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Development of a modified biogeography-based optimisation tool for solving the unequal-sized machine and multi-row configuration facility layout design problem

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ABSTRACT: An effective layout can reduce material flow distances and manufacturing lead-times, whilst increasing productivity, throughput and cost effectiveness. The facilities layout problem (FLP) is a non-deterministic polynomial-time hard problem, which means that the computational time taken to produce solutions increases exponentially with problem size. Metaheuristics are particularly suitable for solving such problems in reasonable time. Biogeography-based optimisation (BBO) is a well-known nature-inspired computing metaheuristic. Its mechanisms mimic an analogy with biogeography which relates to the migration, mutation and geographical distribution of biological organisms. This paper presents a novel BBO optimisation tool that solves the unequal area facilities layout problem to generate multi-row solutions that minimise the total material flow distance. Two novel modifications were made to the conventional BBO: the use of a Genetic Algorithm crossover operator in the migration process; and a changed method for selecting candidate solutions. The local search approaches used data on flow intensities and machine adjacencies. Experiments were conducted using five benchmark datasets obtained from the literature. The statistical analysis of the computational results indicated that the proposed mBBOs produced statistically better solutions than the conventional BBO and other metaheuristics for all datasets and converged more rapidly with comparable execution times.

KEYWORDS: computational intelligence, robust layout design, multi-row layout, non-identical machine, layout design program

INTRODUCTION

The facilities layout problem (FLP) is known to have a major impact on work in process, manufacturing costs, productivity and lead time [1]. "A facility may be a department, a machine tool, a work centre, a manufacturing cell, a machine shop, or a warehouse" [2]. A common layout design task is to assign facilities to a given area in order to optimise the performance measure(s) under the given conditions and constraints. The aim is to produce a smooth flow of materials, workers and information through the system [3]. A superior layout contributes to the overall operational efficiency and can reduce total operating costs by 20–50% [4], an effective layout can reduce material handling costs by 10–30% [5].

Single-row and multiple-row layouts are very famous in research work because they have been widely implemented in many factories [6]. Single-row layout design is often adopted for mass production industries. In many cases, duplicate machines are required within the manufacturing row to avoid the backward flow of materials. For the case of high number of duplicate machines, it may require a high financial investment and affect the length of the manufacturing flow line [7]. To reduce the investment and shorten the flow line, the machines can be placed in parallel or in multiple rows. However, the materials flow directions and moving distance between machines arranged in multiple rows are crucial and complex.

In today's rapidly changing corporate environments, manufacturing facilities may go through periods of expansion and decline due to the dynamic nature of demand. This makes it necessary for companies to cope with varying demand and be able to quickly switch from one product line to another. As a consequence, the facility layout may need to be adapted quickly. Layout problems are complex and mostly non-deterministic polynomial-time hard (NP-hard) problems, which means that the computation time required to solve problems increases exponentially with problem size [8]. For instance, if there are 5, 10, and 20 machines to be placed on a manufacturing shop floor, the number of possible solutions are 5!, 10!, and 20! (or 1.2×10^2, 3.6×10^6, 2.6×10^{32}) solutions, respectively. This simple example shows that even the number of machines increases two times, the number of possible solutions increases exponentially.

Conventional exact optimisation methods are inappropriate because they are not computationally efficient and cannot solve problems in reasonable time, especially for large-sized problems [9]. Metaheuristic algorithms have been used to solve many types of optimisation problem, such as quadratic assignment [10], scheduling [11, 12], timetabling [13], airline flight routing [14], stochastic dynamic facility layout [15], and robust-design machine layout [16] and wind farm layout [17]. They are particularly suitable for solving large combinatorial optimisation problems because they can find good solutions within reasonable execution times [9].

Metaheuristics such as genetic algorithms (GA) [18] and simulated annealing [19] are well-established and widely used. Over the past decade, many metaheuristic algorithms have been developed and compared to others including: ant colony optimisation [20], the backtracking search algorithm [21], biogeography-based optimisation (BBO) [22], and elephant herding optimisation [23]. BBO is a biological-inspired approach that is based on an analogy with biogeography [22], the study of the geographical distribution of biological organisms. The applications of BBO have been widely adopted for solving engineering problems, such as image processing [24] and batch plant scheduling [25].

There has been limited research that has applied the BBO and its modifications to solve layout problems, although it has been applied to a wind farm layout optimisation problem [17], multi-objective facility layout problems [26], production facilities layout based upon a virtual cellular manufacturing system [27]. Sooncharoen et al [28] applied the original BBO to solve the machine layout design problem and identified appropriate settings for the BBO parameters using a design of experiments approach. They recommended that future work should consider improving the algorithm's performance by modifying and/or hybridising the algorithm. This paper therefore presents six novel BBO modifications and compares their performance to other approaches for solving layout design problem.

The objective of this work was to present the development of a tool for solving the facilities layout problem that minimised the total material handling distance (MHD). The tool included a conventional BBO and six modified BBOs (mBBOs): (i) mBBO1 was based on a hybridisation that included a GA operator into the BBO migration process; (ii) mBBO2 adjusted the solution selection mechanism based on the quality of the best solution produced by the migration and mutation processes; (iii) mBBO3 arranged facilities so that machines pairs with the highest flow intensity between them were adjacent; (iv) mBBO4 ranked each pair of machines according the intensity of flow between them and then placed the two highest ranked machines in adjacent positions; (v) mBBO5 positioned machines with low flow intensity between them in nonadjacent positions; and (vi) mBBO6 combined mBBO3 and mBBO5. The modified BBOs were tested and compared to the classical BBO and other metaheuristics in terms of the quality of solutions for various problem sizes.

FACILITIES LAYOUT PROBLEM (FLP)

The FLP is defined as "arranging m indivisible departments (each with area a_i) within a given space" [29]. The objective of the FLP is to find the most efficient arrangement of machines on the shop floor to provide an efficient operation [30]. The efficiency of a layout is commonly measured in terms of material handling costs associated with the material handling distance (MHD) [31]. The total MHD depends on the material handling system used for example, material-handling robots or automated guided vehicles [32].

An effective layout reduces processing times and increases the throughput of the production system, hence increasing overall productivity [32]. The effective machine layout can decrease the moving distance of materials or parts or components flow between machines within a shop floor area. Shortening material handling distance leads to the improvement of manufacturing flow time and performance. At the same time, it can increase throughputs and cost effectiveness.

The appropriate layout design is dependent on various factors such as the material handling system, the flows of parts, the facility shapes, and the pickup and drop-off locations. Machine characteristics include the shape (regular/irregular), size (equal/unequal) [1], and rotatable/non-rotatable [33]. Researchers typically consider machines with regular shape and unequal size. Unequal-size machine layout problems are more difficult to solve than equal-size layout problems [34].

In this paper, we consider unequal-size and non-identical machines with a multi-row layout configuration. The layouts were evaluated in terms of the total MHD for all the machine sequences for all of the parts. The objective function was to minimise the MHD calculated according to equation (1) [35].

$$Z = \sum_{j=1}^{M} \sum_{i=1}^{M} f_{ij} d_{ij}; \quad i \neq j, \tag{1}$$

where M is the number of machines, i and j are indices $(1, 2, 3, \dots, M)$, f_{ij} is the frequency of material flow between machine i and j, and d_{ij} is distance between machine i and j.

BIOGEOGRAPHY-BASED OPTIMISATION (BBO)

Biogeography is the study of the geographical distribution of biological organisms. It involves a range of scientific disciplines including geography, geology and biology [36]. "Ecological biogeography is concerned with ecological processes occurring over short temporal and small spatial scales, whereas at the other end, historical biogeography is concerned with evolutionary processes over millions of years on a large, often global scale" [36]. "The former depends upon 'physical causes operating at the present time', and for the latter, upon 'causes that no longer exist today' " [36]. Biogeography-based optimisation is based upon ecological biogeography [36]. Mathematical models of biogeography describe how species migrate between habitats, how new species arise, and how species become extinct [22].

Factors such as rainfall, temperature, land areas and the diversity of vegetation or topographic features that make a habitat attractive to species are suitability index variables (SIVs). Geographical areas that are attractive to biological species due to SIVs have a high habitat suitability index (HSI) [22]. Locations with a high HSI are likely to have many species; whereas those with a low HSI are likely to have few. For high HSI habitats with a large number of species present, there is likely to be a low immigration rate because the number of species may be reaching saturation. This makes them more static than lower HSI habitats [22]. For low HSI habitats with sparse populations, there is likely to be a high species immigration rate. The suitability of a habitat is proportional to its biological diversity, so it is possible that immigration might increase the HSI. However, some species may become extinct if a habitat's HSI remains low, which could favour further immigration. These factors make the distribution of species relatively dynamic in low HSI habitats and relatively static in high HSI habitats [22].

Biogeography-based optimisation (BBO) has been extensively applied to solve a variety of optimisation problems. It is a population-based optimisation algorithm, in which each individual is a habitat. The HSI is used to represent the quality/'fitness' of solutions, which is dependent upon the SIVs. A good solution is analogous to a habitat with a high HSI, whereas a poor solution is represented by a habitat with a low HSI. In BBO, each individual has its own immigration rate λ and emigration rate μ. Several disadvantages with BBO were identified by [37]: (i) it is poor at exploitative search; (ii) there is no provision for selecting the best members from each generation; and (iii) the resultant fitness of a habitat is not considered during the immigration process, which causes many infeasible solutions to be generated.

Optimisation algorithms can be improved in several ways. Firstly, it can take into account the hybridisation to overcome weaknesses by incorporating the strength of some other technique(s) to improve the solution quality [38]. Secondly, the internal mechanism of an algorithm can be adapted [37]. Thirdly, optimum algorithm parameters can be systematically selected to produce better solutions [39]. This is particularly important because differences in migration rate models significantly affect BBO performance, therefore selecting appropriate levels for parameters is important [40]. This paper further develops the work of Sooncharoen [28] to improve the BBO algorithm's performance for solving machine layout problems though modifications.

MODIFIED BIOGEOGRAPHY-BASED OPTIMISATION TOOL FOR SOLVING THE FACILITIES LAYOUT PROBLEM

The BBO based layout design tool was developed in a modular style using the Visual Basic programming language. Fig. 1 shows the pseudo-code of the proposed BBO used in the tool, which includes the thirteen following steps:

(i) obtain input data – the number of machines, the dimensions of machines (width and length), the

Step	Detail
i	Input problem dataset
ii	Initialise n, I_{max}, P_{mod}, m_{max}
iii	Randomly generate the initial solutions based on the n habitats
iv	Arrange machines row by row
v	Calculate material handling distance (HSI) of solutions
vi	Sort the solutions based on the HSI
	Set a = 1 (first iteration)
	While $a \le$ maximum number of iterations (I_{max}) do
vii	For b = 1 to migrate_num do (migrate_num = round (random number*n))
viii	Calculate the immigration rate (λ_k) and the emigration rate (μ_k)
ix	Do Migration operation (PBX) according to the probability of modification (P_{mod})
	For c = 1 to n
x	Do Mutation operation (2ORS) according to the maximum mutation rate (m_{max})
xi	Evaluate the new solutions and update HSI
xii	Elitist selection
	$a = a + 1$
	End loop while
xiii	Output the best-so-far solution(s)

Fig. 1 Pseudo code of the proposed BBO for facilities layout design.

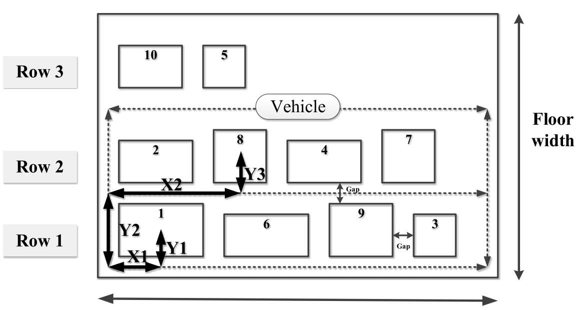

Fig. 2 Machine arrangement for a solution: 1, 6, 9, 3, 2, 8, 4, 7, 2, 10, 5.

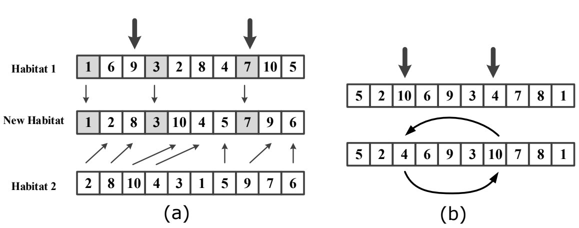

Fig. 3 (a) Position-based crossover (PBX) operator [41]; (b) the two operations random swap (2ORS) mutation operator (in case of $m(S) = 1$) [42].

number of parts and the machine sequences;

(ii) specify parameters – the ecosystem size, i.e. a group of n habitats, the number of iterations (I_{max}), the probability of modification (P_{mod}) and the maximum mutation rate (m_{max});

(iii) randomly generate the initial solutions based on the ecosystem size. A group of habitats is initially generated by randomly sequencing machines. Each habitat (candidate solution) contains a sequence of machines, which is encoded as a numeric string that indicates a sequence of machine numbers, supposed that it is 1,6,9,3,2,8,4,7,2,10,5;

(iv) arrange the machines row-by-row using a placement algorithm that is constrained by the floor length/width and the minimum gap between machines (Fig. 2). Machine arrangement for a solution from step (iii) is determined for suitability index variables (SIVs) for the BBO;

(v) evaluate the total MHD which determines the habitat suitability index (HSI) for the BBO. A shorter MHD equates to a higher HSI/fitness. It is assumed that vehicles move between the rows at the left/right side of the row and then up or down to the destination row [35]; for example, there is a component moving from machine 1 to machine 8, the total material handling distance is the sum of X1 + X2 + Y1 + Y2 + Y3 (see Fig. 2).

(vi) sort the solutions according to the HSI (the lowest to the highest corresponding to the longest to shortest distances);

(vii) calculate the number of solutions for the migration process (migrate_num) which is less than or equal to $P_{mod} x n$;

(viii) calculate the immigration rate (λ_k) and the emigration rate (μ_k) for each solution using (2) and (3), respectively. k is the rank of the solutions from step (vi), I is the maximum immigration rate, and E is the maximum emigration rate. Both I and E are initially set to a value of 1 [22];

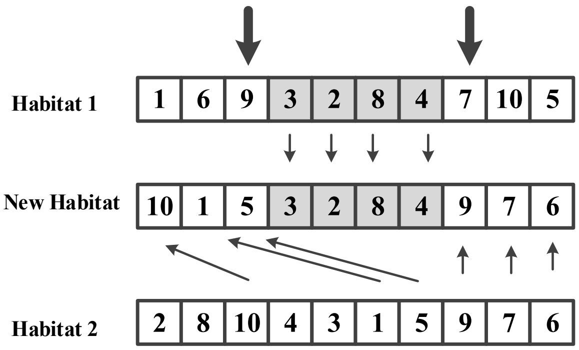

Fig. 4 Two Point Crossover Operator [42]

(ix) apply the migration operation using position-based crossover (PBX) [41]. This is illustrated by Fig. 3a. The selection probabilities for two solutions (habitats) are determined by λ_k and μ_k, respectively. The points of the string that define the elements to be crossed over are randomly chosen from Habitat 1 and placed into a new habitat. The remainder of the new habitat is built from Habitat 2 by avoiding repeated machines;

(x) apply the two operations random swap (2ORS) mutation operator [42] to generate a new solution respecting to probability of existence (P_k) in (4). The 2ORS has been found to be the most efficient operator for the FLP problem [43]. The number of mutations $m(S)$ is calculated using (5). $P_{\max}$ is the maximum number of P_k. In Fig. 3b, two machine indexes which are not duplicate are selected and then their positions are swapped. The number of swaps is equal to the $m(S)$;

(xi) evaluate the HSI of the new solutions;

(xii) replace the existing best solution if better;

(xiii) stop the process according to $I_{\max}$ and report the best solution, which has the shortest MHD.

$$\lambda_k = I\left(1-\frac{k}{n}\right) \tag{2}$$

$$\mu_k = \frac{Ek}{n} \tag{3}$$

$$P_k = \begin{cases} \dfrac{1}{1+\sum_{l=1}^{n}\frac{\lambda_0\lambda_1\cdots\lambda_{l-1}}{\mu_1\mu_2\cdots\mu_l}}, & k=0 \\ \dfrac{\lambda_0\lambda_1\cdots\lambda_{k-1}}{\mu_1\mu_2\cdots\mu_k\left(1+\sum_{l=1}^{n}\frac{\lambda_0\lambda_1\cdots\lambda_{l-1}}{\mu_1\mu_2\cdots\mu_l}\right)}, & 1\leqslant k\leqslant n \end{cases} \tag{4}$$

$$m(S) = m_{\max}\left(\frac{1-P_k}{P_{\max}}\right). \tag{5}$$

The proposed BBO included six modifications called modified biogeography-based optimisation (mBBOs), which is described in the following:

(i) mBBO1, hybridised the two point crossover [44] genetic algorithm operator in the migration process, which had been identified as the best crossover operator for layout design [43]. This is shown in Fig. 4, the machines between two randomly selected points are always inherited from an existing habitat to a new habitat;

(ii) mBBO2 adjusted the solution selection mechanism and the number of solutions in the migration process. The mBBO2 process only operates if the quality of the best solution in the current iteration is worse than the previous iteration. In this case, the solutions for the migration and mutation processes are chosen randomly, which is a similar mechanism to a GA mutation operator. The number of solutions in the migration and mutation processes for mBBO2 were $P_{\mathrm{mod}}xn$, and $m_{\max}xn$, respectively. Table 1 summarises the mechanisms adopted by the BBO, mBBO1 and mBBO2;

(iii) mBBO3 arranges machine pairs with the highest flow intensity between them in adjacent positions;

(iv) mBBO4 ranks each pair of machines according the intensity of flow between them and then places the two highest ranked machines in adjacent positions;

(v) mBBO5 adopts nonadjacent arrangements for pairs of machines with zero flow intensity;

(vi) mBBO6 combines mBBO3 and mBBO5.

The mBBO1 and mBBO2 were modifications to the BBO mechanism, whereas the others aimed to improve the candidate solutions obtained by the local search. The BBO parameter settings for each dataset were adopted from previous FLP problem research. The best settings for the BBO parameters (n, $I_{\max}$, P_{mod}, and $m_{\max}$) were 25, 100, 0.9 and 0.1, respectively [28].

EXPERIMENTAL DATA

The experimental data was obtained from the literature. The first four datasets were obtained from Nearchou [32]. Dataset M10P3 indicates that the problem includes ten non-identical rectangular machines and three parts. For M30P27, the parts and their machine sequences were a combination of the parts in the first four datasets. The machines were considered to be rectangular and unequal size.

The following assumptions defined in [32] were adopted in this work: (i) the material handling distance between machines was measured using the rectilinear distance between the machines' cen-

Table 1 Comparison of BBO, mBBO1, and mBBO2.

Mechanism	BBO	mBBO1	mBBO2
Selection for migration	based on λ_k and μ_k		randomly chosen
No. of solutions for migration process	migrate $\leqslant P_{\max} x n$		migrate $= P_{\mathrm{mod}} x n$
Migration operation	PBX	2PECX	PBX
Selection for mutation	all mutated		randomly chosen
No. of solutions in mutation operation	N	n	$m_{\max} x n$
Mutation operation	2ORS		
No. of mutated pairs in a solution	$m(S)$	one	$m(S)$

Table 2 Comparison of mean total material handling distance (MHD) associated with the layouts produced by ABC, GA, SFLA, and BBO.

Dataset	Mean total MHD (m)			
	ABC	GA	SFLA	BBO
M10P3	187.7	**187.4**	187.9	206.4
M15P9	1398.7	**1382.0**	1412.4	1474.9
M20P5	1366.8	**1361.2**	1375.4	1397.1
M30P10	4658.5	4770.5	4884.4	**4408.3**
M30P27	9553.0	10040.7	9591.0	**8603.4**

Table 3 Comparison of total material handling distance (MHD) associated with the layouts produced by the conventional BBO and the proposed modifications.

Dataset	Algorithm	Total MHD (m)				Time
		Mean	SD	Min	Max	(s)
M10P3	BBO	206.4	8.9	188.9	222.3	0.119
	mBBO1	199.7	4.9	189.5	209.3	0.131
	mBBO2	195.0	6.8	187.0	208.5	0.139
	mBBO3	190.6	3.4	187.0	197.9	0.157
	mBBO4	206.7	2.8	201.2	212.3	0.195
	mBBO5	194.1	5.4	187.6	207.8	0.184
	mBBO6	**189.0**	2.2	187.0	194.1	0.227
M15P9	BBO	1474.9	21.4	1422.3	1521.6	0.352
	mBBO1	1435.7	20.4	1381.0	1470.1	0.369
	mBBO2	1419.7	22.3	1369.8	1460.3	0.434
	mBBO3	1409.6	29.5	1356.0	1462.1	0.392
	mBBO4	1393.1	31.6	1332.8	1472.6	0.403
	mBBO5	1384.4	25.1	1337.7	1436.3	0.411
	mBBO6	**1383.3**	30.1	1335.3	1458.9	0.453
M20P5	BBO	1397.1	24.7	1344.3	1436.4	0.383
	mBBO1	1359.6	22.8	1319.8	1391.5	0.404
	mBBO2	1329.4	25.5	1268.8	1380.6	0.400
	mBBO3	1287.2	33.8	1234.2	1347.0	0.424
	mBBO4	**1279.8**	28.4	1215.3	1320.4	0.442
	mBBO5	1345.0	36.2	1267.7	1406.4	0.436
	mBBO6	1319.4	28.5	1264.3	1364.2	0.480
M30P10	BBO	4408.3	42.3	4321.3	4483.9	1.044
	mBBO1	4267.6	44.4	4175.7	4368.4	1.077
	mBBO2	4171.3	67.9	4003.4	4325.2	1.127
	mBBO3	**3987.9**	81.0	3848.8	4163.2	1.104
	mBBO4	4039.2	51.1	3929.8	4119.9	1.221
	mBBO5	4184.4	100.7	4007.5	4388.8	1.122
	mBBO6	4066.6	70.2	3892.3	4159.1	1.185
M30P27	BBO	8603.4	75.2	8471.4	8736.2	1.932
	mBBO1	8356.9	81.2	8210.0	8587.5	1.967
	mBBO2	8140.3	120.6	7930.9	8405.7	2.015
	mBBO3	8027.0	149.6	7773.9	8271.7	1.984
	mBBO4	8084.3	128.2	7821.4	8365.7	2.051
	mBBO5	8102.2	157.0	7720.4	8331.0	2.004
	mBBO6	**8022.1**	155.5	7743.1	8348.7	2.064

troids; (ii) the machines were arranged in multiple parallel rows; (iii) the shop floor had sufficient area for the machines to be arranged; (iv) the movement of materials was in straight lines; (v) the gap between machines was predefined and constant; and (vi) customer demand, processing times and transportation times were not taken into consideration.

The machines were placed in a multi-row configuration. The arrangement of the machines started at the first row and worked from left to right taking into account the length of the shop floor and the specified gap between machines. If there was insufficient space to place the next machine at the end of the row, it was then placed in the next row as shown in Fig. 2. Materials were transported between machines using the route with the shortest rectilinear distance. This is illustrated in Fig. 2, which shows the transportation route for materials moving from M2 to M4; route 1 would be selected as the travel distance is shorter.

EXPERIMENTAL DESIGN AND ANALYSIS

The computational experiments were performed using seven BBO approaches (BBO, mBBO1, mBBO2, mBBO3, mBBO4, mBBO5, and mBBO6) as described previously. Each algorithm was tested using the five datasets and the results were analysed statistically. For each dataset, each algorithm was replicated thirty times using the recommended parameter settings and compared to others including the artificial bee colony (ABC) [45], genetic algorithms [35], and the shuffled frog leaping algorithm (SFLA) [46]. The computational experiment was based on fair comparison. This means that the number of searches (candidate solutions) carried out by each algorithm was the same. For population-based algorithms, this is the combination of the population size and the number of generations (it-

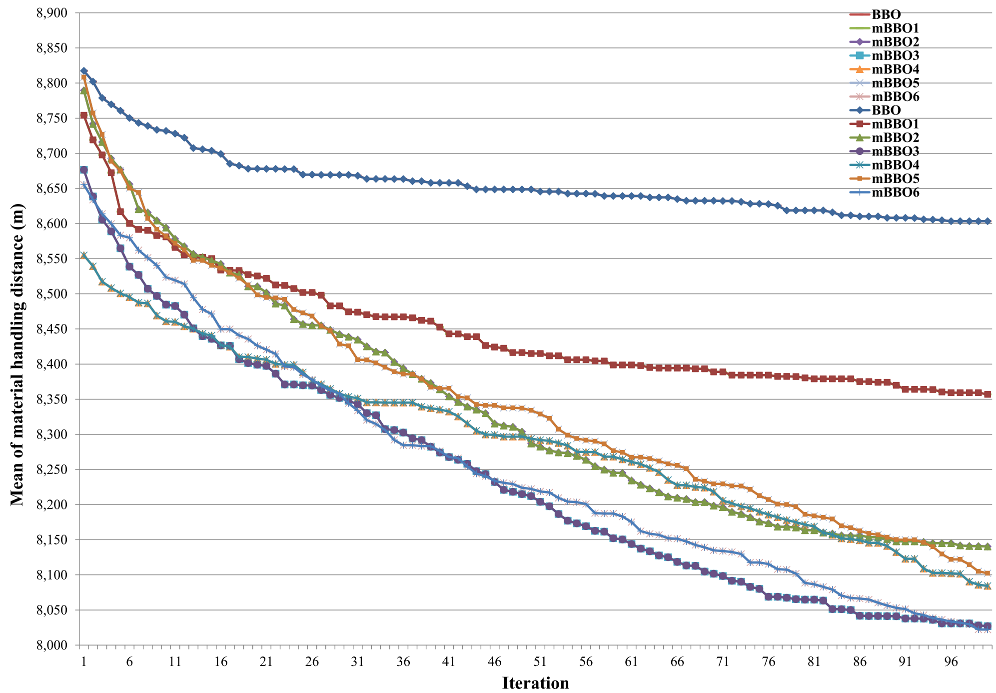

Fig. 5 Comparison of convergence between the BBOs for M30P27 case.

erations). In this work, the total number of searches carried out by each algorithm was set at 2500. The computational results were analysed in terms of the mean, standard deviation (SD) minimum (Min), maximum (Max) of material handling distance (m), and computational time (s).

The experimental results shown in Table 2 indicate that mean material handling distance for the proposed BBO was lower than the other algorithms for the larger datasets M30P10 and M30P27. The modifications to the BBO (mBBOs) aimed to improve its performance further. The computational results are shown in Table 3. The best results are shown in bold.

All of the BBO modification produced better solutions than the standard BBO for all of the datasets. Changing the migration operation in mBBO1 resulted in a higher variety of solutions than the standard approach. In mBBO2, the solution selected for migration was obtained by random selection when the quality of the best solution in the current iteration was worse than the previous iteration. This helped the algorithm to escape from local optima. In terms of the SD value, mBBO2 generated the highest SD for almost all datasets. This indicates that the mBBO2 achieved a greater diversification of solutions.

The modifications mBBO3, mBBO4, mBBO5, and mBBO6 considered the flow intensity between machines to improve the solution quality. The proposed mBBO6 was the best method for M10P3, M15P9, and M30P27. The consideration of the flow intensity between machines when determining adjacencies by mBBO3 and mBBO4 achieved the shortest total material travel distances for M30P10 and M20P5, respectively. The relative performance of the algorithms depends upon the problem characteristics in terms of the number of machines and parts, and machine sequences. The percentage improvements in solution quality for mBBO6 compared to the standard BBO were 8.4%, 6.2%, and 6.8% for M10P3, M15P9, and M30P27, respectively. The percentage improvement in solution quality for mBBO3 was 9.5% for M30P10 and for mBBO4 was 8.4% for M20P5. However, the modifications to the BBO tended to increase the number of instructions performed by the algorithms, which increased the processing times, but not significantly. The best modified BBO outperformed the ABC [45], GA [35], and SFLA [46] except for the M10P3 problem (but the mean total distance obtained by mBBO6 was only 0.8% longer). The results of the Student's t-test indicated that the modified BBOs generated statistically better solutions than the conventional BBO for all of the datasets.

Fig. 5 shows the best-so-far solution achieved in each iteration for the largest problem considered (M30P27). The differences in total MHD obtained from the proposed methods were statistically analysed using the Student's t-test with 95% confident interval (p-value $\leqslant 0.05$). All proposed BBO modifications converged significantly faster and provided better results than the conventional BBO with 95% confident interval. The mBBO1, which adopted a GA operator in the mutation process, was generally the least successful modification for this case. The comparison on the results obtained from mBBO1 and mBBO2 was statistically significant with 95% confident interval. There was no statistically significant difference between mBBO2 and mBBO4. However, the results obtained from mBBO3 differed significantly compared to those from mBBO4 with 95% confident interval. In the early generations, mBBO4 produced the best results, but it was surpassed by mBBO3 and mBBO6 by the thirtieth iteration. The convergence speeds of mBBO3 and mBBO6 were the same, which is confirmed by the statistical analysis result of the Student's t-test (p-value > 0.05).

CONCLUSION

Biogeography-based optimisation has had limited applications in operations management. This research is the first to modify biography-based optimisation for solving the facilities layout problem and achieves better results than other commonly used metaheuristics. The computational experiments were carried out using various sizes of FLP benchmarking datasets. Six novel modifications or hybridisations (mBBOs) were made to the conventional BBO by adapting crossover operator or local search approaches. The experimental results indicated that three proposed mBBOs (mBBO3, mBBO4, and mBBO6) found the solutions with lower mean MHD than those obtained by ABC, GA, and SFLA especially for large problems (M20P5, M30P10 and M30P27). The solutions obtained by the modified BBOs were up to 9.5% better than the BBO, but the execution time was 21.7% longer.

Due to the nature of metaheuristics, the concepts of BBO modifications proposed in this work can be broadly disseminated by adapting or modifying the concepts in other metaheuristics. The further extensions for solving the layout design may explore more specific scenarios, such as multiple criteria design, dynamic demand with re-layout approach, rotatability issue for some facilities, and so on. Future research could consider other applications in various problem domains that include combinatorial optimisation problems (e.g. scheduling, networking, etc) or continuous problems (e.g. mathematical functions).

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