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Urban Greening Using an Intelligent Multi-Objective Location Modelling with Real Barriers: Towards a Sustainable City Planning

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Greenery is one of the important ingredients for urban planning with a sustainable environment. Increasing parks and open spaces (POS) to offer a greater diversity of green spaces have substantial impact on its environment in many mega cities around the world. However, any place cannot be a potential site for POS due to multi-objective modeling nature of POS planning. In this paper, an intelligent multi-objective continuous optimization model is thus developed for locating POS with particular emphasis on greeneries that will potentially benefit and facilitate the planning of a sustainable city. Three environmentally incommensurable factors analyzed with the help of geographic information systems (GIS) namely air-quality, noise-level, and population-distribution have been considered in the model and a genetic algorithm (GA) is used to solve the continuous optimization problem heuristically. The model has been applied to Dhaka city as a case study to find the optimal locations of additional POS to make it a sustainable city by ameliorating its degraded environment. The multiple objectives are combined into a single one by employing a dynamic weighting scheme and a set of non-dominated Pareto optimal solutions is derived. The obtained alternative non-dominated solutions from the robust modelling approach can serve as a candidate pool for the city planners in decision making for POS planning by selecting an alternative solution which is best suited for the prevailing land-use pattern in a city. The model has successfully demonstrated to provide optimal locations of new POS. In addition, we found that locations of POS can be optimized even by integrating it with land cover and uses like lakes, streams, trails (for simplicity which were considered as a barrier constraint in the model) to rejuvenate added beauties in a city. The obtained results thus indicate that the developed multi-objective POS location model can serve as an effective tool for urban POS planning maintaining sustainable environment.

Keywords: Urban Greening; Parks and Open Space; Sustainable Environment; GA and GIS; Intelligent Location Modelling

Introduction

In an integral urban planning, greeneries can predominantly be found in parks, playgrounds, gardens etc. Parks and open spaces (POS) i.e. greeneries in particular can substantially improve the livability of land uses and city environment. Its important functions are: 1) potential amelioration of microclimate, 2) absorbtion of pollutants, 3) reduction of noise levels including a significant improvement of the lifestyle of city-dwellers by allowing admixture with nature and promoting social interactions (Schipperijn et al., 2010; Szeremeta et al., 2009; Gobster, 1998; Morancho, 2003; Uy & Nakagoshi, 2008; Chiesura, 2004; Egger, 2006; Kong et al., 2010; Borrego et al., 2006; Lam, 2005; Poggio & Vrcaj, 2009; Nordh et al., 2009; BenDor et al., 2013; Choumert, 2010; Neema et al., 2013; Neema & Ohgai, 2013; Neema et al., 2008). Importantly, the necessity of POS in landscape planning and design can be realized in densely populated cities around the globe (Lam et al., 2005).

As such a densely populated city, Dhaka has emerged as a fast growing mega-city. In 1975, it started with a population of only 2.2 million which has culminated to 16 million in 2010. In 2015, a predicted population is 21 million. It can be envisaged that due to this rapid growth of population in Dhaka, it is confronted with a big challenge to deal with serious environmental degradation due mainly to the significantly diminished number of POS. Once, Dhaka city was considered as a green city but now it has left with only 21.6% open space (but not green spaces) of its total area with huge population (SDNP, 2005). Statistically, it can be calculated that only approximately 8 sq. meter POS is available per person in Dhaka city (Uddin, 2005), which is rather insufficient for a healthy sustainable city. In

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contrary, POS for greeneries in built up areas of a city like Dhaka is ought to be considered as one of the most valuable, protective and attractive elements. Surprisingly, due to inadequate planning there are insufficient and non-optimal locations of POS in the city. Therefore, an efficient POS planning is indispensable for attaining a sustainable environment in Dhaka city.

However, an intelligent POS planning generally include multiple criteria so that it could stimulate optimum benefits in urban environment. Thus, the planning for POS locations can be considered as a *multi-objective facility location optimization problem*. The relevant objective criteria for the optimal location of additional POSs (for greeneries) mainly are: population distribution, air quality, noise level, and physical barriers. With the considered physical barriers we mean industrial areas, existing parks, lakes, big rivers, airport zones, highways and mountain ranges. Some barriers might hinder POS planning in its interior but some barriers can be used with POS in an integrated way.

Interestingly, many researchers focused on applying operations research models in ecological reserves which considered also wetlands and water bodies (McDonnell et al., 2002; Camm et al., 2002; Drechsler & Wtzold, 2001). But no systematic research has been conducted yet to develop and apply operations research models on POS planning for city greening including barrier concept.

In our previous research (Neema & Ohgai, 2010), we developed a genetic algorithm (GA)-based multi-objective location model for open spaces without considering any barriers. In this paper, we extend the model to include barriers to develop a robust intelligent model for finding optimal locations of POS using our GA-based multi-objective continuous optimization scheme. In this research, we consider POSs particularly for urban greeneries. These POSs include city parks, local parks, playgrounds, neighbourhood open spaces and other green areas. The model thus developed is applied to Dhaka city as a case study.

The paper is organized in the following way. In the next section, we illustrate our intelligent multi-objective model formulation with barriers. Then, we explain the calculation of shortest permitted distance with barrier constraints. After that we briefly describe our algorithms. Then, we apply the model thus develop to Dhaka city (as a case study) for providing more POS. Next, we provide computational results and discussion. Finally, we provide some concluding remarks.

Formulation of Intelligent Multi-Objective POS Model with Barriers

Like most real-world planning problems, urban parks and open spaces planning are ill-structured containing important factors that are difficult to quantify and represent precisely. This type of planning problem often contains more than one objective and decision makers are often required to evaluate solutions according to multiple criteria and their preferences (Zhang & Armstrong, 2008). The solution to such problems requires simultaneous optimization of multiple, often competing criteria (or objectives), is usually computed by combining them into a single criterion to be optimized, according to some utility function. In many cases, however, the utility function is not well known prior to the optimization process. The whole problem should then be treated as a multi-objective problem. In this way, a number of solutions (Pareto-optimal) can be found which provide decision makers with insight into the characteristics of the problem before a final solution is chosen (Fonseca & Fleming, 1991). A detail formulation for a multi-objective continuous optimization model for parks and open space (POS) is given below. First, we need to define the objectives of the model and then explain elaborately the adopted concept in the inclusion of barriers in the model which is the main focus of this study.

Problem Definition and Model Objectives

The multiple objectives of the model are to locate POS by minimizing distances from: populated areas (f_1), air-polluted areas (f_2), and noisy areas (f_3). For locating POS, we define our problem space as a 2-D continuous rectangular region, ξ^2 with known maximum and minimum x, y coordinates. In ξ^2, demands for facilities (POS in our model), u_i are distributed over a set of given points u_j (demand points) with assigned positive weights w_j (population, air quality and noise level in our model). In ξ^2, we denote barrier regions for locating facilities (i.e. POS) by B_k, $k = 1, 2,\cdots, q$. A multi-objective function is set to determine the approximate optimal locations of the facilities without placing in barrier regions as well as minimizing total travel distance with respect to each measure. The multiple objectives are represented by following functions:

- Minimizing population weighted distance

$$\min f_1 = \sum_{i=1}^{m}\sum_{j=1}^{n} \left\langle P_{w_j d}\left(u_i, u_j\right)\right\rangle \cdot P_{c_{ij}} \tag{1}$$

- Minimizing air quality weighted distance

$$\min f_2 = \sum_{i=1}^{m}\sum_{j=1}^{n} \left\langle AQ_{w_j d}\left(u_i, u_j\right)\right\rangle \cdot AQ_{c_{ij}} \tag{2}$$

- Minimizing noise level weighted distance

$$\min f_3 = \sum_{i=1}^{m}\sum_{j=1}^{n} \left\langle NL_{w_j d}\left(u_i, u_j\right)\right\rangle \cdot NL_{c_{ij}} \tag{3}$$

where, u_i denotes the location of facility (where i ranges from 1 to m), u_j the location of a demand point (where j ranges from 1 to n). P, AQ, NL respectively stand for population, air quality and noise level. $P_{w_j d}$, $AQ_{w_j d}$ and $NL_{w_j d}$ are respective weights of demand point u_j for population, air quality and noise level. The allocation decision variables for weighted distances of population, air quality and noise level are given respectively by $P_{c_{ij}}$, $AQ_{c_{ij}}$ and $NL_{c_{ij}}$. $d(u_j, u_i)$ is the travel distance between two points u_i and u_j.

We combine all three single objective functions into a composite function, F. The multi-objective function takes the following form:

$$\min F = \left\{f_1, f_2, f_3\right\} \tag{4}$$

We apply a weighting scheme to obtain the composite function F. Using the scheme in our GA-based model, we generate a different random weight vector, v for each solution (chromosome) where $v = [w_1, w_2 \text{ and } w_3]^T$ (i.e. consists of three weights denoted by w_1, w_2 and w_3 respectively for three objectives i.e. f_1, f_2 and f_3). We then multiply each objective function by the corresponding weight and aggregate to obtain the composite objective function, F. We generate three random numbers between 0 and 1, denoted by r_1, r_2 and r_3 to derive w_1, w_2 and w_3 respectively. We denote T for transpose.

$$\min F = f_1 w_1 + f_2 w_2 + f_3 w_3 \tag{5}$$

$$v = \left[w_1 \ w_2 \ w_3 \right]^T \tag{6}$$

$$w_1 = \frac{r_1}{r_1 + r_2 + r_3} \tag{7}$$

$$w_2 = \frac{r_2}{r_1 + r_2 + r_3} \tag{8}$$

$$w_3 = \frac{r_3}{r_1 + r_2 + r_3} \tag{9}$$

The assumed constraints for the model are:

- We prevent siting of facilities inside barrier regions.
- If facility u_i is allocated to demand point u_j, i.e., where the population weighted distance, $P_{w_j d}$ (u_j, u_i) is at minimum between demand point u_j and facility u_i, then $P_{c_{ij}} = 1$; otherwise it is 0. Similarly, we derive the allocation decision variables for air quality and noise level.
- The distance between two points u_j and u_i is Euclidean distance. We discuss in the next section how to calculate the distance in presence of barriers.
- The total weight for all objectives is equal to 1.

The mathematical representation of the constraints are as follows:

$$\left.\begin{aligned} & u_i \notin B_k, \\ & \sum_{i=1}^{m} P_{c_{ij}} = 1, P_{c_{ij}} = 0 \text{ or } 1, \\ & \sum_{i=1}^{m} AQ_{c_{ij}} = 1, AQ_{c_{ij}} = 0 \text{ or } 1, \\ & \sum_{i=1}^{m} NL_{c_{ij}} = 1, NL_{c_{ij}} = 0 \text{ or } 1, \\ & d\left(u_i, u_j\right) = \left\{ \left| x_i - x_j \right|^2 + \left| y_i - y_j \right|^2 \right\}^{1/2}, \\ & w_1 + w_2 + w_3 = 1, \end{aligned}\right\} \tag{10}$$

Next, we describe the procedure in details to include real barriers in the model.

Inclusion of Barriers in the Model

The barriers B_k, $k = 1, 2, \cdots, q$ consist of *multiple* circular barriers ($B_c = 1, 2, \cdots, c$) and line barriers ($B_l = 1, 2, \cdots, l$) such that $q = c + l$. We assume non-elongated shaped barriers such as industrial areas, airport zones, existing parks, water bodies etc. as circular barriers, B^c and elongated shaped barriers such as lakes, rivers, highways, borders etc. as line barriers, B_l. We further subdivide B^c in two categories i.e. flexible barriers, (FLB_c) and fixed barriers, (FLB_c). We define a FLB_c as the region i.e. a water body where location is not feasible but travel through the water body may be possible using a boat and a FLB_c as the region i.e. industrial plant, existing parks etc. where neither travel nor location is allowed. We further consider a line barrier, B_l as the region (such as a lake) where location is not feasible but in real world, one might expect to have some exit points, ep_ρ (e.g. over bridge) for travel through such elongated shaped barriers.

We adopt the following assumptions for barrier inclusion in the model:

1) Barrier representation: Each circular barrier, B_c is defined by a circle. The area of the B_c is the equivalent area of the existing real barrier. The centroid of existing real barrier is used to draw each B_c. Each line barrier, B_l is defined by a line and it is the center line of an existing real barrier. The exit points, ep_ρ on a line barrier, B_l are determined from the location of exit points on the existing real barrier.

2) Facility location: Facility location is not allowed inside a B_c. A buffered distance is used for all B_l to define the prohibited region of facility location. The prohibited region from B_l is denoted by $B_{l\{\wp\}}$.

3) Travel through the barriers: It is permitted to travel through flexible barriers FLB_c and the distance between two points $u_j, u_i \notin B_k$ in ξ^2 that are separated by a FLB_c is measured in Euclidean metric, $d(u_j, u_i)$. It is not permitted to travel through fixed barriers FLB_c but possible to travel along the boundary of FLB_c. For line barriers B_l, it is permitted to travel only through the defined exit points ep_ρ. The shortest permitted distance between two points $u_j, u_i \notin B_k$ in ξ^2 which are separated by a FLB_c and/or a B_l is denoted by $\tilde{d}\left(u_i, u_j\right)$ > $d\left(u_j, u_i\right)$. Shown in **Figure 1** is a pictorial depiction of the considered problem space with travel distance between facilities and demand points through barriers.

In the following section, we describe in details the calculation of shortest permitted distance, $\tilde{d}\left(u_i, u_j\right)$ in presence of fixed barriers and/or line barriers to incorporate into the model.

Calculation of Shortest Permitted Distance

There are three subsections in this section. We present the calculation of shortest permitted distance between facilities and demand points in presence of fixed barriers, in presence of line barriers and in presence of both fixed and line barriers.

In Presence of Fixed Barriers

We assume that a facility point, u_i and a demand point, u_j which are not inside a barrier, B_k (i.e. $u_j, u_i \notin B_k$) visible when the straight-line joining the points does not intercept a fixed barrier FIB_c. Similarly, the set of facility points u_i that are invisible from a demand point u_j are in the shadow region of u_j (see in **Figure 2(a)**).

If two tangents are drawn from point u_j to FIB_c, two points of tangency can be obtained: right, $t_r\left(u_j\right)$ and left, $t_l\left(u_j\right)$. The conventions for "right" and "left" were adopted based on the bisector that starts from u_j and passes through the center of FIB_c following (Klamroth, 2004). Similarly, two points of tangency i.e $t_r\left(u_j\right)$ and $t_l\left(u_j\right)$ can be found by drawing two tangents from u_i to FIB_c. There are two permitted paths between u_i and u_j:

$\tilde{d}_1\left(u_j, u_i\right)$—a permitted-path constructed with the points of tangency $t_l\left(u_j\right)$ and $t_r\left(u_j\right)$ (see in **Figure 2(b)**).

$\tilde{d}_2\left(u_i, u_j\right)$—a permitted-path through the points of tangency $t_r\left(u_j\right)$ and $t_l\left(u_j\right)$.

Following the technique adopted by Katz and Cooper (Katz & Cooper, 1981) we calculated the permitted-path length as:

$$\begin{aligned} \tilde{d}_1 &= d\left(u_j, t_l\left(u_j\right)\right) + 2r \arcsin\left[\frac{d\left(t_l\left(u_j\right), t_r\left(u_i\right)\right)}{2r}\right] \\ &\quad + d\left(t_r\left(u_i\right), u_i\right) \\ &= d\left(u_j, t_l\left(u_j\right)\right) + r\alpha + d\left(t_r\left(u_i\right), u_i\right) \end{aligned} \tag{11}$$

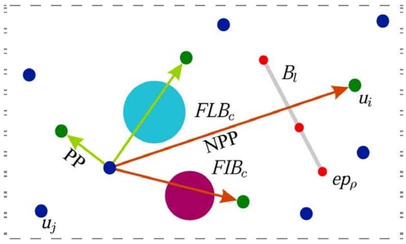
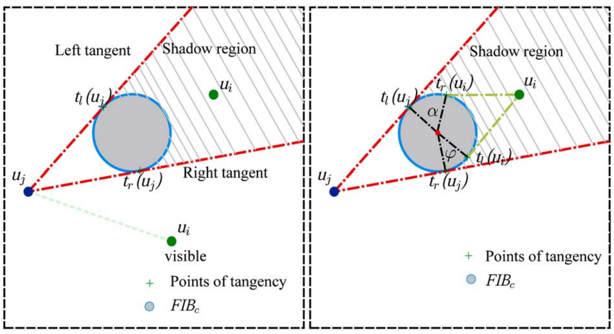


Figure 1.
A schematic of a problem space and travel distance between facilities and demand points in presence of barriers: u_j = demand point, u_i = facility point, FLB_c = flexible barrier, FIB_c = fixed barrier, B_l = line barrier, ep_ρ = exit points of line barrier, NPP = non-permitted path, PP = permitted path.



(a) (b)

Figure 2.
(a) The shadow region of a demand point u_j (b) Permitted path between a facility point u_i and a demand point u_j.

$$\begin{aligned}\tilde{d}_2 &= d\left(u_j, t_r\left(u_j\right)\right) + 2r \arcsin\left[\frac{dt_r\left(u_j\right), t_l\left(u_i\right)}{2r}\right] \\ &\quad + d\left(t_l\left(u_i\right), u_i\right) \\ &= d\left(u_j, t_r\left(u_j\right)\right) + r\phi + d\left(t_l\left(u_i\right), u_i\right)\end{aligned} \tag{12}$$

where, r signifies the radius of FIB_c. α and φ are the angles between the radii to $t_l\left(u_j\right)$ and $t_r\left(u_i\right)$, and $t_r\left(u_j\right)$ and $t_l\left(u_i\right)$ respectively. The shortest one between these two paths is considered as the shortest permitted path.

In Presence of Line Barriers

Here, we assume the two points $u_j, u_i \notin B_k$ are separated by a line barrier, B_l if they are on opposite side of B_l. If a B_l is a straight line, the two end points of B_l are used to derive whether the positions of u_i and u_j are on the same side or on the opposite side of B_l. If a B_l is a curve line, some vertex points are used to define the B_l in the model. The vertices are used for the procedure of deriving whether positions of u_i and u_j are on the same side or on the opposite side of B_l. First, the distances from u_i and u_j to each vertex are calculated. Then the straight lines between the nearest two vertices of u_i and that of u_j are used to derive whether the positions of u_i and u_j are on the same side or on the opposite side of B_l. If there is a B_l between u_i and u_j, the travel distance from u_i to u_j is permitted only through some ep_ρ of B_l. In such a situation, to calculate the shortest permitted distance from u_i to u_j, the following procedure is used:

Suppose, there are four exit points ep_ρ (ρ: 1 to 4) present in B_l (see in **Figure 3**). At first, a straight line is drawn that starts at u_j and ends at u_i. This straight line intersects B_l at a point $intp_\gamma$, here $\gamma = 1$. Next, the distances from $intp_\gamma$ to all ep_ρ are calculated and denoted by d_1, d_2, d_3 and d_4. The shortest one among these four distances is selected. In this illustration, d_2 is the shortest, so ep_2 is the nearest exit point from $intp_\gamma$. The nearest exit point is denoted by ep_ρ^*. So, the shortest permitted travel distance from u_j to u_i is the sum of the distances from u_j to ep_ρ^* and from ep_ρ^* to u_i and the equation is given as below:

$$\tilde{d}\left(u_i, u_j\right) = d\left(u_j, ep_\rho^*\right) + d\left(ep_\rho^*, u_i\right) \tag{13}$$

In Presence of Fixed and Line Barriers

In this section, we assume there are a fixed barrier FIB_c and a line barriers B_l exist in between a demand point u_j and a facility point u_i (see in **Figure 4**). First, tangents are drawn from both u_j and u_i to FIB_c (similar to the treatment presented in subsection 3.1). Then we obtain four tangent points i.e. $t_l(u_j)$, $t_r(u_j)$, $t_l(u_i)$ and $t_r(u_i)$. The tangents from u_i to FIB_c intersects a B_l. Two points of intersection are found as $intp_1$ and $intp_2$. The nearest exit points from $intp_1$ and $intp_2$ are derived using the technique described. The nearest exit points from $intp_1$ and $intp_2$ respectively are ep_2 (denoted by ep_ρ^{*l}) and ep_3 (denoted by ep_ρ^{*r}). The two shortest permitted distances are shown in Equations (14) and (15). The shortest one between d_1 and d_2 is selected as the shortest permitted path.

$$\begin{aligned}\tilde{d}_1 &= d\left(u_j, t_r\left(u_j\right)\right) + \operatorname{arc}\left(t_r\left(u_j\right), t_l\left(u_i\right)\right) \\ &\quad + d\left(t_l\left(u_i\right), ep_\rho^{*l}\right) + d\left(ep_\rho^{*l}, u_i\right)\end{aligned} \tag{14}$$

$$\begin{aligned}\tilde{d}_2 &= d\left(u_j, t_l\left(u_j\right)\right) + \operatorname{arc}\left(t_l\left(u_j\right), t_r\left(u_i\right)\right) \\ &\quad + d\left(t_r\left(u_i\right), ep_\rho^{*r}\right) + d\left(ep_\rho^{*r}, u_i\right)\end{aligned} \tag{15}$$

Next, we describe about the genetic algorithms to formulate the multi-objective POS location model to include the barriers.

Genetic Algorithm for the Multi-Objective POS Model with Barriers

In this section, we present briefly our GA-based model where we mainly focus on the algorithmic steps used for the inclusion of barriers. The flowchart of our GA-based model with barriers is presented in **Figure 5**. Details on genetic algorithms can be found in (Neema et al., 2011). In our GA, each chromosome (i.e. individual) corresponds to a potential solution.

In the initialization process, a population of solutions i.e. chromosomes is created randomly. The number of solutions (population size) in a population is predetermined. Then the solutions are checked for whether the random locations of facilities are inside or outside the barrier regions. Following steps were adopted to prevent siting of a facility inside a barrier region:

Step 1: Generate random locations of facilities u_i in ξ^2.

Step 2: Check facility $u_i \notin B_k$.

Step 3: If $u_i \in B_k$, relocate the u_i. The relocation process is shown in **Figure 6**.

Step 4: If $u_i \in B_c$, draw a straight line starting from the

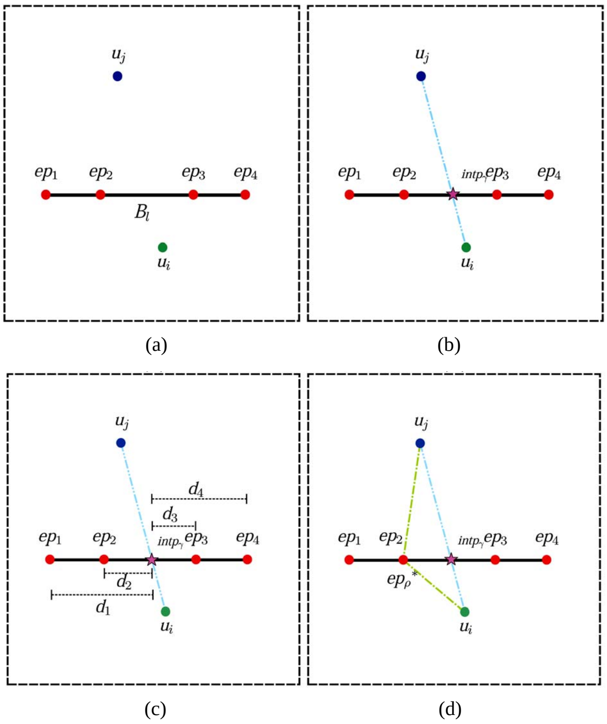


Figure 3.
The shortest permitted distance from u_j and u_i: (a) a B_l with four ep_ρ, (b) the intersection point $intp_\gamma$, (c) distances from $intp_\gamma$ to all ep_ρ, and (d) the shortest permitted distance.

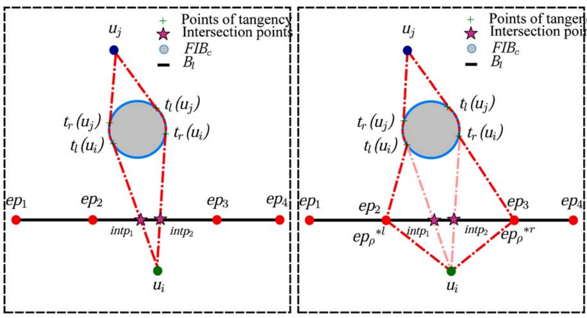


Figure 4.
(a) Presence of fixed and line barrier between a demand point and a facility (b) Permitted path in presence of fixed and line barrier.

center of B_c, that passes through the $u_i \in B_c$, and intersects the boundary of B^c at a point $u_i^* \notin B_c$. u_i^* is the nearest feasible location of the $u_i \in B_c$. Move the $u_i \in B_c$ to $u_i^* \notin B_c$.

The objective functions are utilized in the process of evaluating each solution.

In this step, for the distance measure the following steps are followed:

Step 1: If $u_i \in B_{l\{\wp\}}$ of a B_l, calculate the distances from $u_i \in B_{l\{\wp\}}$ to all ep_ρ of the B_l. Draw a straight line from the nearest ep_ρ to $u_i \in B_{l\{\wp\}}$ and extend so that it intersects the boundary of $B_{l\{\wp\}}$. Move $u_i \in B_{l\{\wp\}}$ to the intersection point. The intersection point is the new location of $u_i \notin B_{l\{\wp\}}$ and is denoted by $u_i^* \notin B_{l\{\wp\}}$.

Step 2: Check whether there is a B_k in between u_j and $u_i \notin B_k$.

Step 3: If there is no B_k or only a FIB_c exists in between u_j and u_i, the distance between u_j and u_i is unconstrained. Calculate all the unconstrained distances between u_i and u_j in ξ^2 using Euclidean metric, $d(u_j, u_i)$.

Step 4: Calculate the distances between u_j and u_i in ξ^2 that are separated by a FIB_c using Equations (11) and (12).

Step 5: Calculate the distances between u_j and u_i in ξ^2 that are separated by a B_l using Equation (13).

Step 6: Calculate the distances between u_j and u_i in ξ^2 that

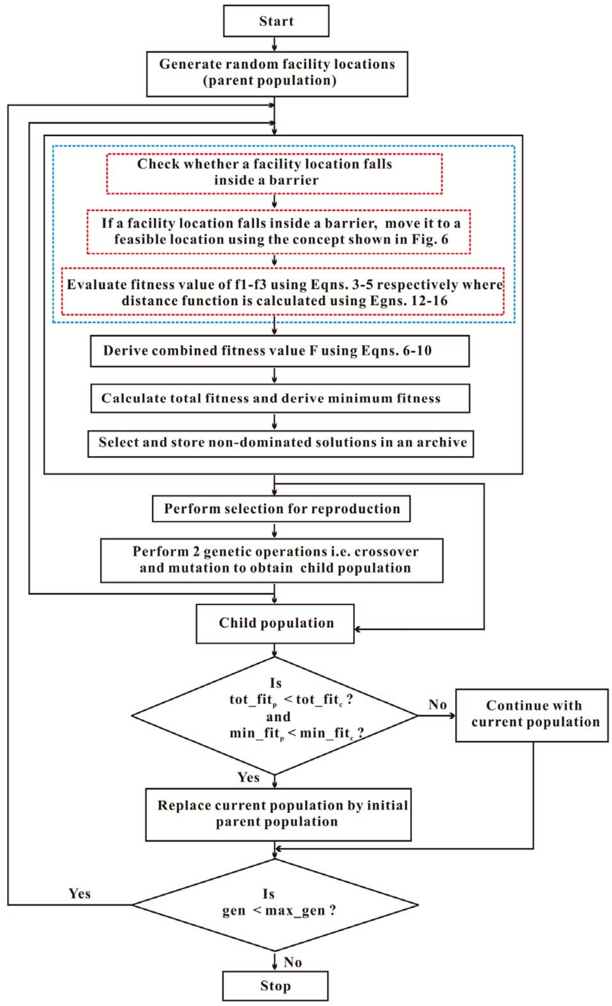


Figure 5.
Flow chart showing the genetic algorithm of multi-objective facility (POS) location problem with barriers.

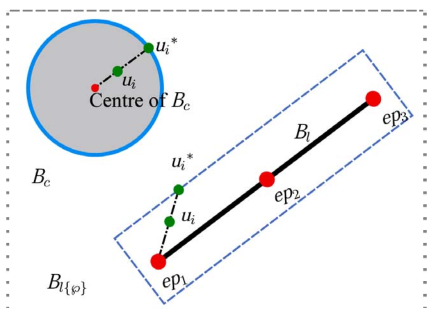


Figure 6.
Relocation of a facility to a feasible location.

are separated by both of FIB_c and B_l using Equations (14) and (15).

The non-dominated solutions are sorted from the obtained solutions to store it in an archive. The selection process for reproduction saves the better solutions. Therefore, the stronger (having better fitness) chromosomes survive, while weaker chromosomes die out. We follow roulette wheel selection method. For the reproduction process, genetic operations are performed in the parent chromosomes. This will generate offspring chromosomes. In our GA, a single-point crossover operation is carried out, where two parent chromosomes interchange their genetic material (bits) after a randomly decided single point. The mutation operation is performed to bring diversity of the solutions in the offspring population. Mutation is a random change of one or more bits. In the reproduction process to perform the next generation, we choose the better one between the parent and the offspring population. The total fitness and the minimum fitness of both population are compared for this selection.

Figure 5 shows the GA process used for multi-objective POS location problem with barriers. The GA process continues until the prefixed number of generations has been reached. After finishing the GA cycle, final sorting of non-dominated solutions is performed among the solutions stored in the archive.

Next, we present a case study applying the multi-objective model with barriers to find the approximate optimal locations of some new POS in Dhaka city.

A Case Study on Dhaka City

In our previous research, we showed 0.22 acres per 1000 people open space is available in Dhaka city. This is far below the recommended standards in different countries in the world (Neema & Ohgai, 2010). As noted parks and green areas in Dhaka city have been diminished significantly during the last four decades. The continuous growth of population is presumebly the underlying mainstay of such depletion. In contrary, a well distributed optimized green space is regarded as one of the main ingredients of an environmentally friendly city. The optimal locations were obtained simultaneously optimizing three multiple objectives i.e. POS near: a) populated areas, b) air quality degraded area, and c) noise pollution areas including a constraint (barrier).

The prime objective of this case study is to locate some new parks and open spaces in Dhaka city. For modelling purpose, we assume there are some demand generating points in the problem space Dhaka. The centroids of city wards (a total of 90 wards) are considered as the demand points whose spatial coordinates and demands are known. As the model is formulated with continuous optimization scheme, any place could be a potential site for a POS. But the problem is that there are various constraints in reality especially many existing barriers of different types and sizes. Therefore, we need to incorporate these barrier constraints into the model to avoid unrealistic POS planning in any of such barriers. The required input data for the model was prepared employing ArcGIS 9.1 software. The following procedures and consideration were adopted:

1) We confined the problem space with the bounding rectangle of the city.

2) The centroids of 90 wards of the city is considered as the demand generating points. Three levels of demand (i.e. population, air quality, noise level) of each ward are assigned as the weights to each demand point. Details can be found elsewhere (Neema & Ohgai, 2010).

3) We consider the existing parks and open space, industrial areas and market areas of the city as fixed barriers FIB_c, the water bodies of the city as flexible barriers FLB_c and the lakes of the city as line barriers B_l. The total number of FIB_c, FIB_c and B_l are respectively 219, 119 and 6. We exclude the rivers from our barrier considerations as it passes mostly through the outside of the ward areas. To simply the model, we merge some small existing barriers.

4) We set the numbers of new POS in the problem space to be 30, each of which contains 50 acres of area. Details of these considerations can be found in ((Neema & Ohgai, 2010) where we estimated that the city needs 1505 acres of area for additional POS. For the sake of simplification of simulation, we assume the size of all new POS is to be equal.

Now, we represent the spatial distribution of existing barriers and different levels of demand for providing more POS. It can be observed that there exist different types and sizes of physical barriers in Dhaka, shown in **Figure 7(a)**. There are a big Industrial region, some existing POS and a lake in the central part, a large existing POS in the northern part, some small industrial regions in the southern part, some lakes in the eastern part, and market areas and small size water bodies throughout the city. Among these barrier regions, we represent the elongated shaped barriers using line shapes B_l whose exit points are denoted by ep_ρ and non-elongated shapes using circular shapes B_c. We included the barriers in the coding of the model to restrict placing new POS locations within these regions.

The calculated ward-wise population distribution (required for objective function f_1) is presented in **Figure 7(b)**. Specifically many highly populated areas are devoid of sufficient numbers of POS. POSs are mostly concentrated in a few places and extensive areas are lack of it.

Depicted in **Figure 7(c)** is the ward-wise air quality distribution (required for objective function f_2) in the city. For air quality data we considered the concentration of SO_2 in the air. An area is considered to be polluted when the average SO_2 concentration is above 40 ppb level.

Evidently, there are significant spatial variations and extremely high concentrations of SO_2 in the central and the south-eastern industrial-zone of the city. The maximum level of SO_2 is 100 ppb which also agrees well with a previous report (Azad & Kitada, 1998). Reportedly, the air-pollution enclaves north-west to south-east regions including the regions that fall alongside the river (Buriganga).

Basically, Dhaka being the capital city and the hub of commercial activity, the air-pollution problem of it is more acute. The air quality of the city is being badly degraded day by day.

Noise level distribution (required for objective function f_3) of the city is presented in **Figure 7(d)**. As expected, the areas of the city with existing POS and lakes have less noise pollution. It reveals that POS and lakes do have a significant impact on reducing noise level. So, noise level is considered as another objective function in the model to reduce noise level of the city by providing more POS (i.e. green areas) near noise polluted areas.

Next, we present modeling results to show the effective implementation of the multi-objective model with barriers.

Results

The genetic algorithm (GA) of the model was coded in C++

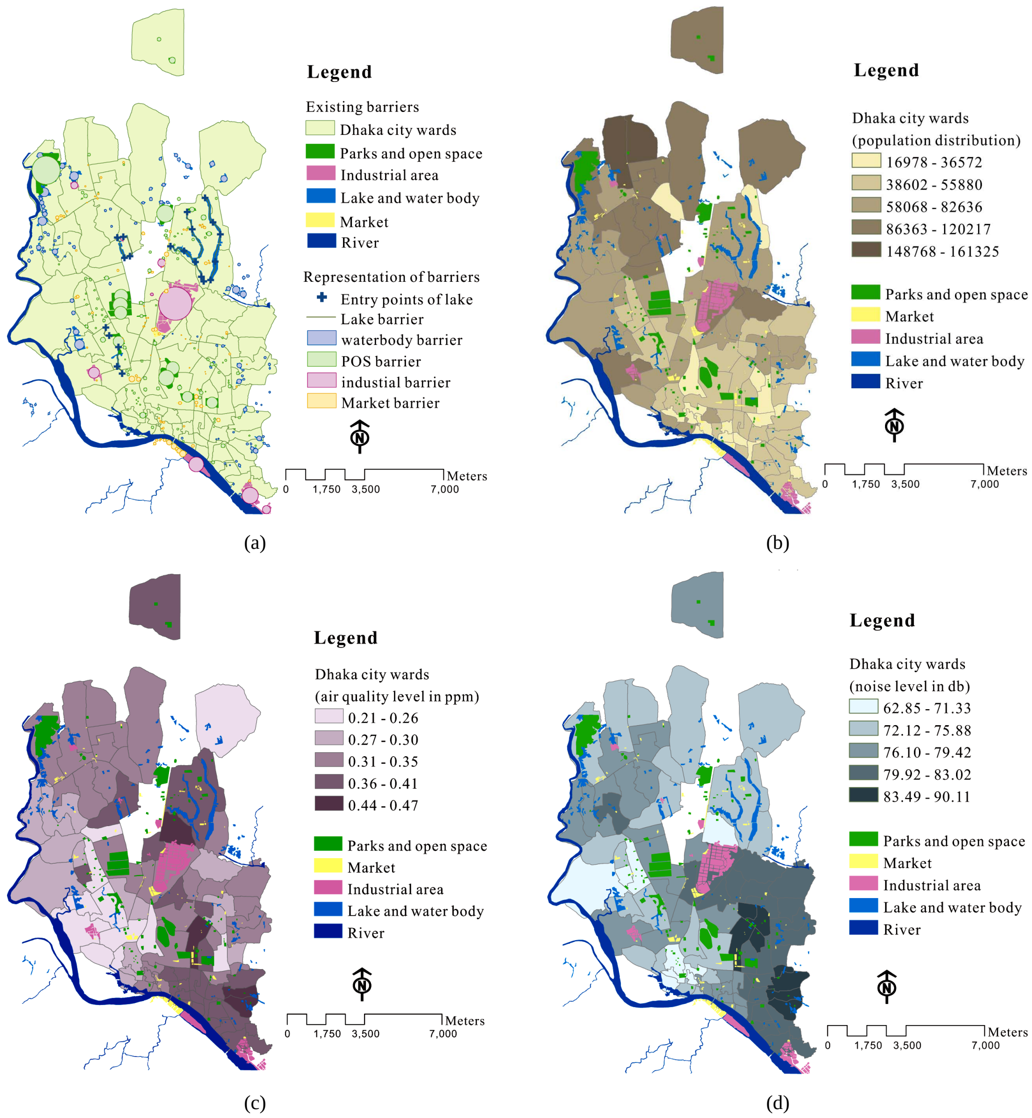


Figure 7.
Ward wise distribution of: (a) barriers, (b) population (c) air quality and (d) noise level.

programming language. The parameters of GA were set as follows: a population size of 100, a crossover rate of 0.25, a mutation rate of 0.009 and the maximum generation of 100. The model parameters have empirically been shown to give better results.

Using different rand seed generators ten independent simulations were conducted.

Multi-objective optimization does not restrict to find a unique single solution of a given problem for multiple objectives optimization. Instead, it generates a pool of non-dominated Pareto optimal solutions. Therefore, first we evaluated the Pareto-optimality of the model. The non-dominated Pareto-optimal solutions obtained from all iterations of each run are presented in **Table 1**. This table shows solutions from three objectives, compromise solutions and associated weight vectors.

Table 2 depicts the statistics of the results of **Table 1**. The table shows that the sum of the mean value of the non-dominated compromise solutions of three objectives is minimum in run 3. So, we considered the results obtained from run 3 as the best.

Next, we derive non-dominated solutions of each iteration from run 3. The results are plotted in **Figure 8** to delineate the Pareto front (i.e. trade off surface). City planners can use these solutions as a candidate pool for decision making. **Figure 8(a)** shows all non-dominated compromise solutions. The lower bound of non-dominated compromise solutions is presented as a close-up view in **Figure 8(b)**.

From the alternative solutions presented in **Table 1**, the decision makers may choose a desirable weight vector based on existing barriers and objective factors. For the POS location planning in Dhaka city, we selected three weight vectors (shown in red italic font) from the obtained results of **Table 1** to derive minimum weighted distances and minimum POS location points.

The underlying reasons to select such weight vectors are to investigate the effects on POS locations with real world barriers if more priority is given to population or air quality or noise

Table 1.
Non-dominated solutions.

Run	Soln	Solutions from three objectives			Compromise solutions from three objectives			Weight vectors		
		f_1	f_2	f_3	f_1w_1	f_2w_2	f_3w_3	w_1	w_2	w_3
1	1	6887143.44	8469454.06	8452588.54	151391.00	8132368.38	150612.32	0.02	0.96	0.02
	2	11842043.58	13434643.41	13422661.71	11371606.23	316951.25	216560.45	0.96	0.02	0.02
	3	6909749.51	8504027.03	8496442.61	2863896.52	3246983.42	1730818.95	*0.41*	*0.38*	*0.20*
2	1	7076954.88	8662485.56	8663683.67	18817.68	16584.21	8624060.36	0.00	0.00	1.00
	2	7014950.12	8591020.86	8587052.83	62189.27	103579.68	8407394.63	0.01	0.01	0.98
	3	7038883.26	8621309.42	8615972.75	62827.83	91546.68	8447578.09	0.01	0.01	0.98
	4	7056233.26	8636960.17	8623082.33	237441.24	6839020.09	1504885.67	0.03	0.79	0.17
3	1	260121.49	238324.36	234548.99	242128.17	8537.66	7821.98	0.93	0.04	0.03
	2	252678.84	230654.18	233047.35	36937.53	**171125.71**	26078.39	0.15	0.74	0.11
4	1	6946966.18	8574622.74	8556127.92	110812.71	14455.98	8405222.28	0.02	0.00	0.98
	2	11885792.30	13500370.53	13486573.06	11217015.78	418665.31	340610.03	0.94	0.03	0.03
5	1	6830041.59	7723299.86	7728392.79	19086.23	7505877.22	195969.39	0.00	0.97	0.03
	2	11657667.16	13242989.67	13242422.38	23588.97	12946438.17	269743.12	0.00	0.98	0.02
	3	6824074.53	7719164.83	7717566.85	2147330.01	1913605.10	3375872.85	0.31	0.25	0.44
6	1	6990346.96	8569324.44	8566024.27	47486.08	7153635.50	1356953.93	0.01	0.83	0.16
	2	6926747.86	8524046.41	8516424.34	2067824.33	3727936.95	2249434.47	*0.30*	*0.44*	*0.26*
	3	6953959.36	8561869.73	8541657.30	2725823.70	2221344.63	2977384.73	0.39	0.26	0.35
7	1	10223703.84	13466379.77	11818530.02	111727.45	28756.24	11664136.46	0.01	0.00	0.99
	2	7001226.37	8557396.71	8556553.17	6720984.04	30709.77	311791.59	0.96	0.00	0.04
	3	6922733.62	8522394.43	8516101.67	6861294.59	52277.80	23340.92	0.99	0.01	0.00
	4	6945123.53	8544967.36	8531930.04	360008.84	7350838.03	750044.55	0.05	0.86	0.09
8	1	7020172.51	8597104.03	8591444.32	692299.02	18403.96	7725801.44	0.10	0.00	0.90
	2	7016226.55	8591482.48	8571351.86	1933874.32	2700387.75	3514779.67	*0.28*	*0.31*	*0.41*
9	1	11901581.45	13501056.83	13488040.56	11730930.92	142255.32	51279.75	0.99	0.01	0.00
	2	11860811.64	13478017.09	13470729.03	65762.92	13014960.46	388117.04	0.01	0.97	0.03
	3	11846746.97	13462899.30	13456584.37	10536650.74	712658.72	775798.89	0.89	0.05	0.06
	4	15133743.99	18387667.69	20027924.57	887261.51	1219814.70	17525099.65	0.06	0.07	0.88
10	1	271047.44	227856.62	217396.43	**3360.09**	**2474.95**	**212340.10**	0.01	0.01	0.98
	2	287367.02	248577.00	237935.77	257234.78	23157.82	2782.60	0.90	0.09	0.01
	3	268483.57	222464.32	217592.01	165940.79	34645.75	49218.64	0.62	0.16	0.23

level. The adopted criteria for these selections include: 1) all the three objectives are important for POS planning in the problem space, the weight of each objective should not less than 20% of total weight and 2) more priority will be given to one objective with respect to others.

The model was executed three times by fixing each weight vector in each run to find a minimum solution. It can be observed that minimum solution with iterations does not alter after 93, 27 and 43 iterations by using the weight vectors v_1, v_2 and v_3 respectively. So, the minimum solution obtained using each weight vector after 100 iterations is taken as the optimum solution.

The distribution of new 30 POS locations with barriers employing a weight vector v_1 or v_2 or v_3 was plotted in GIS environment and is shown in **Figures 9(a)-(c)**. New POS locations are marked with red color and ward numbers (with black color).

Discussion

From the developed multi-objective continuous optimization model for open spaces in urban planning, one can find that not a single sitting of open spaces fall within barriers interior that

Table 2.
Non-dominated solutions.

	1	2	3	4	5	6	7	8	9	10	Avg
ε_a											
ε_1	4795631.25	95319.01	139532.85	5663914.25	730001.74	1613711.37	3513503.73	1313086.67	5805151.52	142178.56	2381203.09
ε_2	3898767.68	1762682.67	89831.69	216560.65	7455306.83	4367639.02	1865645.46	1359395.86	3772422.30	20092.84	2480834.50
ε_3	699330.57	6745979.69	16950.19	4372916.16	1280528.45	2194591.04	3187328.38	5620290.55	4685073.83	88113.78	2889110.26
Sum[b]	9393729.50	8603981.36	**246314.72**	10253391.05	9465837.02	8175941.44	8566477.57	8292773.08	14262647.66	250385.18	7751147.86
Min[c]	7841698.88	8573163.59	234141.63	8530490.98	7436807.97	7924553.05	6936913.31	8149041.74	11924466.00	**218175.14**	6776945.23
Min-max[d]	3246983.42	8407394.63	**171125.71**	8405222.28	3375872.85	2977384.73	6861294.59	3514779.67	11730930.92	212340.10	4890332.89
Num[e]	3	4	2	2	3	3	4	2	4	3	3

[a]Mean value of all non-dominated compromise solutions after a run; [b]Sum of the mean values of the three objectives; [c]Minimum non-dominated aggregated compromise solutions; [d]Maximum of the minimum non-dominated aggregated compromise solutions; [e]Total number of non-dominated solutions in each run.

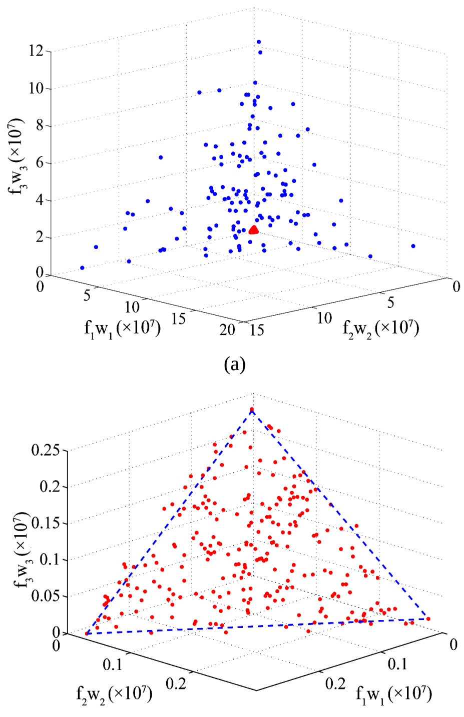


Figure 8.
Pareto-front (trade-off surface) of non-dominated compromise solutions from all iterations of run 3: (a) all solutions and (b) solutions in lower bound.

demonstrates the successful implementation of the model.

With assigned higher priority to degraded air quality, a significant number of new locations of open spaces are found within the wards 60 - 80 (see in **Figure 9(b)**). The distribution of locations of most of the open spaces in these areas (with no large barriers) can be attributed to those wards which have degraded air quality and possess moderately high population. However, some locations of open spaces deviated from the expected results: the locations marked "6", "9", "15", and "27" distributed near existing open spaces and the locations marked "0", "4", "8", "10", "21" located near lake type barrier and water-body type barrier. From urban planning point of view these locations can also be justifiable to obtain an ideal ambience for a beautiful urban planning to rejuvenate city dwellers.

Evidently, when a higher priority was given to degraded sound quality, a significant number of locations of new open spaces were found preferably in the noisy wards as expected (see in **Figure 9(c)**). However, there are some exceptions: five locations of open spaces (marked "6", "9", "15", "22", and "27") are found near existing open spaces. The model also sitted five locations of open spaces marked "0", "4", "8", "19" and "25" near the lake type barrier. These results could be due to the combined effects of the degraded condition of sound quality (south-east part and center of the city) and air quality (east and south-east).

With an exception from the modelling results, a few number of open spaces were found to be located on the peripheries of circular barriers. Using the weight vector, $v_1 = [0.41\ 0.38\ 0.02]^T$ two locations of open spaces marked "1" and "4" have shown to fall on the peripheries (see in **Figure 9(a)**).

Moreover, it can be observed that there are five new locations of open spaces marked "1", "18", "23", "26" and "28" near existing open spaces and five other locations marked "0", "5", "7", "14" and "19" are found near a lake. These results are expected because we are optimizing locations of open spaces using multiple objectives including barriers. We used continuous optimization scheme where locations of open spaces can be anywhere in the space based on weighted combined effects of air- and sound-quality, population density. Barriers are just used as constraints to optimize locations of open spaces in the model. In addition, no buffer region was considered for circular barriers during the optimization process. However, from the urban planning point of view such locations thus obtained can be accepted based on the fact that areas near to lakes are devoid of any open spaces and commercial areas (where air quality is in worst condition) have insufficient existing open spaces. The practical consideration for such locations would be that city planners can change the type of open spaces (for example, locate playground and/or neighborhood open spaces near an existing city park) thus obtained from simulation for locations of new open spaces. The locations of open spaces near lakes and water bodies, can effectively be planned in an integrated way (i.e. open spaces and lakes) by the city planners. This could bring a beautiful image and a better environment to rejuvenate city dwellers. However, details of different types of open

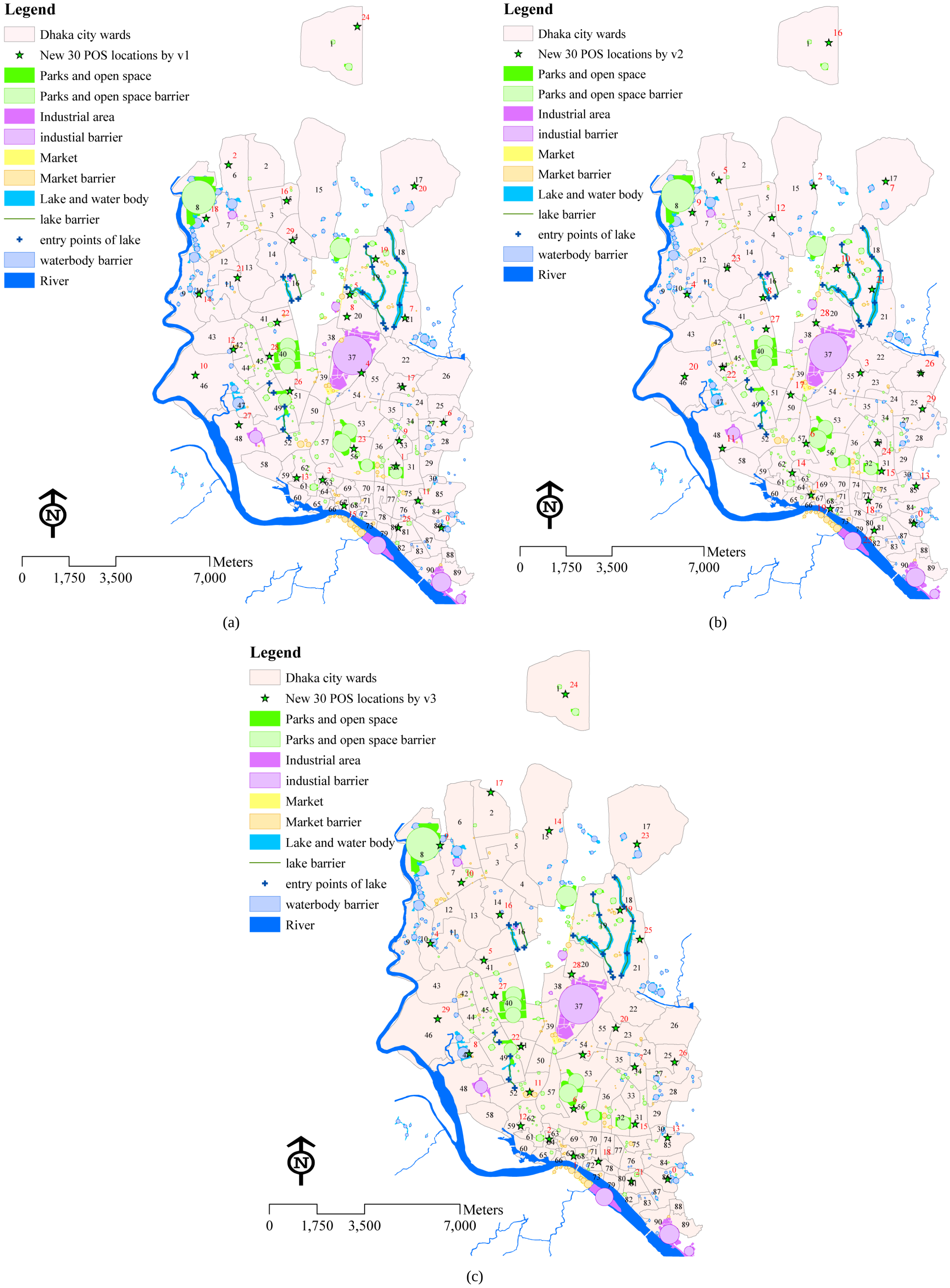


Figure 9.
New 30 POS locations found from the model by using: (a) $v_1 = [0.41\ 0.38\ 0.20]^T$, (b) $v_2 = [0.30\ 0.44\ 0.26]^T$ and (c) $v_3 = [0.28\ 0.31\ 0.41]^T$.

spaces are beyond the scope of this paper.

However, to prevent the sitting (from simulations) of some new open spaces on the peripheries of barriers a pre-determined buffer region can be used. Indeed, considering a buffer zone from line barriers, the model has shown well distribution of open spaces exterior to the existing lake type barriers. For instance, locations of open spaces marked "5", "7" and "19" in **Figure 9(a)**, location marked "21" in **Figure 9(b)** and location marked "9" in **Figure 9(c)** are completely outside to the peripheries of lake type barriers.

Conclusion

In this research, we developed an *intelligent multi-objective continuous optimization model* with a new approach for green urbanism in a city. This modelling approach seeks the optimum places for providing new parks and open spaces for greeneries throughout a city. Application of the model in Dhaka city has successfully demonstrated to provide optimal locations of additional POS. Adequate numbers of POS were found in environmentally degraded areas with air and noise pollution. In addition, the obtained locations of open spaces found near lakes and water bodies have shown to be planned in an integrated way (i.e. open spaces and lakes) by the city planners to bring a beautiful image and a better environment to rejuvenate city dwellers. As the developed powerful continuous optimization scheme in GA-based multi-objective model searches for a pool of non-dominated Pareto optimal solutions, city planners can choose an *alternative solution* which is best suited for the prevailing land-use pattern in a city (if it is necessary by averting locations from city centre and developed residential areas choosing an appropriate solution from the pool). This model could equally be applicable in any city for providing optimum locations of POS. Following our approach, a well-planned urban greening can thus be realized to maintain a healthy sustainable city. However, the scope of the present study is currently limited to site the optimal locations of POS (especially for the purpose of urban greeneries), in future study it would be an interesting research aspect to incorporate wetlands and water bodies to find out optimum locations for all ecological reserves.

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