A Tabu Search with a New Neighborhood Search Technique Applied to Flow Shop Scheduling Problems

Yajie Tian*, **Nobuo Sannomiya**** **and Yuedong Xu****
* Graduate School of Informatics, Kyoto University, Sakyo-ku, Kyoto 606-8501 Japan
e-mail: yjtian@prec.kyoto-u.ac.jp
** Kyoto Institute of Technology, Sakyo-ku, Kyoto 606-8585 Japan
e-mail: sanmiya@si.dj.kit.ac.jp, xyd@si.dj.kit.ac.jp

Abstract

In this paper, a tabu search algorithm with a new neighborhood technique is proposed for solving flow shop scheduling problems. An idea obtained from a simulation study on the adaptive behavior of a fish school is used to determine the neighborhood search technique. The cooperation and the diversity of job data are defined for describing the data structure by using the given information. According to the definitions, job data are classified into four kinds, and two kinds of them are treated in this paper. A large number of computational experiments are carried out for investigating how to assign the local effort and the global effort under a limited search time. The result shows that the allocation of the local and the global effort depends on the job data characteristics, such as cooperation and diversity. The validity of the tabu search algorithm is examined by comparing it with the genetic algorithm. It is found that the proposed tabu search algorithm has better convergence and much shorter computational time than the genetic algorithm.

1 Introduction

As useful tools for solving discrete optimization problems, local search techniques are used widely. Since an original local search is easily trapped in a local minimum, some local search algorithms have been presented for improving the local search techniques. Simulated annealing method has the advantage that it can leave a local minimum [1]. But a disadvantage is that it is possible to get back to solutions already visited. A method which seeks to avoid the disadvantage is the tabu search first presented by Glover [2]. Anyone who uses local search techniques must come across the following problems; which neighborhood should be selected? What should be used as a search algorithm? If you process the schedule of a large-scale complicated problem with a limited search time, you should know how to assign the local effort and global efforts. This paper deals with these problems by using an idea obtained from a simulation study on adaptive behavior of a fish school.

As we know, ecological systems can adapt themselves to the dynamic environments and the adaptability varies with the system characteristics such as cooperation and diversity. As examples of ecological systems, two kinds of fish school models were proposed for investigating the adaptive behavior [3,4]. The simulation results showed that the adaptability of a fish school to environmental variations depends on the school characteristics, such as the cooperation and diversity of the school. A fish school with high cooperation and low diversity can adapt itself to the environmental variations flexibly when each individual interacts with a half of neighboring individuals in the school. By doing that, the school can adjust its cooperation and the diversity to the environment. On the other hand, a fish school with low cooperation and high diversity can adapt itself to the environmental variations flexibly when each individual interacts with almost all of other individuals in the school.

The idea was used to define a neighborhood of the solution in a local search (LS) which was applied to parallel machine scheduling problems [5]. The computational results showed that the reasonable assignment of the local effort and global efforts depends on the structure of job data. For the cooperative and homogeneous data, a suboptimal solution is easy to be found by decreasing the local effort and increasing the global effort. For the repulsive and heterogeneous data, a suboptimal solution is easy to be found by increasing the local effort and decreasing the global effort. Both of them were examined in the case where the total number of search points is limited.

Many production scheduling problems in real world are dynamic and with a limited capacity. Therefore, optimization methods are required to have a high degree of adaptability to variable environments and a quick search function under a limited search time. In this paper, a tabu search algorithm (TS) with a new neighborhood search technique is proposed for solving flow shop scheduling problems. The idea obtained from the simulation results of fish school models is used to determine the neighborhood search technique. The measures of cooperation and diversity of job data are defined roughly for describing the data structure. According to the definitions, job data are classified into four kinds. Two kinds of them, the cooperative and homogeneous data and the repulsive and heterogeneous data are used to discuss the relationship between the structure of job data and the size of neighborhood. A large number of computational experiments are carried out for this purpose. In addition, the proposed TS is compared with

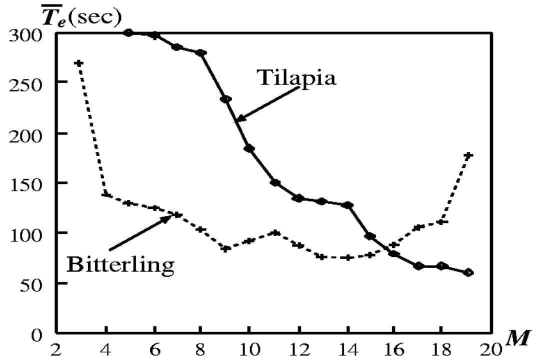

Figure 1: Variation of average value $\bar{T}_e$ of escaping time from the trap with the value of M

the genetic algorithm (GA) for examining the validity of TS. Consequently, it is observed that the proposed TS has better convergence and much shorter CPU time than GA.

2 Simulation of Fish School Models

In our earlier papers [3,4], fish school models as the examples of ecological systems were proposed for investigating the adaptive behavior of a fish school in a water tank with setting a small box-shaped trap in it. Two typical kinds of fish schools called Bitterling and Tilapia were used in the study and the model parameters were estimated by using the time series data obtained from the water tank experiments. The characteristic of Bitterling is that each individual in the school has almost same model parameters and the repulsive force among individuals is small. Therefore, it is called a cooperative and homogeneous model. On the other hand, the characteristic of Tilapia is very different from that of Bitterling, namely, each individual has different parameter values and the repulsive force among individuals is very strong. Therefore, it is called a repulsive and heterogeneous model.

A simulation study on the adaptive behavior of a fish school was carried out by using the two kinds of fish school models. A small box-shaped trap with three sides of walls is set in the water tank and fish can enter and go out freely from one open side of the trap. The number of individuals in both fish schools is set to be $N_f = 20$. The adaptability is defined in such a way that a fish school can escape from the narrow trap as rapidly as possible. In our model we assume that each individual makes an information exchange with M neighboring individuals in the school. The simulations were carried out by varying a control parameter M from 3 to 19. Figure 1 shows the variation of the average value $\bar{T}_e$ of escaping time from the trap for the two fish school models. It is found from the cooperative and homogeneous model (Bitterling) that $\bar{T}_e$ takes a smaller value when $M \cong N_f/2$ and $\bar{T}_e$ increases obviously when M takes a larger value than that. However, for the repulsive and heterogeneous model (Tilapia), $\bar{T}_e$ decreases with M increasing and the smaller value of $\bar{T}_e$ is obtained when M takes a large value. In other words, a high degree of adaptability to environmental variations depends on the quantity M of information exchange which can be adjusted according to the characteristic of a fish school.

3 Tabu Search Algorithm

A TS with a new neighborhood search technique is proposed for solving flow shop scheduling problems. A good deal of enlightenment is obtained from the simulation study of the fish school behavior and is used in the allocation of the local effort and the global effort as well as in the neighborhood search technique.

3.1 Flow shop scheduling problems

The flow shop problem is a general shop problem in which for every $i \in \{1, 2, \cdots, N\}$

- each job J_i consists of H operations O_{ij} with processing time p_{ij} $(j = 1, \cdots, H)$ where O_{ij} must be processed on machine M_j,
- there are precedence constraints of the form $O_{ij} \rightarrow O_{i,j+1}$ $(j = 1, \cdots, H-1)$ for each job J_i,
- each job has a due date d_i, and each machine has a same job order $\pi = \{J_{i_1}\ J_{i_2}\ \cdots\ J_{i_N}\}$.

The objective function is to minimize the sum of the tardiness of each job. Let s_{ij} and $c_{ij}(= s_{ij} + p_{ij})$ be the start time and the completion time of operation O_{ij} in job J_i processed on machine M_j, respectively, then the objective function is given by

$$Z(\pi) = \sum_{i=1}^{N} \max(c_{iH} - d_i, 0) \tag{1}$$

The problem is to find a job order π so that the objective function reaches a suboptimal value.

3.2 Cooperation and diversity of job data

In production process planning, it is considered that the neighborhood search techniques depend on the data structure. We are concerned with the structure of job data, such as the processing times of operations and the due dates of jobs. In this section, the definitions of cooperation and diversity are given for describing the data structure as follows.

Definition 1 The measure of cooperation f_{coop} for job data $\{p_{ij}, d_i;\ i = 1, \cdots, N,\ j = 1, \cdots, H\}$ is given by

$$f_{coop} = \mu f_{due} + (1 - \mu) f_{diff} \tag{2}$$

where μ $(0 \leq \mu \leq 1)$ is the weight of f_{due} and $\mu = 0.5$ is set in this paper. f_{due} expresses the divergence of the due date distribution, and f_{diff} expresses the average value of normalized slack times which are given by

$$f_{due} = \sigma_d / \bar{d} \tag{3}$$

$$f_{diff} = \frac{1}{N} \sum_{i=1}^{N} (d_i - \sum_{j=1}^{H} p_{ij}) / d_i \tag{4}$$

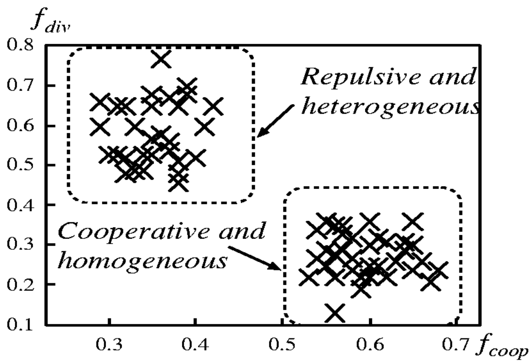

Figure 2: The distribution of two kinds of job data $\times$ shows the values of f_{coop} and f_{div} of the data treated in Tables 1 and 2 in Section 4

where $\bar{d}$ and σ_d are the average value and the standard deviation of $\{d_i\}$, respectively. A job data with a large value of f_{coop} is called cooperative, and otherwise, it is called repulsive.

Definition 2 The measure of diversity f_{div} for job data $\{p_{ij}, d_i;\ i = 1, \cdots, N,\ j = 1, \cdots, H\}$ is given by

$$f_{div} = \sigma_p / \bar{p} \tag{5}$$

where $\bar{p}$ and σ_p are the average value and the standard deviation of $\{p_{ij}\}$, respectively. A job data with a large value of f_{div} is called heterogeneous, i.e. of a high diversity, and otherwise, it is called homogeneous.

According to the above definitions, job data are classified into four kinds, of which two kinds of data as shown in Figure 2, the cooperative and homogeneous (COSM) data and the repulsive and heterogeneous (RPDF) data are treated in this paper. The boundary of each kind of data will be determined in Section 4.

3.3 Main algorithm

We define the total number of search points as L, the size of neighborhood as K and the maximum iteration number as $t^* = L/K$. It is very important how to assign the local effort K and the global effort t^* in tabu search. A concept of negotiating procedure is described by swapping two jobs in π; one is selected randomly as a negotiator, and the other is a job belonging to the neighboring set of the negotiator which is mentioned in Section 3.4. A negotiator list A and a tabu list T are embedded in the tabu search algorithm for avoiding overlapping local searches and reducing unnecessary computational efforts. They are given by

$$A = \{J_i |\ J_i \text{ is a job selected randomly as a negotiator in the negotiating procedure}\} \tag{6}$$

$$T = \{\{J_i, J_k\} \mid \text{By swapping } J_i \text{ and } J_k \text{ in } \pi, \text{ the best job order is selected from the number of negotiating procedures}\} \tag{7}$$

Both A and T are temporary sets, $A = \phi$ when the job order is changed, and $T = \phi$ when the solution is improved. In addition, when the number of elements in A is equal to the total number of jobs, i.e. $|A| = N$, the search procedure will be stopped automatically. Because $|A| = N$ means that any job was as a negotiator, and the negotiating procedure was not able to improve the solution. Consequently it is not necessary to continue the search.

ALGORITHM (TS)

Step1: $t \leftarrow 1$ as an iteration number;
Step2: Generate an initial job order π^{t-1} by arranging the jobs in the order of due dates d_i ($i = 1, \cdots, N$), and obtain the objective function $Z(\pi^{t-1})$;
Step3: Let $A = T = \phi$;
Step4: If $|A| < N$, then select randomly a job $J_i \notin A$ as a negotiator, let $A \leftarrow A \bigcup \{J_i\}$ and go to Step5; otherwise, go to Step8;
Step5: Determine the neighboring set $S(J_i)$ of the negotiator J_i and the number of elements in $S(J_i)$ is K which is described in Section 3.4. Generate K job orders $\pi_k \in N(\pi^{t-1})$ by swapping J_i and $J_k \in S(J_i)$ ($k = 1, 2, \cdots, K$);
Step6: Select the best π^t so that $Z(\pi^t) = \min\{Z(\pi_k)\}$ with respect to $\pi_k \in N(\pi^{t-1})$. If $Z(\pi^t) < Z(\pi^{t-1})$, then $\pi^{t-1} \leftarrow \pi^t$ and $A = T = \phi$, go to Step8; otherwise, go to Step7;
Step7: When $Z(\pi^t) = Z_(\pi^{t-1})$, if the selected job pair $\{J_i, J_k\} \notin T$, then $\pi^{t-1} \leftarrow \pi^t$, $T \leftarrow T \bigcup \{J_i, J_k\}$ and $A = \phi$;
Step8: If $t = t^*(= L/K)$ or $|A| = N$ or $Z(\pi^t) = 0$, then the solution obtained from Step6 is adopted as the suboptimal solution and stop the computation. Otherwise, set $t \leftarrow t+1$ and return to Step 4.

3.4 Definition of neighborhood

The determination of neighborhood depends on the problem under consideration. Construction of an efficient neighborhood function leads to a high-quality local optimal solution and then it is one of the challenges in local search technique. No general rules are available and each situation has to be considered separately [6]. In this paper, a kind of neighborhood function is proposed based on the idea obtained from a simulation study on adaptive behavior of fish school models.

At first, a neighboring set $S(J_i)$ of job J_i mentioned in Step5 of ALGORITHM (TS) is defined as follows.

For the operations on machine M_1 we define the distance between J_i and any other job J_k as

$$\sigma_{ik} = \begin{cases} s_{i1} - c_{k1} & \text{for } c_{k1} \leq s_{i1} \\ s_{k1} - c_{i1} & \text{for } c_{i1} \leq s_{k1} \end{cases} \quad k \neq i;\ k = 1, 2, \cdots, N \tag{8}$$

Then we have

$$S(J_i) = \{J_k \mid k \neq i;\ k \in \{k_1, k_2, \cdots, k_K\};\ \sigma_{ik_l}\ (l = 1, 2, \cdots, K) \text{ are the least } K \text{ values of } \sigma_{ik}\} \tag{9}$$

When $\sigma_{ij} = \sigma_{ik}$ ($j \neq k$) in Eq.(9), select one job from jobs J_j and J_k randomly. Figure 3 shows an example

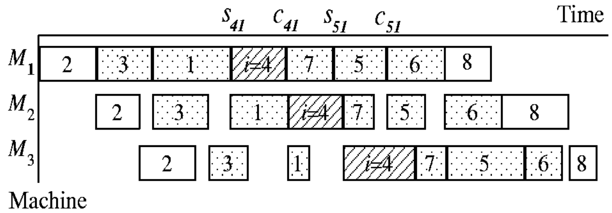

Figure 3: The neighboring set $S(J_4)$ of job J_4

of the Gantt chart for $(N, H) = (8, 3)$ and $K = 5$. Let J_4 be a negotiator, then the neighboring set of J_4 is given by $S(J_4) = \{J_3, J_1, J_7, J_5, J_6\}$. Then, in order to improve the efficiency of the exploration process, the negotiating procedure is carried out by swapping job J_i and $J_k \in S(J_i)$, $k = k_1, k_2, \cdots, k_K$ on every machine. If we select the best job order at the last iteration $t-1$ as π^{t-1}, then the neighborhood $N(\pi^{t-1})$ is generated by the K times of swaps which is given by

$$N(\pi^{t-1}) = \{\pi_k \mid \text{the job order } \pi_k \text{ is obtained from } \pi^{t-1} \text{ by swapping } J_i \text{ and } J_k;\ k = k_1, k_2, \cdots, k_K\} \tag{10}$$

The question is how to determine the size of the neighborhood K. A large number of computational experiments show that the parameter K depends on the structure of job data, such as the cooperation and the diversity which is discussed in Section 4.

4 Computational Experiments

The proposed TS is applied to flow shop scheduling problems. Computational experiments are performed by using ALGORITHM (TS). We treat two kinds of data in this paper, COSM data and RPDF data as shown in Figure 2. The number of jobs is set to be $N = 50$ and the number of machines is set to be $H = 5$. The value K is changed from 15 to 49. The total number of search points are set to $L = 4000$, $L = 6000$ and $L = 25000$, respectively, for various experiments. Then the maximum iteration number is $t^* = L/K$ which varies with K.

In order to find the boundary between COSM data and RPDF data, more than one hundred of job data are generated randomly and adjusted to be $0.25 < f_{coop} < 0.75$ and $0.1 < f_{div} < 0.8$ by using the Definitions 1 and 2. By using the proposed TS, each data is run 50 times by changing random number and the average values are calculated for each K ($\in [15, 49]$). The results show that the best size of neighborhood is obtained from $K \geq 20$ for all the job data and varies with the cooperation and diversity of job data. The best value of K is summarized to be in two regions such as $K \in [20, 35]$ and $(35, 49]$.

The set of job data is divided into the following five

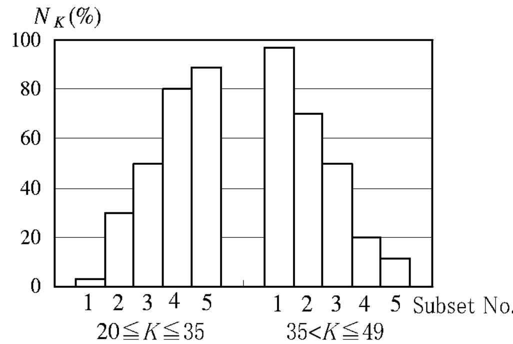

Figure 4: Variation of the rate N_K with K for the data divided into five subsets ($L = 6000$)

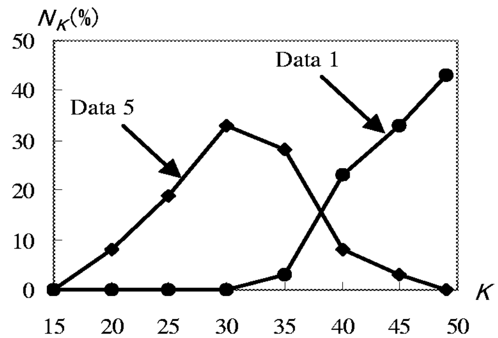

Figure 5: Variation of the rate N_K with K for Data 1 and Data 5 ($L = 6000$)

subsets according to the values of f_{coop} and f_{div}.

Data 1: $f_{coop} \leq 0.45$ and $f_{div} > 0.35$;
Data 2: $f_{coop} \cong 0.45$ and $f_{div} \cong 0.35$;
Data 3: $f_{coop} \cong 0.5$ and $f_{div} \cong 0.35$;
Data 4: $f_{coop} \cong 0.55$ and $f_{div} \cong 0.35$;
Data 5: $f_{coop} \geq 0.55$ and $f_{div} \leq 0.35$

Figure 4 shows the computational results of the five subsets when the total number of search points is set to be $L = 6000$. The horizontal axis expresses the subset number for each region of K. The vertical axis expresses the variation of N_K in each subset, where

$$N_K = \frac{\text{Number of data getting the best solution at K}}{\text{The total number of data}} \tag{11}$$

It is found from Figure 4 that the best solution of K lies in $K \in [20, 35]$ for more than 80% data in Data 4 and 5 and it lies in $K \in (35, 49]$ for more than 70% data in Data 1 and 2. However, the same value of N_K is found from Data 3 for both $K \in [20, 35]$ and $K \in (35, 49]$, which indicates that $f_{coop} = 0.5$ and $f_{div} = 0.35$ are considered to be the boundaries of cooperation and diversity, respectively. Therefore, COSM data are defined as $f_{coop} > 0.5$ and $f_{div} \leq 0.35$, RPDF data are defined as $f_{coop} \leq 0.5$ and $f_{div} > 0.35$.

Figure 5 shows the variation of the value of N_K with the size of neighborhood K for Data 1 (RPDF data) and Data 5 (COSM data). It is observed from Figure 5 that for the COSM data, the suboptimal solution tends to be found when K takes a middle value of job number. On the other hand, for the RPDF data, the suboptimal solution tends to be found when K takes a larger value. This phenomena are similar to those obtained from the simulation results of fish school models as shown in Figure 1 [3,4] and the computational results of parallel machine scheduling problems [5].

Going to a step further, in order to examine the relationship between the size of neighborhood K and the structure of job data, the computational experiments are performed by using two kinds of data as shown by $\times$ points in Figure 2. The total number of search points is set to $L = 4000$, $L = 6000$ and $L = 25000$. The optimal solution Z_{opt} is obtained when $L = 25000$ for each data. We calculate the difference $\bar{Z}_{diff} = \bar{Z}_K - Z_{opt}$, where $\bar{Z}_K$ is the average value of N_p suboptimal objective functions and $N_p = 350$ for the COSM data and $N_p = 300$ for the RPDF data. As mentioned in Section 3.3, the proposed TS has a function such that the computation can stop automatically when $|A| = N$. In this sense, it is considered that the solution process has converged for such a case. The rate of convergence among all data is expressed by R_{conv}.

Table 1 and Table 2 show the difference $\bar{Z}_{diff}$ and the rate R_{conv} of convergence for the COSM data and the RPDF data, respectively. It is observed from Table 1 that for COSM data, in the case of $L = 4000$, the smaller value of $\bar{Z}_{diff}$ is obtained when $20 \le K \le 35$ and the value of $\bar{Z}_{diff}$ increases obviously when $K \ge 40$. In the case of $L = 6000$, the smaller value of $\bar{Z}_{diff}$ is obtained when $25 \le K \le 40$ and the value of $\bar{Z}_{diff}$ increases obviously when $K \ge 45$. In the case of $L = 25000$, even though $R_{conv} = 100$ for each K, the smaller value of $\bar{Z}_{diff}$ is obtained when $K \ge 35$ and the smallest value of $\bar{Z}_{diff}$ is obtained when $K = 35$. On the other hand, it is observed from Table 2 that for RPDF data, the value of $\bar{Z}_{diff}$ decreases obviously with K increasing and the smaller value of $\bar{Z}_{diff}$ is obtained when $K \ge 45$ for all the cases of L.

The COSM data has almost same processing times and a large difference in due dates. In this case the due date is more important than the processing time for searching an optimal solution. If the size of neighborhood K is enlarged, the two jobs with large difference in due date are swapped, which results in a large value of tardiness because of the low diversity of the processing times. In addition, the unnecessary local search leads to reduction of the global search and consequently many search efforts become invalid in the case where the total number L of search points is limited. Therefore, for the COSM data, a better suboptimal solution tends to be obtained by decreasing the local effort up to $\frac{1}{2}N \le K \le \frac{7}{10}N$ and increasing the global effort t^* under a limited total number L of search points.

On the other hand, the RPDF data has small difference in the due dates and large difference in the processing times. In this case both the due dates and the processing times play an important role for searching an optimal solution. Thus, even though the size of neighborhood K is enlarged, we do not have too large difference in due dates between two swapped jobs and also the tardiness can be adjusted by high diversity in the processing time. Therefore, for the RPDF data, a better suboptimal solution tends to be obtained by increasing the local effort up to $K \ge \frac{9}{10}$ and decreasing the global effort t^* under a limited total number L of search points.

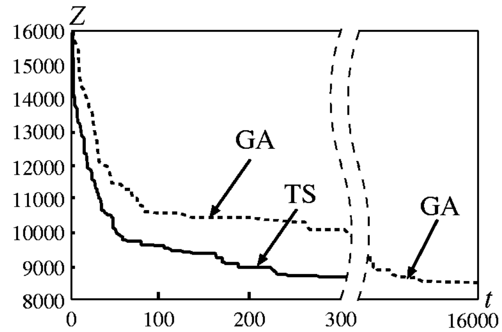

Figure 6: Comparison of the convergence process between TS and GA for COSM data

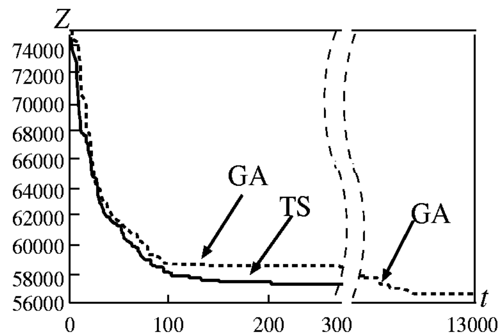

Figure 7: Comparison of the convergence process between TS and GA for RPDF data

To examine the validity of TS, it is compared with a standard genetic algorithm (GA) with crossover probability $P_c = 0.5$ and mutation probability $P_m = 0.01$. The population size is set to be $P = 200$ and the maximum number of generation (or iteration) is set to be $t^* = 25000$ in GA. Therefore, the total number of search points is $L \approx P \times (P_c + P_m) \times t^* = 2550000$ for GA. For the TS, we set the total number of search as $L = 25000$. We treat two kinds of data and $K = 35$ and for the COSM data and $K = 49$ for the RPDF data. Table 3 shows the average $\bar{Z}_{opt}$ of the suboptimal objective value and the average of the computation time for each kind of data. It is found that the suboptimal solution obtained by TS is little worse than that obtained by GA, but the CPU time for TS is much shorter than that for GA because of the function of stopping automatically in TS.

Figure 6 and Figure 7 show the convergence process of an example case for TS and GA, respectively. The

Table 1: Variation of suboptimal objective value with K for COSM data

L	K	15	20	25	30	35	40	45	49
4000	Z_{diff}	334.9	186.5	167.8	144.1	195.4	251.5	249.0	318.2
	$R_{conv}(\%)$	56	18	5	1.9	0.3	0.3	0	0
6000	Z_{diff}	298.9	177.5	104.6	43.7	71.8	56.8	134.7	128.2
	$R_{conv}(\%)$	96	82	46	21	10	2.9	2.0	0.6
25000	Z_{diff}	300.9	153.5	65.3	51.0	0.0	10.5	5.5	7.1
	$R_{conv}(\%)$	100	100	100	100	100	100	100	100

Table 2: Variation of suboptimal objective values with K for RPDF data

L	K	15	20	25	30	35	40	45	49
4000	Z_{diff}	4923.0	3552.7	2717.4	2098.1	1689.7	1673.6	1356.7	1433.3
	$R_{conv}(\%)$	17	2.3	0	0	0	0	0	0
6000	Z_{diff}	4630.1	3066.9	2210.7	1499.6	1138.5	947.2	758.7	743.1
	$R_{conv}(\%)$	75	42	16	4.7	0.3	0	0	0
25000	Z_{diff}	4503.5	3084.2	1915.4	1095.8	674.4	427.6	89.6	0.0
	$R_{conv}(\%)$	100	100	100	100	100	100	100	100

Table 3: Averages of the suboptimal objective value and the CPU time

	COSM data		RPDF data	
	$\bar{Z}_{opt}$	Time (sec.)	$\bar{Z}_{opt}$	Time (sec.)
GA	12389.89	295.28	84720.11	318.87
TS	12439.72	0.79	84996.46	0.87

horizontal axis expresses the iteration number $t \leq t^*$ and the vertical axis expresses the objective value. It is found that TS can reach its suboptimal solution much faster than GA for both kinds of data.

5 Conclusion

A tabu search with a new neighborhood technique has been proposed for solving flow shop scheduling problems. An idea obtained from a simulation study on the adaptive behavior of a fish school has been used in the neighborhood search technique. The definitions of cooperation and diversity of job data have been given for describing the structure of job data. According to these definitions, job data have been classified into four kinds, of which two kinds of data, a cooperative and homogeneous data and a repulsive and heterogeneous data have been discussed in this paper.

A large number of computational experiments show that the quality of the suboptimal solution critically depends on the size of the neighborhood. For the cooperative and homogeneous data, when $\frac{1}{2}N \leq K \leq \frac{7}{10}N$, a better suboptimal solution tends to be obtained, and for the repulsive and heterogeneous data, when $K \geq \frac{9}{10}N$, a better suboptimal solution tends to be obtained in the case where the total number L of search points is limited.

The validity of TS has been examined by comparing it with GA. The computational results show that the quality of the suboptimal solution obtained by TS is little worse than that obtained by GA, but the CPU time for TS is much shorter than that for GA. Consequently, the proposed TS can reach the suboptimal solution much faster than GA for both kinds of data.

This work is partly supported by the Research for the Future Program JSPS-RFTF97I00102 of the Japan Society for the Promotion of Science.

References

[1] Kirkpatrick, S., Gelatt, Jr.C.D. and Vecchi, M.P.(1983), Optimization by Simulated Annealing, *Science*, Vol.220, pp.671-680.

[2] Glover, F.(1986), Tabu Search-Part I, *ORSA J. Computing*, Vol.1 pp.190-206.

[3] Tian, Y., Sannomiya, N. and Nakamine, H.(1999a), A Simulation Study on Adaptability to Environmental Variations Based on Ecological Systems, *Proc. of ACC*99, pp.1759-1763.

[4] Sannomiya, N., Tian, Y. and Nakamine, H. (1999), Emergence of Cooperation in Fish Behavior Models, *Trans. Soc. Instrum. Control Eng.*, Vol.35, No.11, pp.1370-1376 (in Japanese).

[5] Tian, Y., Sannomiya, N., Nakano, T and Tu, Z. (1999b), A Local Search Based on Simulations of Fish School Behavior and Its Application to an Optimal Scheduling Problem, *Proc. of IEEE SMC′*99, pp.V684-V689.

[6] Aarts, E.H.L. and Lenstra, J.K.(1993), Local Search in Combinatorial Optimization, *Wiley Interscience Publication.*