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USING GENETIC ALGORITHMS TO RESOLVE FACILITY LAYOUT PROBLEM

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Abstract

The component layout problem requires efficient search of large, discontinuous spaces. The efficient layout planning of a production site is a fundamental task to any project undertaking. This paper describes a genetic algorithm (GA) to solve the problem of optimal facilities layout in manufacturing system design so that material-handling costs are minimized. The performance of the proposed heuristic is tested over problems selected from the literature. Computational results indicate that the proposed approach gives better results compared to many existing algorithms in this area.

Keywords: facility layout; flexible manufacturing; stochastic programming

1. INTRODUCTION

Component layout plays an important role in the design and usability of many engineering products. The layout problem is also classified under the headings of packing, packaging, configuration, container stuffing, pallet loading or spatial arrangement in the literature. The problem involves the placement of components in an available space such that a set of objectives can be optimized while satisfying optional spatial of performance constraints.

Current tools available in practice to designers to aid in the general mechanical layout process mostly remain at the stages of physical or electronic models with the assistance of manual adjustment and visual feedback.

The difficulty in automating the

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mechanical and electromechanical layout processes stems from: (1) the modeling of the design objectives and constraints; (2) the efficient calculation of the objectives and constraints; (3) the identification of appropriate optimization search strategies.

A number of design goals can be modeled as layout objectives. In addition, a set of constrains often has to be satisfied to ensure the applicability of the layouts. Efficient calculations of objectives and constraints are necessary to solve the layout problems in reasonable time since the analysis of objectives and constraints can be computationally expensive and a large number of evaluations may be required to achieve convergence. The search space of the layout problem is non-linear and multi-model, making it vital to identify a suitable algorithm to navigate the space and find good quality solutions.

The layout goals are usually formulated as objective functions. The objectives may reflect the cost, quality, performance and service requirements. Various constraints may be necessary to specify spatial relationships between components. The specifications of components, objectives, constraints, and topological connections define a layout problem and an optimization search algorithm takes the problem formulation and identifies promising solution by evaluating design alternatives and evolving design states. Analysis of objectives and constraints vary from problem to problem. However, the optimization search technique and geometric representation and the resulting interference evaluation are problem independent and are, thus, the focus for a generic layout tool[1].

The primary objective of the design problem is to minimize the costs associated with production and materials movement over the lifetime of the facility. Such problems occur in many organizations, including manufacturing cell layout, hospital layout, semiconductor manufacturing and service center layout. For US manufacturers, between 20% and 50% of total operating expenses are spent on material handling and an appropriate facilities design can reduce these costs by at least 10%-30% [2,3].

Altering facility designs due to incorrect decisions, forecasts or assumptions usually involves considerable cost, time and disruption of activities. On the other hand, good design decisions can reap economic and operational benefits for a long -time period. Therefore, the critical aspects are designs that translate readily into physical reality and designs that are "robust" to departures from assumptions.

The project manager or planner usually performs the task of preparing the layout based on his/her own knowledge and expertise. Apparently, this could result in layouts that differ significantly from one person to another. To put this task into more perspective, researchers have introduced different approaches to systematically plan the layout of production sites [4,5]

Facility layout planning can generally be classified according to two main aspects: (1) method of facility assignment and (2) layout planning technique.

Mathematical techniques usually involve the identification of one or more goals that the sought layout should strive to achieve. A widely used goal is the minimization of transportation costs on site. These goals are commonly interpreted to what mathematicians term "objective functions". This objective function is then optimized under problem-specific constraints to produce the desired layout. Systems utilizing knowledge-based techniques, in contrast, provide rules that assist planners in layout planning rather than perform the process based purely on a specified optimization goal(s).

Usually the selected fitness function is the minimum total costs of handling of work pieces. In general, those costs are the sum of the transport costs (these are proportional to the intensity of the flow and distances) and other costs.

An effective facility layout design reduces manufacturing lead-time, and increases the throughput, hence increases overall productivity and efficiency of the plant. The major types of arrangements in manufacturing systems are the process, the flow line or single line, the multi-line, the semi-circular and the loop layout. The selection of a specific layout defines the way in which parts move from one machine to another machine. The selection of the machine layout is affected by a number of factors, namely the number of machines, available space, similarity of operation sequences and the material handling system used. There are many types of material handling equipment that include automated guided vehicles, conveyer systems, robots, and others. The selection of the material handling equipment is important in the design of a modern manufacturing facility [6].

The problem in machine layout design is to assign machines to locations within a given layout arrangement such that a given performance measure is optimized. The measure used here is the minimization of material handling cost. This problem belongs to the non-polynomial hard (NP-hard) class. The problem complexity increases exponentially with the number of possible machine locations.

2. LAYOUT SPACE CHARACTERISTICS AND SOLUTION APPROACHES

The problem of plant layout involves distributing different departments, equipment, and physical resources as best as possible in the facility, in order to provide greater efficiency in the production of goods or services.

The aims to be achieved when dealing with a problem of the above type can generally be described from two stances. On the one hand, many researchers describe the problem as one of optimizing product flow, from the raw material stage through to the final product. This is achieved by minimizing the total material handling costs. Solving the problem in this sense requires knowing distances between departments (usually taken from their centroids), the number of trips between departments, and the cost per unit.

On the other hand, layout can be considered as a design problem. Seen from this angle, solving the problem involves not only collecting the quantitative information mentioned above, but also qualitative information, for instance, how different departments are related from the point of view of adjacency.

The layout space is defined as the mathematical representation of the space of configurations mapped against the cost per configuration. Deterministic algorithms are unable to navigate such a space for globally near-optimal solutions, and stochastic algorithms are usually required for solutions of good quality.

The manner of arranging of working devices largely depends on the type of production. NP-hard problems are unsolvable in polynomial time [7](Kusiak

1990). Accurate mathematical solutions do not exist for such problem. The complexity of such problems increases exponentially with the number of devices. For instance, a flexible manufacturing system (FMS) consisting of N machines will comprise a solution space with the size N. The problem is theoretically solvable also by testing all possibilities (i.e., random searching) but practical experience shows that in such manner of solving the capabilities of either the human or the computer are fast exceeded. For arranging the devices in the FMS the number of possible solutions is equal to the number of permutations of N elements. When N is large, it is difficult, if not impossible, to produce the optimal solution within a reasonable time, even with support of a powerful computer. With today's computation power of modern computers it is possible to search for the optimum solution by examining the total space of solutions somewhere up to the dimensions of space 10. In case of problems of larger dimensions it is necessary to use sophisticated solving methods which, during examining the solution space somehow limit themselves and utilize possible solutions already examined [8].

3. LAYOUT SEARCH ALGORITHMS

The layout problem can have different formulations, but it is usually abstracted as an optimization problem. An assignment of the coordinates and orientations of components that minimizes the cost and satisfies certain placement requirements is sought. The problem can be viewed as a generalization of the quadratic assignment problem and therefore belongs to the class of NP-hard problems [9]. Consequently it is highly unlikely that exact solution to the general layout problem can be obtained in an amount of time that is bounded by a polynomial in the size of the problem, resulting in prohibitive computation time for large problems. Heuristic algorithms are typically used to generate acceptable solutions. As will be discussed, general algorithms typically require some level of (stochastic) perturbation to avoid local optima.

Various models and solution approaches have been proposed during past three decades. Heuristic techniques were introduced to seek near-optimal solutions at reasonable computational time for large scaled problems covering several known methods such as improvement, construction and hybrid methods, and graph-theory methods [10]. However, the area of researches is still always interesting for many researchers, since today the problems are solved by new methods and with the possibility of application of much greater computation capacity of modern computers.

A variety of optimization algorithms have been applied to the layout problem. Some of the approaches may be efficient for specific types of problems, but often place restrictions on component geometry, allowable degrees-of-freedom, and the objective function formulation. Others are applicable to a wider variety of problems but may require prohibitively long computing time to solve even simplistic problems. Layout algorithms can be classified into different categories according to search strategies used for design space exploration.

The target of all methods is the minimum transport costs, but they differ in exactingness, particularly in the length of the procedure. However, it cannot be decided with certainty which basic method and/or method of improvement of the layout is the best.

3.1. Fitness function

Researchers using mathematical techniques in facility layout planning have developed many forms to represent their optimization goals or objective functions. Those functions can be categorized in following manner: To minimize the total transportation costs of resources between facilities. To minimize the total transportation costs of resources between facilities (presented through a system of proximity weights associated with an exponential scale). To minimize the total transportation costs of resources between facilities and the total relocation costs (presented through a system of proximity weights and relocation weights).

During the manufacturing process, material flows from one machine to the next machine until all the processes are completed. The objective of solving the facility layout problem is therefore to minimize the total material handling cost of the system. To determine the material handling cost for one of the possible layout plans, the production volumes, production routings, and the cost table that qualifies the distance between a pair of machines/locations should be known. The following notations are used in the development of the objective function:

Gij amount of material flow among machines i and j (i,j=1,2,……..,M)

Cij unit material handling cost between locations of machines i and j (i,j=1,2,…….,M)

Lij rectilinear distance between locations of machines i, and j

C total cost of material handling system.

The total cost function is defined as:

$$C= \sum_{i=1}^{M}\sum_{j=1}^{M} G_{ij} C_{ij} L_{ij} \qquad (1)$$

The evaluation function considered in this paper is the minimization of material handling cost, which is criterion most researchers prefer to apply in solving layout problems. However, the proposed approach applies to other functions as well.

To solve the problem it is necessary to know the matrix of the transport quantities between the individual devices N in a time period. Also the variable transport costs, depending on the transport means used, must be known. For example: connection between two devices can be performed by another transport device then between other two devices. Thus, also different transport cost per unit length result.

The costs of transport between two devices can be determined if their mutual distance Lij is known. During execution of the GA the value Lij changes with respect to the mutual position of devices and with respect to position in the arrangement.

Fitness function thus depends on the distances Lij between the devices. The distance between serving points is multiplied by coefficients Gij and Cij, which measure the amount of material flow and the handling cost between devices and they are constants defined by input matrix, Table 1 and Table 2. The value of the cost function is thus the sum of all values obtained for all the pairs of devices. The aim of optimization process is to minimize this value. Fitness is based on the principle that the cost of moving goes up with the distance.

3.2. Genetic algorithms

Genetic algorithms (GAs) can be defined as meta-heuristics based on the evolutionary process of natural systems [11]. Since their inception, they have been applied to numerous optimization problems with highly acceptable results.

GAs are new approach to solving complex problems such as determination of facility layout. GAs became known through the work of John Holland in the 1960s [11]. The GAs contain the elements of the methods of blind searching for the solution and of directed and stochastic searching and thus give compromise between the utilization and searching for solution. At the beginning, the search in the entire search space and afterwards, by means of crossover, they search only in the surrounding of the promising solutions. So GAs employed random, yet directed search for locating the globally optimal solution [12].

The starting point in GA presented in this work was an initial population of solutions (which was randomly generated). Process shop layout and its randomly generated chromosome are shown on figure1. This population undergoes a number of transformations designed to improve the solutions provided. Such transformations are made in the main loop of the algorithm, and have three basic stages: selection, reproduction, and replacement, as discussed below. Each of the selection-transformation cycles that the population undergoes constitutes a generation; hopefully, after a certain number of generations, the population will have evolved towards the optimum solution to the problem, or at least to a near-best solution.

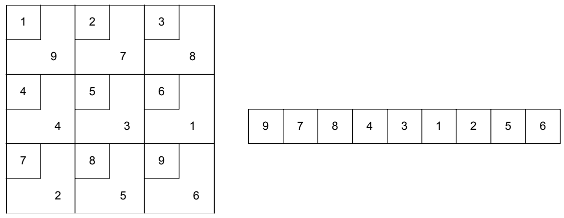

Fig. 1. Type of layout used in calculations and its chromosome representation

The selection stage consists of sampling the initial population, thereby obtaining a new population with the same number of individuals as the initial one. This stage aims at improving the quality of the population by favoring those individuals that are more adequate for a particular problem (the quality of an individual is gauged by calculating its fitness, using equation 1, which indicates how good a solution is).

The selection, mutation, and crossover operators were used to create the new generation of solutions. A fitness function evaluates the designs and decides which will be the survivors into the next generation. Selection is accomplished by copying strings from the last generation into the new generation based on a fitness function value. Mutation is the process of randomly changing one bit of information in the string and it prevents GAs from stagnating during the solution process. Crossover is responsible for introducing most new solutions by selecting two parent strings at random and exchanging parts of the strings.

A parent selection procedure used in this work operates as follows:

1. Generate initial population consisting of 200 members using random number generator.
2. Place all population members in main database.

3. Calculate the fitness C (Eq. (1)) of all population members.

4. Chose the population member whose fitness has minimum value compared with fitness of the other population members as the first parent.

5. Place chosen population member in separate database.

6. Repeat procedure (1-5) once more to produce second parent chromosome.

Now there is two parent chromosomes whose fitness are the best compared to the rest of the population. The probability that the fitness of one of two parents is total minimum of studied example is very small. The starting chromosome in new iteration isn't randomly generated. It is the chromosome obtained by crossover of two parents chromosomes discussed above. Consider a pair of parent chromosomes (P1, P2) shown below:

P1	1	3	6	8	4	2	5	7	9
P2	8	3	1	5	7	9	6	2	4

The way of crossover implementing in this work was chose four central numbers of both parents i.e. (8,4,2,5) in P1 and (5,7,9,6) in P2, but we do not exchange it from P1 to P2 and vice versa (the procedure explained and used by Chan and Tansri [13]; Mak, Wong and Chan [14]as well as by El-Baz [6], we only change their string in original chromosome of one parent in the way they are lined in the other. To be precisely, numbers 8,4,2,5 in P1 should be lined as 2,5,8,4 in P1, and numbers 5,7,9,6 in P2 should be lined as 9,6,5,7 in P2. At this stage genes can not be found to exist in more then one position in the resultant chromosomes. The structures of the resultant chromosomes then become:

P1	1	3	6	2	5	8	4	7	9
P2	8	3	1	9	6	5	7	2	4

The mutation operator is used to rearrange the structure of a chromosome. In this study, the swap mutation was used, which is simply selecting two genes at random and swapping their contents. The probability of mutating a single gene is usually a small number.

Since it is difficult to assume the total optimum solution of the problem investigated, and it became more difficult if number of workstations (machines) increase, the program should be terminated when either the maximum number of generations is reached, or until the propounded limit is attained. In this work we chose the second procedure. As propounded limit the value obtained for the material handling cost of optimal facility layouts presented in benchmark test was used. This value was C = 4818. Only the results with value equal to this were placed in main database, which are presented as optimums in figure 2.

In all experiments the same genetic parameters as used in works [13,14] were used. Those genetic parameters were: the probability of crossover pc = 0.6 and probability of mutation pm = 0.001. The percentage of replication of well-performed chromosomes in each generation was R = 5%.

4. NUMERICAL EXAMPLE

The calculation of numerical example presented was done on standard PCP4 desk-top computer [Pentium (R) 4CPU 2.0 GHz, 248 MB of RAM].

A comparative evaluation of the proposed approach is made using benchmark numerical examples. The example is taken from Chan and Tansri [13] and compared with the work of Mak, Wong and Chan [14] as well as with work of El-Baz [6] whom used same example to evaluate their work. The stopping criterion for iteration was obtaining a value of fitness C (Eq. (1)), equal to the best value obtained in above papers. The plant flow of materials between machines and material handling cost between machines are presented in tables 1 and 2, respectively. The plant configuration layout is 3X3 grid. In this example, using 9 machines, there are 362880 possible solutions in the solution space e.g.(9!).

Table 1. Flow of materials between machines

From/To	1	2	3	4	5	6	7	8	9
1		100	3	0	6	35	190	14	12
2			6	8	109	78	1	1	104
3				0	0	17	100	1	31
4					100	1	247	178	1
5						1	10	1	79
6							0	1	0
7								0	0
8									12
9									

solutions since the number of sampling solutions from the solution space is enlarged. The general cost performance for the four different approaches is studied with the used sampling solution space.

Fig. 2 shows some of the resulting optimal machine layouts giving a material handling cost of value equal to 4818 i.e. solutions that are equivalent compared to ones proposed by models selected for comparison from the literature.

Results presented by Chan and Tansri [13], Mak, Wong and Chan [14] and El-Baz [6] are also the optimal solutions for studied example. Results obtained by proposed approach are the same yet obtained with less

The experimental results shown in Table 3 are expressed in terms of:

1. The material handling cost of the best solution among trials (Best)
2. The number of the trials needed to obtain one of the optimal solutions (#).

In general, an increase in the population and generation sizes can provide better number of iterations, Figure 3. Overall minimum of handling costs obtained is 4818, and layout it presents shown in Fig.2.

The reason for such discrepancies of results presented in this paper and the results proposed by models selected for comparison from the literature, concerning number of iterations, is laying mainly in simplicity of the way of crossover implementing in this work comparing to the procedure explained in previous literature as described in section 3.2.

5. CONCLUSION

This paper proposes an approach using GAs to solve facility layout problems. Algorithm presented here has theoretical

Table 2. Material handling cost between machines

From/To	1	2	3	4	5	6	7	8	9
1		1	2	3	3	4	2	6	7
2			12	4	7	5	8	6	5
3				5	9	1	1	1	1
4					1	1	1	4	6
5						1	1	1	1
6							1	4	6
7								7	1
8									1
9									

4	8	5
3	9	2
7	1	6

7	1	6
3	9	2
4	8	5

6	2	5
1	9	8
7	3	4

5	2	6
8	9	1
4	3	7

5	8	4
2	9	3
6	1	7

4	3	7
8	9	1
5	2	6

Fig. 2. Some of the optimal facility layouts for example studied

Table 3. The experimental results for sample problem

Exp.	No.of triels	Proposed approach	No.of triels	M.Adel El-Baz	Mak et al.	PMX (Chan and Tansri)
	#	Best	#	Best	Best	Best
1	4050	5119	200	5039	5233	4939
2	8595	5150	400	4818	5040	5036
3	180	4872	1000	4818	4818	4938
4	405	4818	2000	4818	4818	4818
5	270	4818	5000	4818	4818	4818
6	360	4818	400	4872	5225	4938
7	2160	4939	800	4818	4927	4992
8	1125	4990	2000	4818	4818	4818
9	765	4818	4000	4818	4818	4818
10	1485	4818	800	4818	5225	4938
11	3105	4818	1600	4818	4927	4992
12	990	4818	4000	4818	4818	4818
13	2160	4818	8000	4818	4818	4818
14	3105	4818	2000	4818	5225	4938
15	225	4818	4000	4818	4818	4927
16	2160	4818	10000	4818	4818	4818
17	3015	4818	4000	4818	4818	4938
18	3240	4818	8000	4818	4818	4862
19	3600	4818	5000	4818	4818	4818
Sum:	40995		63200			

aspect that is finding an ideal workstations position in short time as well as practical significance of saving financials needed for transportation costs in concrete production systems. The proposed GA approach produces the optimal machine layout, which minimizes the total material handling cost. The effectiveness of the proposed approach has been examined by using three benchmark problems. The comparison indicates that the proposed approach is efficient and has a high chance of obtaining the best solution for the facility layout problem with less number of iterations. The solutions for the example studied were calculated in reasonably short time on standard PC equipment. Only demerit of GA presented in this work, compared to results presented by Chan and Tansri [13], Mak, Wong and Chan [14] and El-Baz [6] is that number of trials needed to obtain first optimum is to some extent larger, still overall number of iterations is much lesser (40995 < 63200), with same number of experiments.

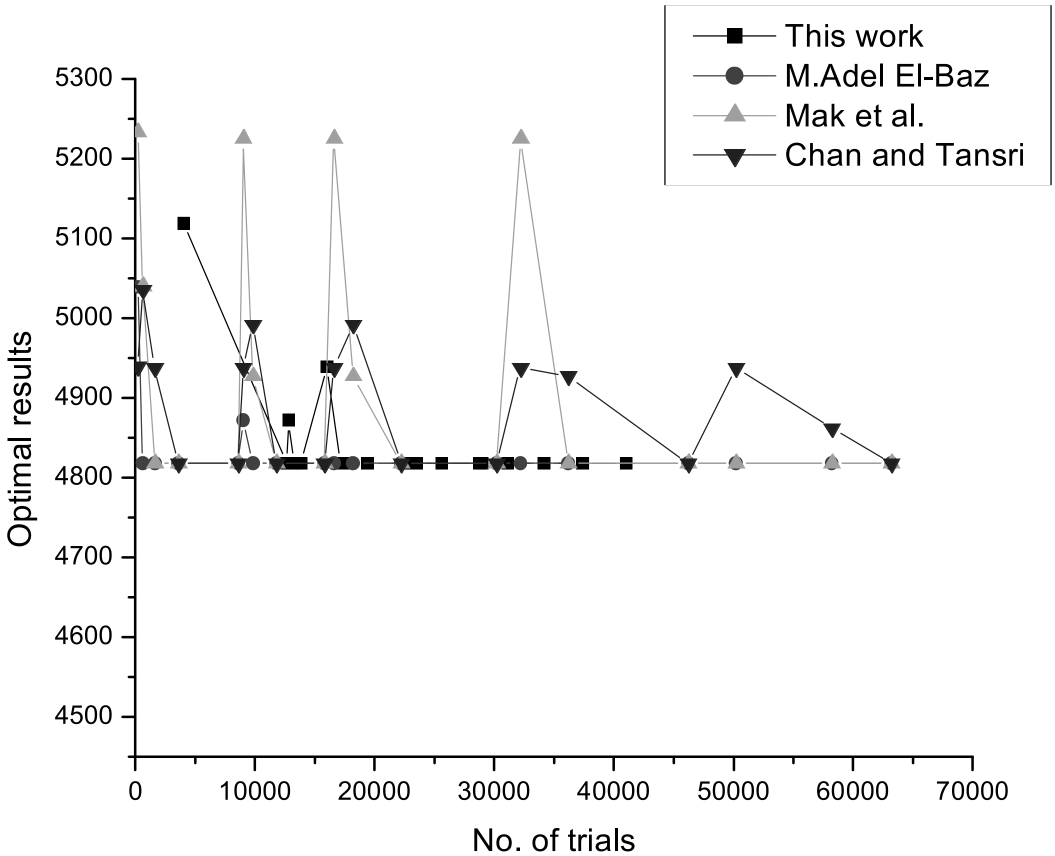

Fig. 3. Comparison of the optimal solutions obtained in this work and literature models

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