A GA-based Multi-Objective Optimization Model for Location Planning of Urban Parks and Open Spaces

A Case Study on Dhaka City

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Abstract: In this paper, we present a new multi-objective location model for urban parks and open spaces (POSs) planning. We developed a Genetic Algorithm (GA) based multi-objective optimization model (GAMOOM) to derive optimum locations of POSs by considering four incommensurable objectives with the provision of POSs near: 1) densely populated areas, 2) air polluted areas, 3) noisy areas, and 4) areas without open spaces. The success of the model is presented through its application as a case study on Dhaka City. Obtained results indicate that the model can successfully provide optimum location of required POSs. The findings from this study also signify that optimum location of POSs obtained by utilizing only the second objective is substantially different than that of others. Moreover, there is also difference in optimum location of POSs by taking into account only the third objective when compared with others. Therefore, considering single objective cannot give optimum results for good POSs planning. So, it is verified that POSs should be planned by optimizing multiple objectives instead of single objective. The outcome of this multi-objective GAMOOM model does have an implication on how POSs should be designed and managed by the planning authority for not only sustainable environment but also better quality of life in a city.

1. INTRODUCTION

City is a multiplex ecological system made up of social, economic and natural sub-systems (Huang and Chen, 2002). Green space comprised of urban parks and open spaces (POSs) is the foundation of the natural system. A number of studies proved that increasing population and enhancing urbanization processes are converting POSs into impermeable hard concrete surface. This does not only destroy sustainable economy and human settlement, but also lead to environmental degradation and reduction of green spaces.

POSs are essential in any city, but become even more important in areas of high population density where homes may not include yard space and in places of intense development where landscaping is scarce. Our previous research findings (Neema, Ohgai, et al., 2008) showed that only 0.22 acre of open space is available per 1,000 people in densely populated Dhaka city which is far below the standard(s). The study concluded that there is a huge shortage of POSs and they are not evenly distributed in Dhaka city.

Undoubtedly POSs improve the ambient environmental quality of the city. They can ameliorate microclimate, absorb pollutants from the air, reduce noise levels and contribute to sustainable urban environment. An effective urban POSs planning is thereby essential to identify, protect, and conserve those special places. The objectives of planned POSs should be its availability near populated areas, air polluted area, noisy areas, areas without open spaces etc. In real-life planning, these objectives conflict with each other and optimizing a particular planning solution with respect to a single objective can result in unacceptable results with respect to the other objectives. Therefore, *multi-objective optimization* is indispensable for efficient POSs planning. A reasonable planning solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution.

Many methods have been used by many researchers on management of urban problems and location planning of urban facilities (Rakas, Teodorovic, et al., 2004; Yang, Jones, et al., 2007). Multi-objective optimization formulations are realistic models for many complex urban problems. From the literature review, no attempt has been taken to utilize multi-objective model for optimizing POSs locations. The first multi-objective GA, called vector evaluated, was proposed by (Schaffer, 1985). Afterwards, several multi-objective evolutionary algorithms were developed including multi-objective genetic algorithm (Fonseca and Fleming, 1993), weight-based genetic algorithm (Hajela and Lin, 1992), random weighted genetic algorithm (Murata and Ishibuchi, 1995), multi-objective evolutionary algorithm (Sarker, Liang, et al., 2002), dynamic multi-objective evolutionary algorithm (Yen and Lu, 2003). But none of these previous GA-based multi-objective optimization models has been used for POSs location planning.

In this paper, a new multi-objective location model based on well-established GA is presented for urban POSs planning. The *GA-based multi-objective optimization model (GAMOOM)* was developed taking four incommensurable objective functions into account: minimizing distance between 1) POSs to highly populated areas, 2) POSs to air polluted areas, 3) POSs to noisy areas, and 4) POSs to areas without POSs. The developed model was *coded with C++ programming language* and tested first with random data sets. Finally the model is validated with real data sets of Dhaka City as a case study. Potential differences between optimizing single objective function and multi-objective functions are analyzed in details.

2. MULTI-OBJECTIVE OPTIMIZATION SHCEME FOR POS PLANNING

Identifying and selecting prominent objectives for a multi-objective model one needs to consider impact of POSs. There are more and more toxic gases (SO2, NOx, Cl2, HF, NH3, Hg, etc) and dust existing in the air with the improvement of industrial level. Under some concentrations, however, many kinds of vegetation can absorb toxic gases. As such, POSs can play a cleaning function to air pollutions.

As one kind of the environmental pollution, noise has a bad effect on residents' health when it is over 70-decibel (Yang, 2003). The most effective method to eliminate noise is to make an optimum POSs system. However it is impossible to construct very wide green belts in the city because of the limited spaces. Noise will be eliminated much better if POSs are planned closer to the noise source. Therefore, for a successful multi-objective model providing more weight to such important factors in a densely populated city like Dhaka expected to provide optimum location of POSs planning.

Keeping in mind the afore-mentioned impacts of various factors, the model was implemented with four objective functions which are very useful for the improvement of city's environment. The factors on which the objective functions are based on are *population, air quality, noise level and land use distribution* (of Dhaka city as a case study).

2.1 Model Formulation and Description

The objective functions are denoted by $f_{h,}$ where h equals 1 to k. The single objectives are combined to obtain multi-objective function, F. In addition, the single objectives are multiplied by priority weights, w_h assigned to each function and then summed to obtain combined weighted multi-objective function, FW. The objective functions are defined in the following way.

The POSs should be located near highly populated areas to provide services to the people. Therefore, we set the first objective of the model to minimize the population weighted distance.

1. Minimize population weighted distance

$$f_1 = \sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij} \times d_{ij} P_j \qquad (1)$$

where, i is the locations of facility 1 to m, j is the locations of customer 1 to n, a_{ij} is the allocation-decision variable with facility i and customer j. The population weighted distance is represented by $d_{ij}P_j$, defining d_{ij} as the Euclidian distance between facility i and customer j, and P_j as the population of customer j. If facility i is allocated to customer j i.e. where population weighted distance, $d_{ij}P_j$ is minimum between each customer j to each facility i then a_{ij} = 1 otherwise 0.

The second objective of the model is to minimize the air quality weighted distance.

2. Minimize air quality weighted distance

$$f_2 = \sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij} \times d_{ij} AQ_j \qquad (2)$$

where, i, j and a_{ij} are same as before. The air quality weighted distance is represented by $d_{ij}AQ_j$, d_{ij} is the Euclidian distance between facility i and customer j, and AQ_j is the air pollution level of customer j.

The third objective of the model is to minimize the noise level weighted distance.

3. Minimize noise level weighted distance

$$f_3 = \sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij} \times d_{ij} NL_j \qquad (3)$$

where, i, j, a_{ij} *and* d_{ij} are defined similarly in the afore-mentioned way . The noise level weighted distance is represented by $d_{ij}NL_j$, *with* NL_j as the noise pollution level of customer j.

The fourth objective of the model is to minimize the land use weighted distance.

4. Minimize land use weighted distance

$$f_4 = \sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij} \times d_{ij} LU_j \qquad (4)$$

where, the land use weighted distance is represented by $d_{ij}LU_j$, *defining* LU_j as the land use pattern of customer j.

The k^{th} objective of the model is to minimize the k^{th} weighted distance.

Minimize k^{th} weighted distance

$$f_k = \sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij} \times d_{ij} k_j \qquad (4)$$

where, the k^{th} weighted distance is represented by $d_{ij}k_j$, *defining* k_j as the k^{th} *weight* of customer j.

Now, all single objective functions are summed-up into a multi-objective function:

Minimize $$F = \sum_{h=1}^{k} f_h \qquad (5)$$

where, $f_h = f_1 + f_2 + f_3 + f_4 + \text{- - - -} + f_k$

Finally, weighted sum of single objective functions are captured in a weighted multi-objective function below:

Minimize $$FW = \sum_{h=1}^{k} f_h w_h \qquad (6)$$

We set the following constraints:

1. Each customer should be served by only one facility

$$\sum_{i=1}^{m} a_{ij} = 1 \qquad (7)$$

2. Total priority weights should be equal to 1

$$\sum_{h=1}^{k} w_h = 1 \qquad (8)$$

This paper presents GA-based multi-objective optimization model to attain four conflicting objectives described before while solving a urban POSs problem.

3. GA FOR GAMOOM

The concept of GA was developed by Holland and his colleagues in the 1960s and 1970s (Holland, 1975). GAs are inspired by the evolutionist theory explaining the origin of species. In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. In a GA, five basic aspects are considered: the representation or coding of problem, the initialization of population, the definition of evaluation function, the definition of genetic operators, and the determination of parameters. The GA process used in GAMOOM model are described below and depicted in *Figure 1*:

The representation scheme determines how the problem is structured and which genetic operations are used. This study followed the representation process of the original GAs of Holland where every chromosome is a string of bits, 0 or 1. Experiments were initiated with randomly generated populations. These arbitrary solution sets were the starting point of the evolutionary process. Evaluation of the chromosomes is an important procedure in GA. Once the initial population is randomly created, each individual is evaluated using the evaluation function to determine its fitness value. After the evaluation of the population, a new population was selected from the previous generation. The selection of individuals to produce successive generations plays an important role in a genetic algorithm. Rank selection method was adopted for the selection of solutions for crossover operation. This method can be implemented very efficiently, and this method gives solutions whose quality compare favorably to the ones produced by other methods. Rank selection first ranks the population and then every chromosome receives a fitness value from this ranking.

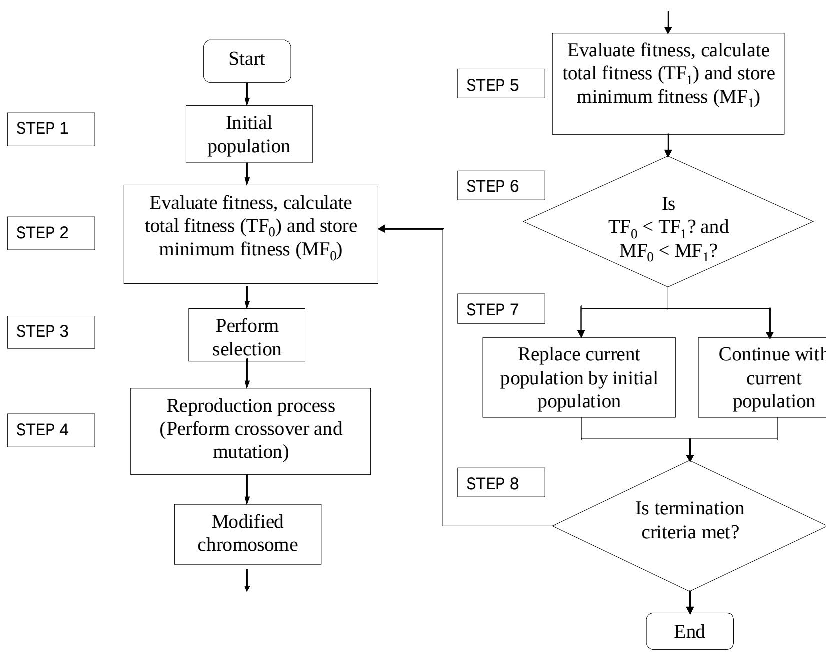


Figure 1. Flow chart showing genetic algorithm process used in GAMOOM

Genetic operators act on parents to generate the offsprings. Crossover and mutation are two common operators of GA. Crossover is a recombination operator that combines subparts of two parent chromosomes to produce offspring that contain some parts of both parents' genetic material. The single point crossover operator was used in this study. A crossover point on two selected parents is randomly selected and the portions of the two chromosomes beyond this point are exchanged to form the offspring. Mutation is a process that reverses the structure of a chromosome. Mutation serves as a policy to prevent solutions from being trapped in local optima and is considered a secondary mechanism in the operation of genetic algorithms. Mutation rate (probability) is usually set to a very low level. The process of mutation depends on the encoding process. For binary encoding a few randomly chosen bits can be switched from 1 to 0 or from 0 to 1. Once new child solutions have been constructed through the GA operators, the child solutions will replace "less fit" members of the population. In this GA process, modified "generational replacement" method was used, which generates a new population of children and replaces the whole parent population if the *sum_fitness* and the *min_fitness* values are better in the child population than in the parent population. If not, the parent population is used for the next iteration. The GA cycle is repeated until a predetermined maximum number of generations is reached.

4. APPLICATION TO THE DHAKA CITY URBAN POS LOCATIONS

Dhaka City comprised of 90 wards has population of around 5.4 millions. Total area of Dhaka City is 35,433 acres based on these wards. Shown in *Figure 2* is the map of Dhaka City depicting ward boundaries. The environment of Dhaka is facing serious threats from pollution caused by the city's rapid expansion, congestion and industrial activities. Within the junk of concrete and polluted environment in Dhaka city, POSs are very essential for its environment and ecological balance.

According to a recent study conducted by World Health Organization (WHO) of Dhaka city, most of the traffic points and many of the industrial, residential, commercial, silent and mixed areas are suffering noises exceeding the standard limits of Bangladesh. Increasing air and noise pollution emanating from traffic congestion and industrial activities are serious problems affecting public health and the quality of life in the city. To reduce pollution levels in Dhaka, sufficient amount of POSs is necessary. The GAMOOM model was developed to attain better environment in Dhaka by providing more POSs to overcome the shortfall of green areas. To realize the impact of these new POSs based on real scenario, the model was executed using collected real data sets of Dhaka City.

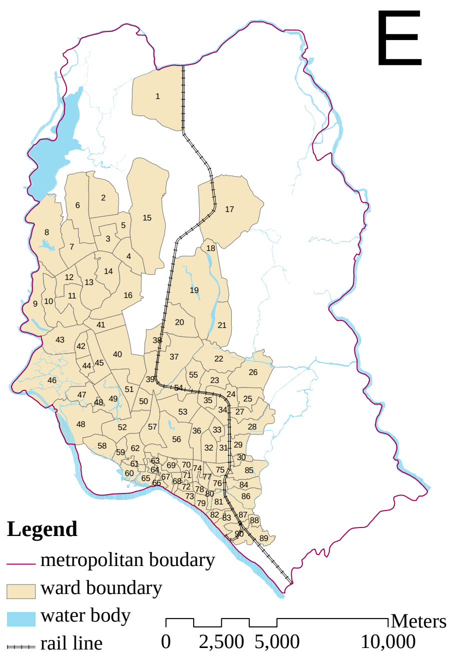


Figure 2. Map of Dhaka City showing ward boundaries

Before this, the model was verified using random data sets to determine the values of the parameters of the model which give the best results. It was observed that the best results can be obtained using population size of 30, crossover rate 0.25, mutation rate 0.009 and generation number 35,000. It was found that there is no change in optimum result after 35,000 generations. So, these parameter values are used while applying the model on real data sets.

4.1 Data Collection and Processing

Four different datasets viz population distribution, air quality, noise level and land use pattern of Dhaka City are used to validate the model. These datasets were collected from a variety of secondary sources. Population data of 90 wards of Dhaka were collected from population census 2001. Different surveys were conducted in Dhaka after 1995 to obtain air quality and noise levels at different locations. In this study, 48 locations of air quality data from (Jaigirdar, 1998) and 33 locations of noise level data from (Ahmed, 1999) were used to predict 90 wards pollution level of Dhaka using standard spatial interpolation method in ArcGIS 9.1 environment. In this study, only concentration of SO2 in the air considered as air pollution. Land use pattern of each ward were identified from a paper map of Dhaka City.

The wards of Dhaka City were divided into five suitability classes in each factor. Then each suitability class was assigned a unique weight to recognize its relative importance. The description of suitability classes are given in *Table 1*.

Table 1. Factors, suitability classes and weights:

Factor	Suitability class	Class description / range of values	Weight
Population	Very high	Areas with very high population density	1
	High	Areas with high population density	2
	Moderate	Areas with moderate population density	3
	Low	Areas with low population density	4
	Very Low	Areas with very low population density	5
Air quality	Very high	Areas with very low air quality	1
	High	Areas with low air quality	2
	Moderate	Areas with moderate air quality	3
	Low	Areas with high air quality	4
	Very Low	Areas with very high air quality	5
Noise influence	Very high	Areas with very much noise pollution	1
	High	Areas with much noise pollution	2
	Moderate	Areas with not much noise pollution	3
	Low	Areas with little noise pollution	4
	Very Low	Areas with very little noise pollution	5
Land use	Very high	Areas without open spaces, industrial areas, roads	1
	High	Commercial areas, Residential areas	2
	Moderate	Water areas	3
	Low	Vacant areas and government reserved areas	4
	Very Low	Existing open space areas	5

4.2 Setting of the number of the Urban POSs in simulation

According to population census 2001, total ward population and ward area of Dhaka City are around 5.4 million (53,91,189) and 35,433 acres respectively. It was found that 0.22 acres of open space is available per 1,000 population. This is far bellow the recommended standards followed in different countries in the world (Neema, Ohgai, et al., 2008) According to US and Singapore standard, 2.5 acres of open space is recommended per 1,000 population. So, if this standard is applied in Dhaka, it requires 13,477.97 acres of open space in total. Excluding existing total area of open space, Dhaka additionally needs 12,287.96 acre of open space. As a congested city, it is not possible to provide such amount of more open space. So, we propose to provide 0.5 acres of POSs per 1,000 population doubling the existing availability. By considering this assumption, Dhaka needs 1,505.59 acres of more POSs. For this study, we set that the number of supplementary urban POSs is 30 for simulation. Therefore, 50 acres of area can be allocated for each POSs. Using GAMOOM model, location of these 30 POSs were derived optimizing four objective functions.

4.3 Implementation and Result Analysis

The centroids of 90 wards of Dhaka City were assumed as *customer/demand* points for the GAMOOM model. First we will present analysis of the results obtained from single objectives. Shown in *Figure 3* are the optimum locations of POSs obtained from single objectives.

As weighted distances are minimized, so it can be expected that the POS locations could be fallen on the low priority areas. *Table 2* shows covered area and population in suitability classes by each factor. These data in percentage are also presented in *Figures 4* to clearly understand how much area is polluted and how many people are living there. These data were compared with the POS locations obtained from single objective functions.

Figure 3(a) shows ward wise population distribution in Dhaka City and optimum locations of POSs by minimizing population weighted distance. It was observed that most of the locations tend to fall near populated areas. Presented in *Figure 3(b)* is the air pollution distribution. The POS locations provided by minimization of air quality weighted distance are also depicted. It was found that SO_2 concentration is more than 0.30 ppm in 70% areas of Dhaka where 70% population are living. GAMOOM model has successfully optimized 60 % of new POSs locations in this polluted area.

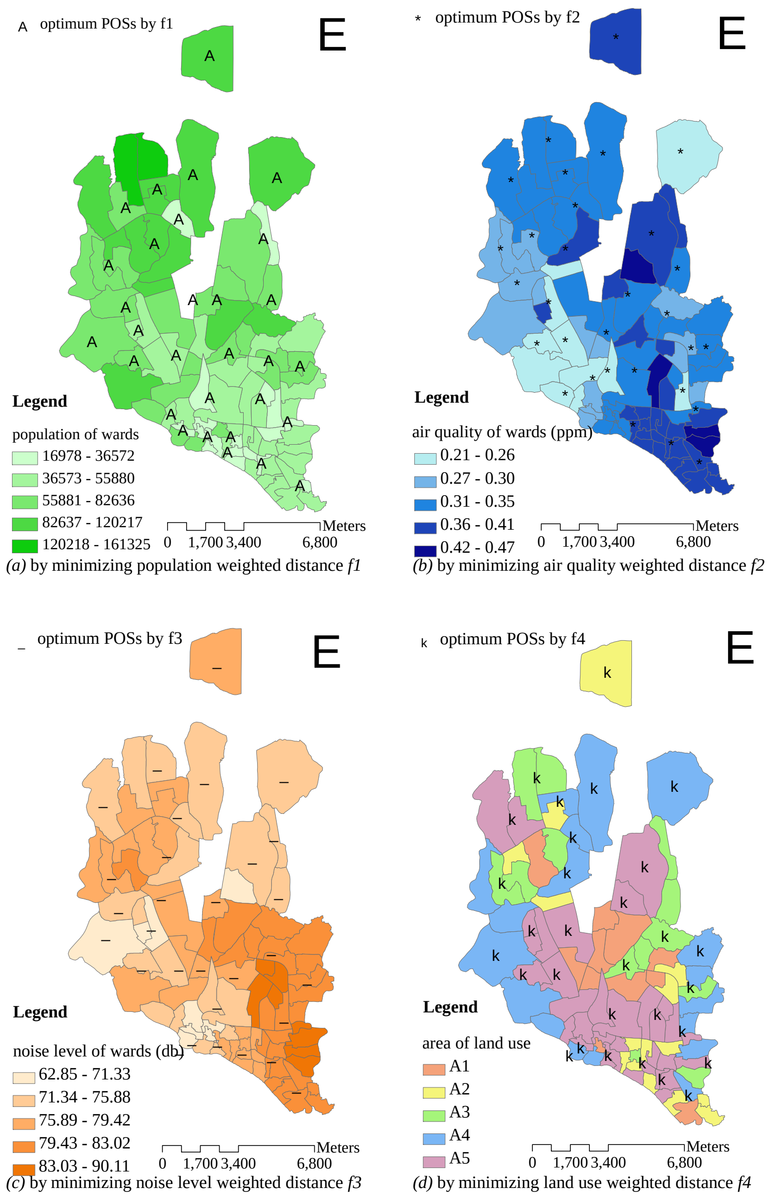
Figure 3(c) presents noise levels in Dhaka and POS locations obtained by minimizing noise level weighted distance. The noise level is significantly very high in the southeast portion of Dhaka. The locations of POS obtained from the model by minimizing land use weighted distance are depicted over land use pattern of different wards in *Figure 3(d)*.

Table 2. Covered area and population in suitability classes

Factor	Suitability class	Covered Area (acre)	Covered Population	Ward no.
Population	Very high	2,162	3,10,093	2, 6
	High	12,878	13,78,355	1, 3, 5, 8, 12, 13,14, 15, 16, 17, 22, 37, 41, 48
	Moderate	10,308	17,16,817	7, 9, 10, 11, 19, 20, 21, 24, 25, 27, 34, 38, 40, 42, 43, 46, 47, 50, 52, 54, 55, 58, 60, 65, 69
	Low	7,691	14,46,940	23, 26, 28, 29, 32, 35, 36, 39, 44, 45, 49, 51, 53, 56, 59, 62, 68, 70, 74, 76, 77, 79, 81, 82, 83, 84, 85, 86, 87, 89, 90
	Very Low	2,394	5,38,984	4, 18, 30, 31, 33, 57, 61, 63, 64, 66, 67, 71, 72, 73, 75, 78, 80, 88
Air quality	Very high	1,391	2,20,335	20, 36, 84, 86
	High	7,637	14,09,947	1, 16, 18, 19, 32, 35, 38, 44, 54, 68, 69, 70, 71, 72, 73, 74, 76, 77, 78, 79, 80, 81, 82, 83, 85, 87, 89, 90
	Moderate	15,390	21,50,820	2, 3, 4, 5, 6, 7, 8, 12, 13, 14, 15, 21, 23, 25, 26, 27, 28, 30, 33, 37, 39, 40, 53, 55, 56, 63, 64, 65, 66, 67, 75
	Low	4,977	9,34,955	9, 10, 11, 22, 24, 29, 34, 42, 43, 46, 50, 51, 60, 61, 62
	Very Low	6,038	6,75,132	17, 31, 41, 45, 47, 48, 49, 52, 57, 58, 59
Noise influence	Very high	1,669	3,68,877	30, 33, 34, 35, 36, 84, 85, 86
	High	6,474	14,10,592	11, 22, 23, 24, 25, 26, 27, 28, 29, 31, 32, 37, 39, 54, 55, 75, 76, 77, 80, 81, 82, 83, 87, 88, 89, 90
	Moderate	9,074	16,69,586	1, 3, 5, 7, 9, 10, 12, 13, 14, 38, 40, 41, 48, 50, 51, 52, 53, 67, 68, 70, 71, 72, 73, 74, 78, 79
	Low	15,368	15,18,139	2, 4, 6, 8, 15, 16, 17, 18, 19, 21, 42, 43, 47, 49, 56, 57, 58, 59, 65, 66, 69
	Very Low	2,848	4,23,995	20, 44, 45, 46, 60, 61, 62, 63, 64
Land use	Very high	2,650	6,74,925	13, 23, 35, 37, 38, 39, 50, 51, 53, 64, 90

	High	3,973	8,56,640	1, 3, 12, 24, 34, 41, 68, 70, 72, 74, 75, 79, 83, 88, 89
	Moderate	6,414	10,45,169	2, 6, 10, 11, 14, 18, 21, 22, 27, 54, 55, 71, 86
	Low	11,970	12,57,962	4,5,9,15,16,17, 25, 26, 28, 29, 43, 46, 48, 58,60,65,85, 87
	Very Low	10,426	15,56,493	7, 8, 19, 20, 30, 31, 32, 33, 36, 40, 42, 44, 45, 47, 49, 52, 56, 57, 59, 61, 62, 63, 66, 67, 69, 73, 76, 77, 78, 80, 81, 82, 84

This sub-section will present analysis of results obtained from multi-objective optimization. *Figure 5(a)* shows optimum locations of more POSs obtained from the model by minimizing combined objective, *F* of four single objectives. Optimum POSs locations and existing POSs locations are shown in *Figure 5(b)*.



(a) by minimizing population weighted distance *f1*

(b) by minimizing air quality weighted distance *f2*

(c) by minimizing noise level weighted distance *f3*

(d) by minimizing land use weighted distance *f4*

A1 = Areas without open spaces, industrial areas, roads, A2 = Commercial and residential areas, A3 = Water areas, A4 = Vacant and govt. reserve areas, A5 = Existing open space areas

Figure 3. Optimum locations of POSs based on single objectives

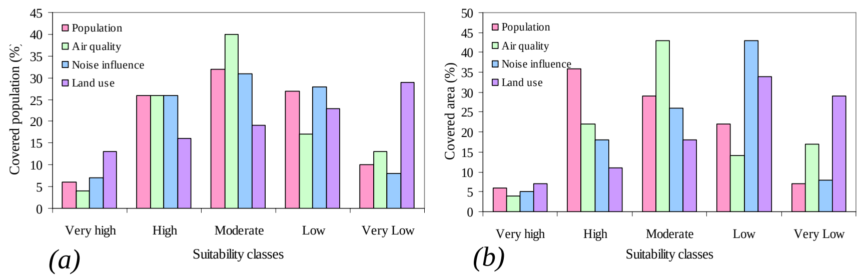
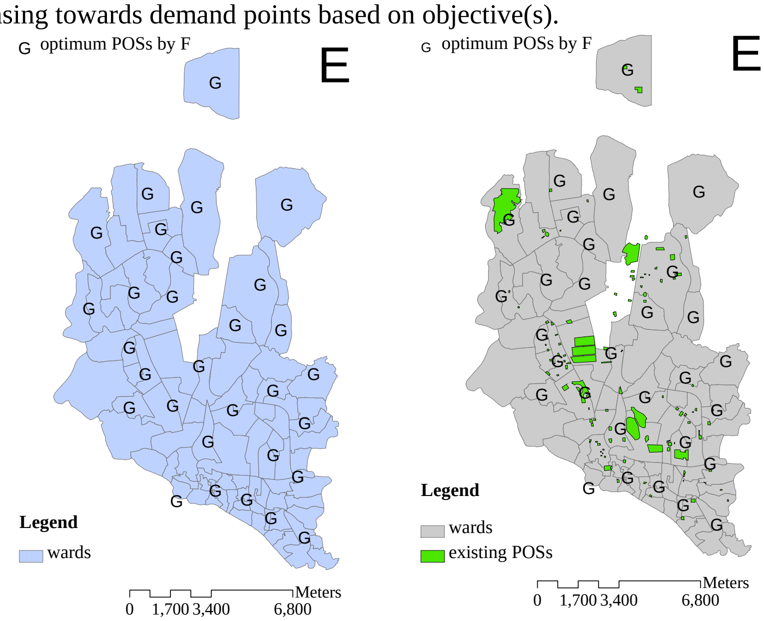


Figure 4: (a) Factor wise covered area in suitability classes, *(b)* Factor wise covered population in suitability classes

One can see that the POSs locations are optimized by the implementation of the model with multi-objective function. However, from this figure, it can be observed that three POSs locations fall over the existing locations of three POSs. In very few instances, this situation could arise as the model is optimizing four objectives together. This can be attributed to the local biasing towards demand points based on objective(s).



(a) *(b)*

Figure 5. (a) Maps showing optimum locations of POSs based on multi-objectives, *(b)* comparison with existing locations of POSs

To compare optimum POS locations based on both multi-objective and single objective functions, ouputs from multi-objective and single objective models are combinedly presented in Figure 6. It was found that optimal locations obtained from objective 2 are significantly different compared to multi-objective solution. This is due to obvious reason of optimizing POSs locations near areas with high air-pollution. Similarly the optimal locations obtained from objective 3 also differ substantially in many locations than multi-objective results. These results signify the importance of using multi-objective model over single objective model.

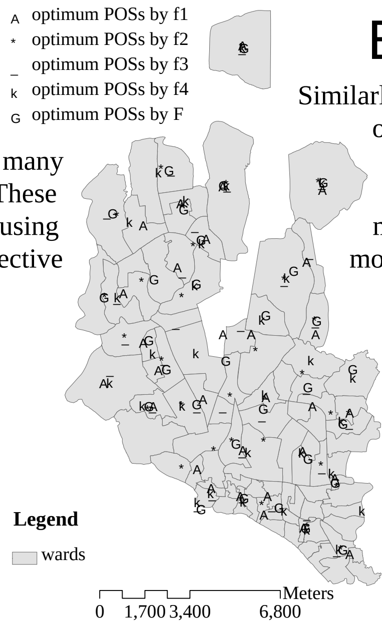


Figure 6. Comparison of optimum locations of POSs based on both multi-objective and single objectives

Figure 7(a) shows optimum POSs locations obtained from weighted multi-objective function, *FW*. In this case, priority weight assigned to each single objective is presented in Table 3. Air quality and noise level are given higher weights based on the fact that Dhaka city is highly polluted by these factors. *Figure 7(b)* gives a comparative representation of optimum POS locations obtained from multi-objective function *F* and weighted multi-objective function *FW*. There is subtle difference in optimized locations in both cases. But the influence of weigths is clearly evident from the results. For example location of POSs with *FW* in wards 49 and 53 are biased due to assigned noise levels and in wards 16 and 6 are biased towards assigned air-pollution levels. This indicates that GAMOOM model can be implemented providing necessary weights to desired objective function.

Table 4 shows a summary of the optimum weighted distances obtained from models optimizing single-objective functions *f*, multi-objective function *F* and weighted multi-objective function *FW*. These optimized solutions were used for finding optimal locations of POSs. As expected in each case optimum weighted distance varies but significant variation is realized while optimizing *F* and *FW*.

Table 3. Priority weights of each function

Factor	Population	Air quality	Noise influence	Land use
Weight	0.2	0.3	0.3	0.2

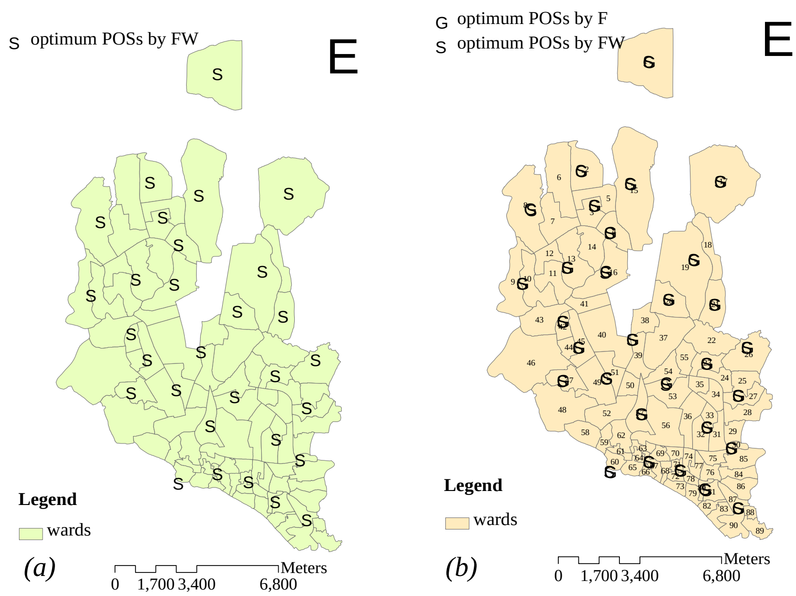


Figure 7. (a) Optimum locations of POSs based on weighted multi-objective *(b)* a comparative representation between multi-objective and weighted multi-objective

Table 4. Minimum weighted distances in meter obtained from the GAMOOM model

Objective functions	f_1	f_2	f_3	f_4	*Minimized F or FW*
f_1	181116.16	0	0	0	181116.16
f_2	0	157167.39	0	0	157167.39
f_3	0	0	145384.87	0	145384.87
f_4	0	0	0	163279.24	163279.24
F	187296.96	163794.04	153503.19	182468.09	687062.28
FW	187271.59	163457.62	153424.93	182824.09	169083.90

5. CONCLUSIONS

We developed a new multi-objective optimization model for effective POSs planning using GA. The model couples four distinguished features to provide POSs near densely populated areas, air polluted areas, noisy areas, and areas without open spaces. It can successfully provide optimum location of more POSs in Dhaka City. For optimization of locating facilities, planners should consider multiple objectives instead of considering single objective. The findings from this study also have implications on how POSs should be designed and managed for sustainable environment by the planning authority of Dhaka City. Though many types of toxic gases present in the air causing air pollution, only concentration of SO2 in the air is considered in this study. Our future research will incorporate other components.

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