads among hidden and yield layer neurons is shown by \( \beta_j \). The random error shown by \( \varepsilon_t \) introduced due to supplementary hidden factors.

![Fig. 3. Example Simplified model of neural network autoregressive (NAR) time series](image)

Model of neural network non linear auto regressive (NAR) time series is shown in Fig. 3. From, January 2012 to December 2016; month wise solid waste data (MSW/day/capita) \( w_t \) (say) has been taken as input data for our model.

The training data, validating data and testing data are the three time steps in which data is randomly divided.

For training, validation and testing 70%, 15% and 15% data of 60 months respectively, has been considered for the model. In this learning method of the network is correlated with training.

To evaluate the network performance testing process is carried out during training. In this paper Levenberg–Marquardt back propagation algorithm (trainlm) was used to generate least amount value of mean square error as well as utmost value of regression coefficient R by adjusting weights by back propagation iterative process.
3. Material And Methods

Results have been replicated by using artificial neural network time series tool (ntstool) in MATLAB (2015b) software. Number of hidden layer neurons was altered by altering the finest ANN time series model. An assortment of ANN structures have been originated during this iteration process. To assess the enhanced system structure, the base estimation of Mean Square Error (MSE) and the greatest estimation of the regression coefficient (R) has been estimated as recital lists. Table 1 represents the assortment of ANN time arrangement models with hidden layer neurons differed from 15 to 25. Regardless, execution estimations of structures with neurons 1–14 have not participated in the table in view of the high estimation of MSE and low estimations of regression coefficient R.

Table 1 Performance Analysis of Training, Testing and Validation

| ANN model structure | MSE  | RMSE  | Regression R  |
|---------------------|------|-------|---------------|
|                     |      |       | Training | Validation | Testing |
| 1-15-1              | 0.0028 | 0.0532 | 0.6684 | 0.9523 | 0.6479 |
| 1-16-1              | 0.0035 | 0.0607 | 0.6373 | 0.9513 | 0.4867 |
| 1-17-1              | 0.0027 | 0.0506 | 0.6891 | 0.9072 | 0.7505 |
| 1-18-1              | 0.0010 | 0.0421 | 0.8222 | 0.6880 | 0.8337 |
| 1-19-1              | 0.0007 | 0.0369 | 0.8852 | 0.7583 | 0.5489 |
| **1-20-1**          | **0.0004** | **0.0203** | **0.9411** | **0.8123** | **0.7390** |
| 1-21-1              | 0.0023 | 0.0466 | 0.7418 | 0.7589 | 0.7154 |
| 1-22-1              | 0.0024 | 0.0473 | 0.7367 | 0.6364 | 0.6035 |
| 1-23-1              | 0.0027 | 0.0410 | 0.7809 | 0.6109 | 0.7007 |
| 1-24-1              | 0.0023 | 0.0464 | 0.7952 | 0.8157 | 0.6250 |
| 1-25-1              | 0.0007 | 0.0355 | 0.9161 | 0.7476 | 0.7069 |

The best neural system structure with 20 hidden layer neurons is considered as the optimized system because of minimal estimation of MSE 0.0004825 and the most extreme estimation of regression coefficient R as 0.9396. The examination among exploratory and anticipated Municipal Solid Waste every day per capita (kg/day/individual) results got from the best ANN 1-20-1* model is outlined in Fig. 4.

Correlation among experimented and anticipated MSW accumulations every day per capita (kg/day/individual) during the training procedure of the neural system is displayed in Fig. 5. All through the training procedure, the framework gains from going before objective information focuses which will be additionally summed up and tested.

![Fig. 4. Experimental and forecasted MSW collection per day per capita (kg/day/person)](image-url)
Fig. 5. Experimental and forecasted MSW accumulation per day per capita through training (ANN 1-20-1 model)

A correlation among experimented and anticipated MSW accumulations every day per capita (kg/day/individual) during the validation procedure of the neural system is appeared in Fig. 6. The framework gets added for example loads are moved up to evaluate the best insightful model all through the validation system.

Fig. 6. Experiential and forecasted MSW compilation per day per capita through validation (ANN 1-20-1 model)

Correlation among experimented and forecasted MSW accumulations every day per capita (kg/day/individual) during the testing procedure of the neural system is shown in Fig. 7. Testing time steps have been chosen discretionarily from input information focuses all through the testing procedure and system execution is assessed further. Segment 0.25263 kg/day/capita has been assessed as the mean estimation of predicted MSW gathered every day per capita and 0.24768 kg/day/capita has been assessed as the mean estimation of the observed MSW gathered every day per capita. Hence from ANN 1-20-1 model the mean absolute error (MAE) derived is 0.00506 kg/day/capita.
Fig. 7. Experimental and forecasted MSW compilation per day per capita through testing (ANN 1-20-1 model)

The number of months and their respective errors between observed and predicted MSW per day per capita is illustrated in Fig. 8. This is watched that the variety between blunders is changing in one course as well as in inverse heading too. The majority of such blunders are found inside certainty limits which additionally approve our proposed model.

Fig. 8. ANN (1-20-1) model derived for number of months versus residuals

4. Conclusion
The number of inhabitants in Greater Noida is developing step by step. Each individual is the probable generator of solid waste is presently getting to be distinctly in charge of this issue. In this manner, perfect masterminding and looking at the executives are required for this issue. To decide this issue we have proposed the reasonable artificial neural network time arrangement model using a nonlinear autoregressive technique for envisioning MSW consistently per capita for Greater Noida city. Throughout training, testing and validation processes a variety of ANN structures have been experimented by altering hidden layer neurons.

The ANN architecture 1-20-1 is chosen as the most amazing arrangement of action on the inception of least estimation of mean square error (MSE) and raised the estimation of regression coefficient R. The optimality of ANN has been chosen by least estimation of MSE and higher estimation of R that presents the arrangement where the weights are improved. The proposed model has been found
suitable for the desire for MSW using simulation as a piece of the coming years. Greater Noida is having the landfill of 20.33 hectares. The landfill has been established to set out the waste only for imminent 7 years. The MCU labor has composed 33,520,794, 69,155,480, 84,195,654, 98,424,023, 120,651,165 kg MSW in years 2012, 2013, 2014, 2015, 2016, respectively.

The experimental enlargement of MSW has been originated 35,634,686, 15,040,174, 14,228,369, and 22,227,142 kg in years 2013, 2014, 2015, 2016, respectively. 28,159,522.61 kg is the average growth of waste collected per year. The expected value of waste collection will be 310,142,651.28 kg in year 2021. The additional landfill area will requisite if the waste get augmented more than 310,142,651.28 kg. In this manner, the anticipated model will oblige for the MCU authorities actualizing their choices for waste administration improvement. As demonstrated by MCU authorities 40 hectares of extra land is required for extra dumping in the coming years.

Barring, the land cost in Greater Noida is high. This is recommended that the extended waste should be used for essentialness restoration reason with the assistance of incinerators, refuse-derived fuel (RDF) plants and Plasma gasification techniques. The results may be upgraded by using step by step based MSW data for increasingly exact desires. The socio-budgetary factors (Masses, urban people, training rate, migration of people for work perspectives in the city, per capita pay, Augmentation of benefits by MCU) can be used as data parameters for solid waste desire and results may be deciphered in increasingly expressive manners.

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