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SUITABILITY INDEX ASSESSMENT FOR COLLECTION BIN ALLOCATION USING ANALYTICAL HIERARCHY PROCESS (AHP) CASCADED TO ARTIFICIAL NEURAL NETWORK (ANN)

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ABSTRACT
Municipal solid waste is an inevitable outcome of anthropogenic activities. Proper sustainable solid waste management is the need of the hour. In this study, a Suitability Index (S.I) has been determined which can measure the relative importance of a district with regard to its necessity or requirement of collection bins in comparison to other districts in a municipality. The S.I was computed using Analytical Hierarchy Process cascaded to Artificial Neural Network. Four criteria viz. Demographic, Social, Economic and Technical considerations and seven factors viz. Population Density (P.D), Street Width (S.W), Waste Generation Rate (W.G.R), Income Group Distribution (I.G.D), Average Minimum Distance between the bins (MIN.D), Available Number of Bins (A.N.B) and Cost of Waste Bins (C.W.B) were considered for developing the model. Available Number of Bins was found to have the highest impact on the model followed by C.W.B, W.G.R, MIN D., I.G.D, P.D, and S.W. This index will particularly help developing countries with resource constraint and unskilled labor force in Solid Waste Management. It will help such countries to easily locate districts in urgent need of collection bins with an easily available set of data and will help in increasing collection efficiency.

1. INTRODUCTION

Creation of Solid Waste is an inevitable part of human activities, especially in the urban crowd. Municipal Solid Waste Management is one of the most pressing problems faced by most of the cities around the globe especially the developing countries. In India, the municipal agencies spend 5-25% of their budget on Solid Waste Management (SWM). But unfortunately, high capital investment in the SWM sector is not necessarily leading to improvements in the quality of service (National Solid Waste Association of India (NSWAI), 2008). Almost 85% of the total expenditure in SWM is spent on collection (Ghose, Dikshit, & Sharma, 2006). Similar reports of huge cost investment in the collection of solid waste have been made by other researchers (Ghiani, Laganà, Manni, & Triki, 2012; Ghiani, Manni, Manni, & Toraldo, 2014; González-Torre, Adenso-Díaz, & Ruiz-Torres, 2003; Kao & Lin, 2002) and municipalities as well.

Location-allocation modeling is the method of optimizing the location of centers or facilities and allocating consumers or demands to those centers (Valeo, Baetz, & Tsanis, 2002). In spite of being one of the significant factors in the successful achievement of SWM, location-allocation problem of sitting storage depots have achieved very less importance around the globe. When determining the type and size of these bins during system planning and design, the solid waste estimation and allocation are not adequately addressed. The vast majority of the studies mainly investigated the vehicular transportation of waste from bins to the disposal sites. Although these processes require heavy vehicles and machinery, the efficiency of these depends upon the number, location, type and size of bins as well as the frequency of waste removal required (Vijay, Gupta, Kalamdhad, & Devotta, 2005). Parrot et al. (Parrot, Sotamenou, & Dia, 2009) noted that the spatial distribution of the garbage accumulation points (GAPs) inside towns often does not take the needs of all local residents into account in terms of quantities of waste produced and distance from their dwelling. They also found that when the average distance to the closest GB is long, there is generally a low percentage (37.4) of people who dump their waste in them. The long-distance explains why households dispose

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of domestic waste in open areas. Similar concerns about the non-convenient location of the GAPs are expressed by Zia & Devadas (Zia & Devadas, 2008).

Various location-allocation modeling has been widely used for facility location planning in both the public and private sectors (Beaumont, 1987). Three different approaches have been attempted by researchers for addressing the location-allocation modeling viz. Geographical Information System (GIS) (El-Hallaq & Mosabeh, 2019; Erfani, Danesh, Karrabi, & Shad, 2017; Kao & Lin, 2002; Khan & Samadder, 2016; Nithya, Velumani, & Senthil Kumar, 2012; Vijay et al., 2005; Vu, Ng, & Bolingbroke, 2018), integer programming (Coutinho-Rodrigues, Tralhão, & Alçada-Almeida, 2012; Ghiani et al., 2012, 2014; Rathore, Sarmah, & Singh, 2019) and algorithm (Di Felice, 2014; Hemmelmayr, Doerner, Hartl, & Vigo, 2013). Some of them have tried to club GIS with the other two to suggest best possible locations of bin allocation (Arribas, Blazquez, & Lamas, 2010; Erfani, Danesh, Karrabi, Shad, & Nemati, 2018; Karadimas & Loumos, 2008; Tralhão, Coutinho-Rodrigues, & Alçada-Almeida, 2010). A detailed literature study of the Location-allocation modeling in SWM has been conducted by Purkayastha et al. (Purkayastha, Majumder, & Chakrabarti, 2015). The use of multi-criteria decision making (MCDM) approaches for location-allocation solutions in solid waste (Mondal, Speier, & Weichgrebe, 2019) has been extremely limited. Moreover, there has been no study on the location-allocation of collection bin using Analytical Hierarchy Process (AHP) cascaded to Artificial Neural Network (ANN).

In the present study, an index known as the Suitability Index (S.I.) has been developed with the application of AHP and ANN to address the location-allocation problem in SWM. The developed index can identify the area or district which is in urgent need of collection bins. This index will be most beneficial for SWM of developing countries who have resource constraints and are operating majorly with unskilled manpower. This index can also prioritize the area or district on the basis of its urgency in terms of collection bin requirement. Therefore SI can aid in providing collection bins to areas with immediate requirements under limited resource constraint conditions.

2. METHODS USED

The main objective of this model is to develop a Suitability Index (S.I.) for location-allocation of the collection bin. The S.I. is a comparative scale which can measure the relative importance of an area or district (hereafter known as a ward) with regard to its necessity or requirement of collection bins in comparison to other wards in a municipality. The study utilized two methods to develop this S.I: Multi-criteria decision making (MCDM) and Artificial Neural Network (ANN).

2.1 Multi-criteria decision making (MCDM)

MCDM methods have found a wide application in decision-making objectives over a wide decade of time. MCDM method is applied to compute the priority or weight of importance of the factors correlated to the objective of the study. There are various type MCDM techniques like Weighted Sum Method (WSM), Weighted Product Method (WPM), Simple Additive Weighting (SAW), and Analytical Hierarchy Process (AHP). In the present study, the AHP method has been used as because in this study relative importance as well as both qualitative and quantitative parameters have been considered. The other MCDM technique such as WSM and SAW doesn't incorporate pair wise comparison or relative weights of importance of criterias and alternatives whereas AHP incorporates it. Moreover they only consider quantitave variables, whereas AHP can include both qualitative and quantitative variables (Ghosh, Chakraborty, Saha, Majumder, & Pal, 2016).

2.2 Artificial Neural Network (ANN)

ANN is a computational model composed of many elements (known as neurons) connected by a variable weight. It was Warren McCulloch, a neurophysiologist, and Walter Pitts, a young mathematician, who in 1943 proposed the first ANN model known as McCulloch-Pitts (MP) Model. In the MP model, the activation (x) is given by a weighted sum of its M input values (a_i) and a bias term (θ). The output signal (s) is typically a nonlinear function f(x) of the activation value x. the objective function of the MP model or basic ANN model is given by:

$$s = f(\sum_{i=1}^{M} w_i a_i - \theta) \qquad (1)$$

3. METHODOLOGY

The objective of the present study is to establish a Suitability Index which will help in determining the priority of locating waste collection bin in a geographical area. Suitability Index (S.I) is the ratio of beneficiary factors to non-beneficiary factors. Suitability Index can be mathematically represented according to equation (2).

$$S.I = \frac{\sum(W\ X\ Beneficiary\ factors)}{\sum(W\ X\ Non-Beneficiary\ factors)} \qquad (2)$$

W = Weightage of the importance factor. This weight of importance is determined by MCDM techniques.

The "Beneficiary factors" are those which increase the probability of a place being suitable for collection bin allocation i.e. with the increase in the value of these factors the S.I value also increases thus increasing the suitability of a place for collection bin allocation. For e.g. population density, waste generation rate, etc.

The "Non-Beneficiary factors" are those which decrease the probability of a place being suitable for collection bin allocation i.e. with the increase in the value of these factors the S.I value decreases thus decreasing the suitability of a place for the collection bin allocation and vice versa. For e.g. cost of the bin, the number of bins already available in an area, etc.

3.1 Weightage Computation of factors using AHP technique

The AHP method requires three steps: (1) Selection of criteria (2) Selection of alternatives (3) Application of aggregation method (Ghosh et al., 2016).

3.1.1 Selection of criteria

For the present study, the weightage of all the beneficiary and non-beneficiary parameters needs to be determined. Henceforth all the beneficiary and non-beneficiary parameters were considered as alternatives. In this study, the weight of importance of the alternatives was established with respect to some criteria established from the expert survey and literature survey. In order to derive this index, a critical literature survey was conducted to find out the factors and criteria which were most significant to the placement of collection bins. The questionnaire adopted for the expert survey was prepared using Google form and is provided in supplementary materials (Annex-A). The expert survey was conducted through face to face interview and Social networking Media (Researchgate, Gmail, LinkedIn, and Facebook). Four criteria which were selected from the extensive literature study were found to be significant according to the expert study as well and are: Demographic Considerations (D1), Social Considerations (S1), Economic Considerations (E1) and Technical Considerations (T1). Four of these criteria are very inclusive in nature on a broader aspect and include all factors affecting bin allocation. According to both literature and expert study four of these criteria were suggested and no other criteria was suggested. Since all these criteria received significant importance according to both expert and literature study, four of them were considered in bin allocation problem in this study.

3.1.2 Selection of alternatives

The alternatives which were found to be most important in deciding locations for collection bin allocations based on expert and literature surveys were: Population Density (P.D), Street Width (S.W), Waste Generation Rate (W.G.R), Income Group Distribution (I.G.D), Cost of Waste Bin (C.W.B), Available Number of Bins (A.N.B) and Minimum Distance between Bins (MIN. D) (Table 1). These alternatives were further divided into beneficiary and non-beneficiary parameters. In this model Population Density (P.D), Street Width (S.W), Waste Generation Rate (W.G.R), Income Group Distribution (I.G.D) and Minimum Distance between Bins (MIN. D) were considered as beneficiary factors i.e. with increase in value of each of these factors the S.I value increased and vice versa. In this model Cost of Waste Bin (C.W.B) and Available Number of Bins (A.N.B) were considered as non-beneficiary factors i.e. with the increase in the value of each of these factors the S.I value decreased.

3.1.3 Application of aggregation method

Both the expert survey and literature survey was carried out further to estimate the importance of criteria and alternatives over each other. An expert survey was conducted on a set of a questionnaire asking to rank the alternatives with respect to each criterion on a scale of 1 to 9, 1 being very weak and 9 being extremely strong. The ranking was provided in the manner that the alternative under criteria which obtained the highest score was ranked 1, the alternative with the second-highest score was ranked 2 and so on. The rank of the criteria and alternative were established based on the literature survey and expert survey. In case if two or more alternatives under the same criteria obtained the same rating then in such cases all those alternatives were given the same rating and the in-between ranks were skipped The same methodology was adopted for other criteria too.

A 4 x 4 matrix was developed to find out the weightage of criteria.

$$c = \{n \, X \, n\} \tag{3}$$

Where, $\{n\} = \{D1,S1,E1,T1\} \in R$, where R is the set of real numbers.

Similarly, the alternatives are compared with each other based on their importance over each other according to each of the criteria 'n':

$$A = \{f_i \, X \, f_j\} \tag{4}$$

Where, $\{f_i\} = \{PD,SW,WGR,IGD,MIND,CWB,ANB\} \in R$, where R is the set of real numbers.

The hierarchy of decision making is shown in Figure 1.

In the case of AHP generally, the Saaty scale is used which was proposed by Saaty in the year of 1980 [10]. The scale utilized either even or odd number to represent the importance of the criteria and alternatives with respect to each other in the Pairwise Comparison Matrix (PCM). For intermediate importance, the rating in between the evens or odds is utilized. But still, there is a lot of confusion regarding what can be used for the representation of a high difference of importance and minor difference of importance between two alternative or criteria.

That is why, in the present study, we use the rank of the criteria and alternatives based on their magnitude or qualitative ratings and then ration of rank of the criteria/alternative compared and the rank of the other criteria/alternative with which it is being compared was found out (the rank is assigned in such a way that the relationship of the criteria with the decision objective can be reflected). The ratio is then reversed to give the exact difference of importance coherent to decision objective.

The direct use of rank to estimate the importance will ensure uniformity and remove the confusion involving the rating that can be given to depict two different levels of importance that exist between two different criteria or alternative.

3.2 Formulation of Suitability Index (S.I.)

The final S.I formula was formulated as:

$$S.I = \frac{(W_{PD} X \, PD^{\iddots}) + (W_{SW} X \, SW^{\iddots}) + (W_{WGR} X \, WGR^{\iddots}) + (W_{IGD} X \, IGD^{\iddots}) + (W_{MIND} X \, MIND^{\iddots})}{(W_{CWB} X \, CWB^{\iddots}) + (W_{ANB} X \, ANB^{\iddots})} \tag{5}$$

Where,

$PD^{\iddots}$=Normalised value of PD	W_{SW}=Weightage of SW
$WGR^{\iddots}$=Normalised value of WGR	W_{IGD}=Weightage of IGD
$MIND^{\iddots}$=Normalised value of MIND	W_{CWB}=Weightage of CWB
$ANB^{\iddots}$=Normalised value of ANB	W_{PD}=Weightage of PD
$SW^{\iddots}$=Normalised value of SW	W_{WGR}=Weightage of WGR
$IGD^{\iddots}$=Normalised value of IGD	W_{MIND}=Weightage of MIND
$CWB^{\iddots}$=Normalised value of CWB	W_{ANB}=Weightage of ANB

TABLE 1: Table showing detail description of the Criteria and sub-criteria used in the AHP method for the present study.

Criteria	Alternatives	Description	Mathematical formulations	Literature reference
Demographic considerations: The demography of an area is very important while designing any waste management technology for an area. Suggested Waste management technology varies from place to place depending on the demography of that place.	Population density (P.D)	Population density is an important parameter in deciding the requirement of total number of bins in an area.	$P.D\ (per\ km^2) = \frac{Population}{Area}$	[3, 4, 6, 8, 12, 17, 19, 21, 22, 28–34]
Social considerations: Suggested Waste management technology will depend upon the social situation of the locality. For e.g. the waste characteristic will be different depending upon the income level of most of the people living in the society.	Street Width (S.W)	Width of the street where the collection bin needs to be provided decides which size of bin can be provided in an area as because each size of bin are collected by a particular collection vehicle which needs a particular width of street for collecting wastes from that bin.	-	[8, 12, 17, 19, 21, 28–31]
Economic considerations: The municipal budget is always a constrain in Solid waste management. Hence to take care of the economic viability we need to consider economic optimization and feasibility before deciding the waste management option.	Waste Generation Rate (W.G.R)	Waste Generation Rate decides the total quantity of bins needed to provide collection bin facilities for all the wastes generated in a locality.	$W.G.R\ (m^3) = [pcwg\ X\ P\ x\ \rho] - A.N.B$ $Pcwg$ = Per capita waste generation $\left(\frac{\frac{kg}{person}}{day}\right)$ P = *Total population of the ward* ρ = *Density of waste* $\left(\frac{kg}{m^3}\right)$ $A.N.B$ = *Available Number of Bin*	[3, 4, 6, 12, 17, 19, 21, 22, 28, 29, 31, 32]
Technical Considerations: It includes the present status of infrastructure available and provided by the municipality.	Income Group Distribution (I.G.D)	Income level of a section of society decides the amount and kind of waste generated and the collection bin facilities needed to account all the waste.	High Income Group (Rating-3) Medium Income Group (Rating-2) Low Income Group (Rating-1)	[8, 30]
	Cost of Waste Bin (C.W.B)	In general their needs to be a compromise between economic viability and resource requirement. The number of extra bins needed in an area in addition to the already provided bins amount to a cost and Cost of Waste Bin (C.W.B) depicts that value.	$C.W.B = M - \sum_{i=1}^{n} N_i\ XC_i$ M = Maximum cost of bins if a ward is provided with actual required number of bins of any one type in "n" Number of types so that the total volume of waste produced in that ward is collected in bins and no waste is left unattended or uncollected. n = Number of types of bins in an municipality N_i = Available Number of Bins of type i (where i=1,2,3,.........,n) C_i (Currency unit as per the country) = Cost of Each Bin of type i	[17]
	Available Number of Bin (A.N.B)	Available Number of Bin (A.N.B) is the quantity of bins already provided to an area. This factor decides whether any further bins should be provided in a area in addition to the already provided bins to address resource constraint situation.	$A.N.B\ (m^3) = \sum_{i=1}^{n} N_i\ X\ V_i$ N_i = Available Number of Bins of type i (where i=1,2,3,.........,n) V_i (m^3) = Volume of Bin of type i (where i=1,2,3,.........,n)	[3, 4, 17]
	Minimum Distance between Bins (MIN. D)	Minimum Distance between Bins denotes the average minimum distance between the bins an area. This factor represents the frequency of bin placement in an area, so that places in an area with low bin frequencies can be identified.	$MIN.D\ (meter) = \frac{d_{min} + d_{max}}{2}$ d_{min} = Minimum distance between bins in a ward d_{max} = Maximum distance between bins in a ward	[3, 4, 6, 8, 19, 22, 33, 34]

3.3 ANN Model Formulation for Suitability Index (S.I.)

To predict S.I. Artificial Neural Network (ANN) was used. GMDH Shell software was used for carrying out the ANN-based prediction. GMDH stands for "Group Method of Data Handling". The main idea of GMDH is to build an analytical function in a feedforward network based on a quadratic node transfer function whose coefficients are obtained using a regression technique (Farlow, 1981). It was first proposed in 1966 by a Russian cyberneticist, A.G. Ivakhnenko.

The inputs of the model were the random normalised values of Population Density (P.D), Street Width (S.W), Waste Generation Rate (W.G.R), Income Group Distribution (I.G.D), Cost of Waste Bin (C.W.B), Available Number of Bins (A.N.B) and Minimum Distance between Bins (MIN. D). The input function of the ANN model is shown in Eqn. 4. The output was the Suitability Index (S.I). The model predicted the S.I value for 1000 data. Then a case study was conducted on Agartala Municipality to predict its S.I for the entire municipality, which has been presented in Section 4.3.

3.4 Description of the case study area

Agartala the capital city of Tripura is one of the eight North-Eastern states of India. It is situated along 23° 45’- 23° 55’ N latitude and 91°15’- 91°20’ E longitude, in the flood plains of the Haora River. The city has been an important border-trading town with trading linkages with Bangladesh. The National Highway (NH)-44 connects Agartala with Assam. The climate of Agartala is tropical monsoon type. The average rainfall of the city is about 220 cm.

The solid waste management of Agartala city is carried out by Agartala Municipal Corporation (AMC) established in 1871. Agartala Municipal area is divided into 4 zones and 35 wards. The overall population of Agartala Municipal area is 4, 70,190 with an overall area of 61.718 sq.km. A map of the Agartala Municipal Corporation (AMC) is shown in Figure 2.

The wastes generated in Agartala are of two types- Municipal solid Waste and Biomedical Waste. In our study we are considering only Municipal Solid Waste (MSW). The major waste generating sources of MSW are household

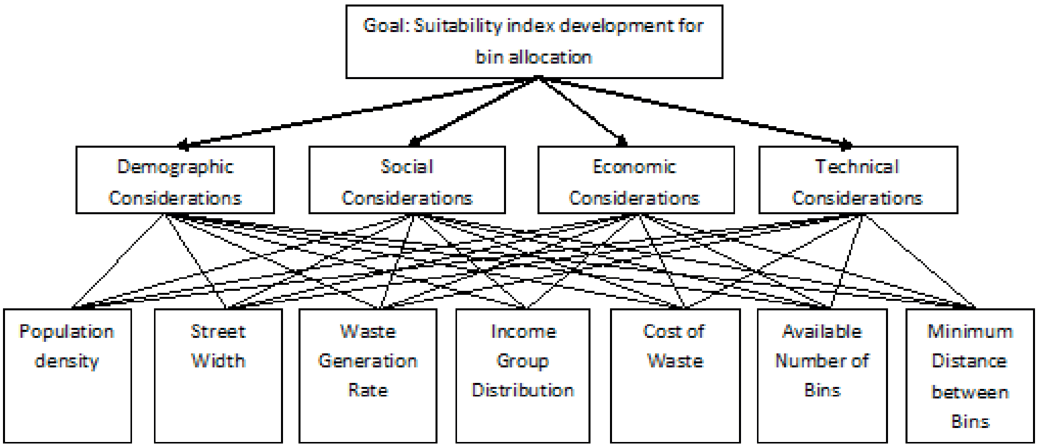


FIGURE 1: Hierarchy Structure of the AHP Modely.

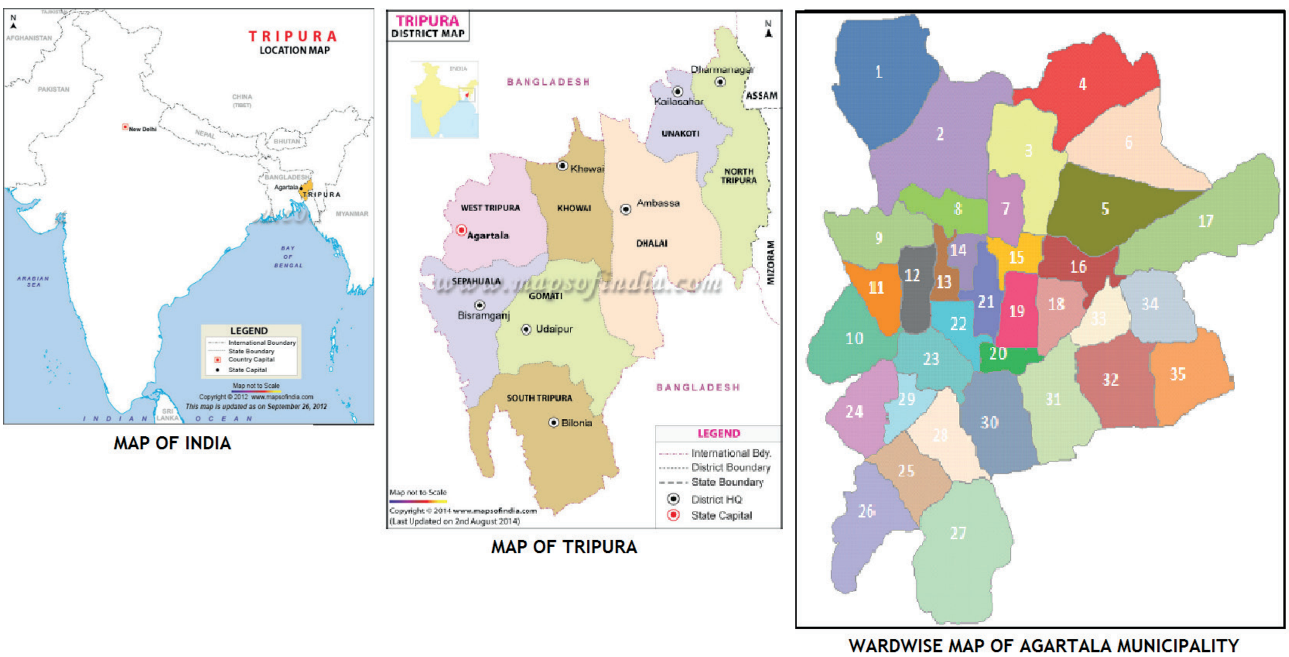


FIGURE 2: Map of the study area.

wastes, institutional wastes, market (vegetable and fish) wastes, street litters and drain silts.

Agartala Municipal Corporation (AMC) has placed more than 447 number of medium (1.1 m^3) (Figure 3a) and 55 large sizes (4.5 m^3) (Figure 3b) bins/containers by the side of major roads and in market and commercial areas.

The data table for formulating the model for AMC area is shown below in Table 2. The data of Population density (P.D), Available number of Bins (A.N.B) and Cost of Waste Bins (C.W.B) has been provided by AMC. The data on Income Group Distribution (I.G.D) isn't available with AMC, so all the wards have been assumed to fall in Middle Income Group based on the economic scenario of the state. The Street Width (S.W) data also couldn't be provided by the AMC so based on the survey of the expert views in AMC the average Street Width was assumed as 3.0 meter. Another reason behind assuming the Street Width as 3.0 metre is that the vehicles used to collect the 4.5 m^3 and 1.1 m^3 bins can't operate through roads with width less than 3.0 metre as per AMC. The cost of each 4.5 m^3 bin and 1.1 m^3 bin is Rs. 65000 and Rs. 30000 respectively as per AMC information. All data related to ward-wise Available number of bins (separately 1.1 m^3 and 4.5 m^3 bin) has been provided by AMC. The per capita waste generation rate per person has been considered as 500 gms/day as per Ministry of Environment and Forest (MOEF) and Central Public Health and Environmental Engineering Organisation (CPHEEO) guidelines.

4. RESULTS AND DISCUSSION

This section has been divided into three parts, viz., results of the AHP method to estimate the weights of importance of the parameters, results from the GMDH model to establish the suitability index and lastly the case study model of Agartala Municipality.

4.1 Weightage computation by AHP

Table 3 shows the rank of the criterias based of expert and literature survey. The rank of the factors with respect to each criteria are presented in Table 4. Technical considerations (T1) and Available Number of Bins (A.N.B) were observed to be the most important criteria and factor respectively. The weightages which were finally obtained using Analytical Hierarchy Process (AHP) are tabulated in Table 5.

4.2 ANN Model of S.I

The S.I model predicted by GMDH shell (Data Science version) software showed the correlation coefficient of the predicted model as 0.994646 which indicates that the predicted model is of good quality. The accuracy of the model is shown in Figure 4a. Figure 4b shows the correlation between S.I and the seven input factors P.D, S.W, W.G.R, I.G.D, C.W.B, AN.B and MIN.D. The highest positively and negatively correlated factor to S.I is W.G.R and A.N.B respectively

The 3D- plot between A.N.B, C.W.B and S.I (Figure 5a) shows that with the decrease in value of A.N.B & C.W.B, the S.I value increases, showing the highest peak at a value of less than 0.05 for A.N.B and less than 0.1 for C.W.B. The peak is at an area with value of A.N.B less than C.W.B because the weightage of A.N.B ($W_{A.N.B}$=0.24012) is greater than weightage of W.G.R ($W_{C.W.B}$=0.18043), so the control of A.N.B on the model is greater than C.W.B. Since C.W.B and A.N.B are non-beneficiary criterias the S.I is constricted to one corner. Both ANB and CWB has a very dominant effect on S.I model indicating that both availability and cost decided the suitability of a location for bin allocation followed by other attributes i.e. W.G.R, MIN.D, I.G.D, P.D and S.W.

The 3D- plot between A.N.B, W.G.R and S.I (Figure 5b) shows that with the constant value of A.N.B & increase in value of W.G.R, the S.I value increases, showing the highest peak at a value of less than 0.05 for A.N.B and greater than or equal to 0.5 for W.G.R. This behaviour of the graph is because of the reason that A.N.B is a non-beneficiary criteria and W.G.R is a beneficiary criteria due to which decrease in value of A.N.B increase the S.I and increase in value of W.G.R increases the S.I. This indicates that the area with higher waste generation rate and lower available number of bins will have higher S.I values.

The 3D- plot between A.N.B, MIN.D and S.I (Figure 5c) shows that at higher values the MIN.D ($W_{MIN.D}$=0.0968) the S.I value spikes up at a lower value of A.N.B. This indicates that if the minimum distance between collection bins in an area is more the suitability of that area for bin allocation increases. It was also observed that at extremely lower value of both MIN.D and A.N.B, the S.I value substantially increa-

FIGURE 3: Pictures of 2-Types of containers used by AMC for secondary collection. (a) 4.5 cu. Meter Bin - (b) 1.1 cu. Meter Bin.

TABLE 2: Data of AMC for computing S.I from the model.

Ward no.	Name	P.D.	S.W.	W.G.R	I.G.D	C.W.B.	A.N.B	MIN.D
1	Barjala	2621.25	3.00	71.00	2	1416818	8.80	277
2	Lichubagan	4341.56	3.00	61.79	2	1338791	22.30	738
3	Kunjaban	6932.91	3.00	44.95	2	879600	34.40	403
4	Chanmari	3413.73	3.00	66.41	2	1291582	13.20	383
5	Indranagar	5330.69	3.00	72.38	2	1512264	6.70	500
6	Nandan nagar	4203.40	3.00	65.13	2	1256836	14.30	199
7	Abhoynagar	17261.41	3.00	57.47	2	1163327	25.50	192
8	Radhanagar	15304.40	3.00	73.66	2	1489336	6.60	576
9	Ranjit nagar	8203.06	3.00	64.14	2	1345291	15.60	303
10	Raj nagar	7347.33	3.00	80.76	2	1682973	2.20	1434
11	West joynagar	21851.74	3.00	47.86	2	1074527	33.50	250
12	Ramnagar	20162.76	3.00	59.95	2	1173182	21.00	251
13	West krishnanagar	20065.60	3.00	49.20	2	879918	30.90	288
14	Krishnanagar	29679.67	3.00	35.28	2	673709	45.50	270
15	Dimsagar/ banamalipur	17250.91	3.00	40.54	2	788273	39.95	333
16	Dhaleshwar	11596.49	3.00	60.53	2	1189000	17.70	329
17	Khayerpur	3805.25	3.00	57.28	2	1100473	22.10	300
18	Shibnagar	9858.45	3.00	42.62	2	815918	36.60	260
19	West shibnagar	16920.22	3.00	59.78	2	1197491	18.85	210
20	Town pratapgar	18757.87	3.00	39.04	2	718473	41.00	325
21	Shantipara	11729.63	3.00	0.00	2	0	79.00	241
22	Melarmath	12704.85	3.00	34.77	2	544127	43.10	214
23	Bardowali	11992.06	3.00	74.02	2	1499182	4.40	1000
24	Bhotto pukur	9310.80	3.00	66.29	2	1403900	13.40	550
25	Arundhuti nagar	13741.97	3.00	53.81	2	1121318	24.50	623
26	South badharghat	4152.72	3.00	77.14	2	1584327	1.10	1434
27	Sidhi ashram	5080.59	3.00	45.53	2	779964	35.30	365
28	Rajlakhie nagar	5265.18	3.00	45.79	2	729245	31.90	214
29	Arundhuti nagar	11538.46	3.00	77.33	2	1589509	2.20	1434
30	Pratapgar/ west pratapgar	9616.30	3.00	67.01	2	1423564	12.30	350
31	East pratapgar	9616.69	3.00	79.35	2	1644627	0.00	1434
32	Jogendranagar	8863.54	3.00	71.49	2	1430264	7.70	333
33	North jogendranagar	9739.36	3.00	68.64	2	1410236	8.90	300
34	Aralia	4693.64	3.00	63.06	2	1200273	18.70	400
35	East jogendranagar	6450.13	3.00	78.55	2	1622864	0.00	1434

ses which means that if both the available number of bins and minimum distance between collection bins in an area is less than the collection bins need relocation and hence the S.I value of the area increases.

The 3D- plot between A.N.B, I.G.D ($W_{I.G.D}$=0.087) and S.I (Figure 5d) depicts that areas with more of high income group have highest values of S.I but the weightage of this lower have low impact on the S.I model. The 3D- plot between A.N.B, P.D ($W_{P.D}$=0.083) and S.I (Figure 5e) shows that the S.I. values slowly increases with a increase in value of P.D. i.e. the suitability of an area for collection bin allocation increases with increase in value of population density but increases at very slow rate indicating that P.D. has a very minimal influence on the S.I. model. The 3D- plot between A.N.B, S.W. ($W_{S.W}$=0.051) and S.I (Figure 5f) represents that the value of S.I for an area increases with the decrease in street width. This might be due to the fact that S.W has the

TABLE 3: Rank of the criterias based literature survey and expert survey.

Criteria	Abbreviation	Score
Demographic Consideration	D1	2
Social Consideration	S1	3
Economic Consideration	E1	4
Technical Consideration	T1	1

TABLE 4: Rank of the factors based literature survey and expert survey.

	D1	S1	E1	T1
P.D	1	3	5	6
S.W	4	6	7	5
W.G.R	2	1	4	4
I.G.D	3	2	3	7
C.W.B	4	3	1	2
A.N.B	7	3	2	1
MIN.D	6	7	6	3

TABLE 5: Weightage computation by AHP.

Factors	Abbreviation	AHP Weightage
Population Density	P.D	0.14980
Street Width	S.W	0.07578
Waste Generation Rate	W.G.R	0.15991
Income Group Density	I.G.D	0.10047
Cost of Waste Bin	C.W.B	0.18043
Available Number of Bin	A.N.B	0.24012
Minimum Distance between bins	MIN.D	0.09349

lowest weightage and hence least or negligible impact on the model especially in comparison to A.N.B, which has the highest impact on the model. Therefore might be due to this reason the S.I shows increased value with decrease in S.W.

4.3 Suitability Index for the case study

The S.I model obtained above was then applied to AMC area for finding out the ward-wise Suitability Index. The model predicted the Suitability Index (S.I) value for all the 35 wards (Figure 6).

According to the S.I Model the first five wards with highest values of S.I are Ward No. 29, 31, 23, 10 and 35 with S.I values of 2.234060498, 2.083174661, 2.028085959, 1.91108766 and 1.859772522 respectively.

The suitability index value for each and every location inside the Agartala Municipality Area can be obtained from

Postprocessed results	Model fit	Predictions
Number of observations	800	200
Max. negative error	-1.39189	-2.26909
Max. positive error	1.0747	1.25886
Mean absolute error (MAE)	0.109201	0.144452
Root mean square error (RMSE)	0.178652	0.282605
Residual sum	-2.30782E-12	-1.33941
Standard deviation of residuals	0.178652	0.282525
Coefficient of determination (R^2)	0.998214	0.989293
Correlation	0.999107	0.994646

(a)

Name	Corr.	Bars
Suitability index	1.000	
A.N.B	-0.310	
C.W.B.	-0.250	
W.G.R	0.110	
MIN.D	0.098	
I.G.D	0.087	
P.D.	0.083	
S.W.	0.051	

(b)

Variable	P.D.	S.W.	W.G.R	I.G.D	C.W.B.	A.N.B	MIN.D	Suitability index
Numeric values	1000	1000	1000	1000	1000	1000	1000	1000
Text values	0	0	0	0	0	0	0	0
Missing values	0	0	0	0	0	0	0	0
Unique values	1000	1000	1000	1000	1000	1000	1000	1000
Zero values	0	0	0	0	0	0	0	0
Most frequent								
Min. value	0.000208657	0.00352632	0.000976689	0.000370506	0.00442318	0.000199995	0.00015408	0.296348
Max. value	0.997402	0.999579	0.999919	0.999481	0.999749	0.999224	0.999228	102.936
Median	0.497878	0.508169	0.508874	0.514606	0.482223	0.500705	0.515461	1.39735
Mean value	0.496112	0.504421	0.505048	0.509758	0.482955	0.493987	0.500926	2.08774
Std. deviation	0.287683	0.291957	0.288516	0.297021	0.282179	0.293303	0.288156	3.97525
2σ outliers	0	0	0	0	0	0	0	14
3σ outliers	0	0	0	0	0	0	0	7
4σ outliers	0	0	0	0	0	0	0	4

(c)

FIGURE 4: (a) Accuracy of the Global model Predicted by GMDH Shell; (b) Correlation of the 7-factors with Sutability Index (S.I); (c) Statistics of the Global model Predicted by GMDH Shell.

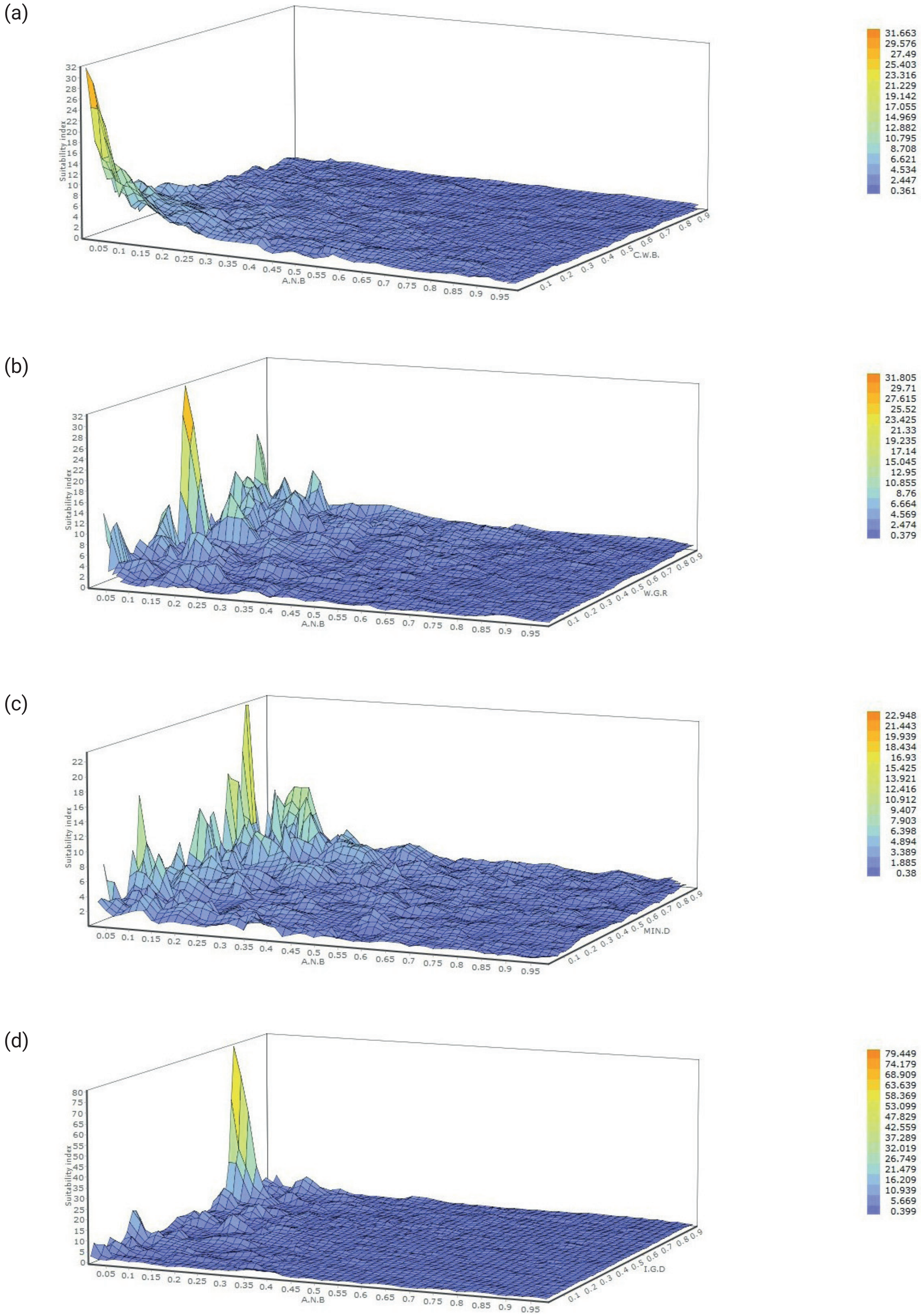
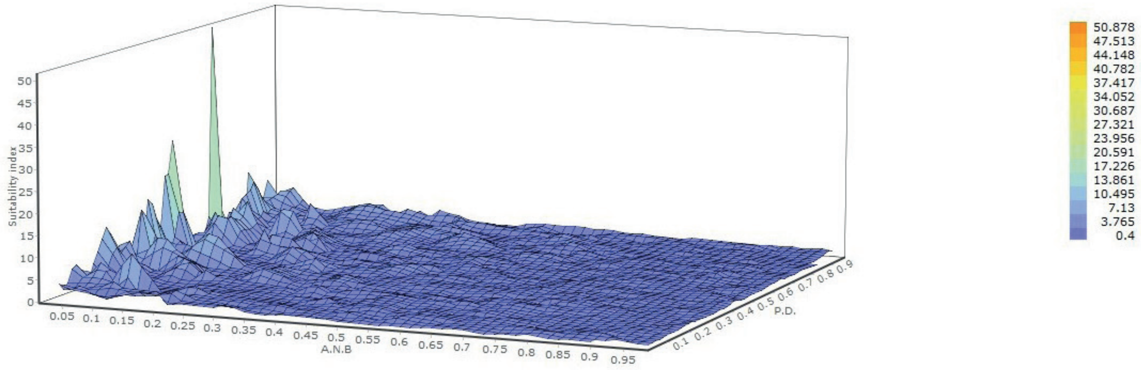


FIGURE 5a-d: (a) 3D-Plot between A.N.B, C.W.B and S.I; (b) 3D-Plot between A.N.B, W.G.R and S.I; (c) 3D-Plot between A.N.B, MIN.D and S.I; (d) 3D-Plot between A.N.B, I.G.D and S.I.

(e)



(f)

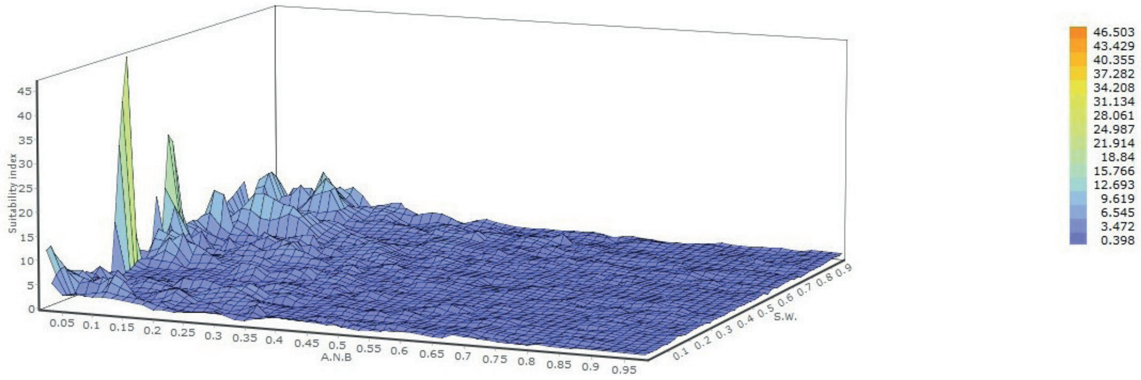


FIGURE 5e-f: (e) 3D-Plot between A.N.B, P.D and S.I; (f) 3D-Plot between A.N.B, S.W and S.I.

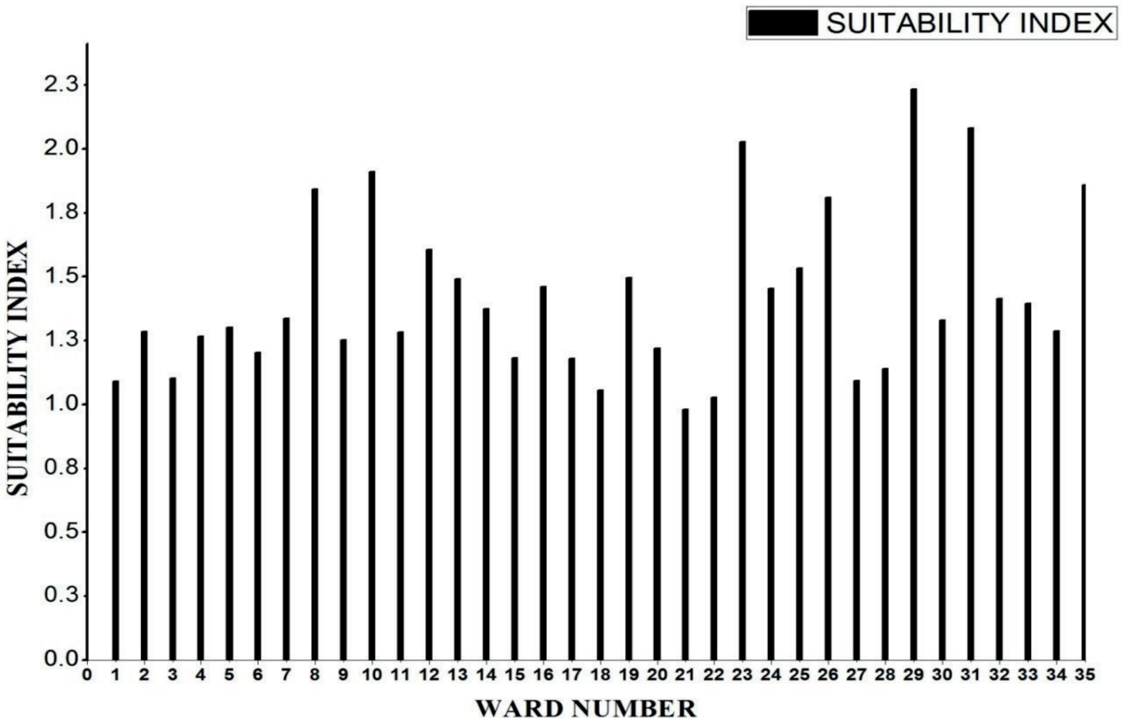


FIGURE 6: Ward-wise Suitability Index.

the contour map shown in Figure 7, which has been made using Surfer 12. Using this map, the areas in most urgent need of collection bins can be found out and the same can be provided with collection bins at the earliest. Subsequently the areas with low S.I values can be provided with collection bin facilities at the earliest convenience.

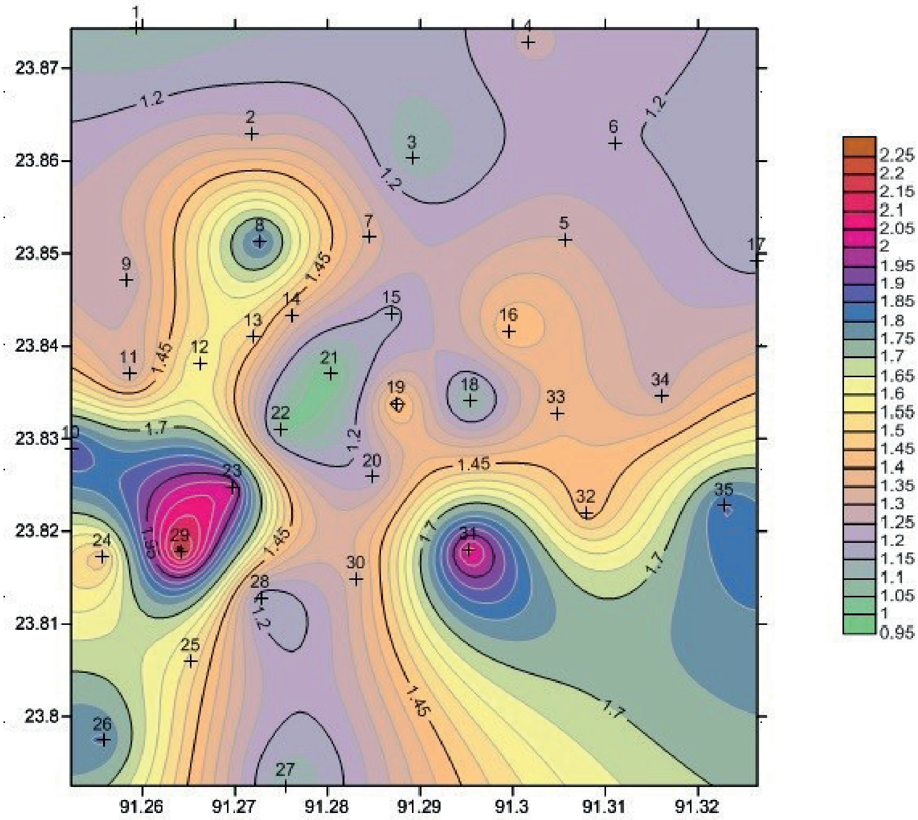


FIGURE 7: Contour Map of Suitability Index (X-axis: Longitude, Y-axis: Latitude).

5. CONCLUSIONS

From the study conducted in this research it is quite clear that the existing location of collection bins are uneven with many wards provided with absolutely no bin. Also it has been observed that there is absolutely no relation between numbers of bins in a ward and its population density. These problems are due to manual placement of bins with absolutely no use of any optimization technique. An optimization technique will help distribute the bins evenly along the wards at point where waste generation is occurring.

This work focuses on formulation and implementation of an innovative Suitability Index by using Analytical Hierarchy Process (AHP) and Artificial Neural Network (ANN). The S.I was found to depend on seven factors which were grouped under beneficiary and non-beneficiary factors. Population Density (P.D), Street Width (S.W), Waste Generation Rate (W.G.R), Income Group Distribution (I.G.D) and Average Minimum Distance between the bins (MIN D.) are beneficiary factors and Available Number of Bins (A.N.B) and Cost of Waste Bins (C.W.B) are non-beneficiary factors. The factor Available Number of Bins (A.N.B) was found to have the highest impact on the model followed by C.W.B, W.G.R, MIN D., I.G.D, P.D and S.W.

The case study conducted in Agartala Municipal area using this model showed that Ward No. 29, 31, 23, 10 and 35 are the first five wards with high Suitability Index value. These wards should be provided with collection bin facilities at the earliest. Using the contour map (Figure 7), the S.I. value at each and every location inside the Agartala Municipality can be obtained with known latitude and longitude.

This index will particularly help the developing countries with resource constraint and unskilled labor involvement in Solid Waste Management to easily locate areas/wards/districts needing most urgently collection bins with an easily available set of data and help increase the collection efficiency. The data related to the seven factors incorporated in this model for computation of Suitability Index are generally easily available with all Government bodies and hence the practical applicability of this Suitability Index is very high, easy and convenient.

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