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Ant Colony Optimization for Multi-Objective Machine-Tool Selection and Operation Allocation in a Flexible Manufacturing System

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Abstract: Assigning operations to feasible and suitable machine-tool combination is one of the significant problems in a flexible manufacturing system (FMS). This assignment affects on the total production costs and thus selecting the best combination is very significant for the system. This paper considers a multi-objective problem that minimizes the machining cost, setup cost and material handling cost. In addition, this problem is solved by the ant colony optimization (ACO) algorithm and the associated results are presented.

Key words: Flexible manufacturing systems · Machine-tool selection · Multi-objective optimization · Ant colony optimization

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). FMSs have two main advantages of high efficiency and variety taken from two well-known production systems, namely flow line for mass production and job shop, respectively. Because of these advantages, more attention to these systems is taken into account. Flexibility of these systems proposes different machine-tool combinations for performing each operation that results several routes for each part type between machines. Each route has a specific completion time and production cost. In general in these systems, many tools can be fixed in machines, in which 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, each operation may be existed more than one feasible machine-tool combination, in which each one has its own machining cost and time dependent to the tool and the machine 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 should 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 significant. In 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 multi-objective problems (MOPs), we face with a set of optimal solutions that 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 (DM) 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:

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

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

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

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

A 0-1 integer goal programming model for assignment of operations to a 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. Chen and Ho [4] considered a model that minimizes the total flow time, machine workload unbalance, greatest machine workload and total cost in the FMS. They proposed an efficient multi-objective genetic algorithm (MOGA) that employs a Pareto dominance relationship to solve the given 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 solved by a hybrid tabu search and simulated annealing method that aims at minimizing the system unbalance and maximizing 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. In addition, in these constructed approach, there is no guarantee on reaching to an optimal solution. One of the most popular meta-heuristics is an ACO algorithm that was first proposed by the Dorigo *et al*. [8] and since that time many researchers have tried to propose varieties of the original one suitable for their problems. Due to the differences between single and multi-objective objective optimization problems, many ACO algorithms were constructed by a number of researchers for multi-objective problems that try to find a better Pareto front [9-18].

In this case, an approach is good to find 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 a multi-objective portfolio problem, is one of the multi-objective meta-heuristics. In this case, 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 addition, there is a pheromone matrix for each objective. 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 algorithm mentioned earlier for this problem.

Problem Description: An FMS consists of many multi-functional CNC machines that liked together through automated guided vehicles (AGVs). Each machine is equipped with a tool magazine that has a specific capacity. In addition, 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 assumptions are considered in the given 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 before, this paper considers the machine-tool selection and operation allocation as a multi-objective problem. Three significant objectives are consisting of the machining cost, material handing cost and setup cost, in which minimizing these objectives in the assignment is significant.

Ant Colony Optimization Algorithm: As mentioned before, in multi-objective optimization problems, there is more than one objective so that optimizing all of them is very important. In this kind of problems, objectives have conflict with each other. In the other words, improvement of one objective leads to deterioration of the others. In this kind of problems, finding optimal solutions is very significant so that some solutions are not any better solution(s) in all objectives. These solutions make a set of solutions, namely *Pareto front*, that are better than a set of other solutions and we eager to find an optimal Pareto front.

Ant colony optimization (ACO) is one of the famous meta-heuristic algorithms inspired by the shortest path searching behaviour of ant varieties. Recently, researchers have proposed many meta-heuristics for multi-objective problems that try to consider all the objectives and finding an *optimal Pareto front*, as mentioned earlier. Iredi *et al*. [15] proposed some general techniques in order to solve bi-criteria problems by ACO for a bi-criteria vehicle routing problem (VRP). In this section, we use an algorithm for a three-objective FMS assignment problem, as this algorithm was proposed by Iredi *et al*. [15] for the bi-criteria VRP. Our proposed algorithm uses a pheromone trail matrix for each objective (i.e., there are three objectives and we consider three pheromone matrices) τ, τ' and τ''. In each iteration (i.e., once ants complete their trips, not necessarily all of them), each of *m* ants in the colony generates a solution to the given problem. During its construction trip, each ant selects the next node *j* to be visited by means of the following probability distribution.

$$p(j)=\begin{cases}\dfrac{\tau_{ij}^{\lambda\alpha}.\tau'^{\gamma\alpha}_{ij}.\tau''^{(1-\lambda-\gamma)\alpha}_{ij}\,\eta_{ij}^{\lambda\beta}.\eta'^{\gamma\beta}_{ij}.\eta''^{(1-\lambda-\gamma)\beta}_{ij}}{\sum_{u\in O}\tau_{ij}^{\lambda\alpha}.\tau'^{\gamma\alpha}_{ij}.\tau''^{(1-\lambda-\gamma)\alpha}_{ij}\,\eta_{ij}^{\lambda\beta}.\eta'^{\gamma\beta}_{ij}.\eta''^{(1-\lambda-\gamma)\beta}_{ij}} & \text{if } j\in O\\ 0 & \text{otherwise}\end{cases} \tag{3}$$

Where parameters α and β are the usual weighting parameters that determine the relative importance of pheromone trail and heuristic information, respectively.

η, η' and η'' are the heuristic values associated to edge a_{ij} according to the first, second and third objectives, respectively. Ω indicates the current feasible set of nodes that ant can select for transferring. τ_{ij} is the pheromone amount between nodes *i* and *j* that is sorted in pheromone matrices; τ, τ' and τ'' for the first, second and third objectives, respectively. γ is a random variable between 0 and 1. λ is a random variables between 0 and γ for each ant at each stage of the algorithm.

In order to force ants search different regions of *Pareto front*. At the end of iterations, once all ants represent their solutions, if it is possible, the global pheromone trail information is updated according to the following common updating rule:

$$\tau_{ij}=(1-\rho).\tau_{ij} \tag{4}$$

Where ρ [0, 1] is the pheromone evaporation rate.

Encoding: In the mentioned assignment problem, there are three objectives minimizing the machining cost, setup cost and material handling cost. According to the available machines and tools and operations that should be performed, there are many nodes that an ant should be selected their route among them. In addition, many of them cannot represent a feasible solution and cannot finish their trips. For example, an ant may be select the best machine-tool combination for many operations in the beginning of its trip so that available time of machines or tool life are not enough for the remaining operations and ultimately the ant can not represent a feasible solution. Furthermore, if an ant selects a machine-tool combination for performing an operation in their trip, all the combination of that tool with the other machines are forbidden for the ant at that iteration, because according to the assumptions in a specific solution a tool just can locate on a machine.

For encoding the assignment problem, the total number of pheromone matrices is equal to the objectives to be optimized, in which each matrix for one objective is considered and then we have three matrices in our problem. A directed graph is constructed for a given set of parts, machine-tool combinations and corresponding operations. Each node indicates a machine-tool combination that indicates performing one operation of a part with a machine-tool combination. For each operation according to the production information, there may be more than one node that can perform it.

At the beginning of the algorithm, each ant can perform many operations with respect to the precedence relationship between operations of each part. Whenever an ant chooses a node, it indicates performing the corresponding operation with the associated machine-tool combination. Next, all other nodes related with this operation are to be removed from the feasible set of nodes that can be visited by the ant in the subsequent steps of traveling. Also, when an ant chooses one machine-tool combination for an operation, the entire nodes that assign the tool of that combination to other machines, should be removed from the feasible set of nodes that can be visited by the ant in its path.

To select a node as the next step for the ant in its trip, another node will be selected as the next one without any violation of the constraints. When there is no such a node, this ant cannot find any solution, thus being omitted form further consideration.

Decision Rule: According to the proposed ACO, each ant initially selects a node from a feasible set of nodes by random at the beginning of the trip. After that, some nodes may no longer be feasible for this ant including the selected node. Therefore, after selecting each node, the feasible set of nodes that can be visited by the ant should be updated and this set gradually becomes smaller. After selection of the initial node, the ant selects the next node j from a feasible set of nodes according to Eq. (3).

Heuristic Information: η, η' and η' are aggregated values, according to the algorithm. Our heuristic algorithm acts as greedy search and tries to find a node leading to the minimum value of each objective, separately. Assuming an ant wants to trip from node i to node j, node i indicates performing the operation o of the part p with the m-l machine-tool combination (p,o,m,l) and node j indicates performing the operation o' of the part p' with the m'-l' machine-tool combination (p',o',m',l'). Also, suppose the machining cost of node j is $C_{p'o'm'l'}$, the material handling cost between machines of two node is $Mh_{mm'}$ and the setup cost for the machine m' is $S_{m'}$. If a machine is used in the production period for performing operation(s) then its setup cost is considered in the setup costs, once. The following formula is proposed to calculate the desirability of move from node i to node j:

$$\eta = \frac{1}{C_{p'o'm'l'}} \tag{5}$$

$$\eta' = \frac{1}{MH_{mm'}} \tag{6}$$

$$\eta'' = \begin{cases} 1 & \text{if } m' \text{ is used in the previous selection of nodes} \\ \dfrac{1}{S_{m'}} & \text{if } m' \text{ must be set up for this operation} \end{cases} \tag{7}$$

These constant values are calculated for each feasible node as heuristic information by the algorithm.

Global Oheromone Update: After ants (not necessarily all of them) construct their tours, the global pheromone updating method should be performed according to Eq. (4). In addition, each ant that generated a solution in the non-dominated front at the current iteration is allowed to update pheromone matrices; τ, τ' and τ'' by laying down an amount equal to $1/l$, where l is the number of ants currently updating the pheromone trails. The non-dominated solutions generated along the run of the algorithm are kept in an external set at the end of iterations and the external set is updated.

Termination Condition: When the convergence condition is satisfied, the best solutions are selected according to the *Pareto* sense. In this study, at the end of iterations, non-dominated solutions found so far are kept. After the pre-determined maximum of iterations, if the algorithm cannot find a solution that dominates the previous non-dominated solutions, the ACO algorithm is stopped.

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

				Machining time		Machining cost	
Part types	Batch size	Operation	Tool option	Machine1	Machine 2	Machine1	Machine 2
1	20	1	1	9	9	10	11
			2	8	8	13	23
		2	1	7	7	21	23
			2	9	7	18	34
2	20	1	1	10	7	12	34
			2	9	7	19	23
		2	1	8	10	56	12
			2	9	9	12	11

Table 2: Details of machines

Machine	Set-up cost	Available machine time	Magazine capacity
1	250	480	2
2	280	480	2

Table 3: Details of tools

Tool	Tool life	Tool size
1	400	1
2	380	1

Table 4: Material handling cost between machines

Machine	1	2
1	1	10
2	10	1

Table 5: Results of solving the problem by the proposed ACO algorithm

	Route of traveling				Objectives		
Ants	First step	Second step	Third step	Fourth step	Machining cost	Material handling cost	Setup cost
ant 1	1,1,1,1	2,1,1,1	2,2,2,2	1,2,2,2	1340	400	530
ant 2*	2,1,2,2	1,1,1,1	2,2,2,2	1,2,1,1	1300	40	530
ant 3	2,1,2,1	1,1,2,1	1,2,1,2	2,2,1,2	1500	400	530
ant 4	2,1,2,1	1,1,1,2	1,2,1,2	2,2,2,1	1540	40	530
ant 5	1,1,2,2	2,1,2,2	1,2,1,1	2,2,1,1	2460	400	530
ant 6*	1,1,2,1	1,2,1,2	2,1,1,2	2,2,2,1	1200	400	530
ant 7	1,1,2,2	1,2,2,2	2,1,1,1	2,2,1,1	2500	40	530

* Ants that represent non-dominated solutions

Numerical Example and Computational Results: The proposed ACO algorithm 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, the problem of machine-tool selection and operation allocation is solved by considering the tool life and tool size of each tool and magazine capacity of each machine. In this section, the result of solving a randomly generated problem with two multi-functional machines and three tools is illustrated. 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.

The results of solving this problem by the proposed ACO are represented in Table 5. This table contains details of trips of ants (i.e., the nods that ant chooses according to the algorithm) that can represent feasible solutions with the minimum machining cost, material handling cost and setup cost for each solution. These results are obtained after running the algorithm with 50 ants. The pheromone evaporation rate is considered as 0.9 and the algorithm stopped after 50 iterations without finding any non-dominated solution that dominate non-dominated ones in the external set.

COCLUSION

This paper has considered a kind of an assignment problem with machine-tool selection and operation allocation in a flexible manufacturing system (FMS). The machining cost, material handling cost and setup cost are three significant objectives that should be minimized. This multi-objective problem has been solved by the ant colony optimization (ACO) algorithm proposed in this study. This paper has also considered the precedence relationship between operations and real constraints, such as tool life, tool size, machine available, ant magazine capacity of each machine. The complexity of the problem has been determined by the number of machines, tools and orders. If the complexity is increased, the computational time may be increased. The proposed algorithm has been able to produce a set of non-dominated solutions for the decision maker in a single run of the proposed ACO algorithm. The decision maker has been able to select a better option for producing operations with considering the limitations and existing equipment.

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