Research Article

Assessing the Performance of Two Bioinspired Algorithms to Solve Single-Row Layout Problem

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The single-row layout problem (SRLP), also known as the one-dimensional layout problem, deals with arranging a number of rectangular machines/departments with equal or varying dimensions on a straight line. Since the problem is proved to be NP-hard, there are several heuristics developed to solve the problem. This study introduces both a Clonal Selection Algorithm (CSA) and a Bacterial Foraging Algorithm (BFA) for SRLP. The performance of the algorithms is assessed by using three (small, medium, and large sized) well known test problems available in the literature. The promising results illustrated that both algorithms had generated the best known solutions so far for most of the problems or provided better results for a number of problems.

1. Introduction

The objective in SRLP is to minimize the total material handling costs (MHC) and to find the optimum layout for machines in one dimension. The SRLP is also known as one-dimensional layout and usually refereed as Linear Ordering Problem, where all machines have unit length. Braglia [1] pointed that the problem is widely implemented in the configuration of manufacturing systems. Kusiak and Heragu [2] stated that the type of material handling device in Flexible Manufacturing System determines the pattern to be used for the layout of machines. Therefore, the design problem that is related with material handling devices such as handling robots and Automated Guided Vehicles (AGV) is usually considered as an SRLP. Further, the problem has applications in real-life applications such as the room arrangement problem along the corridor (i.e., hotels and hospitals) [3]; the arrangement of books on a shelf in a library; the assignment of disk cylinders to files [4].

Suresh and Sahu [5] have identified the problem that has wide application areas, as an NP-complete type. Therefore, several heuristics have been proposed to solve this problem in the literature. The pioneering studies include Karp and

Held [6], Nugent et al. [7], Simmons [3], and Hall [8]. Neghabat [9] introduced a procedure where a complete solution is obtained by inserting one machine at a time to the end of the solution yet obtained. Love and Wong [10] presented a linear mixed integer-programming model for the single row layout problem and solved it using the mixed integer-programming algorithm. Drezner [11] introduced a heuristic that is based on the eigenvectors of a transformed flow matrix. Heragu and Kusiak [12] proposed the heuristic where a pair of facilities with the largest adjusted flow is initially laid; and then the partial order is gradually completed through a loop adding new machines to the right and left of the order that is obtained in the previous iteration. Then, Heragu and Kusiak [13] introduced a linear mixed integer formulation of SRLP and solved it using a penalty method. A Simulated Annealing (SA) algorithm has been developed by Romero and Sánchez-Flores [14]. Heragu and Alfa [15] proposed a hybrid SA algorithm that combines a modified penalty algorithm and an SA to solve SRLP and multirow layout problems. Kouvelis and Chiang [16] used an SA algorithm for solving a machine layout problem with a straight line handling track. Kumar et al. [17] proposed a constructive greedy heuristic that assigns facilities with the larger number

FIGURE 1: SRFLP illustration.

of moves between them. Braglia [18] proposed a combination of SA and Genetic Algorithm (GA) to minimize the total backtracking in the linear ordering of machines. The SRLP is considered with heuristics derived from scheduling problem by Braglia [1]. Ho and Moodie [19] proposed a two-phase layout procedure that combines Flow Line Analysis (FLA) and SA algorithm. Djellab and Gourgand [20] constructed an iterative procedure. Chen et al. [21] proposed an SA. Ficko et al. [22] introduced a GA. Solimanpur et al. [23] formulated the problem as a nonlinear 0-1 programming model and solved by an ant algorithm. Anjos et al. [24] constructed a semidefinite programming relaxation providing a lower bound on the optimal value of the SRLP. Amaral et al. [25] utilized SA to solve SRLP. Ponnambalam et al. [26] assessed the results of several metaheuristics with different FLA methods. Amaral [27] discussed the exact solutions for a facility layout problem. Kumar et al. [28] proposed a scatter search algorithm, Teo and Ponnambalam [29] a hybrid Ant Colony Optimisation and Particle Swarm Optimisation (ACO/PSO) algorithm, and Anjos and Vannelli [30] semidefinite programming and cutting planes. Amaral [31] introduced a new lower bound for the SRLP and Lin [32] proposed a GA. Samarghandi and Eshghi [33] considered the problem by an efficient tabu algorithm. The most recent paper of SRFLP is provided by Datta et al. [34] that utilizes a permutation-based GA.

Most of the aforementioned algorithms have rather high computational time and memory requirements for SRFLP. Boussaid et al. [35] had summarized the main metaheuristics as single solution based metaheuristics and population based. Among these known metaheuristics, this paper introduces two population based bioinspired algorithms, CSA and BFA, that are proven to generate good quality solutions for optimization problems in rather short computational times. The main aim in this paper is to assess the performance of these two novel efficient algorithms with respect to well-known test problems in the SRLP literature for the first time. The machines are assumed rectangular with different dimensions and the distance between the machines is calculated with respect to their centroids. Also, the clearance between each pair of machines is assumed as zero.

This paper is organized as follows. The second section gives brief definitions for the problem in concern. Then, the details of the algorithms are introduced in the third section. After the test problems and their sources are defined, the results available in the literature and the obtained results are compared in section four. The final section discussed the results and potential application areas for the problem.

2. Single Row Facility Layout Problem

SRFLP is common in manufacturing environments since some material handling equipment and machines utilize these simple and useful concepts. Figure 1 illustrates a part of a layout where n machines/departments are arranged on a straight line in a given direction. The distance among the machines (i.e., i and j) is defined as the sum of the center points of the machines (i.e., $l_i/2$ and $l_j/2$) and the clearance (D_{ij}) between the machines, if any

$$\min \quad z = \sum_{i=1}^{n-1} \sum_{j=i+1}^n c_{ij} d_{ij}, \quad (1)$$

$$\text{s.t.} \quad d_{ij} \geq \frac{1}{2} (l_i + l_j) + s_{ij}; \quad (2)$$

$$i = 1, 2, \dots, n-1; \quad j = i+1, \dots, n,$$

$$d_{ij} \geq 0; \quad i = 1, 2, \dots, n-1; \quad j = i+1, \dots, n, \quad (3)$$

$$d_{ij} = \frac{l_i + l_j}{2} + D_{ij}, \quad D_{ij} \geq s_{ij}. \quad (4)$$

Objective (1) is to minimize the total MHC and to find the optimum layout for machines in one dimension. Equations (2) and (3) state constraints and (4) determine the distance among two departments.

The problem is considered in several ways, such as the dimensions of the machines are either not considered or are assumed to be equal [18], the locations of facilities are predetermined [17, 18], and the size of the machines is only considered in the physical layout of the machines [12]. While constructing a layout, Anjos et al. [24] stated that an SRFLP with a large number of machines requires too much time. Therefore, heuristics were developed to solve the problem in a relatively short time.

3. Bioinspired Algorithms Developed for the SRLP

Biologically inspired computing imitates nature and uses main concepts and behavior of these systems to solve complex problems. GA is inspired from evolution, neural networks from the brain, artificial immune systems from the immune system, emergent systems from ants and bees, rendering (computer graphics) from patterning and rendering of animal skins, bird feathers, mollusk shells and bacterial colonies, and cellular automata. Along with various metaheuristics,

FIGURE 2: Encoding for SRFLP.

(a)

(b)

FIGURE 3: Two-stage mutation procedure for CSA.

the definitions and generic pseudo codes for CSA and BFA are also available in Boussaid et al. [35] for interested readers. This study that is tailored to solve SRLP provides the main algorithm steps for population generation, evaluation, reproduction, and termination of CSA and BFA.

3.1. Clonal Selection Algorithm. The clonal selection theory in an immune system is used to explain the basic response of the adaptive immune system to an antigenic stimulus. The theory depends on the idea that only cells that are capable of recognizing an antigen will proliferate [36].

The representation for SRFLP is illustrated in Figure 2. The layout of machines in a manufacturing environment can be represented as a string array. Random layouts are generated randomly as permutations of machines.

Step 1 (initialization). The antibodies are randomly generated based on the predetermined population size.

Step 2 (evaluation). For each antibody in the population, the objective function value (MHC) is calculated.

Step 3 (selection and cloning). Selection of antibodies is made based on the MHC. The layouts that have lower MHC

values have the largest share on the wheel and have more chances to be cloned.

Step 4 (hypermutation). For each antibody in the population, hypermutation operator is applied as illustrated in Figure 3. Then, objective value of the mutated antibody is calculated. If a lower MHC is obtained, the existing antibody is replaced with the mutated one. Otherwise, current antibody is kept.

Step 5 (receptor editing operator). A percentage of the antibodies (worst $R\%$ of the whole population) in the antibody population are eliminated and randomly created antibodies are replaced with them. This procedure enables the algorithm to search new regions in the solution space.

Step 6. Repeat Steps 2–5 until termination criterion is met.

In this study, the algorithm is terminated if the best feasible solution has not improved after a predetermined number of iterations (i.e., 250).

3.2. Bacterial Foraging Algorithm. Bacterial adaptability and evolvability in various habitats have attracted researchers' attention. Bacteria's behavioral strategies are then applied

to natural computation and used to solve computational problem. In his seminal paper published in 2002, Passino pointed out how individual and groups of bacteria forage for nutrients and how to model it as a distributed optimization process, which he named the Bacterial Foraging Optimization Algorithm (BFOA). One of the major operators of BFOA is the reproduction phenomenon of virtual bacteria, each of which models one trial solution of the optimization problem.

Donangelo and Fort [37] studied the evolution of *E. coli* populations through a Bak-Sneppen-type model which incorporates random mutations. Paton et al. [38] described a bacterially-inspired computational architecture for simulating aspects of problem solving. Kim et al. [39] proposed a hybrid approach involving GA and BFA for function optimization problems and test their performance on four test functions. Datta and Misra [40] introduced an improved adaptive approach involving BFA to optimize both the amplitude and phase of the weights of a linear array of antennas. Niu et al. [41] proposed a life cycle model that is developed using an individual based modeling approach that possesses a more flexible and robust capability for simulating bacterial system compared with the population-based modeling approach. Das et al. [42] described a clustering algorithm to partite a given dataset automatically into the optimal number of groups by utilizing bacterial mutation and the gene transfer operation. Chen et al. [43] applied the cooperative approaches to the bacterial foraging optimization. Biswas et al. [44] modeled reproduction in BFA as a dynamics and analyzed the stability of the reproductive system.

Main steps of BFA to solve SRLP that is based on the foraging (i.e., searching food) strategy of *E. coli* bacteria are summarized as follows.

Step 1 (initialization). The bacteria are randomly generated based on the predetermined population size.

Step 2 (chemotaxis). It is a foraging strategy that implements a type of local optimization. The bacteria try to climb up the nutrient concentration, avoid noxious substances, and search for ways out of neutral media. This procedure is similar with biased random walk model.

Step 3 (Swarming). The bacteria move out from their respective places in ring of cells by moving up to the minimal value. The bacteria usually tumble, followed by another tumble or tumble followed by run or swim. As considering the case as an optimization process, the MHC that a bacterium represents is assessed. If the MHC at present is better than the cost at the previous time or duration, then the bacteria take one more step in that direction.

Step 4 (Reproduction). The bacteria are stored in ascending order based on their fitness. Then, a percent of the least healthy bacteria dies and others split into two which are placed in the same location with respect to the following steps.

- (1) N_{clones} copies of the solution are generated so that there are $(N_{clones}+1)$ identical solutions.

- (2) Inverse mutation is applied to each of the N_{clones} copies.
- (3) The solution surviving the mutation is the nondominated solution among the mutated solutions.
- (4) All other solutions are discarded.
- (5) Repeat the procedure for all the solutions in the population.

Meanwhile, the population of bacteria remains constant.

Step 5. Repeat Steps 2–4 until termination criterion is met.

3.3. Algorithm Parameters. Algorithm parameter values might influence whether the algorithm will efficiently find a near-optimum solution in a reasonable time. On the other hand, choosing right parameter values is a time consuming task. Some of the studies that focus on CSA parameters are as follows. Ulutas and Islier [45] introduced a basic design of experiments only to determine CSA parameters for the equal area facility layout problems. Engin and Döyen [46] provided a generic systematic procedure that is based on a multistep experimental design approach to determine the efficient system parameters for scheduling problems. However, to the best of our knowledge, no detailed study to optimize BFA parameters is available.

3.3.1. Population Size. Since CSA and BFA are population based heuristic algorithms, population size is one of the most important parameters.

3.3.2. Elimination Ratio. The vertebrate immune system mechanism, called receptor editing, eliminates a percent of the antibodies in the CSA population. Likewise, a percent of least healthy bacteria in BFA are also discarded from the population. Parameter $R\%$ illustrates the percentage of the worst solutions to be eliminated and replaced with randomly generated ones.

3.3.3. Termination Criterion. Michalewicz [47] presented three kinds of termination conditions that have been traditionally employed. One of the following termination criteria can also be used for CSA and BFA:

- (i) predetermined number of iterations,
- (ii) predetermined number of objective function evaluations,
- (iii) predetermined number of nonimproved iterations.

4. Assessing the Performance of the Proposed Heuristics

The SRLP in concern has machines with unequal dimensions (i.e., side lengths), no clearance among machines, and backtracking is not allowed. The performance of the two algorithms is tested on small and large size test problems. In this study, population size is assigned as 10 for both algorithms. Receptor editing for CSA and reproduction rate

TABLE 1: Problem set 1: small-sized test problems with optimum solutions.

No.	Test problems		Optimum solution			Samarghandi et al. [49]	Solimanpur et al. [23]	BFA/CSA
	Problem name	Reference source	n	OFV	Reference	OFV	OFV	OFV
1	P4	Amaral [31]	4	638.00	Amaral [27]	638.00	638.00	638.00
2	LW5	Love and Wong [10]	5	151.00	Amaral [27]	151.00	151.00	151.00
3	S8_1	Simmons [3]	8	801.00	Amaral [27]	801.00	n/a	801.00
4	S8_2	Simmons [3]	8	2324.50	Amaral [27]	2324.50	n/a	2324.50
5	S9_1	Simmons [3]	9	2469.50	Amaral [27]	2469.50	n/a	2469.50
6	S9_2	Simmons [3]	9	4695.50	Amaral [27]	4695.50	n/a	4695.50
7	S10	Simmons [3]	10	2781.50	Amaral [27]	2781.50	n/a	2781.50
8	S11	Simmons [3]	11	6933.50	Amaral [27]	6933.50	n/a	6933.50
9	LW11	Love and Wong [10]	11	6933.50	Love and Wong [10]	6933.50	n/a	6933.50
10	P15	Amaral [31]	15	6305.00	Amaral [27]	6305.00	n/a	6305.00
11	P17	Amaral [31]	17	9254.00	Amaral [31]	n/a	n/a	9254.00
12	P18	Amaral [31]	18	10650.50	Amaral [31]	n/a	n/a	10650.50

TABLE 2: Problem set 2: medium-sized test problem literature results.

No.	Problem name	n	Amaral [31]		Anjos and Vannelli [30]		Samarghandi and Eshghi [33]	
			OFV	Time	OFV	Time	OFV	Time
1	AV25_1	25	n/a	n/a	4618.00	225.50	4631.00	0.04
2	AV25_2	25	n/a	n/a	37116.50	598.70	37116.50	0.04
3	AV25_3	25	n/a	n/a	24301.00	289.25	24560.00	0.05
4	AV25_4	25	n/a	n/a	48291.50	618.78	48291.50	0.04
5	AV25_5	25	n/a	n/a	15623.00	227.20	15623.00	0.04
6	AV30_1	30	n/a	n/a	8247.00	1540.95	8247.00	0.05
7	AV30_2	30	n/a	n/a	21582.50	1363.16	21582.50	0.05
8	AV30_3	30	n/a	n/a	45449.00	1394.13	46212.00	0.06
9	AV30_4	30	n/a	n/a	56873.50	8962.38	58297.50	0.06
10	AV30_5	30	n/a	n/a	115268.00	3936.00	115826.00	0.07
11	P35_1	35	69439.50	n/a	n/a	n/a	69439.50	n/a
12	P35_2	35	61712.00	n/a	n/a	n/a	61712.00	n/a
13	P35_3	35	69002.50	n/a	n/a	n/a	69002.50	n/a

for BFA are considered as 10% of the population based on previous experimental studies. The first problem set given in Table 1 consists of the test problems with 4 to 18 machines that have optimum solutions.

The first column provides the information for the test problem, problem name, its reference source, and the number of machines (problem size). The optimum objective function value (OFV) for the test problems is provided in the fourth column with its reference. Following columns provide the OFVs obtained by Samarghandi and Eshghi [33] and Solimanpur et al. [23]. The last column states that BFA and CSA had generated optimum OFV for all twelve small-sized test problems. These results were obtained in less than a second for each 10 replications.

Table 2 illustrates the results gathered from the literature for twenty-two medium sized test problems. The first two columns state problem name and number of machines. Available OFVs and solution times from Amaral [31], Anjos and Vannelli [30], and Samarghandi and Eshghi [33] are given in Table 2.

Table 3 provides the results obtained from BFA are given along with the number of best results among 10 replications, best, average, and worst OFV, standard deviation (Std.Dev.) of solutions, and average of CPU seconds. The last column illustrates the improvement compared with the best known solutions. It is clear that BFA had generated all best known results available in the literature for medium sized test problems. As mentioned by Solimanpur et al. [23] and also

TABLE 3: Problem set 2: medium-sized test problem BFA results.

Problem name	Best known so far	BFA						
		No. of best solution	Best	Average	Worst	Std.Dev.	Avg. CPU time (second)	Imp.%
AV25_1	4618.00	9	4618.00	4618.10	4619.00	0.32	5.30	0.00
AV25_2	37116.50	7	37116.50	37139.00	37294.50	55.59	5.90	0.00
AV25_3	24301.00	10	24301.00	24301.00	24301.00	0.00	4.90	0.00
AV25_4	48291.50	6	48291.50	48327.20	48494.50	63.67	2.60	0.00
AV25_5	15623.00	8	15623.00	15630.80	15662.00	16.44	3.80	0.00
AV30_1	8247.00	7	8247.00	8258.90	8326.00	25.00	11.00	0.00
AV30_2	21582.50	4	21582.50	21609.20	21695.50	44.78	12.00	0.00
AV30_3	45449.00	5	45449.00	45465.70	45500.00	19.65	11.50	0.00
AV30_4	56873.50	7	56873.50	56884.10	56929.50	19.04	13.20	0.00
AV30_5	115268.00	5	115268.00	115528.60	116142.00	345.02	8.90	0.00
P35_1	69439.50	4	69439.50	69645.50	70365.50	346.33	21.50	0.00
P35_2	61712.00	1	61712.00	61819.80	62067.00	98.80	18.00	0.00
P35_3	69002.50	2	69002.50	69036.20	69092.50	30.27	14.30	0.00

TABLE 4: Problem set 2: medium-sized test problem CSA results.

Problem name	Best known so far	CSA						
		No. of best solution	Best	Average	Worst	Std.Dev.	Avg. CPU time (second)	Imp.%
AV25_1	4618.00	10	4618.00	4618.00	4618.00	0.00	2.90	0.00
AV25_2	37116.50	8	37116.50	37120.30	37137.50	8.07	5.40	0.00
AV25_3	24301.00	7	24301.00	24305.40	24333.00	10.01	3.50	0.00
AV25_4	48291.50	10	48291.50	48291.50	48291.50	0.00	6.50	0.00
AV25_5	15623.00	8	15623.00	15627.90	15662.00	12.39	3.70	0.00
AV30_1	8247.00	9	8247.00	8250.70	8284.00	11.70	14.90	0.00
AV30_2	21582.50	9	21582.50	21583.00	21587.50	1.58	14.40	0.00
AV30_3	45449.00	8	45449.00	45487.70	45812.00	114.20	9.70	0.00
AV30_4	56873.50	8	56873.50	56878.80	56901.50	11.20	12.80	0.00
AV30_5	115268.00	8	115268.00	115272.00	115304.00	11.31	10.40	0.00
P35_1	69439.50	6	69439.50	69480.10	69591.50	58.16	19.90	0.00
P35_2	61712.00	1	61712.00	61762.10	61811.00	26.14	38.30	0.00
P35_3	69002.50	4	69002.50	69011.30	69024.50	8.23	24.40	0.00

noted by Datta et al. [34], the computational time should not be considered for comparing the performances of two algorithms as the computing machines are generally different. However, the solution times are also provided for interested readers.

Table 4 provides the problem names and best known solutions for medium sized test problems. Then, the results obtained by use of CSA are given in the following columns. Based on the column that states the best results, it is clear that CSA was able to obtain all the optimum solutions among thirteen test problems.

Since the success of the BFA and CSA are obvious for medium sized test problems considering 25, 30, and 35 machines, large sized test problems ranging from 60 up to 80 are also studied. Table 5 illustrates the twenty test problems. Available OFV and solution times from, Anjos and Yen [48], Samarghandi and Eshgi [33], and Datta et al. [34] are listed.

The solutions obtained from BFA are given in Table 6 with the number of best solutions among 10 replications, best,

average, worst OFV, standard deviation, and average CPU time. The OFV generated by BFA were compared with the best known results of Datta et al. [34]. Among the twenty test problems, BFA had reached eight best known results and obtained better results for four test problems that are illustrated in bold. The rest of the eight results had generated slightly (0.034% on the average) higher OFV.

For the P60_2 test problem, best improvement for BFA was recorded as 0.02%. Ten different random seeds were used to evaluate the results generated from the algorithm. Table 7 illustrates the best results in each replication, the number of iteration and the CPU time when the best solution of the related replication was obtained, the total iteration number and total CPU time before the related iteration was terminated.

Table 8 provides CSA results for large sized test problems. The best known solutions so far are again taken from Datta et al. [34]. CSA was able to obtain the same best results for the thirteen and better results for five large sized test problems.

TABLE 5: Problem set 3: large-sized test problem literature results.

No.	Problem name	n	Anjos et al. [24]		Anjos and Yen [48]		Samarghandi et al. [49]		Datta et al. [34]	
			OFV	Time (hour)	OFV	CPU time (second)	OFV	Time (second)	OFV	Time (second)
1	P60_1	60	1493704.00	5	1478464.00	20353	1477834.00	0.82	1477834.00	19.54
2	P60_2	60	843644.00	5	844695.00	18490	841792.00	0.98	841792.00	22.34
3	P60_3	60	656272.50	5	650533.50	17448	648337.00	0.90	648337.50	68.81
4	P60_4	60	405433.00	5	400669.00	17719	398511.00	0.91	398468.00	20.71
5	P60_5	60	319501.00	5	319103.00	18328	318805.00	0.76	318805.00	26.41
6	P70_1	70	1543098.00	7	1533075.00	87930	1529197.00	1.49	1528621.00	64.83
7	P70_2	70	1494182.00	7	1444720.00	87639	1441028.00	1.94	1441028.00	77.49
8	P70_3	70	1524171.50	7	1526830.50	83507	1518993.50	1.76	1518993.50	68.26
9	P70_4	70	974856.00	7	972389.00	82611	969130.00	1.23	968796.00	100.59
10	P70_5	70	4230912.50	7	4218730.50	85367	4218230.00	1.57	4218017.50	60.48
11	P75_1	75	2399583.50	10	2394812.50	144912	2393483.00	2.01	2393456.50	125.26
12	P75_2	75	4348544.00	10	4322967.00	152600	4321190.00	2.19	4321190.00	128.95
13	P75_3	75	1295085.00	10	1255634.00	138459	1248551.00	2.91	1248537.00	157.95
14	P75_4	75	3949276.50	10	3950444.50	149269	3942013.00	2.51	3941891.50	119.92
15	P75_5	75	1816455.00	10	1797676.00	155398	1791408.00	2.09	1791408.00	101.67
16	P80_1	80	2138083.50	10	2073453.50	176849	2069097.00	3.97	2069097.50	75.41
17	P80_2	80	1939938.00	10	1923506.00	174708	1921177.00	5.64	1921177.00	68.75
18	P80_3	80	3332421.00	10	3256577.00	177751	3251413.00	4.79	3251368.00	85.90
19	P80_4	80	3773429.00	10	3747950.00	188203	3746515.00	3.45	3746515.00	77.81
20	P80_5	80	1611495.00	10	1594228.00	169384	1589061.00	3.76	1588901.00	196.51

TABLE 6: Problem set 3: large-sized test problem BFA results.

Problem name	BFA						
	No. of best solution	Best	Average	Worst	Std.Dev.	Avg. CPU	Imp.%
P60_1	5	1477834.00	1478543.40	1480894.00	1197.66	153.40	0.000
P60_2	2	841778.00	841952.40	842438.00	201.52	224.50	0.002
P60_3	1	648963.50	649627.30	650160.50	433.42	156.30	-0.097
P60_4	1	398512.00	399606.50	401111.00	719.14	281.60	-0.011
P60_5	2	318805.00	319335.40	321214.00	863.93	361.60	0.000
P70_1	1	1528604.00	1529981.90	1531726.00	980.04	958.00	0.001
P70_2	2	1441028.00	1441590.20	1442122.00	387.29	757.10	0.000
P70_3	3	1518993.50	1520008.40	1522350.50	1217.79	907.00	0.000
P70_4	2	968796.00	970542.10	973849.00	1450.53	1041.00	0.000
P70_5	1	4218003.00	4219265.30	4220774.50	1223.34	836.70	0.000
P75_1	2	2394527.00	2395851.90	2398617.50	1367.21	1079.40	-0.045
P75_2	2	4321397.00	4323534.30	4327303.00	1841.17	1122.90	-0.005
P75_3	1	1249698.00	1250822.50	1252117.00	872.92	1605.50	-0.093
P75_4	1	3941816.00	3945090.90	3949730.50	2940.35	1536.50	0.002
P75_5	1	1791637.00	1792575.00	1794100.00	736.91	1652.70	-0.013
P80_1	1	2069097.00	2070327.70	2071516.50	708.17	2718.00	0.000
P80_2	1	1921166.00	1921305.50	1921888.00	227.95	1916.40	0.001
P80_3	1	3251413.00	3254638.80	3257272.00	1813.65	2812.00	-0.001
P80_4	1	3746712.00	3749103.40	3752445.00	2066.67	2389.20	-0.005
P80_5	1	1588901.00	1589907.60	1593004.00	1367.44	2582.10	0.000

TABLE 7: BFA results for P60_2.

Replication	Best solution	Best found iteration #	Total iteration #	Best found time	Total time
1	841872000	424	675	378	608
2	842122000	134	385	151	362
3	841872000	65	316	70	282
4	842438000	170	421	163	373
5	841876000	68	319	74	288
6	841778000	443	694	388	598
7	841778000	533	784	471	685
8	841872000	112	363	115	322
9	841872000	123	374	124	337
10	842044000	332	583	311	546

TABLE 8: Problem set 3: large-sized test problem CSA results.

Problem name	No. of best solution	CSA				Avg. CPU	Imp.%
		Best	Average	Worst	Std.Dev.		
P60_1	9	1477834.00	1477886.00	1478354.00	164.44	440.70	0.000
P60_2	2	841776.00	841818.80	841872.00	43.33	504.10	0.002
P60_3	2	648337.50	648815.40	649516.50	356.39	446.70	0.000
P60_4	2	398406.00	398626.30	399281.00	335.25	469.00	0.016
P60_5	8	318805.00	318821.10	318916.00	36.86	407.80	0.000
P70_1	7	1528537.00	1528774.50	1529733.00	483.89	1587.20	0.005
P70_2	8	1441028.00	1441228.20	1443009.00	625.74	1190.60	0.000
P70_3	5	1518993.50	1519120.10	1519552.50	202.76	1394.80	0.000
P70_4	7	968796.00	968893.80	969706.00	285.73	1414.40	0.000
P70_5	4	4218048.50	4218460.10	4219044.50	430.83	1153.00	-0.001
P75_1	1	2393456.50	2394231.40	2396005.50	1029.44	1739.60	0.000
P75_2	2	4321190.00	4321477.70	4322283.00	416.81	2198.60	0.000
P75_3	2	1248551.00	1249343.00	1250309.00	788.84	2062.60	-0.001
P75_4	5	3941816.50	3942544.10	3944059.50	1003.45	1379.00	0.002
P75_5	1	1791408.00	1791884.10	1793044.00	624.40	2375.60	0.000
P80_1	2	2069097.50	2069314.70	2069836.50	273.52	3708.60	0.000
P80_2	4	1921136.00	1921170.40	1921212.00	32.80	2082.00	0.002
P80_3	3	3251368.00	3252695.90	3253829.00	1146.31	1987.80	0.000
P80_4	2	3746515.00	3747259.60	3750294.00	1247.25	2222.80	0.000
P80_5	1	1588901.00	1589531.30	1590593.00	694.64	2698.40	0.000

Only two test problems were slightly worse (0.001% on the average) than the ones provided in the literature.

For the P60_2 test problem, best improvement for CSA was recorded as 0.02%. Ten different random seeds were again used to evaluate the results generated from the algorithm. Table 9 illustrates the best results in each replication, the number of iteration and the CPU time when the best solution of the related replication was obtained, the total iteration number and total CPU time before the related iteration was terminated.

Figure 4 presents the convergence graph for P60_2 the best results is obtained in the 443rd iteration by BFA and in the 137th iteration by CSA. It is clear that CSA has a higher convergence speed than BFA.

5. Conclusions and Results

The single row layout problem has several applications. Although it is based on simple concepts, as the number of machines or departments increase, solution can be obtained in nonpolynomial time. Therefore, several researchers had considered the problem and provided different methods to solve the problem. This study evaluates three performance metrics such as, solution quality, speed of convergence, and frequency of hitting the optimum. CSA and BFA are used to solve the commonly studied test problems in the literature. Optimum and best known solutions were obtained for small and medium sized test problems. For the 20 large sized test problems, BFA obtained better results for the 20% and CSA

FIGURE 4: The convergence graph for P60.2 best result obtained by CSA and BFA.

TABLE 9: CSA results for P60.2.

Replication	Best solution	Best found iteration #	Total iteration #	Best found time	Total time
1	841790000	382	633	904	1399
2	841776000	137	388	343	856
3	841872000	60	311	167	736
4	841858000	417	668	858	1361
5	841872000	57	308	151	656
6	841872000	61	312	169	676
7	841792000	300	551	708	1246
8	841790000	199	450	441	941
9	841790000	371	622	799	1297
10	841776000	226	477	501	1075

25% of the test problems. Further, BFA and CSA obtained 40% and 65% of the best known solutions respectively. Although 40% of the solutions for the large sized test problems obtained from BFA seemed worse than literature results, the average of the improvements were calculated as -0.034% that is very close to zero indeed. Considering the CSA solutions, only two results were worse than the best known solutions that formed the 10% of the test problems. When the results for the CSA and BFA are compared, it can be stated that both algorithms performed well for the small sized and medium sized test problems. On the other hand, CSA outperformed BFA in large sized test problems.

Further research may focus on new strategies to improve BFA search capabilities to obtain better results for layout problems. In addition, data from real life problems such as arrangement of goods in supermarkets can be obtained and the problem can be modeled as SRLP.

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