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Efficient location and allocation strategies for undesirable facilities considering their fundamental properties

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ABSTRACT

The phrase "not in my backyard" (NIMBY) refers to the well-known social phenomena in which residents oppose the construction or location of undesirable facilities near their homes. Examples of such facilities include electric transmission lines, recycling centers and crematoria. Due to the opposition typically encountered in constructing an undesirable facility, the facility planner should understand the nature of the NIMBY phenomena and consider it as a key factor in determining facility location. We examine the characteristics of NIMBY phenomena and suggest two alternative mathematical optimization models with the objective of minimizing the total degree of NIMBY sentiments. Genetic algorithms are proposed to solve our linear and nonlinear integer programs. The results obtained via genetic algorithms for our linear integer programs are compared with those of CPLEX to evaluate their performance. The nonlinear programs are tested with various allocation policies. Sensitivity analysis is conducted about several system parameters.

1. Introduction

1.1. Background

Many facilities that improve human comfort and convenience are welcomed by their neighbors. Subway or bus stations are often embraced by people living in near-by areas because such facilities provide easy access to public transportation and may result in increased property value. Libraries and general hospitals are similarly accepted facilities on account of their usefulness and benefit. However, not all facilities are as warmly received. While facilities such as electrical substations or dumping grounds provide necessary services, they may cause unpleasant odors, health concerns and reduce property values. Therefore it is hard to newly construct or extend these facilities due to the extreme opposition. This resistance is often termed "not in my backyard" (NIMBY) phenomena. Though such facilities are beneficial to the general public, and fulfill essential life demands, we will hereafter refer to them as undesirable facilities.

We will consider two classes of undesirable facility. The first kind has a radius of service, but a customer within the radius of two facilities need not be allocated to the nearest. Examples here include landfills, garbage collection centers, garbage incineration plants and electrical substations. In the second, customers select their facility based on its nearness. This kind of facility is appropriate when considering individual travel distance, such as a hospital or mental wellness facility.

Undesirable facilities are commonly large and intended for public use and benefit. In general, one undesirable facility serves a wide region and, while serving the public good, is considered detrimental to adjacent private interests (e.g. home value). The community which hosts the undesirable facility bears most of the environmental, economic and psychological costs. The other nodes simply enjoy the benefits of the facility (Kunreuther & Kleindorfer, 1986). Therefore, new facility construction or expansion projects face strong opposition from residents who live in a candidate locale. People generally agree on the necessity of such undesirable facilities, but they do not want such facilities near their homes. NIMBY phenomena can cause various negative consequences. First, opposition to a facility may result in closure or withdrawal of a planned facility. Second, it instigates regionalism between candidates. Lastly, perhaps the greatest victims of the NIMBY phenomena are the residents themselves. If some essential facility is not located well due to extreme opposition, people have to travel excessive distances and spend additional time to obtain the service (Dear, 1992). Further details and insight about the NIMBY phenomena can be found in George and Rabe (1994) and Smith and Marquez (2000).

Academic research seeking to minimize the social costs caused by NIMBY phenomena by solving the undesirable facilities location

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problem may help to resolve some of the issues. Our research is motivated by this opportunity. In this research, we propose two mathematical optimization approaches to the facility location and customer allocation problems that depend on the characteristic of the undesirable facilities. The rest of the paper is organized as follows. In Section 1.2, we introduce related research in this field. Section 2 provides a detailed description of our research and the mathematical formulations. In Section 3, we develop algorithms to solve the resulting linear or nonlinear binary integer programs. We present numerical examples and sensitivity analysis in Sections 4 and 5. Concluding remarks and suggestions for further work are given in Section 6.

1.2. Literature review

NIMBY phenomena have been studied via qualitative methods. Erkut and Moran (1991) applied the Analytic Hierarchy Process to locate a landfill facility. They considered three factors to determine the site of the unpleasant facility: environmental, social and economic factors. Groothuis and Miller (1994) considered two dimensions of the NIMBY syndrome, tolerance and avoidance. They conducted surveys, and applied regression analysis to investigate the relationship between NIMBY phenomena and compensation. Dear (1992) studied NIMBY phenomena with a focus on community relationships. He investigated several factors to access community attitudes and suggested alternative approaches to community relations when locating undesirable facilities.

Several researchers proposed auction mechanisms for locating undesirable facilities. Kunreuther and Kleindorfer (1986) suggested a sealed-bid mechanism for the siting process of noxious facilities. They assumed that any community that decides not to use the facility can be excluded from the algorithm. Quah and Tan (1998) also propose a cost – benefit analysis and auction mechanism to evaluate the available conflict-resolution instruments. They suggested two alternatives based on compensation payments in their study.

Some research considers political approaches. Fredriksson (2000) offers a political economy explanation for siting hazardous waste treatment facilities in the US federal system. Feinerman, Finkelshtain, and Kan (2004) considered political factors such as lobbying and suggested a political approach in a real problem of landfill siting in the center and south regions of Israel.

Mathematical optimization approaches have been employed for various situations. They have focused on total distance from the facility, repulsion from neighborhoods, environmental effect, and so on. Church and Garfinkel (1978) deal with a location problem of an obnoxious facility so as to maximize the sum of its weighted distances to the nodes. Melachrinoudis and Cullinane (1986) proposed a minimax approach. They minimized the maximum weighted inverse square distance from the undesirable facility. Melachrinoudis (1999) also developed a maxmin–minisum bicriteria location model with rectilinear distances. Using this bicriteria location model, they tried to minimize the total transportation cost while preventing too close a placement because of the undesirable effect of semi-obnoxious facilities. Recently, Colebrook, Gutierrez, and Sicilia (2005) proposed a new bound based algorithm to maximize the total weighted distance to all nodes for the p-median problem (which requires that exactly p facilities be located). Fernandez, Fernandez, and Pelegrin (2000) considered a mathematical model to minimize the global repulsion of the inhabitants of the region.

Unlike the mathematical optimization papers mentioned previously, others have concentrated on multiple criteria optimization. Erkut and Neuman (1992) presented a three-objective mixed-integer programming formulation to minimize total cost for locating facilities, minimize total opposition and maximize equity. Opposition and disutility are assumed to be nonlinearly decreasing functions of distance, and increasing functions of facility size. This problem was solved by an enumeration algorithm. Recently, Erkut, Karagiannidis, Perkoulidis, and Tjandra (2008) also suggested other criteria for locating municipal solid waste management facilities in North Greece. They considered five objectives: minimize the greenhouse effect, minimize the final disposal to the landfill, maximize the energy recovery, maximize the material recovery and minimize the total cost (including the installation cost, transportation cost and treatment cost). They applied the lexicographic minimax approach to obtain a fair non-dominated solution. Various types of criteria have been considered in the undesirable facility location problem; see Banias, Achillas, Vlachokostas, Moussiopoulos, and Tarsenis (2010) and Colebrook and Sicilia (2007) for more.

Based on the survey article of Owen and Daskin (1998), location problems can be classified into four categories: median problem, covering problem, center problem and fixed charge facility location problem. Our study belongs to the fixed charge facility location problem which has a fixed charge associated with locating each potential facility. In our research, the objective is to minimize the total degree of NIMBY phenomena. Since compensation could play a role to help eliminate NIMBY phenomena (Groothuis, Groothuis, & Whitehead, 2008) minimizing the total degree of NIMBY phenomena can be interpreted as minimizing the total compensation cost, where the compensation cost for candidate location j has a fixed charge (of course, costs associated with construction can be included). In most fixed charge facility location research, the fixed charge is a constant F_j, to locate a facility at location j. However, the fixed charge can also possess a functional form such as the popular concave function. Concave fixed charges are used to reflect economies of scale such as occurring with construction costs (see Kelly & Khumawala, 1982; Soland, 1974 and Klincewicz, 2002). In our research, the degree of NIMBY phenomena caused by locating an undesirable facility at candidate location j is an increasing function of the number of nodes assigned to location j. We consider three classes of functions for the NIMBY phenomena: linear, convex and concave.

The fixed charge problem has been studied with maximum service distance and closest assignment constraints (see Nozick, 2001 and Guha, Meyerson, & Munagala, 2003). However, in the functional fixed charge problem, to our knowledge, none have included maximum service distance and closest assignment constraint. In this article, we will extend our functional fixed charge location problem to include maximum service distance and closest assignment to describe two classes of undesirable facility.

The contributions of this work are as follows. We, for what is to our knowledge the first time,

(1) Propose the use of the functional fixed charge problem for the minimization of costs associated with NIMBY phenomena.
(2) Illustrate how two classes of undesirable facilities can be formulated using maximum service distance and closest assignment constraints.
(3) Extend the *functional* fixed charge problem to include maximum service distance and closest assignment constraints.
(4) Develop and test genetic algorithms for our linear, convex and concave functional fixed charge problems. By having a simple chromosome and developing allocation methods, we improve the convergence rate of the proposed genetic algorithm.

(5) In the maximum service distance model, we propose an allocation method with fixed locations (chromosome). In the linear objective function case, we suggest an optimal allocation method. In the nonlinear objective function case, we suggest an allocation method based on random allocation order.

It is worth noting that while the functional fixed charge facility location problem is well known, none have yet sought to apply it in the NIMBY context.

2. Mathematical modeling

2.1. Problem description

In this study, we will propose a single criteria mathematical optimization model for locating and allocating undesirable facilities. We consider NIMBY phenomena directly through our objective function structure. Our objective structure allows us to address the fact that residents who host the plant in their locale absorb all of the environmental costs, while residents of other locations enjoy the benefits of the facility. The degree of NIMBY phenomena of those residents hosting the facility will be high because they absorb the negative effects directly for everyone. However, if undesirable facilities are located at each locale and cover only their regional demand, the degree of NIMBY phenomena at a given location will be less relative to a large facility and because they do not need to sacrifice for another location. The cost of NIMBY phenomena for a facility is a function of the total number of nodes served by that undesirable facility. Using this basic insight, we develop mathematical models with linear, convex and concave objective functions for representing the cost of NIMBY phenomena. Considering the properties of undesirable facilities, we suggest two alternative mathematical models in this research. Naturally, all of our cost structures may include construction costs as well.

2.2. Assumptions

1. There are no existing undesirable facilities; all undesirable facilities should be newly built. (This can easily be relaxed.)
2. There are demand nodes. Each demand node has its own demand quantity and two-dimensional location information.
3. All demand nodes are candidate nodes for locating an undesirable facility. (This can easily be relaxed.)
4. Each demand node is served by exactly one undesirable facility.
5. The maximum number of facilities is given; it is less than the total number of candidate nodes.
6. A facility located at a node will serve all of the demand for that node.

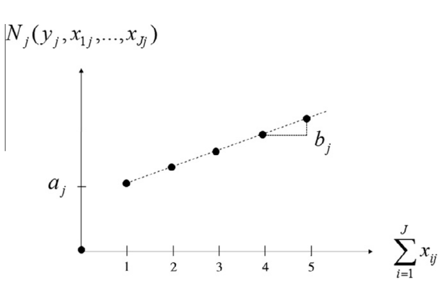

Fig. 1. Linear trend objective function.

2.3. Notation

i, j	Indices for nodes
J	Number of all nodes
d_{ij}	Euclidian distance between node i and node j
$N_j(y_j, x_{1j}, \ldots, x_{Jj})$	Total degree of NIMBY phenomena experienced by node j when an undesirable facility is located at j under allocation $x_{1j}, \ldots, x_{Jj}$
a_j	Basic degree of NIMBY phenomena at a node j when a facility located at node j serves only node j
b_j	Marginal degree of linear trend NIMBY phenomena at a node j when an additional node is served by the undesirable facility located at j
R	Maximum service distance restriction of an undesirable facility
K	Maximum number undesirable facilities to be located
β	Scaling parameter for convex objective function
γ	Scaling parameter for concave objective function
y_j	Binary location decision variable indicating that an undesirable facility is located at node j
x_{ij}	Binary allocation decision variable indicating that node i is assigned to the facility at node j

2.4. Objective functions

We consider three types of function to express the cost associated with the degree of NIMBY phenomena. These linear, convex and concave costs will serve as the objective functions as we develop mathematical programs to minimize the cost associated with the installation of NIMBY facilities.

2.4.1. Linear trend

If the degree of NIMBY phenomena increases by a constant for each additional node served by an undesirable facility located at j, the cost associated with the NIMBY phenomena due to the facility at locale j has the linear form:

$$N_j(y_j, x_{1j}, \ldots, x_{Jj}) = a_j y_j + b_j \left(\sum_{i=1}^{J} x_{ij} - y_j \right) \tag{1}$$

This linear trend objective function model will be solved by our genetic algorithm and compared with the result of Cplex in the sequal. Fig. 1 depicts a linear trend objective function.

2.4.2. Convex trend

As is often done in the literature (cf. Ko & Hwang, 2009), we will use an exponential function for our convex cost associated with the NIMBY phenomena due to the facility at locale j:

$$N_j(y_j, x_{1j}, \ldots, x_{Jj}) = a_j y_j e^{\beta\left(\sum_{i=1}^{J} x_{ij} - 1\right)} \tag{2}$$

Fig. 2 depicts a such a convex cost term. We will solve the resulting program via genetic algorithm. Numerical examples and various sensitivity analyses will be conducted in Sections 5 and 6.

2.4.3. Concave trend

As often done in the literature (cf. Shepard, Olivera, Reckwerdt, & Mackie, 2000), we will use a logarithmic function for our concave objective function:

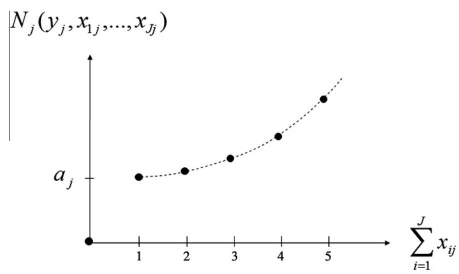

Fig. 2. Convex trend objective function.

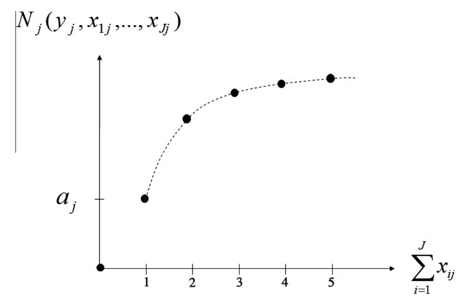

Fig. 3. Concave trend objective function.

$$N_j(y_j, x_{1j}, \ldots, x_{Jj}) = a_j y_j \left(1 + \gamma \ln\left(\sum_{i=1}^{J} x_{ij}\right)\right) \tag{3}$$

Fig. 3 depicts such a concave objective function. Such a function may be used to express economies of scale. We will solve the resulting program via a genetic algorithm; numerical examples and sensitivity analyses will be conducted.

2.5. Mathematical model with maximum distance restriction

We first consider a mathematical program in which a maximum distance restriction is imposed. That is, there is a given service radius for a facility, and nodes outside are not eligible to receive service from that facility. We will use this to model facilities that address daily demands, e.g. landfill, garbage collection center, garbage incineration plant and electrical substation. The maximum distance restriction is a key factor for locating the undesirable facilities.

We allow the three types of objective functions suggested in Section 3.4. The following mathematical program seeks to minimize the cost of locating and allocating customer nodes to NIMBY facilities, subject to a maximum service radius condition

$$\text{Minimize} \quad \sum_{j=1}^{J} N_j(y_j, x_{1j}, \ldots, x_{Jj}) \tag{4}$$

$$\text{Subject to} \quad \sum_{j=1}^{J} d_{ij} x_{ij} \leqslant R \quad \forall i \tag{5}$$

$$\sum_{j=1}^{J} x_{ij} = 1 \quad \forall i \tag{6}$$

$$\sum_{i=1}^{J} x_{ij} \leqslant M y_j \quad \forall j \tag{7}$$

$$x_{jj} = y_j \quad \forall j \tag{8}$$

$$\sum_{j=1}^{J} y_j \leqslant K \tag{9}$$

$$x_{ij}, y_j \in \{0, 1\} \quad \forall i,\ j \tag{10}$$

Here, M is a large non-negative number. The objective function (4) can use the linear, convex and concave functions. (We allow only one type at a time, however.) The constraints (5) impose the maximum service radius restriction. Each node i is assigned to one and only one facility by (6). A node i can only be assigned to a facility at node j if such a facility exists; constraint (7) ensures this. Constraint (8) requires that, if a facility is located at node j, node j will be served by that facility. Constraint (9) restricts the maximum number of undesirable facilities that can be established. All location and allocation decision variables are restricted to be binary variables in (10).

2.6. Mathematical model with closest assignment restriction

For certain classes of facilities, customers may generally wish to use the nearest facility. In this case, the nodes should be assigned to the nearest facility. The following program will suffice to minimize the total cost associated with the NIMBY phenomena:

$$\text{Minimize} \quad (4)$$

$$\text{Subject to} \quad \sum_{k=1}^{J} d_{ik} x_{ik} \leqslant d_{ij} + M(1 - y_j) \quad \forall i, j \tag{11}$$

$$(6), (7), (9), (10)$$

Here, constraint (11) enforces the restriction that each node will be served by the closest open facility. Constraint (8) is removed; it is implied by (11).

Note that closest assignment constraints have been used since they were introduced by Rojeski and Revelle (1970). In their paper, they located public facilities such as medical clinics and surplus food distribution warehouses. They used closest assignment for minimizing total population distance. Dobson and Karmarkar (1987) also used closest assignment constraints. They located facilities on a network in the presence of competition; customers are assumed to visit the closest facility.

3. Solution procedure

3.1. Genetic algorithm

Genetic algorithms were first introduced by Holland (1975) and currently enjoy wide use as an alternative procedure for generating optimal or near-optimal solutions for location problems. They are inspired by genetic mutation in the theory of the evolution of life and employ a "chromosome" representing the problem solutions that are subject to random mutation and evolution based on the quality of a chromosome. In 2006, Arostegui, Kadipasaoglu, and Khumawala (2006) suggested a genetic algorithm for a location problem, and showed an empirical comparison with tabu search and simulated annealing. Jia, Ordonez, and Dessouky (2007) applied their genetic algorithm on a large-scale emergency problem and showed that it generates good solutions in a reasonable time.

Genetic algorithms can also be used as a tool to solve nonlinear problems. Gallagher and Sambridge (1994) introduce and recommend genetic algorithms as a powerful tool for large-scale nonlinear optimization problems. Deb (2001) also solved a multi-objective nonlinear problem using genetic algorithms. See Practical Genetic Algorithms (2004) for more information about genetic algorithms and applications.

The overall procedure of proposed genetic algorithm is as follows;

STEP 1: Set generation index $i = 0$ and current best fitness value = ∞.
STEP 2: Generate initial population (set of chromosomes) of ith generation.
STEP 3: For each chromosome, allocate the non-established nodes to the facilities using our allocation algorithm.
STEP 4: Calculate fitness value of each chromosome using fitness function in Section 4.1.3. If the best fitness value of ith generation is smaller than the current best fitness value, update the current best fitness value and save the corresponding chromosome.
STEP 5: If i is less than the predetermined number of generations, create the next generation of the population by selection, crossover and mutation operations. Otherwise, go to STEP 7.
STEP 6: $i \leftarrow i + 1$ and go to STEP 3.
STEP 7: Finish the GA process.

3.1.1. Chromosome structure

In our proposed genetic algorithm, a chromosome is a binary J-tuple. That is, a chromosome $c = (c_1, \ldots, c_J)$ is an element of $C = \{0,1\}^J$; refer to Fig. 4. Its length J is thus the number of nodes in our system. Each element of such a vector is called a gene.

The jth binary element c_j of this vector will indicate whether an undesirable facility will be established at node j or not. If $c_j = 0$, no undesirable facility will be located at node j. If $c_j = 1$, an undesirable facility will be established at the node j.

3.1.2. Initial population

The initial population P is composed of m chromosomes, $P = (c^{(1)}, c^{(2)}, \ldots, c^{(m)})$. In each such chromosome, the individual binary gene values c_i, $i = 1, \ldots, J$, are generated randomly with equal probability of 0.5.

3.1.3. Fitness function

A fitness function is used to evaluate the quality of each chromosome with respect to the original objective function of the mathematical program. Our fitness function, which depends on the chromosome and an allocation X (to be derived from C later), is

$$FF(c) = \sum_{j=1}^{J} N_J(c_j, x_{1j}, \ldots, x_{Jj}) + \sum_{i=1}^{J} p_1 \left| 1 - \sum_{j=1}^{J} x_{ij} \right| + p_2 \left\{ \sum_{J=1}^{j} c_j - K \right\}^{+} \tag{12}$$

where $\{\cdot\}^+ = \max\{\cdot, 0\}$ and p_1, $p_2 > 0$ are penalties. The first of the three terms enables $FF(c)$ to characterize the objective function of our mathematical program. The second term penalizes infeasible solutions that do not assign exactly one facility to each node as in constraint (6). The third term penalizes locating more than K facilities in violation of constraint (9).

Here, an allocation X must also be given. This will be determined for a given chromosome by a method described in Section 4.2. With the allocation x_{ij}, for a given chromosome c, $FF(c)$ may be obtained.

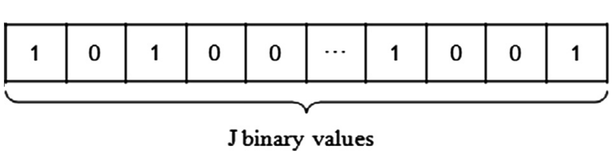

Fig. 4. An example of our chromosome structure.

3.1.4. Selection

To generate a new chromosome (new candidate solution), genetic algorithms typically select two existing chromosomes at random and then apply a crossover and mutation scheme to generate a new candidate solution. The procedure we use to select the chromosomes that will be subject to crossover and mutation is now described.

While it is important to randomly select the chromosome, it may be beneficial to select chromosomes with a small fitness function value. This may increase the probability of generating a good child. We therefore increase the probability of selecting a chromosome with small fitness function value using the roulette wheel selection scheme. The details follow.

Let $P = \{c^{(1)}, c^{(2)}, \ldots, c^{(M)}\}$ denote a population of M chromosomes and use $FF_{MAX}(p) = Max\{FF(c^{(1)}, x^{(1)}), \ldots, FF(c^{(M)}, x^{(M)})\}$, where $x^{(m)}$ is the allocation we will derive from $c^{(m)}$ in Section 4.2. $FF_{MAX}(p)$ is the maximum value of the fitness function over all chromosomes in the population P. Select a chromosome as follows:

STEP 1: Let $G(C^{(m)}) = [FF(c^{(M)}, x^{(M)}) - FF_{MAX}(p)]^2$.
STEP 2: Select a single chromosome from the population P, where the probability of selecting chromosome $c^{(m)}$ is $G(C^{(m)}) \Big/ \sum_{m=1}^{M} G(c^{(m)})$.

Let c^s denote the selected chromosome. Repeat this procedure again using population P to obtain a second chromosome. These two are the parents we will use for crossover.

3.1.5. Crossover

Crossover is a genetic algorithm operator that seeks to generate a good child (new chromosome). The crossover operator combines two parent chromosomes selected via the previously described procedure. The crossover, to be detailed next, is applied with predetermined probability p_x (we use $p_x = 70\%$ here). Otherwise the chromosome in the same index as in the previous population is copied as its own child.

We use a two-point crossover scheme. The overall procedure follows. For convenience, let $c^{(1)} = \{c_1{}^{(1)}, \ldots, c_J{}^{(1)}\}$ and $c^{(2)} = \{c_1{}^{(2)}, \ldots, c_J{}^{(2)}\}$ denote our selected parent chromosomes.

STEP 1: Generate two random integers uniformly within $\{1, \ldots, J\}$. Call them R_1 and R_2 with $R_1 \leqslant R_2$.
STEP 2: Create a child, denoted as $c^{(x)}$, as follows:

$$c(x) = \left\{ c_1^{(1)}, \ldots, c_{R1}^{(1)}, c_{R1+1}^{(2)}, \ldots, c_{R2}^{(2)}, c_{R2+1}^{(1)}, \ldots, c_J^{(1)} \right\} \quad \text{for } R_1 < R_2. \quad \text{If } R_1 = R_2, c^{(x)} = c^{(1)}$$

If the same chromosome was picked twice in the selection stage as parents, the result of crossover operation will be the parent itself. Fig. 5 shows an example of our two point crossover mechanism with $R_1 = 5$ and $R_2 = 14$.

3.1.6. Mutation

The child $c^{(k)}$ is now subject to a process called mutation. Each gene of the child, $c_j^{(k)}$, will remain unchanged with probability $1 - p_m$ Otherwise, with probability p_m the gene $c_j^{(k)}$ will be replaced with a 0 or a 1, each equally likely. All gene mutations are independent. Here, we use $p_m = 0.03$.

3.2. Allocation method

The chromosome of the proposed genetic algorithm describes the location of undesirable facilities. However, a solution to our problem also requires an allocation of nodes to the established facilities. The following algorithm is used in our genetic algorithm

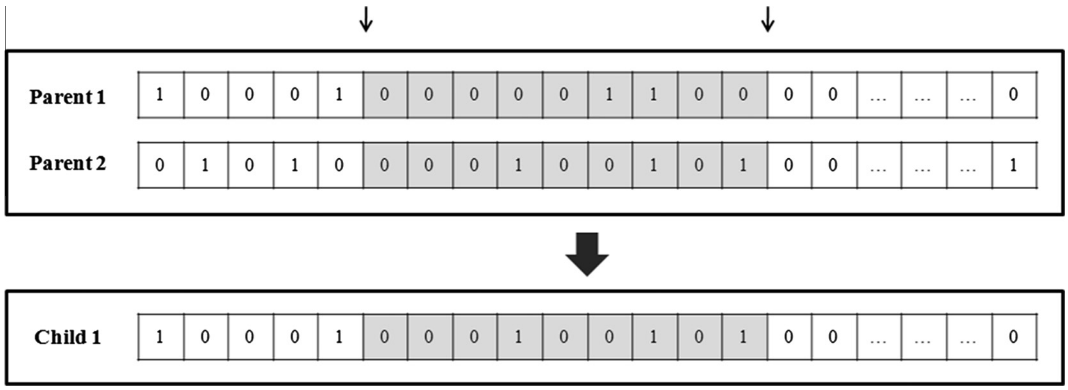

Fig. 5. An example of the two point crossover scheme.

Table 1
Parameters of proposed mathematical model.

Basic degree of NIMBY phenomena when located undesirable facility serve only that node	a_j	Rand (30,55)
Linear slope of degree of NIMBY phenomena in linear mathematical model case	b_j	Rand (35,45)
Maximum distance restriction of undesirable facility*	R	$200\sqrt{5}$
Parameter for determining number of random order assignments	α	0.2
Scaling parameter for convex mathematical model	β	0.5
Scaling parameter for convex mathematical model	γ	3
X-coordinate		Rand (0,1000)
Y-coordinate		Rand (0,1000)
Number of population		150
Number of generation		150
Crossover probability		0.7
Mutation probability		0.03

* R is a 10% of max Euclidean distance.

to obtain an allocation x for a given chromosome c (note that $y = c$ in the notation of our location problem).

Throughout, nodes on which a facility is located are assigned to that facility. Hereafter, we only address the allocation of nodes without a co-located facility.

3.2.1. Mathematical model with maximum distance restriction

For the maximum distance restriction model, we develop an efficient method to generate a good allocation among fixed facility locations.

3.2.1.1. Linear trend. For the linear objective function, each non-established node selects that undesirable facility within the maximum distance restriction whose linear cost slope b_j is smallest. Precisely $x_{ij} = 1$ if $j = \operatorname{argmin}\{b_k : d_{ik} \leqslant R\}$; otherwise, $x_{ij} = 0$. In the case where multiple nodes achieve the minimum, the closest is selected (arbitrarily if there is more than one closest). Nodes that are not within a range R of an established facility are not assigned. In this case, by the fitness function in formulation (12), a penalty will be charged to induce evaluation away from such infeasible situations. Note that assignment is independent of the order in which the nodes are assigned (we will use an order dependent approach later for our other cost functions).

Lemma 1. *For the linear objective function, ignoring nodes not covered in the radius R of any facility, the proposed assignment algorithm guarantees an optimal assignment with fixed locations.*

Proof. Let P_1 be the set of established undesirable facilities given in the vector y. Let P_2 be the set of non-established nodes, with $P_1 \cup P_2 = \{1, 2, \ldots, J\}$, $P_1 \cap P_2 = \emptyset$. Since we ignore isolated nodes, assume that every location in P_2 is located within a distance R from at least one undesirable facility in P_1. Let S_j, $j \in P_2$ be the set of undesirable facilities that can serve $j \in P_2$. Let l_j denote the marginal cost associated with the allocation of $j \in P_2$, $l_j = min_{k \in sj}\{b_k\}$. Therefore, the total cost associated with the NIMBY phenomena is

$$\sum_{j=1}^{J} N_j(y, x) = \sum_{j \in p_1} a_j + \sum_{j \in p_2} l_j = \sum_{j=1}^{J} \left\{ a_j Y_j + l_j \sum_{i=1}^{J} (x_{ij} - 1) \right\} \tag{13}$$

The term $\sum_{j \in P1} a_j$ is the basic degree of NIMBY phenomena caused by the fixed location of the facilities. The term $\sum_{j \in P2} l_j$ is the sum of minimum possible slope values. As a result, proposed assignment method guarantees an optimal assignment with fixed locations.□

3.2.1.2. Convex and concave trend. For convex and concave $N_j(y_j, x_{1j}, \ldots, x_{Jj})$, we expect that the allocation order will affect the overall cost; unlike the linear model. Therefore, two allocation methods are suggested. In the first, each non-established node is allocated to an available facility in order from node 1 to node J. In the second, a non-established and not yet assigned node is selected at random. It is then assigned a facility and the procedure repeats.

For each non-established and not yet assigned node (once it is determined that it is their turn for allocation), all facilities within a radius R are polled to determine how much their cost will increase if our node is assigned to them. We then assign our node to that undesirable facility which will provide the smallest increase (or any nearest in the event of ties; each equally likely). These procedures are repeated until every non-established node is assigned. In our algorithm, each chromosome generates $\alpha \cdot J$, $0 < \alpha \leqslant 1$, random order allocations using the method above. The best of these allocations is selected as the final allocation. (The constant α will be specified later).

3.2.2. Mathematical model with closest assignment restriction

In the closest assignment restriction model, the closest assignment restriction dictates that every non-established node is assigned to the closest open undesirable facility. If there are more than two facilities of equal distance, the non-established node is assigned to an undesirable facility which will provide the smallest cost increase. This procedure is conducted from smallest to largest node number.

Table 2
Result of linear mathematical model with maximum distance restriction.

J	K	Cplex			Genetic algorithm			Gap (%)
		Average solution value	Standard deviation	Average CPU time (second)	Average solution value	Standard deviation	Average CPU time (second)	
10	3	379.65	12.46	0.08	379.65	12.46	0.72	0.00000
30	9	1058.95	14.88	0.17	1058.95	14.88	3.2	0.00000
50	15	1748.6	15.09	0.23	1748.7	15.15	7.68	0.00570
100	30	3459.8	17.89	0.25	3460.05	17.88	27.82	0.00720

4. Numerical example

In order to evaluate the proposed mathematical models, example problems are solved with the parameters shown in Table 1 for the cases of nodes 10, 30, 50 and 100 nodes.

4.1. Mathematical model with maximum distance restriction

4.1.1. Linear trend objective function

In the linear model, our proposed genetic algorithm is solved and compared with Cplex 12.1 using the exact same model parameters. For each problem size, Cplex and the genetic algorithm were implemented on twenty random problems with different parameters as indicated in Table 1 (e.g., different location information, a_j, b_j). As shown in Table 2, Cplex solved every problem in less than 1 s. The suggested genetic algorithm provides the Cplex optimal or near optimal solution for various sizes of problems with reasonable computation time. For small size problems, the GA finds the Cplex optimal value. However, as problem size increases, the GA does not provide the Cplex optimal solution in several cases among the twenty trials. This is because, as the problem size increases, the solution space also increases. For a large space, the GA may not explore it fully.

Cplex is state-of-the art optimization software. However, our suggested mathematical models contain (nonlinear) convex and concave terms in the objective function. Unfortunately, Cplex does not provide a mechanism for nonlinear integer optimization. Therefore, our genetic algorithm whose quality we have verified using the linear objective function will be implemented to optimize the nonlinear integer problems.

4.1.2. Convex trend objective function

We suggested two allocation order methods for the convex trend objective function: repeated random order assignment and one directional assignment method. The results of both assignments are compared to determine the significance of assignment order.

Table 3 compares the results of these two assignment methods embedded in the GA. Both methods give similar solution values. Because the repeated random order assignment method generates $\alpha \cdot J$ random order allocations for a chromosome, it requires more computation than the one directional assignment method. It is clear that with the nonlinear objective function, assignment order affects the solution value. However, due to the evolutional characteristic of the genetic algorithm, there is a little difference between the two assignment methods at the conclusion of the GA.

4.1.3. Concave trend objective function

In the concave trend objective function case, the solution value and computation patterns are similar with the convex case; see Table 4. The repeated random order assignment method gives similar or slightly smaller solution value than the one directional assignment method. However due to the evolutional procedure of the genetic algorithm, the differences are small. On the other hand, the repeated random order assignment method requires many times more computation than the convex model. Also in this concave trend case, we observed the effect of the economies of scale. As there are just small increments in solution values when an undesirable facility tries to cover another node, the solutions tend to have many nodes assigned to few locations.

4.2. Mathematical model with closest assignment restriction

4.2.1. Linear trend objective function

For the linear model, our GA is compared with Cplex 12.1; see Table 5. Our GA gives similar solutions as Cplex for the closest assignment restriction linear model. They give Cplex optimal or near optimal solutions for various problem sizes. As for the maximum distance restriction model, we will use our genetic algorithm to cover the limitations of Cplex. We expect our genetic algorithm will give good solutions in nonlinear integer problems based on its performance quality here.

Table 3
Result of convex mathematical models with maximum distance restriction.

J	K	Repeated random orders assignment		One directional assignment		Gap (%)
		Sol. value	CPU time (second)	Sol. value	CPU time (second)	
10	3	410	1.24	410	0.85	0.00
30	9	952	19.13	953	4.14	−0.11
50	15	1691	82.18	1622	10.11	4.07
100	30	3381	610.59	3311	35.95	2.07

Table 4
Result of concave mathematical models with maximum distance restriction.

J	K	Repeated random orders assignment		One directional assignment		Gap (%)
		Sol. value	CPU time (second)	Sol. value	CPU time (second)	
10	3	458	1.35	458	0.83	0.00
30	9	720	21.06	720	3.9	0.00
50	15	852	87.61	879	9.02	−3.17
100	30	1146	624.63	1185	31.88	−3.40

Table 5
Result of linear mathematical model with closest assignment policy.

J	K	Cplex		Genetic algorithm		Gap (%)
		Sol. value	CPU time (second)	Sol. value	CPU time (second)	
10	3	363	0.05	363	0.82	0.00
30	9	1063	0.06	1063	4.48	0.00
50	15	1763	0.67	1763	12.18	0.00
100	30	3496	8.92	3551	47.47	1.57

Table 6
Result of nonlinear mathematical model with closest assignment constraints.

J	K	Convex mathematic model		Concave mathematic model	
		Solution value	CPU time (second)	Solution value	CPU time (second)
10	3	424	0.84	324	0.81
30	9	982	4.76	336	4.46
50	15	1833	12.33	382	11.66
100	30	3744	47.14	444	45.56

Table 7
Parameters for sensitivity analysis of two different scenarios.

	J	K	R	a_j	b_j	β	γ
Scenario 1	50	15	20,000	Rand (10,35)	Rand (50,60)	0.8	5
Scenario 2	50	15	20,000	Rand (50,75)	Rand (20,30)	0.2	1

4.2.2. Convex and concave trends objective function

We now study the convex and concave mathematical models with our closest assignment genetic algorithm. The proposed algorithm solved these nonlinear models quickly; a 100-node nonlinear problem in less than a minute.

We next compare the concave and convex models; see Table 6. Contrary to the convex model, the solution value does not much change in the concave model as the problem size increases (for fixed cost parameters). This is because the concave trend objective function tends to give few established undesirable facilities that cover many nodes because of the economies of scale.

5. Sensitivity analysis

We conducted sensitivity analysis to observe the result of changes to decision values in various situations.

5.1. Sensitivity analysis on the behavior of residents

The NIMBY syndrome is highly dependent on resident's emotion and behavior. Here we consider two scenarios.

Scenario 1) Residents are aware that the undesirable facility is a necessity. Therefore, they agree to build an undesirable facility in their locale. However, they do not want to sacrifice for residents of other locales. They are reluctant to allow other residents to use the undesirable facility located in their region. In this situation, the basic degree of NIMBY phenomena a_j itself is relatively low. However, if other residents are assigned to use their undesirable facility, the degree of NIMBY phenomena will increase steeply. Therefore, b_j, β, γ will be relatively high.

Scenario 2) Residents desperately oppose to establish undesirable facilities in their locale. Therefore, the basic degree of NIMBY phenomena a_j is extremely high. However, if government negotiate with residents and persuade them, it is relatively easy to open the undesirable facility for residents of other locales. Thus, b_j, β, γ will be relatively low.

We use the parameters in Table 7 to compare these two conflicting scenarios.

Table 8 provides the results for the two different scenarios. In Scenario 1, our GA constructed many undesirable facilities and each undesirable facility served a relatively small number of other nodes. This is as expected since in Scenario 1, establishing an undesirable facility is relatively easy but expanding it is relatively difficult. On the other hand, in Scenario 2, our GA constructs a small number of undesirable facilities and opens those facilities for many other residents. Our GA provides the results intuitively expected. Further, it should give near optimal location and allocations for the parameters provided.

Table 9
provides the parameters for this sensitivity analysis.

J	K	R	a_j	β	γ	Number in initial population	Number of generations
50	15	20,000	Rand (30,55)	0.5	3	1	1

5.2. Comparison of assignment methods

In this section, we will investigate the sensitivity of the repeated random order assignment method to the parameter α. Using a single fixed location vector y throughout, the repeated random order assignment method is used with various α values. The assignment algorithm is implemented twenty times for each α value. The average solution value of the twenty different implementations is used to evaluate the effect of the repeated random order assignment algorithm.

Table 9 provide parameters for sensitivity analysis of the repeated random order assignment method.

Fig. 6 shows the relationship between the solution values and various α values.

Details including CPU time are given in Table 10. In both the convex and concave case, higher α values give good and stable solutions. This is obvious; high α values generate more random order assignments and select the best one. The one directional assignment algorithm is also implemented for comparison. Every implemented random order assignment algorithm gives a better solution value than the one directional assignment.

In this analysis, we did not modify the chromosome for locations so that we can clearly evaluate the effect of the assignment algorithms. Therefore, the evolutional characteristic of our genetic algorithm does not appear. However, if we repeat our algorithms, the average solution value between the two assignment algorithms is expected to be similar as we showed in the numerical example section previously. Computation time also increased as the α value increased.

Table 8
Comparison of two scenarios.

	Linear			Convex			Concave		
	Solution value	Established facilities	Average assigned node	Solution value	Established facilities	Average assigned node	Solution value	Established facilities	Average assigned node
Scenario 1	1986	15	3.33	1428	15	3.33	528	7	7.14
Scenario 2	1190	4	12.5	1309	10	5	693	3	16.67

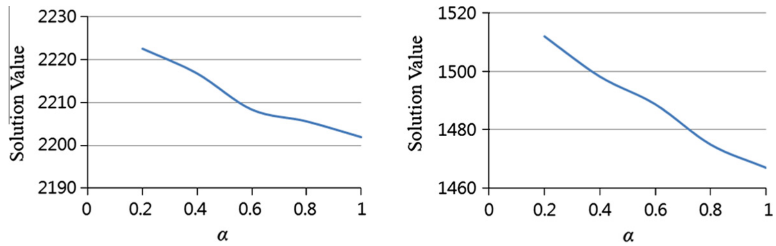

Fig. 6. Solution values decrease with increasing α: convex space (left) and concave space (right) cases.

Table 10
Comparison of random order assignment and one directional assignment in convex and concave cases.

α	Convex case				Concave case			
	Average solution value	Standard deviation	CPU time	Gap (%)	Average solution value	Standard deviation	CPU time	Gap (%)
Random order assignment								
0.2	2222.55	23.2	0.005	−0.25	1512.15	58	0.005	−1.84
0.4	2216.75	22.56	0.009	−0.51	1498.3	38.44	0.009	−2.78
0.6	2208.3	18.01	0.012	−0.66	1488.75	37.18	0.013	−3.44
0.8	2205.55	14.19	0.015	−1.02	1474.85	33.93	0.016	−4.44
1	2201.85	11.49	0.018	−1.19	1466.85	30.39	0.022	−4.99
One directional assignment								
2228					1540			

6. Concluding remarks

Undesirable facilities provide necessary services for people. However at the same time, these facilities may have negative consequences for the local neighborhood. Therefore, when establishing an undesirable facility, decision makers may face strong opposition from local residents. This is the so called "not in my backyard" (NIMBY) phenomenon. In this research, two alternative mathematical models are suggested for locating undesirable facilities to minimize the total degree of NIMBY phenomena. The proposed models are linear and nonlinear integer programs. A genetic algorithm and assignment methods are developed to seek optimal or near optimal solutions. To validate the mathematical models and assignment algorithms, the results are compared with Cplex in the linear case. For the nonlinear case, assignment algorithms are compared. Sensitivity analysis on resident behavior and assignment algorithms are conducted. It is observed that our algorithms provide optimal or near optimal solutions in reasonable time in the linear case. In the nonlinear case, the proposed assignment algorithms show a potential to minimize the degree of NIMBY phenomena.

In future studies, it is recommended to consider capacity restrictions in the linear and nonlinear optimization model. In addition, various terms can be included in the objection function, as for other multi criteria undesirable facility location problems.

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