Applications of Dynamic Scheduling Technique to Space Related Problems ~ Some Case Studies

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Shinichi Nakasuka and Tetsujiro Ninomiya
Department of Aeronautics and Astronautics, University of Tokyo
Hongo 7, Bunkyo-ku, Tokyo 113, JAPAN
TEL: +81-3-3812-2111 ext.6590 FAX: +81-3-3818-7493
e-mail: nakasuka@space.t.u-tokyo.ac.jp

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ABSTRACT

The paper discusses the applications of "Dynamic Scheduling" technique, which has been invented for the scheduling of Flexible Manufacturing System, to two space related scheduling problems; operation scheduling of a future space transportation system, and resource allocation in a space system with limited resources such as space station or space shuttle.

DYNAMIC SCHEDULING

"Reactive Scheduling", in which the next operation to be performed is decided only when it is required, using a certain heuristic scheduling rule, has been widely utilized in manufacturing control or resource allocation of multiprocessor system. It has been pointed in many literatures that by employing sophisticated scheduling rules (called "dispatching or routing rules"), a schedule of some quality can easily be obtained with quite little computational load. This method is quite robust to the various changes and anomalies in the production lines, because the scheduling decisions are deferred until required. The weak point of this strategy is, however, that these rules only refer to local information for decision making, and so the performance of the generated schedule is sometimes much degraded in the global sense.

In the field of manufacturing control, "Dynamic Scheduling" has been proposed [1] to compensate for this shortcoming of the reactive scheduling. In this method, many scheduling rules are prepared beforehand, from which one is selected considering the instantaneous situations at each decision timing, such as machine status, buffer contents or current production requirements. Therefore, the scheduling decisions reflect more global information, which results in uniformly good scheduling performance in any line status or production requirements. For this objective, knowledge is required that predicts which rule is the best in a certain instantaneous situation, and machine learning has been utilized for acquiring such knowledge. For example, in [1], the relationships between the situation and the best rule is obtained in the form of decision trees.

SCHEDULING OF SPACE TRANSPORTATION SYSTEM

OTV Network and Its Scheduling

"OTV Network" has been proposed [2] as the low-cost, next generation space transportation infrastructure (Fig.1). This system is based on the space fuel stations (3 in Fig.1) and reusable OTVs (2 in Fig.1). The OTVs, dropping in at fuel stations for fuel supply on their way (C), carry out various missions such as satellite delivery (D), recovery or other satellite servicing. When one mission is completed, OTV nominally returns to the Low Earth Orbit (E), gets refurbished and waits for the next mission. This concept is much alike the truck

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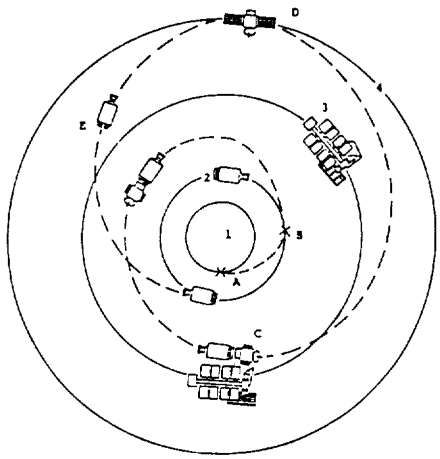

Figure 1. Transportation scenario of OTV Network

transportation system on the Earth such as trucks carry loads sometimes dropping in at gas stations.

For this OTV Network to work effectively and especially with low cost, various operations within the network must be thoughtfully scheduled so that the requirements as a transportation system (such as to deliver payloads by their due dates) can be satisfied while suppressing the total required cost as low as possible. The scheduling items include which payload to carry next with which OTV, which fuel station to use, which transfer trajectory to take, or what the OTV should do when its current mission is finished, etc. The scheduler must also deal with various anomalies such as failures of certain elements of the network system, urgent missions or mission changes.

Proposed Intelligent Scheduler

To meet these requirements, we have developed an intelligent scheduling system based on cooperation of distributed decision makers [3]. The decision making activities are assigned to several intelligent managers implemented in the computer, and they cooperatively perform decision making based on their own heuristic knowledge or the results of internal simulations where their knowledge is insufficient. Principally, the schedule is made in a so called reactive scheduling fashion, that is, the network operations are simulated according to a time line, and at each decision point one decision candidate is selected. The managers drive the lower level scheduler to predict future effects of each decision candidate, and with this predicted performance data they can pin-point one best candidate at each decision point. Reactive scheduling method is employed at the lower level for quickly simulating the optimal decision sequence to obtain such performance data.

Application of Dynamic Scheduling

The dynamic scheduling is applied to the reactive scheduling part of the proposed scheduling system, and the relationships between the situation and the best rule are obtained by machine learning using Neural Network with the back propagation algorithm. The employed Neural Network has three layers each of which has 18, 20, and 12 nodes. The data input into the input layer is a set of attributes representing the instantaneous situation of the OTV Network at the decision timing (such as the number of waiting satellites at each station), and the output layer dictates the most suitable decision rule from among 12 candidate scheduling rules (such as Minimum Slack Time Rule) which seem effective in deciding the next actions. For the back propagation learning, total 3630 data as to "18 attributes vs. the best rule" are generated by searching for the best rules exhaustively in various situation settings of the OTV Network, which have been utilized as the teaching signal for the Neural Network.

Some Simulation Results

In order to evaluate the effects of the employed scheduling architecture, the following three type schedulers are compared;

Sch.1) Single level, reactive scheduler alone

Sch.2) Proposed hierarchical scheduler without dynamic scheduling

Sch.3) Proposed hierarchical scheduler with dynamic scheduling

Table 1 summarizes the typical performance and required computation time for these schedulers. It indicates that by employing the hierarchical scheduling architecture, due date violations can be mitigated without too much additional fuel consumption. In addition, dynamic scheduling further improves the performance in both of tardiness and fuel consumption, and as a result the proposed scheduler can suppress the maximum and mean tardiness as small as one sixth of the reactive scheduler even with less fuel. The weak point of the proposed scheduler is its large computational load (about 10 times of the reactive scheduler case), but it can be said that the combinatorial explosion is suppressed to some extent.

Table 1. Summary of Scheduling Performance

Scheduler	Sch.1	Sch.2	Sch.3
Hierarchical Scheduling	off	on	on
Reactive Scheduling Rule	fixed	fixed	dyna.
Maximum Tardiness[1)]	14.0	4.4	2.6
Mean Tardiness	1.4	0.58	0.23
Number of Delayed Missions	10	9	5
Fuel Consumption[2)]	215	224	202
Computational Time[3)]	27	259	262

Note)
1) "Tardiness" means delay from due date (days).
2) Additional to the minimum requirement.
3) Measured using a computer with 300 MIPS performance (sec). (Mission density: 30 missions in 80 days)

RESOURCE ALLOCATION

Resource Allocation Problem

Resource allocation is a very important problem especially in space, where the resource such as man power, electric power, water or tools are strictly limited and it is usually required that quite many tasks be performed within a limited time. The scheduling system must make the most of these limited recource to efficiently perform as many tasks as possible, and besides, in a case when a certain anomaly such as a malfunction of a certain tool or a degradation of power supply occurs, quickly remake the total schedule. In this case study, the dynamic scheduling technique is applied to a certain assumed resource allocation problem. Table 2 briefly describes the requirements given by the tasks and constraints in the assumed problem. Each task has its priority value, and the total scheduling performance is calculated by summing the priority values of the tasks to be completed within the fixed time.

Table 2. Requirements and Constraints for Resource Allocation Problem

Requirements:	(for each task respectively)
Starting Time	(Specified for some tasks)
Duration	Time required for the task
Man power	Number of required crews for;
- Type 1	Continuous attendance required
- Type 2	Occasional absense allowed
- Type 3	Occasional attendance required
Electric power	Power required for the task
Constraints:	
Time Limit	Total time allowed
Labor Hour	A crew's maximum labor hour/day
	Maximum hour of continuous work
Sleep Hour	A crew's required sleeping hour/day
Maximum power	Max. daytime power to be utilized
Battery power	Max. nighttime power to be utilized
Battery capacity	Max. energy to be loaded

Scheduling Strategies

Three type scheduling strategies are compared;
Sch.1) automatic scheduling using dynamic scheduling
Sch.2) automatic scheduling using a fixed simple scheduling rule
Sch.3) manual scheduling after some training

In both of Sch.1 and Sch.2, scheduling is performed by iterating the process of picking up one task from the pool of tasks which have not been scheduled yet then placing the task in a certain position in the scheduling table and allotting the required resources according to a certain rule. During the training of manual scheduling, it has been found that the selection of the next task to be scheduled determines the scheduling performance. Considering this, Sch.1 employs dynamic scheduling for this selection while Sch.2 utilizes a certain fixed rule. For the dynamic scheduling, 10 heuristic rules are prepared from which one is selected at each decision timing considering 22 attributes describing the situation at that timing. Examples of the rules are "select the task with the highest priority value" or "select the task with the least duration time" and so on, and the attributes include "the rate of operation of the crews" or "the maximum time window during which one, two and three crews are available", and so on. The relationships between the attributes and the best rules are acquired by the back propagation algorithm, using the data obtained by scheduling randomly generated small set of tasks with an exhaustive search strategy.

Performance Comparisons

Figure 2 and 3 describes the performance and required scheduling time of the three strategies and the exhaustive search result (i.e., optimum solution). Three levels of complexity, 1) 4 tasks in 150 minutes, 2) 6 tasks in 150 minutes and 3) 6 more complex tasks in 200 minutes are tried. Ten problems are generated randomly for each level, and maximum, averaged and minimum marks are calculated. It is observed that the fixed rule scheduling can generate schedule in quite a short time, but its performance is sometimes much degraded. On the other hand, the dynamic scheduling performs much better with slightly larger computational load, and the required time is still several orders less than the exhaustive search or manual scheduling. Moreover its computational time and performance do not get much worse even for more complex problems. These results indicate the effectiveness of the dynamic scheduling for quickly generating an acceptable schedule.

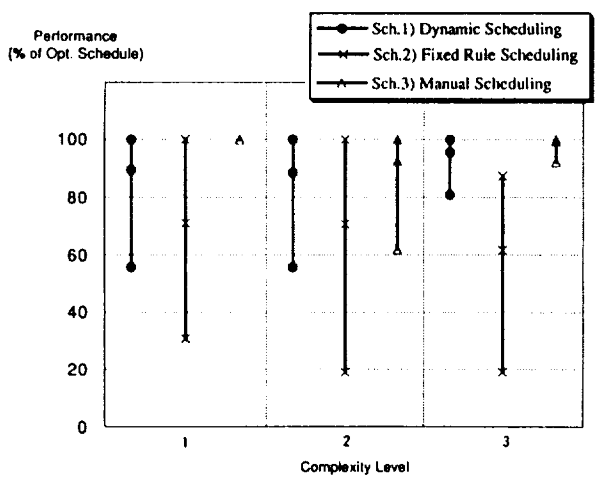

Figure 2. Performance of Three Scheduling Strategies

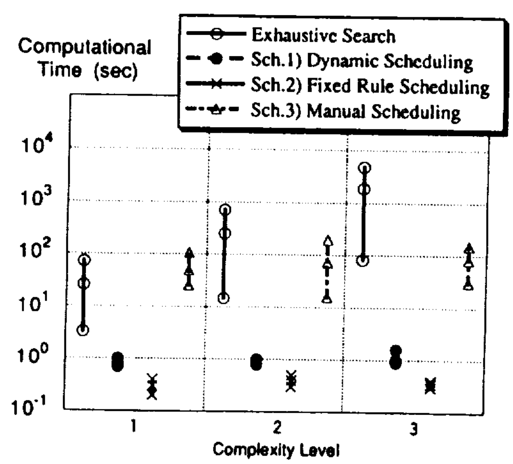

Figure 3. Required Computation Time

CONCLUSIONS

Dynamic scheduling has been applied to two space related problems; the scheduling of space transportation system and the resource allocation in a space system. The simulation results indicated that the dynamic scheduling can be effectively utilized as a sub-element of an overall scheduling system especially where the quick response is required, and that it will also provide an effective aid to an onboard rescheduling in case of some anomalies.

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