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SIMULATION-BASED OPTIMIZATION METHOD FOR RELEASE CONTROL OF A RE-ENTRANT MANUFACTURING SYSTEM

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ABSTRACT

Release control plays an important role in the operational performance of manufacturing systems. In this research, a simulation-based optimization method is proposed for the release control of a re-entrant manufacturing system. First, a simulation system is developed for a real re-entrant job shop. Secondly, a genetic algorithm, Memetic-climbing algorithm and Memetic-SA algorithm are designed to generate a near-optimal release control solution, respectively. Finally, the proposed methods are validated and verified by simulations. The simulation results show that the simulation-based optimization method has the ability to obtain near-optimal release control solutions in a reasonable time.

1 INTRODUCTION

Release control is one of the most important component of complex manufacturing systems. It decides when and how many raw materials (jobs) will be input into a production line. Its objective is to fully use the capacity of the production line and meet the due date requirements of the customers.

The existing research on release control could be divided into static release control and dynamic release control. The former makes input decisions according to the due dates and average cycle times of the products with little or no consideration on the fluctuating capacity or workload of the production system. If the capacity can't be estimated correctly, the high amount of WIP (Work-in-Process, i.e., lots in the production line) and longer cycle time may be expected. The latter decides the input rate according to the amount of WIP or the workload in the production line and can be expected to have better performance, such as less queue time, shorter cycle times and less tardiness. For example, (Qi et al. 2009) presented a workload limited release methodology (WIPLCtrl) for the overall shop floor, which behavior was analyzed using the Markov process model of a transfer line system to observe its potential advantage relative to the conventional measure of system workload using the WIP level. (Phan et al. 2009) proposed a continuous time Workload Control (WLC) concept based on the workload norms suitable for the needs of make-to-order job shops. (Savla and Frazzoli 2010) designed a task release control policies that can stabilize the dynamical queue for the maximum possible arrival rate, where the queue was said to be stable if the number of tasks awaiting service does not grow unbounded over time. (Wang and Chen 2009) proposed a theory-of-constraint based release policy on the basis of system bottleneck being detected and applied it to hot orders.

In this paper, we propose a simulation-based optimization method for release control of a real re-entrant production line. The simulation results show that this method can improve the makespan performance issue effectively.

2 DESCRIPTION OF THE PROBLEM

The re-entrant production line discussed in this paper is shown in Table 1. It has 11 stations and 2 machines. The main difference between stations and machines is that the former must be finished by operators and the latter can be finished automatically by themselves. There are 4 products (Product 1, 2, 3 and 4) processed on it at the same time. The complexities of this production line are as follows.

Table 1: Parameters of the Re-entrant Production Line

No.	Operator	Working Style	Processing Style	Re-entrant Number by Products 1-4
Station 1	1	Manual operation	Piece or batch processing without or with capacity limit	(5,4,4,4)
Station 2	2	Manual operation	Batch processing without capacity limit	(1,1,1,1)
Station 3	3	Manual operation	Batch processing with capacity limit	(1,1,1,1)
Station 4	4	Manual operation	Piece processing	(1,0,2,2)
Station 5	5,6	Manual operation	Piece or batch processing with capacity limit	(3,3,0,3)
Station 6	7,8	Manual operation	Batch processing with capacity limit	(1,0,2,2)
Station 7	9	Manual operation	Batch processing without capacity limit	(1,1,0,1)
Station 8	9	Manual operation	Batch processing without capacity limit	(0,0,0,1)
Station 9	10	Manual operation	Piece or batch processing without capacity limit	(3,3,2,4)
Station 10	10	Manual operation	Piece or batch processing with capacity limit	(2,2,4,2)
Station 11	10	Manual operation	Piece processing	(0,1,2,1)
Station 12	11,12	Manual operation	Batch processing without capacity limit	(1,1,1,1)
Station 13	13	Manual operation	Piece or batch processing without capacity limit	(2,1,1,1)
Machine 1	/	Auto-operation	Batch processing without capacity limit	(1,0,2,1)
Machine 2	/	Auto-operation	Batch processing without capacity limit	(1,1,0,1)

(1) **Mix processing style:** some stations have mix-processing style, e.g., Stations 1, 5, 9, 10 and 13. It is difficult to decide how to scheduling the jobs with different processing requirements.
(2) **Re-entrant processing flows:** Stations 1, 4, 5, 6, 9, 19, 12 and 13 are all re-visit by Products 1, 2, 3 or 4. The re-entrant processing flows make their scheduling difficult.
(3) **Coupling of operators and stations:** one operator may manage more than one station (such as Stations 7 and 8, Stations 9, 10 and 11). These stations cannot be operated simultaneously.
(4) **Processing steps with time limit:** some processing steps have time limits. For example, after finishing of step 15 of product 1, its step 18 should be finished in one hour.

The above difficulties make it difficult to optimize the operational performance of the re-entrant production line with proper scheduling methods. Some research also demonstrates that the release control takes a more important role on the operational performance of a re-entrant system than the scheduling methods. As a result, we attempt to find an optimal or near-optimal release control plan to optimize its operational performance, while selecting first-in-first-out (FIFO) rule as the scheduling rule for the piece processing stations/machines and random batch size (RBS) rule for batch processing stations.

In addition, the difference between this production line with common re-entrant systems is that a number of jobs are not released to the production line unless the former released jobs are finished by the production line. Therefore the concerned operational performance is the makespan issue.

3 SIMULATION SYSTEM

We use eM-Plant software from the UGS Company, an object oriented graphical modeling and simulation software, to build the simulation system of the re-entrant system introduced in Section 2. Due to the existence of mix-processing stations, such as Stations 1, 5, 9 and 10, we set a recipe on a station as a machine in the simulation platform. To avoid more than one recipes on a station being implemented simultaneously, we design a "lock" mechanism, i.e., the machines in the simulation model representing different recipes on the same station of the actual system cannot be at working state at the same time to guarantee the feasibility of the simulation model. In addition, the transportation time of the jobs between the machines is neglected. The framework of the simulation system is composed of database, dynamic modeling and scheduling rules.

The database stores the information related to the real production line (such as its machines, the processing flows of its products and the jobs to be scheduled) and scheduling plans (dataset of the start time and finish time of a step of a job on a machine) generated by simulations that can be used to evaluate the performance of a dispatching rule or a release control strategy or guide the operations of the production line.

Dynamic modeling is to build a simulation model of a production line with related data. Its process is to upload data, handle data, and finally organize data into a simulation model with a specified structure. With this technology, simulation models of different production lines can be built easily with the same style.

Scheduling rules include dispatching rules and release control strategies. The former determines the processing order of the queued jobs before a machine. The latter decides the time, volume and order of the jobs released to the production line. According to the processing style of the machines, there are two dispatching rules applied to the simulation model, i.e., FIFO for the piece processing style and RBS for batch processing style. The release control strategy in this paper is to determine the release order of the jobs with a given number. We consider a simulation-based optimization method with three different methods (i.e., a genetic algorithm, a Memetic-climbing algorithm and a Memetic-simulated annealing algorithm) that will be discussed detailed in next section.

4 SIMULATION-BASED OPTIMIZATION METHOD FOR RELEASE CONTROL

Here we give a simulation-based optimization method with three different intelligent algorithms (genetic algorithm, Memetic-climbing algorithm and Memetic-simulated annealing algorithm) to determine the release control sequences.

The workflows to obtain an optimal release plan by using a genetic algorithm, Memetic-climbing (M-C) algorithm and Memetic-simulated annealing (M-S) algorithm, respectively, are shown in Figure 1.

(1) The workflow of genetic algorithm (GA)

The workflow of genetic algorithm is as follows.

Step 1: Generate a population composed of a number of chromosomes generated randomly. The encoding scheme is to generate a random sequence of the jobs as chromosome.

Step 2: Compute the fitness of each chromosome. That is, take each chromosome as a release plan to run the simulations to obtain the makespan performance of the re-entrant system taken as its fitness.

Step 3: Determine whether the terminal condition is satisfied. Here it is set to the maximum iterations. If yes, go to step 6.

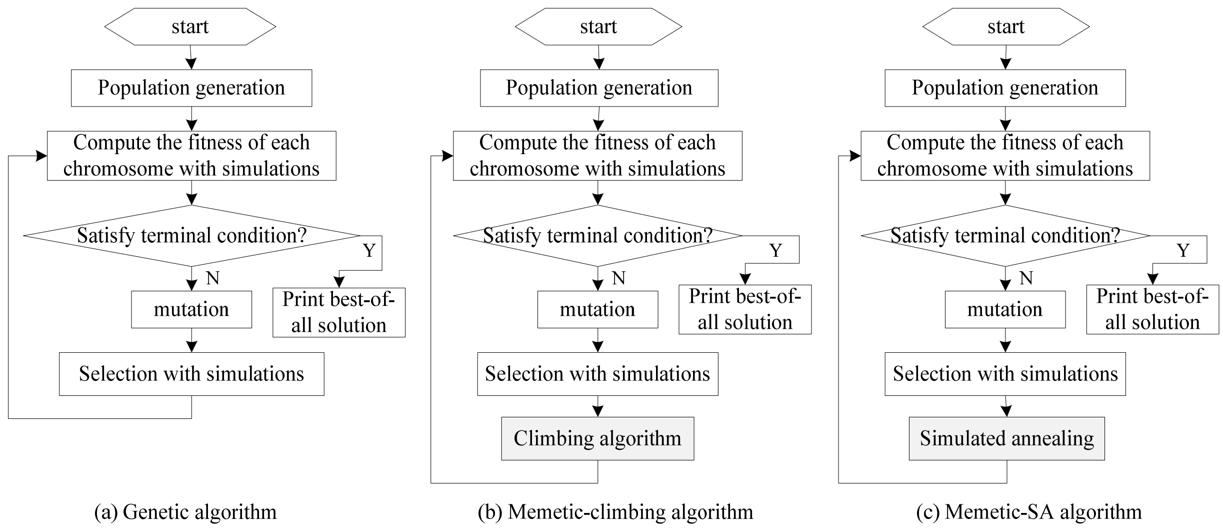

Figure 1: Workflows to obtain an optimal release plan

Step 4: Implement the mutation operation on the chromosomes in the population. Here we only consider mutation to guarantee the generated off-spring chromosomes to be feasible solutions. The mutation operation is to randomly select two cross bits to switch their genes with a mutation probability.

Step 5: Compute the fitness of the off-springs by simulations, similar to step 2. Then select the same number of chromosomes from the parents and off-springs as that of initial population to compose a population of next generation by using a roulette selection method. It means the population size will not be changed during the search process. Go to Step 3.

Step 6: Print the best-of-all chromosome as the optimal solution.

(2) The workflow of the Memetic-climbing (M-C) algorithm

The workflow of the M-C algorithm only adds a climbing algorithm to the above genetic algorithm. The climbing algorithm is a neighborhood search method. In this paper, its main idea is as follows. For each chromosome in the population obtained by the selection operation, build a neighbor space with 2-opt method. Compare the fitness of its neighbor nodes with its fitness by simulations to find a best one instead of it. Then we obtain a new population with higher average fitness.

(3) The workflow of the Memetic-simulated annealing (M-S) algorithm

The workflow of the M-S algorithm only adds a simulated annealing (SA) algorithm to the above genetic algorithm. SA is a meta-heuristic algorithm pursuing global optimization. In this paper, its main idea is as follows. For each chromosome in the population obtained by the selection operation, build a neighbor space with 2-opt method. Compare the fitness of its neighbor nodes with its fitness by simulations to find a best one instead of it or accept a near-optimal solution with a probability.

(4) Simulation results

The iterations of GA, M-C and M-S are set to 15, 10 for GA and 5 for climbing algorithm, and 10 for GA and 5 for simulated annealing algorithm, respectively. They have the same population size with 100 chromosomes. The mutation probability is set to 0.1. The initial temperature and temperature drop coefficient of SA is 100 and 0.8, respectively. The number of jobs to be scheduled is 200. So the length of chromosomes is 200, too. The objective is to minimize the makespan of the jobs. The simulation results are shown in Figure 2. The simulation results show that the average difference of the best fitness and the worst fitness is about 5%. So the simulation-based optimization method can achieve the expected performance. M-S can obtain better performance comparing to M-C and GA. In addition, M-S can obtain a near-optimal solution more quickly, too.

Then we consider the impacts of population size, mutation probability and maximum iterations on the performance. The simulation results are shown in Figure 3.

When the population size is less than 100, the makespan performance of all algorithms are a little worse. However, the search efficiencies of M-C and M-S are better than GA. When the population size is

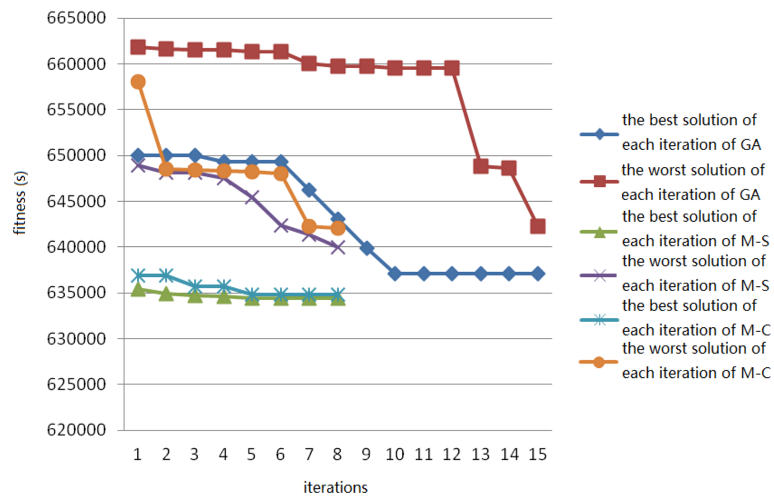

Figure 2: Simulation results of GA, M-C and M-SA

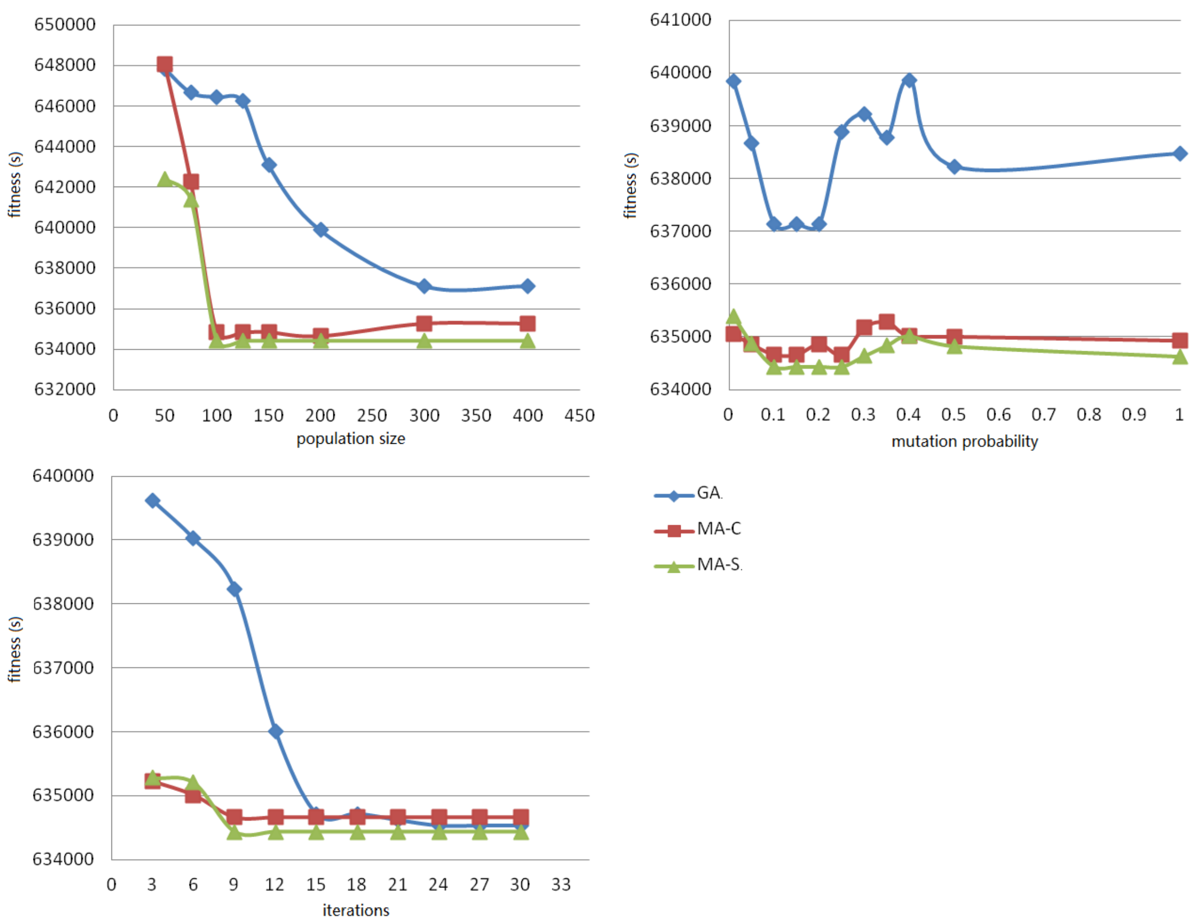

Figure 3: Impacts of population size, mutation probability and maximum iterations on the performance

bigger than 100, the fitness of M-C and M-S is little changed. It means they can obtain optimal solutions with less number of chromosomes. However, GA is more dependent on the population size.

The change of mutation probability has less impact on the performance of M-C and M-S. It has serious impact on GA. The better selection on mutation probability for GA is between 0.1 to 0.25. It means M-C and M-S are more robust than GA.

M-C and M-S obtain the best solution at the 9th iteration. GA obtains its best solution at the 24th iteration. However, M-C is more easier to be trapped into local optimum comparing to M-S. So the selection of the local search algorithms is very important to improve the performance of a Memetic algorithm.

5 CONCLUSIONS

In this paper, we propose a simulation-based optimization method with three different intelligent algorithms to obtain a optimal release plan for a real re-entrant system. The simulation results show that Memetic algorithms can obtain better performance than a simple meta-heuristic method by introducing local search. Our future work is to generate a large number of samples by using the method proposed in this paper and learn release knowledge from these samples to obtain high-speed near-optimal release decisions to meet the industrial requirements.

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