International Journal of ChemTech Research
CODEN (USA): IJCRGG, ISSN: 0974-4290, ISSN(Online):2455-9555
Vol.10 No.13, pp 283-299, 2017

Futuristic Projection of Solid Waste Generation in Dehradun City of Uttarakhand using Supervised Artificial Neural Network-Non-Linear Autoregressive Neural Network (NARnet)

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Abstract : Solid waste management has become a pressing problem in every city. Municipal Solid Waste characteristics and quantities change significantly with time. The model in the present study enables the solid waste management personnel to have prior information on the amount of future waste. A prediction model has been developed that uses the present waste generation data, along with different environmental and economic factors. These factors have been implicitly incorporated using quantity of solid waste as a time-series dataset to simulate a supervised Artificial Neural Network (ANN) in MATLAB - Nonlinear Autoregressive Neural Network (NARnet). The values of input parameter current solid waste quantity are used for estimation of output which is, amount of solid waste generated for future period of about three months, thus facilitating the pre-planning of waste management. In current work different architectures of neural network have been examined by varying the combinations of number of hidden layers, neurons in each layer and the choice of activation functions. Based on the performance criteria, the best optimized ANN architecture has been used for the prediction of quantity of solid waste.
Keywords : solid waste generation, artificial neural network, time series data, prediction of solid waste quantity.

1. Introduction

Municipal solid waste characteristics and quantities change significantly with time. Some of the affecting factors include - change in the food consumption pattern, population growth, migration, underlying economic development, employment changes, weather conditions, geographical situation, hobbies, and household size[1]. All these factors along with response to recycling of waste influence the future generation of solid waste tremendously. This warrants a need to design and develop a reliable model to assess the impact of factors, affecting solid waste generation. The model is proposed to provide prediction that will play a very important role in overall process of management and disposal of the solid waste that may be generated in future. The model enables the solid waste management personnel to have prior information on the amount of future waste. Thus, facilitating its disposal planning.

Prime prerequisite for Solid Waste Management system is reasonably reliable solid waste quantity prediction. The available statistical models work very well with data which are linear in nature and can fit into one of the existing trends. But the solid waste data representing quantity of waste collected by local SWM authorities -on-day- to day basis are nonlinear (wt. in metric tonnes) in nature, due to which, the prediction with accuracy by the use of statistical models becomes a challenge. Prediction of solid waste generation though use of ANN is widely available in literature. Determination of solid waste quantity generated in future is a useful scientific advance from planning perspective and would provide the time and opportunity for the solid waste personnel and their organization to adopt necessary steps required for the disposal such as capacity, machinery and estimated area for a municipal landfill expected to be used in future. If this information is known well in advance to the concerned authorities, the complete process of solid waste disposal from collection to its choice of disposal methods can be planned well in advance and be much more organized. This would result in a more effective solid waste management system for the city.

Located in the lush green Garhwal region, 236 km to the north of Indian sub-continent is a valley called Dehradun. It is the capital of the state of Uttarakhand. The population of the city is about 578,420(2011 census). Dehradun is in the foothills of Himalayas nestled between the Ganga on the east and the Yamuna on the west. The city is well connected and in proximity to Mussoorie and Auli, popular himalayan tourist destinations, Haridwar, Rishikesh holy cities and the himalayan pilgrimage circuit of Char Dham.

This makes Dehradun city a tourist hot spot causing migration patterns that are seasonal in nature. Being the current capital of Uttarakhand, the growth rate of the city is on the rise. Coupled with this is the industrialization in the vicinity, generating multitude of job opportunities for people in and around the city resulting in migration of workforce. In recent years, the increase in emigration has created an increase in waste generation resulting in municipal solid waste menace. Though the idealistic approach of waste management is to control waste generation at source, aiming towards a zero waste, as per the current scenario, the city of Dehradun is far from it. This necessitates the focus towards waste handling, which is very likely to be improved provided, necessary planning is invested upon. An appropriate model for the prediction of future values of solid waste is essential for the proper plan and choice of waste disposal methods in future.

2. Related Work

McBean and Fortin worked with municipal solid waste management using socio-economic factors, their correlations, solid waste composition and quantities. Their model uses generation coefficients associated with individual material components for estimation of the quantity of solid waste generated by the domestic and industrial sources[2]. Dyson and Chang considered the factors such as effects of population, level of income, and the size of dwelling unit in a linear regression model which was unable to handle various issues. A new approach, namely system dynamics modeling- presents various trends of solid waste generation in a rapidly growing urban area with a limited base of samples using simulation tool-Stella[3]. Beigl et al.used a model for the European cities, that made use of the explanatory variables, Gross Domestic Product rate of infant mortality rate, such as size of household, which were termed as one of the core set of significant regional development indicators. Evaluation of the data collected by them indicated a significant relation between regional development and municipal solid waste generation[4]. Benitez et al. gave prediction for the residential solid waste by development of a linear mathematical model using education, income per household, and number of members in family, being used as explanatory variables[5]. Buenrostro et al. reported income as an influential factor for solid waste generation by forecasting both the residential and the non-residential solid waste using multiple linear regression analysis[6]. Dayal et al. investigated and assessed climatic conditions and socio-economic status, as holding heavy impact on solid waste characteristics[7].

Recently, there have been some investigations to assess the application of the artificial neural networks (ANN)-multi-layer perceptron-in short-term and medium-term forecasting, but very limited efforts have been condu **Futuristic Projection of Solid Waste Generation in Dehradun City of Uttarakhand using Supervised Artificial Neural Network-Non-Linear Autoregressive Neural Network (NARnet)** cted for the long-term forecasting. Kumar et al. have used radial basis function approach of artificial neural network model for the long term forecast of solid waste for the city of Eluru and to reduce the discrepancy between the predicted value and the observed value of the municipal solid waste[8]. Zade and Noori predicted weekly solid waste values, using feed forward ANN by taking the generated waste as a time series input to the neural network for the city of Mashhad, emphasizing ANN as prediction tool[9]. Noori et al. extended the previous study with the application of Principal Component Analysis and Gamma test techniques for weekly forecasting. They applied these techniques on the set of influential input parameters to find those which affect the generation of solid waste the most. In their study they have also compared a few ANN training algorithms. Their results show that with different pre-processing technique a different algorithm would provide the best result. They concluded that both the pre-processing techniques were almost similar hence, either can be used[10].

Noori et al. evaluated results of the uncertainty of predictions of solid waste generation by hybrid of wavelet transform-ANN and wavelet transform-ANFIS models[11]. Noori et al. gave an improved Support Vector Machine model, using combination of both the PCA and SVM techniques for prediction of weekly generation of solid waste of Mashhad city. This model has more advantages over the traditional SVM model as noted by the author[12]. Karaca and Ozkaya were able to control the leachate generation rate in landfills by the use of ANN. They selected the best network architecture, training algorithm and have also discussed further development along with the advantages and the disadvantages[13]. Using a limited sample set Chen and Chang reported a new theory gray fuzzy dynamic modeling, for solid waste prediction in urban areas [14].

In multivariate models, solid waste generation can be presented as a delay of time. The time delay would easily represent the dependency of an input parameter on itself for a particular period of time. Due to high correlation observed between dependent variable and same variable intervals, the delaying of the parameters has significant impact on prediction of generation of solid waste. This serves in the model as an independent variable[1]. As the input parameter depends on itself, the effect of the other parameters for the past few measures becomes indirectly included for the current value. For this reason, the effects of the other input parameters aiding in the prediction of future generation of solid waste are negligible. Due to this there is no need to model other factors that may have effect on the generation of solid waste.

3. Materials& Methods

3.1. Current Work

The purpose of current work is to provide a reasonably accurate and reliable model for the prediction of solid waste with an aim to decrease the uncertainty present in prediction. The purpose is also to predict the future measures of weekly solid waste generated (possibly a period of 12 weeks). This futuristic prediction is proposed to be a useful advance in the proper planning and organization of the solid waste and its disposal.

In the current work, those variables which have the highest influence on SWG are selected as the input parameters. The choice of the selected variables depends on the attributes, such as their ability to be forecasted for a long forecasting horizon and the relative high accuracy with which the forecast can be made. Few such factors identified with the highest impact on solid waste prediction are population and household size. After the selection of parameters, the developed ANN model is trained, tested and validated for the period for which data have been collected, and the model architecture found most reliable is determined based on the selected performance measures. Eventually, the predicted future values based on the currently available data are validated.

3.2. Preprocessing

Before modeling the neural network, it is essential to refine the data by pre-processing techniques due to the following reasons: noise reduction and low learning rates of ANN. The various parameters for generation of solid waste are taken as, population growth, economic development and household size[1]. The parameter solid waste can be presented as a delay of time and incorporated as an independent variable in the model and hence, in the present work, the input parameter is only solid waste generated[1]. The weekly time series data set of the input parameter is depicted in Figure 1.

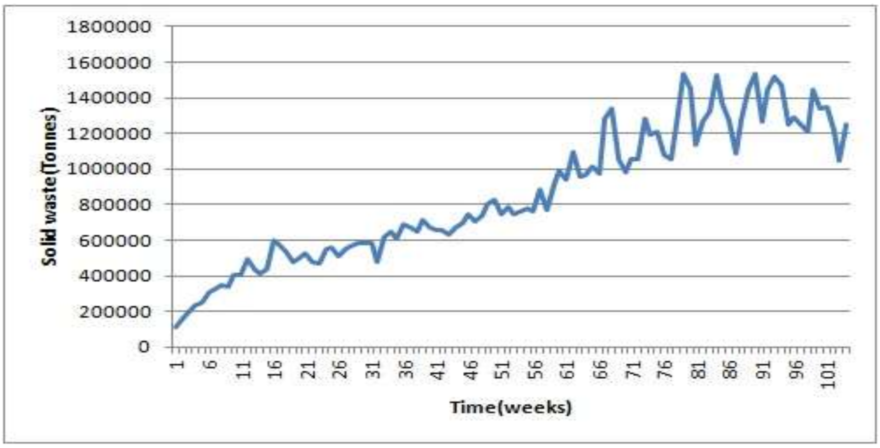


Figure 1. Collected Data

After the training of the network is completed, this ANN model is used for future value prediction. The results of training the ANN on the raw collected data would make it evident that the independent variable in future prediction would be highly changed with respect to the data from the observed period.

To make the model being trained in range of the observed data meet the values occuring in the predicted range, the observed data needs to be taken to the same scale as data from the prediction period i.e. pre-processing of data. To achieve this goal, the Stationary Chain concept in time series is used. A time series variable is said to be stationary when statistical measures such as mean, variance, and correlation coefficients remain constant over a period of time.

The first pre-processing step is to obtain the trend line that the data follows and to remove it. This makes the data mean remain constant[1]. Various trend lines can be applied to the given data and the most suitable one can be found. The suitability of the trend line can be measured by the coefficient of determinationR^2. The more this value is closer to 1, the better is the result. The R^2values of various trend lines are given in the Table 1.

Table 1. Results of various trend lines

Sr. No.	TREND LINE	COEFFICIENT OF DETERMINATION(R^2)
1	**Linear**	**0.903**
2	Logarithmic	0.7506
3	Exponential	0.8511

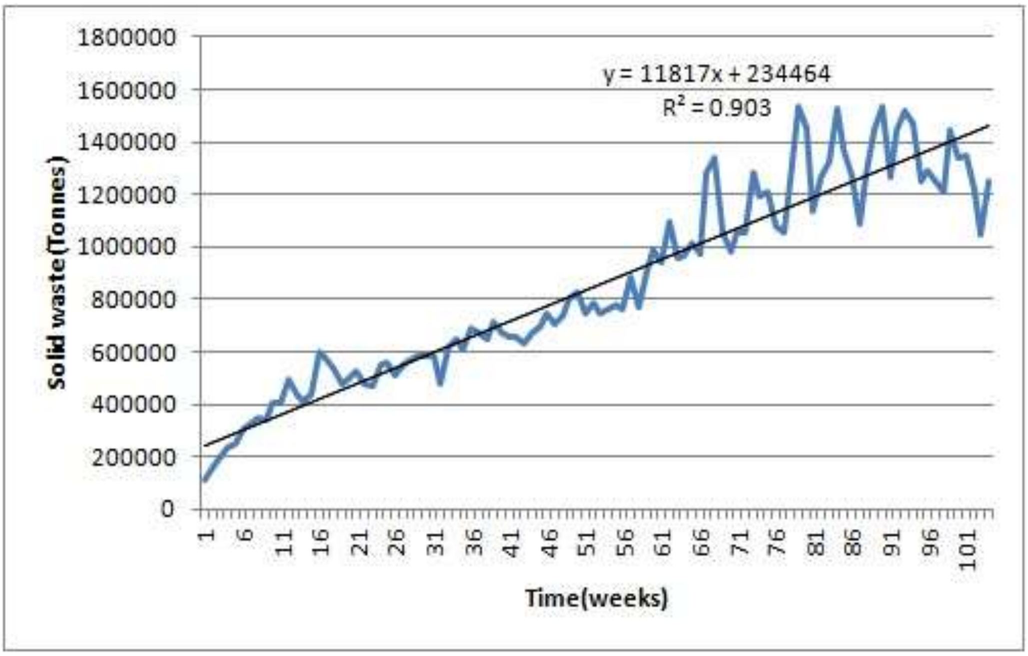


Figure 2. Trend of generated solid waste for the observed period

From Table 1 it can be observed that the data follows the linear trend line, the Figure 2 depicts this trend line onto the data. The equation for the linear trend line is given by Equation 1.

$$y = 11817x + 234464 \quad (1)$$

where y is the solid waste amount and x is the week number for which it is being calculated.

The second pre-processing step is to normalize the data. This method not only alters the scale of the data but also makes the variable more static. The normalization equation used is given in Equation 2.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

wherex_{norm} are the normalized values,x_{min} is the minimum, x_{max} is the maximum of the input values. These results are shown in Table 2.

Annexure: 1

Table 2: Normalized weekly solid waste data.

Weeks	Solid Waste	Weeks	Solid Waste	Weeks	Solid Waste	Weeks	Solid Waste
1	0.349121	27	0.520677	53	0.371923	79	1
2	0.39814	28	0.523383	54	0.374093	80	0.873033
3	0.425574	29	0.52556	55	0.389551	81	0.448716
4	0.463438	30	0.51472	56	0.347382	82	0.600484
5	0.467632	31	0.503207	57	0.487433	83	0.66552
6	0.519024	32	0.349604	58	0.327823	84	0.912931
7	0.531146	33	0.510994	59	0.486588	85	0.697387
8	0.542388	34	0.539889	60	0.577404	86	0.555423
9	0.519133	35	0.47395	61	0.507197	87	0.294867
10	0.591269	36	0.555649	62	0.683848	88	0.524916
11	0.57089	37	0.519616	63	0.4951	89	0.730096
12	0.673909	38	0.471749	64	0.485728	90	0.831013

13	0.589961	39	0.542172	65	0.537856	91	0.462644
14	0.539948	40	0.474913	66	0.468619	92	0.684856
15	0.551306	41	0.438253	67	0.855734	93	0.763504
16	0.754081	42	0.424652	68	0.908508	94	0.682045
17	0.703984	43	0.381448	69	0.532153	95	0.380407
18	0.630964	44	0.414876	70	0.413626	96	0.416367
19	0.543672	45	0.430677	71	0.498664	97	0.35323
20	0.558316	46	0.477277	72	0.481058	98	0.289413
21	0.573225	47	0.406941	73	0.762146	99	0.578399
22	0.503871	48	0.439955	74	0.628704	100	0.41701
23	0.478992	49	0.502424	75	0.633532	101	0.420432
24	0.567449	50	0.524361	76	0.447662	102	0.23065
25	0.556143	51	0.400192	77	0.401561	103	0
26	0.480595	52	0.439382	78	0.645319	104	0.245698

Evaluation Criteria

Several statistical methods are available for the evaluation of neural networks. In present work, the performance of the ANN model is assessed by the following measurements: Root mean square error (RMSE), Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE). These performance measures indicate the deviation of the prediction from their mean.

This is elucidated by Equation 3 [15]. RMSE being a quadratic scoring rule measures the average magnitude of the error, and the fact that the errors are squared before they are averaged, ensures that RMSE gives a relatively high weight to large errors. When large errors are particularly undesirable, RMSE serves as a good measure.

$$RMSE = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^{target} - y_i^{output}\right)^2} \qquad (3)$$

Mean square error is the square of RMSE given by Equation 4.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i^{target} - y_i^{output}\right)^2 \qquad (4)$$

The mean absolute error (MAE) serves to measure how close forecasts or predictions are, to the eventual outcomes. The mean absolute error is given by Equation 5 [15]

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i^{target} - y_i^{output}}{y_i^{target}}\right| \qquad (5)$$

Mean absolute percentage error serves to measure the accuracy of a series in statistics as depicted by Equation 6 [15]. This is more so done for trend estimation.

$$MAPE = 100 \times MAE \qquad (6)$$

The measures mentioned above, provide the average error but fail to provide any error distribution information, necessitating the testing of robustness of the network output result through some other performance evaluation criterion such as threshold statistics (TS) [16].

The TS provides not only performance index in terms of weekly predicting Waste Generation (WG) but also the distribution of the prediction errors. The TS for a level of x% is a measure of the consistency in forecasting errors from a particular model as shown in Equation 7. TS represented as TS_x is expressed as a percentage. This criterion can be represented for various levels of absolute error (AE) from the model. For x% level it is computed as given in Equation 7.

$$TS_x = \left(\frac{Y_x}{n}\right) \times 100 \quad (7)$$

where Y_x is the number of predicted WG (out of n total computed) for which AE is less than x% from the model.

4. Artificial Neural Network

Recent literature shows, artificial neural network (ANN) has been used in nonlinear system modeling where functional relationship between input and output variables is not known. ANNs designed and developed as cellular information processors work on the perceived notion of the human brain and its neural system. One of the significant factors of ANNs is its ability to learn. After the process of learning, it can construct a complex nonlinear system through a set of input/output samples. Therefore, ANN is amply trusted for modeling the solid waste generation and make futuristic predictions.

Traditional architecture of ANN composes of three layers, input layer to distribute inputs in network, hidden layer to process input to output & output layer to deliver results. Design of ANN based model is primarily concerned with design of the hidden layer which may actually have multiple sub-layers placed in series or parallel or series-parallel architecture. The number of neurons in each sub layer is another variable which has to be chosen carefully. The neurons in the sub-layer and their number is another significant detail to be carefully chosen.

Among various available network types, feed forward- error feedback multilayer perceptron has been used for this study. Feed forward multilayer perceptron can have more than one hidden layer. In present experiments, a maximum of two hidden layers were considered sufficient for prediction of generated weekly municipal solid waste. In this network, the data flows forward to the output persistently. Input is processed at hidden layer with identified or chosen non-linear activation transfer functions. The input layer contains the data from the input parameter and is connected to the hidden layer through synaptic weights. These weights are numeric values which can be adjusted by the use of various learning functions (gradient descent, conjugate gradient, adaline etc.).Further the connection from hidden layer proceed to the output layer, much in the same fashion as from input layer to hidden layer. This is depicted in Figure 3.

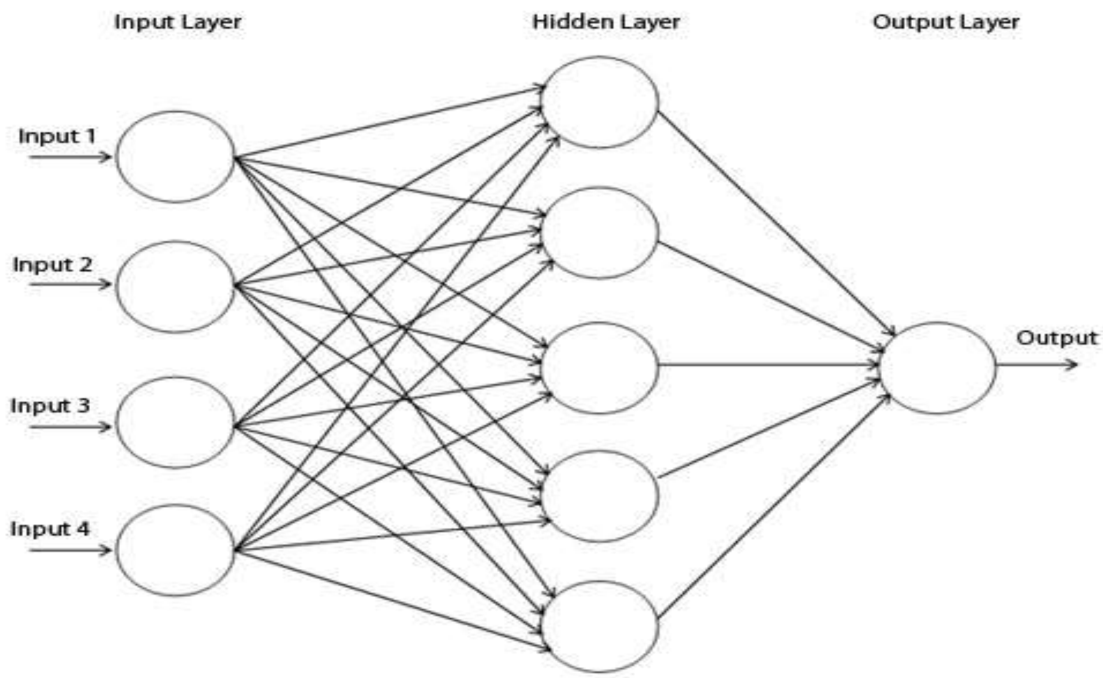


Figure 3. A Sample schematic diagram of neural network

The output obtained at each neuron is a function of its inputs. The output of the jth neuron in any layer is shown below by Equations 8 and 9.

$$U_j = \sum_{i=1}^{n} X_i * w_{ij} \quad (8)$$

$$Y_j = f(U_j + t_j) \quad (9)$$

Except in input layer, for every neuron, j, in a layer, each of the i inputs, X_i, to that layer is multiplied by a previously established weight, w_{ij}. These are summed together and resulting value, U_j, is then biased by a previously established threshold value, t_j, and sent through an activation function (usually sigmoid function), f. The resulting output, Y_j, acts as an input to the next layer or is the final output, assuming there are no more hidden layers.

One of the learning rule for multilayer perceptron is the error back propagation. In present work, the delaying variables that decrease the accuracy of forecasting have not been used, because they increase the error in long-term forecasting significantly. Default network type for most MLPs is feed forward back propagated multi-layer perception. The architecture with multiple neuron layers with non-linear transfer functions, permits learning of non-linear and linear relationships between input and output vectors by the network.

Some of the training algorithms that can be used are: gradient descent, conjugate gradient and levenberg-marquardt. The standard back propagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient), which the performance function is decreasing most rapidly. In the CG algorithms, a search is performed along conjugate directions for faster convergence than steepest descent directions. Levenberg -Marquardt algorithm is designed to approach second order training speed without having to compute the Hessian matrix.

The use of STA (Stop Training Algorithm) reduced the training time four times and it provided better and more reliable generalization performance. The available data are split into three parts: (1) Training Set (2) Testing Set (3) Validation Set. To determine the network parameters weights and biases, the training set data is used. To assess the strength and utility of the predicted relationship and to verify the effectiveness of the stopping criterion, the testing set data is used. To avoid over fitting and to estimate the network performance and decide when the training stopped, the validation set data is used. This division of data implements STA in practice.

Owing to religious tourism, the solid waste generated follows a monthly pattern. The monthly pattern of waste generation affects the estimation of the amount of waste generated in the city. Hence, a weekly time series model of waste generation with 4 time lags (equal a month) has been developed for forecasting the solid waste generation in Dehradun. This is elucidated by Figure 4 which depicts the auto-correlation of the input solid waste data. As the solid waste generation data follows a monthly pattern, this necessitates us to provide a lag time of 4 to the NARnet (non-linear autoregressive neural network). In other words, the solid waste data for week # 5 is related to the solid waste data for week #4, #3, #2 and #1. For week 6 it depends on week 5, 4, 3 and 2. This pattern is repeated for the measure of solid waste data for each week. So to generalize it, in developed model, weight of waste in t+1 week (W_t+1), is a function of waste quantity in t (W_t), t-1 (W_{t-1}), t-2 (W_{t-2}) and t-3 (W_{t-3}) weeks[16]

$$W_{t+1} = f(W_t, W_{t-1}, W_{t-2}, W_{t-3}) \quad (10)$$

Equation 10 represents the generalized formula for the solid waste generation dependency. This equation would be the input to the neural network. Here W_t would be the input sent and the others i.e. W_{t-1}, W_{t-2}, W_{t-3} would be sent as feedback loop into the network.

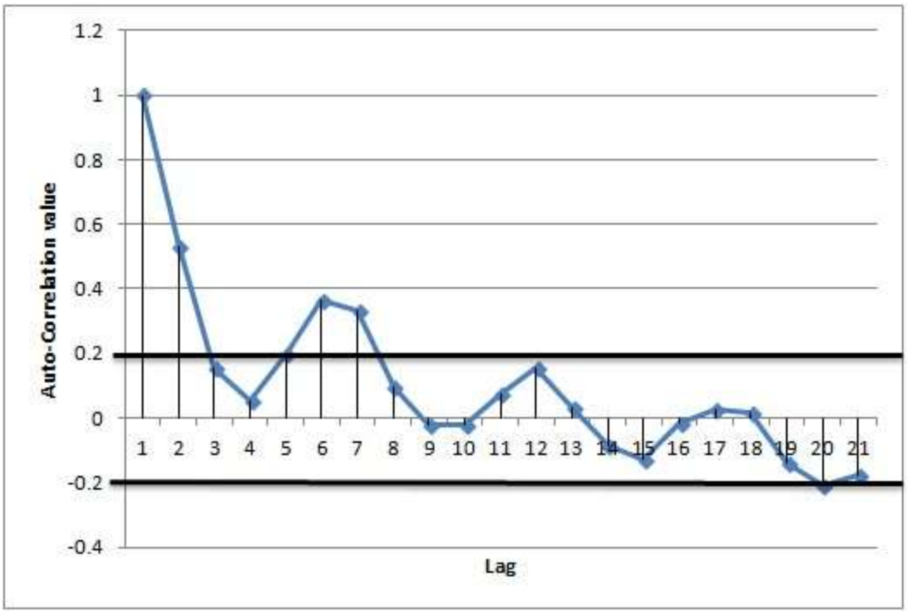


Figure 4. Auto-Correlation of input data

4.1. The ANN Model

Data analysis and pre-processing are very important steps before utilizing the data. After pre-processing, the artificial neural network model was developed based on the nonlinear autoregressive network (NARnet). In this network the output of the network goes as a feedback to the input layer. In present work, a number of design factors were considered for the modeling of the neural network like the number of neurons in hidden layers. Different activation functions were tested. After careful investigation in each layer: a sigmoidal function for the hidden layer and a linear function for the output layer were selected. The hidden layers were varied between 1-2 layers as a maximum of two hidden layer results in best outputs without making the network too complicated and different numbers of neurons (5-20) were applied to the hidden layers.

After pre-processing, input data was classified to three blocks; 70% for training, 15% for validation, and 15% for testing. Owing to validation error increased six times sequentially, the training would stop. Training was restarted using network weights, obtained from previous run until acceptable results were reached.

The selection of the network architecture was finalised after trying out different neural network architectures by altering the number of neurons (5-20 for the hidden layers) and hidden layers (1-2 Layer). The resulting performance measures are shown in Table 3(in Annexure 1).

Annexure:2

Table 3: Performance Measure of varied Hidden layer architecture

Hidden Layer 1	Hidden Layer 2	MSE	RMSE	MAE	MAPE	Hidden Layer 1	Hidden Layer 2	MSE	RMSE	MAE	MAPE
5	No	0.017859	0.133637	0.196584	19.65841	5	5	0.013629	0.116744	0.171171	17.1171
6	No	0.009231	0.096079	0.112815	11.2815	5	6	0.026313	0.162213	0.135188	13.5188
7	No	0.019926	0.141159	0.14122	14.12202	5	7	0.041989	0.204912	0.213133	21.31326
8	No	0.009405	0.096978	0.122553	12.25535	5	8	0.012675	0.112583	0.15325	15.32497
9	No	0.020283	0.142419	0.199456	19.94556	5	9	0.034625	0.186078	0.158581	15.85815
10	No	0.027188	0.164887	0.24148	24.14803	5	10	0.024399	0.156202	0.141632	14.16321
11	No	0.028636	0.169222	0.193117	19.31167	5	11	0.03847	0.196137	0.291874	29.18739
12	No	0.058062	0.24096	0.201288	20.1288	5	12	0.140193	0.374423	0.283277	28.3277

13	No	0.032254	0.179594	0.203954	20.39539	5	13	0.083179	0.288407	0.146346	14.6346
14	No	0.026391	0.162454	0.202787	20.27871	5	14	0.055842	0.23631	0.138325	13.83247
15	No	0.017369	0.131792	0.192288	19.22877	5	15	0.04305	0.207485	0.138981	13.89808
16	No	0.037919	0.194728	0.228682	22.86816	5	16	0.06404	0.253061	0.23986	23.98602
17	No	0.050385	0.224466	0.360153	36.01529	5	17	0.0279	0.167033	0.131588	13.15878
18	No	0.013921	0.117988	0.174265	17.42651	5	18	0.047804	0.21864	0.25395	25.395
19	No	0.026957	0.164185	0.264959	26.49589	5	19	0.012313	0.110963	0.151679	15.16791
20	No	0.05542	0.235415	0.318791	31.87907	5	20	0.04582	0.214055	0.29156	29.15604
6	5	0.021275	0.145859	0.14898	14.89801	7	5	0.014077	0.118646	0.16278	16.27796
6	6	0.010661	0.103251	0.118576	11.85758	7	6	0.015467	0.124365	0.123377	12.33772
6	7	0.009826	0.099126	0.136847	13.68474	7	7	0.014372	0.119882	0.149213	14.92126
6	8	0.036626	0.191379	0.202184	20.21839	7	8	0.012202	0.110465	0.125989	12.5989
6	9	0.029822	0.17269	0.220752	22.0752	7	9	0.009282	0.096345	0.103116	10.31156
6	10	0.008868	0.094172	0.12912	12.91204	7	10	0.021963	0.1482	0.143138	14.31379
6	11	0.017054	0.130589	0.202964	20.2964	7	11	0.017049	0.130573	0.190996	19.09965
6	12	0.030753	0.175366	0.234468	23.44683	7	12	0.066035	0.256972	0.189708	18.97077
6	13	0.012388	0.111302	0.162494	16.24942	7	13	0.011548	0.107463	0.170746	17.07458
6	14	0.03792	0.194729	0.19364	19.36402	7	14	0.014588	0.120782	0.197041	19.70406
6	15	0.012837	0.113302	0.12366	12.36601	7	15	0.015776	0.125601	0.193733	19.37333
6	16	0.026405	0.162497	0.144634	14.46342	7	16	0.05449	0.233431	0.306524	30.6524
6	17	0.058296	0.241445	0.332981	33.29806	7	17	0.040671	0.201671	0.160446	16.04463
6	18	0.040424	0.201057	0.253365	25.33654	7	18	0.130951	0.361872	0.516072	51.60718
6	19	0.026365	0.162372	0.228167	22.81667	7	19	0.032263	0.179619	0.125588	12.55877
6	20	0.068322	0.261385	0.192461	19.24615	7	20	0.180603	0.424974	0.545154	54.51539
8	5	0.015377	0.124005	0.109452	10.9452	9	5	0.035189	0.187587	0.185411	18.54106
8	6	0.011398	0.106764	0.100209	10.02094	9	6	0.00764	0.087406	0.089035	8.903515
8	7	0.006977	0.083526	0.132042	13.20424	9	7	0.010242	0.101203	0.119141	11.9141
8	8	0.013296	0.11531	0.105837	10.58371	9	8	0.017758	0.133259	0.13481	13.48099
8	9	0.012347	0.111117	0.142343	14.23433	9	9	0.024398	0.156198	0.11482	11.48199
8	10	0.089417	0.299027	0.346271	34.62708	9	10	0.013477	0.11609	0.152305	15.2305
8	11	0.012454	0.111595	0.124594	12.45942	9	11	0.067714	0.26022	0.155073	15.50733
8	12	0.017849	0.133599	0.190495	19.04954	9	12	0.027509	0.16586	0.230227	23.02267
8	13	0.055476	0.235532	0.329546	32.95458	9	13	0.019382	0.13922	0.165251	16.52513
8	14	0.031584	0.177718	0.16474	16.47396	9	14	0.109895	0.331504	0.222296	22.22962
8	15	0.021566	0.146852	0.205011	20.5011	9	15	0.085705	0.292754	0.311877	31.18771
8	16	0.025796	0.160611	0.234869	23.48685	9	16	0.026932	0.164111	0.153897	15.38969
8	17	0.06468	0.254323	0.238936	23.89359	9	17	0.062142	0.249282	0.152462	15.24616
8	18	0.020143	0.141926	0.110111	11.0111	9	18	0.005518	0.07428	0.096885	9.688451

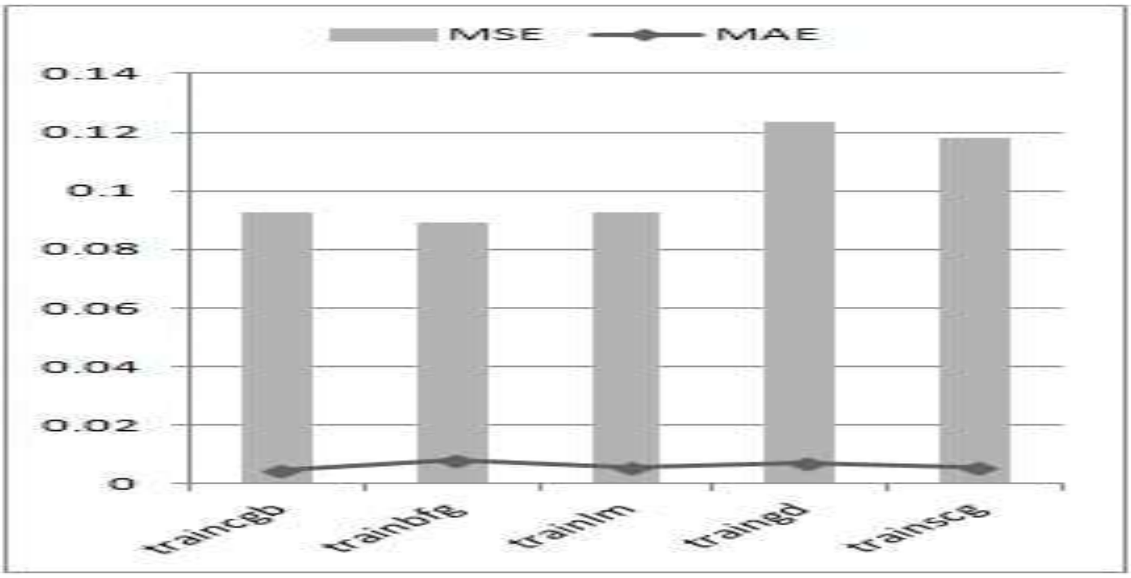
8	19	0.017683	0.132977	0.165474	16.54737	9	19	0.248781	0.49878	0.521177	52.11767
8	20	0.058915	0.242725	0.372445	37.24452	9	20	0.063711	0.252411	0.372765	37.27646
10	5	0.01911	0.13824	0.143094	14.30945	11	5	0.00838	0.091542	0.10494	10.49399
10	6	0.033117	0.181982	0.146	14.60003	11	6	0.016321	0.127754	0.154867	15.48671
10	7	0.009425	0.097083	0.122894	12.28942	11	7	0.010778	0.103818	0.10041	10.04097
10	8	0.01237	0.111221	0.109724	10.97238	11	8	0.02498	0.158051	0.14719	14.71897
10	9	0.022624	0.150412	0.128899	12.88985	11	9	0.019362	0.139147	0.12594	12.59402
10	10	0.031006	0.176084	0.139861	13.98611	11	10	0.012677	0.112592	0.11542	11.54195
10	11	0.011261	0.106116	0.123366	12.33663	11	11	0.040284	0.20071	0.182465	18.24651
10	12	0.038621	0.196523	0.141933	14.19333	11	12	0.020753	0.14406	0.222474	22.24739
10	13	0.011898	0.10908	0.147997	14.79969	11	13	0.061602	0.248197	0.345506	34.55063
10	14	0.03301	0.181687	0.242879	24.28789	11	14	0.01832	0.13535	0.145022	14.50224
10	15	0.056732	0.238185	0.162267	16.22668	11	15	0.038215	0.195486	0.145856	14.58558
10	16	0.11879	0.344659	0.268318	26.83177	11	16	0.439343	0.662829	0.955751	95.57512
10	17	0.013658	0.116869	0.129249	12.92494	11	17	0.110596	0.33256	0.445329	44.53292
10	18	0.070475	0.265471	0.219962	21.99625	11	18	0.036386	0.190752	0.186192	18.61923
10	19	0.059603	0.244136	0.145664	14.56636	11	19	0.046118	0.214751	0.148356	14.83555
10	20	0.082177	0.286665	0.292793	29.27927	11	20	0.036768	0.191751	0.184626	18.46264
12	5	0.01392	0.117981	0.140571	14.05711	13	5	0.029077	0.170521	0.297743	29.77427
12	6	0.016075	0.126789	0.188518	18.8518	13	6	0.031691	0.178021	0.207583	20.75829
12	7	0.016075	0.126789	0.188518	18.8518	13	7	0.011191	0.105785	0.124919	12.4919
12	8	0.015934	0.126229	0.156481	15.64813	13	8	0.034026	0.184462	0.210821	21.08206
12	9	0.021732	0.147418	0.144201	14.42012	13	9	0.081011	0.284624	0.307175	30.71752
12	10	0.044558	0.211087	0.25584	25.58396	13	10	0.052395	0.2289	0.151765	15.17651
12	11	0.008725	0.093406	0.129378	12.93777	13	11	0.069575	0.26377	0.360709	36.07086
12	12	0.010311	0.101544	0.099603	9.960267	13	12	0.03964	0.199098	0.167461	16.74608
12	13	0.016858	0.129838	0.123186	12.3186	13	13	0.049903	0.223389	0.222644	22.26436
12	14	0.092918	0.304825	0.397026	39.70263	13	14	0.016602	0.128848	0.147032	14.70319
12	15	0.009855	0.099273	0.089939	8.993884	13	15	0.05721	0.239186	0.346862	34.68617
12	16	0.019576	0.139914	0.122881	12.28812	13	16	0.085677	0.292706	0.331391	33.13914
12	17	0.027134	0.164724	0.17509	17.50896	13	17	0.100734	0.317386	0.205839	20.58393
12	18	0.01792	0.133865	0.107369	10.73691	13	18	0.061755	0.248505	0.220842	22.08422
12	19	0.091067	0.301774	0.421889	42.18894	13	19	0.026184	0.161816	0.15591	15.59101
12	20	0.029857	0.17279	0.183534	18.35344	13	20	0.040397	0.20099	0.251506	25.15057
14	5	0.025538	0.159805	0.232545	23.25452	15	5	0.007026	0.08382	0.106463	10.64628
14	6	0.026951	0.164168	0.236696	23.66957	15	6	0.013178	0.114798	0.139159	13.91588
14	7	0.026456	0.162652	0.124679	12.46793	15	7	0.027488	0.165796	0.15801	15.80104
14	8	0.019812	0.140756	0.185278	18.52784	15	8	0.031599	0.177761	0.145741	14.57413

14	9	0.019109	0.138235	0.153683	15.3683	15	9	0.058265	0.241381	0.210214	21.02138
14	10	0.0251	0.158429	0.211182	21.11816	15	10	0.036805	0.191846	0.23187	23.18699
14	11	0.022154	0.148841	0.152174	15.21738	15	11	0.019894	0.141047	0.172862	17.28623
14	12	0.010858	0.104201	0.137411	13.74109	15	12	0.044719	0.21147	0.246693	24.66929
14	13	0.010359	0.101778	0.134788	13.47883	15	13	0.014984	0.122408	0.167147	16.71469
14	14	0.100097	0.316381	0.19337	19.33702	15	14	0.050421	0.224546	0.346384	34.63839
14	15	0.016884	0.129939	0.128802	12.88017	15	15	0.08895	0.298244	0.411212	41.1212
14	16	0.036927	0.192163	0.212492	21.24924	15	16	0.042191	0.205404	0.300484	30.04836
14	17	0.016972	0.130278	0.178843	17.88426	15	17	0.021804	0.147661	0.168324	16.8324
14	18	0.09324	0.305353	0.417759	41.77593	15	18	0.050067	0.223757	0.234053	23.40533
14	19	0.102654	0.320397	0.281621	28.16207	15	19	0.082374	0.287009	0.274808	27.48081
14	20	0.052666	0.229491	0.292831	29.28306	15	20	0.055677	0.23596	0.303834	30.38338
16	5	0.009196	0.095894	0.125366	12.53661	**17**	**5**	**0.004817**	**0.069407**	**0.092724**	**9.272387**
16	6	0.010369	0.101826	0.151318	15.1318	17	6	0.058453	0.241771	0.337555	33.75552
16	7	0.007115	0.084351	0.114089	11.40886	17	7	0.018456	0.135853	0.102608	10.26076
16	8	0.017916	0.133853	0.189084	18.90838	17	8	0.064747	0.254454	0.233479	23.34785
16	9	0.078089	0.279444	0.275567	27.5567	17	9	0.015869	0.125971	0.159724	15.97243
16	10	0.01243	0.111491	0.130088	13.00883	17	10	0.024384	0.156154	0.129606	12.96062
16	11	0.093089	0.305106	0.215073	21.50732	17	11	0.020003	0.141431	0.177086	17.70859
16	12	0.021482	0.146568	0.156077	15.60769	17	12	0.01094	0.104594	0.129097	12.90971
16	13	0.011244	0.106038	0.138819	13.88186	17	13	0.056442	0.237574	0.214842	21.48419
16	14	0.050315	0.224309	0.237488	23.74876	17	14	0.053341	0.230956	0.178955	17.89551
16	15	0.022925	0.15141	0.188345	18.83449	17	15	0.047255	0.217381	0.269157	26.91574
16	16	0.052693	0.22955	0.164814	16.48139	17	16	0.013969	0.11819	0.130796	13.07963
16	17	0.118274	0.34391	0.315331	31.53309	17	17	0.034501	0.185744	0.19743	19.74298
16	18	0.035677	0.188883	0.238689	23.86886	17	18	0.099385	0.315254	0.283851	28.38505
16	19	0.160067	0.400084	0.349089	34.90886	17	19	0.013535	0.116338	0.182214	18.22138
16	20	0.027057	0.16449	0.201153	20.11534	17	20	0.015081	0.122807	0.134232	13.42324
18	5	0.009913	0.099565	0.130108	13.01082	19	5	0.007427	0.08618	0.118724	11.87245
18	6	0.015636	0.125042	0.141324	14.13243	19	6	0.012048	0.109764	0.141167	14.1167
18	7	0.028219	0.167985	0.120927	12.09265	19	7	0.019425	0.139374	0.112902	11.29016
18	8	0.008611	0.092794	0.113186	11.31856	19	8	0.012875	0.113468	0.177987	17.79867
18	9	0.00775	0.088033	0.116722	11.67216	19	9	0.02872	0.16947	0.130592	13.05923
18	10	0.028289	0.168193	0.146327	14.63271	19	10	0.019971	0.14132	0.158418	15.84183
18	11	0.007168	0.084663	0.117776	11.77761	19	11	0.011095	0.105335	0.161686	16.16858
18	12	0.038976	0.197424	0.191134	19.11342	19	12	0.031407	0.17722	0.213783	21.37833
18	13	0.022161	0.148866	0.190753	19.07533	19	13	0.019992	0.141394	0.177487	17.74865
18	14	0.05149	0.226914	0.333196	33.31958	19	14	0.021154	0.145443	0.156973	15.69729

18	15	0.0559	0.236432	0.351781	35.17814	19	15	0.059028	0.242958	0.233105	23.31053
18	16	0.02298	0.151592	0.128447	12.84466	19	16	0.009329	0.096589	0.124183	12.41832
18	17	0.13741	0.370689	0.357226	35.72264	19	17	0.022642	0.150472	0.197446	19.74457
18	18	0.024049	0.155079	0.168772	16.87719	19	18	0.050992	0.225814	0.233837	23.3837
18	19	0.03655	0.191181	0.248769	24.87695	19	19	0.034641	0.186121	0.187183	18.71829
18	20	0.030824	0.175568	0.257592	25.75924	19	20	0.04656	0.215778	0.30929	30.92898
20	5	0.022892	0.151302	0.161026	16.10262	20	13	0.119404	0.345549	0.436637	43.66366
20	6	0.012884	0.113508	0.110524	11.05239	20	14	0.010197	0.100981	0.149955	14.99551
20	7	0.008947	0.094589	0.126212	12.62115	20	15	0.023115	0.152037	0.160321	16.03214
20	8	0.045211	0.212629	0.183763	18.37632	20	16	0.033613	0.183338	0.263338	26.33376
20	9	0.077614	0.278592	0.249075	24.9075	20	17	0.117961	0.343454	0.380306	38.03062
20	10	0.068554	0.261829	0.15503	15.503	20	18	0.01355	0.116404	0.129694	12.96938
20	11	0.025488	0.159651	0.201652	20.16524	20	19	0.017935	0.133923	0.179632	17.96317
20	12	0.025561	0.15988	0.234142	23.41424	20	20	0.081861	0.286114	0.397729	39.77293

It can be inferred from Table 3 that number of neurons as 17 in hidden layer 1 and number of neurons as 5, in hidden layer 2, gives the best performance based on all four performance criteria. Finally, a three layers structure was implemented for the network by trial and error (Exhaustive Search). The initial layer is the input layer. After that is the first layer - hidden layer 1 with 17 neurons in it with a sigmoid activation function. Next is the second layer - hidden layer 2 - with 5 neurons in it with sigmoid activation function. And finally is the output layer with one neuron, with the linear transfer function, as one output is to be delivered. For the training of the network, the neural network was trained using different learning algorithms like conjugate gradient, gradient descent, levenberg-marquardt and others. The performance results of all these learning algorithms were compared and are summarised in Figure 5.

Val
ue



Algorithms

Figure 5. Impact of different training algorithms

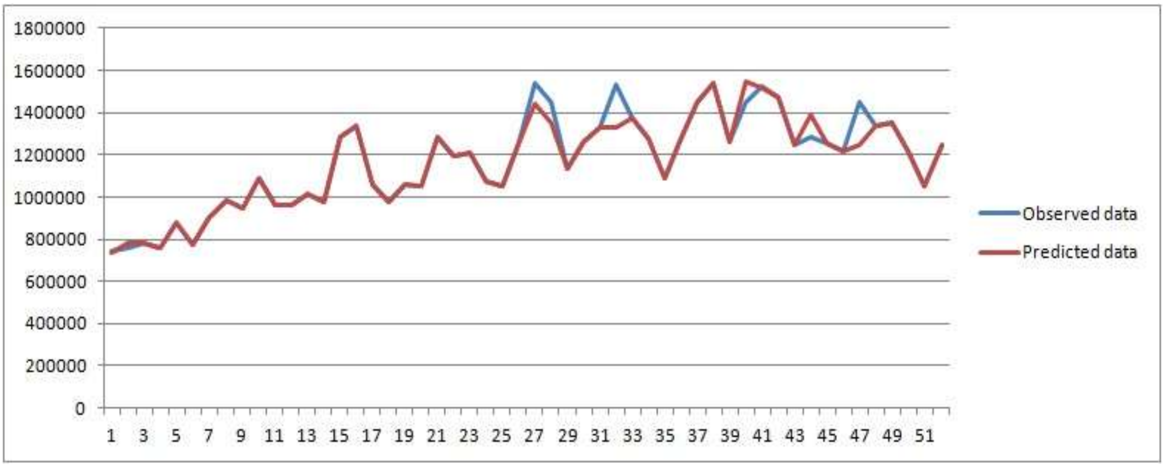
On comparison it can be seen that conjugate gradient method with Powell-Beale restarts (traincgb) gives the best results of all other learning algorithms. The finally developed ANN architecture is a 3 layer model with 17-5 neurons in the first and second hidden layers respectively, trained by conjugate gradient method with Powell-Beale restarts.

Sol id Wa ste (To nn es)

5. Results

5.1. Prediction

As input to the developed neural network, the predicted values of independent variables are presented, in order to obtain the values of future waste generation. These values were obtained by a modified algorithm which extrapolated the neural network model for the future value prediction model [17,18]. This extrapolation was also validated by training the network on only half of the input data set and using it to predict the possible values that could be obtained from it for the second half of the input dataset. The results are presented below in Figure 6.



Time(Weeks)

Figure 6: Validation for future prediction

After getting the predicted data from the model, it is scaled back to its original range by performing the inverse of Equation 2 and then adding the future values of the trend line shown in Figure 2, the Equation 1 is used for this. Previously removed components are added again to the time series to rescale and make data real. From Figure 6 it can be seen that this method of prediction is valid, so using this same method for the prediction of the values for a period upto next 6 months we obtain the results shown in Figure 7.

Time (Weeks)

Solid Waste (Tonn

Figure 7: Future Predicted Values for next 6 months

6. Conclusion

In present work, long-term SWG time series is evaluated using ANN. Only the solid waste amount generated per week is considered as the input time series. Based on the model chosen, it was put to use for the prediction of weekly solid waste generation for a period ranging from next 3 to 6 months. Before prediction the extrapolation method was validated against the already present data and then used to generate the prediction for solid waste. Based on these investigations it was observed that: Firstly, in long term prediction, specifically a stationary condition can provide more reliable and accurate simulation. Stationary conditions are created by removing the trend and standardizing the residuals. Secondly, in forecasting the solid waste, the estimation of the future values for valid explanatory variables is of prime importance. Hence, the variables that can be forecasted with high accuracies for a long forecasting horizon, should be used in simulation.

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