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Solving FMS Assignment Problem with Grouping Genetic Algorithm

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A B S T R A C T

Operations assignment to feasible and suitable machine-tool combination affects the total production costs and selecting the best combinations is important for these systems, this is one of the significant problems in flexible manufacturing systems (FMSs). In this paper, minimizing the machining cost, setup cost and material handling cost for the given multi-objective problem is considered. Also, this problem is solved with a grouping genetic algorithm and the associated results are presented.

1. Introduction

In a flexible manufacturing system (FMS), some multi-functional machines are linked together through material-handling system and the whole system controlled by a central computer. In this system, part types are moved by automated guided vehicles (AGVs). Flexibility of these systems proposes different machine-tool combinations for performing each operation that results several routes for each part type between machines. Each routes has a specific completion time and production cost. In these systems, many tools can be fixed in machines that each machine has the specific tool storage and part types move around the machines till performing all its operations by feasible machine-tool combinations. In order words, for each operation may be existed more than one feasible machine-tool combination, each with its machining cost and time depending to the tool and the machine that used for each partial assignment. On the other hand, depending on the layout of machines in the FMS and the route that AGVs travel for moving part types, the material handling cost is different for each complete assignment of operations.

In these systems, finding feasible machine-tool combinations for a complete assignment of operations that must be performed in the planning horizon with respect to minimizing the machining cost, material handling cost and setup cost as a multi-objective problem is very

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significant. In the real-world problems, decisions are usually based on more than one criterion that conflict with each other. In single objective optimization problems, the feasible set of solutions is totally ordered according to the objective function. In contrast, in the multi-objective problems (MOPs), we face with a set of optimal solutions, which are quite difficult to order. In these problems, a vector whose components represent the trade-off in the decision search space will be produced. Then the decision maker implicitly chooses an acceptable solution by selecting one of these vectors. In the multi-objective concept, a solution is Pareto frontier if there is no feasible vector that will decrease some objectives without causing a simultaneous increase in at least one objective (in a minimization problem). Multi-objective optimization is characterized by the fact that several objectives should be optimized simultaneously. Since, these objectives are usually in contrast, there is no solution that optimizes all the objectives together. In multi-objective optimization, a solution is called a non-dominated solution when there are no other better solutions with regard to all of the objectives. Suppose a multi-objective optimization problem with k objectives to be minimized, then we have:

$$\text{Minimize } F(X) = \{F_1(X),\ldots,F_k(X)\} \qquad (1)$$

Solution X is called a non-dominated solution if there is no solution like X' that:

$$\forall k\text{: } F_k(X') \leq F_k(X) \text{ and } \exists\, l \;\; F_l(X) \leq F_l(X') \qquad (2)$$

The set of non-dominated solutions make an optimal Pareto front.

A 0-1 integer goal programming model for assignment of operations to machine-tool combination in an FMS environment is developed by Chan and Swarnkar [1]. They coded the developed model by an ant colony optimization (ACO) approach. Buyurgan et al [2] presented a heuristic approach for tool selection in an FMS. Lee et al [3] developed an integrated model that performs an operation sequence and tool selection simultaneously and minimizes the tool waiting time when a tool is absent. Minimizing the total flow time, machine workload unbalance, greatest machine workload and total cost in the flexible manufacturing system is considered by Chen and Ho [4]. They proposed an efficient multi-objective genetic algorithm that employs a Pareto dominance relationship to solve the problem. Gamila and Motavalli [5] presented a 0-1 mixed-integer programming (MIP) model for a loading problem in an FMS in order to generate a detailed operation schedule. Swarnker and Tiwari [6] extended and modeled a loading problem of FMSs and using a hybrid tabu search and simulated annealing-based heuristic method to solve this problem in order to minimize the system unbalance and maximize the throughput rate. Nagarjuna et al [7] presented a heuristic method based on a multi-stage programming approach to minimize the workload unbalance while satisfying the technological constraints, such as availability of machining time and tool slots. Because of the NP-hard nature of many combinatorial optimization problems, many researchers have used meta-heuristics to solve these kinds of problems in the reasonable time. Also, in these constructed approach, there is no guarantee on reaching to an optimal solution. One of the most popular meta-heuristics is an ACO approach that was first proposed by the Dorigo et al [8] and since that time many researchers try to propose varieties of the original one suitable for their problems. Due to the differences between single objective optimization problems and multi-objective ones, many ACO approaches were constructed by a number of researchers for multi-objective problems that try to find better Pareto front [9-18]. In this case, an approach is better, which finds better Pareto fronts. It means that a Pareto fronts dominates the fronts found by another one. Pareto ant colony optimization, which was first proposed by Doerner et al. [11] that applied for multi-objective portfolio problem, is one of the multi-objective meta-heuristic approaches. In this approach, the global pheromone updating method is performed by using two different ants that produced the best and second best solutions at the end of iterations. In this approach, there is a pheromone matrix for each objective. Also, each time an ant travels an edge, the local pheromone update mechanism is applied and the pheromone of that edge decreases so that force other ants to travel other edges (i.e., diversification). When ants complete their travels, the global pheromone updating method is applied based on the best solutions found by the ants so that in the next iteration ants pay more attention to the best solution found so far (i.e., intensification). Mahdavi et al [19] considered the machine-tool selection and operation allocation problem in an FMS environment. They used the Pareto ACO approach mentioned earlier for this problem.

2. Problem description

In an FMS each machine is equipped with a tool magazine that has a specific capacity. Also, each tool has its tool slot that can be different from other tools. Tools located in the machines in the beginning of the planning horizon and part types are move around the machines by AGVs. The following assumption is considered in our problem:

- Each tool has its tool life.
- Each tool occupies an equal number of slots on different machines.
- Time availability of machines is limited.
- A tool cannot be duplicated in the same tool magazine.
- Parts are moved between machines with AGVs.
- The processing time of each operation in a batch is assumed to be identical.
- The processing time and cost of each operation with each machine-tool combination is not equal necessarily.

As mentioned earlier in this paper, we consider the machine-tool selection and operation allocation as a multi-objective problem. Three considered objectives are machining cost, material handing cost and setup cost, in which minimizing these objectives in the assignment is significant.

3. Multi objective grouping genetic algorithm

The Grouping Genetic Algorithms (GGA) was developed by Falkenauer [20] to solve clustering problems. In fact, GGAs are a genetic framework for grouping problems and are an extension of the conventional Genetic Algorithms adapted to grouping problems.

The main objective is to assignment of operations to machine-tool selection. These problems can be easily transformed to grouping problems. Falkenauer [20] pointed out the weaknesses of standard GAs when applied to grouping problems and introduced the grouping GA (GGA) to match the structure of grouping problems. The GGA's operators (crossover, mutation and inversion) are group-oriented.

3.1.Encoding

There are other applications of Genetic Algorithms to solve grouping problems, but what makes GGA a well-designed solution is the coding used by Falkenauer [21]. Most Genetic Algorithms (GA) dealing with grouping problems will choose the objects assignation as the information to store in a gene.

In GGA, the chromosomes are enhanced with a group element containing the group composition. All the operators work on the group element of the chromosomes. This coding has however a technical consequence, namely that the different chromosomes in the same population have different lengths. One of the problems associated with the coding of grouping problems, is the fact that the same solutions can be coded with chromosomes that are different. A simple method can be used to identify these identical solutions.

3.2.Initialization

Once the coding has been defined, the GGA must initialize the population. The method used depends on the particular problem because the different solutions must satisfy the hard constraints. The GGAs are meta-heuristic and heuristics are used most of the time to initialize the population. The heuristic must be adapted to produce different solutions.

3.3.Crossover

Crossover is one of the most important operators in genetic algorithms. The GGA crossover consists of five steps:

- Select randomly two crossing site and delimit the crossing section in each of the two parents.
- Inject the contents of the crossing section of the first parent at the first crossing site of the second parent. Recall that this means injecting some of the groups from the first parent into the second one.

- Eliminate all objects which occur twice from the groups that they were members in the second parent.
- If necessary, adapt the resulting groups according to hard constraints of the problem and optimise the cost function.
- Apply the points 2 through 4 to the two parents with their roles reversed in order to generate the second child.

With two parents it is possible to create two children by inserting the selected bins of the first parent into the second one, and by doing the reverse.

3.4.Mutation

The role of a mutation operator is to insert new characteristics into a population to enhance the search space of the Genetic Algorithm.

According to the nature of the particular grouping problem, creating new group(s) from randomly selected objected is applied for the proposed GGA.

3.5.Inversion

The role of the inversion operator is to propose the same solution to the GGA, but differently. A single solution may have different presentations, and because crossovers work through crossing sites, the way in which a solution is presented influences the crossover operator's results. The first group appearing in the group element of a chromosome is likely less probability to be chosen than the other groups. It is therefore important to include this operator in our GGA.

3.6.Termination Condition

In the mentioned assignment problem, there are three objectives minimizing the machining cost, setup cost and material handling cost. When the convergence condition is satisfied, we select the best solutions according to the Pareto sense. In this work, at the end of iterations, we keep non-dominated solutions that find so far and after the pre-determined maximum number times, if the algorithm cannot find a solution, which dominates the previous non-dominated solutions, the GGA algorithm is stopped.

3.7.Grouping genetic algorithm

Figure 1 shows the main steps of the proposed GGA for the FMS problem.

4. Numerical example

The proposed GGA has been coded in C#.Net and executed on a Pentium processor running at 2.5 GHz and 2 GB of RAM. To illustrate the application of the proposed approach, we solve the problem of machine-tool selection and operation allocation by considering the tool life and tool size of each tool and magazine capacity of each machine. In this section, we represent the result of solving a randomly generated problem that has two multi-functional machines and three tools. Details of the part types and machining costs and times, multi-functional machines and tools are shown in Tables 1, 2 and 3, respectively. The material handling cost between machines is given in Table 4.

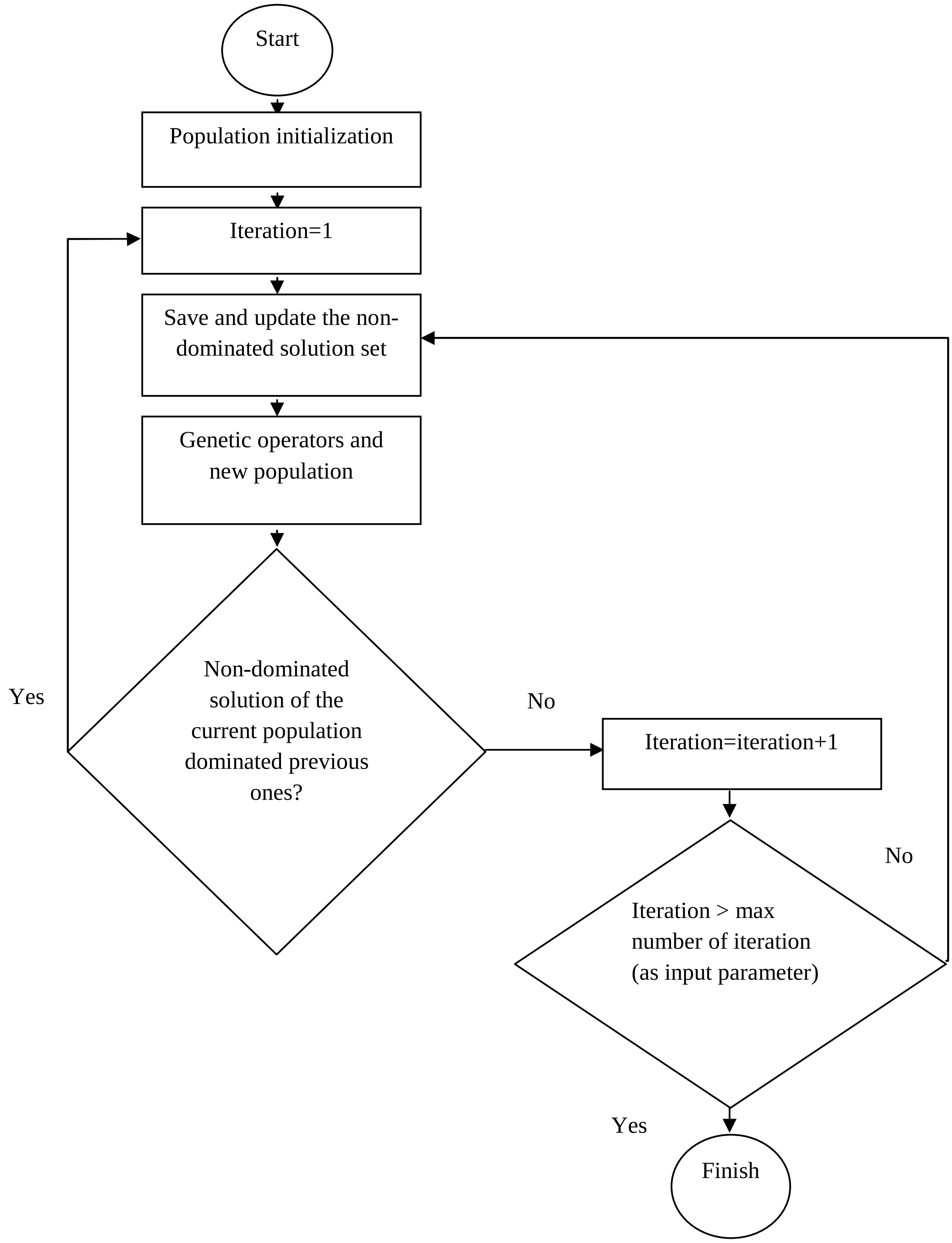

Figure. 1. The proposed GGA

Table 1. Machining costs and times associated with different machine-tool combinations

Part types	Batch size	Operation	Tool option	Machining time		Machining cost	
				Machine1	Machine 2	Machine1	Machine 2
1	30	1	1	2	3	12	28
			2	8	2	43	32
		2	1	5	9	23	43
			2	6	6	56	23
2	35	1	1	7	1	12	12
			2	9	7	11	22
		2	1	3	4	23	10
			2	2	8	12	11

Table 2. Details of machines

Machine	Set-up cost	Available machine time	Magazine capacity
1	300	480	4
2	200	480	3

Table 3. Details of tools

Tool	Tool life	Tool size
1	460	1
2	460	1

Table 4. Material handling cost between machines

Machine	1	2
1	1	5
2	5	1

The results of a run of the proposed GGA with small size of population for the mentioned problem are represented in Table 5. In this table, details of machine-tool selection for each operation are shown.

Table 5. Solutions of solving the problem by the proposed GGA

Non-dominated solution	*poml*(part-operation-machine-tool)	Objectives		
		Machining cost	Material handling cost	Set-up cost
1	1122,1122,2122,2222	3212	65	200
2*	1121,1221,2122,2222	1987	65	200
3	1112.1212,2122,2222	2673	325	500
4	1121,1212,2121,2222	2344	325	500
5	1112,1222,2122,2212	2334	325	500
6*	1111,1211,2111,2211	1999	65	300

* Non-dominated solution

5. Conclusion

In this paper, a machine-tool selection and operation allocation problem in an FMS environment as a multi-objective problem is considered. The machining cost, material handling cost and setup cost are three significant objectives that to be minimized. The multi-objective problem is solved by the GGA proposed in this paper. This paper considers the precedence relationship between operations and real constraints, such as tool life, tool size, and machine available, magazine capacity of each machine as hard constraint. The proposed algorithm can produces a set of non-dominated solutions for the decision maker in a single run of the algorithm, and the decision maker can select a better option for producing operations with considering the limitations and existing equipment.

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