Application of Biogeography-Based Optimisation for Machine Layout Design Problem

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***Abstract*—The design task for machine layout is to arrange machines into a limited manufacturing area. Material handling distance is usually considered as a key performance index of internal logistic activities within manufacturing companies. Machine layout design problem is classified into non-deterministic polynomial-time hard (NP-hard) problem. The objectives of this paper were to: describe the application of Biogeography-Based Optimisation (BBO) for designing machine layout with minimum total material handling distance; and investigate the appropriate setting of BBO parameters. The BBO searches for the global optimum mainly conducted through two steps: migration and mutation. Both steps are controlled by immigration and emigration rates of the species in the habitat, which are also used to share information between the habitats. The computational experiments were designed and conducted using five MLD benchmarking datasets adopted from literature. The statistical analysis on the experimental results suggested that all BBO parameters have statistical impact on the quality of the solutions obtained except the smallest-size problem.**

***Index Terms*—biogeography-based optimisation, machine layout problem, metaheuristics**

I. Introduction

With high competitive market, lean manufacturing company has to respond promptly regarding to the customers' needs. Machine layout design is one of the crucial manufacturing designs for optimising productivity. The design usually involves the arranging machines on the limited shop floor. Material handling distance can be considered as a performance index for internal logistic activity within a chain of supply [1] and mostly measured for determining the efficiency of layout. According to Tompkin *et al*. (2010), the material handling cost was accounted at 20–50% of the total manufacturing costs and it can be decreased at least 10–30% by an efficient layout design [2].

Machine layout problem can be classified as a combinatorial optimisation and NP-hard problems [3]. The number of all possible solutions based on the number of machines to be sorted so the total of solutions are going to be exponential when the size of the problem expanded, e.g. for designing a layout of ten machines, a number of possible solutions are 3,628,800 (10!). A number of the approximation algorithms, such as Simulated Annealing [4], Genetic Algorithm [5], Rank-based Ant System [6], Tabu Search [4], Shuffled Frog Leaping [7] and Bat Algorithm [8], have been successfully applied to solve the machine layout problems, but they do not guarantee the optimum solution [9]. The Biogeography-based Optimisation [10] has been applied to solve several problems e.g. travelling salesman problem [11], scheduling [12], cognitive radio system [13], and multi-objective problem [14]. From literature reviewing on the ISI web of Science database from 2008-2014, there has been no specific report on the application of BBO for designing machine layout. The objectives of this paper were to apply the Biogeography-based Optimisation (BBO) for solving machine layout problem aiming to minimise the total material handling distance, and to investigate the appropriate setting of BBO parameters.

The remaining sections of this paper are organised as follows. The next is to describe the multi-row machine layout design (MLD) problem followed Biogeography-Based Optimisation for solving MLD problem and its pseudo-code. Then, the experimental results are presents. Discussions and conclusions are drawn in the last.

II. Machine Layout Design in Multi-Row Layout Configuration

The characteristics of the layout problem can be categorised with different criteria such as size (equal and unequal size), shape (regular and irregular shape), and layout configurations (single row, multi-rows, loop layout, open field layout and multi-floor layout) [15]. In multi-row layout configuration, machines are arranged row by row, from left to right, starting at the first row (R1) and respecting the length of floor (F_L) and the gap (G) as shown in Fig. 1 [6]. When there was not enough area for placing the next machine at the end of the row, it was then placed in the next row. Material transportation between machines relates to handling equipment e.g. automated guided vehicles, material can be moved to left or right side of the row and then move up or down to the destination row. The distance of material handling was evaluated from the shortest distance. For example, in Fig. 1, transportation of materials from M12 to M4, route (3) was shorter than route (4), thus was selected. The appropriate flow path was evaluated from the shortest distance. The objective function is to minimise the material handling distance as (1) [8].

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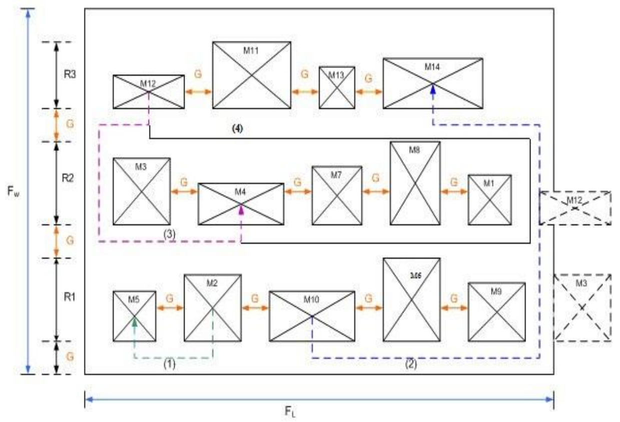

Figure 1. Multi-row machine layout design [6]

$$Z = \sum_{j=1}^{M} \sum_{i=1}^{M} f_{ij} d_{ij} \qquad ; i \neq j \qquad (1)$$

M is a number of machines, i and j is machine sequences (i and $j = 1, 2, 3, \ldots, M$), f_{ij} is frequency of material flow between machine i and j, d_{ij} is distance between machine i and j.

In order to formulate the problem, the following assumptions were made: i) the material handling distance between machines was determined from the machine's centroid, ii) machines were arranged in multiple rows, iii) there was enough space in the shop floor area for machine arrangement, iv) the movement of material flow was a straight line, v) the gap between machines was similar, and vi) the processing time and moving time were not taken into consideration.

III. Biogeography-Based Optimisation Based Layout Design

The Biogeography-based Optimisation (BBO) presented by Dan Simon in 2008 is the stochastic search algorithm based on the migration and mutation of species from the habitat to others. The geographical area with high habitat suitability index (HSI) means that it is well suited as residences for biological species. Habitat with a high HSI has a large number of species which can emigrate to nearby habitats. But few species immigrate into this habitat because it is almost saturated with species. Conversely, habitat with a low HSI has a small number of species so an immigration rate is high. In Fig. 2, E and I indicate to the maximum of immigration and emigration rates, respectively. Both of them are mostly set to 1. S_{max} presents the largest number of species that the habitat can support. S_0 is the equilibrium point, in which the immigration rate and the emigration rate are equal [11]. S_1 represents a few species in habitat (Low HSI), while S_2 represents many species in a habitat (High HIS). The immigration rate for S_1 is higher than S_2. In the same way, the emigration rate for S_1 is lower than S_2 [10]. Both immigration and emigration rate can be used to probabilistically share information between habitats via migration and mutation process.

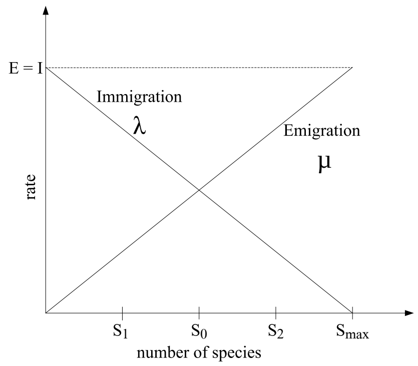

Figure 2. Habitat migration rate and habitat suitability index (HIS) [10]

The pseudo-code of the proposed BBO for the machine layout design shown in Fig. 3 can be described as follow:

Initialise n, I_{max}, P_{mod}, m_{max}
Randomly generate the initial solutions based on the n
Arrange machines row by row
Evaluate the fitness function (HSI) for the solutions
Sort the solutions in ecosystem based on the fitness (HSI)
Set i = 1 (first iteration)
While i ≤ I_{max} do
    For j = 1 to migrate_num do (migrate_num = round (random number x n))
        Migration operation
    End loop for
    For k = 1 to n
        Mutation operation
    End loop for
    Evaluate the new solutions and update HSI
    Elitist selection
    i = i + 1
End loop while
Output the best solution

Figure 3. Pseudo code of the proposed BBO for machine layout design

i) input data - the number of machines, the dimensions of machines (width and length), the number of products, and the machine sequences;

ii) specify parameters - the ecosystem size (n) , the number of iterations (I_{max}), the probability of modification (P_{mod}) , and the maximum mutation rate (m_{max});

iii) randomly generate initial solutions based on the defined ecosystem size;

iv) arrange the machines row by row based on the floor length and width;

v) evaluate the fitness function (HSI) and sort the solutions according the HSI;

vi) calculate the immigration rate (λ_k) and the emigration rate (μ_k) for each solution using (2) and (3), respectively;

vii) apply migration process for modifying the solution respecting λ_k and μ_k . The number of solutions (migrate_num) for migration is not more than P_{mod};

viii) apply mutation process to generate new offspring respecting probability of existence (P_k) in (4) and mutation rate (m_S) in (5);

ix) evaluate the fitness function (HSI) of new solutions and replace the existing solutions if they are better;

x) stop the BBO process according to the I_{max}. When the BBO process is terminated, the best-so-far solution is reported.

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

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

$$P_k = \begin{cases} P_0 = \dfrac{1}{1+\sum_{l=1}^{n}\dfrac{\lambda_0\lambda_1\ldots\lambda_{l-1}}{\mu_1\mu_2\ldots\mu_l}}, k=0 \\ P_k = \dfrac{\lambda_0\lambda_1\ldots\lambda_{k-1}}{\mu_1\mu_2\ldots\mu_k\left(1+\sum_{l=1}^{n}\dfrac{\lambda_0\lambda_1\ldots\lambda_{l-1}}{\mu_1\mu_2\ldots\mu_l}\right)}, 1\le k\le n \end{cases} \tag{4}$$

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

k is the rank of the habitat after sorting according to HIS

IV. Experimental Results

The computational experiments were aimed to investigate the appropriate setting of BBO parameters including a combination of ecosystem size and number of iterations (n/I_{max}), the probability of modification (P_{mod}), and the maximum mutation rate ($m_{\max}$). All BBO parameters were investigated in three levels. The experimental design and the range of values considered for each factors are shown in Table I.

TABLE I. Experimental Factor and its Levels

Factors	Levels	Values		
		Low (0)	Medium (1)	High (2)
Ecosystem size/number of iterations (n/I_{max})	3	25/100	50/50	100/25
Probability of modification (P_{mod})	3	0.1	0.5	0.9
Maximum mutation rate (m_{max})	3	0.1	0.5	0.9

The computational experiments were conducted using five MLD benchmarking datasets [16] so that they had different sizes according to the number of machines and products. Dataset M10P3 means that there are three products to be processed on ten non-identical rectangular machines. The machine layout designing program was developed and coded using the Visual Basic Language. With three values of three parameters, each of which took five replications, and the total computational runs of 135 were carried out.

The results obtained from the computational experiments were analysed using the analysis of variance (ANOVA) as shown in Table II, in which the P values are given. With 95% confident interval, it can be seen that the combination of ecosystem size and the number of iterations (n/I_{max}), and maximum mutation rate (m_{max}) has a significant effect on the material handling distance in almost all datasets except M10P3 dataset. The probability of modification (P_{mod}) has a significant effect on the material handling distance in all datasets. The appropriate parameter setting based on the minimum material handling distance on each dataset is shown in Table III.

Minimum, mean, and standard deviation (SD) of total material handling distances for each dataset are summarised in Table IV. The problem dataset M30P27 had the highest values of mean and SD because of the number of machines and type of products. When the number of machines was increased, the feasible solutions were increased. A variety of solutions had an effect on the standard variation.

TABLE II. The P Values from ANOVA for Each Dataset

Source	M10P3	M15P9	M20P5	M30P10	M30P27
n/I_{max}	0.191	0.000	0.013	0.000	0.001
P_{mod}	0.001	0.000	0.000	0.000	0.000
m_{max}	0.800	0.000	0.000	0.000	0.000
n/I_{max}* P_{mod}	0.004	0.045	0.173	0.060	0.103
n/I_{max} * m_{max}	0.135	0.000	0.099	0.000	0.000
P_{mod} * m_{max}	0.016	0.000	0.000	0.000	0.000
n/I_{max}* P_{mod}* m_{max}	0.031	0.000	0.123	0.103	0.004

TABLE III. Appropriate Setting of BBO Parameters for Each Dataset

Dataset	n/I_{max}	P_{mod}	m_{max}
M10P3	50/50	0.9	0.1
M15P9	25/100	0.5	0.1
M20P5	50/50	0.9	0.1
M30P10	25/100	0.9	0.1
M30P27	25/100	0.9	0.1

TABLE IV. Values of Material Handling Distance (unit: metres) for Each Dataset

Dataset	Minimum	Mean	SD	Time (sec)
M10P3	85,791.39	88,790.02	2,870.28	2.29
M15P9	533,564.19	563,223.59	13,514.21	3.73
M20P5	476,625.34	521,419.22	17,855.37	4.61
M30P10	1,846,848.63	1,912,197.83	36,593.85	7.57
M30P27	3,298,488.50	3,376,527.20	39,362.01	9.13

When considering the computational time, dataset M30P27 took the longest time which was about 9.13 seconds while M10P3 took only 2.29 seconds. The average computational time required to solve each dataset depends on the problem size.

V. Conclusions

This paper presents the application of Biogeography-Based Optimisation (BBO) for designing machine layout in multi-row environment. The algorithm was aimed to minimise the total of material handling distance. The computational experiments were conducted using five benchmarking datasets. The analysis of computational experiments suggested that the BBO performance was depended on its parameter setting. The appropriate parameters had been found difference on each benchmarking dataset. This suggested that the application of BBO should be considered on its parameter setting in order to optimise the performance of BBO algorithm. Future research may focus on improving the performance of BBO by modification or hybridisation.

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