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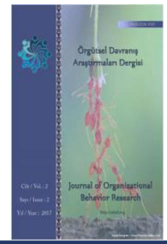

A DEVELOPED MULTI-OBJECTIVE ARTIFICIAL BEE COLONY ALGORITHM FOR LOCATING EMERGENCY SERVICE FACILITY

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ABSTRACT

Unlike production facilities, service facilities do not have traditional distribution channel. Emergency service facilities are the end point of the system where in the demand occurs. Sometimes the costumers go to the facilities like hospitals and some other times conversely like fire stations. In public service organizations that mostly seek for customer satisfaction, decreasing the distance between servers and receivers and covering more population are most important goals. Finding the best location of emergency service facility and allocating them to the demand areas to optimize the covered population and also the distance between demand areas and service center are the main purpose of the present research. Solving model using exact and Meta-Heuristic Algorithms showed that ABC results are in a perfect situation comparing with global solution and other Meta- Heuristics in various aspects like analyzing time and quality of solutions. Even comparing with powerful and known Meta-Heuristics such as NSGA-II, PSO and SA, the presented multi objective ABC (MOABC) Algorithm often achieved better solutions in less time in both real and simulated data section.

Keywords: *Service Facility Location, Location Allocation Model, Artificial Bee Colony, Meta-Heuristic Algorithms*

INTRODUCTION

The facility location related to public services is very important. Because selecting a correct location has some outcomes such as reducing social costs and increasing public interest (Shariff et al., 2012). The most important feature that distinguishes the public servicing systems from production systems is the direct presence of customers in these services; and also the focus on the customer and on time servicing to them is always one of the main activities of emergency services systems. Therefore, the correct allocation of the demand to these service facilities has the direct effect on the efficiency and effectiveness of total system. Spending correct expenses to create service centers and paying attention to the communications and the availability ease shows the importance of the correct location subject and determining appropriate location for these groups of organizations (Zanjirani Farahani et al., 2018), in a way that the easy and rapid usage possibility is provided for all citizens. This necessity becomes more obvious when the population increase process and so the cities growth, the location cost growth and the non–equal dispersion of the population in different parts of city are regarded. Finally, as providing the using possibility from emergency services systems is the governments' duty, nowadays, it's essential to present a system to increase the customers' satisfaction and bring lower expenses for the provider, one of the access ways to these aims is the route we pass in this essay.

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One of the challenges in emergency services management is finding the optimal location for serving centers in a way it can answer the services demand enough and minimizes the expense of services for the demands. In fact, it's a location allocation (LA) model which was presented first by Cooper in 1963. It's usually considered as a complex and multi–criteria decision model which often has contradictory and multiple aspects. Many studies have indicated the complexity in LA problems with different degrees which include the objectives incompatibility, high number of feasible solutions, the objective functions and constrains complexity and also high mass of data (Shariff et al., 2012). LA models have a very important role in programming public services. Many previous studies related with facility location are formulated via maximal covering location problem (MCLP). MCLP which first was suggested by Church and ReVelle in 1974, was one of the highly used models applied in emergency service management. It maximizes the under services covered population with limited budget and also regarding the certain number of service centers. If the demand is allocated within the legal maximal distance for servicing facilities, it is so – called covering demands. Numerous studies are performed using MCLP to model optimization problems. Many procedures are suggested to solve these models such as exact algorithms, heuristic and meta– heuristic algorithms. A comprehensive review about these researches exists in (Zanjirani et al., 2012). In recent years MCLP has been used successfully to solve bigger and more complex problems. It also has been used to solve models having more than one objective function (multi – objectives) (Zanjirani et al., 2010). The MCLP model is often useful in the domain of establishing emergency services like firefighting, police and ambulance station. In which the appropriate and on–time performance is necessary.

Some models such as LA and MCLP would not be solved through traditional methods in large dimension and high complexity. To overcome these complexities, many algorithms naming meta– heuristic algorithms– inspired from nature– are used assisting to solve complex models (Lin et al., 2018). Problems which are modeled and analyzed as mathematical optimization problems use different methods and algorithms as well because of using different objective functions (Li et al., 2015). Table (1) indicates some of the most important meta-heuristic algorithms.

Table 1. Meta-Heuristic algorithms

algorithm	creator	year
Metropolis-Hastings Algorithm	Hastings	١٩٧٠
Genetic Algorithm	Holland	١٩٧٥
Genetic Programming	Smith	١٩٨٠
Simulated Annealing	Kirkpatrick et al.	١٩٨٣
Taboo Search	Glover	١٩٨٦
Artificial Immune System	Farmer et al.	١٩٨٦
Memetic Algorithm	Moscato	١٩٨٩
Ant Colony Algorithm	Dorigo	١٩٩٢
MOGA For Multi-objective Optimization	Fleming	١٩٩٣
NSGA For Multi-objective Optimization	Fonseca	١٩٩٤
Particle Swarm Optimization	Kennedy and Eberhart	١٩٩٥
Covariance Matrix Adaptation Evolution Strategy	Hansen and Ostermeier	١٩٩٦
Differential Evolution	Storn and Price	١٩٩٧
Cross-Entropy Method	Rubinstein	١٩٩٧
X Algorithm	Knuth	٢٠00

Harmony Search	Geem et al.	٢٠٠١
NSGA-II For Multi-objective Optimization	Deb et al.	٢٠٠٢
Bee Colony Optimization	Nakrani and Tovey	٢٠٠٤
Glowworm Swarm Optimization	Krishnanand and Ghose	٢٠٠٥
Artificial Bee Colony Algorithm (ABC)	Karaboga	٢٠٠٥
Honey-Bee Mating Optimization	Haddad et al.	٢٠٠٦
Imperialist Competitive Algorithm	Atashpaz and Lucas	٢٠٠٧
Firefly Algorithm	Yang	٢٠٠٨
Monkey Search	Mucherino and Seref	٢٠٠٨
Cuckoo Search	Yang and Deb	٢٠٠٩
Bat Algorithm	Yang	٢٠١٠

In this article, artificial bee colony algorithm is the main and there are 8 Meta–heuristic algorithms include Ant Colony Algorithm (ACO), Bat Algorithm (BA), Cuckoo Search (CS), Firefly Algorithm (FA), Imperialist Competitive Algorithm (ICA), Non–dominated sorting Genetic Algorithm (NSGA–II), Particle Swarm Optimization (PSO) and Simulated Annealing (SA). Different urban areas are considered as potential demand areas and the problem is solved in two parts and three segments naming actual data (model with small dimensions) and simulated data (model with large and super-large dimensions).

LITERATURE REVIEW

In recent years, numerous studies are done in the field of single–objective and multi–objective optimization using ABC and other meta–heuristic algorithms. Lin et al. (2018) pointed to both advantages and disadvantages of Bee colony Algorithms. The advantages are having a simple structure, comfortable running and acceptable performance. The disadvantage is having low convergence speed (like other meta–heuristic algorithms). To solve this problem, they presented a new algorithm naming Artificial Bee having integrated and local data interaction (ABCLGII). The experimental results showed that the presented algorithm is often better than Artificial Bee colony Algorithms or in the same level based on some criterion such as strength, convergence speed and results quality.
Zanjirani Farahani et al. (2018) presented a comprehensive review for existing models and application in this area concentrating on service facility location in urban zones. After analyzing many studies, they stated that allocation-location models and routing-location models are the most using models in this domain. Additionally, it is recommended to the readers to have a comprehensive review on covered location models in Zanjirani Farahani et al. (2012) research. Ding et al- model (2017) having 3 objective functions (fuel cost, pollution and loss) was tested with ABC development through creating dynamic population (ABC–DP). Almost in all cases, the suggested algorithm achieved better quantities in objective functions comparing with two other algorithms (ABC and GA). The study showed that the presented algorithm could achieve the convergence sooner comparing with two other algorithms. Also, they confirmed the simulated data, convergence force and the accuracy of presented algorithm. Luoa et al. (2017) presented a method for optimizing Artificial Bee Algorithm called (ε-MOABC) method. In this study, the population of presented algorithm includes:

1. Employed bees for adjusting the route according to the provided data by other employed bees.

2. Onlooker bees for choosing food sources and updating their location.
3. Scout bees to delete low quality food sources (unsuitable). The results of data analysis demonstrated that not only this new presented algorithm is for optimizing multi – objective functions but also it has a suitable efficiency for optimizing with different and numerous objectives – functions. Additionally, while we compare it with other evolutionary algorithms like genetic algorithm, presented Bee algorithm is considerable. Kalayci et al. (2017) used ABC algorithm to optimize the portfolio limitedly and decrease the calculation volume in a logic time. They believe that such problems as mixed integer non–linear programming problems are complex by themselves and their calculation complex would increase considerably by the increase in the problem dimensions. In this regard, the researchers used ABC algorithm instead of accurate methods that made the optimal outcome achievement impossible. The study results were compared with previous study results and some algorithms like TS, PSO and GA and its efficiency and function were verified. Saif et al. (2017) proposed multi–objective ABC algorithm for order– driven programming and timing in multiple assembly lines. The related objectives are:
    1. Minimizing raw material consumption.
    2. Minimizing activity performance time in multiple production lines.
    3. Minimizing the late delivery fine because of simultaneous orders.

The results showed that in all functions ABC algorithm had better results comparing with Pareto evolutionary algorithm (SPEA). However, it is mentioned that there is error in some parts of this algorithm that leads to unacceptable solutions. This problem shows that they don't have enough power to present better results against existing problems. Zhang et al. (2016) performed a study titled "multi – objective optimization for designing sustainable supply chain network "to provide better services and products for customers and they used some algorithms such as multi objective genetic algorithm (MOGA) and multi–objective artificial bee colony (MOABC) algorithm based on collective intelligence. They believed that the industrial problems entity is different from numeral optimization regarding solutions searching area, variables interrupted entity and variable limits, so a different procedure is needed. So, they presented MOABC algorithm which had better quantities in different aspects in compared with MOGA algorithm in result segment after testing numeral instances in different aspects.

Kiran (2015) studies mentioned this point that the ABC algorithm first developed for continues problems, presents a special method for discrete optimization problems to correspond this algorithm with binary models for facility location optimization. He has developed ABC algorithm and suggests changing food source location (solutions achieving by artificial bees into binary values (ABC_{bin})). The accuracy and function for suggestive procedure was compared with known algorithms like PSO and was tested via the change in control parameters. The results demonstrated that the suggestive algorithm is a simple optimization device and also a suitable substitution while regarding the power of achieving solutions and the quality of gained solutions. Saeidian et al. (2016) assessed and compared genetic algorithm and bee colony algorithm to solve the allocation–location model in earth quake relief center. Nine optimized sites were chosen among existing options for allocation. The objective is to minimize the distance between sites and areas. The algorithms are assessed through both simulated and real data and results are as follows: The convergence process was gradual for BA and rather progressive for GA. both algorithms had a high level of repeatability. For both types of real data and simulated data, GA was faster. Finally, regarding some criteria like simplicity, irritation and speed, the genetic algorithm is evaluated as to be more suitable.

The multi-objective maximal covering location–allocation problem (MOMCLAP)

The used model in this study is adopted from Shavandi and Mahlooji (2006) study and it is developed in a deterministic and multi objective form. In MOMCLAP model, we meet two objectives:

1. Maximizing the customers' population coverage and
2. Minimizing the distance between the customers and servers. These two objectives happen in a multi – objective integer programming model in which the objectives act to maximize the demand coverage and to decrease the serving distance in an opposite way. One of the benefits of this model is to finding the location of some organization branches in which the initial establishing cost can be reduced through integrating some service centers in one place.

$$F_1 = maximize\ \sum_{i,j}^{m,n} p_i z_{ij}\, x_{ij} \qquad (١)$$

$$F_2 = minimize\ \sum_{i,j}^{m,n} d_{ij}\, x_{ij} \qquad (٢)$$

s.t:

$$x_{ij} \leq y_j \qquad \forall_{i,j} \qquad (٣)$$

$$\sum_{j=1}^{n} x_{ij} \leq 1 \qquad \forall_i \qquad (٤)$$

$$\sum_{j=1}^{n} y_j = N \qquad (٥)$$

$$z_{ij} = \begin{cases} 0, & d_{ij} \geq u \\ \frac{u - d_{ij}}{u - s}, & s \leq d_{ij} \leq u \\ 1, & d_{ij} \leq s \end{cases} \qquad (٦)$$

$$x_{ij} \in \{0,1\} \qquad i = 1,2,\dots,m$$

$$y_j \in \{0,1\} \qquad \mathrm{j} = 1,2,\dots,\mathrm{n}$$

Indices: i= demand areas (dots); i = 1, 2, …m; j = places for potential centers (candid places for establishing the center); j = 1, 2, … n. Decision variables: x_{ij}= 1or 0 If area i would be covered by j station, it is 1, else it is 0, Y_j =0 or 1. If the serving center is built in j location, it is 1, else it is 0. parameters: p_i: area population i, z_{ij}: i area population referring coefficient toward j area center based on the distances, d_{ij} the distance from i area to j area, N the number of service centers, u and s are the minimum and the maximum area standard distance for receiving services respectively, m the number of demand area under service, n the potential number of service areas for establishing service centers. In the above model: the first objective function (equation (1)) maximizes covered population in the standard distance. The second objective function (equation (2)) minimizes the sum of distances from service centers to service receivers. The first constrain (equation (3)) indicates that when service receiver i receives services from center j that the service centers are established in the area j. The second constrain (equation (4)) indicates that each demand area only can receive service from one center at the same time. The third constrain (equation (5)) indicates the number of all service centers which we intend to establish them. One of the benefits for these models is that we can cover the maximum demand with a particular budget. Of course, it's better to use the above model (also other location models) accompanying other models or existing scientific domains in location, because in these models variables don't consider all dimensions related to facility location. So, it's better to use these models as supplements in the facility location problems.

Bee Meta – heuristic Algorithm (BA)

Algorithms inspired from bee are a new type of algorithms in the swarm intelligence area which attracted attentions in recent years. These algorithms try to use the principles hidden in swarm behaviors of bees. These algorithms are used in various fields like optimization, network routing, robotic and multi agent systems (Karaboga, 2005). Bee algorithms have different types and one of the most useful and known of them is Artificial Bee Colony or ABC algorithm.

- ***Artificial Bee Colony algorithm (ABC)***

ABC algorithm was first presented for functions optimization by Karaboga in 2005. Every solution (i.e. a location in searching area) shows a potential food zone. The solution quality equals to that food source quality. Agents or artificial bees search and use food source in searching area. ABC uses 3 types of bees to search solution areas: employed bees (EB), onlooker bees (OB), scout bees (SB). EB bees are related to current solutions of algorithm. In each step in algorithm, EBs try to find the solution, recover it by local searching. Then they try to use OB for the current source. OBs choose them among recovered places based on the quality (fitness). In fact, better solutions attract more OB. If an applied OB finds a better place, the EB updates its place; otherwise, it stays in its own place. Additionally, if an EB couldn't improve its food location in certain steps, it would leave its location. Then it would change into a SB and would find a new location in searching area accidentally. ABC main algorithm is as follows:

1. Producing initial population.
2. Repeating the steps.
3. Employed bees would establish on their food sources.
4. Onlooker bees would establish on food sources based on nectars.
5. Scout bees would be sent to search area to find new food sources.
6. The best found food sources would be saved.
7. The steps would repeat till the stopping condition happens.

In the first step, ABC algorithm produces the initial population accidentally and creates SN the solution. SN equals to the number of OBs or EBs. Each x_i solution is a D dimensional vector in which D is optimization parameters number. And i = 1, 2 … SN. After that, all locations or solutions in the determined cycle of C = 1, 2… MCN situates in the process of investigating SBs, OBs, and EBs. The OB chooses the food source regarding the possibility related to that source i.e. P_i. It's calculated from equation (7) (Karaboga, 2005):

$$\mathrm{p}_i = \frac{\mathrm{fit}_i}{\sum_{\mathrm{n}=1}^{\mathrm{SN}} \mathrm{fit}_\mathrm{n}} \qquad (٧)$$

In which fit_i is the fitness value for solution i and it's a portion of its nectar volume from that food source in location i. Also, SN is the number of food sources and it's equal to OBs or EBs number. To produce new food situations from an old food location, the equation (8) would be used (Karaboga, 2005):

$$\mathrm{V}_{\mathrm{ij}} = \mathrm{x}_{\mathrm{ij}} + \phi_{\mathrm{ij}}\left(\mathrm{x}_{\mathrm{ij}} - \mathrm{x}_{\mathrm{kj}}\right) \qquad (٨)$$

$j \in \{1, 2 \ldots, D\}$ and $k \in \{1,2 \ldots .SN\}$ would be chosen randomly, however k should be different from i. ϕ_{ij} is a random number between [-1 ,1] and if the produced parameter value by this way would be more than the determined limit, the parameter can take an acceptable value (limit value). Supposing that the left source is x_i and $j \in \{1, 2 \ldots, D\}$, SBs find the new food source which are replaced by x_i. This substitution is done according to equation (9) (Karaboga, 2005):

$$x_i^j = x_{min}^j + rand[0,1](x_{max}^j - x_{min}^j) \qquad (٩)$$

ABC algorithm is a stochastic optimization algorithm based on swarm intelligence and It's so simple and strong (Karaboga and Akay, 2009). ABC and its developed versions performance was compared with other known innovative algorithms like GA, ACO and PSO in constrained and unconstrained problems and showed acceptable efficiency and convergence speed which we study in this essay in the following.

- ***Developed multi–objective artificial bee colony algorithm.***

Considering the numerous reported studies showing low convergence speed and time consumption in running the algorithm (especially in high iterations), we used non–dominated sorting and crowding distance techniques to improve the ABC multi–objective algorithm (Perez et al., 2017). This technique was used first in NSGA–II algorithm by Deb et al in 2002 and created a considerable improvement in multi–objective genetic algorithm.

In this way, when initial population becomes arranged based on fitness criteria, the crowding distance will be calculated and the choice process will be started from initial population. The choice is based on two criteria:

1) **Population rank**: the population would be chosen in lower ranks.
2) **Crowding distance**: supposing that 2 members have the same rank, we choose a member that has more crowding distance. The choice priority is often according to the ranking and then based on crowding distance. Crowding distance computation (CD) is as follows:

1. We put CD_1 and CD_n (the crowding distance for first and n^{th} solutions) equal to infinity.
2. We calculate objective function value per all non-dominate vectors in one Pareto front and then arrange them in an ascending way.
3. We calculate d_{ij} for all objectives ($j = 1 \ldots K$) regarding equation (10) per all ranked members from i = 2 till i = n-1 in a Pareto front:

$$d_{ij} = \frac{\left|f_j^{i-1} - f_j^{i+1}\right|}{\left|f_j^1 - f_j^n\right|} \qquad (١٠)$$

In equation (10), f_j^i is the value of j^{th} objective function for the solution i^{th}.

4. We calculate crowding distance value for solutions based on equation (11):

$$CD_i = \sum_{j=1}^{k} d_{ij} \qquad (١١)$$

5. To choose better solutions based on crowding distance in a Pareto front, first we arranged CD_is in a descending way. Then we choose the necessary solutions based on the best crowding distances. Developed multi–objective ABC algorithm pseudo–code can be seen in table (2) in details:

Table 2. MOABC pseudo–code

1. Parameters Setting
1.1. Determine variable number and limit
1.2. Determine number of bees
1.3. Set Maximum Cycle Number(MCN)
2. Initialization
2.1. Generate SN food source in searching space randomly
۲ , ۲. Evaluate population fitness
2.3. Non-dominated sorting
2.4. Crowding distance sorting using equation (10) and (11)
۳. Main Loop
3.1. Set the cycle to 0(Iteration=0)
3.2. Repeat cycle
3.3. Produce new solution for each employed bee using equation (8) and calculate fitness value (Employed Bees Phase)
3.4. Non-dominated sorting
3.5. Crowding distance sorting using equation (10) and (11)
3.6. Calculate p_i for each solution using equation (7)
3.7. Select solutions according p_i, produce new solution using equation (8) and calculate fitness for each bee (Onlooker Bees phase)
3.8. If there is an abandoned solution, replace with new solution using equation (9) (Scout Bees phase)
3.9. Non-dominated sorting
3.10. Crowding distance sorting using equation (10) and (11)
3.11. Save best solution
3.12. Add to previous cycle until the cycle equals to MCN(go to 3.2)
4. Result and outputs
4.1. Best solution and objective function value
4.2. Algorithm run time
4.3. Algorithm efficiency criteria

Computational results

Finding optimal solution via classic methods is a complex and time consuming work. Many existing meta–heuristic methods in problems having large sizes are time consuming too, and they are not usually suitable for using in ordinary computer systems in commercial usage (Luoa et al., 2017). Therefore, testing novel meta–heuristic methods to find a more efficient and faster algorithm for solving a problem with this complexity degree is important. In this segment, we explain the results for two produced problem categories using: 1. Real data (small model) and 2. Simulated and random data (large and super large model) which the first part has 22 nodes and the second part has 200 and 500 nodes in different shapes. These problems are solved and compared with MATLAB 2013b software and also mentioned algorithms assistance.

- ***Real data***

In this part, location allocation model will be solved with two objectives:

1) Maximizing customers population coverage
2) Minimizing the distance between customers and servers through binary integer programming and meta-heuristic algorithms in MATLAB software.

The basic parameters for model (areas population, the areas distance from each other) are achieved using gathered data from 22 zones in Tehran and other model parameters are changeable. Additionally, the results for solving model in different status can be seen in table (3) (the numbers of service centers (N) are equal to 5, 10 and 20 percent of total nodes). It should be mentioned that the numbers in table (3) are gained after the determined numbers of running each algorithm and registration the best quantities for objective functions and their mean. According to table (3):

Table 3. Small model result

n=2٢		Best solution		Average of solutions		Difference with global optimum(percent)	
		F_1^*	F_2^*	$\bar{F}_1$	$\bar{F}_2$	$\frac{F_2^{0pt}-\bar{F}1}{F_2^{0pt}}\times 100$	$\frac{F_2^{0pt}-\bar{F}2}{F_2^{0pt}}\times 100$
N=٢	Global optimum	٨٩٠٠٢٣٤	137.1	٨٩٠٠٢٣٤	137.1	0	0
	ABC	٨٩٠٠٢٣٤	137.1	٨٨٥٣٦٧٤	140.432	0.5	2.4
	ACO	8845873	136.52	٨٦٩٧٨١٩	١٤١,٧٨٢	٢,٢	٣,٤
	BA	8472381	١٦١,٦٨	8387227	169.722	٤,٨	١٧,٩
	CS	٨٩٠٠٢٣٤	137.1	8874394	136.938	0.3*	0.1*
	FA	8244253	162.47	8201907	165.772	7.8	21
	NSGA-II	8790342	139.3	8525472	147.312	4.2	7.4
	ICA	8152698	168.92	7558842	194.12	15	41
	PSO	8828769	136.2	8571199	146.528	3.6	6.8
	SA	8828769	136.2	8746194	143.03	1.7	4.3
N=٣	Global optimum	9187991	١٠٨,٤٧	9187991	108.47	0	0
	ABC	9187991	108.47	9200198	113.184	0.1*	4.3*
	ACO	9179527	116.41	9154314	118.252	0.3	9
	BA	8553513	144.36	8354755	153.784	9	41.7
	CS	9177715	115.5	9157977	117.654	0.3	8.4
	FA	8967313	133.01	8861152	136.608	3.5	26
	NSGA-II	8942778	130.28	8888080	134.994	3.2	24
	ICA	8314316	164.35	7886772	180.636	14.1	66.5
	PSO	9090423	120.94	8971239	128.956	2.3	18.8
	SA	9227293	113.88	8941766	122.646	2.6	13
N=٥	Global optimum	9366220	94.08	9366220	94.08	0	0
	ABC	9219336	94.57	9208704	97.385	1.6	3.5*
	ACO	9278400	96.05	9138802	104.514	2.4	11
	BA	8805786	142.7	8436514	155.948	9.9	66
	CS	9284423	97.07	9242376	102.816	1.3*	9.2
	FA	9239753	98.06	8897622	119.13	5	26.6
	NSGA-II	9208971	113.93	8974437	122.786	4.1	30.5
	ICA	7701918	190.58	7039688	217.298	24.8	131
	PSO	9126975	104.71	9112783	110.452	2.7	17.4
	SA	9293036	104.84	9145936	106.636	2.3	13.3
*Best value							

1. In the case N=2, ABC solutions are different from optimal solution in average per first objective function (F_1) and second objective function (F_2) with only 0.5 and 2.4 percent, respectively. Additionally, ABC is in the second position with a slight difference among meta-heuristic algorithms per average value of both objective functions. The first ranks of objective functions mean belongs to Cuckoo search algorithm (CS).
2. When N= 3, ABC solutions had differed on average 0.1 and 4.3 percent per F_1 and F_2 with the optimal solution. Also, ABC was in the first rank higher than other algorithms among used Meta heuristic algorithms per F_1 and F_2 mean value.

3. When N= 5, ABC solutions had differed on average 1.6 and 3.5 percent per F_1 and F_2 with the optimal solution. Also, ABC was in the first rank higher than other algorithms among used Meta heuristic algorithms per F_2 mean value and it was in the second rank after CS algorithm with a little difference per F_1 mean value.

Simulated data

In this part, for evaluating algorithms performance, we created some experimental problems in large dimensions (200 nodes) and super large dimensions (500 nodes) and a comparison is done between solved instance problems results through these algorithms. Model main parameters including nodes distance from each other (d_{ij}) and nodes population (a_i) are produced accidentally and from similar intervals with actual modes. To compare the performance of each algorithm, the best gained results, the mean of gained results and the mean of consumed time to reach the solution which was achieved from 500 iteration with 20 initial populations for large problems and 10 for super large problems are brought in tables (4) and (5).

Table 4. Large model result

n=200 Iteration=500 population=20		Best solution		Average of solutions		Average of run time(second)
		F_1^*	F_2^*	$\bar{F}_1$	$\bar{F}_2$	
N=10	ABC	32223.77	3067.03	30754.29	3211.86	109.54*
	ACO	21860.79	4333.65	21162.06	4380.31	242.40
	BA	21322.11	4359.49	19836.22	4520.67	212.53
	CS	23539.28	4164.77	22071.40	4206.19	299.46
	FA	25309.05	4032.79	23500.88	4180.59	300.62
	NSGA-II	29006.53	3588.01	26288.54	3732.47	225.85
	ICA	19378.02	4738.83	17399.57	4849.64	298.68
	PSO	26931.09	3538.64	25770.32	3890.42	232.82
	SA	34620.37*	2876.44*	34173.63*	2892.52*	1001.71**
N=20	ABC	33927.95	2890.54*	32960.28	3030.912*	116.0902*
	ACO	22538.91	4216.427	20635.59	4447.513	429.5423
	BA	23729.21	4160.482	22406.83	4295.897	164.8518
	CS	25099.69	4094.439	23063.13	4157.579	420.6275
	FA	26854.16	3839.83	25644.98	3948.421	382.8518
	NSGA-II	29914.27	3424.973	28602.19	3504.637	198.3891
	ICA	17162.32	4842.787	16267.44	4985.976	591.0426
	PSO	30801.21	3575.968	27302	3792.269	208.8359
	SA	34901.64*	3055.402	33374.71*	3124.914	630.9278**
N=40	ABC	35763.50	2920.74*	35033.34	2977.78*	125.22*
	ACO	22838.75	4330.05	21975.28	4352.24	229.71
	BA	24135.88	4092.32	22633.10	4255.40	134.30
	CS	22452.22	4155.18	22025.12	4298.94	364.25
	FA	27243.22	3853.92	24732.09	4076.16	463.66
	NSGA-II	34709.89	3221.35	31685.86	3280.78	236.93
	ICA	16172.27	4965.69	14473.62	5062.54	510.27
	PSO	30358.92	3439.54	28305.91	3715.00	286.99
	SA	35932.58*	3118.94	35322.79*	3168.51	989.72**

*Best value
**Algorithm disability to finding solution in reasonable time(10 min)

Regarding table (4):

1. When N=10, ABC solutions are in the second rank in the part of the best solutions and solutions mean per both 2 objective functions. And it's in the first rank per problem solving time mean in numerous running. The first rank for the best value and objective functions mean in this part belongs to simulated annealing (SA) algorithm. But regarding the need for the long time for solving problem by SA and the disability of this algorithm to find the solution in proper time, it can be said that the best results are related to ABC.
2. When N= 20, ABC solutions are in the second rank in the part of the best solutions and solutions mean per F1 value and it's in the first rank per F2 value and also it's in the first rank per problem solving time mean in the numerous running. The first rank for the best quantity and objective functions mean per F1 in this part belongs to simulated annealing algorithm (SA). But by considering the long time to solve the problem by SA and the disability of this algorithm to find the solution in proper time, it can be said that the best results are related to ABC.
3. When N= 40, ABC solutions are in the second ranking in the part of best solutions and the mean of solutions per F_1, they are in the first ranking per F_2 and they are also in the first ranking per mean of the problem solving time in the numerous run. The first ranking for the best value and objective functions means per F_1 belongs to simulated annealing (SA) algorithm. But because of the long time to solve the problem by SA and this algorithm disability in finding the solution in the proper time, the best results are related to ABC.

Table 5. Super large model result

n=500 Iteration=500 population=10		Best solution		Average of solutions		Average of run time(second)
		F_1^*	F_2^*	$\bar{F}_1$	$\bar{F}_2$	
N=25	ABC	62828.29*	9614.71*	60913.11*	9876.06*	325.88*
	ACO	42997.75	11760.13	42997.75	11760.13	737.00**
	BA	45465.65	11371.94	42531.84	11859.57	517.97
	CS	45166.16	11737.16	43725.36	11772.42	1889.15**
	FA	46134.39	11206.55	45979.29	11347.03	975.24**
	NSGA-II	54826.96	10556.47	52511.18	10704.73	466.65
	ICA	34759.53	12765.59	34759.53	12765.59	1382.08**
	PSO	48704.90	11492.14	48064.17	11526.20	1091.89**
	SA	57208.20	10268.18	56773.93	10328.18	3296.80**
N=50	ABC	62701.95*	9716.57*	61412.49*	9928.14*	330.66*
	ACO	43404.75	11762.76	42738.00	11941.16	1017.34**
	BA	46235.17	11330.50	46127.28	11439.57	770.61**
	CS	45710.17	11558.87	44639.54	11763.42	1630.65**
	FA	44575.84	11879.87	43336.61	12162.23	822.32**
	NSGA-II	54632.04	10388.42	53038.94	10842.67	551.53
	ICA	30859.92	13315.07	30859.92	13315.07	1438.66
	PSO	47613.38	11322.06	46930.98	11371.75	819.97**
	SA	54171.00	10394.72	53433.74	10567.17	2562.98**
N=100	ABC	63226.29*	9701.41*	62379.74*	9777.34*	367.59*
	ACO	45509.57	11797.91	43277.86	11870.14	1100.59**
	BA	42574.79	11842.74	41781.10	12047.23	724.75**
	CS	43819.48	11939.04	42499.08	12014.04	2034.37**

	FA	43386.82	11576.06	43041.96	11748.03	829.39**
	NSGA-II	54725.95	10446.45	51933.79	10736.20	579.49
	ICA	31610.38	13059.30	31610.38	13059.30	1633.74**
	PSO	49048.63	11174.49	48284.27	11231.83	888.23**
	SA	60759.79	10015.32	59305.16	10229.28	2215.73**
*Best value **Algorithm disability to finding solution in reasonable time(10 min)						

Regarding table (5):

1. When N=25, ABC best solution are in the first ranking in the part of the best solutions and solutions mean per F_1 and F_2. Also, they are in the first ranking per problem solving time average in numerous run. Regarding the very large dimensions of this problem in this part, because of the long time for solving the problem by the most Meta–heuristic algorithms, the disability of these algorithms to find solution in proper time is completely obvious. Therefore, it can be said that the best results in the best time are related to ABC.
2. When N=50, ABC best solution and the mean of solutions per both objective functions are in the first ranking, they are also in the first ranking per the mean of problem solving time in numerous run. Regarding the super large dimensions of the problem in this part, because of the long time for problem solving by the most of meta– heuristic algorithms, the disability of these algorithms in finding solutions in proper time is completely obvious. So, the best results in the best time are related to ABC.
3. When N=100, ABC best solution and the mean of solutions per both objective functions are in the first ranking, they are also in the first ranking per the mean of problem solving time in numerous run. Regarding the super huge dimensions of the problem in this part, because of the long time for problem solving by the most of meta–heuristic algorithms, the disability of these algorithms in finding solutions in proper time is completely obvious. So, the best results in the best time are related to ABC.

- ***Algorithm efficiency comparison***

The convergence to Pareto optimal solutions and providing near optimal solutions in shorter time are two basic objectives of multi objective algorithms. But as the objectives have a little conflict with each other (approaching optimal solutions collection and keeping diversity and the spread of the solutions), so there's no criterion which can decide on algorithms performance solely and absolutely. if there is a chance to achieve such a criterion, it would be possible to comment about the excellence of one algorithm against another one. Therefore, the presented algorithms in this study are also compared with common multi objective problems criteria.

➢ ***Pareto archives number of solutions***

An algorithm that can present more non–dominate solution number in Pareto archives would be more successful in drawing real Pareto optimal level and confront the decision marker with more options.

➢ ***Mean ideal distance***

This criterion which is used to measure the proximity to real Pareto optimal level can be calculated by the equation (12):

$$\mathrm{MID} = \frac{\sum_{i=1}^{n} c_i}{n}$$

(١٢)

In this equation n is the numbers of solutions in Pareto optimal collection and c_i is the Euclidean distance for each member of Pareto collection from ideal area which is achieved from equation (13):

$$c_i = \sqrt{(f_{1i} - f_1^*)^2 + (f_{2i} - f_2^*)^2 + \cdots + (f_{mi} - f_m^*)^2} \qquad (١٣)$$

In this equation f_{mi} means the m^{th} value of objective function in i^{th} solution. It's clear that in comparative Pareto optimal collectives, the smaller this criterion, the more its collection desirability.

- ***Maximum diversity or spread***

This criterion measures the length of the space cube diameter which is built via the end values of non-dominated solution in the target space. Therefore, the bigger is this criterion, the more spread is the Pareto archives solutions.

$$D = \sqrt{\sum_{m=1}^{M} (\max_{i=1:|Q|} f_m^i - \min_{i=1:|Q|} f_m^i)^2} \qquad (١٤)$$

- ***Spacing***

This criterion which is one of the density measurements criteria calculates the proportional spaces for consecutive solutions:

$$S = \sqrt{\frac{1}{|Q|} \sum_{i=1}^{|Q|} (d_i - \bar{d})^2}$$

(١٥)

In the above equation |Q| is the reagent of Pareto archives measurement and d_i and $\bar{d}$ can be achieved through the following equations:

$$d_i = \min_{k \in Q \wedge k \neq i} \sum_{m=1}^{M} |f_m^i - f_m^k| \qquad (١٦)$$

$$\bar{d} = \sum_{i=1}^{|Q|} \frac{d_i}{|Q|}$$

(١٧)

In fact, spacing criterion measures the criterion diversion of different values of d_i. When the solutions are beside each other monotonously, then the spacing value (s) is small too. So, an algorithm is more desirable that it's final non–dominate solutions have small spacing values (Rabbani et al., 2016).

Table 6: Comparison of the effectiveness of algorithms

	criterion

Meta-Heuristic algorithm	number of solutions	Mean ideal distance	Maximum diversity	Spacing
ABC	4.0667	1.1148*	391.5966*	0.7229
ACO	3.6667	1.1185	388.2330	0.5773
BA	4.3333	1.2807	242.9296	0.7039
CS	2.7333	1.1353	206.5371	0.3802
FA	3.5385	1.1334	252.5866	0.5514
NSGA-II	3.5714	1.1381	129.5992	0.7257
ICA	2.2500	1.4056	163.7384	0.1250*
PSO	3.4286	1.1737	134.3297	0.4923
SA	4.5833*	1.1399	128.6061	0.8037
*Best value				

Reading table (6): In the criterion, mean ideal distance and maximum diversity ABC algorithm is in the first ranking and higher than highly used algorithms such as GA, PSO, SA, and ACO. Additionally, from the criterion point of view for solution numbers, ABC is in the third ranking for the most solutions number with a little space.

DISCUSSION AND CONCLUSION

Analyzing the model through exact and meta–heuristic algorithms in different parts show that the gained results from ABC algorithms is in a good condition.

Comparing with the optimal solution and other meta–heuristic algorithms regarding the analysis speed and the solutions quality, this comparison becomes more interesting when we observe that ABC algorithm often surrounds better solutions in a shorter time comparing with powerful and highly used algorithms like PSO, SA and NSGA–II, even many mentioned algorithms can't solve the problem in a reasonable and logic time (super large problems). It should be mentioned that the algorithms disability for finding competitive solutions in a logic time is not a reason for their lack of efficiency in other optimal problems. Choosing proper algorithm for different problems most likely has high influence on their ability to solve problems.

Overly, ICA, BA and FA algorithms had not a desired performance in none of different parts. So, using these algorithms in such problems is not logic. Also, the current study used a lot of meta–heuristic algorithm to compare better and gain more accurate results unlike most existing studies in location domain which usually one or two meta–heuristic algorithms.

The other feature of this study is simultaneous usage of old and known meta– heuristic algorithms like NSGA-II, PSO, SA and ACO beside new and novel algorithms like CS, BA, FA, ICA and ABC which have attracted attentions in recent years and presented considerable outcomes regarding the results in some of these new algorithms. The examination of the used model and developed MOABC algorithm by both real data and simulated data are another feature of the current research which are examined and proved in large and super large scale. It's suggested to use different models regarding the type of services location problem. Two efficient models which can be used in this part are set covering model or network-routing models. They have high accuracy.

In the part of Meta heuristic algorithms, it is suggested to use developed Meta–heuristic algorithms for binary problems as main algorithm to solve it when mathematical model is changed into large scale model. The performance mechanism for developed algorithms are like main algorithm which are used to search a better solution space and to improve the problem solving time with a little change. Ultimately, it is suggested to use different methods and software to calculate the functions and to write the related code.

References

Church R., ReVelle C. (1974) the maximal covering location problem. Papers Region Sci Assoc, 32:101–118.

Cooper L. (1963) Location-Allocation problems. Oper Res, 11(3): 331–343.

Deb K., Pratap A., Agarwal S., Meyarivan T. (2002), A fast and elitist multi objective genetic algorithm (NSGA-II). IEEE Trans Evol Comput 6(2):182–197.

Ding M., Chen H., Lin N., Jing Sh., Liu F., Liang X., Liu W. (2017), Dynamic population artificial bee colony algorithm for multi-objective optimal power flow. Saudi Journal of Biological Sciences, 24: 703–710.

Kalayci C. B., Ertenlice O., Akyer H., Aygoren H. (2017), An artificial bee colony algorithm with feasibility enforcement and infeasibility toleration procedures for cardinality constrained portfolio optimization. Expert Systems with Applications, 85: 61–75.

Karaboga D. (2005). An idea based on honey bee swarm for numerical optimization. Technical report TR06. Turkey: Computer Engineering Department, Erciyes University.

Karaboga D., Akay B. (2009), A comparative study of Artificial Bee Colony algorithm. Applied Mathematics and Computation, 214: 108-132.

Kiran M. S. (2015), The continuous artificial bee colony algorithm for binary optimization. Applied Soft Computing, 33: 15–23.

Li Zh., Wang W., Yan Y., Li Zh. (2015), PS–ABC: A hybrid algorithm based on particle swarm and artificial bee colony for high-dimensional optimization problems. Expert Systems with Applications, 42:8881–8895.

Lin Q., Zhua M., Lia G., Wanga W., Cuia L., Chena J., Lu J. (2018), A novel artificial bee colony algorithm with local and global information interaction. Applied Soft Computing, 62: 702–735.

Luoa J., Liua Q., Yanga Y., Lia X., Chena M. R., Caoa W. (2017), An artificial bee colony algorithm for multi-objective optimization. Applied Soft Computing, 50: 235–251.

Perez C. J., Vega-Rodríguez A. M., Reder K., Florke M., (2017) A Multi-Objective Artificial Bee Colony-based optimization approach to design water quality monitoring networks in river basins. Journal of Cleaner Production, 166: 579-589.

Rabbani M., Siadatian R., Farrokhi-Asl H., Manavizadeh N. (2016), Multi-objective optimization algorithms for mixed model assembly line balancing problem with parallel workstations. Cogent Engineering, 3: 1158903.

Saeidian B., Mesgari M. S., Ghodousi M. (2016), Evaluation and comparison of Genetic Algorithm and Bees Algorithm for location–allocation of earthquake relief centers, international Journal of Disaster Risk Reduction, 15: 97-107.

Saif U., Guan Z., Zhang L., Zhang F., Wang B., Mirza J. (2017), Multi-objective artificial bee colony algorithm for order oriented simultaneous sequencing and balancing of multi-mixed model assembly line. J Intell Manuf, DOI 10.1007/s10845-017-1316-4.

Shariff S.S. R., Moin N. H., Omar M. (2012), Location allocation modeling for healthcare facility planning in Malaysia. Computers & Industrial Engineering, 62: 1000–1010.

Shavandi H., Mahlooji H. (2006), A fuzzy queuing location model with a genetic algorithm for congested systems. Applied Mathematics and Computation, 181: 440–456

Zanjirani Farahani R., Asgari N., Heidari N., Hosseininia M., Goh M. (2012), Covering problems in facility location: a review. Computers & Industrial Engineering, 62(1): 368–407.

Zanjirani Farahani R., Fallah S., Ruiz R., Hosseini S., Asgari N. (2018), OR models in urban service facility location: A critical review of applications and future developments, European Journal of Operational Research, Article in Press, https://doi.org/10.1016/j.ejor.2018.07.036.

Zanjirani Farahani R., SteadieSeifi M., Asgari N. (2010), Multiple criteria facility location problems: a survey. Applied Mathematical Modeling, 34(7): 689–709.

Zhang Sh., Lee C. K. M., Wu K., Choy K. L. (2016), Multi-objective optimization for sustainable supply chain network design considering multiple distribution channels. Expert Systems with Applications, 65: 87–99.