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Genetic Algorithm for Solving Mobile Robot Scheduling Problem in Flexible Manufacturing Environment

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Abstract: The scheduling genuinely a complex process, aimed at optimizing operational activities in pursuit of one or more objectives by leveraging production data which may include previous schedules. The scheduling problem in Flexible Manufacturing System (FMS) is commonly categorized as Nondeterministic Polynomial (NP)-hard combinatorial optimization problems and it remains as an endure problem to industrial practitioners and researchers. As part of real production scheduling, once one task is finished processing on a machine, transportation equipment such as mobile robot transports the completed task to the next machine. The problem of scheduling mobile robot in FMS pertains to the task allocation process for the robots, considering the transportation costs and the time spent to complete all operations. In recent years, Genetic Algorithm (GA) has been a remarkably effective search algorithm for solving a wide range of scheduling problems in a manner that achieves near-optimal solutions. This paper presents the metaheuristic techniques, specifically genetic algorithm, to address the NP-hard scheduling problem of two identical mobile robots in Job-Shop FMS environment. The algorithm is developed with the aim of finding feasible solutions to the integrated problem by minimizing the amount of time it takes to finish all tasks, commonly referred to as makespan. The performance of GA is evaluated with some numerical experiments which is executed via Matlab software. The scheduling results shows that the developed GA able to obtained the near-optimal solution of minimal makespan and converge within a short period of time.

Keywords: Genetic algorithm, scheduling, optimization, flexible manufacturing.

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1. INTRODUCTION

The Flexible Manufacturing System (FMS) has been prominently recognized in recent years as one of the major themes that have promising characteristics such as some sort of responsiveness and ability to change more promptly and effectively than in the past [1]. In general, the FMS is customary to be highly automated production system that has a capable of producing a wide variety of parts by utilizing the same equipment and control system. An optimal utilization and scheduling of the available resources and equipment are essential for exploiting the automation to the fullest potential. Scheduling is basically the allocation of resources, i.e., machines, robots and processing units, over the specified time to execute a predetermined collection of tasks [2].

In general, jobs or machines scheduling is generally the only topic covered in scheduling literature, i.e., parallel machine [3], single machine [4], [5], and job shop [6]. It is typically assumed in conventional machine scheduling models that material handling systems are always available and ready to move parts at any time should a need arise [7], and therefore, no consideration is given to the material handling or transportation times in the scheduling process. Real-world production environments, however, require the transportation of tasks between machines. Mobile robots are often implemented and tested as their transport vehicles that begins with a few or even just one mobile robot, commonly for small to large-sized manufacturing facilities.

In conjunction with real production scheduling, once one task is finished processing on a machine, material handling devices such as mobile robot, transports the completed task to the next machine. Indeed, any parts or tasks in a manufacturing system usually visit distinct machines for specific operations, resulting in the demand for material handling devices such as mobile robots to move and transfer parts between machines [8]. Thereby, scheduling mobile robot should be regarded as equally important as scheduling the machines in FMS and should be taken into account concurrently for the actual evaluation of cycle time. Manufacturing systems with integrated mobile robots serving as vehicles for transportations can significantly profit from their optimal scheduling. The scheduling genuinely a complex process, aimed at optimizing operational activities in pursuit of one or more objectives by leveraging production data which may include previous schedules.

In FMS, the problem of scheduling in is commonly categorized as NP-hard combinatorial optimization problems and it remains as an endure problem to industrial practitioners and researchers. These facts lead to the numerous researchers have been analysed the mobile robot integration and scheduling within the manufacturing industry. There are two NP-hard problems involved in this problem. Those are job-shop scheduling and vehicle scheduling problems, similarly to the problem of pick-up and delivery from one location to another. There is no denying the complexities in solving the related problem and this is the primary reason why most research endeavours on this area have focused on heuristic/metaheuristic approaches for solving the problem efficiently. This is due to the fact that solving NP-hard problems often requires exponential computation time, and identifying whether the solution has reached its real optimality is difficult [9],[10]. In the case of incomplete or imperfect information is present and computation capacity is limited, the new heuristic may execute a satisfactory result to an optimization problem since it is more practical in finding a nearly ideal and reasonable solution within a marginal period of time [11].

There are related literatures on several techniques to solve the mobile robot scheduling in FMS environment using metaheuristics approaches including genetic algorithm [12], [13], [14], hybrid metaheuristic [15], swarm intelligence-based optimization algorithms [16], [17] and artificial intelligence based approaches [18], [19]. Among these methods, genetic algorithm (GA) is a remarkably applicable search algorithm that exploits the past performance of former solutions by impersonating the nature of the evolutionary process, has been employed for developing a heuristic to permute the simultaneous jobs – mobile robot scheduling problems towards finding near-optimal solutions such as reported in [8], [20], [21], [22]. This is primarily attributed to its specialization in focusing on a specific area of solution instead of searching across the entire solution space, resulting in a nearly optimal solution being attainable much faster [11].

This article presents the application of GA to solve the integrated scheduling problem in FMS environment. The issue is featured with scheduling a job-shop and two identical mobile robots in a given FMS environment where such problems fall under the category of NP-hard combinational problems. A criterion of performance is the reduction of the makespan to a minimum. In essence, the goal of this research is to determine the optimal schedule of the order of tasks' execution to be assigned to dual mobile robot for transportation of jobs in FMS environment.

2. METHODOLOGY

2.1 Problem Formulation

In general, the FMS encompasses diverse tasks (or jobs) with multiple operations being performed on a number of machines and mobile robots. There are basically three functional areas in the FMS design layout: four different machines (or workstations), a loading/unloading (L/U) station and a charging station, with two identical mobile robots to perform related transportation tasks.

Each job should be processed by machines which may require several machines or one machine in each of the stages. Consequently, jobs may be processed on one of the machines at each stage of production and may visit one or more stages of production throughout the course of the process, resulting in different routes of the process for each job. Once the job is started, each operation must be completed without interruption, i.e., no preemption. The L/U station serves as the hub for distributing and collecting components. Transportation tasks between the machines are accomplished by mobile robots. At any given time, each robot is limited to carry a maximum of one job. At the start of the production process, these robots are always stationed at the L/U machine. Each mobile robot can execute a range of actions concurrently, including an "empty trip" when the robot travels to a machine for necessary job pickup after completing the machining of the current operation. Additionally, there's the "loaded trip" by which the robot transports the job to the machine where the next operation is scheduled to be executed.

In the context of a given FMS environment, where machines are fixed according to standard FMS layouts, the objective of the outlined scheduling problem is to achieve an efficient job processing and transportation costs of mobile robots. This is done with the overarching goal of minimizing the makespan i.e., the total time needed for the completion of all jobs. The layouts of machine locations which shows the travelling times of mobile robots between the machines adopted from [23], [24], are deployed for the computer experiments in this paper. Table 1 presents the machine-to-machine distances or mobile robot travel time matrix from machine-to-machine while the demonstration of machine locations and mobile robot flow paths in FMS layout can refer to Fig. 1. As well, the problem instance that comprises of 5 jobs, 13 operations and 4 machines is generated as shown in Table 2 for the use of illustrating the application of GA.

Table 1. Travel time matrix

To From	L/U	M1	M2	M3	M4
L/U	0	4	6	8	6
M1	6	0	2	4	2
M2	8	12	0	2	4
M3	6	10	12	0	2
M4	4	8	10	12	0

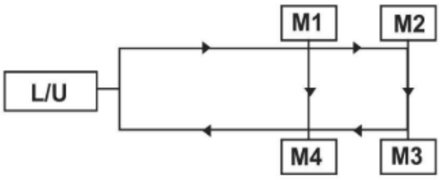

Figure 1. FMS Layout

Table 2. Job reference for an example FMS scheduling

Ref. Data	Ref. No.												
Jobs/Tasks	1			2			3			4		5	
Operations	1	2	3	1	2	3	1	2	3	1	2	1	2
Machines	1	2	4	1	3	2	3	4	1	4	2	3	1
Processing Times	8	16	12	20	10	18	12	8	15	14	18	10	15
Job No. Representations	1	2	3	4	5	6	7	8	9	10	11	12	13

2.2 Fitness Function

In order to schedule job-shops (or machines) and mobile robots, a mathematical model is necessary. Here, the optimization model for the related objective (fitness) functions is mathematically demonstrated as follows:
Fitness Function,

$$f = min\, C_{max} \tag{1}$$

The objective is to determine a feasible schedule that minimizes the makespan, C_{max}, which is denoted as the maximum value among the completion times of each job, C_i, for i is ranges from 1 to n where n represents the number of scheduled jobs. This can be described as follows,

$$C_{max} = \text{Max}\,(C_i, \dots . C_n) \tag{2}$$

The makespan is computed based on the total operation completion time which is defined by the following equations,
Operation completion time,

$$T_{ij} = t_{mm'} + t'_{mm'} \tag{3}$$

$$O_{ij} = T_{ij} + P_{ij} \tag{4}$$

Total completion time,

$$C_i = \sum O_{ij} \tag{5}$$

where, i = job/task
j = operation
T_{ij} = mobile robot's transportation/traveling time
P_{ij} = processing times

Due to the fact that scheduling is a combinatorial problem, it is necessary to choose a method that is appropriate to optimize the problem.

In this article, the problem under study is focused on the flexible manufacturing environment, wherein the material transport system relies on a platform of mobile robots. The integrated scheduling problem bears a significant resemblance to the problem of pick-up and drop-off jobs within a given environment and, certainly, it has been classified as NP-hard problems, for which a polynomial-time solution is highly unlikely expected to exist [25]. Therefore, this research attempts to employ genetic algorithm for optimizing the feasible schedule with minimal makespan. The algorithm's performance will be examined based on travelling time matrix and the reference job dataset as presented in Table 1 and 2, respectively.

2.3 Genetic Algorithm

The application of GA to the field of computer science was formerly invented by John Holland in the 1970s [11]. It requires only pertinent encoding scheme and a fitness (objective) function that measures the quality of each encoded individual, which is called a chromosome. This algorithm comprises three distinct phases within its search mechanism: initiation of appropriate chromosome (or solution) representations, evaluation of fitness, and genetic operators i.e., selection, crossover, and mutation. Fig. 2 illustrates the basic GA procedures that were applied in this study.

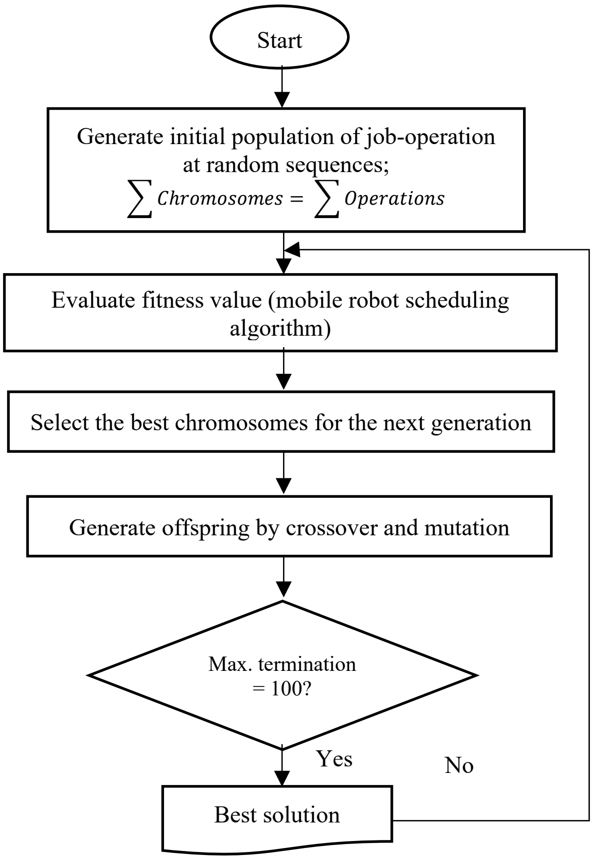

Figure 2. Procedures of designing GA

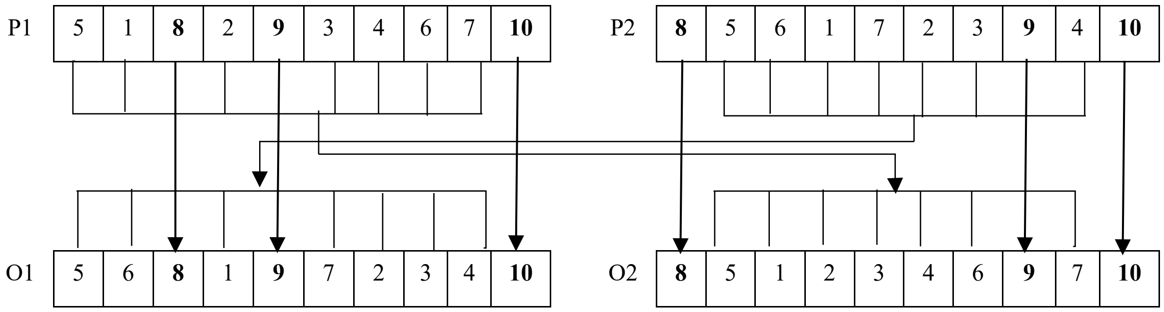

Figure 3. The basic procedure of job-based POX strategy in crossover process

The related steps of the GA in solving the described scheduling problem can be summarized as follows,

1. Generate an initial population of chromosomes that signifies the operation sequence. Each operation represents the processing of a particular task on a specific machine and is expressed by the job representation integer number, as refer to Table 2. The individual chromosome's length corresponds to the cumulative count of operations across all jobs.
2. Chromosomes are evaluated for their fitness (or objective) value of makespan (Eq. 1 – 4), aligned with the operation sequence and mobile robot assignment.
3. Select individuals with comparatively higher fitness from the current population. Those high-fit individuals will have a higher likelihood of being chosen to take part in the reproduction process as parent chromosomes.
4. In crossover operation, copy and exchange the selected job-operation numbers contained in parent chromosomes to produce the new offspring.
5. Fill in the remaining positions of the offspring by the unselected job-operations numbers based on their order in parent chromosomes.
6. After crossover, some offspring undergo operation shift mutation by inverting the substring between two randomly selected positions within a chromosome.
7. Repeat steps 4 – 7 until the order of crossover rate (P_c) or mutation rate (P_m) are completed.
8. Substitute the previous population of chromosomes with the newly generated one.
9. Sort the combined parent and child chromosomes based on fitness function cost and the best solution is returned in the current population.
10. Proceed back to step 2 and iterate until the termination criteria is satisfied (i.e., the number of generations reach its maximum, G_{max}).

This developed GA coding structure utilizes the operations-based coding which is comparable to be utilized in the flexible job shop scheduling [26],[27], with no information of transportation included in the chromosome representation of GA except in the fitness evaluation. Furthermore, the implementation of GA in this study has employed the modified crossover method called as POX (precedence operation crossover) strategy in order to complete the crossover process of operation-based sequence strings. The typical process of this strategy can be exemplified as in the Figure 3.

From Figure 3, the POX-based process is constructed to guarantee that precedence constraints are never violated. Basically, a job (or task) is randomly chosen from each parent chromosome, denotes as P1 and P2. The matched operations are then marked and directly copied into the corresponding positions of their respective offspring, denoted as O1 and O2. For instance, let's consider task number 3 being chosen, which encompasses a total of 3 operation numbers expressed by job numbers 8, 9, and 10. This can be illustrated as shown in Figure 4 below.

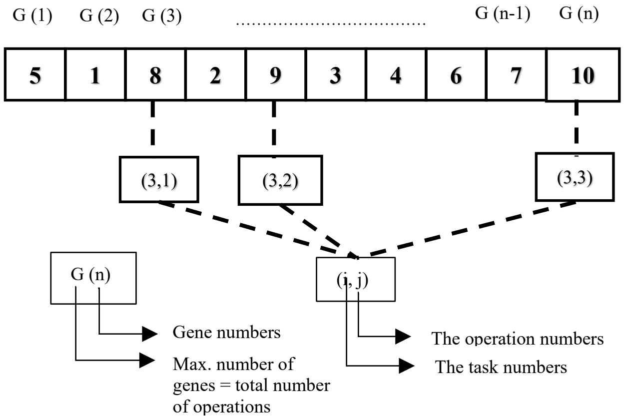

Figure 4. A feasible chromosome representation structure

In the case of direct copying, the positions of each respective operation are not altered during the crossover process, so that the precedence relationship will remain intact. Subsequently, the vacant positions of the offspring 1 (O1) is filled by the number of unselected jobs based on their appearance order in parent 2 (P2), and vice versa.

Noted that, jobs are scheduled according to the operation sequence derived by GA. Based on the sequence, each of mobile robot will be assigned to handle the transportation tasks using the heuristic within the fitness evaluation module. In brief, a scheduling list on each chromosome contains a sequence of locations which mobile robots can refer to when claiming their task. First scheduled operations in the chromosome sequence will find the earliest available mobile robot to reach the machine or L/U station for picking up the job, and then moves to the subsequent machine as determined by the job's operation sequence. The assignment of mobile robots is formulated based on available heuristics i.e., the earliest/nearest rule [8],[28]. It consistently checks the status of the job and mobile robot, calculates the availability of the robot at the necessary demand point, and then allocates tasks accordingly.

3. COMPUTATIONAL RESULTS

In this section, the performance results of the developed GA in solving the studied problem are presented. Considering the integrated scheduling algorithm in FMS environment, the developed algorithm aimed to search for the best solution on the minimal makespan. The corresponding layout and reference dataset as in Table 1 and 2, were used in the experiment to examine the searching performances of the GA. This algorithm was programmed and run with MATLAB 2022b software. The best selected on parameters used in computer experimental calculations for the genetic algorithm are described in Table 3.

Table 2. Parameter used in computer experiments

Parameter	**Value**
Population size	100
Maximum genetic generation	100
Crossover probability	0.4
Mutation probability	0.08

In corresponds to FMS layout (Fig. 1), the relationship curves between the best (minimum), worst (maximum) and mean of individuals of the GA is illustrated in Figure 4. The curve of the best solution shows the convergence at a faster rate. The developed algorithm capable of finding the minimal makespan with the best value of 86 and the computation time in this case was merely a few seconds. In view of the gap between the curves of maximum and minimum values, there appears to be substantial exploration activity taking place in search of the best solutions.

The complete scheduling results obtained from the optimization are presented in Table 4, by which the processing sequence of operations is determined and each of mobile robots are assigned to transport the jobs. In addition, Figure 5 graphically depicts the best solution of the respective problem that is obtained from the optimized scheduling results table. This Gantt chart representation is prepared for a clear understanding of the developed schedule based on the start and completion time of processing operations and processing times on machines as well as the schedules of mobile robots. Note that, the time intervals of each mobile robot (MR) to complete the transportation of its assigned jobs/operations to the destination machines, comprising both the empty trip (unloading) and loaded trip phases, are visually represented using dark and light gray colored bars.

Table 3. The scheduling results

	Order sequences	Makespan
Operation sequence	1 – 10 – 4 – 7 – 12 – 2 – 8 – 5 – 11 – 9 – 13 – 6 – 3	86
MR Assignment	1 – 2 – 1 – 2 – 2 – 1 – 2 – 2 – 1 – 2 – 2 – 1 – 1	

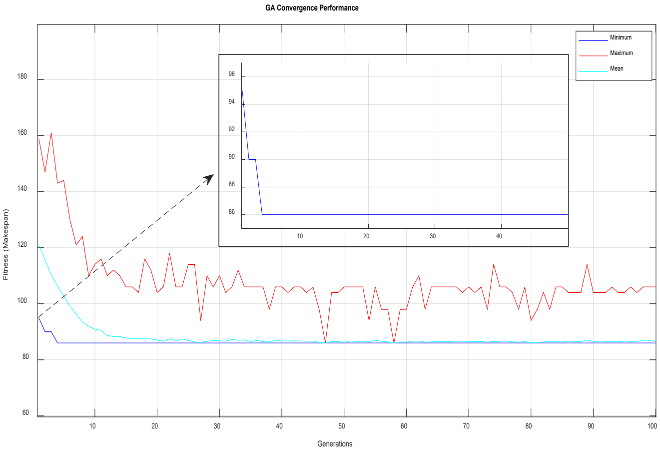

Figure 4. Performance of the developed GA

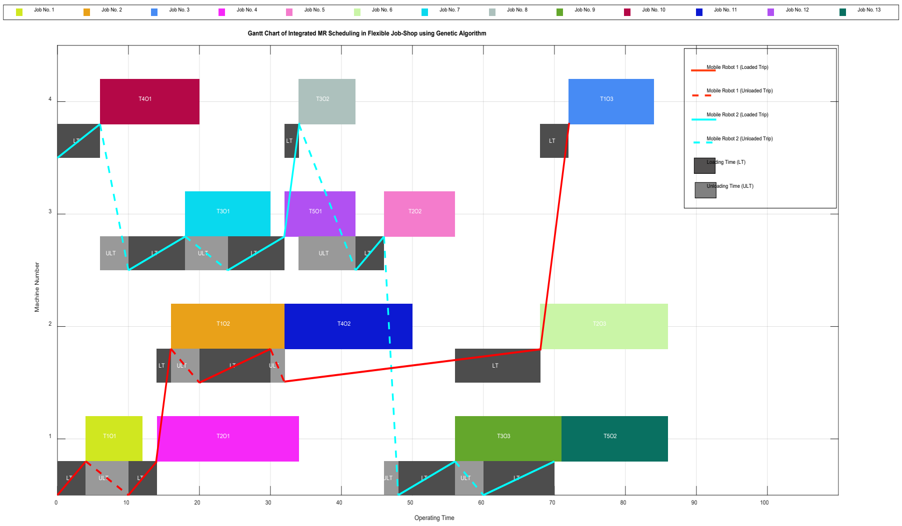

Figure 5. The Gantt Chart of the integrated scheduling results

4. CONCLUSION

In this paper, the integrated scheduling problem of mobile robots and job operations within the context of an FMS environment was addressed. It holds significance to establish the sequence in which job operations should be processed on specific machines and transported by mobile robots in order to acquire the tasks completion in the shortest possible time. A metaheuristic approach, genetic algorithm, was developed to search the best solutions for the studied problem with a single objective: minimizing the time necessary to finish all assigned tasks (or makespan) to be selected as performance criterion in the optimization. The numerical experiment is conducted based on the commonly used job dataset and FMS layout. The generated results demonstrated the effectiveness of the developed algorithm that is capable of finding the best solution at a faster convergence speed. For further research, the developed algorithm can be evaluated in context with other competing approaches and a comparative analysis of the obtained solutions could be performed for the purpose of performance evaluation in solving the specified problem.

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