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Analyzing the location of city logistics centers in Istanbul by integrating Geographic Information Systems with Binary Particle Swarm Optimization algorithm

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ABSTRACT

The advantages of logistics centers for companies, cities, and countries have been discussed in the literature and generally mathematical model-based evaluations besides multi-criteria approaches are proposed for site selection processes. However, since mathematical modeling of multiple site selection often turns out to be NP-hard problem structure, it is not always possible to obtain an optimal solution by the solvers. For this reason, various meta-heuristic approaches have emerged to solve these complex models. In this context, the aim of this study is to propose an integrated methodology which seeks an optimum result efficiently regarding a logistics center location selection problem. Thus, the optimal clustering of logistics mobility in a metropolitan area was carried out with GIS and a meta-heuristic approach. GIS produced the spatial information needed by p-median model, then the meta-heuristic approach determined the optimal result that considers the logistics costs. BPSO algorithm has employed as the meta-heuristic and it is observed that the algorithm can reach the optimum results within superior times for the problem sizes tested where binary integer programming verified the optimums and the algorithm continued to reach improved solutions where the exact algorithms failed for larger instances. The integrated solution methodology is applied to a large metropolitan region and it is found that it can be used properly by the urban city planners and supply chain managers to analyze critical nodes of transportation networks of megacities.

1. Introduction

Logistics centers which are seen as the backbone of the logistics structure supports effective and efficient freight movements within the entire logistics network by integrating different transport modes, and consolidating shipments. Beyond supporting the freight mobility, all logistics functions are carried out at these facilities such as de-unitizing, storing, order picking, sorting, packaging, handling, insurance, customs clearance. Moreover, the strategic importance of logistics centers is derived from being the focal point of various economic activities within the value networks such as sourcing, production, storage, and transportation of goods (Rikalović et al., 2018). Therefore, these centers are not only the center of transportation, but also the centers of the entire economical system.

Logistic centers have been discussed frequently in the literature for a long time (Rimiene and Grundey, 2007) with positive aspects (Meidute and Vasiliasuskas, 2006; Onden et al., 2016; Peker et al. 2016). Due to the advantages of the facilities, interest in the logistics centers has increased over time. Logistics centers of different sizes have been established in the world (Rodrigue et al., 2016) with significant increase in national and international transportation volume. The increasing number in these facilities show that the stated benefits are not limited to the academic dimension.

As logistics centers are strategic facilities occupy vital position in the logistics system (Liu et al., 2012) the efficiency of this system largely depends on its locations (Milosavljević et al., 2018). Therefore, the correct positioning of the logistics centers can be considered as an important strategic decision for optimization of the transportation network (Milosavljević et al., 2018) and a critical point of the entire supply network (Rikalović et al., 2018).

As with all strategic decisions, cost is undoubtedly one of the most important parameters to ensure the availability and effective flow of

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goods in a supply chain. In that sense, as Thai and Grewal (2005) argued the location problem plays a crucial role in logistics. However, besides other quantitative variables, the solution of the problem should decrease transportation costs while increasing the measures regarding the job performance, competitive capacity, and profitability (Thai and Grewal, 2005). According to Rikalović et al. (2018) the effect of the location can change the total operating costs by 50%. Facility installation costs and land costs also must be affordable. In addition, facilities must be close to demand and supply zones. Accessibility is another important requirement that facilities must meet.

In addition to other logistics facilities (Acar et al., 2015; Chun-Wei and Sheng-Jie, 2013), city logistics centers need to be in the right location in order to be efficient and effective in their complex environment particularly in mega cities.

It is reported that, 55% of the world's population lives in urban areas today, as an estimation has expected that 68% of the world population will live in cities by 2050 (UN DESA, 2018). So, the urban logistics will become vital for the health, well-being, and the prosperity of the inhabitants. Particularly, a dynamic, effective, and efficient urban logistics system might facilitate that people live, work, and play in a high-quality environment in mega-cities (Rao et al., 2015). In this regard logistics centers in mega-cities have become the pivotal element of the logistics system to provide the supply and the delivery of goods. Additionally, these centers are important to reduce the born costs both for the growing number of companies which are operating in urban areas and the inhabitants (Pamucar et al., 2016). This argument is supported by a study which found that using logistics terminals might reduce the companies' costs from 5 to 20%. Particularly, using logistics terminals in urban areas might reduce the number of vehicle kilometers by 60% (Murphy and Poist, 2003).

In order to accurately reflect the complex structure of the solution environment encountered in the location analysis of these city logistics centers, a number of solution methods have been developed for finding the most suitable location (Milosavljević et al., 2018), such as multi-criteria decision analysis (MCDA) methods (e.g. Ishizaka et al., 2013; Regmi and Hanaoka, 2013; Dehe and Bamford, 2015), Geographical Information Systems (GIS) to analyze and visualize geographical and spatial data (Estivill-Castro and Houle, 2001) which can be incorporated with MCDA methods (Greene et al., 2011; Javadi and Shahrabi, 2014).

Hale and Moberg (2003) provided earlier studies related to site selection including the mathematical models before GIS and MCDA integration became popular. These methods can be clustered as continuous, discrete and network models. The network models can be classified as p-median, p-center and other. However, classical optimization approaches mostly cannot reach the optimum solutions for these models while high numbers of alternatives were in consideration.

To overcome the complexity of the models meta-heuristics applications are suggested to be used such as genetic algorithm (Alp et al. 2003; Chaudhry et al. 2003), simulated annealing (Chiyoshi and Galvao, 2000; Levanova and Loresh, 2004), neural networks (Shamsipour et al., 2012), tabu search (Rolland et al., 1996; Salhi, 2002; Sun, 2012), ant colony optimization (Yousefikhoshbakht et al., 2016; Levanova and Loresh 2004), particle swarm optimization (PSO) (Sevkli et al., 2014). In a more recent study, Ganguly (2020) has proposed to use PSO heuristics for multi-objective distributed generation penetration planning with loads where the concept is applicable to logistic systems and logistics centers selection. In the literature it has been shown that Binary Particle Swarm Optimization (BPSO) is very effective and robust for solving hard optimization problems especially problems like discrete multiple site selection (Lin and Guan, 2018).

The aim of this study is to fill in the literature gap where there is no complete methodology for city logistics center location selection problem where GIS and metaheuristic algorithms are efficiently integrated. This study proposes a comprehensive integrated solution methodology for a logistics center location selection problem and applies the methodology to a real urban data set. The methodology mainly consists of the following two steps: (1) Geographic analysis part by spatial and network analysis, (2) Optimizing the mathematical model (P-median) and applying BPSO algorithm to reach the optimum solution. The reasons for applying the BPSO in this paper are basic concept, easy implementation and coding, having the limited parameters and computational efficiency when compared with mathematical algorithm and other metaheuristic algorithms.

To validate the current study in urban area, the proposed methodology is applied to one of the world's largest cities, Istanbul. According to UN DESA (2018) report, Turkey's urban area population is about 75% in 2018, and it is expected to increase 86% by 2050. Istanbul is a unique case in Turkey for its inhabitants, total area, geographically separated area which cause complex transportation network, and logistically and economic importance.

The remainder of the paper is organized as follows: Section two is devoted to the methodology which expresses theoretical background of the analysis. An application of the proposed methodology with detailed analysis is given in section three. Section four is reserved for discussions of the results. Conclusions and further research opportunities are reported in section five.

2. Methodology

As introduced in the previous section, the study involves a two-step methodology to reach the decision for logistics centers location problem. The first step is geographic analysis part, which are spatial analysis and network analysis. Spatial analysis calculates the priority values of the alternatives that represent the logistics densities in the considered regions and network analysis shows the exact driving distances between alternatives. That step has been consisted of data collection and creation and spatial analyses. The second step is the optimizing through mathematical modeling. For the latter step, firstly mathematical model is needed to be solved with existing solvers for manageable sizes and to be shown that the existing solvers capabilities are insufficient to solve for large sized model structures which are common for logistics network problems. Then for reaching the optimum solutions meta-heuristics approach is necessary, and BPSO algorithm is suggested as meta-heuristics tool. The general structure of the methodology is illustrated in the Fig. 1.

2.1. Network analysis

The first calculation of the GIS analysis is the OD distance calculation which means distances between any selected facilities. In order to calculate the matrix, firstly the hierarchical transportation network should be built based on the characteristics of the network. Then, candidate nodes which might be a supply or demand node or logistics center should be located on vertex nodes of the road transportation system. In this step vector geographic data is required which are created in the previous step and the network building can be completed with a GIS software. GIS software packages are capable of calculating exact distances between any two nodes or multiple nodes with mile/km metrics or time basis based on shortest paths via Dijkstra Algorithm (Dijkstra, 1959). Employing this capability, distance input is created with the given analysis steps.

2.2. Logistics activity mapping

Spatial characteristics of a study area can be analyzed by various approaches. Spatial statistical approaches are one of the comprehensive methods to deal with the problems due to their capabilities to consider data's geographical attributes. In order for clustered groups of logistic densities to be generated, initially it must be determined that the data pattern is in a clustered structure. Hot spot analysis is a way to analyze the spatial pattern of the logistics activities similarly to the stated

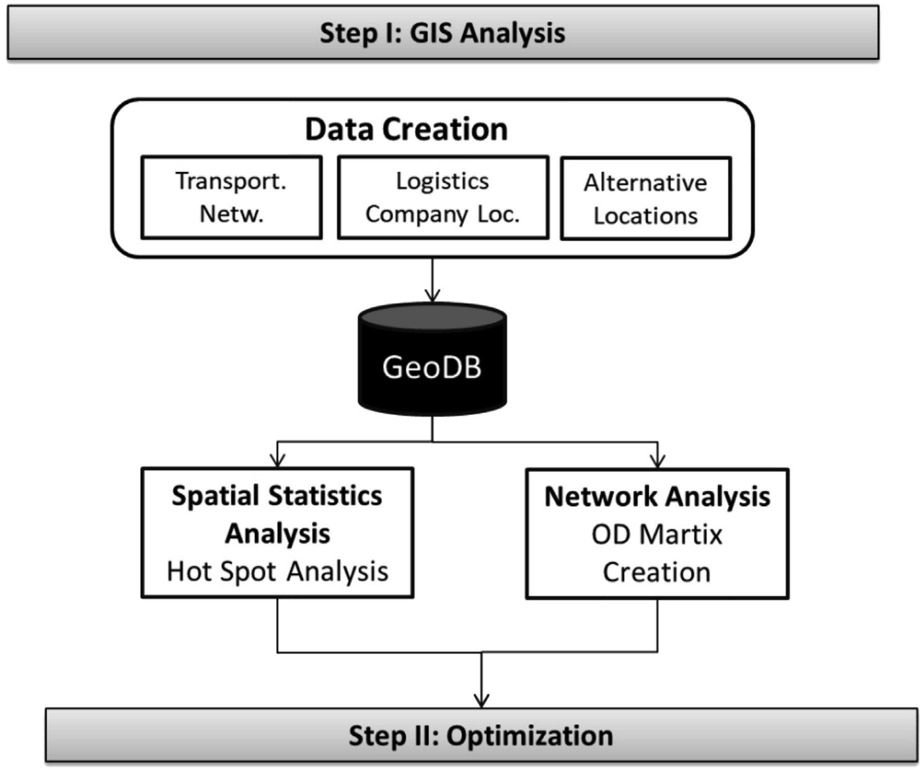

Fig. 1. Study methodology.

problem structures. The assumption here is if a considered region has logistics facilities, the area is a hot spot in the context of logistics activities. The results can be integrated with different solution approaches such as mathematical models, decision support systems, and so on.

Hot spot analysis considers the study area in the divided sub-regions and calculates *Moran's I* statistics based on the neighbor characteristics. "*I*" statistics can be expressed mathematically with the Eq. (1) (Truong and Somenahalli, 2011).

Notations for the Eq. (1) are given below;

w_{ij}: the proximity weight of location "*I*" and location "*j*";

x_i is the severity index at location *j*;

$\bar{x}$ is the global mean value;

n is the total number of focused location.

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})(\sum_{i}^{n}(x_i-\bar{x})^2)} \tag{1}$$

"*I*" is to analyze the pattern if it is clustered or randomly distributed. For continuing the clustering analysis, it is expected the considered data is clustered. *Z-score* can be used to analyze the pattern where *E[I]* is expected value for a random pattern, *VAR [I]* is the variance. *Z-score* calculation is given in Eq. (2). The *Z-score* is the standardized value for expressing the deviation from expected value. It explains whether the data is clustered or randomly distributed with the specified significance level. The best *Z* value is needed to be tested empirically and the convenient distance threshold is found where the highest *z-score* is (ESRI, 2014).

$$Z = \frac{I - E(I)}{\sqrt{VAR(I)}} \tag{2}$$

$G_i(d)$, Getis-Ord Statistics (Getis and Ord, 1992) is able to draw the hot spot borders with the calculated threshold value in the previous step. The mathematical statements for $G_i(d)$ statistics are given in the Eqs. (3) and (4).

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{ij}(d)x_j}{\sum_{j=1}^{n} x_j} \tag{3}$$

$$Z(G_i^*) = \frac{I - E(I)}{\sqrt{VAR(I)}} \tag{4}$$

The $G_i(d)$ statistics measures the degree of association coming from the calculation of the concentration of the weighted points within a radius of a distance *d* from the origin point. *n* express the number of subdivided regions where each region $i = 1,2,\ldots n,$ is has known coordinates and Euclidean distances. Each *i* has associated with it a value *x* (a weight) taken from a variable *X*. The variable has a natural origin and it is positive. The $G_i(d)$ statistic allows hypotheses testing about the spatial concentration of the sum of *x* values associated with the *j* points within *d* of the i^{th} point. Z_i in the Eq. (4) can be used to compare with specified level of significance.

Using Hot-spot Analysis, the approach examines the land characteristics then maps the hot-spots if the considered features in the study area are clustered. The attained results are useful when a mathematical model is employed to represent a real-world application. The calculated hot-spots are the h_i parameters used in the mathematical model which is explained in the next sub-section.

2.3. Mathematical model

P-median problem is proposed by Hakimi (1964) in the mid of 1960s and after the proposition, the problem has been one of the most popular location problem structure in the literature (Levine, 2006). Hakimi (1965) also showed that the selected facilities are found on the vertex node on the network. The objective function searches the minimum distances during locating several facilities in a network when "*m*" nodes are considered for "*n*" candidate facilities. Problem is an example of combinatorial NP-hard optimization problems (Estivill-Castro and Houle, 2001; Peeters et al., 2015)

During mathematical modelling and analysis phase, suitability of characteristics of the p-median model is applied to the decision environment as expressed previously. Thus, within the analysis incapacitated weighted p-median model is used to determine the final location decision. The model formation is given in the following Eqs. (5)–(10).

Parameters

d_{ij} distance between origin node "i" and destination node "j"

h_i logistics density value of node "i"

P number of logistics centers

$$Y_{ij} = \begin{cases} 1 if \ \ node \ \ \text{i} \ \ is \ \ assigned \ \ to \ \ facility \ \ at \ \ point \ \ \text{j}; \\ 0 Otherwise \end{cases}$$

$$X_j = \begin{cases} 1 if \ \ a \ \ facility \ \ is \ \ located \ \ at \ \ point \ \ "j"; \\ 0 Otherwise \end{cases}$$

Objective Function:

$$\text{Minimize} \ \ Z = \sum_{i}^{n} \sum_{j}^{n} h_i d_{ij} Y_{ij} \tag{5}$$

Constrains:

$$\sum_{j=1}^{n} Y_{ij} = 1, \forall \ i \tag{6}$$

$$\sum_{j=1}^{n} X_j = P \tag{7}$$

$$Y_{ij} - X_j \leq 0, \forall \ i, j \tag{8}$$

$$Y_{ij} \in \{0, 1\}, \forall \ j \tag{9}$$

$$X_j \in \{0, 1\}, \forall \ i, j \tag{10}$$

The objective function (Eq. (5)) minimizes the demand-weighted total distance. Eq. (6) ensures that each of nodes must be assigned to a facility. Eq. (7) requires exactly P facilities to be located. Eq. (8) ensures that each of nodes can only be served by an open facility. Eqs. (9) and (10) state that the location variables and the assignment variables must be binary.

2.4. BPSO and adaption to the problem

PSO algorithm is one of the successful optimization techniques which is inspired from the social behavior such as flocks of birds and schools of fish (Eberhart and Kennedy, 1995). Each of individual within swarm exhibited social behaviors is called "particle". PSO algorithm is simple and requires a few operators for solving engineering problems. Although the original PSO algorithm is developed for continuous optimization problems, it is transformed for dealing with binary problems and represented good performances on discontinuous solution spaces. The BPSO algorithm operates bit strings rather than real numbers (Poli et al., 2007). In original PSO, each particle has its own velocity and position which are updated in all iterations by using Eq. (11) and equation (12). As it is seen from the first equation, while determining particle's velocity, the particle uses not only its best position in all iterations but also the best position their neighbors in all iterations according to the fitness value. The notations of the parameters for PSO algorithm are given in Table 1.

$$v_i^{k+1} = (w_k v_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (g_i^k - x_i^k)) \tag{11}$$

$$x_i^{k+1} = v_i^{k+1} + x_i^k \tag{12}$$

On the other hand, in the BPSO algorithm, while the position of particle is being determined, equation (13) is used. During the positioning the particle in the binary version of PSO, the velocity is used as a probability threshold which is found by using logistics transformation equation (Kennedy and Eberhart, 1997). When the logistics transformation equation is applied, the result is between zero and one. The random number (r) is simultaneously generated in order to compare the logistics transformation ($S(v_i^k)$) and random number. If this random number (r) is less than logistics transformation ($S(v_i^k)$), the position of particle is being accepted as 1, otherwise 0.

$$S(v_i^k) = 1/(1 - e^(- v_i^k) \tag{13}$$

Table 1
Nomenclatures for Original PSO Algorithm.

v_i^k	Velocity of the i^{th} particle in k^{th} iteration
x_i^k	Position of the i^{th} particle in kth iteration
p_i^k	Particle's best position in k^{th} iteration
g_i^k	Swarm's best position in k^{th} iteration
$S(x_i^k)$	Solution of the i^{th} particle in kth iteration
c_1 *and* c_2	Learning factors
r_1 *and* r_2	Random number from 0 to 1
w	nonnegative inertia factor

Table 2
Algorithmic Schema for BPSO Algorithm.

1. Initialization (for $k = 0$)
2. For $i = 1$ to N
3. Generate initial solution randomly between (0, 1) (x_i^k)
4. Calculate initial solutions ($S(x_i^k)$)
5. Assign p_i^k = initial position(x_i^k)
6. Assign p_i^k = best position among the all particles
7. Generate initial velocities randomly (v_i^k)
8. Improve the solution (for $k = 1$ to $iter_{max}$)
9. For $i = 1$ to N
10. Update velocities (v_i^{k+1})
11. Modify the current positions by using logistics transformation equation (x_i^{k+1})
12. Calculate initial solutions ($S(x_i^{k+1})$)
13. Update the best position of the i^{th} particle (p_i^{k+1})
14. Update the best position of the particle group (g_i^{k+1})
15. Finalize the algorithm ($k = iter_{max}$)
16. Assign the best solution = (g_i^k) and stop.

The algorithmic schema for BPSO algorithm is shown in Table 2.

When the logistics transformation equation is applied, the result is between zero and one. The random number (r) is simultaneously generated in order to compare the logistics transformation ($S(v_i^k)$) and random number. If this random number (r) is less than logistics transformation($S(v_i^k)$), the position of particle is being accepted as 1, otherwise 0.

BPSO algorithm has a drawback for solving this type of problem due to possibility of trapping local optimum. In order to overcome this problem, the algorithm steps presented in Table 2 are modified hence particles' searching ability in solution space is improved. The changes in the algorithm are that; in every "T" iteration updating velocity and position steps starts last particle of swarm and ends the first particle of swarm (Steps 9–16 in Table 3). These simple changes affect the particles' the best position positively and improve particles' searching ability in solution space. The algorithmic schema for proposed BPSO algorithm is shown in Table 3.

3. Application

The proposed methodology is validated through a case study to select city logistics centers in Istanbul, a city with unique urban characteristics and complex transportation network. As of year 2020, the official population count of Istanbul is estimated at approximately 15 million; located on a total area of 5343 square kilometers. Metropolitan region of Istanbul is divided into two main parts by Bosporus strait

Table 3
Algorithmic Schema for Proposed BPSO Algorithm.

1. Initialization (for $k = 0$)
2. For $i = 1$ to N
3. Generate initial solution randomly between (0, 1) (x_i^k)
4. Calculate initial solutions ($S(x_i^k)$)
5. Assign p_i^k = initial position(x_i^k)
6. Assign p_i^k = best position among the all particles
7. Generate initial velocities randomly (v_i^k)
8. Improve the solution (for $k = 1$ to $iter_{max}$)
9. If ($k\%T \neq 0$)
10. For $i = 1$ to N
11. Update velocities (v_i^{k+1})
12. Modify the current positions by using logistics transformation equation (x_i^{k+1})
13. Else
14. For i = N to 1
15. Update velocities (v_i^{k+1})
16. Modify the current positions by using logistics transformation equation (x_i^{k+1})
17. Calculate initial solutions ($S(x_i^{k+1})$)
18. Update the best position of the ith particle (p_i^{k+1})
19. Update the best position of the particle group (g_i^{k+1})
20. Finalize the algorithm ($k = iter_{max}$)
21. Assign the best solution = (g_i^k) and stop.

where one part lies in Asia and the other in Europe. Besides, European part of the city is further divided into two parts by Golden Horn a natural harbor (estuary). These divided parts are linked by bridges which creates significant congestion and delays in urban transportation. Other means of transportations such as maritime and underground railway tunnels are also available to connect the geographically divided parts making the network broader.

In addition to the population, Istanbul has a substantial economy in regard to production and service industries. The Brookings Institution has announced Istanbul as the fourth fastest-growing metropolitan economy in the world, adding an additional 460,000 jobs and expanding GDP per capita by 3.9 percent in its Global Metro Monitor Report released in 2018. Istanbul has ranked 12th in the "highest performers on economic performance index" among 300 largest metropolitan economies of the world, and the highest performer in Eastern Europe and Central Asia region in the period of 2014–2016 (Brookings Institution, 2018). These economical values also create high dense logistics mobility in the city. For the reasons stated above, Istanbul stands out as a suitable case city for solving network problems related to logistics.

In this application, multiple network settings defining various problem sizes and hence different levels of problem complexity are tested on the current case study. The network structure is designed to be 15, 30, 45, 60, 75 and 150 nodes representing both demand and supply regions (Fig. 2).

3.1. GIS calculations

GIS analyzing power is used for estimating two parameters in the mathematical model. The first is the distance matrix while the second is the logistics densities which are used as priority values of the alternative locations. Spatial statistics methods are used to measure the spatial sprawl of the logistics facilities in Istanbul. The mapping of the statistical clusters for logistics facility locations is completed in two steps: First, the city is divided into 959 sub-regions based on the district areas. Second, the pattern of the logistics facilities is analyzed with Morans' I pattern analysis. The spatial analysis revealed that the disparity of the logistics facilities in the study area follows clustered structure. Accordingly, a spatial statistics tool such as hot spot analysis is a convenient tool to map such logistics facility clusters (Grubesic and Murray, 2001). Thus, the clustering technique is used and facilities are statistically clustered with Getis-Ord Gi* statistics. ArcGIS 10.3.1 software is used to perform the calculations. Fig. 3 summarizes and visualizes the findings.

The second usage area of GIS is the network analysis. Distances between alternative nodes should be represented in matrices, and in that step, transportation network of the city is build based on the preference hierarchy of the roads. The aim of using network analysis via GIS is to calculate exact length values on the city's road network. Within the calculation of Origin Destination (OD) matrix that expresses the distances between i and j, d_{ij}, is created and used in the mathematical model. The network analysis is performed six times to create the OD tables with the node sizes of 15, 30, 45, 60, 75 and 150.

3.2. Solving the p-median model with Zero-One Integer Programming and BPSO

In this section, application of the solution approach of the weighted and unweighted p-median problems is described. The model represents the location analysis environment for logistics center locations which has been solved using BPSO algorithm and Zero-One Integer Programming. The considered location selection problems involve locations of *"p"* facilities on a network when *"m"* nodes are considered for *"n"* candidate facilities with minimum total weighted or unweighted distances of serving the all nodes; as described earlier in Section 2.3.

Estimating the values of "p", "m" and "n" parameters is needed for the case application. These parameters define the size of the considered problem. In addition, the priorities of the nodes are another feature of the model where nodes with no demand densities are equivalent to the unweighted p-median problem structure. Otherwise, if nodes have demand densities, it is called weighted p-median problem. Therefore, the demand density has a significant impact on the optimal objective function. To test the model efficiency for various problem sizes and levels of complexity, six different network problem instances with 15, 30, 45, 60, 75 and 150 nodes have been considered to cover a range of limited network to a relatively sophisticated network structures. The problem size is reflected to the solution time and choosing the proper network structure is crucial to reach a tradeoff between the level of accuracy and solution efficiency. Larger numbers of nodes help to better specify the optimal location (with high resolution) but add extra computational burden and hence require longer solution time. In contrary, smaller numbers of nodes can reach an approximate solution (with low resolution) with less computations and competing solution times.

The third determination about problem is the centralization level of the logistics facilities. The decision is to determine the number of logistics centers in the analysis which is represented by parameter p in the mathematical model. In the analysis, the effects of travelled distances between 1 and 5 facilities is considered and reported.

After determining the distances between nodes and priorities of the alternatives, p-median model is solved with spreadsheets and BPSO algorithm. The model firstly is solved with spreadsheets and optimal results are calculated for the node sized 15, 30, 45 and 60. While calculation the model sized 75 nodes, optimum solution was not reached due to the complexity of the problem structure and exceeding computational capacity. BPSO algorithm are coded by using MS Visual Studio package program and run on an Intel Core i3 CPU, 2.13 GHz with 4 GB RAM. One hundred particles are used in each iteration and the maximum number of iterations is determined as 1000. Both learning factors ($c_1 and c_2$) are 2. The maximum and minimum velocities of particle are 5 and – 5, respectively. Non-negative inertia factor for using to slow the particles' velocities is determined as 0.9. There are no hardware differences between BPSO and Zero-One Integer Programming spreadsheets while solving p-median model. Therefore, spreadsheets run on the same computer.

BPSO algorithm is applied for unweighted and weighted p-median models of 15, 30, 45, 60, 75 and 150 nodes, and each p-median model has different number of median. By using BPSO algorithm, above-

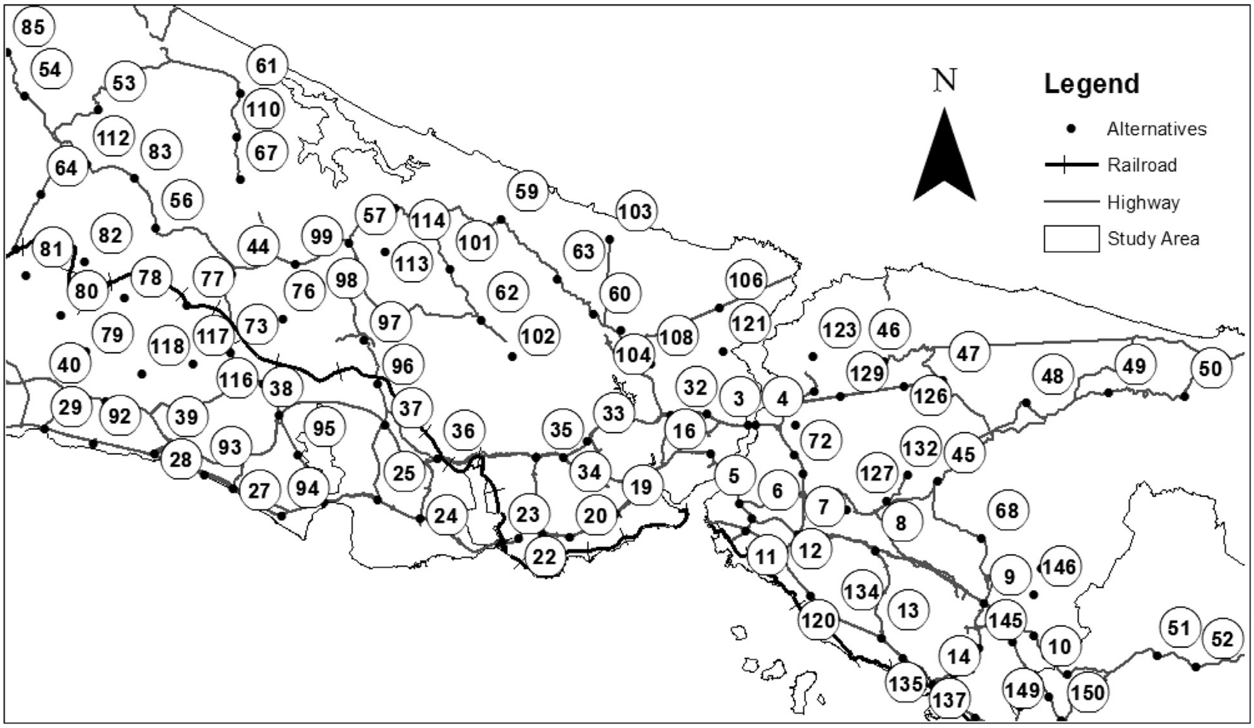

Fig. 2. Alternative nodes on the study area.

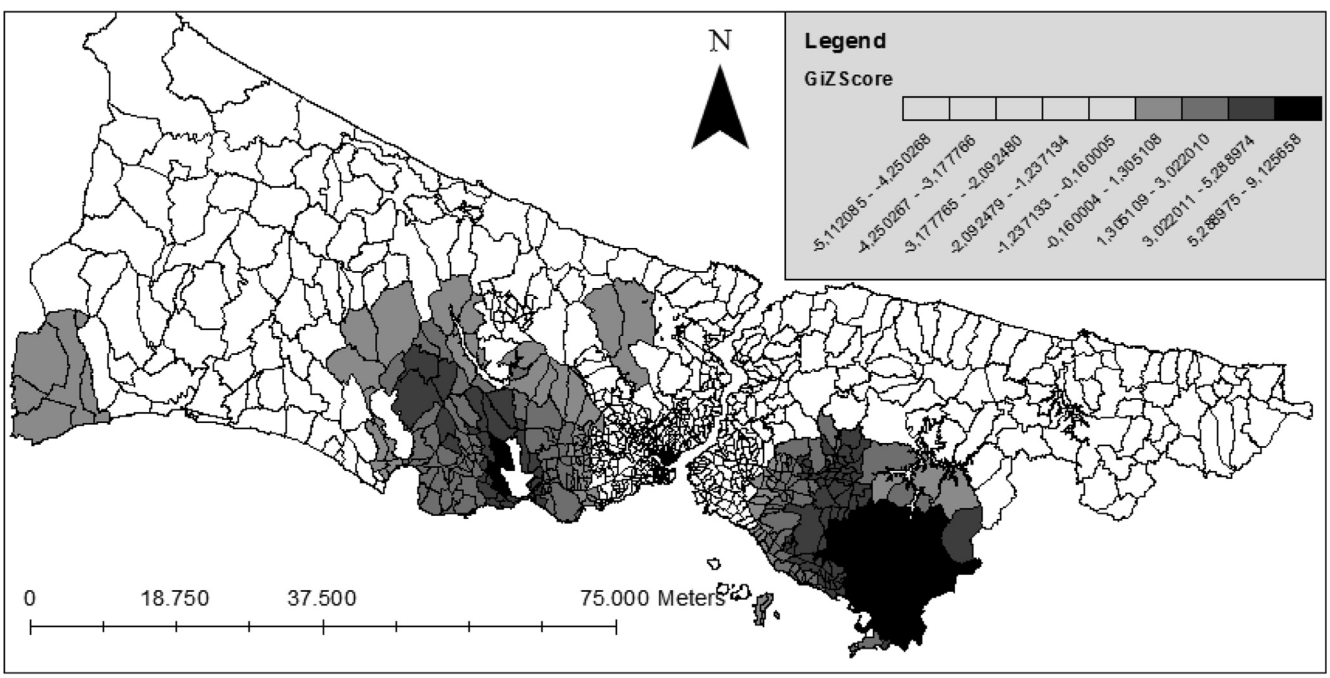

Fig. 3. The results of the logistics facility clustering analysis.

mentioned problems for spreadsheets are overcome, and not only the optimal solutions for weighted and unweighted p-median models of 15, 30, 45 and 60 nodes are found but also the satisfactory results are gained for unweighted and weighted p-median models of 75 and 150 nodes. These results of weighted and unweighted p-median networks for 15, 30, 45, 60, 75 and 150 nodes with different median numbers are shown Table 4.

All facility location problems in network (p-median models) shown in the Fig. 2 are solved by both Zero-One Integer Programming and BPSO algorithm. After solving the all problems, the results of all solutions are given in Table 4.

As we mentioned before, it is important criterion that p-median models have priority or not. Both weighted p-median models and unweighted p-models are solved using Zero-One Integer Programming and BPSO algorithm respectively and each column of the approach is separated for weighted and unweighted results. In the same problem row, the total transportation and investment costs are different because of the priority. For instance, the total transportation and investment cost for the weighted p-median model which has 15 nodes (the network size is fifteen) and $p = 1$ is \$655,759. On the other hand, the total

Table 4
The Results of Zero-One Integer Programming and BPSO Algorithm.

Network Size	p-number	Zero-One Integer Programming				BPSO Algorithm			
		Unweighted		Weighted		Unweighted		Weighted	
		Solution Time	Total Cost	Solution Time	Total Cost	Solution Time	Total Cost	Solution Time	Total Cost
15	1	2,1	202,392	2,3	655,759	2,2	202,392	2,2	655,759
	2	2,1	113,332	2,3	365,435	2,5	113,332	2,7	365,435
	3	2,3	88,315	2,3	262,820	3,1	88,315	3,4	262,820
	4	2,2	69,053	2,2	194,373	3,4	69,053	3,7	194,373
	5	2,3	53,945	2,3	146,026	3,8	53,945	4,2	146,026
30	1	26,7	788,382	29,1	2,304,077	4	788,382	4,2	2,304,077
	2	26,5	521,453	28,8	1,455,232	4,8	521,453	4,9	1,455,232
	3	26,7	364,363	29,1	1,006,046	5,7	364,363	5,8	1,006,046
	4	26,6	260,448	28,7	709,895	6,4	260,448	6,5	709,895
	5	26,4	215,938	31,8	607,280	7,2	215,938	7,6	607,280
45	1	132	1,495,975	144	3,275,338	6,1	1,495,975	6,2	3,275,338
	2	128	858,127	144	1,846,798	7,4	858,127	7,3	1,846,798
	3	128	641,959	131	1,357,880	8,7	641,959	8,6	1,357,880
	4	132	537,339	132	1,063,868	9,8	537,339	11,3	1,063,868
	5	132	444,205	133	883,840	11	444,205	11	883,840
60	1	411	2,448,637	475	4,234,138	7,8	2,448,637	8	4,234,138
	2	413	1,572,167	471	2,659,446	9,5	1,572,167	9,6	2,659,446
	3	413	1,345,296	527	2,112,396	12,7	1,345,296	11,4	2,112,396
	4	421	1,104,019	516	1,791,806	12,8	1,104,019	13,2	1,791,806
	5	419	956,402	486	1,510,982	16,1	956,402	14,8	1,510,982
75	1					9,8	3,627,781	10,5	5,718,478
	2					12,7	2,303,235	12,3	3,664,664
	3					14,2	1,983,824	14,3	3,051,457
	4					16	1,648,487	17,6	2,492,576
	5					20,3	1,427,801	21,5	2,202,167
150	1					20,1	8,644,035	20,1	13,659,852
	2					24,2	4,826,281	27,5	7,572,957
	3					27,8	3,761,577	32,4	6,157,696
	4					32,2	3,271,245	38,6	4,994,451
	5					35,9	2,931,719	43	4,486,394

transportation and investment cost for the same problem without priority (nodes have not demand density) is $202,392.

In each p-median model, the results of solution time and total cost are shown in Table 4. However, for the results of the p-median model with 75 network size and the p-median model with 150 network size could not be obtained by using Zero-One Integer Programming. Thus, there are no solution times and total costs about these two p-median models.

4. Discussion

In this section, the methodology presented in here is compared to Zero-One Integer Programming. The comparisons of the results for various configuration of p-median problem are shown in the Table 5. In third and fourth columns of Table 5, the solution times and total costs percentage differences are reported for unweighted p-median models. In fifth and sixth columns, the solution times and total costs of both techniques are collated for p-median with demand priority model. If the value is positive in Table 5, that means Zero-One Integer Programming gives better solution than BPSO algorithm. Negative values indicates that BPSO algorithm gives better solution than the other technique.

For both weighted and unweighted p-median models with 15 nodes networks there is no cost difference between Zero-One Integer Programming and BPSO algorithm. However, Zero-One Integer Programming reaches the optimal solution faster than BPSO algorithm in the almost all 15 nodes network models. On the other hand, as the network size increases, the comparison of the solution times are changing. In the 30 nodes network models, 45 nodes network models and 60 nodes network models, BPSO algorithm not only gives solution much faster than Zero-One Integer Programming but also finds the optimal solution for all models. BPSO algorithm performs 72.7% to 98.3% better timewise in obtaining the optimal solution. The last but not least, indirect inference in the Table 4 means that the BPSO algorithm can find acceptable good solutions while solving the p-median problem for network sizes even 75 nodes and 150 nodes. On the other hand, Zero-One Integer Programming cannot reach any solutions for the same p-median problems within the capacity of the hardware used. There are naturally no comprehensive comparisons between Zero-One

Table 5
The Comparison Table of the Results Obtained by Zero-One Integer Programming and BPSO Techniques.

Network Size	Number of Median	Unweighted		Weighted	
		Time Change	Cost Change	Time Change	Cost Change
15	1	4,8%	0,0%	−4,3%	0,0%
	2	19,0%	0,0%	17,4%	0,0%
	3	34,8%	0,0%	47,8%	0,0%
	4	54,5%	0,0%	68,2%	0,0%
	5	65,2%	0,0%	82,6%	0,0%
30	1	−85,0%	0,0%	−85,6%	0,0%
	2	−81,9%	0,0%	−83,0%	0,0%
	3	−78,7%	0,0%	−80,1%	0,0%
	4	−75,9%	0,0%	−77,4%	0,0%
	5	−72,7%	0,0%	−76,1%	0,0%
45	1	−95,4%	0,0%	−95,7%	0,0%
	2	−94,2%	0,0%	−94,9%	0,0%
	3	−93,2%	0,0%	−93,4%	0,0%
	4	−92,6%	0,0%	−91,4%	0,0%
	5	−91,7%	0,0%	−91,7%	0,0%
60	1	−98,1%	0,0%	−98,3%	0,0%
	2	−97,7%	0,0%	−98,0%	0,0%
	3	−96,9%	0,0%	−97,8%	0,0%
	4	−97,0%	0,0%	−97,4%	0,0%
	5	−96,2%	0,0%	−97,0%	0,0%

Integer Programming and BPSO algorithm while solving the p-median logistic center models for the network sized 75 nodes and above. It should be noted that without having exact solutions the optimality of BPSO algorithm results cannot be verified. Considering that BPSO algorithm provides acceptable solutions for the network sized 75 nodes or more, it can be concluded that BPSO algorithm is very appropriate tool for solving p-median logistic center models with or without demand density.

5. Conclusion

The importance of the logistics centers as a strategic facility within the logistics networks has been commonly accepted in recent years. This facility where different types of logistics processes are executed, acts like a bridge between service providers and costumers. This centers not only provide an integrated logistics processes to service providers but also help service providers by decreasing the logistics costs while executing all logistics processes. Moreover, a logistics center can link different transportation modes so it can handle different types of containers, pallets, totes and so on, and can distribute all these containers to different locations. The determination of location of such an important logistic center cannot be done easily. This location selection problem for logistics center needs to connect different nodes (locations). While connecting the all nodes to each other, the transportation costs between all nodes must be decreased. Particularly, in such megacities, logistics centers provide decreasing of logistics cost, traffic congestion, and delays.

The aim of this study is to propose a methodology for logistics center location selection problem with GIS and BPSO algorithm. In this context, an integrated solution methodology for the special type of facility location selection problem is proposed and application on a real data set of Istanbul, a mega-city, is provided. The solution methodology involves two phases in order to determine logistic center location decision. The first phase is covering both spatial and network analysis of GIS. It is the geographic analysis which determines the priority values of the alternative facility locations that show us the effects of logistics intensities in the specified regions, and network analysis gives us the exact driving distances between alternatives in the network. That phase involves the data collection and creation and the performing of spatial analyses. Then, the results of the first phase are used as input data for next phase. When the exact driving distances are gathered, the mathematical model can be constructed. In the second phase, the mathematical model is solved by using Zero-One Integer Programming and BPSO algorithm. In this phase, firstly mathematical model is solved with existing solvers and proven that the existing solvers capabilities are insufficient to solve for large sized model structures. The results of Zero-One Integer Programming show that the model structure is complicated to solve for high number of considered alternatives. Then, to deal with these types of the problems, meta-heuristics approaches are necessary and BPSO is applied to the large size problems. BPSO algorithm solves the models with considerably lower time and gives the acceptable solutions for the large sized network problem. The other important result is using GIS eliminated unnecessary calculations and simplifies the model structure which leads easy to solve the model.

This study represents a proposed BPSO algorithm and GIS integration approach for the analysis of the logistics center location selection in an urban area. The suggested methodology in this study can be used by the urban city planners to analyze critical nodes of transportation networks of the mega cities as well. Also, it can be used by governmental decision makers to analyze and decide the location of such critical facilities.

The proposed methodology has some limitations. The first limitation is that for analyzing spatial characteristics of area, hot spot analysis is applied. But, there are various approaches that analyzes the spatial characteristics of area. Secondly, BPSO gives acceptable solution in a short span of time for solving the large sized network problems. However, if the problem size get bigger, it is not known exactly how the proposed methodology will behave.

In order to shed light on future studies, the study can be applied with necessary criteria considerations based on the applied problem. Moreover, the proposed methodology can be applied to the different mega cities with different criteria sets. Lastly, different heuristic and meta-heuristics algorithms can be applied to the logistics center location selection problem in case the problem size enlarges.

CRediT authorship contribution statement

Emre Çakmak: Methodology, Software, Formal analysis. **İsmail Önden:** Conceptualization, Methodology, Software, Visualization. **A. Zafer Acar:** Conceptualization, Project administration. **Fahrettin Eldemir:** Supervision.

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