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A capacitated bike sharing location-allocation problem under demand uncertainty using sample average approximation: A greedy genetic-particle swarm optimization algorithm

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Abstract. This paper considers a stochastic location-allocation problem for a capacitated bike sharing system (S-L&A-CBSS), in which bike demand is uncertain. To tackle this uncertainty, a Sample Average Approximation (SAA) method is used. Because this problem is an NP-hard problem, a hybrid greedy/evolutionary algorithm based on Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), namely greedy GA-PSO, is embedded in the SAA method in order to solve the given large-sized problems. The performance of the proposed hybrid algorithm is tested by a number of numerical examples and used for empirical test based on Tehran business zone. Furthermore, the associated results show its efficiency in comparison to an exact solution method in solving small-sized problems. Finally, the conclusion is provided.

1. Introduction

In recent years, bike sharing systems have received great focus as a sustainable, economically cost-effective, and healthy transportation alternative by researchers and urban transport planners to reduce air pollution, intensive traffic jams, and carbon emissions. Vogel et al. [1] and Bordagaray et al. [2] analyzed data from bike sharing station to explore activity patterns within these systems. Ando et al. [3] analyzed the possibility of extension and the necessary conditions for bicycle rental system in a local city of Japan. A journey advisor application was presented by Yoon et al. [4] for serving travelers to navigate the city using the existing bike sharing system. Lathia et al. [5] used data analysis and mining techniques to consider the effects of the user-access policy modification on London's bicycle hire scheme. Bordagaray et al. [6] proposed a methodology to model the quality perceived by public-bicycle-system users in order to identify the important variables and their significance for the overall evaluation. Through executing a pilot project at the University of Tennessee, Knoxville campus, Ji et al. [7] presented the operational notions and system necessities of a completely automated electric bike sharing system. Jappinen et al. [8] modeled a shared bike system and measured its effect on public transport travel times. They concluded that bicycle sharing systems can complete the traditional public transport system, and they could increase the competitiveness and attractiveness of urban sustainable transportation.

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In 2014, effect of bike sharing system on car use was considered by Fishman et al. [9].

Lin and Yang [10] expressed that station locations and capacities have a special and strategic role in the success of bike sharing system; therefore, some scholarly studies have been dedicated to this matter. Lin and Yang [10] developed a model to find station locations and traveler paths to travel from origins to destinations by riding bikes rented from bike sharing system. Then, Lin et al. [11] extended the previous research by adding a decision variable related to the bicycle stock level at station. In the last two mentioned papers, authors used expected demand value to tackle demand uncertainty. Romero et al. [12] presented a methodology for optimizing station locations with minimum social cost. In their approach, interactions between private and public transportation systems are considered. Garcia-Palomares et al. [13] determined demand and its characteristics, station locations, and their capacity through a GIS-based method and location-allocation models.

On the other hand, considering that demand uncertainty is an important subject to consider in transportation modeling [14], as shown in Table 1, demand is considered as an uncertain parameter in some urban transportation studies. Urban public transportation, like other transportation systems, is facing uncertain demands; therefore, it is necessary to consider demand uncertainty in bike sharing systems as a part of the urban transportation.

To the best of the authors' knowledge, there is no study to consider a bike sharing system with stochastic demands using a hybrid evolutionary algorithm in stochastic optimization as a soft-computing approach. Hence, in these systems, strategic decisions, such as location and capacity, are made usually under stochastic environment; therefore, addressing this issue can be an interesting subject deserving to be studied more. One of the well–known methods which deals with stochastic nature of optimization problems is the Sample Average Approximation (SAA).

Ahmed et al. [21] developed a solution strategy based on sample average approximation for stochastic programs with integer recourse. The sample average approximation method was used by Kleywegt et al. [22] to optimize stochastic discrete optimization problems. Wei and Realff [23] used the SAA method with bounding techniques and used it for solving stochastic mixed integer nonlinear programming problems. By combining the sample average approximation with dual decomposition, Schütz et al. [24] proposed a method for solving stochastic supply chain design problem. Contreras et al. [25] integrated the sample average approximation method

Table 1. Summary of some studies for transportation problem with uncertain demands.

Authors	Objective	Solution method	Problem
Chen and Yang [15]	Minimizing the total travel time	Genetic algorithm	Transportation network design problem
Ukkusuri et al. [16]	Minimizing the total travel time	Genetic algorithm	Traffic network design problem
Hua et al. [17]	Minimizing the total system cost of the worst case	Sensitivity analysis combining with the methods of sequence average algorithm	Urban traffic network design problem
Saez et al. [18]	Minimizing waiting and in-vehicle ride times	Genetic algorithm	Bus scheduling problem
Huang et al. [19]	Minimizing the total cost of the transit system	Genetic algorithm	Bus frequencies problem
Liu et al. [14]	Minimizing the performance of the overall traffic network	Genetic algorithm	Transportation network design problem
Cao et al. [20]	Minimizing total travel time and cost	Genetic algorithm combined with the Frank-Wolfe algorithm	Transportation network design problem

with a Benders decomposition algorithm by Monte–Carlo simulation–based algorithm and used it to solve stochastic uncapacitated hub location problems. Through integrating PSO algorithm within the sample average approximation method, Aydin and Murat [26] generated a new hybrid algorithm for solving the capacitated reliable facility location problems efficiently. The mentioned studies confirm that most of network designs apply new soft–computing methods to solve applicable problems more efficiently under more realistic conditions such as stochastic environment.

Since using SAA requires solving the problem repeatedly and based on NP-hardness problem, the exact methods are not suitable for this purpose. Metaheuristic algorithms are used in transportation problems frequently, and some of them are presented in Table 2; therefore, these algorithms can be used here as well.

The outline of this paper is as follows: In Sec-

Table 2. Summary of some studies for transportation problem using evolutionary algorithms.

Authors	Objective	Solution method	Problem
Mohtashami et al. [27]	Minimizing the make-span, transportation cost, and the number of truck trips	NSGA-II MOPSO	Cross-docking scheduling problem
Martinez-Salazar et al. [28]	Minimizing the total operation cost Balancing of workloads	SSPMO* NSGA-II	Transportation location routing problem
Cao et al. [29]	Minimizing transportation costs and unsatisfied demands	Differential evolution algorithm	Vehicle routing problem
Lotfi and Tavakkoli-Moghaddam [30]	Total variable and fixed cost	Genetic algorithm using priority-based encoding	Fixed charge transportation problem
Bolat et al. [31]	Minimizing the average journey time	Particle swarm optimization	Car-call allocation problem
Yaghini et al. [32]	Minimizing the total cost	Hybrid algorithm of simplex method and simulated annealing metaheuristic	Network design problem
Lin et al. [33]	Minimizing operating cost Maximizing customer satisfaction	Simulated annealing algorithm	Vehicle routing problem
Yu et al. [34]	Maximizing service quality Minimizing operational costs	Parallel genetic algorithm	Bus route headway problem
Ghoseiri and Nadjari [35]	Minimizing the costs	Multi-objective ant colony optimization	Multi-objective shortest path problem
Musa et al. [36]	Minimizing the total transportation cost	Ant colony optimization	Transportation problem of cross-docking network

*Scatter tabu search procedure for non-linear multi-objective optimization.

tion 2, two mathematical models for a bike sharing system with the aforementioned properties are developed. In Section 3, a greedy hybrid evolutionary algorithm is presented in a sample average approximation procedure structure. Usefulness of soft–computing approach for the mentioned bike sharing system is discussed as well. In Section 4, some illustrative examples are considered, followed by a conclusion in the last section.

2. Model formulation

2.1. Problem description

To define the problem, consider the following scenario: Assume that a group of travelers is going to travel from a set of origins (o) to a set of destinations (g) using a bike sharing system consisting of a set of bike stations (S) with limited capacity. Passengers walk from their origins to the nearest bike stations and receive a bicycle, and then ride it to another station close to their destinations; after delivering the bike, they walk to the final destination. Each station has a specified covering radius, and if the stations serve passengers out of their covering radius, a penalty cost is imposed on the bike sharing system. Some demands may not be satisfied since the bike sharing system is capacitated, while bike shortage in stations is allowable with paying shortage penalty cost.

The success of bike sharing systems depends on some decisions about station locations, capacities, and traveling paths which should be made by the system planner. There are candidate locations where some of them should be selected for establishing bike stations. Also, their capacities and traveling paths should be defined. These decisions are made so that the total cost of the bike sharing system, consisting of traveling, station and lane construction, shortage and holding costs, should be minimized.

In order to ensure that a suitable model for the mentioned purpose is provided, it is required to make real–life circumstances available. Due to the uncertainty of travelers' demands, the location–allocation of the bike sharing system should be considered under uncertain environment. In most of studies, expected value of uncertain demand is considered during the modeling of the bike sharing system [10,11,37], but in this study, we try to consider uncertainty nature of demands.

2.2. Mathematical model for the stochastic BSS location–allocation problem

Unlike classical models, such as [10,11], in the presented mathematical model, the bike sharing system is designed with considering bike station capacities, inventory decisions, and allowable shortage. Moreover, demands are taken as stochastic and a hybrid metaheuristic algorithm embedded with the stochastic nature is developed for optimizing the model. Indices, parameters, decision variables, and the model are presented as follows:

Indices

$o \in O$	Origins
$g \in G$	Destinations
$s, n \in S$	Potential pick-up/drop-off stations
$i \in I$	Scenario

Input parameters

R_{ogi}	ith scenario of yearly mean of travel demand from origin o to destination d
N	Number of days per year (used to compute daily demand)
h	Annual bike holding cost
r	Bikes replenishment period at bike stations (in days)
m	Bike shortage cost.
d_{os}	Distance from origin o to station n
d_{sn}	Distance from station s to station n
d_{ng}	Distance from station n to destination g
f_s	Fixed cost of locating a station at s
E_{sn}	Construction cost of a bike lane from station s to n; it is equal to 0 if there already exists a bike lane between stations s and n
C_{os}	1 if a bike station located at candidate site s cannot cover demand at origin o, 0 otherwise
C'_{ng}	1 if a station located at candidate site n cannot cover demand at destination g, 0 otherwise
u_1	Unit traveling cost on links from origins to bike stations per person
u_2	Unit traveling cost by bike on links from pick-up station to drop–off station per person
u_3	Unit traveling cost on links from bike stations to destinations per person
k	Unit penalty cost for uncovered demands at origins and destinations
a	Cost for adding a bike dock to a station
U_s	Upper bound of capacity of station s
P_i	Probability that demand under scenario i is realized;

Decision variables

X_s	1 if bike station s is opened, 0 otherwise

B_{osngi}	1 if the demand from origin o to destination g under scenario i travels by bike through stations s and n, respectively, 0 otherwise
	Number of bikes at station s under scenario
L_{sni}	1 if a bike lane is required to be connected between bike stations s and n under scenario i, 0 otherwise

Based on the above–mentioned notations, the mathematical model is formulated as follows:

$$\text{Min } Z = \sum_{s\in S}(f_s X_s) + P_i \Bigg\{ \sum_{s\in S} a X_s v_{si} + \sum_{s\in S}\sum_{n\in S} E_{sn} L_{sni} + \sum_{s\in S}\frac{h}{2} v_{si} + u_1 \sum_{o\in O}\sum_{s\in S} d_{os} \sum_{n\in S}\sum_{g\in G} B_{osngi} R_{ogi} + u_2 \sum_{s\in S}\sum_{n\in S} d_{sn} \sum_{o\in O}\sum_{g\in G} B_{osngi} R_{ogi} + u_3 \sum_{n\in S}\sum_{g\in G} d_{ng} \sum_{o\in O}\sum_{s\in S} B_{osngi} R_{ogi} + k\left(\sum_{o\in O}\sum_{s\in S} C_{os} \sum_{n\in S}\sum_{g\in G} B_{osngi} R_{ogi} + \sum_{g\in G}\sum_{n\in S} C'_{ng} \sum_{s\in S}\sum_{o\in O} B_{osngi} R_{ogi}\right) + N \sum_{s\in S} m A_{si} \Bigg\}, \qquad (1)$$

subject to:

$$\sum_{s\in S}\sum_{n\in S\neq s} B_{osngi} = 1, \quad \forall o\in O, \forall g\in G, \forall i\in I, \qquad (2)$$

$$2L_{sni} \le X_s + X_n, \quad \forall s\in S, \forall n\in S\neq s, \forall i\in I, \qquad (3)$$

$$L_{ssi} = 0, \quad \forall s\in S, \qquad (4)$$

$$B_{osngi} \le L_{sni} \quad \forall o\in O,\ \forall s\in S,\ \forall n\in S\neq s, \forall g\in G,\ \forall i\in I, \qquad (5)$$

$$v_{si} \le U_s X_s, \quad \forall s\in S, \forall i\in I, \qquad (6)$$

$$A_{si} \ge \frac{r}{N}\sum_{o\in O}\sum_{g\in G}\sum_{n\in S} B_{osngi} R_{ogi} - v_{si}, \quad \forall s\in S, \forall i\in I, \qquad (7)$$

$$B_{osngi} = \{0,1\}, \quad \forall o\in O,\ \forall s\in S,\ \forall n\in S\neq s, \forall g\in G,\ \forall i\in I, \qquad (8)$$

$$X_s = \{0,1\}, \quad \forall s\in S, \qquad (9)$$

$$L_{sni} = \{0,1\}, \quad \forall s\in S, \forall n\in S, \forall i\in I, \qquad (10)$$

$$v_{si} \ge 0, \quad \forall s\in S, \forall i\in I, \qquad (11)$$

$$A_{si} \ge 0, \quad \forall s\in S, \forall i\in I. \qquad (12)$$

In objective function (Eq. (1)), the total cost is calculated. The first three terms are related to strategic decisions costs. The first one includes construction cost of active stations and their assigned bike docks; the second one calculates lane construction costs; in the third one, bike holding costs are calculated. Other remaining terms of objective function are related to the operational decisions. Terms 4-6 contain traveling costs between origins to stations, pair of stations, and stations to destinations, respectively. The next term includes the total penalty cost for demands assigned to stations which are not inside their covering radius. The total penalty cost of missed demands is calculated in the last term.

Constraint (2) guarantees that a pair of origin and destination should be connected through only one path. Constraints (3) and (4) assure that a lane can be constructed only between different established stations. Constraint (5) guarantees that only an established lane can be assigned to a path. Constraint (6) limits allocated capacity of each active station to its upper bound. Constraints (7) and (12) determine the shortage in the case of higher allocated demands than each station capacity. Constraints (8)-(12) define variable types.

By increasing the problem dimensions, the number of variables and constraints will increase nonlinearly. For a model with n_1 origins, n_2 destinations, and m candidate bike station locations, the model will have $2m + m^2(n_1 \times n_2 + 1)$ variables and $2n_1 \times n_2 \times m(m-1) + m^2$ constraints. As a result, a model for the usual problem may not be solved by commercial optimization software in a reasonable computational time; therefore, a hybrid meta-heuristic algorithm is proposed in this paper to solve the problem. Moreover, in some cases, there are some stochastic parameters without a known distribution function; therefore, a sampling plan equipped by a hybrid algorithm is presented in the next section.

3. The proposed SAA method equipped by a hybrid greedy genetic-PSO algorithm

In real cases, there are usually unlimited scenarios for bike demands in each station, and they have stochastic nature while they do not have a known distribution function. Because there are unlimited scenarios, it is not possible to calculate expected value of demands, and so a sampling plan should be employed to consider some possible scenarios. By considering the previous studies, the SAA method approximates the best number of needed scenarios and it is selected for dealing with the location-allocation modeling of stochastic bike sharing. Due to Np-hardness of the model and a large number of calculations in the SAA method, we need to use an evolutionary algorithm for this purpose. In the following, we describe the SAA method, and then the hybrid evolutionary algorithm, used inside the SAA, is presented briefly.

SAA is a stochastic method based on a sampling used broadly for solving stochastic optimization problems with an unmanageably large number of samples [21-26]. In this method, the objective function problem is divided into two stages. In the first stage, there are strategic variables; in the second stage, there are stochastic variables. N samples are selected randomly; the second stage is repeated for N samples. Because N scenarios are not large, there is no need for much computation. The model is solved M times for different N samples in each iteration to find the best value of the needed scenarios. The average of objective function values in M iterations will obtain the lower bound of the problem. Then, one of the strategic variables' values in the mentioned iterations is selected; for different N samples in each iteration to find the best value of the needed scenarios. The average of objective function values in M iterations will obtain the lower bound of the problem. Then, one of the strategic variables' values in the mentioned iterations is selected; to understand how favorable this answer is, the model is solved just once for $N' \, (N \ll N')$ samples again in the second stage, while the strategic variables are fixed based on the selected solution from the previous stage, and the obtained value from this phase can be an upper bound for the problem [21]. Thus, we can say that in this method, the calculations are done only with N scenarios, but the results are reliable because they are repeated for M iterations. As mentioned before, each optimization of the SAA method should be done by a hybrid metaheuristic algorithm. However, the proposed SAA sampling plan equipped by the hybrid greedy GA-PSO algorithm is mentioned in the following pseudocode:

1. Set initial sample sizes N and N' and set the number of iterations M;
2. For $m = 1, \ldots 0, M$, do steps (a) through (d):
   (a) Generate a sample of size N;
   (b) Solve the SAA problem by the greedy GA_PSO and save the optimal objective $\hat{V}_N^m$ and the solution vector of bike station locations $\hat{L}_N^m$;
   (c) Generate a sample of size N';
   (d) Fix the bike station location variable based on $\hat{L}_N^m$ and solve the SAA problem by the greedy GA_PSO for N' samples and save the optimal objective $\hat{V}_N^m$.
3. Estimate optimality gap as follows:

$$g_m = \hat{V}_{N'}^m - \left(\frac{\sum\limits_{m-1}^{M} \hat{V}_N^m}{M} \right).$$

4. Select the best solution.

The proposed hybrid algorithm inside the SAA sampling method is depicted with more details in Figure 1; Figure 2 explains the procedure in summary. In the next subsection, more details about solution representation, used operators, and main stages of the algorithm are described.

3.1. The proposed algorithms for the optimization stage of the solution method

As mentioned before, in each iteration of the SAA scheme, we need to optimize a problem, so a hybrid algorithm is developed. It consists of two phases. In the first one, location decisions are made by the genetic algorithm, and the lane construction and path decisions are made by a greedy search, while in the second stage, the decisions of bike capacities of station are made by the PSO algorithm according to the previous stage decisions. In the following, more details of the mentioned stages are provided:

a) ***The first phase of the algorithm***: In the first phase, Genetic Algorithm (GA) is used. Its solution contains three parts. The first one determines station locations called the location sub-chromosome Figure 3. The second and third ones define demand nodes allocation and lane construction decisions, respectively. During the genetic algorithm operators of crossover, mutation, insertion, swap and inversion are used for diversifying and intensifying new solutions as the first part of the solution (as depicted in Figures 4-8), while other parts are determined by a greedy search algorithm.

Different percentages (i.e. 70, 40, 10, 60, and 10%) of the old generation cases are selected randomly for the crossover, mutation, swap, reversion, and insertion operators, respectively; after

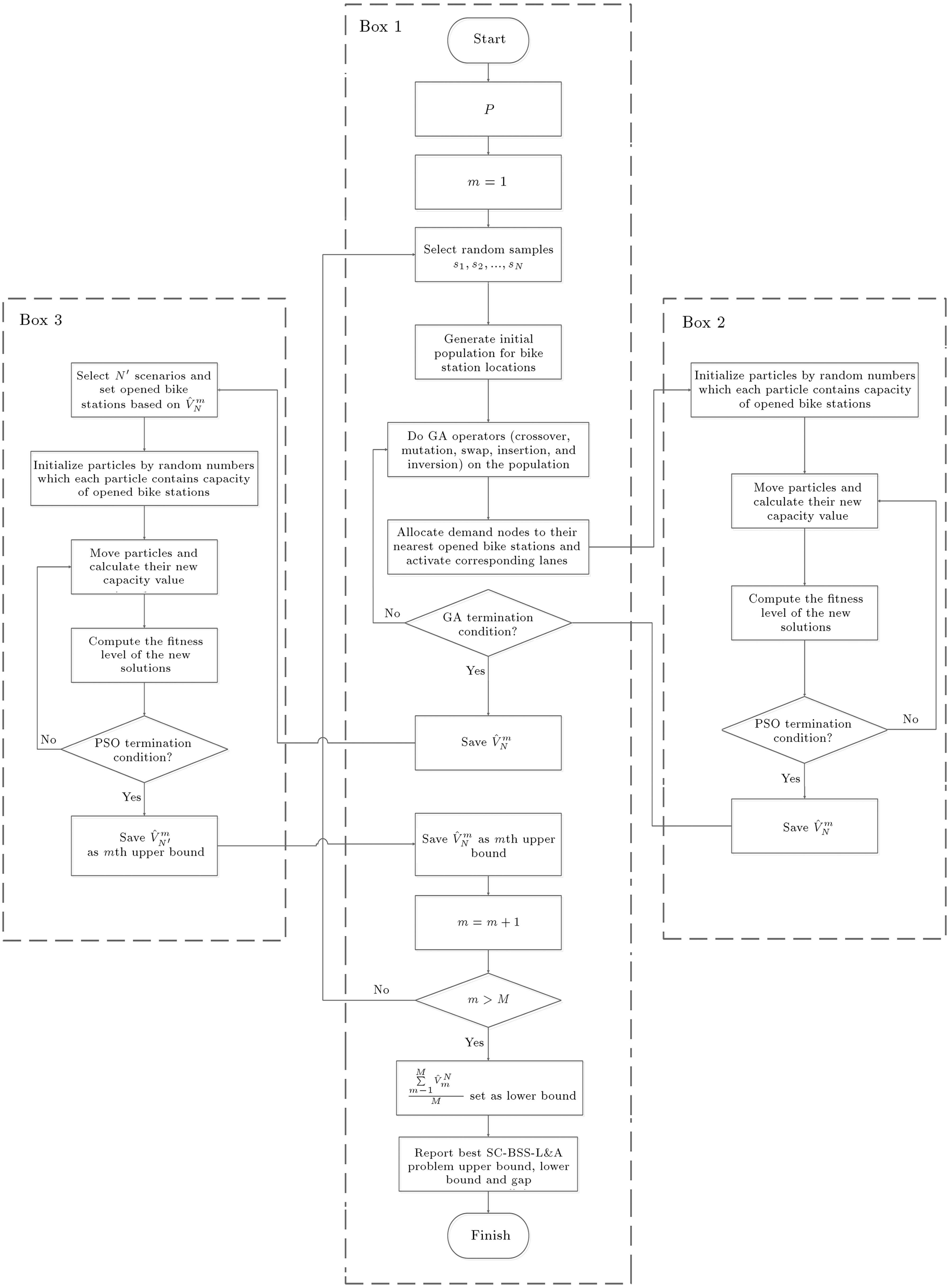

Figure 1. Detailed flowchart of the greedy GA–PSO algorithm during the sampling scheme for S–L&A–CBSS problem.

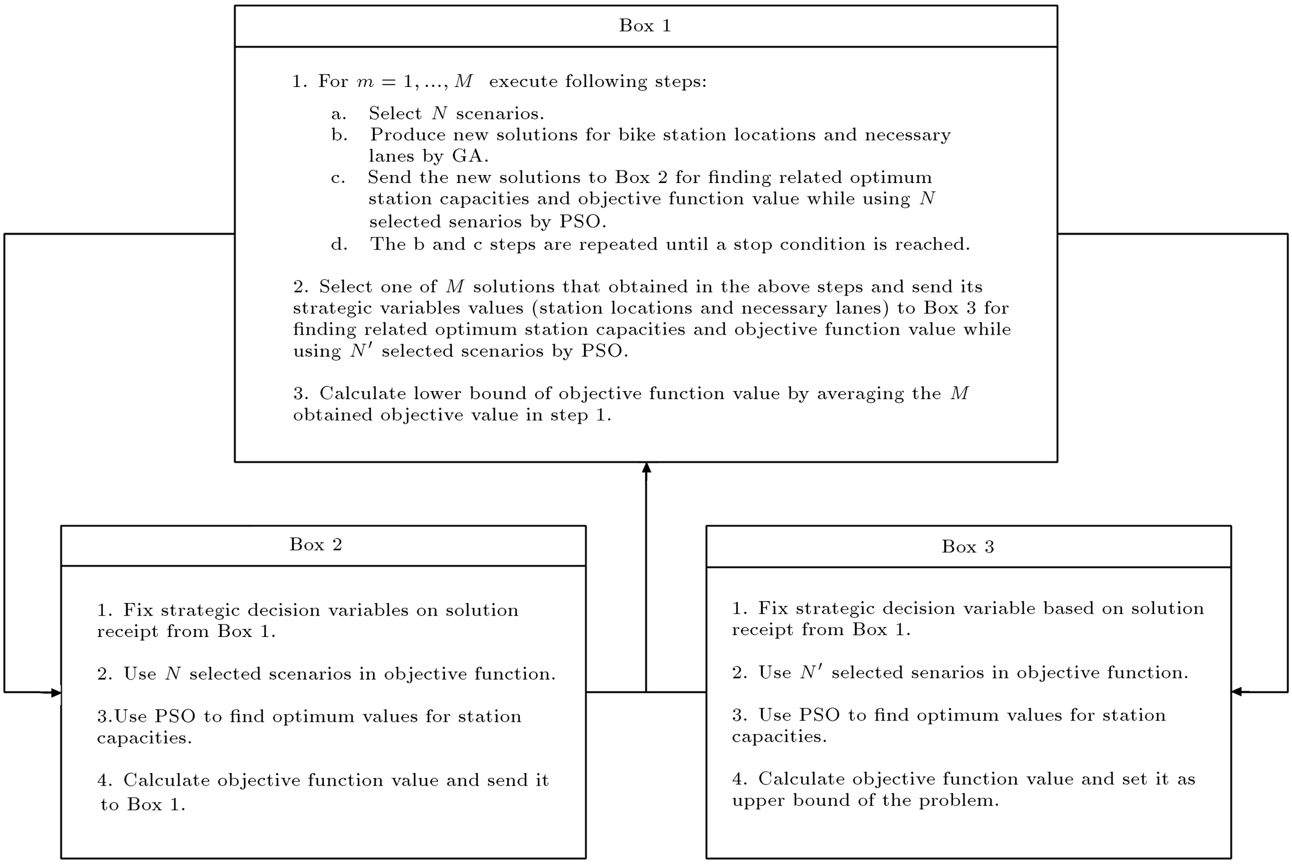

Figure 2. Summarized flowchart of the greedy GA–PSO algorithm during the sampling scheme for S–L&A–CBSS problem.

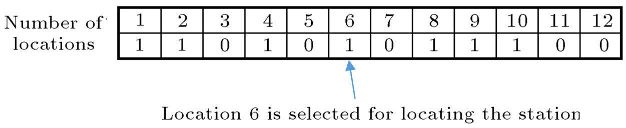

Figure 3. Schematic representation of the location sub-chromosome for S–L&A–CBSS problem.

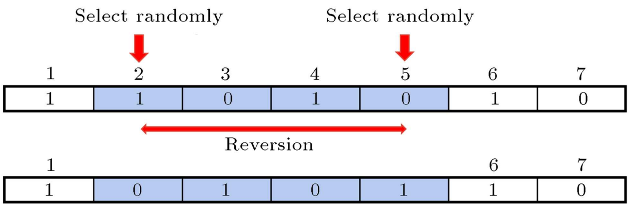

Figure 4. Reversion operator procedure for the greedy GA-PSO.

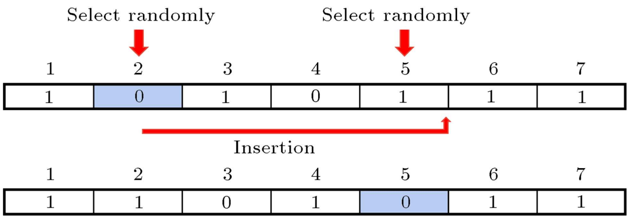

Figure 5. Insertion operator procedure for the greedy GA-PSO.

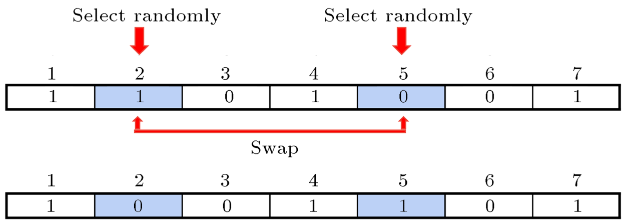

Figure 6. Swap operator procedure for the greedy GA-PSO.

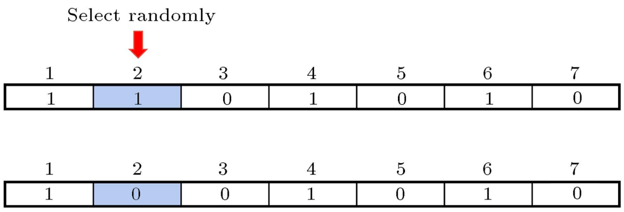

Figure 7. Mutation operator procedure for the greedy GA-PSO.

producing new solutions by the mentioned operations, the best solutions are selected for the new generation. All possible paths for all pairs of origin and destination through active stations are considered, and then the shortest path is selected in the path sub-chromosomes (Figure 9)

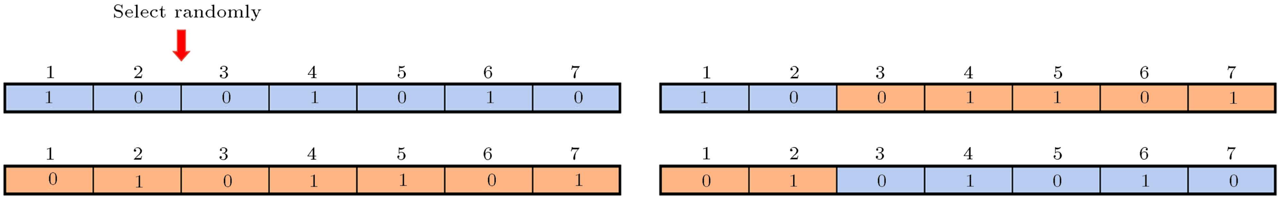

Figure 8. Crossover operator procedure for the greedy GA-PSO.

	X	S_1	S_2	y
1	1	2	9	1
2	1	2	7	2
3	1	2	7	3
4	1	2	10	4
5	1	2	10	5
6	1	2	12	6
7	2	2	9	1
⋮	⋮	⋮	⋮	⋮
24	4	5	11	6
25	5	2	9	1
26	5	2	7	2
27	5	3	7	3
28	5	3	10	4
29	5	3	10	5
30	5	2	12	6
31	6	5	9	1
32	6	5	12	2
33	6	3	12	3
34	6	3	10	4
35	6	5	12	5
36	6	5	12	6

Figure 9. Schematic representation of the path sub-chromosomes related to the best routs for the S-L&A-CBSS problem.

	1	2	3	4	5	6	7	8	9	10	11
1	0	0	0	0	0	1	0	1	0	1	1
2	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	1	0	1	0
4	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0
6	1	0	0	0	0	0	1	0	0	1	1
7	0	0	0	0	0	1	0	0	0	0	0
8	1	0	1	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0
10	1	0	1	0	0	1	0	0	0	0	0
11	1	0	0	0	0	1	0	0	0	0	0

A lane should be constructed between station 1 and 8

Figure 10. Schematic representation of the constructed lanes sub-chromosome for the S-L&A-CBSS problem.

and necessary bike lanes will be activated based on the allocation structure shown in the constructed lanes sub-chromosome (Figure 10). After that, for defining station capacities and calculating objective function's value of each chromosome, the second phase should be followed;

b) ***The second phase of the algorithm***: The chromosome defined in the first phase is used as an input of the second phase of the algorithm. Then, capacities of active stations are chosen based on the input chromosome to minimize the total cost. For this purpose, with respect to the relatively continuous demand variable nature, a PSO-based algorithm is used for finding the optimum active station capacities in this phase. Each particle

No. of stations	1	3	6
Station capacity	20	10	12

Figure 11. Particles for the second phase of the greedy GA-PSO in the S-L&A-CBSS problem.

represents active station capacities. As an example, a particle with capacities of three active stations is depicted in Figure 11.

4. Illustrative examples

In this section, we will present some data instances with different dimensions for location-allocation problem of bike sharing system with stochastic demands to demonstrate the characteristics of the proposed algorithm performance compared to the exact method.

4.1. Data settings

Some instances have been generated randomly to evaluate the performance of algorithm as well as model validity. As an example, for the smallest example with 3 origins, 3 destinations, and 6 candidate locations for establishing bike stations, we generated different demand scenarios of each origin-destination pair based on a uniform distribution between 0.8 and 1.2 multiplied by a basic demand table (Table 3). The rest of the parameters of S-L&A-CBSS problem instances are presented in Tables 4 and 5. Other instances with different dimensions are generated based on the same procedure.

Table 3. Basic table of the bike demands between origins and destinations for the first instance.

	g_1	g_2	g_3
o_1	14050	28940	30070
o_2	29800	9977	25910
o_3	31020	44990	49260

Table 4. Fixed construction cost of stations for the first instance.

Stations	f_s
s_1	5005480
s_2	2894000
s_3	5285200
s_4	4100000
s_5	5001900
s_6	4936100

Table 5. Other parameter values for the S-L&A-CBSS problem instances.

Parameters	Value	Parameters	Value
N	365	C_{os}	300 meter
h	200 per year	C'_{gn}	300 meter
r	1 day	u_1	0.2 per meter
m	50 per demand	u_2	0.04 per meter
d_{os}	U(100, 2600)	u_3	0.2 per meter
d_{sn}	U(150, 2700)	p	300 per demand
d_{ng}	U(5, 2700)	a	1000 per bike
E_{sn}	300 per meter	U_s	200 docks

For assessing this algorithm in real case dimensions, a part of Tehran business zone is selected. Origin and destination nodes were selected close to the public and important centers such as shopping centers, governmental offices, museums, public library, bus and metro stations, etc.

4.2. The proposed algorithm and exact method results

In this section, the proposed algorithm and exact method were used to assess the efficiency of the proposed algorithm. We carried out the test on all examples by GAMS 24.1.2 software and we tested their different MIP solvers for solving examples; the result shows that the BARON solver has more efficient performance; therefore, the results obtained by this solver are selected as a measure for considering the proposed algorithm performance. The proposed evolutionary algorithm was implemented in MATLAB R2013a software. All examples were implemented on a PC under Windows 7 (64 bit) with Intel(R) Core(TM) i7, 2670QMCPU @ 2.20GHz and 6 GB RAM. Table 6 presents the solution quality of the test results of

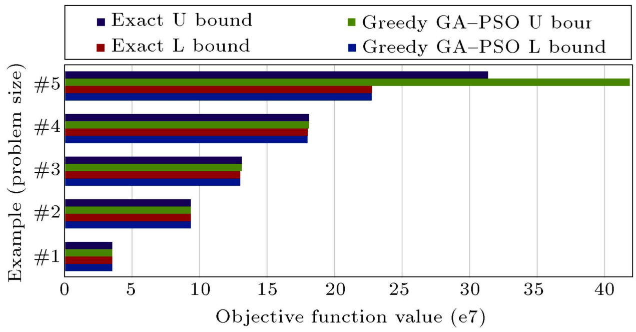

Figure 12. Objective function values calculated by the greedy GA-PSO algorithm and the exact method.

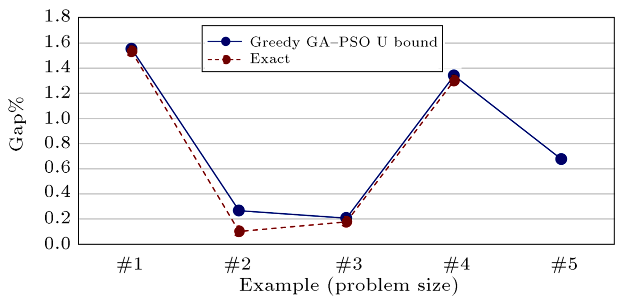

Figure 13. Gaps between lower and upper bounds achieved by the greedy GA-PSO algorithm and the exact method.

the proposed algorithm and the exact method. For considering stochastic nature of the problem, we set $M = 10$, $N = 20$, and $N' = 2000$ in the hybrid SAA-based algorithm. The final results are reported in Table 6 for all of the instances. The lower and upper bounds are calculated according to the number of N or N' scenarios. The mentioned bounds are reported in the table for each instance. The gap column shows that gaps between lower and upper bounds are divided into the upper bounds multiplied by 100. The comparison of the results confirms that the proposed algorithm behaves similarly to the exact solution method in small-sized instances, while the exact method is inefficient in finding the lower and upper bounds of the problem by increasing the problem size, as illustrated in Figures 12 and 13. By comparing the results achieved by both methods, it is clear that the proposed algorithm is more efficient than the exact method for the S-L&A-CBSS problem.

The computational times of the proposed algorithm and the exact method have been compared, and the results are depicted in Figure 14. It confirms that by increasing the size of S-L&A-CBSS problem, the proposed algorithm is more efficient than exact solution approaches. As presented in Figure 14, the computational time increases with an increasing number of problem dimensions while this increase is linear in the proposed algorithm and is nearly exponential for the exact method; therefore, for solving location-allocation

Table 6. Comparison of results for the SAA based greedy GA-PSO algorithm and exact solution in both solution quality and computational time for the S-L&A-CBSS problem in different instances.

Exp.[a]	No. of origins	No. of destination	No. of potential stations	N/N'	Method	Objective value e+7									
						M									
						1	2	3	4	5	6	7	8	9	10
#1	3	3	6	N	SAA-GA-PSO	3.53	3.51	3.52	3.53	3.53	3.54	3.53	3.52	3.53	3.53
					Exact	3.53	3.51	3.52	3.53	3.53	3.56	3.53	3.52	3.53	3.53
				N'	SAA-GA-PSO	3.53	3.53	3.53	3.53	3.53	3.53	3.53	3.53	3.53	3.53
					Exact	3.53	3.53	3.53	3.53	3.53	3.55	3.53	3.53	3.53	3.53
#2	4	4	8	N	SAA-GA-PSO	9.32	9.38	9.34	9.33	9.34	9.35	9.30	9.35	9.38	9.34
					Exact	9.37	9.35	9.37	9.37	9.35	9.34	9.32	9.32	9.34	9.33
				N'	SAA-GA-PSO	9.35	9.35	9.35	9.35	9.35	9.35	9.35	9. 35	9.35	9.35
					Exact	9.35	9.35	9.35	9.35	9.35	9.35	9.35	9.35	9.35	9.35
#3	5	5	10	N	SAA-GA-PSO	1.30	1.30	1.30	1.30	1.30	1.30	1.29	1.30	1.30	1.30
					Exact	1.31	1.32	1.32	1.30	1.31	1.31	1.31	1.31	1.32	1.31
				N'	SAA-GA-PSO	1.30	1.30	1.30	1.30	1.30	1.30	1.30	1.30	1.30	1.30
					Exact	1.31	1.31	1.32	1.30	1.31	1.31	1.31	1.31	1.31	1.31
#4	6	6	12	N	SAA-GA-PSO	1.80	1.80	1.81	1.79	1.80	1.81	1.79	1.80	1.80	1.79
					Exact	1.81	1.81	1.82	1.80	1.80	1.81	1.81	1.81	1.81	1.80
				N'	SAA-GA-PSO	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.80
					Exact	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81
#5	7	7	13	N	SAA-GA-PSO	2.27	2.28	2.28	2.28	2.28	2.28	2.27	2.28	2.28	2.27
					Exact	5.46	5.31	3.36	3.37	5.48	2.29	5.46	3.37	5.50	2.27
				N'	SAA-GA-PSO	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28
					Exact	3.90	3.95	2.43	2.43	3.90	2.28	3.90	2.43	3.89	2.27
#6	20	18	30	N	SAA-GA-PSO	1.74	1.74	1.74	1.74	1.74	1.74	1.74	1.74	1.74	1.74
					Exact	–	–	–	–	–	–	–	–	–	–
				N'	SAA-GA-PSO	1.74	1.75	1.74	1.74	1.75	1.74	1.74	1.74	1.74	1.74
					Exact	–	–	–	–	–	–	–	–	–	–

Exp.[a]	No. of origins	No. of destinations	No. of potential stations	SAA-GA-PSO				Exact			
				U bound	L bound	Gap%	Time (s)	U bound	L bound	Gap%	Time (s)
#1	3	3	6	3.53E+07	3.53E+07	0.0016	933	3.53E+07	3.53E+07	0.0015	69
#2	4	4	8	9.35E+07	9.34E+07	0.0003	1999	9.35E+07	9.35E+07	0.0001	170
#3	5	5	10	1.30E+08	1.30E+08	0.0002	3829	1.31E+08	1.31E+08	0.0002	2162
#4	6	6	12	1.80E+08	1.80E+08	0.0013	5858	1.81E+08	1.81E+08	0.0013	11274
#5	7	7	13	2.28E+08	2.28E+08	0.0007	6719	3.14E+08	4.19E+08	-0.3343	12388
#6	20	18	30	1.74E+09	1.74E+09	0.0008	19905	–	–	–	–

[a]Exp.: Example.

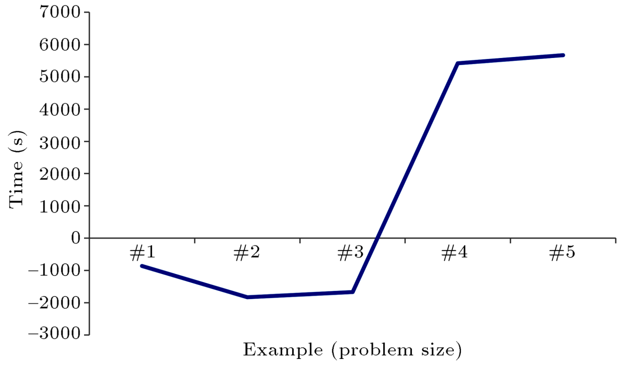

Figure 14. The difference between the computational times of the greedy GA-PSO algorithm and the exact method.

problems of bike sharing system with usual sizes, the exact method loses its effectiveness in practice, and then it is needed to be replaced with another algorithm such as the hybrid greedy GA-PSO algorithm.

5. Sensitivity analysis

We performed the sensitivity analysis on the greedy GA-PSO algorithm with respect to the number of scenarios (N) and iterations (M). Moreover, a sensitivity analysis was performed to evaluate the effect of the bike shortage cost on the model behavior. Figure 15 presents change of the gap by increasing of number of scenarios (N) in different levels of M. As illustrated in the mentioned figure, the gap is decreased by increasing N. However, the decreasing slope is higher for small values of M.

To evaluate the model performance, another sensitivity analysis was performed. The most important factor in the model was the bike shortage cost, while customers cannot receive the bike sharing system service due to the shortage. By increasing the shortage cost, we expected to have a more sensitive behavior of the model to the customer demands. By different experiments with different shortage cost values, we observed that the model tends to have a higher gap between lower and upper bounds with increasing the

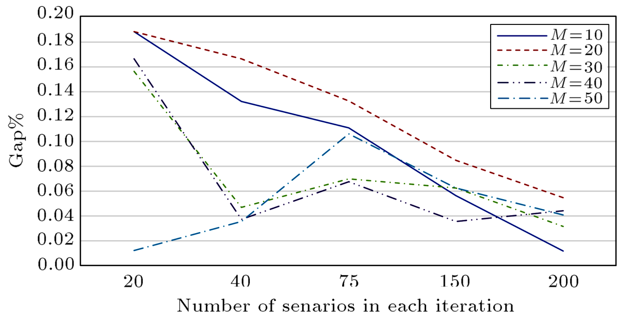

Figure 15. Effect of the number of scenarios on the gap between lower and upper bounds.

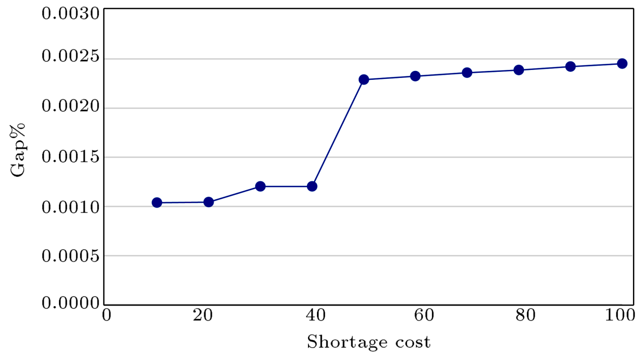

Figure 16. Effect of the shortage cost on the gap between lower and upper bounds.

shortage cost as depicted in Figure 16. Due to the increasing demand sensitivity while it has stochastic nature, the results can be confirmed. The mentioned experiment can show reasonable behavior of the proposed model.

6. Summary and concluding remarks

Using the bike sharing system in cooperation with other public transportation systems is an alternative transportation paradigm that would reduce air pollution, intensive traffic jams, and carbon emissions. However, the success of such systems depends on finding the optimum locations for the bike stations in under real-world environment in which there are demand uncertainties. In this paper, a location-allocation model, which includes capacity decisions, was presented and the SAA method was used to tackle uncertainties of the problem. Because of the NP-hardness of the problem, the exact methods were not practical for the real-sized problems; therefore, a hybrid greedy/evolutionary algorithm based on genetic algorithm and particle swarm optimization was developed. Different analyses confirmed the validity of the proposed model as well as the efficiency of the hybrid algorithm. The model can be extended by considering different stochastic demand patterns for bikes and docks simultaneously in which bike stations in different times of days will be faced with different demand patterns. Moreover, the fleet balance of the BSS in uncertain environment and using large-scale optimization techniques can be another direction for the future study. Finally, due to possibility for the bike-sharing problems to face many objectives, considering the problem in such an environment will be an interesting subject for more studies.

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