Best Dispatching Rule Analysis for Dynamic Scheduling Problem with Periodical Demand*

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***Abstract*— Dynamic scheduling can be used in scenarios in which jobs may arrive irregularly, and therefore, the schedule of jobs may need to be changed. In actuality, due to various reasons, demand for a service can suddenly change. In previous papers, various methods using genetic programming (GP) have been proposed. Using GP, an appropriate dispatching rule that determines the job sequence can be derived in a short amount of time, and derived rules are better than existing dispatching rules. However, the derived dispatching rules are not analyzed in previous papers. In this paper, dispatching rules that use GP are analyzed; the characteristics of the rules are described, and they are compared with previous dispatching rules.**

I. INTRODUCTION

Dynamic scheduling can be used in scenarios in which jobs may arrive irregularly, and therefore, the schedule of jobs may need to be changed. In actuality, due to various reasons, demand for a service can suddenly change. Regarding the schedule, the dispatching rules that determine the job order sequence are essential. In the static scheduling problem, only one optimal schedule is determined.

On the other hand, methods using genetic programming (GP) have been proposed [1], [2], [3], [4]. Using these GP techniques, an appropriate dispatching rule can be derived in a short amount of time, and derived rules are better than existing dispatching rules. However, the derived dispatching rules are not analyzed in previous papers. Therefore, it is necessary to analyze these rules to determine how similar they are to previous dispatching rules. In this paper, dispatching rules that use GP are analyzed; the characteristics of the rules are described, and they are compared with previous dispatching rules.

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II. DYNAMIC SCHEDULING PROBLEMS

A. Assumptions

Dynamic scheduling is a scheduling process in which, if a new job arrives before the current job is completed, the current schedule is reoptimised. Fig. 1 illustrates such a circumstance. The left of Fig. 1 shows the fixed schedule for the current jobs. And the right of Fig. 1 shows a case such that a new job J3 arrives and the modified schedule.

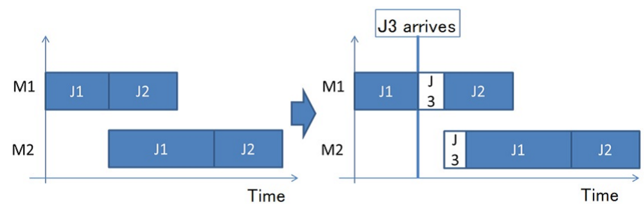

Fig. 1. Dynamic scheduling

The following assumptions are made in this paper:

- Job J_i has N_i operations, and jobs are processed from 1 to N_1 sequentially.
- Each machine cannot process multiple jobs in parallel.
- The job being processed cannot be stopped during processing.
- Job J_i can be started after time r_i.
- Job J_i has to be completed by the due date d_i.
- There is no priority among jobs.
- Jobs arrive periodically after jobs begin to be processed. However, there are different kinds of jobs.
- Rescheduling is done when 20% of the jobs remain. In this case, jobs that are being processed are NOT done and arriving jobs are considered.

One performance measure is the weighted sum of tardiness T_i, which represents the difference between the due date and the time at which the job was completed for J_i and a makespan $C_{\max}$, which is the time taken to finish all jobs. Note that these definitions were also used in previous papers [1], [2], [3], [4].

B. Dispatching rules

A dispatching rule determines the order in which jobs are processed. In this paper, the following rules are considered. **EDD** chooses the job with the soonest due date. **FCFS** chooses the job that arrives first. **SLACK** chooses the job with the shortest slack time, which is the amount of time until the due date. **ATC** considers the length of the waiting queue and the slack time. **SPT** chooses the job with the shortest processing time. **SRPT** chooses the job with the shortest remaining processing time. **CR+SPT** considers the remaining processing time and the due date. **(SL/RPN)+SPT** considers the number of remaining operations and the due date.

III. GENETIC PROGRAMMING MODEL

Genetic programming (GP) is a type of evolutionary computation method for the exploratory optimisation of structure data such as mathematical formulas that uses genes defined in a tree structure, and it is an extension of Genetic Algorithm (GA) [5]. In this paper, we consider three types of methods that use GP to analyze the effect of islands: (1) Island GP (IGP) [2], (2) Population selection GP (PsGP)[3], and (3) Population fluctuation GP (PfGP)[4].

In the IGP model, all individuals are divided into many populations called islands, and then a solution search is performed using GP. IGP performs solution searches in parallel, and an individual is selected randomly. In the PsGP model, populations related to the jobs' characteristics are prepared and processed by a suitable population of jobs. Additionally, individuals do not migrate to other islands. In the PfGP model, a framework in which the number of populations fluctuates is developed and a solution search is performed efficiently for any characteristics of new arriving jobs.

IV. NUMERICAL EXPERIMENTS

A. Experimental conditions

In the numerical experiments, regression analysis is used. In this analysis, the fitness values for the rule generated using GP and the dispatching rules given in section II are calculated. In this method, 10000 runs are performed, and then the correlation coefficient is calculated for each dispatching rule. Then, these values are compared to find the maximum value for all dispatching rules. If this value is higher than the threshold value θ, we can suppose that this dispatching rule is similar to the rule generated using GP.

For dynamic scheduling problems, a new set of jobs arrives when a time of $0.8C_{\max}$ has elapsed after the arrival of the previous set of jobs, and the number of arrivals of the new job group is 100. A random number determines the processing time of the operation, but changing the parameter that determines the maximum value in period 4 and the parameter that determines the delivery date of the job in period 3 causes the characteristics of the job group to change in period 12.

B. Results and discussion

The experimental results for 10 jobs and 10 operations are given in Table I. The numbers in bold indicate the highest value for each set of conditions. In this table, NEW means that a new dispatching rule for which the correlation coefficient for all dispatching rules is less than θ can be generated, and UD means that the correction coefficient is zero for all dispatching rules, i.e. the generated rule is undesirable.

TABLE I
EXPERIMENTAL RESULTS (10 JOBS, 10 OPERATIONS)

Model	θ	EDD	FCFS	SLACK	ATC	SPT
IGP	0	**43.91**	31.65	10.05	1.20	1.80
	0.5	**41.68**	28.82	8.52	0.65	0.28
	0.9	17.46	9.84	0.80	0.00	0.00
PsGP	0	28.97	**47.06**	5.11	1.34	2.50
	0.5	25.63	**42.15**	3.61	0.39	0.45
	0.9	10.75	19.12	0.13	0.00	0.00
PfGP	0	**41.09**	36.69	7.31	0.64	1.35
	0.5	**39.49**	34.16	6.43	0.46	0.32
	0.9	17.64	14.87	0.44	0.00	0.00
Model	θ	SRPT	CR+SPT	(SL/RPN)+SPT	NEW	UD
IGP	0	9.72	0.98	0.50	0.01	0.18
	0.5	9.33	0.35	0.49	9.70	0.18
	0.9	3.92	0.00	0.00	**67.80**	0.18
PsGP	0	13.16	0.69	0.50	0.01	0.66
	0.5	12.21	0.24	0.40	14.26	0.66
	0.9	7.45	0.00	0.00	**61.89**	0.66
PfGP	0	11.58	0.75	0.53	0.01	0.05
	0.5	11.27	0.30	0.47	7.05	0.05
	0.9	6.37	0.00	0.00	**60.63**	0.05

In Table I, if θ increases, the value of NEW also increases; however, the values of the other rules decrease. Note that UD remains the same regardless of the value of θ. We can claim that the EDD and FCFS rules are appropriate. These rules are simple compared to the other dispatching rules.

V. CONCLUSIONS AND REMARKS

This paper analyzes the dispatching rules generated by three kinds of GP methods: Island GP, Population selection GP, and Population fluctuation GP. The results show that the generated rules are similar to the EDD and FCFS rules, regardless of the models used and the value of θ, except for when θ is higher. If θ is higher, a new dispatching rule is generated.

The characteristics of generated dispatching rules have been made clear; however, the GP method should be improved to increase the performance of the generated rules. An analysis that consists of finding the characteristics of a new GP method represents future research work.

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