Developing a Hybrid Multi Population Genetic Algorithm for the Dynamic Facility Layout Problem with Budget Constraint

Dileep K S[#1], Prof. Cijo Mathew[#2], Prof. (Dr.) Biju B[#3]

[1]PG Scholar, [2]Assistant professor, [3]Professor,

Department of Mechanical Engineering, MA College of Engineering, Kothamangalam, Kerala, India

Abstract - *Complexity has always been a major issue to develop a solution algorithm for dynamic facility layout problem. Many researchers have proposed different algorithms for dynamic facility layout problem. From literature survey it was realized that the performance of the algorithm can be further boosted by a more intelligent search. This work develops an effective hybrid multi-population genetic algorithm to solve dynamic facility layout problem. Using a suggested heuristic procedure, to intensify the search, a powerful local search mechanism based on simulated annealing is created. The proposed algorithm helps to save the computational time by skipping infeasible space. The proposed multi population genetic simulated annealing algorithm is compared with the results from dynamic facility layout problem with budget constraint proposed by Parham Azimi, Hamid Reza Charmchi [16] for different benchmark problem instances from Balakrishnan and Cheng [6]. The proposed algorithm provides good results for the problems under consideration with reduced computational time.*

Keywords — *Dynamic facility layout problem, computational time, Material handling cost, Re-arrangement cost, Budget constraint*

I. Introduction

The facility layout problem is contained in the determination of the most efficient facilities arrangement within a factory. The facility can be known as a manufacturing cell, an administrative office building or a machine. An efficient layout motivation an economical material handling (MH) between facilities and consequently decreases the work-in-process and inventory holding costs. An efficient layout also furnishes to the overall efficiency of operations and can save many overall costs such as manufacturing costs and inventory carrying costs.

The layout problem is to organize the physical positions required for several departments in a given space provided for the departments. In general case the facility layout problem is often solved by intuition, using the artistic and spatial skills of the human designer; however, there are quantitative considerations associated with the layout problem. Layout problems are found in many types of manufacturing systems. Typically, layout problems are related to the location of facilities (e.g. machines, departments) in a plant. Various facility layout problems are; Static Facility Layout Problem (SFLP), Dynamic Facility Layout Problem (DFLP) and Stochastic Facility Layout Problem

The SFLP approach assumes the flow of materials between departments, in the form of a from-to chart; it is also deterministic and stable over the entire time-planning horizon. The SFLP approach is a suitable method for analysing a single period layout problem by considering the product demand is stable for a long time period. The SFLP approach aims to determine the optimal location of departments by minimising the total MHC of moving the required material between the departments.

The general SFLP approach assumes that the flow of materials between departments in the form of a from-to chart is deterministic and stable over the entire time-planning horizon. Changes in product demand and product mix in a dynamic environment discredit these assumptions, where markets are competitive and volatile in nature. Therefore, the SFLP approach is not a suitable method for obtaining a good layout when flow data changes over time. Changes in the flow are the result of many factors, such as: fluctuations in product demand; changes in product mix; introduction of new products; and elimination of existing products. All these factors affect the flow of materials between departments and render the present facility layout inefficient and can increase the MHC, which may necessitate a change in the layout. In order to maintain a good facility layout that operates effectively in a dynamic environment and which can handle changes in product demand and product mix, it is necessary to continuously assess the variations in product demand, the flow between departments/machines and the existing layout in order to determine the need for redesigning the layout

Forecasting techniques are the most commonly used techniques to project future product demands and product mix, which are the main input data for solving DFLP. However, forecasts are usually not accurate and thus the design of facility layout based on such forecasts turns out to be inefficient. This leads to the need for stochastic FLP approaches that are adjustable enough to reduce the effects of the uncertainty and accommodate any possible changes in future product demands. The stochastic FLP approaches aim to incorporate the true nature of many manufacturing environments and consider the uncertainty in product demands during the design of the facility layout. In today's economy, manufacturing industries must be able to operate efficiently and respond quickly to changes in product mix and demand. Therefore, this work considers the problem of arranging and rearranging (when there are changes between the flows of raw materials between departments) manufacturing facilities such that the sum of the material handling and rearrangement costs is to be minimized. This problem is known as the dynamic facility layout problem (DFLP).

II. LITERATURE REVIEW

The DFLP was first introduced in detail by Rosenblatt (1986). The author proposed an optimization approach based on dynamic programming. He considered only a margin set of good layouts for each period. But, this method is computationally unaffordable for real size problems; because dynamic facility layout problem is NP-hard and only small problems can be solved optimally in an acceptable computational time. The number of possible solutions for a DFLP instance with N departments and T periods is (N!)T. So the effective algorithms for the DFLP are heuristics and meta-heuristics [1].

Urban (1992) proposed a heuristic algorithm based on the computerized relative allocation of facilities technique (CRAFT). Urban used the principle of forecasting windows for solving the DFLP. The author considers the case in which rearrangement costs are assumed to be fixed. The idea of incomplete dynamic programming helps to reduce the computational time by eliminating the need to evaluate branches at each of the stages when rearrangement costs are not considered. Test problems considering in size from six departments and four periods to 15 departments and eight periods are solved and the author concluded that the concept of incomplete dynamic programming is efficient for developing lower and upper bounds for the general DPLP with fixed costs [2].

Balakrishnan et al. (1992) continued the work of Rosenblatt (1986) by developing a different formulation to DFLP. This formulation is called the Constraint Dynamic Facility Layout Problem (CDFLP). They considered the case where a budget constraint exists for layout redesigning. For example, this may occur when the funds are limited to redesign the layout. So, under this constraint the DFLP is solved. They suggested the use of the Constrained Shortest Path (CSP) algorithm. This is a combination of the simplex method and enumerations strategy for the CDFLP [3].

Lacksonen and Enscore (1993) introduced five heuristics to solve the DFLP. The heuristics considered in their study were based on dynamic programming, branch and bound, cutting plane algorithm, cut tree algorithm, and CRAFT. Test problems considering in size from six departments and three periods to 30 departments and five periods are solved. According to the results, the Cutting Plane algorithm is found to be the best of the five algorithms for all test problems [4].

There have been many meta-heuristics suggested for DFLP as Well. Conway and Venkataraman [5] solved the DFLP by a simple genetic algorithm. Balakrishnan and Cheng (1997) presented a nested loop genetic algorithm (NLGA) to solve the DFLP [6].

Kaku and Mazzola (1997) presented a tabu search (TS) for the DFLP. This TS is a two-stage search process that incorporates the diversification and intensification designs. Balakrishnan et al. [7] presented two heuristics that improved Urban’s steepest-descent pairwise exchange heuristic. Kaku and Mozzola (1997) employed a tabu search approach in which diversification strategy and intensification strategy are used to generate better solutions.

Baykasoglu and Gindy (2001) suggested an SA approach to solve the DFLP. The computational results show that, especially for larger-sized problems, the proposed SA approach outperforms the previous GA presented in Conway and Venkataramanan (1994) and Balakrishnan and Cheng (2000). The first heuristic uses Urban’s heuristic to generate solutions for the DFLP [8].

Erel et al. (2003) also purposed a three-stage heuristics to solve the DFLP using dynamic programming. In the first phase, a group of good layouts is gained by weighted flow data from the T time periods. In the second stage, the group of solutions gained in the first stage and dynamic programming is used to obtain solutions to the DFLP. In the third stage, a irregular descent pair wise shifting strategy is used to improve the solutions obtained in the second stage [9]. McK-endall et al. developed two simulated annealing algorithms (SA). The first one is a direct adaptation of SA, and the second algorithm is the similar as the first one, but with a look-ahead/look-back strategy [10].

Rodriguez et al. (2006) suggested a hybrid meta heuristic based on the genetic algorithm and tabu search for the DFLP in which tabu search was used as a local optimizer to discover all global optima. The parallelization of the GA and TS were based on an asynchronous master-slave model which precedence to a substantial economy in computation time [11].

Balakrishnan and Cheng (2006) introduced a new approach for DFLP called rolling horizon problem. In the standard DPLP the multi-period plan is developed at the beginning of period one. But, in the rolling horizon problem, against DFLP, after the first period, the details for period one is dropped and the multi-period plan is recomputed according to the remaining periods of planning horizon [12].

Sahin and Turkbey introduced a new hybrid tabu simulated annealing algorithm for DFLP. Their algorithm was basically an approach enhanced with a tabu list to avoid cycling and reduces computation time. They also solved the same problems using a perfect SA algorithm and a perfect tabu search algorithm for comparison purposes [13].

Hani pourvaziri (2014) proposed that a novel hybrid multi-population genetic algorithm (HMPGA) used to solve DFLP. They also introduce a heuristic algorithm to develop the individuals of the initial populations. They describe a representation of layouts that can be used efficiently in genetic encoding. In their multi-population strategy each population evolves independently from each other. After a pre-calculated number of generations, all the populations are combined and make a new population (main population). The prime population continues to evolve until stopping criteria is satisfied. In this way, they can guarantee that the different parts of the solution space are most likely searched.

III.PROBLEM FORMULATION AND METHODOLOGY

The mathematical establishment of the discrete representation of the DFLP is presented below. This model is in form of quadratic binary integer programming. This representation of the model is developed by McKendall et al. The parameters and indices are:

N number of departments
T number of time periods
i, j, k, l index for departments
t index for time periods
$A_{t,i,j,l}$ cost of transfering department i from location j to l in period t
$C_{t,i,j,k,l}$ the cost of material flow between department i placed in location j to location l in period t, and 0 otherwise
The decision variables are;
$X_{t,I,j}$ binary variable taking appraisal 1 if department i is assigned to locations j in period t and 0 otherwise
$Y_{t,I,j,l}$ binary variable taking appraisal 1 if department i is shifted from locations j to location l in period t and 0 otherwise
LB_t left over budget from period t to period *t* + 1
B_t available budget for period *t*
AB_t allocated budget for period *t*.
The objective function is to minimize the total cost of layout rearrangements and material handling cost.

$$MinZ = \sum_{t=2}^{T}\sum_{t=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N} Atijl * Ytijl$$
$$+ \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} Ct,i,j,k,l * Xt,i,j + Xt,k,l$$

Subject to

$$\sum_{j=1}^{N} Xt,i,j = 1 \quad i = 1,2,\dots\dots N; t = 1,2,\dots T \quad (1)$$
$$\sum_{i=1}^{N} Xt,i,j = 1 \; j = 1,2\dots.N; \quad t = 1,2\dots T \quad (2)$$
$$Yt,i,j,l = Xt-1,i,j \times Xt,i,l \quad i,j,l = 1,2,\dots N; t = 2,\dots T$$
$$Xt,i,j \in \{0,1\} \quad i,j = 1,2\dots N \quad t = 1,2,\dots.T \quad (4)$$
$$Yt,i,j,l \in \{0,1\} \; i,j,l = 1,2,\dots.N; t = 2,\dots.T$$

In this mathematical model only three constraints and two decision factors they are

- The first constraint is each location department is assigned to only one location department during each period.
- The second constraint describes exactly one department is assigned to each location in each period.
- And third constraint specifies if a department is shifted between locations in two consecutive periods.
- Four and five are the decision factor for checking the position of the various departments

But according to real time situations budget constraint can be added to the existing mathematical model, as shown below

- Budget for rearranging the departments.

$$LB_t = B_t - \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N} Atijl * Xt-1,ij * Xtil$$
$$\forall t = 1,2,\dots.,.T$$
$$B_t = AB_t + LB_{t-1}, \forall t = 1,2,\dots.,.T$$
$$\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N} Atijl * Xt-1,ij * Xtil \leq Bt$$
$$\forall t = 1,2,\dots.,.T$$
$$X_{tij} \in \{0,1\}, \forall i,j = 1,2,\dots.,.N,$$
$$\forall t = 1,2,\dots.,.T$$
$$LB_t, B_t, AB_t \geq 0, \forall t = 1,2,\dots.,.T$$

A. Assumptions

- The distances between locations are familiar and stable.
- Planning horizon is classified to T period.
- In one time period, one department should be put on only one location and one department can be placed to only one location.
- In one time period, the material flow between each pair of departments is known and does not change over the period.
- The objective is to discover the layout plan (i.e., the layout for all periods) which reduces the sum of the material handling and rearrangement costs.

A common genetic algorithm consists of one single population; however, better results can be accomplished by adding multiple populations in parallel. This method is classified into two phases-genetic algorithm and simulated annealing. The hybrid algorithm incorporates the best features of genetic algorithm (searching wide regions of solution spaces) and simulated annealing (improving comprehensive solution of local region). Genetic algorithm develops a set of new results applying the crossover and mutation operators and then simulated annealing further improves the final best solution of genetic algorithm. The basic concept is to use the genetic operators of genetic algorithm to quickly converge the search to near-global minima/maxima, which will further be refined to a near-optimum solution by simulated annealing using annealing process. The flow chart for Multi-Population Genetic Simulated Annealing Algorithm is shown in Figure. 1.

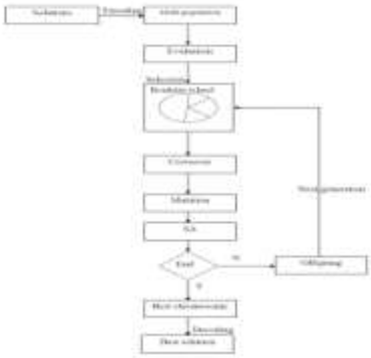

Fig. 1 Multi-Population Genetic Simulated Annealing Algorithm

The layout which minimizes cost over the planning horizon is identified. The results obtained by the proposed Hybrid multi population genetic algorithm is compared with the results from dynamic facility layout problem with budget constraint proposed by Parham Azimi, Hamid Reza Charmchi (2012) for different problem instances from Balakrishnan and Cheng are shown in Table.1 to Table. 6.

Table.1 Results for the data set of 6 department and 5 period problems

Problem	Material handling cost and rearrangement cost	
	Best solution	MPGSAA
Data set 1	106419	106419
Data set 2	105731	106365
Data set 3	107609	105174
Data set 4	107984	106721
Data set 5	107870	107462
Data set 6	107698	106314
Data set 7	108114	107714
Data set 8	107248	107215

Table.2 Results for the data set of 6 department and 10 period problems

Problem	Material handling cost and rearrangement cost	
	Best solution	MPGSAA
Data set 1	220776	220776
Data set 2	216767	216767
Data set 3	206178	206178
Data set 4	216828	216171
Data set 5	210958	218812
Data set 6	207966	217966
Data set 7	218291	218291
Data set 8	189324	189324

Table.3 Results for the data set of 15 department and 5 period problems

Problem	Material handling cost and rearrangement cost	
	Best solution	MPGSAA
Data set 1	480208	480208
Data set 2	483921	483921
Data set 3	492274	504837
Data set 4	484856	484856
Data set 5	487935	487935
Data set 6	488199	488199
Data set 7	487007	476732
Data set 8	494369	500679

Table.4 Results for the data set of 15 department and 10 period problems

Problem	Material handling cost and rearrangement cost	
	Best solution	MPGSAA
Data set 1	985031	985031
Data set 2	981478	981478
Data set 3	993049	992651
Data set 4	974385	974385
Data set 5	980346	980421
Data set 6	972765	972765
Data set 7	990976	990976
Data set 8	985817	985817

Table.5 Results for the data set of 30 department and 5 period problems

Problem	Material handling cost and rearrangement cost	
	Best solution	MPGSAA
Data set 1	579704	579704
Data set 2	572396	572396
Data set 3	579406	579406
Data set 4	578631	582100
Data set 5	559078	559078
Data set 6	567166	572814
Data set 7	570521	570521
Data set 8	586310	586310

Table.6 Results for the data set of 30 department and 10 period problems

Problem	Material handling cost and rearrangement cost	
	Best solution	MPGSAA
Data set 1	1172520	1172520
Data set 2	1175998	1170865
Data set 3	1179660	1180487
Data set 4	1152874	1152874
Data set 5	1141881	1141881
Data set 6	1154691	1154691
Data set 7	1210573	1210573
Data set 8	1201885	1201885

From the tables 5.1 to 5.6, it is evident that the proposed MPGSAA gives lesser material handling cost and rearrangement cost as that of best solution.

The results also showed that the computational time for the proposed MPGSAA is much lower than that of best solution.

IV. CONCLUSIONS

In this work the problem of dynamic facility layout problem is studied in detail. A detailed literature survey was done on the topic to know about the various works that have been done in the area. From the study it was found that much research work has not been conducted in DFLP with budget constraint. Hence in this thesis work a new methodology is suggested for solving the Dynamic Facility Layout Problem (DFLP) with budget constraint.

The Multi-Population Genetic Simulated Annealing Algorithm (MPGSAA) was developed and its performance was compared with other previously proposed heuristics for this model. And the proposed MPGSAA gives lesser material handling cost and rearrangement cost than that of best solutions in referred papers. The results also showed that the computational time for the proposed MPGSAA is much lower than that of best solution.

Applicability of other heuristic techniques such as tabu search, ant colony optimization, particle swarm optimization etc. to the model of DFLP can be extended as a future work.

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