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# Particle Swarm Optimization to Solve Multi-Center Location Problem on Small Networks

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## Abstract:

This paper addresses the multi-center location problem, in which a set of p centers to be located to minimize the maximum distance between a center p and its nearest demand point. The problem is NP-hard. Therefore, polynomial time-bounded algorithms are unlikely to yield an optimal solution. Particle swarm optimization (PSO) is a metaheuristic algorithm that has been shown to be effective in solving such hard and complex optimization problems.

This paper presented a new PSO for the multi-center location problem on small networks. Three objectives are considered as follows: ( $^{1}$ ) developing a new PSO algorithm to solve the problem, ( $^{7}$ ) applying the developed algorithm to a set of well-known benchmark location problems, and comparing the results. ( $^{7}$ ) verifying the stability of the algorithm. The result is a simple but effective algorithm for solving multi-center problems on networks. The new proposed PSO algorithm solved multi-center location problems, when all candidate solutions can be investigated. PSO was found to be stable and the average time of runs increases linearly as the number of centers increases. The advantage of this algorithm is that, it calculates the optimal solution for each candidate solutions

Keywords: Swarm Optimization – Center Location – Networks.

# **\. Introduction**

Location science is a very attractive research area. Center location problems are especially prominent in emergency service locations, because saving lives is significantly more vital than any transportation costs involved in providing that service. The center location problem also is an important subject of strategic planning. It is also a very popular and common operations research problem. The location of a single center is easier than locating many facilities, which is known as the multi-center location problem. Location decisions arise in both government and private sectors. For example, governments, must decide where to locate emergency highway patrol cars, fire stations and ambulances. Offices, production and assembly plants, distribution hubs, and retail outlets must all be located optimally in the private sector. Poor location choices might result in higher expenses and lower competitiveness. (Daskin  $\Upsilon \cdot \Upsilon \Upsilon$ ).

(Hakimi 1975) was the first to propose the single center problem for locating a station in such a way that the station's maximum distance from a group of communities (demand points) connected by a highway system is reduced. By addressing a finite series of minimum set coverage problems, (Minieka 197., Christofides and Viola 1991) develped methods for solving multicenter (p-center) location ptoblems. (Christofides 1910) shown that only a subset of the edges may be considered. However, this method failed to overcome generic p-center problems. (Kariv and Hakimi 1979 showed that the multi-center location problem is NP-hard problem. This type of problems is hard to solve since it is non-linear, and non-convex (Brandeau and Chiu 1919). The complexity and non-linearity of the multi-center location problem requires novel method to be developed. (Davidovica et al. 7.11) developed a bee colony optimization method to solve vertex location problem on networks, also (Kaveh and Nasr  $7 \cdot 11$ ) solved the same problem using a modified harmony search technique. (Rabie et al. ۲۰۱۳, Rabie et al. ۲۰۱۳, Rabie ۲۰۲۱) presented PSO algorithms for large-scale p-center and p-median location problems. (Current et al.  $\gamma \cdot \cdot \gamma$ , Farahani and Hekmatfar  $\gamma \cdot \cdot \gamma$ , Laporte et al.  $\gamma \cdot \gamma \circ$ , Laporte et al.  $\gamma \cdot \gamma \circ$ ) provide an overview of p-center problem on networks.

Particle Swarm optimization (PSO) was introduced by Kennedy and Eberhart in 1990, as an intelligence nature-inspired algorithm, based on natural swarm behavior. Since that, PSO has sparked a lot of attention and interests. PSO has been applied to many optimization areas (Yang  $7 \cdot 12$ ).

This paper aims to develop an efficient PSO algorithm to solve multi-center location problem on networks. To test the efficiency our developed PSO algorithm, we performed an extensive experiment on different multi-center location problems on small networks in the literature. The paper is divided as follows; Section  $\uparrow$  defines the location problem. Section  $\uparrow$ introduces PSO algorithm. Section  $\notin$  shows how PSO solves multi-center location problem. Section  $\circ$  is a numerical example, and section  $\uparrow$  is for the computational experiments. Finally, is the conclusion.

# **Y. Multi-Center Location Problem on Networks**

Multi-location problems on network, is a collection of vertices (nodes) v<sup>1</sup>, v<sup>7</sup>,...,vn (denoted by the set V), with non-negative weight w(v), and a collection of edges(links) e<sup>1</sup>, e<sup>7</sup>,...,em (denoted by the set E) joining all or some of these nodes has a positive length b(e) (Christofides  $19V\circ$ ). Multi-center "Minimax p-center" location problems on networks locates more than one facility/center on a network to minimize the maximum distance between a demand point and its nearest center (Daskin  $199\circ$ ).

The study of networks is usually known in mathematical literature as graph theory and in engineering and applied science as network analysis, though many researchers have attempted to approach the network location problems (Handler and Mirchandani 1979).

(Hakimi 1975) was the first to tackle this type of location problems on a network. The author proposed an enumerative approach for finding single center (p=1). Since the publication of Hakimi's study on the "absolute center and median", the literature on network location problems has exploded (ReVelle and Eiselt  $\gamma \cdot \cdot \circ$ ). Many studies have been conducted to improve Hakimi's technique, including (Hakimi and Maheshwari  $\gamma \gamma \gamma$ , Hakimi et al.  $\gamma \gamma \gamma \Lambda$ , Kariv and Hakimi  $\gamma \gamma \gamma \eta$ , Minieka  $\gamma \eta \Lambda \gamma$ , Sforza  $\gamma \eta \eta \cdot \gamma$ ).

## **Y, N.** Problem Formulation

Given a set connected nodes (V) and edges (E), the goal is to locate p centers anywhere on the network to minimize the maximum of the distances from each node to its nearest center. Let G(V, E) be a finite undirected connected network with no loops. b(e) is a positive edge length;  $e \in E$ . wv is a positive vertex weight;  $v \in V$ .  $X = [x^{\gamma}, x^{\gamma},..., xp]$ , represent p locations to be found. Let d(v, X) = min [d(v, x^{\gamma}), d(v, x^{\gamma}),..., d(v, xp)] represent the shortest path distance on G from any point v in G to a facility location.

$$\min_{X \text{ on } G} f(X) = \max_{1 \le i \le v} w_i \, d(v_i, X) \tag{1}$$

For a given edge e(uz) which link between node u and node z, and if we let t denote the distance between a point x on edge e(uz)to u along the edge then the distance from a point  $v_i$  on G to x is:

 $d(v_i, x) = \min(d(v_i, u) + t, d(v_i, z) + b(uz) - t)$  (2)



Figure 1: An illustrative example of a distance d(vi,x).

# **\*.** Particle Swam Optimization (PSO)

PSO is a problem-solving algorithm, which iteratively attempts to enhance a set of candidate solutions. Each particle's move is governed by its local best-known position, and it moves toward the best-known places. PSO algorithm is a powerful optimization tool which appeared, likely more than other meta-heuristic algorithms (Sedighizadeh et al.  $7 \cdot 71$ ).

PSO was introduced by (Kennedy and Eberhart 1990), and there has been a steady increase in the number of research papers reporting its successful application in solving a variety of optimization problems, including finding optimal routes, scheduling problems and function optimization problems, since that time (Ahmed & Glasgow,  $7 \cdot 17$ ).

The position and velocity of any particle are updated as follows (Kennedy and Eberhart 1990):

$$Vel_{i}^{k+\prime} = wt_{k}Vel_{i}^{k} + c_{\gamma}r_{\gamma}(Pbest_{i}^{k} - X_{i}^{k}) + c_{\gamma}r_{\gamma}(Gbest^{k} - X_{i}^{k}) \quad (\tilde{\gamma}) X_{i}^{k+\prime} = X_{i}^{k} + Vel_{i}^{k+\prime}$$
(<sup>\$</sup>)

where,

 $Vel_i^k$  Velocity of particle *i* at iteration *k*.

- $c_1, c_7$  Positive constant weighting. They called the cognitive and social parameters. They typically set to equal  $\Upsilon$ (Sumathi and Paneerselvam  $\Upsilon \cdot \Upsilon \cdot$ ).
- $r_1, r_1$  Two random numbers uniformly selected in the range of  $[\cdot, \cdot, \cdot]$ .

 $X_i^k$  Position of particle *i* at iteration *k*.

*Pbest*<sup>k</sup> The best position of particle *i* at until iteration *k*.

 $Gbest_i^k$  The position of the global best swarm particle until iteration k.

 $wt_k$  inertia weight updated as (Shelokar et al.  $\forall \cdot \cdot \forall$ ):

$$wt_k = (wt_{max} - wt_{min}) * \frac{(k_{max} - k)}{k_{max}} + wt_{min}$$
 (°)

 $wt_{min}$  and  $wt_{max}$  are the minimum and maximum values of  $w_{tk}$  respectively;  $k_{max}$  is the number of iterations.

According to Equations  $\tilde{\phantom{r}}$  and  $\epsilon$ , Figure  $\tilde{\phantom{r}}$  shows the basic flow of the original PSO algorithm can be described as shown below:

#### **Basic flow of PSO**

- 1. Initialize the swarm by randomly assigning each particle to an arbitrarily initial velocity and a position in each *d*-dimension in the solution space.
- 2. Evaluate the desired fitness function to be optimized for each particle's position.
- 3. For each individual particle, update its historically best position so far, *Pbest* if its current position is better than its historically best one.
- 4. Identify/Update the swarm's globally best particle that has the swarm's best fitness value, and set/reset its index as g and its position at *Gbest*.
- 5. Update the velocities of all the particles using equation 3.
- 6. Move each particle to its new position using equation 4.
- 7. Repeat steps 2-6 until convergence or a stopping criterion is met (e.g., the maximum number of allowed iterations is reached; a sufficiently good fitness value is achieved; or the algorithm has not improved its performance for a number of consecutive iterations).

Figure **\***: The basic flow of PSO (Ahmed and Glasgow **\***•**)\***)

# 4. PSO for Multi-Center Location Problem on Networks

The basic idea of our PSO algorithm is that for each edge, in the set of candidate solution, we generate randomly swarm (points) on the edge in the range between  $\cdot$  and the length of the edge, then we evaluate the objective function for each particle in the swarm. After that we proceed to the PSO approach to improve the minimum value of the objective function.

As Figure r shows, the proposed PSO algorithm starts by reading the network vertices and edges then the parameters have to determined and initialized.

In step  $\checkmark$ , the shoretest distance matrix is calculated using Dijkstra's algorithm (Christofides  $19\sqrt{\circ}$ ). Step  $\pounds$ , the set of candidate solutions is generated, which contains all the combination of edges. For looping for each candidate solution starts. Step  $\circ$ , select the first candidate solution, then generate the swarm on its edges, in step 1. Step  $\vee$  evaluates the objective function of the swarm. Step  $\wedge$  update *Pbest* and *f*(*Pbest*) values. Step  $\wedge$ , a new for looping starts to update swarm position and velocity. Step  $\vee Gbest$  and *f*(*Gbest*). At the end of the iterations the minimum value of *f*(*gbest*) is reported.

Step 1. Read network G(V, E), where V is the set of vertices/nodes, E is the set of edges, b(e) is the length of edges.  $w_l$  is the set of weights that may be associated to the vertices; in case of no weights set  $w_l = 1$ . Step 2. Let p (# centers), ss (swarm size), iterations (# iterations), E (the number of edges),  $c_1$  (cognitive parameter), c2 (social parameter), wt<sub>max</sub> (the maximum value of inertia weight), wt<sub>min</sub> (the minimum value of inertia weight), and  $wt_k$  (inertia weight). Set  $H = \binom{|E|}{p}$ ; which is the total number of candidate solutions. Step 3. Calculate  $D_{Y_X Y}$  using Dijkstra's algorithm (Christofides, 1975); the matrix of the shortest paths between each two nodes in G. V is the number of vertices/nodes. Step 4. Generate the set of candidate solutions CS. The set contains all the combination of edges with size H in rows and p in columns. for  $h \le H$ .

- Step 5. Pick  $CS_h = [e_{1st}, e_{2nd...}, e_{pth}]$ , the  $h^{th}$  combination from the set of candidate solutions.
- Step 6. Generate randomly  $X_{ss x p}$  (swarm on edges); the particles position ranging from 0 to the length of each edge, and set  $Vel_{ss \times p} = 0$  to initiate the velocity of the swarm.
- Step 7. Evaluate the objective function:

$$\min_{X \text{ on } G} f(X) = \max_{1 \le l \le v} w_l \, d(v_l \,, X) \tag{6}$$

where  $d(v_l, X)$  represent the shortest path distance on G from the point  $v_l$  in G to a facility location. Step 8. Let Pbest = X, with f(Pbest) = f(X)

Step 9. Update the swarm position and velocity

for  $k \leq iterations$ .

for  $i \le ss$ ,

- Let Gbest= Pbest (arg(min(f(Pbest)))),
- Generate  $r_1$  and  $r_2$  randomly following a uniform distribution values in range [0,1] with p dimension.
- Calculate inertia weight  $(wt_k)$ ,

$$wt_k = (wt_{max} - wt_{min}) * \frac{(iterations - k)}{iterations} + wt_{min}$$
(7)

- Calculate the velocity ( $Vel_i^{k+1}$ ),  $Vel_i^{k+1} = wt_k Vel_i^k + c_1 r_1 (Pbest_i^k - X_i^k) + c_2 r_2 (Gbest^k - X_i^k)$ (8)
- Calculate the new position  $(X_i^{k+1})$  $X_i^{k+1} = X_i^k + Vel_i^{k+1}$ (9)
- If  $X_i^{k+1} < 0$ ; then  $X_i^{k+1} = 0$ ; else if  $X_i^{k+1} > b(e)$ ; then  $X_i^{k+1} = b(e)$ .
- Evaluate  $f(X_i^{k+1})$  of the new position;
- if  $f(X_i^{k+1}) < f(X_i^k)$ , then  $X_i^k = X_i^{k+1}$ . if  $f(X_i^{k+1}) < f(Pbest_i^k)$ , then  $Pbest_i^k = X_i^{k+1}$  with  $f(Pbest_i^k) = f(X_i^{k+1})$ . end for

end for

Step 10. Store *Gbest* and *f*(*Gbest*) for candidate solution *h*,

end for

Step 11. Report the best solution Gbest with the objective function equal to min(f(Gbest)).

#### Figure ": The basic flow of the proposed PSO for multi-center location problems

#### •. Numerical Example

This section introduces an example to illustrate the proposed PSO algorithm to solve multi-center location problem. For simplicity let us consider an example from (Christofides and Viola 1971) to find two multi-centers (p=7), for the network presented in Figure  $\xi$  which has 7 nodes/vertices and 9 edges.



Figure 4: Example of a network from Christofides and Viola (Christofides and Viola Viola Viv)

#### The basic steps the proposed PSO for (p=Y):

Step	۱. Read	the foll	owing	network	G
			0		

edges	<i>e</i> <sub>1</sub>	$e_2$	<i>e</i> <sub>3</sub>	<i>e</i> <sub>4</sub>	<i>e</i> <sub>5</sub>	<i>e</i> <sub>6</sub>	<b>e</b> 7	<i>e</i> <sub>8</sub>	e9
Node# \	١	0	۲	۲	٣	٦	٤	٦	0
Node# ۲	۲	١	٣	٦	٤	٣	0	٤	۲
Length <i>b(e)</i>	٣	٤	٤	٦	٣	٧	٨	۲	۲

Step 7. Let p = 7, and set  $H=\binom{9}{7} = 77$ . The PSO parameters:  $c_1=c_2=7$   $wt_{max}=1,7$ , and  $wt_{min}=...,1$ .

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

**Step** <sup> $\epsilon$ </sup>**.** Create set of candidate solutions. for p=7, we will check all the two combinations of edges with total 77 candidate solutions.

		CS1	CS <sub>2</sub>	CS <sub>3</sub>	CS <sub>4</sub>	CS <sub>5</sub>	CS <sub>6</sub>	 CS36
dge	1 <sup>st</sup> Node	1	1	1	1	1	1	 6
1st E	2 <sup>nd</sup> Node	2	2	2	2	2	2	 4
dge	1 <sup>st</sup> Node	5	2	2	3	6	4	 5
2 <sup>nd</sup> E	2 <sup>nd</sup> Node	1	3	6	4	3	5	 6

for h<=H,

Step •. Pick  $CS_1 = [e_1, e_2] = [(Node^{\uparrow}, Node^{\uparrow}), (Node^{\circ}, Node^{\uparrow})].$ 

**Step '.** Generate randomly  $X_{ss \ x \ p}$  with size  $ss = ! \cdot ; ! \cdot$  particles positions on range from  $[ \cdot \text{ to } "]$  for  $e_1$  and from  $[ \cdot \text{ to } !]$  for  $e_2$ ; set  $Vel_{ss \ x \ p} = \cdot$ .

SS	1	2	3	4	5	6	7	8	9	10
X <sub>ss, 1</sub>	1.9672	0.1071	2.5474	2.8020	2.0362	2.2732	2.2294	1.1767	1.9664	0.5136
X <sub>ss,2</sub>	2.8242	0.1273	1.1077	0.1847	0.3885	3.2938	2.7793	1.2684	3.8009	0.1378

**Step V.** Evaluate the objective function. For example, to evaluate the objective function of the first particle  $X_{lxp}$ ;

 $f(X) = \max[\min(X_{1,1}+d(1,V), b(e_1)-X_{1,1}+d(1,V), X_{1,2}+d(0,V), b(e_2)-X_{1,2}+d(1,V))];$ 

X <sub>1,1</sub> =1.9672 X <sub>1,2</sub> =2.8242	$A_l = X_{l,l} + d(1, V)$	$A_2 = b(e_1) - X_{1,1} + d(2, V)$	$A_3 = X_{1,2} + d(5, V)$	$A_4 = b(e_2) - X_{l,2} + d(1, V)$	$\begin{array}{c} \operatorname{Min}\left(A_{1},A_{2}\right)\\ A_{3},A_{4} \end{array}$				
Node 1	1.9672	4.0328	6.8242	1.1758	1.1758				
Node 2	4.9672	1.0328	9.8242	4.1758	1.0328				
Node 3	8.9672	5.0328	11.8242	8.1758	5.0328				
Node 4	11.9672	8.0328	10.8242	11.1758	8.0328				
Node 5	5.9672	8.0328	2.8242	5.1758	2.8242				
Node 6 7.9672 7.0328 <b>4.8242</b> 7.1758									
$f(X_{1,p}) = Max (Min (A_1, A_2, A_3, A_4))$									

Therefore, the objective function (OF) value of the first particle is equal to  $\Lambda, \cdot, \tau, \Lambda$ , which means that, if we locate the first center on  $e_1$ ,  $\eta, \eta, \eta, \eta$  units far from Node  $\Lambda$  and the second center on  $e_2$  $\gamma, \Lambda, \gamma \in \gamma$  units far from Node  $\circ$  the maximum distance will be

۸,•۳۲۸.	By	the	eval	luation	of	all	particles	s in	the	swarm	the	resu	lt
will be:													

SS	1	2	3	4	5	6	7*	8	9	10
X	1.9672	0.1071	2.5474	2.8020	2.0362	2.2732	2.2294	1.1767	1.9664	0.5136
	2.8242	0.1273	1.1077	0.1847	0.3885	3.2938	2.7793	1.2684	3.8009	0.1378
f(X)	8.0328	8.1273	7.4526	7.1980	7.9638	7.7268	7.7706	8.8233	8.0336	8.1378

**Step ^.** Let *Pbest=X*, and f(Pbest)=f(X)

SS	1	2	3	<u>4*</u>	5	6	7*	8	9	10
Pbest	1.9672	0.1071	2.5474	2.8020	2.0362	2.2732	2.2294	1.1767	1.9664	0.5136
	2.8242	0.1273	1.1077	<u>0.1847</u>	0.3885	3.2938	2.7793	1.2684	3.8009	0.1378
f(Pbest)	8.0328	8.1273	7.4526	7.1980	7.9638	7.7268	7.7706	8.8233	8.0336	8.1378

#### Step <sup>4</sup>. Update both of swarm position and velocity

for  $k \leq =$  iterations,

for  $i \leq ss$ ,

- Generate  $r_1 = [\cdot, 9 \in 19, \cdot, 9 \in V]$  and  $r_2 = [\cdot, 7199, \cdot, 1747]$ .

- Calculate inertia weight 
$$(wt_k)$$
,  
 $wt_1 = (1.7 - ..1) * \frac{(7 \cdot - 1)}{7 \cdot 1} + ..1$ 

- Calculate the velocity of first particle,  $Vel_{1}^{\vee} = wt_{1}Vel_{1}^{\vee} + c_{1}r_{1}(Pbest_{1}^{\vee} - X_{1}^{\vee})$  $+ c_{1}r_{1}(Gbest - X_{1}^{\vee})$ 

$$Vel_{1}^{Y} = 1,1 \le 0 * [\cdot, \cdot] + Y * [\cdot, 9 \le 19, \cdot, 070 \lor] * ([1,91 \lor Y, Y, AY \le Y] = [1,91 \lor Y, Y, AY \le Y]$$

$$[1,91 \lor Y, Y, AY \le Y] + Y * [\cdot, 7199, \cdot, 1 \lor AY] * ([Y, A \cdot Y \cdot, \cdot, 1 \land \xi \lor] = [\cdot, 07 \le Y, -\cdot, 9 \le \cdot \lor];$$

- Calculate the new position,  $X_{1}^{r} = X_{1}^{r} + Vel_{1}^{r}$   $X_{1}^{r} = [1,97V7,7,\Lambda757] + [\cdot,0757, -\cdot,95\cdotV] = [7,0\cdot15, 1,\Lambda\Lambda70],$ 

accept the new position, since it is between bounders of the two edges  $[\cdot, \tilde{r}]$  for  $e_1$  and  $[\cdot, \xi]$  for  $e_2$ .

# - Evaluate the new position $f(X_1^{\mathsf{Y}}); f(X_1^{\mathsf{Y}}) = \mathsf{Y}.\mathfrak{sqat}$

- if  $f(X_1^{\prime}) < f(\overline{X_1^{\prime}})$  i.e.  $\forall, \xi \in \Lambda, \xi \in X_1, \xi \in X_1^{\prime}$  then  $X_1^{\prime} = X_1^{\prime}$  i.e.  $X_1^{\prime} = [\uparrow . \circ \cdot \uparrow \xi, \uparrow . \Lambda \land \uparrow \circ].$
- if  $f(X_1^r) < f(Pbest_1)$  i.e.  $\forall, \xi \in A \cap \{A, V, V\}$ , then  $Pbest_1^r = X_1^r$  i.e.  $Pbest_1^r = [\uparrow . \circ \cdot \uparrow \xi, \uparrow . \land \land \uparrow \circ]$ with  $f(Pbest_1^r) = \forall . \xi \in A \cap \{A, V\}$ .

end for

end for

**Step '** · . Store *Gbest* and f(Gbest) for candidate solution h, end for

**Step 11.** Report optimal solution,  $\min_{h \in CS} (f(Gbest))$ 

We run the implemented code of the PSO with the following parameters:  $p=\Upsilon$ ,  $ss(swarm-size)=\Upsilon \cdot$ ,  $iterations=\Upsilon \cdot$ ,  $c_1=c_2=\Upsilon$  and  $H=\Upsilon\Upsilon$ ,  $wt_{max}=\Upsilon,\Upsilon$ , and  $wt_{min}=\cdot,\Upsilon$ . The experiments were performed  $\Upsilon \cdot$  runs independently. Table  $\Upsilon$  shows the summarized results.

The first column of Table  $\$  provides the optimal solution from (Christofides and Viola  $\$   $\$  ) is given. Second column shows the proposed PSO result. Column three and four show the average objective function values obtained from  $\$  runs and their standard deviations. The fifth column contains the average runs execution time in seconds. Table  $\$  shows that when all candidate solutions have been evaluated efficiently by using PSO and the optimal solution obtained for the absolute center problem ( $p=\$ ), and also PSO has a steady performance.

_(ᡟ · runs).	T			
Optimal				
	Min	Average	Σ	Average CPU Time
۳,۰	۳,0	۳,0٤	• , • • • 0	•,177

Table 1: The PSO stability evaluation for Network in Example 1  $^{\rm r}$   $^{\rm r}$  runs).

Table  $\checkmark$  shows the optimal solution of all the candidate solutions for the network in above example for  $(p=\curlyvee)$ . The optimal of the network is to locate the first center on edge  $e_2$ ;  $\urcorner, \circ \circlearrowright$  units far from Node  $\circ$  and the second center on edge  $e_3$ ;  $\urcorner, \circ \circlearrowright$  units far from Node  $\urcorner$  and the maximum distance is equal to  $\urcorner, \circ$ .

	۱ st	edge	۲nd	edge			
CS	۱ <sup>st</sup> Node	۲ <sup>nd</sup> Node۲	۱ st	۲nd	Gp	est	f(Gpest)
			Node	Node	-		
$e_1, e_2$	١	٥	۲	١	٣	۲,۱۳٦	٧
<i>e</i> <sub>1</sub> , <i>e</i> <sub>3</sub>	١	۲	۲	٣	•	1,1820	٦
<i>e</i> 1, <i>e</i> 4	١	٢	۲	٦	1,•/17	٦	٦
<i>e</i> 1, <i>e</i> 5	١	٣	۲	٤	١,٨٦٨٥	٣	٦
<i>e</i> 1, <i>e</i> 6	١	٦	۲	٣	•,0077	0	٥
<i>e</i> 1 , <i>e</i> 7	١	٤	۲	٥	۲,۱٦٩١	٥	٥
$e_1, e_8$	١	٦	۲	٤	٣	۲	٤
<i>e</i> 1 , <i>e</i> 9	١	0	۲	۲	1,9190	۲	٦
<u>e2, e3</u>	<mark>0</mark>	<mark>۲</mark>	<mark>۱</mark>	٣	<mark>1,•0£1</mark>	<mark>۳,0</mark>	<mark>٣,0*</mark>
<i>e</i> <sub>2</sub> , <i>e</i> <sub>4</sub>	٥	۲	١	٦	•,7901	٦	٧
<i>e</i> <sub>2</sub> , <i>e</i> <sub>5</sub>	٥	٣	١	٤	1,7890	•	٤
$e_2, e_6$	٥	٦	١	٣	1,7171	٧	٤
$e_2, e_7$	0	٤	١	0	۲,٥	1, 2. VO	٤,٥
$e_2$ , $e_8$	٥	٦	١	٤	۳,۳۹۱٦	٤,٥	٤,٥
<i>e</i> <sub>2</sub> , <i>e</i> <sub>9</sub>	٥	٥	١	٦	•,977٣	۲	٧
<i>e</i> 3 , <i>e</i> 4	۲	۲	٣	٦	۲	۳,1۷0۹	٥
<i>e</i> 3, <i>e</i> 5	٢	٣	٣	٤	•	١,.٠.٨	٧
<i>e</i> <sub>3</sub> , <i>e</i> <sub>6</sub>	۲	٦	٣	٣	۲	•,£179	٥
<i>e</i> <sub>3</sub> , <i>e</i> <sub>7</sub>	٢	٤	٣	٥	۳,۷۰۰۹	٨	٤
<i>e</i> <sub>3</sub> , <i>e</i> <sub>8</sub>	٢	٦	٣	٤	•,7000	۲	٤
<i>e</i> 3, <i>e</i> 9	٢	٥	٣	٦	٣,١٢٦٢	*	٤
<i>e</i> <sub>4</sub> , <i>e</i> <sub>5</sub>	۲	٣	٦	٤	۲,٥	1,9•£V	0,0
<i>e</i> <sub>4</sub> , <i>e</i> <sub>6</sub>	٢	٦	٦	٣	۲,٥	٤,097٨	0,0
<i>e</i> 4 , <i>e</i> 7	٢	٤	٦	٥	*	٥	٥
<i>e</i> <sub>4</sub> , <i>e</i> <sub>8</sub>	۲	٦	٦	٤	٠	۲	٤
<i>e</i> 4 , <i>e</i> 9	۲	٥	٦	٦	1,727	۲	٦
<i>e</i> 5, <i>e</i> 6	٣	٦	٤	٣	۲,017۲	٠	٦
<i>e</i> 5 , <i>e</i> 7	٣	٤	٤	٥	•	٨	٤
<i>e</i> 5, <i>e</i> 8	٣	٦	٤	٤	۱,٦٠٠١	٠	٦
<i>e</i> 5 , <i>e</i> 9	٣	٥	٤	٦	•	•	٤
<i>e</i> <sub>6</sub> , <i>e</i> <sub>7</sub>	٦	٤	٣	0	٧	Α.	٤
<i>e</i> <sub>6</sub> , <i>e</i> <sub>8</sub>	٦	٦	٣	٤	0,.779	•	٦
<i>e</i> <sub>6</sub> , <i>e</i> <sub>9</sub>	٦	0	٣	٦	٧	•	٤
<i>e</i> <sub>7</sub> , <i>e</i> <sub>8</sub>	٤	٦	0	٤	1,1051	•	٦
<i>e</i> 7, <i>e</i> 9	٤	0	0	٦	•	۲	٦
<i>e</i> 8 , <i>e</i> 9	٦	0	٤	٦	٣,91٤٧	۲	٦

Table **T**: The result of all the **T** candidate solutions.

## **7.** Computational experiments

The computational experiments were done by solving two different networks; (Daskin,  $7 \cdot 17$ ) with *p* ranged from 1 to  $\circ$ , (Handler and Mirchandani 1979) with *p* ranged from 1 to  $\epsilon$ . All computational experiments were carried out on a processor Intel Corei<sup>V</sup>, with CPU  $1, \wedge \cdot$  GHz and  $\wedge$  GB of RAM, under Windows  $1 \cdot, 7 \epsilon$ -bit. The code was written and executed in MATLAB.

#### Frist, (Daskin 2013) with p from 1 to 5

To examine the stability of our PSO; extensive experiments have been conducted, through performing independently  $\gamma$  runs for different values of p ranging from 1 to  $\circ$  to compare with the results of (Daskin (1,1)) and different values for ss (swarm size) with the following values: °, 1., 10, 7., 70, and T. (Daskin  $(\cdot, )$  applied a relaxation algorithm to find the optimal solution for the p centers with  $\neg$  nodes and  $\neg$  edges; figure  $\neg$ . In Table  $\neg$ results are summarized. The first column contains the swarm size. The second is for the number of centers p. The third column shows the optimal results from (Daskin 7.17). The number of reached optimal solution by our PSO out from 7. runs is in column four. Column five and six show the average values of objective function acquired from all <sup>Y</sup> runs, and also their standard deviations. In column seven, PSO's average running times to achieve the final answer in each of the  $\gamma$  runs are listed. The most important conclusion to be drawn from the Table  $\tau$  is that PSO was able to obtain optimal solutions in oth of to runs  $(9\circ \%)$ . It's important to note that in all of these situations, a swarm size of ° can be used to obtain the number of centers. The majority of bad results come from solving the problem with  $p=\gamma$ . Table  $\Gamma$  also shows that PSO exhibits stable performances.



Figure °:: Example of a network from (Daskin ۲۰۱۳)

Table	": The PSO stability evaluation for (Daskin	۲.	۱۳)
	Network.		

Swarm	Centers	Ontimal		PSO F	Results	
size (ss)	( <i>p</i> )	(Daskin ۲۰۱۳)	#Reached optimal	Average PSO	Σ	CPU Time (s)
	١	١٤,٠٠	۲.	١٤,٠٠	* , * *	۰,۳
	۲	٩,٠٠	14	٩,•٨	۰,۱۸	۰,۹
۳.	٣	٤,0.	۲.	٤,0.	* , * *	۲,٩
	٤	۳,0.	۲.	۳,0۰	* , * *	0,9
	0	۳,0.	۲.	۳,0۰	* , * *	٨,٢
	١	١٤,٠٠	۲.	15,**	• , • •	۰,۳
	٢	٩,٠٠	14	٩,•٨	۰,۱۸	١,٧
۲0	٣	٤,0.	۲.	٤,0.	* , * *	0,7
	٤	۳,0.	۲.	۳,0۰	* , * *	۱۱,۰
	0	۳,0.	۲.	۳,0۰	* , * *	10,7
	١	١٤,٠٠	۲.	۱٤,٠٠	• , • •	۰,۲
	٢	٩,٠٠	١٩	۹,•۳	٠,١١	١,٣
۲.	٣	٤,0.	۲.	٤,0.	* , * *	٤,٣
	٤	۳,0.	۲.	٣,0.	• , • •	٨,٥
	0	٣,0.	۲.	٣,0.	• , • •	۱١,٧

Swarm	Centers	Ontimal		PSO F	Results	
size (ss)	( <i>p</i> )	(Daskin ۲۰۱۳)	#Reached optimal	Average PSO	Σ	CPU Time (s)
	١	١٤,٠٠	۲.	15,**	۰,۰۰	۰,۲
	۲	۹,۰۰	18	٩,١٨	•,7 ±	١,١
١٥	٣	٤,0.	۲.	٤,0.	• , • •	٣,٥
	٤	٣,0.	۲.	۳,0۰	• , • •	٧,١
	0	۳,0.	۲.	۳,0۰	• , • •	٩,٥
	١	١٤,٠٠	۲.	١٤,٠٠	• , • •	۰,۱
	۲	٩,٠٠	17	٩,٢٠	•,7 ±	۰,۸
۱.	٣	٤,0.	۲.	٤,0.	• , • •	۲,0
	٤	۳,0.	۲.	۳,0۰	• , • •	0,7
	0	۳,0.	۲.	۳,0.	• , • •	٦,٣
	١	١٤,٠٠	۲.	15,**	۰,۰۰	۰,۱
	۲	٩,٠٠	18	9,10	•, ٢١	۰,٤
٥	٣	٤,0.	14	٤,0١	• , • ۲	١,٤
	٤	٣,0.	۲.	٣,٥٠	* , * *	۲,۸
	0	۳,0.	۲.	٣,٥.	• , • •	٣,٧

Figure 3 shows that as the number of swarm size increased, the number of reached best known increased; however, the best swarm size is  $3 \cdot$  particles.



The number of reached best known out of 100 runs

# Figure ٦: The relationship between the size of the problem and the time it takes to solve it.

The average run time has a linear relationship with the problem size, as seen in Figure  $\vee$ . This linear relationship has been verified using ANOVA test and all the *p*-values are less than  $\cdot, \cdot \circ$ .



Figure <sup>v</sup>: The relationship between the problem size and the run time

The solution of (Daskin (, ))) network example for p values ranging from ) to  $\circ$  is presented as follows:

<i>p=1</i>	<sup>\ st</sup> Node	Ynd Node	Gpest	f(Gpest)
۱ <sup>st</sup> center	٣	٤	١	١٤
<i>p</i> =2	<sup>\ st</sup> Node	Ynd Node	Gpest	f(Gpest)
<sup>\ st</sup> center	١	٤	٩	٩

<i>p=3</i>	<sup>\ st</sup> Node	Ynd Node	Gpest	f(Gpest)
<sup>\ st</sup> center	١	۲	٤,0	
<sup>Ynd</sup> center	٥	٣	۲,٦٧	٤,0
<sup>¶rd</sup> center	٦	٤	٤,٤	
<i>p=4</i>	۱ <sup>st</sup> Node	<sup>Ynd</sup> Node	Gpest	f(Gpest)
<sup>\ st</sup> center	١	٤	•	
Y <sup>nd</sup> center	۲	0	٠	
<sup><b>v</b>rd</sup> center	0	٣	٣,0	٣,٥
<sup>th</sup> center	٦	٤	٣,٥	
<i>p</i> =5	<sup>\ st</sup> Node	<sup>Ynd</sup> Node	Gpest	f(Gpest)
<sup>\ st</sup> center	٣	١	٠	
Y <sup>nd</sup> center	١	٤	٩	
<sup><b>Trd</b></sup> center	۲	0	٣,٣٣	٣,٥
<sup>th</sup> center	٦	٤	۳,0.	
° <sup>th</sup> center	0	٦	•	

#### Second, (Handler and Mirchandani 1979) p=1 to 4

We also tested our PSO algorithm on larger network from (Handler and Mirchandani 1979). The authors solved optimally multi-center location problem from p=1 to  $\xi$ , using a relaxation algorithm and applied the algorithm on a network with  $\circ^{r}$  nodes with  $\wedge$  edges for  $p=\xi$  (Figure  $\wedge$ ).



Figure A: Example of a network Handler (Handler and Mirchandani ۱۹۷۹)

For all the bellow results, we run the implemented code of the PSO with the following parameters:  $ss=\Upsilon \cdot$ ,  $iterations=\Upsilon \cdot$ ,  $c_1=c_2=\Upsilon$ ,  $wt_{max}=\Upsilon,\Upsilon$ , and  $wt_{min}=\cdot,\Upsilon$ . The results show that PSO approach can find optimal solution for Handler network. These results match with the optimal solution obtained by Handler in (Handler and Mirchandani  $\Upsilon \Lambda \Upsilon$ ).

<i>p</i> =1	<sup>\ st</sup> Node	<sup>Ynd</sup> Node	Gpest	f(Gpest)
<sup>\ st</sup> center	۱۳	11	۲,0	٣٥,٥
<i>p=2</i>	<sup>\ st</sup> Node	<sup>Ynd</sup> Node	Gpest	f(Gpest)
<sup>\ st</sup> center	۲ ۷	۲.	1	70
<sup>Ynd</sup> center	07	07	٣,10	, 0

<i>p=3</i>	۱ <sup>st</sup> Node	۲ <sup>nd</sup> Node	Gpest	f(Gpest)
۱ <sup>st</sup> center	<b>7</b> V	۳۸	•	
<sup>Ynd</sup> center	١٣	А	۲	١٨
<sup>¶rd</sup> center	٤٧	٤٦	•	
<i>p=4</i>	۱ <sup>st</sup> Node	Ynd Node	Gpest	f(Gpest)
<i>p=4</i> <sup>\st</sup> center	۱ <sup>st</sup> Node ۱۲	Y <sup>nd</sup> Node	<i>Gpest</i> ৲,০	f(Gpest)
<i>p=4</i> <sup>\st</sup> center <sup>\trace{nd}</sup> center	۱ <sup>st</sup> Node ۱۲ ۲۸	Ynd Node V YV	<i>Gpest</i> ٦,० ٨,١०	<i>f(Gpest)</i> ۱۲,0
<i>p=4</i> <sup>1 st</sup> center <sup>7 nd</sup> center <sup>7 rd</sup> center	) st Node ) Υ ΥΛ ε ٩	Y nd         Node           V            YV            ٤ Λ	<i>Gpest</i> ٦,0 Λ,10	<i>f(Gpest)</i> ۱۲,0

## Hassan Mohamed Rabie (IJIMCT) Vol.4 Issue (2) 2022

# **v**. Conclusions

In this paper, a new particle swarm algorithm was developed to solve the multi-center location problem on networks. PSO effectively searches the search space for near-optimal and optimal solutions in a reasonable amount of time.

We have conducted an extensive empirical study. The computation results show that the propsed PSO approach despite of its simplicity and ease-of-use, it is an effective approach to find good feasible solution for the multi-center location problems.

The new proposed PSO algorithm which can solve *p*-center location problems, when all candidate solutions can be investigated. PSO was found to be stable and the average time of runs increases linearly as the number of centers increases. This algorithm has the advantage of obtaining the optimal solution for all the candidate solutions. The results demonstrate that the PSO method can provide good optimal solutions for multi-center locating problems on small networks.

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