

Two new algorithms of cuckoo and forest optimization to solve single row facility layout problem

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Abstract

Nowadays, due to inherent complexity of real optimization problems, it has always been a challenging issue to develop a solution algorithm to these problems. Single row facility layout problem (SRFLP) is a NP-hard problem of arranging a number of rectangular facilities with varying length on one side of a straight line with aim of minimizing the weighted sum of the distance between all facility pairs. In this paper two new algorithms of cuckoo optimization and forest optimization are applied and compared to solve SRFLP for the first time. The operators of two algorithms are adapted according to the characteristics of SRFLP and results are compared for two groups of benchmark instances of the literature. These groups consist of instances with the number of facilities less and more than 30. Results on two groups of instances show that proposed cuckoo optimization based algorithm has better performance rather than proposed forest optimization based algorithm in both aspects of finding the best solution and Computational time.

Keywords: Facility Layout Problem, Single Row Facility Layout Problem, Cuckoo Optimization Algorithm, Forest Optimization Algorithm.

1. Introduction

In facility layout problem (FLP) we wish to arrange a number of facilities in a given space to satisfy an objective function. Single row facility layout problem is a specific case of FLP which is arrangement of n facilities on a line so as to minimize transportation costs among facilities. SRFLP has attracted significant attention in recent years [1]. Generally SRFLP can be described as follows:

Assume there are n rectangular facilities. They should be arranged on one side of a straight line in a given direction. Parameters of the problem are the length l_i ($i=1, 2, \dots, n$) of each facility i and a $n \times n$ matrix $C = [c_{ij}]$ where c_{ij} is usually the flow between facilities i and j ($i, j=1, 2, \dots, n$ with $i < j$). This matrix is a symmetric matrix. The distance between each pair of facilities is calculated as the distance between their centers. The objective of the problem is to arrange the facilities to minimize the weighted sum of the distance between all facility pairs. Denoted

by Π_n the set of all permutations π of $N = \{1, 2, \dots, n\}$, the SRFLP can be formulated as follows [2]:

$$\left\{ \sum_{i=1}^{n-1} \sum_{j=i+1}^n c_{ij} d_{ij}^{\pi} \mid \pi \in \Pi_n \right\} \quad (1)$$

Where d_{ij}^{π} is the distance between facilities i and j with respect to permutation π . In This model all permutations of N are searched to find a permutation with minimum objective function value. Please note that due to symmetrical property of cost matrix C , there is no difference between c_{ij} and c_{ji} .

Garey et al. in 1974 showed that the minimum linear arrangement problem which is a special case of the SRFLP is NP-hard, so by implication SRFLP is NP-hard [3]. In this paper with regard to this model, proposed algorithms to solve SRFLP are applied and compared.

In the literature, because of theoretical attractiveness and numerous practical situations of

SRFLP, many papers have been presented in this area. SRFLP has numerous practical applications in real world. For example arrangement of rooms in hospitals, departments in office buildings or in supermarkets [4], arrangement of machines in flexible manufacturing systems [5], design of warehouse layouts and assignment of files to disk cylinders in computers storage [6] are some of these applications in the literature.

In addition to these applications, there are some practical applications of a special case of SRFLP in which the facilities have unit lengths. These applications include the design of error correcting codes [7], wire length minimization in VLSI design, graph drawing and reordering of large sparse matrices [8, 9].

Regarding numerous applications of SRFLP, several methods have been proposed in the literature to solve it. These methods can be categorized into exact, heuristic and meta-heuristic algorithms. The exact methods have been applied to solve small instances of the SRFLP to optimality, and their relaxations have been used to obtain good bounds for larger SRFLP instances. The first exact method to solve SRFLP was a branch and bound algorithm presented by Simmons in 1969 [4]. After that, different exact methods have been presented in the literature including combinatorial branch and bound, mathematical programming [10, 4], dynamic programming [6], branch and cut [5, 6, 11], cutting planes approach [11, 12] and semi-definite programming [7, 13, 14].

Because in this paper we study two meta-heuristic algorithms to solve SRFLP, we tend to review heuristic and meta-heuristic algorithms suggested in the literature for SRFLP. For more information about exact methods that have been presented in the literature to solve SRFLP, researchers are referred to review paper of Kothari and Ghosh [1]. Since exact algorithms for the SRFLP are computationally expensive, they have been applied to relatively small instances, with up to 42 facilities. Heuristic and meta-heuristic algorithms are faster than exact methods but they do not guarantee optimal solution [1]. In recent years different meta-heuristic algorithms have been applied to solve various engineering problems because of the complexity of these problems. For example reference [15-25] present different meta-heuristic algorithms for different engineering problems. In the literature, heuristic and meta-heuristic algorithms to solve SRFLP are divided into 2 groups of construction and improvement methods. Construction methods construct the sequence of facilities until a complete permutation

is obtained. Neghabat in 1974 presented a constructive algorithm to obtain a complete solution by adding one machine at a time to the end of the current solution [26]. A heuristic method based on the eigenvectors of a transformed flow matrix was introduced by Drezner in 1987 [27]. A linear mixed-integer formulation of the SRFLP and a penalty technique to solve it was presented by Heragu and Kusiak in 1991 [28]. Kumar et al. in 1995 and Djellab and Gourgand in 2001 introduced a constructive greedy heuristic method to solve SRFLP [29, 30]. Also heuristic procedures to extract a feasible solution to the SRFLP from an optimal solution to the semi-definite programming (SDP) relaxation was presented by Anjos et al. in 2005, Anjos et al. in 2008, Anjos and Yen in 2009 and Hungerlander and Rendle in 2011 [7, 11, 13, 31].

Improvement methods start with one or more permutations of facilities as initial solutions and improve them until stopping criteria is reached or solution cannot be improved. Seven meta-heuristic algorithms of Tabu Search (TS), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Ant Colony Optimization (ACO), Scatter Search (SS) and Imperialist Competitive Algorithm (ICA) have been applied to solve SRFLP in the literature. Also some hybrid algorithms based on simulated annealing and genetic algorithm, ant colony optimization and PSO, etc. have been studied in different papers to solve SRFLP. Romero and Sanchez-Flores in 1990, Heragu and Alfa in 1992 and Gomes de Alvarenga et al. in 2000 applied SA to solve SRFLP [32, 33, 34]. Solimanpur et al. in 2005 presented an ant colony algorithm to solve this problem [35]. Different papers including papers of Datta et al. in 2011 and Ficko et al. in 2004 used Genetic algorithm to solve SRFLP [36, 37]. Kumar et al. in 2008 and Kothari and Ghosh in 2014 presented a Scatter search algorithm to solve SRFLP [38, 39]. Gomes de Alvarenga et al. in 2000 and Samarghandi and Eshghi in 2010 applied Tabu search to solve SRFLP [34, 40]. In 2010 Samarghandi et al. presented a particle swarm optimization to solve this problem [41]. Akbari and Maadi and Lian et al. in 2011 proposed an imperialist competitive algorithm to solve SRFLP [42, 43]. Also there are some hybrid algorithms to solve SRFLP such as: a hybrid algorithm based on simulated annealing and genetic algorithm by Braglia in 1996 and a hybrid algorithm based on ant colony optimization and PSO by Teo and Ponnambalam in 2008 [44, 45].

Cuckoo optimization algorithm (COA) is a new introduced meta-heuristic algorithm introduced by

Rajabioun in 2011 [46]. COA has proven its excellent capabilities such as faster convergence and better global minimum achievement rather than other meta-heuristic algorithms [47]. Cuckoo optimization algorithm is applied to solve different nonlinear problems and has shown good capability in diverse optimization tasks. This algorithm has been tested so far on different types of practical instances in some scopes such as: teleportation systems, machine error compensation, noise canceller design, chemical machine process and machine process [48-55]. This algorithm has been much better than the rest meta-heuristic algorithms and shows its efficiency [47]. This subject can be a motivation to apply COA in other scopes of optimization such as SRFLP.

Forest optimization algorithm (FOA) is a new evolutionary algorithm which is inspired by few trees in the forest. This algorithm was introduced by Ghaemi and Feizi-Derakhshani in 2014 [56]. Since FOA is a new introduced algorithm, there is no paper in the literature that uses this algorithm and this paper can be a start to apply FOA to solve different optimization problems. Also forest optimization algorithm is introduced to solve continues problems and this paper presents a forest based algorithm that solves discrete problem of SRFLP with changing operators of the FOA regarding characteristics of SRFLP.

As in the literature only seven meta-heuristic algorithms have been implemented to solve SRFLP, this paper introduces two new algorithms of cuckoo optimization and forest optimization to solve SRFLP for the first time. The performances of two algorithms are compared to each other using SRFLP instances of the literature with different sizes.

Our paper is organized as follows. In section 2, proposed cuckoo optimization based algorithm to solve the SRFLP is presented. Section 3 describes the proposed forest optimization based algorithm for solving this problem. In section 4 computational results of two algorithms are compared followed by the conclusions of the paper in section 5.

2. Proposed cuckoo optimization based algorithm

As said before Cuckoo optimization algorithm (COA) is an evolutionary algorithm inspired by the life of a bird named Cuckoo. This algorithm is based on specific egg laying and breeding of cuckoos. Cuckoo optimization algorithm starts with an initial population of cuckoos that have some eggs to lay in some host birds' nest. Those

eggs that are more similar to the host birds' eggs are survived and can grow up to become a mature cuckoo. Other eggs are detected by host birds and expelled out. In such cases cuckoos migrate to places where are more suitable for generation survival and egg-laying. The number of grown eggs shows nests suitability of the area. The goal of cuckoo optimization problem is finding the situation in which maximum number of eggs to be saved. Environmental features and the migration of groups of cuckoos hopefully lead them to converge and find the best environment for breeding and reproduction. This best environment is global or the best solution to the problem. In this process after chicks become mature, they make some groups. Each group has his typical habitat. The habitat with the best situation is the destination of cuckoos of other groups. After moving, each group resides in the area near current location. Regarding the number of each cuckoo eggs and the distance of cuckoo to the best residence, some eggs laying radii assigned to it. After that cuckoos start to lay eggs in some random nests inside this radius. This process continues until the best position is obtained. In the best position, the most of cuckoo habitats are gathered around the same global solution [46]. Figure 1 shows the flowchart of cuckoo optimization algorithm.

COA was introduced basically to solve continues optimization problems. Until now this algorithm has been modified to solve discrete optimization problems and has had impressive results. In the next sections the stages of proposed cuckoo optimization based algorithm to solve SRFLP are described. The implementation of COA in SRFLP is as follows:

2.1. Generating initial cuckoo habitat

As the goal of optimization problem is to find an optimal solution in terms of variables, a representation pattern that is usually a vector of decision variables should be defined. For example in genetic algorithm this vector is defined as chromosome, or in particle swarm optimization this array is named particle position. In COA it is called habitat. In a N_{var} dimensional optimization problem, a habitat is an array of $1 \times N_{var}$ representing current living position of cuckoo. This array is defined as follows:

$$\text{Habitat} = [x_1, x_2, \dots, x_{N_{var}}] \quad (2)$$

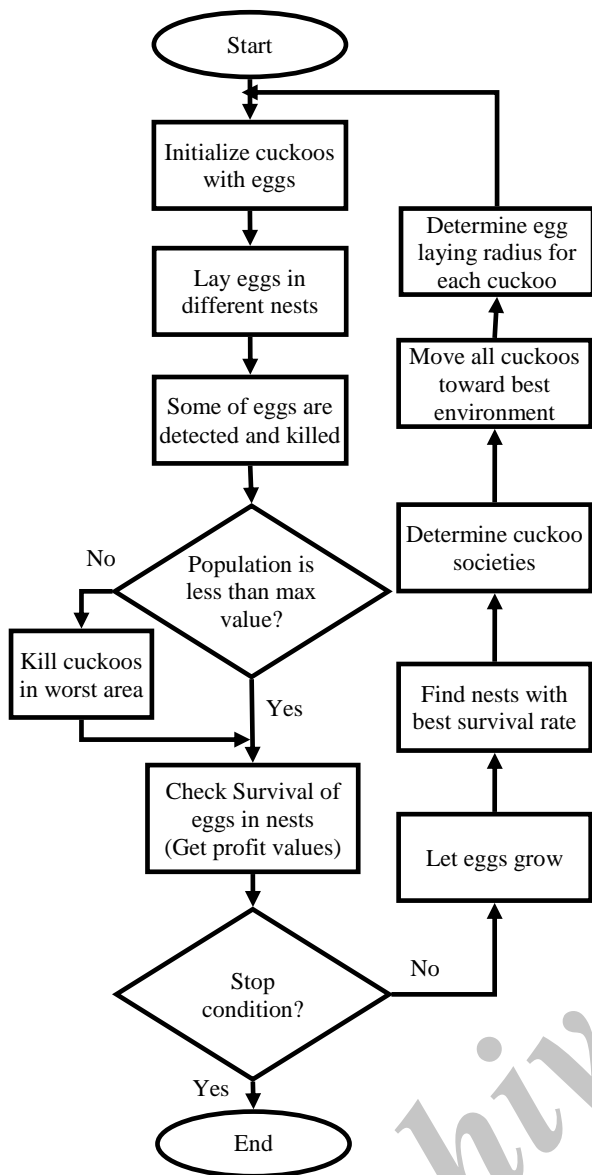


Figure1. Flowchart of COA.

Such as other meta-heuristic algorithms the profit of a habitat is obtained by evaluation of profit function f_p at a habitat as follows:

$$\text{Profit} = f_p(\text{habitat}) = f_p(x_1, x_2, \dots, x_{N_{\text{var}}}) \quad (3)$$

As it can be seen, COA is an algorithm that maximizes the benefit function. To use COA for solving minimization problems it is sufficient to multiply a negative mark in cost function as follows:

$$\text{Profit} = f_p(\text{habitat}) = -f_p(x_1, x_2, \dots, x_{N_{\text{var}}}) \quad (4)$$

To start COA, a matrix of size $N_{\text{pop}} \times N_{\text{var}}$ should be created and for each habitat of initial population some randomly produced eggs are supposed to be assigned. The number of eggs that each cuckoo lays is between 5 and 20 eggs. These values are the upper and lower limits for egg laying at different iterations. Another habit of real

cuckoos is that they lay eggs within a maximum distance from their habitat. This maximum range is called Egg Laying Radius (ELR). In an optimization problem with upper limit of var_{hi} and lower limit of var_{low} for variables, for each cuckoo an egg laying radius (ELR) which is proportional to the total number of eggs, number of current cuckoo's eggs and also variable limits of var_{hi} and var_{low} is determined. The ELR is defined as follows:

$$\text{ELR} = \alpha \times \frac{\text{Number of current cuckoo's eggs}}{\text{total number of eggs}} \times (\text{var}_{\text{hi}} - \text{var}_{\text{low}}) \quad (5)$$

Where α is an integer, supposed to handle the maximum value of ELR.

To solve SRFLP with n facilities using COA, according to the problem definition, a habitat is represented as an n dimensional vector of integer numbers between 1 to n which shows a permutation allocating rectangular facilities to a straight line. For example figure 2 shows a habitat of COA in SRFLP with 10 facilities.

2	3	6	8	9	10	1	4	7	5
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Figure2. Habitat representation.

Using equation 1 as cost function that should be minimized for COA, the profit of each habitat can be calculated using equation 4. For generating initial population two procedures are used in this paper. The first one is based on theorem 1 of the paper of Samarghandi and Eshghi [40]. In this procedure it is assumed that in the cost function coefficients $c_{ij} = c$, now if we sort facilities in non- descending order such that the shortest facility is denoted by 1 and the longest one by n , then figure 3 shows the optimum solution when n is odd number and figure 4 shows the optimum solution when n is an even number. With this procedure and another procedure which is randomly generating of permutation allocating rectangular facilities to a straight line, initial population is created. After producing initial population, the process of laying eggs will be started.



Figure3. Optimal layout when n is odd.



Figure4. Optimal layout when n is even.

2.2. Cuckoos' style for egg laying

In this stage each cuckoo starts laying eggs randomly in some other host birds' nests within

her ELR. A clear view of this concept is shown in figure 5.

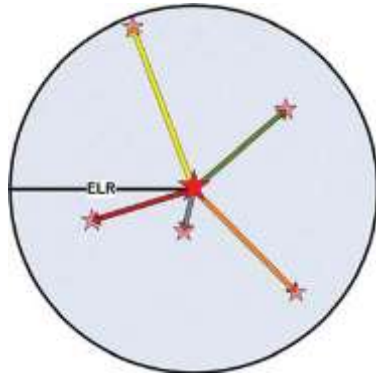


Figure 5. Random egg laying in ELR, central red star is the initial habitat of the cuckoo with 5 eggs; pink stars are the eggs' new nest.

After all cuckoos' eggs are laid in host birds' nests, some of them that are less similar to host birds' own eggs, are detected by host birds and thrown out of the nest. Thus after laying process, $p\%$ of all eggs with less profit values will be destroyed. P usually is 10 in this step. Rest of eggs grow in host nests and are fed by host birds. The important point about the cuckoo chicks is that only one egg per nest is allowed to grow because when cuckoo egg hatches and the chick comes out, she throws out host bird eggs and if host bird chicks are hatched sooner, cuckoo chick eat the most food that host bird brings (because of her 3 times bigger body, she pushes other chicks and eats more) and after some days, host bird chicks starving to death and just cuckoo chick survives. For implementation of this step of COA in SRFLP, it is mentioned that in proposed algorithm because of the definition of habitat and structure of the problem, there is no ELR and some changes in the structure of habitats are used for laying eggs operator. For this aim swap operator is used. The steps of proposed swap operator are as follows:

- 1- Consider a mature cuckoo habitat for laying eggs.
- 2- To lay eggs, Exchange the position of two facilities of a habitat and make an egg.

Using this operator eggs are laid and algorithm continues to the next section.

2.3. Immigration of cuckoos

After growing young cuckoos, they live in their own area and society for some time. At the time of spawning, the migration to new and better habitats where there are more chance to eggs surviving and more food for young cuckoos starts. After forming cuckoo groups in different areas (the search space of the problem), the society with the best profit is selected as target point of a group

for other cuckoos to migrate. When mature cuckoos live in all over the environment it is tough to recognize which cuckoo belongs to which group. To solve this problem, the grouping of cuckoos is done with K-means clustering method (a k between 3 and 5 seems to be sufficient). After formation of groups, the average profit value is calculated to achieve the relative optimality of that group habitat. After that the group with highest amount of profit is selected as target group which other groups will migrate toward it. During moving toward the target point, the cuckoos do not fly all the way to the destination habitat. They only fly a part of the way and also have deviation. This movement is shown in figure 6. As is clear in figure 6 each cuckoo flies only $\lambda\%$ of the total direction toward the destination habitat and also has a deviation of φ radians. These two parameters of λ and φ help cuckoos to search the environment more. λ is a random number between 0 and 1, and φ is a number between $-\pi/6$ and $\pi/6$. When all cuckoos migrate to target habitat and also new habitats are specified, some eggs are given to mature cuckoos. After that considering the number of eggs for each cuckoo, an ELR is specified for it and new egg laying process restarts.

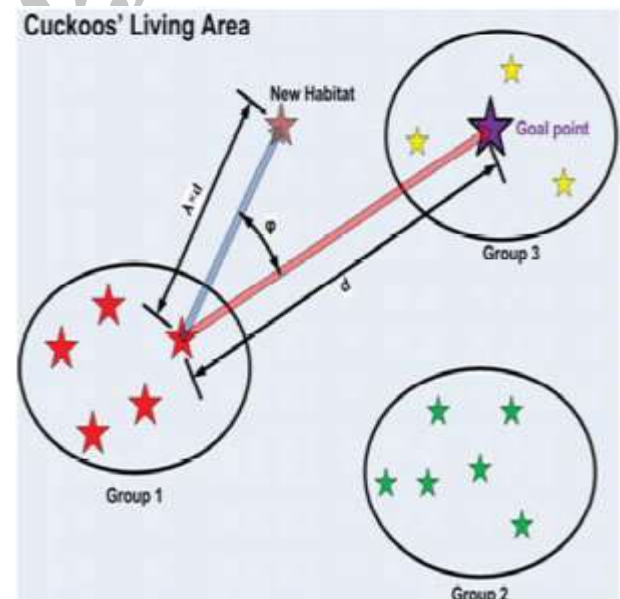


Figure 6. Immigration of a sample cuckoo toward goal habitat.

To simulate this operator of COA for SRFLP, considering the characteristics of SRFLP, proposed steps of immigration operator are applied in following procedure:

At first the target habitat that other cuckoos should migrate toward it is considered. (a habitat with highest profit). Then a group of facilities in the target habitat is selected. Figure 7 shows an

example of a target habitat with 10 facilities and selected group of facilities of the habitat. An array of a migrant cuckoo who wants to immigrate toward target habitat is considered (figure 8). That selected group of facilities which is in target habitat is copied exactly to the array of new position of migrant cuckoo. For other facilities in new position of migrant cuckoo which are not in selected group, from the first cell of migrant cuckoo habitat array, each facility which is not in the facilities of the selected group is placed in the cells of the array of new position of migrant cuckoo sequentially. Figure 9 shows array of new position of migrant cuckoo.

8	5	2	1	6	4	3	9	10	7
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Figure7. Target habitat and selected group of facilities.

4	7	6	5	10	9	3	8	2	1
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Figure8.A migrant cuckoo habitat.

7	5	10	1	6	4	3	9	8	2
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Figure9.New position of migrant cuckoo.

2.4. Eliminating cuckoos in worst habitats

Because there is always equilibrium in birds' population in nature (because of food limitation, being killed by predators and inability to find proper nest for eggs), a number N_{max} is determined as maximum number of cuckoos that can live in the environment. In this step only those N_{max} number of cuckoos that have better profit values survive and others demise.

After some iteration the algorithm moves to one best habitat with the characteristic of maximum similarity of eggs to the host birds and also with the maximum food resources. This habitat has the best profit value and is the best solution to the problem. In COA convergence of 95% of cuckoos to the same habitat puts an end to the algorithm. The stopping condition for this algorithm like other evolutionary algorithm can be the number of iterations. In proposed algorithm the number of iterations is considered as stopping condition. The pseudo-code of proposed COA to solve SRFLP is described in algorithm 1.

Algorithm 1: Proposed COA

Input: Number of facilities (n), Flow matrix (F), Facilities length matrix (L), maximum number of iterations ($maxiter$), minimum number of eggs (min_egg), maximum number of eggs (max_egg).

Output: An approximation of an optimal solution to the PCSP instance.

Initialize cuckoo habitats with N individuals by using

section 2.1.

Compute fitness for each cuckoo

Find best cuckoo as *best cuckoo*

for $i=0$ to $maxiter$

 for each cuckoo

 dedicate some eggs with random number between $\{min_egg, maxegg\}$

 end

 for each cuckoo

 for each egg of selected cuckoo

 Perform laying operator by using section 2.2.

 end

 end

Sort cuckoo habitats according to their fitness value and update *best cuckoo*

Select the best N cuckoos and reduce the extended cuckoos.

for each cuckoo

 Let new cuckoos populations immigrate toward best cuckoo by using section 2.3.

end

Compute fitness for each cuckoo and update *best cuckoo*

end

Return the *best cuckoo* as the result

3. Proposed forest optimization based algorithm

Forest optimization algorithm (FOA) is a new evolutionary algorithm which is inspired by few trees in the forest which can survive for several decades, while other trees could live for a limited period. As said before this algorithm was introduced by Ghaemi and Feizi-Derakhshani in 2014 [56].FOA involves three main stages of 1- local seeding of the trees 2- population limiting 3- global seeding of the trees. Like other meta-heuristic algorithms FOA starts with the initial population named trees. Each tree represents a solution of the optimization problem. A tree besides the cells of variables of the problem has a part that represents the age of the tree. At first the age of a tree is set '0'. After initialization of the trees the operator of local seeding will generate new young trees (or seeds in fact) from the trees with age 0 and add new trees to the forest. Then all trees except new generated ones get old and their age increases by '1'. The next step is the population limiting. In this step there is a control on the population of trees in the forest and some trees will be omitted from the forest. Omitted trees form the candidate population for global seeding stage.

In the third stage which is global seeding of the trees, a percentage of the candidate population is chosen to move far in the forest. The aim of

global seeding is adding some new potential solutions to the forest in order to get rid of local optimums. After that the trees are ranked with regard to their fitness values. The tree with the best value of fitness function is chosen as the best tree and its age is set '0' in order to avoid the aging of the best tree as the result of local seeding stage. In this way, it will be possible for the best tree to locally optimize its location by local seeding operator. These 3 stages will be continued until the stopping conditions are met. Figure 10 shows the flowchart of the forest optimization algorithm.

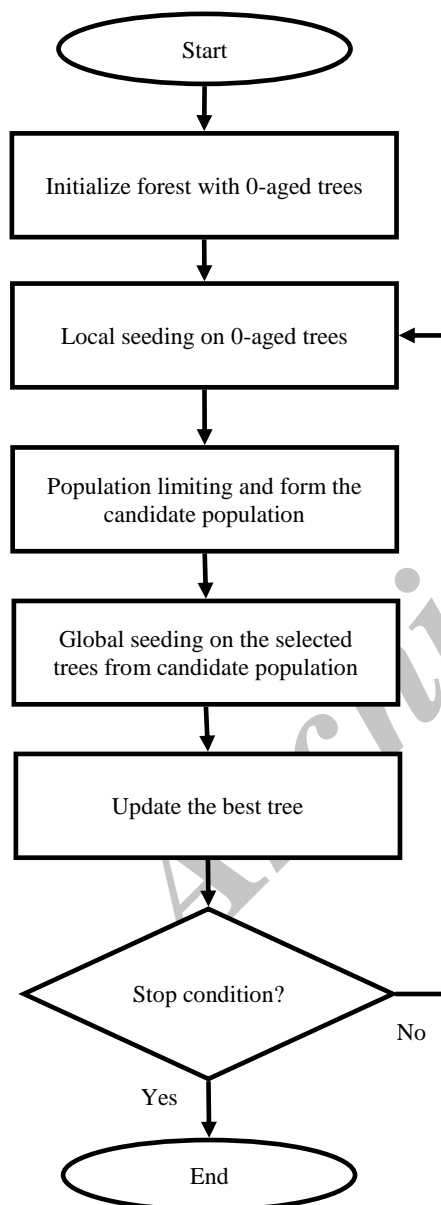


Figure 10: Flowchart of FOA.

As said before Since FOA is a new introduced algorithm, there is no paper in the literature that uses this algorithm and this paper can be a start to apply FOA to solve different optimization problems. Also as FOA is introduced to solve

continues nonlinear programming, this paper introduced a discrete version of forest optimization algorithm to solve SRFLP. In next sections using operators of FOA, a forest optimization based algorithm is introduced to solve SRFLP.

3.1 Initialize trees

As mentioned before, in FOA the potential solution of each problem is considered as a tree. A tree is usually a vector of variables that variables have lower and upper limits. In addition to the variables, each tree has a part related to the age of the tree. The age of a tree for each newly generated tree is set '0' as a result of local seeding or global seeding. After local seeding stage the age of the trees except the new generated trees in local seeding stage increases by '1'. This increase in age is used later as a controlling population in limiting stage. Thus in FOA a tree is represented as an array of $1 \times (N_{var} + 1)$ that N_{var} is the dimension of optimization problem and one cell is considered for age of a tree. Equation 6 represents a tree:

$$\text{Tree} = [x_1, x_2, \dots, x_{N_{var}}, \text{Age}] \quad (6)$$

In definition of a tree, the age of a tree has a maximum range that is a predefined parameter named life time. This parameter should be determined at the start of the algorithm. When a tree's age reaches to life time parameter, that tree is omitted from population of trees and is added to the candidate population. The big number of life time parameter increases the age of the trees in each iteration and forest will be full of old trees, which don't take part in the local seeding stage. Otherwise very small value for this parameter causes trees get old very soon and they will be omitted at the beginning of the competition. So this parameter should provide a good chance of local search. The best life time value is determined 6 in the FOA.

In SRFLP a tree is represented as n+1 dimensional vector which first n cells are integer numbers of 1 to n that represent a permutation allocating rectangular facilities to a straight line and the last cell is age. Figure 11 shows a tree with 10 facilities.

4	7	6	5	10	9	3	8	2	1	0
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Figure 11: a tree representation in SRFLP with 10 facilities and age of zero.

Fitness function of FOA is the same as COA which is equation 1 and should be minimized. For generating initial population, the same procedures used in COA are applied for FOA. All initial trees

in this step have the age '0'. With this population, algorithm starts the next stage that is local seeding of the trees.

3.2. Local seeding of the trees

In the nature during seeding procedure of the trees some seeds fall just near the trees and after some time they will grow. Now, the competition between near young trees starts and those trees with better growing conditions such as enough sunlight and better location are survived. Local seeding of trees is simulated regarding this natural event. This operator is performed on the trees with the age '0' and adds some neighbors of each tree to the forest. The number of seeds that fall on the land near the trees and then turn into the trees as neighbors is considered as a parameter of the FOA named local seeding changes or LSC.

The value of this parameter to solve different optimization problems depends on the dimension of the problem domain. In the FOA for problems with the bigger dimension of 5, 2/10 is recommended for LSC and for dimensions less than 5 the value of LSC will be 1. In local seeding operator at first a variable of a tree with the age '0' is selected. After that a random number named r is generated in the range of $(-\Delta x, \Delta x)$. Then the value of the selected variable is added to the r . Δx is a small value and it is smaller than the related variable's upper limit. Now a new tree with age '0' is added to the forest.

For simulating of local seeding operator to solve SRFLP, swap operator is used to generate new trees. In this operator for each tree with age '0' two facilities are selected randomly and their locations are exchanged. With this operator and using LSC parameter many new trees are added to the forest. In the next stage of algorithm a limitation on the number of trees should be considered as the operator of population limiting.

3.3. Population limiting

To avoid infinite expansion of the forest, after generating numerous trees in the stage of local seeding of the trees, number of trees should be limited. In FOA two parameters of life time and area limit restrict the population of the trees. At first the trees with the age more than life time parameter are removed and will form the candidate population. The second limitation is area limit in which after ranking the trees according to the fitness value if the number of trees exceed the limitation of the forest, extra trees are omitted from the forest and added to the candidate population. The value of area limit parameter is considered to be the same as the

number of the initial trees. After population limiting the global seeding stage is performed on some percentage of the candidate population as will be described in the next section.

3.4. Global seeding of the trees

There are different kinds of trees and numerous animals and birds fed on the seeds and fruits of these trees in the nature. So In spite of local seeding of the trees, seeds are distributed in the entire forest and consequently the habitat of the trees expands. Also different natural process such as wind and flow of water helps distributing the seeds in the entire forest widely. Using this natural process, global seeding stage is defined to simulate the distribution of the seeds of the trees in the forest.

Global seeding operator is performed on a determined percentage of the candidate population from the previous stage. This percentage is another parameter of the algorithm named transfer rate and should be defined at the start of the algorithm.

Steps of Global seeding of the trees are defined as following: regarding transfer rate parameter, the trees from the candidate population are selected. Then some variables of each tree are selected randomly. After that the value of each selected variable is changed with another randomly generated value in the related variable's range. As a result a tree with age '0' is added to the forest. This operator performs a global search in the search space. During this stage another parameter that is the number of variables whose values will be changed is defined as global seeding changes or GSC.

During global seeding operator in proposed algorithm to solve SRFLP, after determination of GSC, swap operator is done. The number of repetition of swap operator is the number of GSC. After producing new trees these trees with age '0' are added to the forest.

3.5. Updating the best so far tree

In this stage after sorting trees according to the value of their fitness function, the tree with the best fitness function value is selected as the best tree. After that the age of this tree turns to '0'. As mentioned before in this way it will be possible for the best tree to locally optimize its location by local seeding operator.

3.6. Stop conditions

In FOA three stopping conditions of predefined number of iterations, reaching to the specified level of accuracy and observance of no change in

the fitness value of the best tree are defined. In proposed forest optimization based algorithm the number of iterations is considered as the stopping condition. The pseudo-code of proposed FOA to solve SRFLP is described in algorithm 2.

Algorithm2: Proposed FOA

Input: number of facilities (n), Flow matrix (F), Facilities length matrix (L), Number of initial trees (N), maximum number of iterations (maxiter), Local seeding change (LSC), Global seeding change(GSC), transfer rate, life time, area limit.

Output: An approximation of an optimal solution to the SRFLP instance.

Initialize forest with N individuals by using section 2.1. The age of each tree is initially set zero

```

for i=0 to maxiter
  for each trees with age 0
    for j=0 to LSC
      Perform local seeding on selected trees by using
      section 3.2.
    end
  end
  increase the age of all trees by 1 except for new
  generated trees in this stage
  Remove the trees with age bigger than life time
  parameter and add them to the candidate population.
  Sort trees according to their fitness value
  Remove the extra trees that exceed the area limit
  parameter from the end of forest and add them to the
  candidate population.

  Choose transfer rate percent of the candidate
  population
  for each selected tree
    Perform global seeding by using section 3.4
    Set the age 0
  end
end
Return the best tree as the result

```

4. Comparison of cuckoo and forest optimization algorithms

Cuckoo optimization and forest optimization algorithms are coded in C#. Algorithms are run on an Intel (R) core(TM) i5-3210 CPU @2.05 Gigahertz and 4.00Gigabytes ram under the Windows 8.1 Operating system.

The performance of two algorithms is evaluated on several benchmark instances. These instances are divided into two groups of instances with the number of facilities less than 30 and instances with the number of facilities more than 30. All instances are available at <http://www.gerad.ca/files/sites/Anjos/flplib.html>.F

or instances with the number of facilities less than 30, the maximum number of iterations is set 150 and for another group of instances is considered as 300. For each instance, each algorithm is run 20 times. In the following section, computational experience of two algorithms for two groups of instances is reported.

4.1. Instances with the number of facilities less than 30

Initially algorithms are tested on some instances with $n \leq 30$ in the literature. The optimum solutions of this set of instances are known. Throughout the experiments the following parameter values are used for FOA and COA respectively:

For COA the initial population of cuckoos is set 30. The lower limit for egg laying is considered 3 and the upper limit for egg laying is set 5. In FOA the number of initial trees is considered 30, $GSC = 1 + \left\lfloor \frac{n}{10} \right\rfloor$, $LSC = 5$ and transfer rate is set $(0.9 * n)$. The results of applying two algorithms of COA and FOA are shown in table 1.

In table 1 the first column shows the problem number. The number of facilities of instances is presented in second column. The next column is the objective function value of optimum solution of instances from the literature. Columns 4, 5, and 6 are related to cuckoo optimization algorithm. Column 4 is the objective function value of achieved COA solution. Column 5 shows the computational time of cuckoo optimization algorithm and column 6 calculates the gap between objective function values of optimum solution and achieved COA solution of the instances. As seen in table 1 the proposed COA algorithm is able to achieve the best solutions reported in the literature. The next 3 columns of 7, 8, and 9 are results of applying FOA. In column 7 the value of objective function of achieved FOA solution is shown. Column 8 shows the computational time of forest optimization algorithm and column 9 calculates the gap between objective function values of optimum solution and achieved FOA solution of the instances. This gap is calculated as follows:

$$\text{Gap} = \frac{\text{achievedFOAsolution} - \text{optimumsolution}}{\text{optimumsolution}} \quad (7)$$

Regarding table 1 the average gap between objective function values of optimum solutions and achieved FOA solutions of all instances is 0.0017.

In comparison of two proposed algorithms it is notable that proposed COA has better performance rather than FOA in both aspects of

achieving the best solution and computational time. Table 2 shows the mean and standard deviation (SD) of objective function values of

instances. As said before each instance is run 20 times. Figure 12 depicts and compares the computational time of two algorithms.

Table1. Results for problem set1.

Problem Number	Number of Facilities	Optimal Value	FOA Result	FOA Time (Sec)	FOA Gap	COA Result	COA Time(Sec)	COA Gap
1	4	78	78	0	0	78	0	0
2	4	638	638	0	0	638	0	0
3	8	801	801	0	0	801	0	0
4	8	2324.5	2324.5	0	0	2324.5	0	0
5	9	2469.5	2469.5	0	0	2469.5	0	0
6	9	4695.5	4695.5	0	0	4695.5	0	0
7	10	2781.5	2781.5	0	0	2781.5	0	0
8	11	6933.5	6933.5	0	0	6933.5	0	0
9	15	63.05	63.05	0	0	63.05	0	0
10	20	15549	15592	1	0.002765451	15549	1	0
11	25	4618	4625	4	0.001515808	4618	3	0
12	25	37116.5	37129.5	12	0.000350249	37116.5	9	0
13	25	24301	24325	12	0.000987614	24301	8	0
14	25	48291.5	48344	14	0.001087148	48291.5	9	0
15	25	15623	15633	14	0.000640082	15623	10	0
16	30	8247	8313	25	0.00800291	8247	18	0
17	30	21582.5	21725.5	25	0.006625738	21582.5	17	0
18	30	45449	45627	24	0.003916478	45449	17	0
19	30	56837.5	57013.5	25	0.003096547	56837.5	18	0
20	30	115268	116067	26	0.006931672	115268	17	0

Table2. Mean and SD results for instances of set one in 20 times of run.

Problem number	COA-Mean	COA-SD	FOA-Mean	FOA-SD
1	78	0	78	0
2	638	0	638	0
3	801	0	801	0
4	2327.8	3.012474066	2331.7	5.380520421
5	2474.1	5.412947441	2475.8	6.66708332
6	4702.1	5.319774431	4704.7	5.826662853
7	2786.7	4.236744033	2789.7	6.300793601
8	6941.5	4.716990566	6943.5	5.979130372
9	63.05	0	63.05	0
10	15588	22.25982929	15607.4	14.27585374
11	4622.8	6.57267069	4633	9.082951062
12	37154.6	39.49272085	37171.8	38.6144403
13	24330.4	26.83840532	24358	35.46124645
14	48336.6	57.97995343	48388.4	45.04220243
15	15661.2	35.10982768	15684.6	29.16847613
16	8268.8	20.31501907	8328.6	13.50185172
17	21599.6	18.84608713	21764.8	32.21335127
18	45513	39.91240409	45713.4	79.10625766
19	56928.5	70.48049376	57128.3	78.31714372
20	115467.2	177.3899659	116325.4	264.8882783

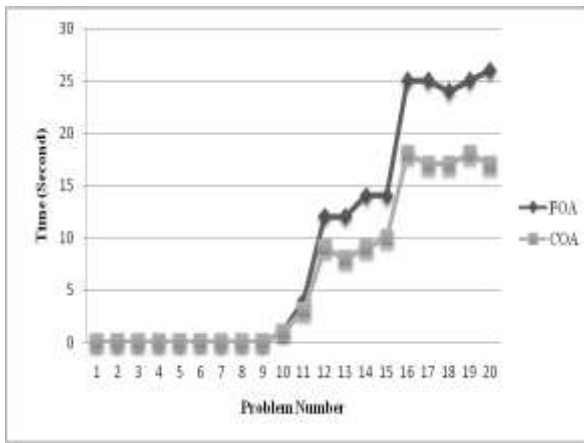


Figure12. Comparison of computational times of two CO and FO based algorithm for instances with the number of facilities less than 30.

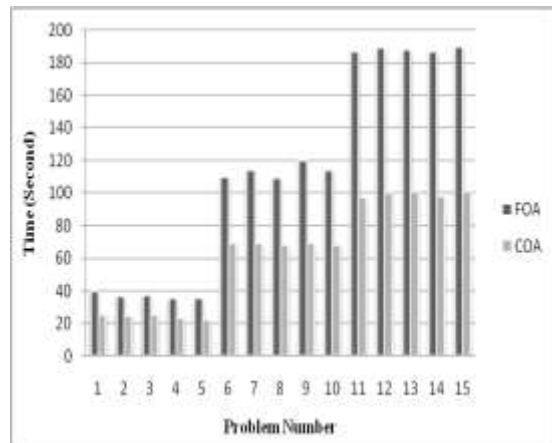


Figure13. Comparison of computational times of two CO and FO based algorithm for instances with the number of facilities more than 30.

figure 12 the horizontal axis shows the computational time and vertical axis depicts the problem number.

4.2. Instances with the number of facilities more than 30

The same computational results for the second set of problems with number of facilities more than 30 are shown in table 3.

According to the table 3, COA with the average gap of 0.0013 has the better performance rather than FOA with the average gap of 0.0017. Also

the computational time of COA is less than FOA for all instances and these results demonstrate better performance of COA to solve SRFLP.

Table 4 shows the mean and standard deviation of objective function values of instances of set 2. As said before each instance is run 20 times. Figure 13 shows and compares the difference between computational times of two algorithms.

In figure 13 the horizontal axis shows the computational time and vertical axis depicts the problem number.

Table3. Results for problem set2.

Problem Number	Number of Facilities	Best known value from literature	FOA Result	FOA Time (Sec)	FOA Gap	COA Result	COA Time (Sec)	COA Gap
1	40	107348.5	107886	39	0.005007056	107536.5	25	0.001751305
2	40	97693	97693	36	0	97693	24	0
3	40	78589.5	78689.5	37	0.001272435	78686.5	25	0.001234262
4	40	76669	77295	35	0.008164969	77191	23	0.006808488
5	40	103009	103127	35	0.001145531	103018	22	8.7371E-05
6	60	1477834	1500899	110	0.015607301	1477834	69	0
7	60	648337.5	649097.5	114	0.001172229	648792	69	0.000701024
8	60	841792	851120	109	0.011081122	841792	68	0
9	60	398468	398710	120	0.000607326	398480	69	3.01153E-05
10	60	318805	320678	114	0.005875065	318805	68	0
11	70	1518993.5	1530590	187	0.007634332	1530191	97	0.007371658
12	70	1441028	1443709	189	0.001860477	1441467	100	0.000304644
13	70	1518993.5	1527075.5	188	0.005320628	1520453.5	101	0.000961163
14	70	968796	969880	187	0.001118915	969464	98	0.000689516
15	70	4218017.5	4227125.5	190	0.002159308	4218797.5	101	0.000184921

Table4. Mean and SD results for instances of set two in 20 times of run.

Problem number	COA-Mean	COA-SD	FOA-Mean	FOA-SD
N40_1	107791.8	237.6574741	107994.4	226.8453217
N40_2	97957.2	331.4131862	97997.2	414.8670872
N40_3	78997.1	414.9904216	79077.9	289.8569475
N40_4	77356.4	156.4106774	77598	310.6565628
N40_5	103483.6	427.486608	103765.4	586.7161153
n60_1	1478014	402.4922359	1501299	547.7225575
n60_2	648976.1	694.2137999	649159.4	652.3557695
n60_3	842162.4	828.2395789	851520	894.427191
n60_4	398775.8	264.9607518	399198	681.5937206
n60_5	318944.2	311.2606625	320707	884.421845
N70_1	1530418.2	260.7799843	1531022.8	276.3099712
N70_2	1441707	328.6335345	1444283.6	413.8892362
N70_3	1521250.7	711.4087785	1528030.2	962.3980856
N70_4	969872.4	704.0914714	970038.8	614.6276921
N70_5	4218891.9	544.4941926	4227575.3	640.7808317

5. Conclusion

This paper considers the single row facility layout problem. Some exact and heuristic methods have been developed in recent years to solve this problem but as this problem is NP-hard, finding optimum solution for the large instances of this problem is not possible in a reasonable time. Nowadays different meta-heuristic algorithms are introduced in the literature to solve SRFLP but we still need to have a fast algorithm that can obtain a near-optimum solution for large instances of the problem. Cuckoo optimization and forest optimization algorithms are two meta-heuristic algorithms that are introduced recently.

In the literature these algorithms have not applied to solve SRFLP yet. In this paper the performance of COA and FOA to solve SRFLP is compared. As COA and FOA are defined to solve continues optimization problems in the literature, to solve SRFLP that is a discrete problem at first a cuckoo based algorithm and a forest based algorithm are proposed. Then To test the performance of two algorithms, two groups of instances with the number of facilities less and more than 30 are used. Computational results on two algorithms show that COA has better performance rather than FOA in both aspects of achieving the best solution and computational time.

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دو الگوریتم جدید بهینه‌سازی فاخته و بهینه‌سازی جنگل برای حل مسأله‌ی چیدمان تسهیلات تک ردیفه

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چکیده:

امروزه با توجه به پیچیدگی ذاتی مسائل بهینه‌سازی واقعی، همواره توسعه‌ی یک الگوریتم برای حل این مسائل به عنوان یک موضوع چالش برانگیز مطرح بوده است. مسأله‌ی چیدمان تسهیلات تک ردیفه، یک مسأله‌ی NP-hard برای چیدمان تعدادی تسهیلات مستطیلی شکل با طول متغیر بر روی یک سطر و با هدف حداقل سازی مجموع وزن دار فاصله‌ی بین هر جفت از تسهیلات است. در این مقاله برای اولین بار دو الگوریتم بهینه‌سازی فاخته و بهینه‌سازی جنگل برای حل مسأله‌ی چیدمان تسهیلات تک ردیفه به کار گرفته شده و با یکدیگر مقایسه شده‌اند. عملگرهای هر دو الگوریتم با توجه به ویژگی‌های مسأله‌ی فوق تغییر داده شده و با مسأله وفق داده شده‌اند و نتایج حاصل برای دو گروه از مثال‌های معیار موجود در ادبیات پژوهش مقایسه شده‌اند. در گروه اول تعداد تسهیلات کوچکتر مساوی ۳۰ و در گروه دوم تعداد تسهیلات بزرگتر از ۳۰ است. نتایج حاصل نشان‌دهنده‌ی عملکرد بهتر الگوریتم پیشنهادی مبتنی بر بهینه‌سازی فاخته نسبت به الگوریتم پیشنهادی مبتنی بر بهینه‌سازی جنگل، در هر دو گروه از مثال‌ها چه از نظر یافتن بهترین جواب و چه از نظر زمان محاسباتی الگوریتم است.

کلمات کلیدی: مسأله‌ی چیدمان تسهیلات، مسأله‌ی چیدمان تسهیلات تک ردیفه، الگوریتم بهینه‌سازی فاخته، الگوریتم بهینه‌سازی جنگل.