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Cellular manufacturing, which is also referred to as group technology among researchers, has primarily been used as a means to increase productivity, efficiency and flexibility. Under group technology, similar jobs, which have similar shape, material, and processing operations are assigned to the same group. Moreover, dissimilar machines are assigned to the same cell to meet the processing requirements of jobs in a group or multiple groups. Group scheduling problems have been studied extensively in the past as implementation of group technology became more prevalent in industry. However, most of the work that has been done has focused on single-criterion optimization.

A bi-criteria group scheduling problem in a flow shop with sequence-dependent setup time is investigated in this research. Cellular manufacturing and flow shop are two popular scenarios in industry. To mimic real industry practice, dynamic job releases and dynamic machine availabilities are assumed. The goal is to minimize the weighted sum of total weighted completion time and total weighted tardiness, which satisfy the producer and customer goals separately. Normalized weights are assigned to both criteria to describe the trade-off between the two goals. Two different initial solution finding mechanisms are proposed, and a tabu-search based two-level search algorithm is developed to find near optimal solutions for the problem. An example problem is used to demonstrate the applicability of the search algorithm. A mathematical model is developed and implemented to evaluate the quality of the solutions obtained from the heuristics in small problem instances. Further, to uncover the difference in performance of initial solution finding mechanisms and heuristics, a detailed experimental design is performed. The results show that different heuristics have different performance in solving problems generated with different parameters.

Keywords: Bi-criteria, sequence-dependent setups, tabu search, experimental design

Bi-Criteria Group Scheduling With Sequence-Dependent Setup Time in A Flow Shop

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Dongchen Lu, Author

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

Cellular manufacturing (CM) was developed in the 1970s. This approach has primarily been used as a means to increase productivity, efficiency and flexibility. In CM, groups of jobs are processed through production lines, which help manufacturing companies make use of the similarity of jobs and boost efficiency. Similar jobs, which have similar shape, material, and processing operations are assigned to the same group. Moreover, dissimilar machines are assigned to the same cell to meet the processing requirements of jobs in a group or multiple-groups. Doing so enables attaining a significant reduction in setup time and work-in-process inventories, in addition to reducing the complexity of the production line.

A major setup is required for processing each group on every machine. Setup operation includes preparing the machine, bringing required tools, setting the required jigs and fixtures, inspecting the materials and cleanup (Allahverdi et al, 1999). Thus, setup should be considered as a separate operation on machines rather than considering it as a part of processing time. Scheduling problems involving setup times can be divided into two classes: those with sequence-independent setup times and those with sequence-dependent setup times. The setup is sequence-dependent if its duration depends on both the current and the immediately preceding job (Allahverdi et al. 1999).

Sequence-dependent setup time is an important feature in investigating a scheduling problem. Several studies discussed the importance of considering it. Panwalker et al. (1973) performed a survey which revealed that 75% of the manufacturing managers had experienced sequence-dependent setup time. Sequence-dependent setup time was proven to have a significant effect on managing manufacturing capacity, as noted by Wortman (1992).

Sequencing and scheduling have been applied to improve efficiency of production since the beginning of the last century. A number of sequencing methods were created to help manufacturers meet customers' requirements. It is important for manufacturing companies to meet the customer requirements in a timely manner, which means that orders from the customer should be finished and delivered on time. Various manufacturing firms are resorting to scheduling algorithms to help them meet the customer requirements in a timely manner. However, the manufacturing firms themselves have also many requirements and objectives to achieve in order to improve the efficiency and to reduce their operational costs. Sometimes, those objectives from the customers and supplier can be incompatible.

Most of the machine-scheduling problems are combinatorial optimization problems, and the most common performance measures addressed in the literature are functions of the job completion times. Examples of such objectives to be minimized include the makespan (the time difference between the start and finish of a sequence of jobs or tasks. i.e., the completion time of the last job to leave the system), the total weighted-completion time, the maximum lateness, the total weighted tardiness (the time difference between the due date and the completion time of a job; when the completion time is less or equal to the due date, tardiness is 0), and the weighted number of tardy jobs (Pinedo, 2002). The first two objectives are focused on improving resource utilization and productivity, which are more aligned with the supplier's requirements, while the others are mainly perceived as measures of conformity with due dates, which are more aligned with the customers' requirements. Thus, minimizing the total weighted completion time is considered as one of the objectives in this research. The supplier needs to meet its own goal of minimizing completion time in order to increase efficiency and reduce work-in-process inventory. As the manufacturing industry develops, delivering the products to customers on time becomes a practical problem. In the report of Panwalker et al.'s (1973) survey, meeting due dates was identified as the single most important scheduling criterion. The total weighted tardiness, as the most frequently cited due date related performance measure (Tan and Narasimhan (1997), Tan et al. (2001), Schaller (2007), Pandya and Logendran (2010)) should be considered in the research to represent the customers' requirement. Thus, minimizing the total weighted completion time, and total weighted tardiness at the same time, could be a reasonable set of objectives for a scheduling problem in order to meet both the supplier and customers' requirements.

From all of the above, it is clear that there is a need for a manufacturing company to satisfy its customers' requirements as well as its own requirements. This research focuses on scheduling groups of jobs in a flow shop with sequence-dependent setup times to *simultaneously* satisfy the requirements from both sides. The flow shop in this research consists of several stages with only one machine in each stage. The release times of jobs and the availability times of machines are assumed to be dynamic. These assumptions are in conjunction with what we would typically observe in industry practice. Jobs can be released at any given time during the current planning horizon, depending upon the customer's request or order. Similarly, at the start of the current planning horizon, a subset of machines might be processing jobs from the previous planning horizon, making them unavailable, again at the start of the current planning horizon. Sequence-dependent setup times often occur in a CM system. The jobs within a group are similar that the setup time between them can be ignored. However, the setup times between groups can be sequence-dependent and significant because of the dissimilarities between them.

CHAPTER 2: LITERATURE REVIEW

The research on scheduling problems has been an ongoing activity for many years. In order to have a clear view of the development of the research, this review starts with some of the early developments of scheduling research. Because this research involves the optimization of objectives from the supplier as well as the customers, literatures from both sides are reviewed. Finally, the recent efforts on bi-criteria optimization are reviewed to substantiate the importance of the research documented in this thesis.

2.1 Supplier-oriented Objective Minimization

In the early stage of production scheduling, most of the work focused on the supplier. Herbert et al. (1970) studied an n-job m-machine sequencing problem. A simple heuristic algorithm was developed to minimize total completion time of very large scheduling problems. This approximate sequencing method provides optimal or near-optimal solutions. The context of the problem is very simple, as setup time was not taken into consideration and each processing stage only has one machine. This work stimulated a lot of researchers to work on scheduling problems.

Group technology has developed rapidly and impacted significantly on the development of totally integrated manufacturing facilities and flexible manufacturing systems. Radharamanan (1986) developed a heuristic algorithm and programmed it for computer applications. The developed algorithm has been used to determine the optimal group and the optimal job sequence for a batch type production process with functional layout to minimize makespan. This algorithm was far simpler and easier to compute, compared to the other similar heuristic algorithms and certainly in comparison to other optimization methods such as branch–and-bound method.

Logendran and Nudtasomboon (1991) developed a new heuristic algorithm for minimizing the makespan criterion of a group scheduling problem. The new algorithm was based on the fact that a higher priority should be given to jobs with higher mean total processing time in generating partial schedules, which eventually lead to determining a complete schedule for the problem. The results based on a real world application were presented. The new heuristic showed a superior performance over the previous heuristics.

Liaee and Emmons (1997) considered scheduling with and without the group technology assumptions (GTA) under a variety of performance measures. If GTA are considered, the jobs in the same group must be scheduled contiguously (next to each other), while without GTA the jobs in the same group need not be scheduled contiguously. Scheduling with GTA requires that jobs in the same group not to be split into sublots. Consequently, the number of sublots in each job is one, and it is logical to schedule the jobs in the same group together. Scheduling without the GTA assumes that jobs in a group can be split into sublots, and therefore two interrelated decisions concerning the number and size of each sublot would have to be made (Cheng et al., 2000). This research focuses on scheduling problems under GTA, in which setup time only occurs when transferring between different groups. Several heuristics as well as a branch-and-bound approach to solve the sequence-dependent flow shop group scheduling problem have been proposed by Schaller et al. (2000), who considered different ratios between average setup time and average run time to be an element in computational experiments. Dynamic conditions such as non-availability of all jobs at the beginning of the planning horizon were investigated by Reddy and Narendran (2003) in their simulation experiments on sequence-dependent group scheduling problems. Salmasi et al. developed tabu search (TS) based heuristics to minimize total flow time (2010) and makespan (2011) assuming static job releases and machine availabilities.

Because of large workloads required by jobs within groups on some machine types, flexible flow shops are becoming very popular in industry practice. Logendran et al. (2005) proposed three different algorithms based on TS to minimize makespan in a flexible flow shop. One algorithm is recommended for solving the proposed problems through statistical comparison. The importance of initial solution finding mechanisms is also demonstrated in this study. Hendizadeh et al. (2008) studied a complex group scheduling problem. The sequence-dependent family setup times were brought into the picture in a flow-line scheduling problem to minimize makespan. This paper presents various TS based meta-heuristics for the problem, which provide better performance than heuristics from many previous works. The result of this paper shows the advantage of TS-based heuristics in solving scheduling problems.

2.2 Customer-oriented Objective Minimization

As the manufacturing industry develops, more and more manufacturers are facing fierce competition for attracting customers to purchase their products. Consequently, delivering the products to customers on time becomes a practical problem.

The first investigation about minimizing tardiness in group scheduling problem was performed by Nakamura et al. (1978). Their work proved basic theorems that establish the relative order in which pairs of groups are processed in an optimal schedule. Two practical algorithms for determining the optimal group schedule and the near optimal group schedule are proposed. Ozden et al. (1985) proposed a dynamic programming-based formulation in group technology environment. They stated that the group technology concept became a simplifying factor of this scheduling problem, facilitating the exact solution faster with more jobs than it was possible ever before.

Lots of work has been done on scheduling problems without GTA. To overcome impractical long computational times when solving large problems by branch-and-bound algorithm, Rubin and Ragatz (1995) developed a genetic search algorithm (GSA) for a job scheduling problem. A Simulated Annealing (SA) algorithm was developed by Tan and Narasimhan (1997). Lee et al. (1997) proposed a three-phase heuristic for the problem of minimizing the total weighted tardiness on a single machine in the presence of sequence-dependent setup times, considering n jobs that are all available for processing at time zero. A new sequencing rule, which has been proven to significantly outperform other rules from previous literature, was developed based on the result of the first phase algorithm. The procedure they suggested has been successfully implemented in an industrial scheduling system. Tan et al. (2001) compared four methods for minimizing total tardiness on a single machine in a sequence-dependent setup environment. The comparative performance of branch-and-bound, GSA, SA, and random-start pairwise interchange was evaluated in their study. The experimental results suggested that SA and random-start pairwise interchange are viable solution techniques that can yield good solutions to a large combinatorial problem when considering the tardiness objective with sequence-dependent setup times. Branch-and-bound may be the preferred solution technique in solving smaller problems, and it is the only solution technique tested that will confirm an optimum solution has been reached. The TS based algorithm is widely used to solve scheduling problems, especially to solve practical scheduling problems. Tabu-search-based heuristic solution algorithm was used by Logendran and Subur (2004) to ultimately find the best solution for an unrelated-parallel machine scheduling problem, which has its origins at the NASA - Johnson Space Center, Houston, Texas. Logendran et al. (2007) had again demonstrated the advantage of a tabu-search-based algorithm in their study of minimizing the weighted tardiness of jobs in unrelated parallel machine scheduling with sequence-dependent setups. In this study, the practical considerations such as dynamic release of jobs and dynamic availability of machines were incorporated.

The amount of research that has been pursued in group scheduling is comparatively less than that in common job scheduling problems. Ghosh and Gupta (1997) gave an improved dynamic program for a single-machine group scheduling problem with sequence-independent setup times. Hariri and Potts (1997) considered a problem of scheduling N jobs on a single machine to minimize the maximum tardiness. They developed two heuristic algorithms to solve the problem, which turned out to be effective in solving problems with up to 50 jobs. Shaller et al. (2004) considered the problem of scheduling on a single machine to minimize total tardiness with family setup times. Under GTA, optimal branch-and-bound procedures were proposed. In addition, a heuristic procedure was also proposed to solve larger problems without GTA.

2.3 Dual Objective Minimization

Makespan and maximum tardiness are among the most commonly used criteria in the flow shop scheduling research. Makespan is a measure of system utilization while maximum tardiness is a measure of performance in meeting customer due dates.

Allahverdi (2005) addressed the m-machine flow shop job scheduling problem with the objective of minimizing a weighted sum of makespan and maximum tardiness. He proposed a new heuristic and showed that it is better than two existing ones. Varadharajan et al. (2005) proposed a multi-objective simulated-annealing algorithm (MOSA) to minimize makespan and total flow time of jobs in a flow shop. SA technique is widely used in solving supplier-oriented problems. This MOSA obtained Pareto-optimal solutions through the implementation of a simple probability function that helps to generate many solutions on the non-dominated front. It is important to note that MOSA approaches the problem of solving multi-criteria scheduling problems in a different way rather than considering the weighted sum of objective functions. Without the weights assigned to different objectives, the focus of the scheduling algorithm would be unclear and the trade-off between objectives becomes blurry.

Another widely used algorithm in bi-criteria scheduling problem is multi-objective genetic algorithm (MOGA). Mansouri (2005) proposed a MOGA solution approach for a sequencing problem to coordinate set-ups between two successive stages of a supply chain, which can be transformed to a scheduling problem. The experiments conducted on a number of test problems show that the MOGA is capable of finding Pareto-optimal solutions for small problems and near Pareto-optimal solutions for large instances within a short CPU time.

Eren and Güner (2006) studied a bi-criteria scheduling problem with sequence-dependent setup times on a single machine. They proposed an integer programming model based on a TS algorithm to solve this problem. It is shown that TS has a good performance in this bi-criteria scheduling problem.

Batch manufacturing accounts for 60 to 80% of all manufacturing activities in the world. The high level of variety and the small lot sizes of products have been the major challenges in this type of manufacturing. CM addresses some of the problems and helps to gain economic advantage of batch manufacturing. Hendizadeh et al. (2007) considered a flow shop scheduling problem of a manufacturing cell that contains families of jobs whose setup times are dependent on the manufacturing sequence of the families. Two objectives, the makespan and total flow time, have been considered simultaneously in this work. MOGA was used in this study and its performance reported to be good.

MOGA and MOSA were compared in the work of Mansouri et al. (2009). They studied a two-machine flow shop scheduling problem with sequence-dependent setup time. It was observed that MOGA outperforms MOSA in terms of the quality of solutions on larger problems. According to different characteristics of different problems, there is usually a possibility of developing unique algorithms for different problems. Mehravaran and Logendran (2011) proposed a TS algorithm to solve a job scheduling problem to minimize the work-in-process inventory while maximizing the customer service level in a supply chain with unrelated-parallel machines. TS was proven to be effective in solving this bi-criteria problem.

To summarize, the scheduling environment of this research is dynamic in both job release time and machine availability to mimic the real practice. The objective of the research focuses on finding optimal/near-optimal schedule that minimizes the weighted sum of the weighted tardiness and weighted completion time of all jobs in a flow shop environment. Sequence-dependent setup time is employed as it is a widely implemented and researched manufacturing factor. TS is used to be the framework of the heuristic algorithm based on its successful performance in single and bi-objective optimization problems.

CHAPTER 3: PROBLEM STATEMENT

In this research, it is assumed that *a* groups (G_1, G_2, ..., G_n) are assigned to be processed through a flow shop with multiple stages (S_1, S_2, ..., S_n) with one machine in each stage. Each group includes n_g jobs ($g=1,2,\ldots,a$). The immediately preceding group that is processed on each machine determines the setup time of the next group on that machine (sequence-dependent setup time). Driven by the need to investigate a more meaningful group scheduling problem, the purpose of this research is to find the best sequence of processing groups (and jobs in each group) by considering a bi-criteria goal. Lots of studies had been pursued to minimize goals from either the supplier side or the customer side, but none so far from both sides, which would be a more challenging research topic to investigate. Thus, this research considers minimizing the total weighted completion time (goal from the supplier side) and the total weighted tardiness (goal from the customer side) together. Normalized weights are assigned to the two criteria to represent the trade-off between completion time minimization and tardiness minimization. The assumptions made in this research are:

- None of the jobs is skipping any machine. All jobs and groups are processed in the same sequence on all machines. Lots of industries carry out their production in this way. For instance, in industrial practice, conveyer is a common thing to pass jobs between stages. If conveyers are used, then all jobs should be processed in the same sequence on all machines.
- Jobs in each group have dynamic release times. In other words, jobs may not necessarily be available at the beginning of the planning horizon.
- Machines in each stage have dynamic availability time, which means at the beginning of the current planning horizon machines may not be available because they can be processing jobs from the previous planning horizon.
- Jobs in each group can have different weights.

- The jobs within a group are similar that the setup time between them can be ignored. However, the setup times between groups can be sequence-dependent and significant because of the dissimilarities between them.

This problem belongs to dynamic flow shop problems. Figure 1 shows the classification of all scheduling problems, including the proposed research problem.

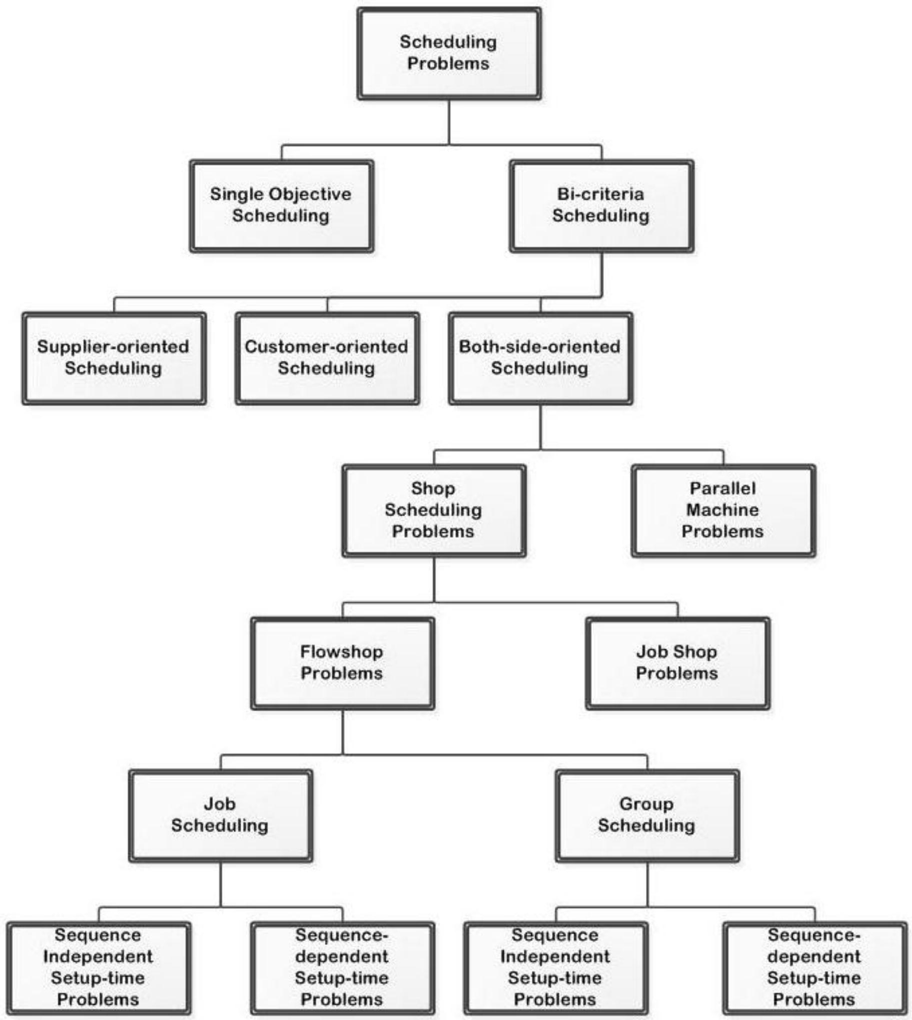

Figure 1 The scheduling tree diagram

The size of the problems investigated in this research is as follows:

- Number of groups: Group scheduling problems including 2 to 16 groups are investigated. This is based on the reviewed papers (Logendran et al. (2006), Salmasi et al. (2010), Schaller et al. (2000)). Most of the research focused on at most 10 groups but Salmasi (2005) investigated problems with up to 16 groups in his dissertation.
- Number of jobs in a group: Problems including 2 to 10 jobs in a group are considered in this research. Based on the papers reviewed, the previous investigations were limited to up to 10 jobs in a group. Moreover, because jobs are classified into different groups based on their similarities, there shouldn't be too many jobs in one group.
- Number of stages in the flow shop: Cellular manufacturing is intended to decompose the production activities and simplify them. Too many machines in a cell would violate the goal sought in applying cellular manufacturing. Thus, problems of up to 6 machines in a cell are investigated in this research.

The setup time is considered to be another important factor in this research. As sequence-dependent setups are required when transferring from one group to another on each machine, the ratio between setup time and run time could significantly affect the complexity of the research. Because of that, the setup time ratio (STR) is chosen to be a main-factor in the experimental design (in Chapter 7) which will interact with the factors in the sub-plot.

As stated above, at the beginning of the current planning horizon, machines in all stages may not be available because they could be processing the jobs from the previous planning horizon. It is clear that the first group that is scheduled to be processed in the current planning horizon will be preceded by the last group from the previous planning horizon. This "last group" is referred to as the reference group "R" in the research. Thus each group will have a sequence-dependent setup time with respect to the preceding group "R", in case they are scheduled to be processed first in the current planning horizon.

CHAPTER 4: MATHEMATICAL MODELS

The mathematical programming model for this bi-criteria problem is demonstrated below. This model belongs to Mixed Integer Linear Programming models.

4.1 Model

The indices, parameters, decision variables and the mathematical model are shown as follows:

Indices:

$g = 1, 2,\ldots,a$	groups
$i = 1, 2,\ldots,m$	machines
$j = 1, 2,\ldots,n_g$	jobs
$k = 1, 2,\ldots,a$	slots on each machine

Parameters:

N_{max}	Maximum number of jobs in all groups, $\max\{n_1, n_2,\ldots, n_g\}$
s_{igp}	Setup time on machine i for group g if group p is the preceding group
r_{gji}	$\begin{cases} \text{Run time of job } j \text{ in group } g \text{ on machine } i & ; \text{For real jobs} \\ -M & ; \text{For dummy jobs} \end{cases}$
α	Weight assigned for total completion time
β	Weight assigned for total tardiness
w_{gj}	Weight assigne*d for job j in group g
d_{gj}	Due date of job j in group g
rt_{gj}	The release time of job j in group g
at_i	The availability time of machine i

Variables:

t_{gj}	Tardiness of job j in group g
X_{kij}	The completion time of job j in the k^{th} slot on machine i

W_{kg} = $\begin{cases} 1; \text{If group } g \text{ is assigned to slot } k \\ 0; \text{Otherwise} \end{cases}$

Y_{kjb} = $\begin{cases} 1; \text{If job } j \text{ is precessed after job b in slot } k \\ 0; \text{Otherwise} \end{cases}$

Set_{ik} The setup time for a group assigned to slot k on machine i

$AS_{kg(k+1)p}$ = $\begin{cases} 1; \text{If group } g \text{ is assigned to slot } k \text{ and} \\ \quad \text{group } p \text{ is assigned to slot } k+1 \\ 0; \text{otherwise} \end{cases}$

C_{ki} The completion time of k^{th} slot on machine i

Model:

$$Minimize\ Z = \alpha \sum_{g=1}^{a} \sum_{k=1}^{K} \sum_{j=1}^{N_{max}} W_{kg} w_{gj} X_{kjm} + \beta \sum_{g=1}^{a} \sum_{k=1}^{K} \sum_{j=1}^{N_{max}} W_{kg} w_{gj} t_{gj} \quad (1)$$

Subject to:

$\sum_{g=1}^{K} W_{kg} = 1$	g=1,2,…,a	(2)
$\sum_{g=1}^{K} W_{kg} = 1$	k=1,2,…,a	(3)
$\sum_{g=0}^{k} \sum_{p=1}^{k} AS_{kg(k+1)p} = 1$	k=1,2,…,a-1	(4)
$AS_{kg(k+1)p} \le W_{kg}$	k=1,2,…,a-1 g,p=1,2,…,a $g \neq p$	(5)
$AS_{kg(k+1)p} \le W_{(k+1)g}$	k=1,2,…,a-1 g,p=1,2,…,a $g \neq p$	(6)
$Set_{ik} = \sum_{g=0}^{a} \sum_{p=1}^{a} AS_{(k-1)gkp} S_{igp}$	k=1,2,…,a i= 1,2,…,m $g \neq p$	(7)
$X_{k1j} \ge \sum_{g=1}^{a} W_{kg}(rt_{gj} + r_{gj1})$	j= 1,2,…, N_{max} k=1,2,…,a	(8)
$X_{kij} \ge C_{(k-1)i} + Set_{ik} + \sum_{g=1}^{a} W_{kg} r_{gji}$	k=1,2,…,a i= 1,2,…,m j= 1,2,…, N_{max}	(9)
$X_{kij} - X_{kij'} + MY_{kjj'} \ge \sum_{g=1}^{a} W_{kg} r_{gji}$	k=1,2,…,a i= 1,2,…,m j,j'= 1,2,…, N_{max} $j<j'$	(10)

$$X_{kij} - X_{kij'} + M(1 - Y_{kjj'}) \geq \sum_{g=1}^{a} W_{kg} r_{gji} \qquad i = 1,2,\ldots,m \;\; k=1,2,\ldots,a \;\; j<j' \tag{11}$$

$$X_{kij} - X_{k(i-1)j} \geq \sum_{g=1}^{a} W_{kg} r_{gji} \qquad k=1,2,\ldots,a \;\; j = 1,2,\ldots, N_{max} \;\; i = 2,3,\ldots,m \tag{12}$$

$$C_{ki} = Max\{X_{kij}\} \qquad k=1,2,\ldots,a \;\; i = 1,2,\ldots,m \tag{13}$$

$$W_{kg} X_{kmj} - d_{gj} \leq t_{gj} \qquad k=1,2,\ldots,a \;\; g=1,2,\ldots,a \tag{14}$$

$$t_{gj} \geq 0 \qquad g=1,2,\ldots,a \;\; j = 1,2,\ldots, N_{max} \tag{15}$$

$$X_{kij}, C_{ki}, Set_{ik} \geq 0 \quad C_{0i} = at_i \quad W_{kg}, AS_{kg(k+1)p} = 0,1 \quad Y_{kjj'} = 0,1 \; (j < j')$$

In order to locate positions of groups in a given sequence, it is assumed that slots exist for groups. Also, all groups need to be processed through the flow line, thus every group must be assigned to one and only one of the slots. There is no guarantee that all groups will have same number of jobs. But to simplify creating the mathematical model, it is assumed that every group has the same number of jobs, comprised of real and dummy jobs. The number of jobs in each group is then set to be equal to N_{max}, which is the maximum number of real jobs among all groups. For instance, when N_{max} is equal to 6, a group with 3 real jobs is going to have 3 dummy jobs. Dummy jobs have no run times and no setup times on each and every machine. The release time of dummy jobs are also set to 0. The objective of the model is to minimize the weighted sum of total weighted completion time and total weighted tardiness based on normalized weights α and β, which indicate the tradeoff between the two criteria.

Based on the model, *K* slots are set on each machine and all groups have to be assigned to one of them. It is quite clear that on every machine, each slot should only contain one group. On the other hand, each group on every machine can only be assigned to one slot. Constraints (2) and (3) support this fact.

Sequence-dependent setup indicates that the setup time of a group on a machine is dependent on both itself and the group processed preceding it. Constraint (4) is included in the model to support this. $AS_{kg(k+1)p}$ is equal to one only when group g is assigned to slot k and group p is assigned to slot $k+1$. $AS_{kg(k+1)p}$ must be zero when group g is not proceeding group p in slot k and $k+1$. Constraints (5) and (6) are supporting this fact. Constraint (7) obtains the setup time of groups on each machine. The sequence-dependent setup times on machines are obtained based on the group assigned to a slot and the group assigned to the preceding slot.

Because dynamic job releases are assumed, the jobs from all groups may not be released in the beginning of the planning horizon. Constraint (8) indicates that a job can only start processing on the first machine after it is released. Constraint (9) is added to aid constraint (8) to find the completion time of jobs on machines. The completion time of a job that belongs to a group should be greater than the summation of the completion time of the group processed in the previous slot, the setup time for the current group, and the run time of the job. Take the first machine for instance: a job can start processing only after the previous group finished its process on the machine, the setup time for the current group is performed, and this job is released. When the group is assigned to the first slot, $C_{0i} = at_i$ guarantees that the first job of this group can only start processing after the machine becomes available and the setup is performed.

Constraints (10) and (11) are a set of either/or constraints. The jobs' sequences within a group can be found by this set of constraints, which make use of the difference between two jobs' completion times to identify their sequences. If job j in a group is processed after job j' in the same group, then the difference between the completion time of two jobs on all machines should be greater or equal to the run time of the preceding job j.

After a job finished its processing on machine i-1, this job can continue processing on the next machine i. Thus, the completion time of a job on a machine will be greater than or equal to the summation of the completion time of the job on the preceding machine plus the run time of the job on that machine. Constraint (12) guarantees that the jobs will at least have a completion time on machine *i* that is equal to its completion time on machine *i*-1 plus its run time on machine *i*. A completion time of a group on a machine should be the biggest completion time of its jobs on the same machine. Constraint (13) supports that fact. Tardiness is one of the criteria of this model. Constraint (14) and (15) calculates the tardiness of jobs among all groups. Tardiness of jobs should be either 0 (when the job meets its due date) or a positive value (when the job has a larger completion time than its due date).

4.2 Complexity of the Problem

The normalized weights, which show the priority of each criterion, can be used to analyze the complexity of the proposed problem.

Notice that in the mathematical model, when α is set to 0, the problem is reduced to a multi-stage total-weighted tardiness minimization problem with realistic assumptions, which in turn reduces to a single machine total weighted tardiness minimization job scheduling problem, already proven to be strongly NP hard by Lenstra et al. (1977). Likewise, when β is set to 0, the problem is reduced to a multi-stage total weighted completion time minimization problem, which in turn reduces to a two-machine (two stages) total weighted completion time minimization job scheduling problem, already proven to be strongly NP-hard by Garey et al. (1976). Therefore, the proposed bi-criteria problem is strongly NP-hard.

4.3 Example

An example is shown to demonstrate the problem. There are three groups in the example problem. Group 1 has 3 jobs; group 2 has 2 jobs; group 3 has 3 jobs. There are 3 machines on which all jobs need to be processed. The run time of jobs on each machine are shown in Table 4.1. Columns represent weight/machines and rows represent jobs. For instance, in group three (G_3), job three (J_{33}) has a weight of 2, a run time of 4 on machine one (M_1), a run time of 3 on machine two (M_2), and a run time of 5 on machine three (M_3).

Table 4. 1 The run time of jobs in groups

G_1					G_2					G_3				
	Weight	M_1	M_2	M_3		Weight	M_1	M_2	M_3		Weight	M_1	M_2	M_3
J_{11}	1	3	4	3	J_{21}	2	4	5	4	J_{31}	1	3	4	1
J_{12}	3	2	1	4	J_{22}	2	3	1	2	J_{32}	3	1	3	2
J_{13}	1	1	5	4						J_{33}	2	5	4	5

The sequence dependent setup time of each group on each machine is shown in Table 4.2. “R” stands for the reference group or the group that was assigned last in the previous planning horizon when a group in the current planning horizon is sequenced to be processed first.

Table 4. 2 The setup time for groups

M_1				M_2				M_3			
	G_1	G_2	G_3		G_1	G_2	G_3		G_1	G_2	G_3
R	4	2	3	R	2	5	4	R	4	5	3
G_1	-	3	4	G_1	-	3	1	G_1	-	3	5
G_2	1	-	3	G_2	3	-	5	G_2	1	-	2
G_3	3	5	-	G_3	3	3	-	G_3	4	3	-

As dynamic release time and machine availability are assumed, the machine availability time is shown in Table 4.3. One of the criteria of the problem is the weighted tardiness. So the due date of jobs is needed to evaluate the tardiness. Table 4.4 shows the release time and due date of jobs.

Table 4. 3 The machine availability time

	Availability
M_1	1
M_2	7
M_3	8

According to the rank order of groups and jobs, a possible schedule can be made. This schedule would be: $G_1(J_{11} – J_{12} – J_{13}) – G_2(J_{21} – J_{22}) – G_3(J_{31} – J_{32} – J_{33})$.

The Gantt-chart of this schedule is demonstrated in Figure 2. In this Gantt-chart, the setup time of groups is shown in the form of S_{ijk}, where i stands for the previous group, j stands for the preceding group, k stands for machine. On top of the actual Gantt-chart is a representation of the release time of jobs.

Table 4. 4 Release time and due date of jobs in groups

G_1			G_2			G_3		
	Release	Due		Release	Due		Release	Due
J_{11}	3	25	J_{21}	5	25	J_{31}	5	22
J_{12}	8	19	J_{22}	2	32	J_{32}	4	35
J_{13}	6	30				J_{33}	7	33

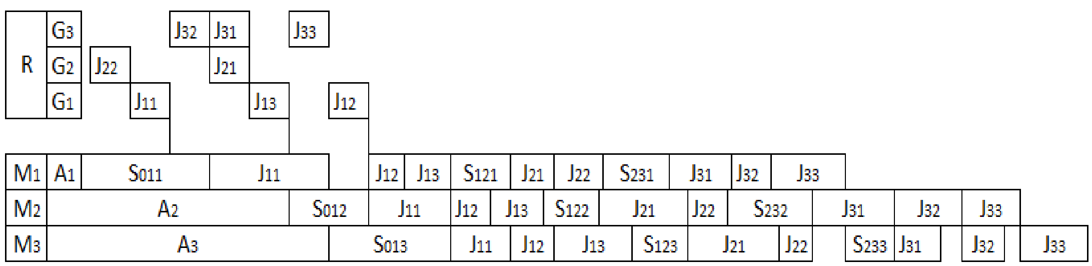

Figure 2 The Gantt chart of processing groups and jobs in rank order

It is obvious that machine availability time and job release time are having a combined effect on the whole process. Based on this Gantt-Chart, the completion time of each job on the last machine is shown in Table 4.5.

Table 4. 5 The completion time of jobs in groups

G_1		G_2		G_3	
J_{11}	15	J_{21}	30	J_{31}	37
J_{12}	19	J_{22}	32	J_{32}	41
J_{13}	23			J_{33}	48

If α is set to 0.6 and β is set to 0.4, the objective function value based on this sequence is 314.2. The weighted completion time and weighted tardiness are shown in Table 4.6.

If the problem is solved optimally by the mathematical models, the optimal solution for the bi-criteria function value is equal to 284. The total weighted tardiness and total weighted completion time are 65 and 430 for the optimal solution.

Table 4. 6 Weighted tardiness and weighted completion time of jobs

G_1			**G_2**			**G_3**		
	Weighted tardiness	Weighted completion time		Weighted tardiness	Weighted completion time		Weighted tardiness	Weighted completion time
J_{11}	0	12	J_{21}	10	60	J_{31}	19	37
J_{12}	0	57	J_{22}	0	64	J_{32}	6	84
J_{13}	0	20				J_{33}	30	96

CHAPTER 5: HEURISTIC ALGORITHM

Since the proposed bi-criteria problem is the combination of two NP-hard problems, existing optimization procedures, such as CPLEX (2009), is highly likely to require a large amount of time to identify an optimal solution. To find near optimal solutions in a reasonable time, high level metasearch heuristic algorithms are proposed. The proposed search algorithm fulfills the requirement of time efficiency, problem size capability and superior quality of the results.

The concept on which the proposed search algorithms are based is TS. This chapter will first introduce the background of TS and then describe the proposed two level search in detail. Finally, an example problem is used to show the application of the heuristic algorithm.

5.1 Introduction

Glover (1986) developed TS to solve combinational optimization problems. Later, Glover (1989, 1990a, 1990b) finalized the concept and additional formalization of TS.

TS is a general framework which is designed to guide other methods. It starts with an initial solution and then begins perturbation towards better solutions. Different perturbing methods lead to different set of moves for transforming from one solution to another. The three primary features are listed below:

- The use of flexible memory structures to store information during the search process. It allows the evaluation criteria and historical search information to be to explored more economically and effectively than by rigid memory structures (as in branch-and-bound) or by memoryless systems (as in simulated annealing and other randomized approaches).
- A control mechanism that is based on the interplay between imposing and freeing the constraints on the search process (embodied in the tabu restrictions and aspiration criteria).

- The combination of memory functions of different time spans, from short term to long term, to implement strategies for intensifying and diversifying the search.

The innovation of TS is that it implements and emphasizes "memory" in the structure. The memory used in TS is both explicit and attributive. Explicit memory records complete solutions, typically consisting of elite solutions visited during the search. The search can be expanded around the memorized elite solutions. Alternatively, TS uses attributive memory for guiding purposes. This type of memory records information about solution attributes that change in moving from one solution to another.

To understand the TS metaheuristic, first consider a general combinatorial optimization problem of the form:

$$\text{Minimize} \quad c(x)$$
$$\text{Subject to} \quad x \epsilon X,$$

where X is a discrete set of feasible solutions. Traditional local search procedure generates a monotone sequence of improving solutions by perturbing or moving from initial solution $x_0 \epsilon X$. When a local optimum is identified, which has a better or at least equal evaluation compared to its neighbors, the search procedure would be stuck in there and give up the chance to find other local optima. TS prevents the search from getting stuck in the local optima because in each iteration, TS chooses the best move regardless of whether or not it has a better evaluation than its parent. When the search actually finds a non-improving move, it identifies the parent solution as the local optimum and starts getting away from it immediately.

The following components help TS develop its memory function:

- **Tabu List**: After an iteration in which a non-improving move is accepted, the neighborhood of the new solution contains its parent solution that can now be selected because it has a better evaluation. If that move is accepted, the search will be moving back and forth between these two solutions. Tabu List stores information that is used to avoid generating solutions visited recently. A move is considered tabu and is discarded if it is recorded in the tabu list, or if its tabu tenure has not passed. Tabu tenure is the number of iterations for which the move stays tabu. It is equal to the size of the tabu list that is updated in a cyclic fashion, removing the last move recorded before recording a new move as tabu. Depending on the design, tabu tenure may be fixed or may be modified during the search process in order to further influence the search. Tabu list is a short-term (short time distance based) and attributive type of memory structure.

- **Aspiration Criterion**: The search process will possibly deny some moves that would generate good solutions because limited information (job numbers/positions) is tracked in the tabu list. As a matter of fact, the effect of a tabu tenure on preventing the search to go back and forth is decreasing along the number of iterations. Thus, old tabu tenure has a greater chance to block the search from going after a better solution. To counteract this potentially negative effect, TS introduces aspiration criterion to override the tabu status of a move. The simplest and most widely used form of aspiration criterion is to override the tabu status of a move if it produces a better solution than the best solution found so far in the search process.
- **Candidate List**: At the end of each iteration of the search, TS selects the best move (based on tabu list and aspiration criterion) among the neighbors that generated from the current solution. If the move that is selected is an improving move, then the new solution has the potential of being a local optimum. The solution is a local optimum if its children have no better objective function values. These potential local optima are recorded in a list called the Candidate List.
- **Index List**: If a solution indeed becomes a local optimum, which has no worse objective function value than its parent and children, it is recorded in an Index List. Candidate and Index lists are explicit memory structures that are used to control the search so that neighborhoods of already explored solutions are not visited again, to

monitor when elite solutions are identified, and to identify patterns that are common in the elite solutions.

To summarize, tabu list and aspiration criterion controls the search direction so the search will go after improvements of objective function value without moving in a circulatory pattern. Candidate list and index list keep track of the "good" solutions found so far and prevent the search from exploring the same solution space. In addition to the components discussed above, the following features are also very important to define the scope of TS:

- **Initial Solution**: As discussed previously, an initial solution is required to trigger the search. It can be chosen arbitrarily (ex. by index sequence) or generated using an initial solution finding mechanism (ex. earliest due date rule) that identifies a potentially good solution.
- **Neighborhood Function**: To move from one solution to another, a neighborhood function should be designed to define a new set of neighborhood solutions based on the current one. Generating neighborhood solutions is also known as perturbation of the current solution. There is no need to design complicated neighborhood function because TS provides different means for exploring the solution space effectively.
- **Objective Function Evaluation**: The purpose of the search is to identify a solution (or solutions) that optimize some objective function. Thus, each time a neighborhood solution is generated, its objective function value must be evaluated or the incremental value of the move that results in the solution must be computed. The aspiration criterion is tightly connected with objective function evaluation, because the minimizing/maximizing of the objective function value is what the search algorithm is aspiring.
- **Long Term Memory Function**: After searching in a particular area in the solution space for a while, the search will experience more difficulty to identify better solutions. To overcome this difficulty, more complex strategic memory structure should be implemented to intensify and diversify the search. Long term memory components of TS operate

primarily as a basis for intensifying and diversifying the search. TS has an intensification strategy by temporarily locking in certain locally attractive attributes (those belonging to moves recently evaluated to be good), while it also has a diversification strategy by forcing new choices to introduce attributes that are not explored recently. Long term memory components can be used to record patterns occurred in elite solutions. Therefore, long term memory is frequency based, which keep track of the certain patterns occurred or certain moves selected during the search. In an intensification strategy, TS seeks new solutions with these patterns fixed by correspondingly restricting or penalizing available moves, or by crafting a new initial solution that is obtained by putting together common components of elite solutions. Likewise, in a diversification strategy, solutions with the most occurred patterns may be discouraged by either penalizing certain moves, but also by crafting a new initial solution that has not been explored thoroughly by the elite solutions found so far. Long term memory components, which usually based on maximal or minimal frequencies, are used for intensification or diversification purposes. Based on the previous researches (Salmasi, 2005, and Gelogullari, 2005) there are two ways of implementing long term memory in production scheduling problems: Salmasi's way (conventional long term memory) is widely used among production scheduling researches; Gelogullari's way (non-conventional long term memory) is an innovation based on the concept of long term memory. To gain some insight about those two structures, this research implemented both ways, which are introduced below.

- Long Term Memory Function Based on Maximal Frequency (LTM-Max): The move or pattern that is found most frequently in the elite solutions is used to guide intensification. In group scheduling, for instance, the number of times each job/group is assigned to each position in the elite sequences can be recorded in different frequency matrixes during a short term search. Then, the job/group-position pair corresponding to the maximal number in the matrix can be fixed in the initial solution and the search can restart and progress accordingly. In conventional LTM-Max, the job/group position pair is always fixed in the entire short term search procedure until the search restarts and a new job/group pair is identified. Similarly, a new initial solution can be constructed by assigning jobs to positions, starting with the assignment corresponding to the highest frequency, then continuing with the assignment corresponding to the second highest frequency, and so on. In non-conventional LTM-Max, after the search restarts with the new initial solution, none of the jobs/groups and their positions is fixed. In other words, non-conventional LTM-Max only restarts the search with a new job/group sequence.

  - Long-Term Memory Function Based on Minimal Frequency (LTM-Min): In contrast to LTM-Max, the least frequently encountered move or pattern is identified and advantageously used to diversify the search. In the production scheduling example, conventional LTM-Min identifies the job/group-position pair corresponding to the minimal entry in the matrix and then keeps it fixed throughout the search. Based on minimal frequencies, non-conventional LTM-Min uses the frequency matrix to construct a new starting solution as different as possible from the solutions generated throughout the previous short term search.

- **Stopping Criteria**: Since TS will not stop when it encounters a local optimum, other specific stopping criteria must be employed. Usually, the search should be terminated when the best solution found so far has not improved for a certain number of iterations (number of iterations without improvement), or a certain number of local optima has been identified (entries into the index list).

Several parameters guide the search process, such as TLS, variable TLS, number of iterations without improvement (IWI), and entries into the index list (EIL). The search algorithm involves two levels: job sequence search (inside level) and group sequence search (outside level). The value of the parameters needs to be tested for both inside level and outside level. At the beginning of the search, the parameters should be evaluated based on the characteristic of the problem, for instance, number of groups, number of jobs, etc. Test problems are generated and tested to figure out the best formulas to evaluate appropriate parameter values by the given problem characteristics. Among all of the parameters, TLS is the most sensitive parameter which can affect the search result significantly. Therefore, during parameter testing, IWI and EIL can be fixed to a large number. And the size of the tabu list can be tested from 1 to a large number. The first value that gives a best search result is recorded. And then, best IWI and EIL are tested similarly. Notice the best parameter value founded should be kept fixed when the other parameters are tested. After several problems are tested, problem characteristics and the corresponding parameter values are fed into computer software. Linear regression is performed and the formulas to evaluate search parameters (dependent variables) by the problem characteristics (independent variables) are decided.

5.2 Components of the Proposed Search Algorithm

As discussed before, within the context of group scheduling, job sequence and group sequence are to be explored by a two-level search. Initial solution needs to be identified before the actual search can be performed. The outside level of the search involves the search for a better group sequence. Starting with a given group sequence, the inside level involves the search for a better job sequence. The final solution is composed of the best group sequence together with its best job sequence that results in the minimum objective function value. A perturbation of group sequence is applied in the outside level TS. After each outside perturbation, the inside search is invoked to perturb jobs within each group. Once the best job sequence corresponding to the given group sequence is identified, the search process is returned to the outside search to seek for a better group sequence. After several switches of the search direction, and when the stopping criterion is satisfied, the search algorithm returns the best solution identified for the problem.

The next subsections address several issues related to the search algorithm.

5.2.1 Initial solution finding mechanism

As the proposed problem has a need to satisfy two criteria simultaneously, the initial solution finding mechanism should include the characteristics that contribute to both criteria. However, the objective of minimizing total weighted tardiness and the objective of minimizing total weighted completion time are two contrasting objectives that cannot be considered simultaneously. Therefore, each objective is considered separately to get different sequences. Then a mechanism is developed to combine the sequences obtained from the two different objectives, by using normalized weights.

For the objective of minimizing total weighted completion time, Ham et al. (1985) provided a procedure for minimizing total completion time on a single machine with sequence-dependent setup time. This procedure is relaxed to make it fit to the research problem addressed here. While the jobs are sequenced by weighted shortest run time rule, the sequence of groups can be calculated by the following steps:

Step1: Calculate the required minimum setup time (Min_S_i) for each machine

Step2: Find the order of groups based on the following inequalities:

$$\frac{Min\_S_1 + T_1}{b_1} \leq \frac{Min\_S_2 + T_2}{b_2} \leq \cdots \leq \frac{Min\_S_i + T_i}{b_i}$$

T_i denotes the total run time of group i. b_i denotes the number of jobs in group i. This procedure is performed for each stage. The best of the sequences by considering the minimization of total weighted completion time is taken as the sequence for minimizing total weighted completion time.

For the objective of minimizing total weighted tardiness, two mechanisms are used to get job sequences. Earliest due date (EDD) is a widely used rule which is also very effective in tardiness related objectives. Another one is weighted earliest due date (wEDD), which introduces weights of jobs in addition to the due dates. When sequencing the jobs according to EDD or wEDD, the group identity of the jobs is ignored. Therefore, the resulting sequence is only a job sequence. However, under group technology assumption (GTA), the jobs that belong to the same group should be processed consecutively. A mechanism is developed to adjust the sequence so jobs from the same group can be processed consecutively.

An example is used to demonstrate the mechanism. Table 5.1 shows the group identity of jobs, as well as their due dates.

Table 5. 1 Jobs and due dates

Group	Job	Due Date
1	1	29
1	2	36
1	3	18
2	1	45
2	2	12
2	3	10
3	1	35
3	2	24

The sequence obtained after sequencing jobs by their due dates is shown in Table 5.2. As noted before, the current sequence does not meet GTA. In order to obtain a group sequence, ranks are assigned to jobs.

The jobs' ranks are used to calculate the ranks of groups. Groups are assigned with the average rank of their jobs. For example, in group 1, jobs have a total rank of 3+5+7=15, so group 1 is assigned with a rank of 15/3=5. Table 5.3 shows the group ranks.

Table 5. 2 Sequence of jobs without GTA

Group	Job	Due Date	Rank
2	3	10	1
2	2	12	2
1	3	18	3
3	2	24	4
1	1	29	5
3	1	35	6
1	2	36	7
2	1	45	8

Table 5. 3 Ranks of groups

Group	Job	Due Date	Rank	G Rank
1	1	29	5	5
1	2	36	7	
1	3	18	3	
2	1	45	8	3.7
2	2	12	2	
2	3	10	1	
3	1	35	6	5
3	2	24	4	

Finally, groups are sorted by their ranks (ties are broken arbitrarily by group index). Jobs in a group are also sequenced by their ranks. Table 5.4 shows the final sequence obtained by EDD rule for the example problem.

As shown in the table, in the final sequence, a job with a higher rank (large due date) may be processed before a comparatively low rank job (small due date) because of GTA.

Since the initial solutions are obtained by considering both objectives, a mechanism is developed to combine the sequences from both sides. Based on the example problem above, the sequence to minimize total weighted completion time (WCT) is shown in Table 5.5.

Table 5. 4 Final EDD sequence

Group	Job	Due Date	Rank
2	3	10	1
2	2	12	2
2	1	45	8
1	3	18	3
1	1	29	5
1	2	36	7
3	2	24	4
3	1	35	6

Table 5. 5 WCT sequence

Group	Job	Due Date	Rank
1	3	18	1
1	1	29	2
1	2	36	3
3	1	35	4
3	2	24	5
2	2	12	6
2	3	10	7
2	1	45	8

The normalized weights reflect the trade-off between the two objectives. The two sequences are obtained by considering the two objectives separately. Thus, the normalized weights are used in the sequence combination mechanism. The rank each job gets from each sequence is multiplied by the normalized weight assigned to the objective. And then the results from both sides are added up to obtain the final rank of a job. Table 5.6 shows the ranks from each objective and the final ranks of jobs.

Take job 1 of group 1 for instance. In the EDD sequence, rank 2 is assigned to the job. In the WCT sequence, rank 5 is assigned to the job. When $\alpha = 0.6$ and $\beta = 0.4$ the final rank for this job is calculated by $2 \times 0.6 + 5 \times 0.4 = 3.2$. After final ranks are obtained, the jobs and groups are sequenced by the similar mechanism which is used before for obtaining the EDD sequence. Table 5.7 shows the final sequence.

Table 5. 6 Sequence combination

Group	Job	Due Date	EDD Rank	WCT Rank	Final Rank
1	1	29	2	5	3.2
1	2	36	3	6	4.2
1	3	18	1	4	2.2
2	1	45	8	3	6
2	2	12	6	2	4.4
2	3	10	7	1	4.6
3	1	35	4	8	5.6
3	2	24	5	7	5.8

Table 5. 7 Final sequence

Group	Job	Rank
1	3	2.2
1	1	3.2
1	2	4.2
2	2	4.4
2	3	4.6
2	1	6
3	1	5.6
3	2	5.8

5.2.2 Neighborhood function

When a solution (sequence) is fed into the search, some perturbations should be made to move the solution around in the feasible solution area. As mentioned before, group scheduling involves two levels, the group level and job level. Thus, two different neighborhood functions are developed to perturb a given sequence in two levels. While σ denotes a given sequence, the neighborhood functions are demonstrated as follows:

- At the group level, $NG(\sigma) = \{ \sigma' : \sigma'$ is a neighbor sequence obtained from σ. The neighbors are obtained by performing exchange moves between any two groups in the sequence. The sequence of jobs within each group remains the same.}

  For instance, a sequence of a 3 group problem can be $\sigma = G_2(J_{22} - J_{21}) - G_1(J_{12} - J_{11} - J_{13}) - G_3(J_{31} - J_{32}) - G_4(J_{42} - J_{41})$. The possible neighborhoods of this sequence are:

$$NG(\sigma) = \{G_1(J_{12} - J_{11} - J_{13}) - G_2(J_{22} - J_{21}) - G_3(J_{31} - J_{32}) - G_4(J_{42} - J_{41});$$

$$G_3(J_{31} - J_{32}) - G_1(J_{12} - J_{11} - J_{13}) - G_2(J_{22} - J_{21}) - G_4(J_{42} - J_{41});$$

$$G_4(J_{42} - J_{41}) - G_1(J_{12} - J_{11} - J_{13}) - G_3(J_{31} - J_{32}) - G_2(J_{22} - J_{21});$$

$$G_2(J_{22} - J_{21}) - G_3(J_{31} - J_{32}) - G_1(J_{12} - J_{11} - J_{13}) - G_4(J_{42} - J_{41});$$

$$G_2(J_{22} - J_{21}) - G_4(J_{42} - J_{41}) - G_3(J_{31} - J_{32}) - G_1(J_{12} - J_{11} - J_{13});$$

$$G_2(J_{22} - J_{21}) - G_1(J_{12} - J_{11} - J_{13}) - G_4(J_{42} - J_{41}) - G_3(J_{31} - J_{32}) \}$$

- At the job level, $NG(\sigma) = \{ \sigma' : \sigma'$ is a neighbor sequence obtained from σ. The neighbors are obtained by performing exchange moves between any two jobs within the same group in the sequence. The sequence of groups remains the same.}

  For instance, consider the same sequence used above: $\sigma = G_2(J_{22} - J_{21}) - G_1(J_{12} - J_{11} - J_{13}) - G_3(J_{31} - J_{32}) - G_4(J_{42} - J_{41})$. The possible neighborhoods of this sequence are:

$$NJ(\sigma) = \{G_2(J_{21} - J_{22}) - G_1(J_{12} - J_{11} - J_{13}) - G_3(J_{31} - J_{32}) - G_4(J_{42} - J_{41});$$

$$G_2(J_{22} - J_{21}) - G_1(J_{11} - J_{12} - J_{13}) - G_3(J_{31} - J_{32}) - G_4(J_{42} - J_{41});$$

$$G_2(J_{22}-J_{21})-G_1(J_{13}-J_{11}-J_{12})-G_3(J_{31}-J_{32})-G_4(J_{42}-J_{41});$$

$$G_2(J_{22}-J_{21})-G_1(J_{12}-J_{13}-J_{11})-G_3(J_{31}-J_{32})-G_4(J_{42}-J_{41});$$

$$G_2(J_{22}-J_{21})-G_1(J_{12}-J_{11}-J_{13})-G_3(J_{32}-J_{31})-G_4(J_{42}-J_{41});$$

$$G_2(J_{22}-J_{21})-G_1(J_{12}-J_{11}-J_{13})-G_3(J_{31}-J_{32})-G_4(J_{41}-J_{42})\}$$

5.2.3 Evaluation of the objective function

Each neighborhood solution encountered during the perturbation should be evaluated considering the objectives. Figure 3 shows the flowchart of the procedure implemented in the computer program for computing the objective function value of a given sequence.

5.2.4 Tabu list

Exchange moves in outside search are used to perturb the group sequence and generate neighborhood solutions in the outside TS. After an exchange move is selected and performed, this move is stored in the tabu list. There are several ways to store a move. Suppose that in a group sequence given by G_2-G_1-G_3-G_4, G_2 and G_4 are selected to switch positions in the current iteration.

- A move can be saved by recording the positions of the groups that exchanged their position. In this case, 1-4 is going to be recorded in the tabu list.
- A move can be saved by recording the numbers of the groups that exchanged their position. In this case, 2-4 is going to be recorded in the tabu list.
- A move can be saved by recording the positions and numbers of the groups that exchanged their position. In this case, 1,2-4,4 is going to be recorded in the tabu list.

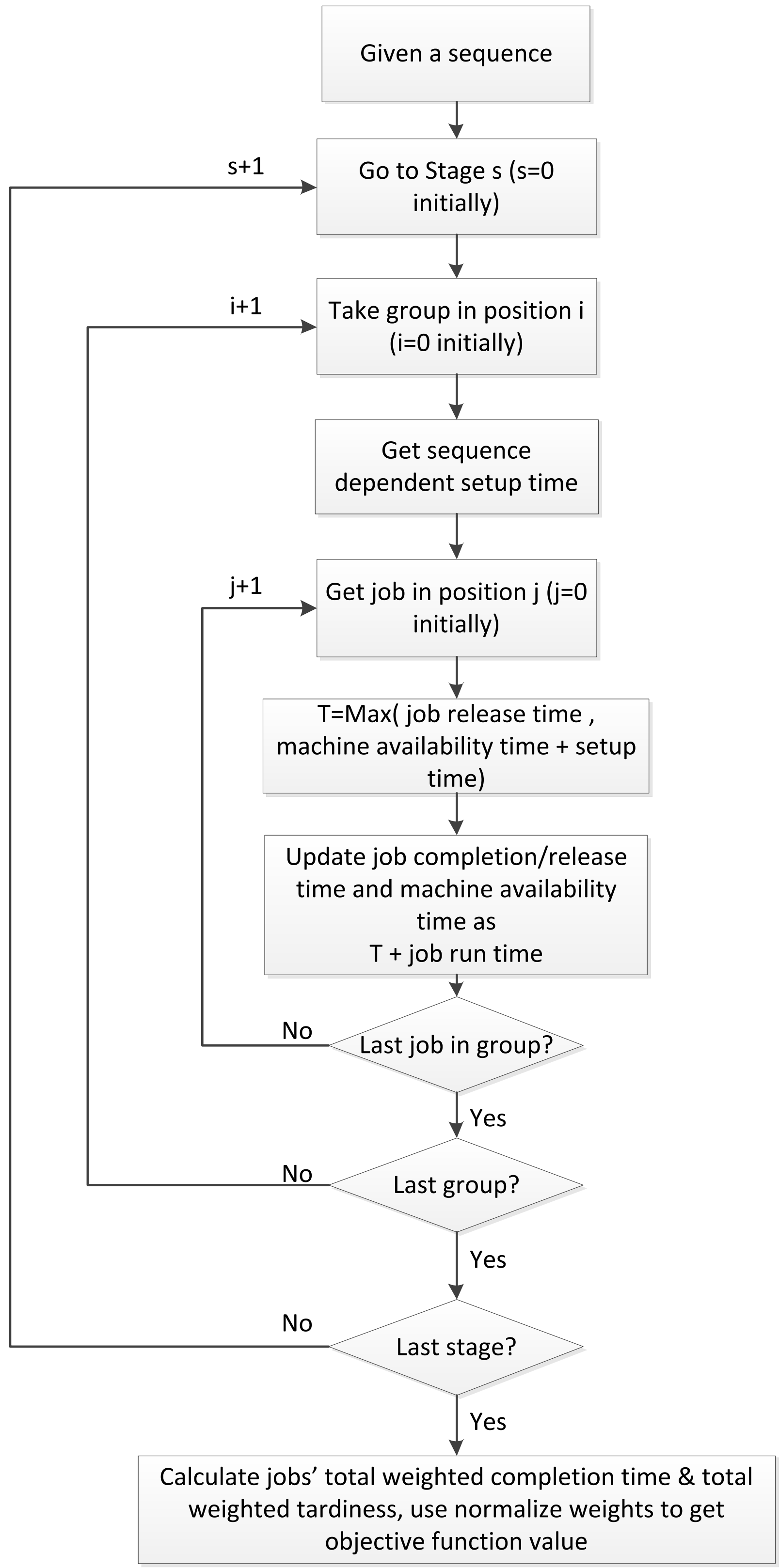

Figure 3 Flowchart of objective function evaluation

Similar concepts hold true in the inside search. Recall that a tabu tenure can prevent a move from being executed. Therefore, the first mechanism of recording a tabu tenure is going to forbid exchange moves between groups in position 1 and position 4 in the next few iterations depending on the tabu list size. The second mechanism is going to forbid exchange moves between group 2 and group 4 in the next few iterations. The third mechanism is going to forbid exchange moves between group 2 and group 4 when positions 1 and 4 are occupied by these two groups.

The third mechanism is too complex to implement a tabu tenure, which contains specified information. Although the information is exact and accurate, this kind of tabu tenure is going to slow down the search significantly. Therefore, disregarding the third mechanism, an experiment was conducted to get some insights into which kind of tabu tenure works better for this research. 100 problems were generated by considering the number of groups from 2-4, and number of jobs in a group from 2-10. The first and second tabu tenure record mechanisms are tested on same problems. The performance of each tabu tenure recording mechanism is evaluated by the number of times the algorithms identifies the best solutions. The result is shown in Table 5.8 below.

Table 5. 8 Tabu tenure experiment results

Total Number of Times	Identified By Tabu Tenure Type 1	Identified By Tabu Tenure Type 2
374	214	160
	57.22%	42.78%

The total number of times that algorithms identified the best solutions for different problems is 374. Out of that, algorithms using the first kind of tabu tenure identified the best solutions 214 times (57.22%), and algorithms using the second kind of tabu tenure identified the best solutions 160 times (42.78%). Thus, recording the positions of the exchanged groups/jobs is selected to be the better tabu tenure for this research.

Variable tabu list size strategy is also used to incorporate flexibility into the search algorithm.

5.2.5 Long-term memory

A frequency-based long term memory (LTM) is implemented in both outside and inside levels of search. This frequency based long term memory updates the number of occurrences of job-position/group-position combinations in accepted solutions among iterations of search. In other words, every time the best neighbor of a group/job sequence is identified, the LTM matrix is updated.

5.2.6 Aspiration criterion

The solution which has a better objective function value than the best solution found so far will always get accepted even if the move resulting in this solution is in the tabu list. Therefore, aspiration criterion overrides the tabu status.

5.2.7 Empirical tests of search parameters

Several parameters are affecting the performance of the TS algorithm. The most important one is the tabu list size. As noted before, tabu list is a short-term and attributive type of memory structure. Therefore, the size of this short-term memory structure can affect the direction of the search steps significantly. In order to properly direct the search algorithm, the best tabu list sizes for different problems should be a dependent variable to the characteristics of the problems.

Similar concept holds true for the stopping criteria evaluation. Therefore, the best value for outside tabu list size (OTLS), outside number of iterations without improvement (OIWI), outside number of entries to the index list (OEIL), inside tabu list size (ITLS), inside number of iterations without improvement (IIWI), and inside number of entries to the index list (IEIL) are tested on problems generated by different characteristics. And then, proper formulae are estimated by DataFit (2008) software. The inside search parameters are tested first, because the inside search is in a lower level which provides service (returns results) to outside level search. As tabu list size is the most important parameter, it will be tested first. For every problem, with the other two parameters set to large numbers (25 in this research), the tabu list size is tested from 1 to 20. The tabu list size which provides the solution with the lowest objective function value is recorded. With the best tabu list size identified, the number of iterations without improvement and the number of entries into the index list are tested similarly. Table 5.9 shows the test results for these search parameters.

The empirical formulae obtained are shown below, which are estimated using the software *DataFit*.

For problems with number of groups from 2-5:

ITLS	ROUNDUP((NOJ-NOG)*0.2,0)
IIWI	ROUNDUP((NOJ-NOG)*0.09,0)
IEIL	ROUNDUP((NOJ-NOG)*0.1,0)
OTLS	ROUNDDOWN(NOG/3+1-ROS/15,0)
OIWI	ROUNDDOWN(NOG/3+0.8+ROS/16,0)
OEIL	ROUNDDOWN(NOG/3+1+ROS/9,0)

For problems with number of groups form 6-10:

ITLS	ROUNDUP((NOJ-NOG)*0.11,0)
IIWI	ROUNDUP((NOJ-NOG)*0.21,0)
IEIL	ROUNDUP((NOJ-NOG)*0.06,0)
OTLS	ROUNDDOWN(NOG/3+0.6-ROS/15,0)
OIWI	ROUNDDOWN(NOG/3+1.8+ROS/16,0)
OEIL	ROUNDUP(NOG/3+ROS/9+2,0)

For problems with number of groups form 11-16:

ITLS	ROUNDUP((NOJ-NOG)*0.05,0)
IIWI	ROUNDUP((NOJ-NOG)*0.07,0)
IEIL	ROUNDUP((NOJ-NOG)*0.06-3.3,0)
OTLS	ROUNDDOWN(NOG/3+0.3-ROS/14,0)
OIWI	ROUNDDOWN(NOG/3+1.2+ROS/15,0)
OEIL	ROUNDUP(NOG/3+ROS/9+4,0)

Table 5. 9 Search parameter test results

NOJ	NOG	STR	ITLS	IIWI	IEIL	OTLS	OIWI	OEIL
4	2	2	1	1	1	1	1	1
5	2	5	1	1	1	1	1	2
6	2	10	1	1	1	1	2	2
7	3	2	1	1	1	1	1	2
10	3	5	2	1	1	1	2	2
9	4	10	1	1	1	1	2	3
10	4	2	2	1	1	2	2	2
12	4	5	2	1	1	2	2	2
14	4	10	2	1	1	1	2	3
16	5	2	3	1	2	2	2	2
18	5	5	3	2	2	2	2	3
20	5	10	3	2	2	2	3	3
26	5	2	3	5	2	2	4	4
32	5	5	3	6	2	1	3	5
37	6	10	4	7	2	1	4	6
39	6	2	4	7	2	2	4	5
40	7	5	4	7	2	2	4	5
42	7	10	4	8	3	2	4	6
45	7	2	5	8	3	2	4	5
43	8	5	4	8	3	2	4	6
50	8	10	5	9	3	2	4	6
51	9	2	5	9	3	3	5	6
59	9	5	6	11	3	3	4	6
63	10	10	6	12	4	3	5	7
96	11	2	5	6	2	3	5	8
102	11	5	5	7	3	3	5	9
105	12	10	5	7	3	3	5	10
115	12	2	6	8	3	4	5	9
114	13	5	6	8	3	4	5	9
123	13	10	6	8	4	3	5	10
125	14	2	6	8	4	4	6	9
128	14	5	6	8	4	4	6	10
132	15	10	6	9	4	4	6	11
137	15	2	7	9	5	5	6	10
148	16	5	7	10	5	5	6	10
155	16	10	7	10	6	4	6	11

Besides these parameters, the variable tabu list size is also implemented and tested. The OIWI/IIWI is used to trigger the change of tabu list size. When the search is running with variable TLS, if the iterations without improvement reach 1/3 of the empirically determined OIWI/IIWI suitable for the problem, the tabu list size is decreased. The search is resumed with the decreased TLS, and upon reaching another 1/3 of the empirically determined OIWI/IIWI, the tabu list is increased in size. With increased TLS in place, the search is resumed and when the iterations without improvement reach the full empirically determined OIWI/IIWI, it is terminated. The best increase and decrease of TLS based on the original size of tabu list is shown below in Table 5.10.

Table 5. 10 Variable TLS

ITL	ITL-Inc	ITL-dec	OTL	OTL-Inc	OTL-dec
2	3	1	2	3	1
3~5	ITL+2	ITL-2	3~6	OTL+2	OTL-2
6~7	ITL+3	ITL-3			

5.3 Algorithmic Steps of the Proposed TS Algorithms

As the problem involves two levels of search, the flowcharts of outside and inside TS algorithms are presented and the algorithmic steps involved in them are described. The pseudo codes for both inside and outside level search are presented in Appendix B.

5.3.1 Outside TS

Figure 4 shows the steps of the outside TS algorithm.

Step 1. Initialization: Accept an initial solution σ_0 in the beginning of outside level search. Perform inside TS on σ_0 to identify the best job sequence based on its group sequence. Let σ^* and σ denote the best solution found so far and the current solution, respectively. In the beginning, σ^* and σ are the same as σ_0. Admit the current solution to the outside candidate list (OCL) and outside index list (OIL). Initialize an empty outside long-term memory (OLTM) matrix of size $a \times a$, where a is the number of groups. For each group g assigned to position p in σ, set OLTM[g,p]=1. Set the number of iterations without improvement (OIWI) to 0. Let $obj(\sigma)$ denote the objective function value of σ and set outside aspiration level (OAL) equal to $obj(\sigma)$. Create an empty outside tabu list with its size calculated by the empirically determined formula.

Step 2. **Neighborhood:** Generate the neighborhood of the current solution σ as $NG(\sigma)$. Discard any solution in OCL. Invoke inside search to find and evaluate job sequences for each solution in $NG(\sigma)$.

Step 3. Select Best Move: Select the best solution and the move that created it in $NG(\sigma)$. If the move is not tabu (not stored in OTL), apply the move to σ. If the move is stored in OTL, check whether the solution satisfies aspiration criterion (whether the solution has a better objective function value than the aspiration level). If so, apply the move to σ. If not, select the next best neighborhood, and continue similarly.

Step 4. Update Necessary Components: Let the accepted move be the one that exchanges the groups in position p and p'. Admit this move (p, p') to OTL. Increase OLTM[g,p] by 1 for each group g assigned to position p in σ. If σ is better than its parent (potential local optimum), then append it to OCL. If it is found to be better than its child in the next iteration, admit it to OIL because it is indeed a local optimum. If σ is better than the best solution found so far, then set $\sigma * = \sigma$, OAL = $obj(\sigma)$, and OIWI = 0; otherwise increase OIWI by 1. If variable OTL is used in the search, adjust the OTL size when OIWI reaches the 1/3 and 2/3 of the empirically determined value as described above.

Step 5. Stopping Criteria: Stop if either of the following holds.

- If the best solution has not been updated for the last $\overline{\text{OIWI}}$ iterations.
- If the number of local optima reaches $\overline{\text{OEIL}}$

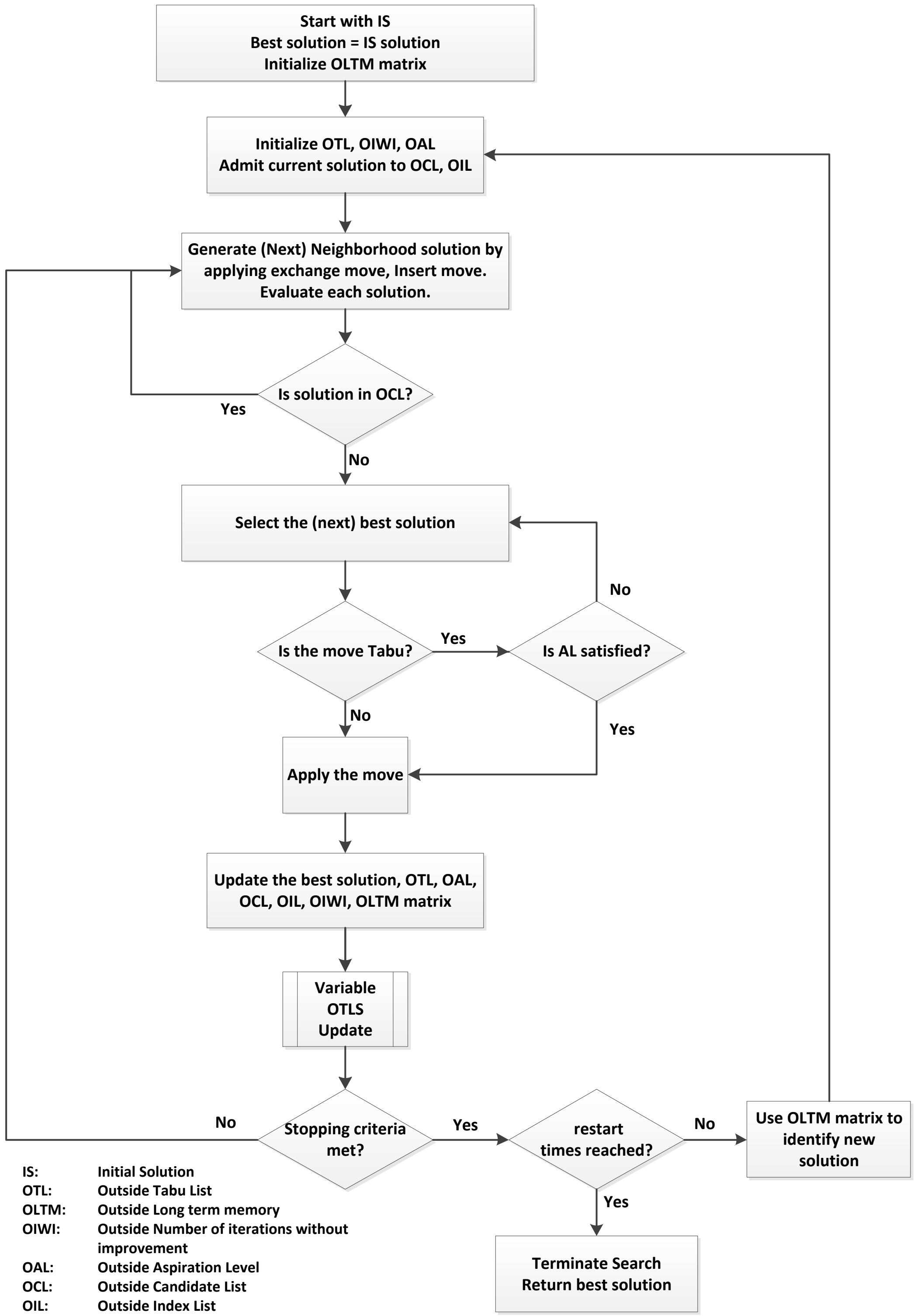

Figure 4 Outside search flowchart

If none of the two stopping criteria is met, go back to Step 2.

Step 6. Restart: A short term search will terminate when either one of the stopping criteria is met. If LTM is used, the search will restart twice with different starting solutions. For intensification, LTM-Max is used. For diversification, LTM-Min is used. Under conventional LTM-Max, identify the maximal entry in OLTM matrix corresponding to the assignment of group g to position p. Fix this group-position combination in the next short-term search, but remove this combination from further consideration (i.e., in the next restart, the frequency of this group-position combination will not be considered). Under non-conventional LTM-Max, start from the first position in the LTM matrix, identify the group that has been assigned most frequently in the position, put this group in the first position and remove this group from further consideration, move to the next position and continue similarly. LTM-Min uses similar strategies, but instead of selecting the most frequent group-position combination, it selects the least frequent group-position combination. After a new solution σ' is constructed, initialize OTL, OIWI, OAL, admit σ' to OCL and OIL, and go back to Step 2.

5.3.2 Inside TS

Figure 5 shows the steps of the inside TS algorithm.

Step 1. Initialization: Accept an initial solution σ_0 provided by the outside search in the beginning of inside search. Let σ^* and σ denote the best solution found so far and the current solution, respectively. In the beginning, σ^* and σ are the same as σ_0. Admit the current solution to the inside candidate list (ICL) and inside index list (IIL). Initialize empty inside long-term memory matrixes ILTM_g of size $n_g \times n_g$, where $n_g$is the number of jobs in group g. For each job j in group g assigned to position p in σ, set $\text{ILTM}_g[j,p]$=1. Set the number of iterations without improvement (IIWI) to 0. Let $obj(\sigma)$ denote the objective function value of σ and set inside aspiration level (IAL) equal to $obj(\sigma)$. Create an empty inside tabu list with its size calculated by the empirically determined formula.

Step 2. **Neighborhood:** Generate the neighborhood of the current solution σ as $NG(\sigma)$. Discard any solution in ICL. Evaluate each solution in $NG(\sigma)$.

Step 3. Select Best Move: Select the best solution and the move that created it in $NG(\sigma)$. If the move is not tabu (not stored in ITL), apply the move to σ. If the move is stored in ITL, check whether the solution satisfies aspiration criterion (whether the solution has a better objective function value than the aspiration level). If so, apply the move to σ. If not, select the next best neighborhood, and continue similarly.

Step 4. Update Necessary Components: Let the accepted move be the one that exchanges the jobs in group g between position p and *p'*. Admit this move (*g, p, p'*) to ITL. Increase $\text{ILTM}_g[j,p]$ by 1 for each group g assigned to position p in σ. If σ is better than its parent (potential local optimum), then append it to ICL. If it is found to be better than its child in the next iteration, admit it to IIL because it is indeed a local optimum. If σ is better than the best solution found so far, then set $\sigma *= \sigma$, IAL = $obj(\sigma)$, and IIWI = 0; otherwise increase IIWI by 1. If variable ITL is used in the search, adjust the ITL size when IIWI reaches the 1/3 and 2/3 of the empirically determined value as described above.

Step 5. Stopping Criteria: Stop if either of the following holds.

- If the best solution has not been updated for the last $\overline{\text{IIWI}}$ iterations.
- If the number of local optima reaches $\overline{\text{IEIL}}$

If none of the two stopping criteria is met, go back to Step 2.

Step 6. Restart: A short term search will terminate when either one of the stopping criteria is met. If LTM is used, the search will restart twice with different starting solutions. For intensification, LTM-Max is used. For

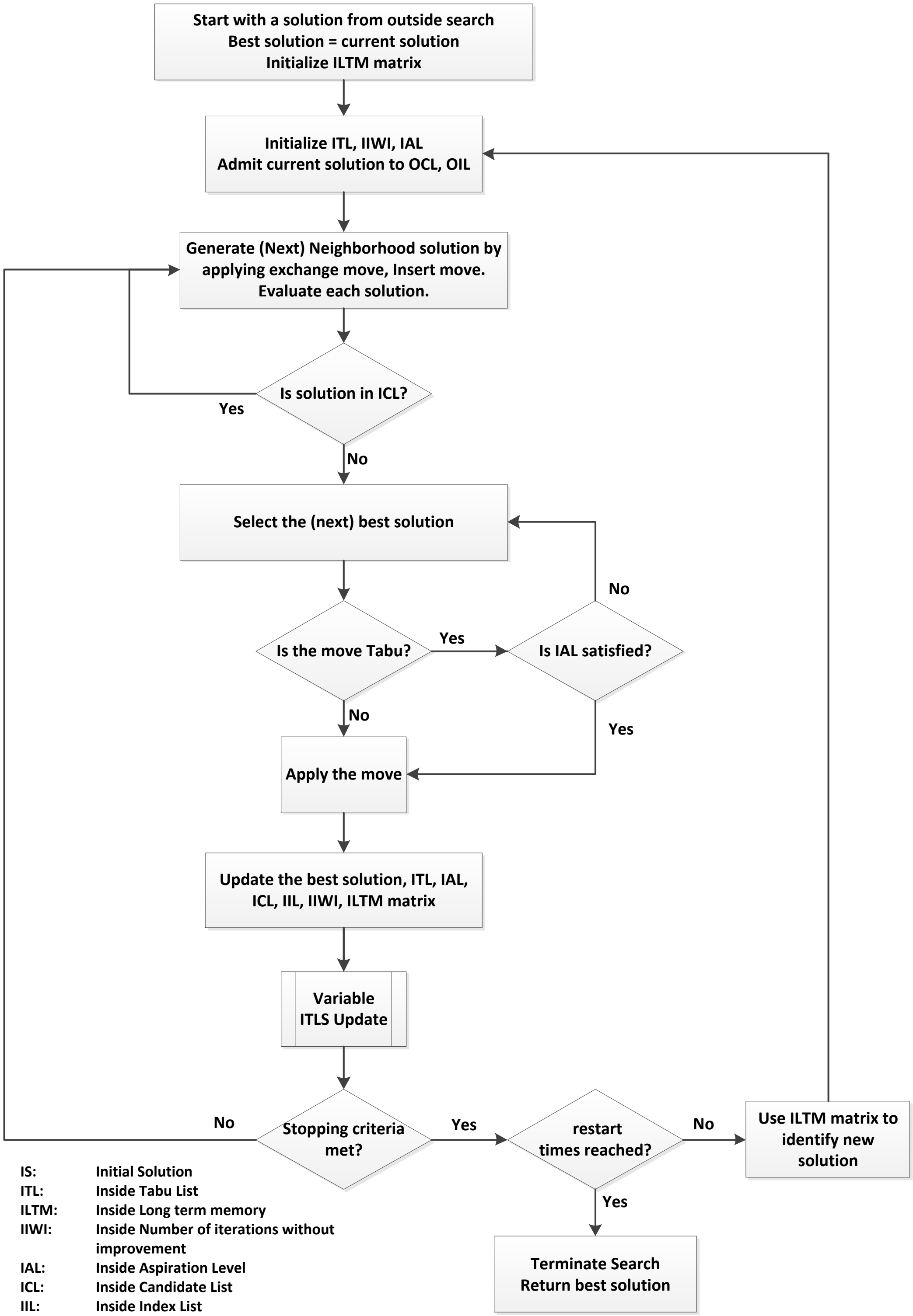

Figure 5 Inside search flowchart

diversification, LTM-Min is used. Under conventional LTM-Max, identify the maximal entry among all ILTM_g matrixes corresponding to the assignment of job j to position p in group g. Fix this job-position combination in this group in the next short-term search, but remove this combination from further consideration (i.e., in the next restart, the frequency of this job-position combination will not be considered). Under non-conventional LTM-Max, start from the first position in every ILTM_gmatrix, identify the job that has been assigned most frequently in the position, put this job in the first position in group g and remove this group for further consideration, move to the next position in group g and continue similarly. LTM-Min uses similar strategies, but instead of selecting the most frequent group-position combination, it selects the least frequent group-position combination. After a new solution σ' is constructed, initialize ITL, IIWI, IAL, admit σ' to ICL and IIL, and go back to Step 2.

5.4 Example Problem

To demonstrate the search algorithmic procedures of this two level TS, an example problem is needed. The data of the problem should be generated following certain rules so that the problem is meaningful and challenging to the search algorithm.

5.4.1 Data generation

The job release time and the machine availability time are generated from Exponential distribution with a mean of 20 (20 minutes per arrival/release). To mimic a scenario that is closer to industrial practice, we introduce accumulated machine availability time, which allows us to estimate a time when a machine can be completely ready to start processing jobs in the current planning horizon. As there is only one machine in each stage, a one-to-one transfer equation is used to estimate machine availability:

$$a_i' = \max[a_{i-1}', a_i + \bar{s}_i] + \bar{r}_i, where\ i = 2, \dots, k$$

In this formula, a_i'denotes the accumulated machine availability time of machine i. a_i denotes the availability time generated from an exponential distribution for machine i. $\bar{s}_i$ is the average setup time of all jobs in the current planning horizon on machine i. $\bar{r}_i$ is the average runtime of all jobs in the current planning horizon on machine i. The availability time of machine 1 stays the same as the value generated from exponential distribution. The runtime of the jobs is randomly generated from a uniform distribution between 1 and 20. The weights of the jobs are generated using uniformly distributed integers in the interval [1, 3]. To emphasize the importance of the sequence-dependent setup time between jobs belonging to different groups, setup times in each stage are guided by an approximate ratio between average setup time and average run time. The ratio can be 2, 5, or 10 (Schaller et al., 2000). Since the runtime is generated from [1, 20], the 3 levels of setup times can be generated from [1, 40], [1, 100], or [1, 200].

The generation of proper due dates is a very important part in scheduling problems. Meaningful due dates can provide better solutions in evaluating the performance of the algorithm. The due dates should not be generated simply by picking numbers from a given distribution. Taking advantage of the previous work (Pandya and Logendran, 2010), we use tardiness factor (τ), range factor (R), and C_{max} (the maximum completion time of all jobs released) to generate meaningful due dates. The average due date $\bar{d}$ and the estimated makespan C_{max} have a mathematical relationship defined by $\tau = 1 - \bar{d}/C_{max}$. A large τ indicates tight due dates and a small τ signifies loose due dates. The measure of variability of due dates is defined by $R = (d_{max} - d_{min}) / C_{max}$, which is the difference between maximum due date and minimum due date over the maximum completion time. A narrow range of due date is given by a small R, while a large R gives a wide interval of the due dates. Hence, both R and τ are constraining the generation of meaningful due dates from a uniform distribution. In this research, R is set to 0.2 and τ is set to 0.8. A random number from 0 to 1 is picked to generate a due date. If the number falls into [0, τ], the due date is generated from a uniform distribution$[\bar{d} - R\bar{d}, \bar{d}]$; if the number falls into (τ, 1], the due date is generated from a uniform distribution $[\bar{d}, \bar{d} + (C_{max} - \bar{d})R]$. Table 5.11 gives the relationship between parameter combinations (τ and R) and the characteristics of due date.

Table 5. 11 Due date classification

	R	Degree of tightness	Width of range
0.2	0.2	Loose	Narrow
0.2	0.5	Loose	Medium
0.2	0.8	Loose	Wide
0.5	0.2	Medium	Narrow
0.5	0.5	Medium	Medium
0.5	0.8	Medium	Wide
0.8	0.2	Tight	Narrow
0.8	0.5	Tight	Medium
0.8	0.8	Tight	Wide

With the exception of flow shop flexibility and machine capability, we take advantage of the data generation methodology proposed by Pandya and Logendran (2010). In a problem with m groups and k stages, C_{max} is obtained using the following equation:

$$C_{max} = e_{m,n_m,k}$$

$e_{m,n_m,k}$ denotes the release time of the last job in the last group on the last stage. As there are several stages in a flow shop, the average completion time of a job evaluated for the previous stage serves as the release time for jobs in the following stage. The following equation is introduced to estimate the release time of a job in the first position in a group at $(i+1)^{\text{th}}$ stage:

$$e_{g1(i+1)} = \max\left[e_{g1i}, e_{(g-1)n_{g-1}(i+1)} + \gamma \times \bar{s}_{gi}\right] + r_{g1i}$$

$$Where\ e_{g10} = rt_{g1}, e_{0n_{g-1}i} = a_i'$$

Similarly, the release time estimation equation for jobs that are not in the first position in a group is as follows:

$$e_{gj(i+1)} = \max\left[e_{gji}, e_{(g-1)n_{g-1}(i+1)}\right] + r_{gji}\ , j = 2, \cdots, n_g$$

$$Where\ e_{gj0} = rt_{gj}, e_{0n_{g-1}i} = a_i'$$

$\bar{s}_{gi}$ denotes the average setup time of group g on stage i. The total number of jobs in group g is denoted by n_g. rt_{gj} denotes the original release time when the job is ready to be processed through the flow shop. In reality, a quality schedule would try to changeover from one group to another that requires the smallest setup time in a particular stage. In other words, the use of the average setup time is somehow providing an inaccurate estimate of the makespan for the first stage. Hence, γ is introduced as an adjustment to the average setup time. To identify a rational value of γ, the coefficient of variation (CV) is defined for the sequence-dependent setup times for a group on a machine. CV = $s/\bar{x}$ where s is the sample standard deviation and $\bar{x}$ is the mean. A linear relationship between γ and CV is assumed: CV = 0.01 corresponds to γ = 0.9 and CV = 1.0 corresponds to γ = 0.1.

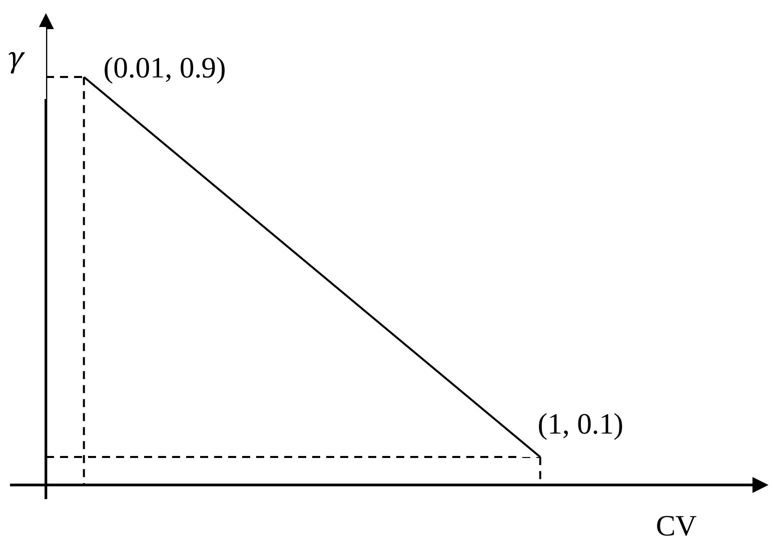

Figure 6 Relationship of γ and CV

We have to compare the release time of a job in stage i with the machine availability time in that stage combined with a rational setup time, which is estimated with the help of γ. If a job is released before the machine available time in a stage then the job has to wait until the machine is available and the setup is performed on the machine. Similarly, an available machine in a stage has to wait for the job to be completed in the previous stage to start processing it.

5.4.2 Application of the search algorithm

The example problem has 7 groups, 25 jobs and 4 stages. The main data is shown in Table 5.12.

Table 5. 12Example problem

Group	Job	Release	Run time				Weight	Due
			Stage 1	Stage 2	Stage 3	Stage 4		
			26	58	89	130		
1	1	21	6	4	16	10	1	161
	2	13	20	5	2	6	3	175
	3	22	8	8	8	4	3	315
	4	28	19	13	19	10	1	156
2	1	22	2	15	14	1	1	165
	2	28	9	3	11	16	2	249
	3	36	2	1	4	10	4	257
	4	34	7	19	7	14	3	228
3	1	29	12	3	10	10	4	259
	2	28	20	12	1	11	4	299
	3	19	8	8	9	2	3	239
	4	21	8	17	7	20	1	277
4	1	18	13	1	19	12	2	340
	2	21	7	9	1	18	3	302
	3	28	13	15	19	7	1	336
	4	23	12	16	14	14	2	286
5	1	26	6	2	12	16	4	336
	2	14	14	7	3	18	4	263
	3	32	20	9	18	10	3	214
	4	13	3	4	19	11	4	228
6	1	14	19	11	8	15	2	220
	2	36	16	9	10	14	2	160
	3	23	6	13	5	20	4	247
7	1	28	5	7	14	18	4	330
	2	29	13	19	2	10	4	239
	3	30	8	17	7	19	4	253
8	1	35	18	9	19	3	3	205
	2	29	15	15	9	17	3	338
	3	35	6	18	6	9	2	264

The setup time matrixes (Table 5.13-5.16) are shown below. Seven actual groups are represented in 7 columns in the table. “R” stands for the reference group or the group that was assigned last in the previous planning horizon when a group in the current planning horizon is sequenced to be processed first. A large range of the setup time is important in emphasizing the influence of sequence-dependent setup time and can facilitate the search algorithm to put more effort on group sequence search.

Table 5. 13 Setup time in stage 1

	Groups						
Ref	G_1	G_2	G_3	G_4	G_5	G_6	G_7
R	7	4	9	31	30	31	37
G_1	-	22	22	36	5	37	6
G_2	39	-	2	13	2	26	15
G_3	33	8	-	1	23	10	40
G_4	19	3	6	-	40	35	37
G_5	11	37	23	17	-	36	2
G_6	28	9	22	9	17	-	24
G_7	25	39	37	29	23	36	-

Table 5. 14 Setup time in stage 2

	Groups						
Ref	G_1	G_2	G_3	G_4	G_5	G_6	G_7
R	31	25	35	14	31	29	29
G_1	-	5	33	6	24	2	32
G_2	16	-	40	3	4	38	34
G_3	1	39	-	13	37	38	33
G_4	1	34	23	-	24	1	13
G_5	24	25	30	36	-	9	23
G_6	10	25	38	19	40	-	29
G_7	40	16	9	6	6	38	-

Table 5. 15 Setup time in stage 3

	Groups						
Ref	G_1	G_2	G_3	G_4	G_5	G_6	G_7
R	31	28	32	18	36	8	27
G_1	-	24	38	36	31	4	30
G_2	3	-	12	28	29	39	8
G_3	5	35	-	32	19	34	18
G_4	37	35	10	-	4	15	27
G_5	30	33	10	3	-	18	35
G_6	38	2	1	22	11	-	27
G_7	31	33	10	37	17	29	-

Table 5. 16 Setup time in stage 4

	Groups						
Ref	G_1	G_2	G_3	G_4	G_5	G_6	G_7
R	30	2	16	4	18	17	37
G_1	-	34	16	21	35	19	30
G_2	33	-	1	10	38	5	18
G_3	18	11	-	1	14	37	21
G_4	13	25	10	-	22	26	24
G_5	20	34	5	21	-	38	18
G_6	15	39	17	21	10	-	3
G_7	29	14	26	10	37	6	-

The initial solution finding mechanism is described first as it is a prerequisite for the TS algorithm. On the completion time minimization aspect, the group and job sequences can be identified using the mechanism given in Section 2. On the tardiness side, only the job sequence can be obtained by applying EDD or wEDD rule. The way to derive the group sequence from a given job sequence is to assign ranks to jobs and sum up the ranks of jobs belonging to one group, and then sort the groups by their ranks in an increasing order. For instance, group 6 (G_6) has three jobs – J_{61}, J_{62}, and J_{63}. J_{61} is at the 12th position in the job sequence (assigned rank 12), J_{62} is at the 2nd position (rank 2) in the job sequence and J_{63} is at the 15th position (rank 15) in the job sequence. Hence, G_6 gains a rank of 29. A similar approach is used in combining two sequences from different goals with normalized weights taken into consideration. When sequences from both sides are obtained, jobs and groups in total completion time minimization sequence are assigned with increasing ranks. Then, the jobs and groups' ranks are combined separately with their ranks in the other sequence. For instance, G_6 has a rank of 18 in the completion time minimization sequence (gained by summing up J_{61}, J_{62}, and J_{63}'s ranks). It also has a rank of 29 from the tardiness minimization sequence. When $\alpha = 0.6$ and $\beta = 0.4$, G_6 is assigned with a final rank of 22.4 ($0.6 \times 18 + 0.4 \times 29$), while its job J_{61} (with rank 6 on the completion time side) is assigned with a final rank of 8.4 ($0.6 \times 6 + 0.4 \times 12$). Finally, groups are sorted by their ranks in an increasing order and jobs within a group are sorted in the same way. Table 5.17 shows the 2 different initial solutions obtained by the initial solution finding mechanisms.

Table 5. 17 Initial solutions (ISs) for the example problem

IS	Sequence
IS1(CT+EDD)	$G_6(J_{62}$-J_{61}-$J_{63})$-$G_5(J_{53}$-J_{51}-$J_{52})$-$G_3(J_{32}$-J_{31}-J_{33}-$J_{34})$-$G_1(J_{14}$-J_{11}-J_{13}-$J_{12})$-$G_7(J_{71}$-J_{72}-$J_{73})$- $G_2(J_{24}$-J_{22}-J_{21}- $J_{23})$-$G_4(J_{41}$-J_{43}-J_{42}-$J_{44})$
IS2(CT+wEDD)	$G_3(J_{32}$-J_{31}-J_{33}-$J_{34})$-$G_1(J_{14}$-J_{11}-J_{13}-$J_{12})$-$G_6(J_{62}$-J_{61}-$J_{63})$-$G_2(J_{24}$-J_{22}-J_{21}-$J_{23})$-$G_7(J_{71}$-J_{72}-$J_{73})$- $G_4(J_{41}$-J_{43}- J_{42}-$J_{44})$-$G_5(J_{53}$-J_{51}-$J_{52})$

With the initial solution identified, the TS can be performed. Due to the structure of the problem, a two-level TS algorithm is proposed. The outside level of the search involves the search for a better group sequence. Starting with a given group sequence, the inside level involves the search for a better job sequence. The final solution is composed of the best group sequence together with its best job sequence that results in the minimum objective function value. A perturbation of group sequence is applied in the outside level TS. After each perturbation, the inside search is invoked to move jobs within each group. Once the best job sequence corresponding to the given group sequence is identified, the search process turns back to the outside search to seek for a better group sequence. After several switches of the search direction, and when the termination criterion is satisfied, the search algorithm returns the best identified solution for the problem.

A perturbation of the sequence is actually a generation of the current solution's neighborhood. The mechanism used in this research to identify a neighborhood is called an exchange move. In the outside level, an exchange move is a move that exchanges the position of two groups. In the inside level, an exchange move can only be performed between jobs within the same group. We demonstrate the application of the algorithm on the initial solution identified with IS2. Starting from this initial solution, the algorithm first admits this solution to the outside candidate list (OCL) and outside index list (OIL), sets outside aspiration level (OAL) as the evaluation of IS2. Then, the algorithm performs inside search to identify the best job sequence of the current group sequence. To initialize the inside search, the current solution is first admitted to the inside candidate list (ICL) and inside index list (IIL). Then the inside number of iterations without improvement (IIT) is set to 0, inside aspiration level (IAL) is set to the objective function value of the current solution (16189.4 in the example problem), and the inside tabu list (ITL) is set as an empty list. For the example problem, ITL size is set as 2. The neighborhoods need to be generated by applying inside exchange moves. The inside exchange move needs to identify a group first and then select two jobs to exchange. For instance, the first exchange move is performed in G_3, between J_{32} and J_{31}; the second exchange move is performed between J_{32} and J_{33}. After all possible exchange moves in G_3 are performed, the algorithm chooses the next group and performs exchange moves on it. Each inside exchange move is evaluated by the objective function if the move results in a different sequence than the sequences already in ICL. After all possible exchange moves are executed and evaluated, the move that gives the best (lowest) objective function value is selected. If the move is not tabu (i.e., the move is not stored in ITL), then it is appended to the current solution. If the move is in ITL, whether the move has a lower objective function value than IAL is checked. If this move does not give a lower objective function value, the next best move is selected and the search continues similarly. In the example problem, the exchange move between J_{33} and J_{34} is selected with 15276.2 as the objective function value. After an exchange move is applied to the current solution, ICL, IIL, IAL, IIT and ITL are updated. If the sequence gives a better evaluation than its parent, then it will be appended to ICL. If it is found to be better than its child in the next iteration, it will be appended to IIL as it is a local optimum. If the sequence has a better evaluation than IAL, then IAL is updated as the current solution's objective function value and IIT is set as 0, otherwise IIT is increased by 1. In the example problem, after the first iteration, the move between J_{11} and J_{14} is admitted to ITL and ICL, and IAL is updated as 15276.2. The stopping of the inside search is ruled by two stopping criteria, IIWI and the number of entries into IIL ($\overline{\text{IEIL}}$). The search parameters are determined by the empirical formulas from section 5.2.7. For the example problem, IIWI is set as 11, $\overline{\text{IEIL}}$ is set as 4 (calculated by the empirical formula given in section 5.2.7). The inside search stops when either of the two criteria is met. If the stopping criteria are not met, the search will continue to generate neighborhoods, by applying the best move and updating the parameters. In the example problem, the inside search stops after 20 iterations are made and returns the best solution for the current group sequence. Table 5.18 shows the entries into ICL.

If long term memory is implemented, LTM-matrix will be used to identify a sequence to restart the search with. In inside search, each group has its own LTM-matrix. Table 5.19 shows the LTM-matrix of G_3.

Table 5. 18 Iterations of inside search

Solution number	ICL sequence	Evaluation	IL sequence?
IS	$G_3(J_{32}-J_{31}-J_{33}-J_{34})-G_1(J_{14}-J_{11}-J_{13}-J_{12})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_7(J_{71}-J_{72}-J_{73})-G_4(J_{41}-J_{43}-J_{42}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	16189.2	Y
1	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{14}-J_{11}-J_{13}-J_{12})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_7(J_{71}-J_{72}-J_{73})-G_4(J_{41}-J_{43}-J_{42}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	15276.2	N
2	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{14}-J_{11}-J_{13}-J_{12})-G_6(J_{61}-J_{62}-J_{63})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_7(J_{71}-J_{72}-J_{73})-G_4(J_{41}-J_{43}-J_{42}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	14505.6	N
3	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{14}-J_{11}-J_{13}-J_{12})-G_6(J_{61}-J_{62}-J_{63})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_7(J_{71}-J_{72}-J_{73})-G_4(J_{41}-J_{43}-J_{42}-J_{44})-G_5(J_{51}-J_{53}-J_{52})$	14275.4	N
4	$G_3(J_{32}-J_{31}-J_{33}-J_{34})-G_1(J_{14}-J_{11}-J_{13}-J_{12})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_7(J_{71}-J_{72}-J_{73})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	13477.4	N
5	$G_3(J_{32}-J_{31}-J_{33}-J_{34})-G_1(J_{14}-J_{11}-J_{13}-J_{12})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	13387.6	N
6	$G_3(J_{33}-J_{31}-J_{32}-J_{34})-G_1(J_{14}-J_{11}-J_{13}-J_{12})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	12404.8	Y
7	$G_3(J_{33}-J_{31}-J_{32}-J_{34})-G_1(J_{11}-J_{14}-J_{13}-J_{12})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	12680.2	N
8	$G_3(J_{33}-J_{31}-J_{32}-J_{34})-G_1(J_{11}-J_{14}-J_{13}-J_{12})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	10113.2	N
9	$G_3(J_{33}-J_{31}-J_{32}-J_{34})-G_1(J_{11}-J_{14}-J_{13}-J_{12})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	9862.4	Y
10	$G_3(J_{33}-J_{31}-J_{32}-J_{34})-G_1(J_{11}-J_{14}-J_{12}-J_{13})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	11930.8	N
11	$G_3(J_{33}-J_{31}-J_{32}-J_{34})-G_1(J_{11}-J_{14}-J_{12}-J_{13})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{42}-J_{41}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	11854.2	N
12	$G_3(J_{33}-J_{31}-J_{32}-J_{34})-G_1(J_{11}-J_{14}-J_{12}-J_{13})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{42}-J_{41}-J_{43}-J_{44})-G_5(J_{52}-J_{51}-J_{53})$	11241.6	N
13	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{11}-J_{14}-J_{12}-J_{13})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{42}-J_{41}-J_{43}-J_{44})-G_5(J_{52}-J_{51}-J_{53})$	10626.2	N
14	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{11}-J_{13}-J_{12}-J_{14})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{42}-J_{41}-J_{43}-J_{44})-G_5(J_{52}-J_{51}-J_{53})$	10012.6	Y
15	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{11}-J_{13}-J_{12}-J_{14})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{52}-J_{51}-J_{53})$	10110.2	N
16	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{11}-J_{13}-J_{12}-J_{14})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{72}-J_{73}-J_{71})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{52}-J_{51}-J_{53})$	9899.4	Y
17	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{12}-J_{13}-J_{11}-J_{14})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{23}-J_{24})-G_7(J_{72}-J_{73}-J_{71})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{52}-J_{51}-J_{53})$	10029.4	N
18	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{12}-J_{13}-J_{11}-J_{14})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{21}-J_{22}-J_{23}-J_{24})-G_7(J_{72}-J_{73}-J_{71})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{52}-J_{51}-J_{53})$	10567.2	N
19	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{12}-J_{11}-J_{13}-J_{14})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{21}-J_{22}-J_{23}-J_{24})-G_7(J_{72}-J_{73}-J_{71})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{52}-J_{51}-J_{53})$	10836.8	N
20	$G_3(J_{32}-J_{31}-J_{34}-J_{33})-G_1(J_{12}-J_{11}-J_{13}-J_{14})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{21}-J_{22}-J_{23}-J_{24})-G_7(J_{72}-J_{73}-J_{71})-G_4(J_{41}-J_{44}-J_{43}-J_{42})-G_5(J_{52}-J_{51}-J_{53})$	11531.2	N

Table 5. 19 LTM-matrix of G_3

	Position			
	P1	P2	P3	P4
J_{31}	0	21	0	0
J_{32}	15	0	6	0
J_{33}	6	0	4	11
J_{34}	0	0	11	10

If conventional LTM is used, the job-position combination with the highest (LTM-max)/lowest (LTM-min) frequency among all groups will be identified (ties are broken arbitrarily by group index number) and fixed in the next restart of the search. If non-conventional LTM is used, every group will have a new job sequence identified based on its LTM-matrix (the frequencies are reviewed from the 1st position to the last position, and ties are broken arbitrarily by job index). For instance, when using non-conventional LTM-max, G_3 will have J_{32}-J_{31}-J_{34}-J_{33} as its new job sequence in the next restart.

Thereafter, the algorithm switches to outside level to perform group exchange moves. The outside number of iterations without improvement (OIT) is set as 0. The outside tabu list (OTL) is set as an empty list. For the example problem, the size of OTL is set as 2. The positions of G_1 and G_3 are exchanged first and the inside search under group sequence G_1-G_3-G_6-G_2-G_7-G_4-G_5 is invoked. After this inside search, the best job sequence for this group sequence gives an evaluation of 12692.8. Then another neighborhood is generated and inside search is performed on it. Resembling the inside search, the outside search selects the group sequence and its best job sequence (including the initial group sequence with its best job sequence) that gives the best (lowest) objective function value when the group sequence is different from any of the sequences inserted into OCL so far. If the move is not tabu (i.e., the move is not stored in OTL), it is applied to the current solution. If the move is in OTL, whether the move has a lower objective function value than OAL is checked. If this move does not give a lower objective function value, the next best move is selected and the search is continued similarly. In the example problem, the exchange move between G_7 and G_1 and its best job sequence gives the best objective function value of 10458.6. After the best neighborhood and its job sequence are identified, OCL, OIL, OAL, OIT and OTL need to be updated. If the move gives better evaluation than its parent, then it is appended to OCL. If this move is found to be better than its child in the next iteration, it will be appended to OIL as it is a local optimum. If the move has better evaluation than OAL, then OAL is updated as the current evaluation and OIT is set as 0, else OIT is increased by 1. In the example problem, the exchange move between G_7 and G_1 is appended to OTL and OCL, OAL is updated as 10458.6, and OIT is set as 0. The stopping criteria for the outside search are OIWI and number of entries to the OIL ($\overline{\text{OEIL}}$). Calculated by the empirical formula using the parameters from the example problem, OIWI is set as 5, and $\overline{\text{OEIL}}$ is set as 3. The outside search stops when either of the stopping criteria is met. The outside search of the example problem stops after 10 iterations are made. Table 5.20 shows the entries into OCL. The best solution for the example problem is solution number 9 with an objective function value of 8544.8 which is proven to be near optimal by CPLEX with a deviation of 1.6% from the lower bound (8402.2). Notice in each iteration the job sequences in a group are different from before, because each outside search invokes inside search to find the best job sequence.

The use of LTM in the outside search is similar to inside search. However, only 1 LTM-matrix is needed in outside search. Table 5.21 shows the LTM-matrix of the example problem before the 1st restart.

If conventional LTM is used, the group-position combination with the highest (LTM-max)/lowest (LTM-min) frequency will be identified (ties are broken arbitrarily by group index number) and fixed in the next restart of the search. If non-conventional LTM is used, a new group sequence is identified based on its LTM-matrix (the frequencies are reviewed from the 1st position to the last position, and ties are broken arbitrarily by job index). For instance, when using non-conventional LTM-max, G_1-G_5-G_6-G_2-G_7-G_4-G_3 will be the new group sequence in the next restart. In this example problem, LTM is not contributing in identifying better solutions.

Table 5. 20 Iterations of outside search

Solution number	OCL sequence	Evaluation	IL sequence?
IS	$G_3(J_{33}-J_{31}-J_{32}-J_{34})-G_1(J_{11}-J_{14}-J_{13}-J_{12})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{21}-J_{22}-J_{24}-J_{23})-G_7(J_{71}-J_{73}-J_{72})-G_4(J_{41}-J_{42}-J_{43}-J_{44})-G_5(J_{53}-J_{51}-J_{52})$	9862.4	Y
1	$G_3(J_{32}-J_{34}-J_{31}-J_{33})-G_7(J_{73}-J_{72}-J_{71})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{23}-J_{24}-J_{21}-J_{22})-G_1(J_{13}-J_{12}-J_{11}-J_{14})-G_4(J_{42}-J_{43}-J_{41}-J_{44})-G_5(J_{52}-J_{53}-J_{51})$	10458.6	N
2	$G_3(J_{34}-J_{32}-J_{31}-J_{33})-G_7(J_{72}-J_{71}-J_{73})-G_6(J_{62}-J_{63}-J_{61})-G_2(J_{24}-J_{21}-J_{22}-J_{23})-G_1(J_{12}-J_{13}-J_{14}-J_{11})-G_5(J_{52}-J_{51}-J_{53})-G_4(J_{43}-J_{42}-J_{41}-J_{44})$	9193.2	Y
3	$G_1(J_{12}-J_{13}-J_{14}-J_{11})-G_5(J_{52}-J_{51}-J_{53})-G_6(J_{62}-J_{63}-J_{61})-G_2(J_{22}-J_{21}-J_{24}-J_{23})-G_7(J_{72}-J_{71}-J_{73})-G_3(J_{33}-J_{321}-J_{31}-J_{33})-G_4(J_{42}-J_{43}-J_{41}-J_{44})$	11297.6	N
4	$G_1(J_{12}-J_{13}-J_{14}-J_{11})-G_5(J_{52}-J_{51}-J_{53})-G_6(J_{62}-J_{63}-J_{61})-G_2(J_{24}-J_{21}-J_{22}-J_{23})-G_7(J_{72}-J_{71}-J_{73})-G_4(J_{42}-J_{41}-J_{43}-J_{44})-G_3(J_{34}-J_{32}-J_{31}-J_{33})$	11070.6	N
5	$G_1(J_{12}-J_{13}-J_{14}-J_{11})-G_5(J_{52}-J_{51}-J_{53})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{21}-J_{22}-J_{23})-G_3(J_{34}-J_{32}-J_{31}-J_{33})-G_7(J_{72}-J_{71}-J_{73})-G_4(J_{42}-J_{41}-J_{44}-J_{43})$	11027.6	N
6	$G_1(J_{13}-J_{12}-J_{14}-J_{11})-G_5(J_{52}-J_{51}-J_{53})-G_3(J_{34}-J_{32}-J_{31}-J_{33})-G_6(J_{63}-J_{61}-J_{62})-G_2(J_{24}-J_{21}-J_{22}-J_{23})-G_7(J_{72}-J_{71}-J_{73})-G_4(J_{42}-J_{41}-J_{44}-J_{43})$	9857.8	Y
7	$G_1(J_{13}-J_{12}-J_{14}-J_{11})-G_5(J_{51}-J_{52}-J_{53})-G_4(J_{42}-J_{41}-J_{44}-J_{43})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{21}-J_{22}-J_{23})-G_7(J_{72}-J_{71}-J_{73})-G_3(J_{34}-J_{32}-J_{31}-J_{33})$	10909.8	N
8	$G_1(J_{13}-J_{11}-J_{14}-J_{12})-G_5(J_{52}-J_{51}-J_{53})-G_4(J_{42}-J_{41}-J_{44}-J_{43})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{21}-J_{22}-J_{23})-G_3(J_{34}-J_{32}-J_{31}-J_{33})-G_7(J_{72}-J_{71}-J_{73})$	9914.8	N
9	$G_1(J_{13}-J_{11}-J_{14}-J_{12})-G_5(J_{52}-J_{51}-J_{53})-G_4(J_{42}-J_{41}-J_{44}-J_{43})-G_3(J_{34}-J_{33}-J_{32}-J_{31})-G_7(J_{72}-J_{71}-J_{73})-G_6(J_{62}-J_{61}-J_{63})-G_2(J_{24}-J_{21}-J_{22}-J_{23})$	8544.8	Y
10	$G_1(J_{13}-J_{11}-J_{14}-J_{12})-G_5(J_{52}-J_{51}-J_{53})-G_4(J_{42}-J_{41}-J_{44}-J_{43})-G_3(J_{34}-J_{33}-J_{32}-J_{31})-G_7(J_{72}-J_{71}-J_{73})-G_2(J_{24}-J_{22}-J_{21}-J_{23})-G_6(J_{61}-J_{62}-J_{63})$	10796.6	N

Table 5. 21 LTM-matrix of outside search

	Position						
	P1	P2	P3	P4	P5	P6	P7
G_1	8	1	0	0	2	0	0
G_2	0	0	0	6	4	1	1
G_3	3	0	1	2	0	2	2
G_4	0	0	4	0	0	3	4
G_5	0	8	0	0	0	1	2
G_6	0	0	6	3	0	1	1
G_7	0	2	0	0	5	3	1

CHAPTER 6: THE OPTIMAILITY OF TS-BASED HEURISTIC ALGORITHM

The major advantage of the search algorithm is that it can find a near optimal solution in a very short time. The efficacy of the search algorithm should be tested. The quality of the final solution obtained by the algorithm and the total computation time it takes are the criteria commonly used to assess the performance of the algorithm. Typically, the optimal solution is compared with the final solution obtained by the algorithm to assess its performance. Because the problem is strongly NP-hard, the optimal solution (using the branch-and-bound enumeration technique) for the mathematical model of a given problem may not be identified within a reasonable time. If the optimal solution is unknown, we need to compare the solution obtained by the search algorithm to a suitable lower bound for the problem that is being investigated. The mathematical model developed in Chapter 4 is used to quantify the effectiveness of the search algorithm by optimally solving small problem instances.

The example problem used in Chapter 5 is used again to show how a model can be formulated for a given problem instance. There are three sets of binary variables: W_{kg}, Y_{kjb}, and $AS_{kg(k+1)p}$. W_{kg} receives a value of 1 if group g is assigned to slot k or 0 otherwise. Y_{kjb} receives a value of 1 if job j is processed after job b in slot k or 0 otherwise. $AS_{kg(k+1)p}$ receives a value of 1 if group g is assigned to slot k and group p is assigned to slot k+1 or 0 otherwise. Generally, there will be a total of $a \times K$ W_{kg}s, $\sum_{k=1}^{K}\sum_{g=1}^{a} {n_g}^2$ Y_{kjb}s, and $\sum_{k=1}^{K}\sum_{g=1}^{a}(a-1)$ $AS_{kg(k+1)p}$s. Thus, the example problem will have $7 \times 7 + 7 \times (4 * 16 + 3 * 9) + 7 \times 7 \times 6 = 980$ binary variables. However, the inter-connections between variables make it not as difficult as it seems. For instance, if W_{11}=0, then AS_{112p}=0 for all k'(since group 1 is not assigned to slot 1, the other groups cannot be following group 1 in slot 2).

In order to identify the optimal solution for small problem instances, their corresponding formulated model was solved using the branch-and-bound enumeration method incorporated in CPLEX 9.0 computer software. CPLEX (also referred to as ILOG CPLEX) was developed by Robert E. Bixby of *CPLEX* Optimization Inc. *CPLEX* Optimization was acquired by ILOG in 1997 and finally ILOG was acquired by IBM in 2009. The software was installed and run on an Intel Core *i*3-370, 2.4GHz processor with 4 GB RAM. The large amount of computation time needed to identify the optimal solution is partly due to the large number of binary variables included in the model. Based on the tests, CPLEX is not efficient to find the optimal solution even for small problem instances, although it uses the branch-and-bound technique, which is an implicit enumeration algorithm for solving combinatorial optimization problems. However, CPLEX can offer a lower bound when it cannot identify an optimal solution within the allotted time.

Ten problem instances were generated and solved using CPLEX. As mentioned above, CPLEX may not give the optimal solution even for small problems. The total number of variables that can be handled in CPLEX 9.0 is limited to 2100000000. The data generated for these problem instances used the same procedure as described in Section 5.4.1 of Chapter 5. Table 6.1 shows the results of CPLEX runs.

Table 6. 1 Results of solving the problems by CPLEX 9.0

Problem Instance	Number of Groups	Setup Time Ratio	Number of Jobs	CPLEX Solution	Optimality	Time (Sec)
1	2	2	7	703	optimal	1679
2	2	2	9	1699	optimal	6924
3	3	10	13	1457.8	optimal	6534
4	3	5	14	3527.4	optimal	7635
5	3	10	15	10028.2	optimal	10002
6	3	5	12	7521	optimal	10203
7	4	2	17	12501.8	optimal	8688
8	5	10	21	11996.4	optimal	12182
9	5	2	21	19344	optimal	9862
10	6	5	26	18150.6	lower bound	28800
11	6	10	28	23226	lower bound	28800
12	7	5	29	15298.2	lower bound	28800

6.1 Comparison between the optimal solution and solution obtained by the heuristic algorithm

The quality of the solution found by the tabu-search based heuristic algorithms can easily be assessed by comparing it to the optimal solution obtained by CPLEX. The search heuristics begin with an initial solution (IS) as a starting point. Two ISs are proposed in section 5.2.1: EDD+WCT sequence and wEDD+WCT sequence. Starting from an IS, the TS begins the exploration in the solution space. TS has few features that affect its performance as a heuristic algorithm. These features include short-term (STM)/long-term memory (LTM) function and fixed/variable tabu list size (TLS). There are two different approaches in the application of long-term memory function: the maximum frequency (LTM-max) and the minimum frequency (LTM-min). Because conventional (C) LTM and non-conventional (NC) LTM are all implemented in this research, the total number of combinations of different features of TS is 10. The heuristic algorithms developed in this research encompass the combinations of these features, as shown in Table 6.2.

Table 6. 2 TS-based heuristic algorithms used in this research

Types of Heuristic	Memory Function	Size of TLS
TS1	Short	Fixed
TS2	Short	Variable
TS3	C LTM-max	Fixed
TS4	C LTM-min	Fixed
TS5	C LTM-max	Variable
TS6	C LTM-min	Variable
TS7	NC LTM-max	Fixed
TS8	NC LTM-min	Fixed
TS9	NC LTM-max	Variable
TS10	NC LTM-min	Variable

Each IS is used in conjunction with each type of tabu-search heuristics (TS). Thus, there are a total of 20 heuristic combinations. Each combination is tested on 9 problem instances whose optimal solutions can be found by CPLEX presented in Table 6.1. The last three problem instances are not used here since

CPLEX 9.0 could not find the optimal solution for them in 8 hours (28800 seconds), because in a typical manufacturing environment a computer could be left overnight (around 8 hours) to solve a problem.. For each problem, the solutions obtained by the algorithm are compared to the optimal solutions obtained by CPLEX 9.0. The percentage deviation of the algorithms from the optimal solutions is evaluated and reported in Table 6.3.

Table 6. 3 Percentage deviation of the solutions obtained by the heuristics for small problems

Problem	IS1									
	TS1	TS2	TS3	TS4	TS5	TS6	TS7	TS8	TS9	TS10
1	4.10	0.00	4.10	0.82	0.00	0.00	4.10	3.47	0.00	0.00
2	2.45	4.52	3.12	2.45	2.31	2.24	1.84	0.69	2.45	2.69
3	5.62	4.55	0.94	2.33	2.91	2.77	0.48	1.05	4.41	3.05
4	5.93	0.94	0.00	0.94	0.00	0.12	0.00	0.00	0.00	0.00
5	2.84	0.00	0.23	0.84	0.00	0.00	0.23	0.23	0.00	0.00
6	5.98	2.91	2.12	1.53	2.91	3.58	3.11	4.58	2.36	0.24
7	2.85	0.78	1.72	0.78	0.78	0.78	0.89	0.78	2.26	2.40
8	3.43	3.04	2.91	3.04	2.89	1.02	3.04	1.82	2.42	3.04
9	2.17	3.83	1.28	0.88	3.29	2.17	0.63	2.17	2.17	1.12
Average	3.93	2.29	1.82	1.51	1.68	1.41	1.59	1.64	1.79	1.39
	IS2									
	TS1	TS2	TS3	TS4	TS5	TS6	TS7	TS8	TS9	TS10
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.35	5.82	1.15	1.35	1.35	1.35	1.35	0.13	1.35	1.35
3	0.00	1.89	0.00	0.00	0.99	0.63	0.00	0.00	0.99	0.67
4	5.53	0.41	4.33	3.36	5.52	0.41	0.97	4.21	0.41	0.30
5	2.05	2.10	2.05	2.05	2.05	0.57	0.17	1.76	1.31	0.72
6	1.26	2.82	1.26	0.00	1.26	1.26	0.28	0.00	1.26	1.26
7	4.88	6.02	0.31	3.12	0.37	4.88	4.88	3.79	4.88	2.60
8	1.28	1.38	1.28	1.28	1.28	1.28	1.28	1.28	0.20	1.28
9	4.19	4.16	1.09	4.16	4.16	2.09	3.07	3.83	0.14	0.14
Average	2.28	2.73	1.27	1.70	1.89	1.39	1.33	1.67	1.17	0.92

The average percentage deviation of all heuristic combinations is 1.77%. TS based heuristic shows very good overall performance on small problems. IS2/TS10 appears to be the most effective heuristic combination in identifying the optimal solutions for small problems (with an average percentage deviation of 0.92%). The next best combination is IS2/TS3, with an average of 1.27%. The next one is IS1/TS10. Based on the performance of heuristics aided by ISs, IS2 (wEDD+WCT) turned out to have a better performance than IS1. The average percentage deviation from IS1 aided heuristics is 1.91%, compared to 1.64% from IS2. TS10 seems to be a good algorithm when solving small problems. Notice that the result in this section is based on numerical values obtained for several small problem instances, which cannot be relied upon to make objective conclusions. To reveal the significance of the difference between ISs/TSs, a detailed statistical design is presented in the next chapter. The purpose of these comparisons is to demonstrate the performance and advantage of heuristic algorithms. A detailed design of experiment to uncover the significance of algorithms and ISs is presented in Chapter 7. For the 3 instances with their lower bound identified by CPLEX, the comparison is shown in Table 6.4. Because we are comparing lower-bounds, which may not be close to the true optimal solutions, and the solutions obtained by the heuristics, the deviations became larger. But the smallest deviations for each problem are still around 5 percent.

Table 6. 4 Percentage deviation between heuristics and lower bounds

Problem	IS1									
	TS1	TS2	TS3	TS4	TS5	TS6	TS7	TS8	TS9	TS10
10	9.31	8.49	4.94	8.82	5.41	8.16	4.64	8.49	9.22	8.05
11	6.44	9.73	5.31	5.23	7.91	6.1	8.34	9.25	6.29	9.64
12	9.74	9.25	5.13	8.25	7.42	6.01	4.54	7.75	4.2	4.38
	IS2									
	TS1	TS2	TS3	TS4	TS5	TS6	TS7	TS8	TS9	TS10
10	4.4	5.54	4.4	4.54	4.4	4.4	4.4	4.4	4.4	4.4
11	4.59	8.9	4.59	4.59	4.59	4.59	4.59	4.59	4.59	4.59
12	5.41	9.91	5.02	5.41	5.41	5.41	5.41	5.41	5.41	5.41

To reveal the overall optimality of the heuristic algorithms against CPLEX, Table 6.5 is presented to show the difference between the solution found by CPLEX and the best solution from all heuristics. Except for instances 10-12, for which CPLEX cannot give optimal solutions in the given 8 hours, the heuristics can always find a solution with a deviation less than 0.5 percent from the optimal solution. Even when CPLEX can only provide lower-bounds of problems, the heuristic algorithms can still give solutions with a deviation less than 5 percent compared to those lower-bounds.

Table 6. 5 Difference between CPLEX solution and best solution from heuristics

Problem	Best deviation (%)	Optimality
1	0	Optimal
2	0.13	Optimal
3	0	Optimal
4	0	Optimal
5	0	Optimal
6	0	Optimal
7	0.31	Optimal
8	0.2	Optimal
9	0.14	Optimal
10	4.40	lower bound
11	4.59	lower bound
12	4.20	lower bound

The computational time of the TSs is very short compared to CPLEX computational time, which proves the time-wise advantage of tabu-search based algorithm. Table 6.6 shows the computation time of each algorithm. The computation time presented in the table is the sum of time IS takes to generate the IS and the time TS takes to complete the search to finally identify the best solution.

Table 6. 6 Computation time (sec) of the heuristics for small problems

Problem	IS1									
	TS1	TS2	TS3	TS4	TS5	TS6	TS7	TS8	TS9	TS10
1	0.12	0.05	0.05	0.13	0.05	0.05	0.05	0.05	0.13	0.05
2	0.10	0.07	0.07	0.11	0.07	0.07	0.07	0.14	0.12	0.13
3	0.05	0.14	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
4	0.09	0.11	0.09	0.13	0.13	0.09	0.09	0.09	0.09	0.09
5	0.07	0.10	0.11	0.07	0.07	0.07	0.11	0.07	0.07	0.13
6	0.13	0.10	0.10	0.10	0.10	0.10	0.10	0.14	0.10	0.10
7	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
8	0.05	0.14	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
9	0.04	0.08	0.04	0.04	0.04	0.11	0.04	0.04	0.08	0.04
Average	0.09	0.10	0.08	0.09	0.08	0.08	0.08	0.08	0.09	0.08
	IS2									
	TS1	TS2	TS3	TS4	TS5	TS6	TS7	TS8	TS9	TS10
1	0.05	0.11	0.08	0.08	0.11	0.14	0.08	0.09	0.11	0.07
2	0.09	0.12	0.09	0.09	0.09	0.13	0.09	0.11	0.09	0.09
3	0.07	0.14	0.09	0.09	0.11	0.10	0.07	0.11	0.12	0.12
4	0.09	0.05	0.05	0.14	0.05	0.12	0.11	0.12	0.05	0.05
5	0.08	0.06	0.12	0.06	0.11	0.06	0.06	0.10	0.06	0.08
6	0.13	0.09	0.14	0.09	0.09	0.14	0.09	0.09	0.09	0.09
7	0.04	0.05	0.10	0.14	0.09	0.07	0.09	0.11	0.13	0.11
8	0.12	0.11	0.11	0.11	0.11	0.12	0.11	0.11	0.12	0.11
9	0.07	0.10	0.09	0.12	0.13	0.07	0.07	0.09	0.07	0.14
Average	0.08	0.09	0.10	0.10	0.10	0.11	0.09	0.10	0.09	0.10

CHAPTER 7: RESULTS AND DISCUSSION

Chapter 6 showed that tabu-search based heuristic algorithms are highly efficient in comparison to the implicit enumeration technique (namely branch-and-bound) in solving small problem structures. The branch-and-bound technique embedded in CPLEX takes hours to solve a small problem structure, compared to less than 0.1 seconds by the heuristic algorithms. The focus of this chapter is on evaluating the comparative performance of the tabu-search based heuristics, aided by IS generation methods. In other words, the intent of this research is to evaluate the performance of each algorithm as the size of the problem structure grows from small to medium and then large.

As mentioned in chapter 5, the size of the problem structure is determined by number of groups as follows:

Small size: 2-5 groups, 2-5 jobs in each group, 2-3 stages

Medium size: 6-10 groups, 6-9 jobs in each group, 4-6 stages

Large size: 11-16 groups, 10-12 jobs in each group, 7-9 stages

The classification of problem sizes is determined by reviewing the previous works (Logendran et al. (2006), Salmasi et al. (2010), Schaller et al. (2000)) and considering the computational time. Logendran et al. (2006) considered number of groups that were varied from 3 to 5, 6 to 9, and 10 to 12, for small, medium, and large problem instances in a flexible flow shop scheduling problem. Problems were generated with number of families varying between 3 and 10 by Schaller et al. (2000). Because of the development of computer chips, a wider range of groups can be covered and solved now in a relatively short time. Salmasi et al. (2010) considered minimizing makespan in a sequence-dependent group scheduling problem and classified number of groups from 2 to 5, 6-10, 11-16 for small, medium and large problem instances. In this research, most of the small problem structures can be solved in less than a second. The medium problem structures require less than 10 seconds to be solved. Solving a large problem structure may require as much as 60 seconds. The increase in the computation time is due to the increase in complexity of the problem, presented in the form of an enlarged search space. The increase in search space causes the algorithm to consider more neighborhood solutions before selecting the best solution and then applying the move that results in the best solution. The increase in search space also delays the termination of the search as more moves are required before the stopping criterion is met.

The test problems are generated using the data generation methodology presented in chapter 5. Once the sizes of the problem structures are established, an experiment can be conducted to address the following research issues:

1. To analyze the performance of the two IS generation methods on each size of the problem structure.

2. To analyze the performance of the ten tabu-search based heuristics on each size of the problem structure.

3. To examine if the performance of the ten tabu-search based heuristics is affected by the IS generation methods used.

7.1 Experimental Design

A multi-factor split-plot experimental design is used to address research questions 1, 2 and 3. The objective function value (total weighted completion time multiplied by α plus total weighted tardiness multiplied by β) and the total computation time of the algorithms are used as response variables for performance measurement. Lots of factors may have impacts on objective function value/computation time, but the interest in identifying the significance of the impacts may vary. The factors that are used to generate a particular problem are called problem parameters, which include problem size (small, medium, and large), setup time ratio (2, 5, and 10), scenario ($\alpha - \beta$). Those factors, along with replicate (block) are put in the main plot of the design. Two factors, namely the IS finding mechanisms and different types of tabu-search based heuristics (TS), are placed in the subplot, as they are the factors of primary importance in this research. There are a total of two different levels of IS and ten different levels of TS.

Three different sizes of problem structures were defined in the beginning of this chapter. Within a problem structure, one can generate different problem instances (test problems) using the procedure described in section 5.4.1. All the problems are randomly generated and no two problem instances are exactly the same. Thus an experiment involving various problem instances and various problem structures will have fairly large variability in results. This variation can be reduced by treating each problem instance as a block. Blocking the problem instance is necessary to eliminate the influence of the differences between the problem instances (caused by random generation of problems). Thus, the differences in the performances of the algorithms, if identified, can be wholly attributed to the effect of the algorithms and not to the difference between problem instances.

The experiment includes all three sizes of problem structures. Within each problem size, setup time ratio and scenario $(\alpha - \beta)$ can vary. At this point, the experimental design looks like a randomized complete block design. Randomized complete block design is one of the most widely used experimental designs. Blocking can be used to systematically eliminate the effect of nuisance factor on the statistical comparisons among treatments. Blocking is an extremely important design technique, used extensively in industrial experiments.

In order to uncover the answers to the research questions raised in the beginning of this chapter, a split-plot design is employed. To summarize, factors that define a particular problem (size, setup time ratio, replicate (block), and scenario) stay in the main plot. IS and TS are put in the subplot. Thus, the effect of ISs and TSs (all 20 (2 levels of IS * 10 levels of TS) combinations of factors) are tested without the influence of problem parameters. Also, the interaction between IS/TS and problem parameters can be tested more accurately. The experiment is performed on Intel Core I3 2.1 GHz machine with 4 GB RAM. The test problems and results are presented in Appendix A. The distribution of the objective function value is shown to be normal so data transformation is not required. Figure 7 gives the normal probability plot of objective function values.

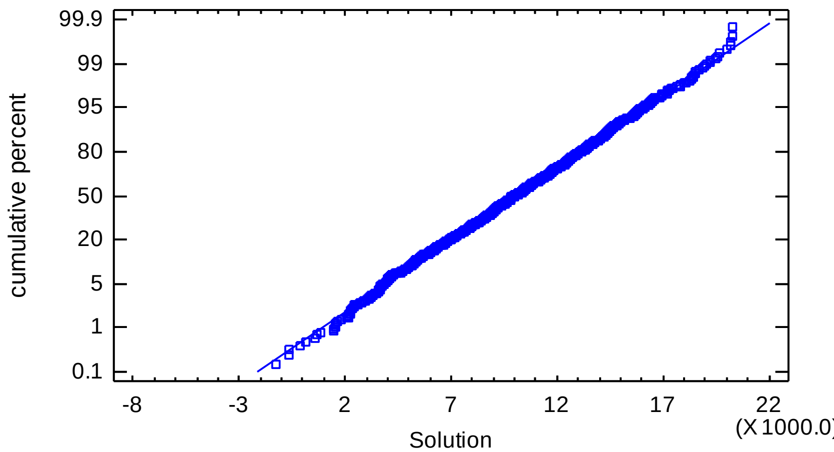

Figure 7 Normality of solution

Three different hypotheses need to be tested and they can be stated as follows:

Hypothesis 1

H0: There is no difference in the objective function value obtained for the problem instances using the two initial solutions.

H1: One of the initial solution generation methods tends to yield a smaller objective function value than the others.

Hypothesis 2

H0: There is no difference in the objective function value obtained for the problem instances using the ten tabu search heuristics.

H1: At least one of the tabu search heuristics tends to yield a smaller objective function value than the others.

Hypothesis 3

H0: There is no interaction between initial solution and tabu search heuristic.

H1: There is interaction between initial solution and tabu search heuristic.

The resulting ANOVA table is given in Table 7.1.

Table 7. 1 ANOVA of objective function value in split-plot design

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Size	2.84E+11	2	1.42E+11	4.65E+01	0.00
Replicate	2.39E+10	1	2.39E+10	7.83E+00	0.00
Scenario	2.09E+09	2	1.04E+09	3.42E-01	0.70
Setup Time Ratio	7.16E+10	2	3.58E+10	1.17E+01	0.00
Size*Scenario	3.64E+09	4	9.11E+08	2.98E-01	0.66
Size*Setup Time Ratio	2.99E+10	4	7.48E+09	2.45E+00	0.09
Scenario*Setup Time Ratio	3.43E+08	4	8.57E+07	2.80E-02	0.11
Size*Scenario*Setup Time Ratio	6.11E+08	8	7.64E+07	2.50E-02	0.00
Main plot error	7.94E+10	26	3.05E+09		0.00
Algorithm	4.77E+08	9	5.31E+07	6.78E+00	0.00
Initial Solution	3.04E+07	1	3.04E+07	3.88E+00	0.03
Initial Solution*Algorithm	7.35E+07	9	8.17E+06	1.03E+00	0.80
Size*Algorithm	7.73E+08	18	4.30E+07	5.49E+00	0.00
Scenario*Algorithm	1.48E+08	18	8.22E+06	1.05E+00	0.11
Setup Time Ratio*Algorithm	7.09E+08	18	3.94E+07	5.03E+00	0.00
Size*Scenario*Algorithm	3.02E+08	36	8.40E+06	1.07E+00	0.47
Size*Setup Time Ratio*Algorithm	9.63E+08	36	2.68E+07	3.42E+00	0.00
Scenario*Setup Time Ratio*Algorithm	2.34E+08	36	6.49E+06	8.29E-01	0.49
Size*Initial Solution	6.55E+07	2	3.27E+07	4.18E+00	0.02
Scenario*Initial Solution	1.59E+06	2	7.94E+05	1.01E-01	0.90
Initial Solution*Setup Time Ratio	3.17E+07	2	1.59E+07	2.03E+00	0.13
Size*Scenario*Initial Solution	3.60E+06	4	9.00E+05	1.15E-01	0.37
Scenario*Initial Solution*Setup Time Ratio	7.72E+06	4	1.93E+06	2.46E-01	0.60
Size*Initial Solution*Setup Time Ratio	1.29E+07	4	3.23E+06	4.13E+00	0.31
Sub-plot error	6.54E+09	827	7.83E+06		
Total (corrected)	5.07E+11	1079			

Both TS and IS are showing strong significance in the ANOVA table. Also, some interactions between IS/TS and other problem parameters are showing to be significant at 5% level. To uncover the best IS/TS, Tukey's test needs to be performed. Tukey's test is a single-step multiple comparison procedure and statistical test, generally used in conjunction with an ANOVA to find which means are significantly different from one another. Named after John Tukey, it compares all possible pairs of means, and is based on a studentized range distribution q (this distribution is similar to the distribution of t from the t-test). Table 7.2 gives the best TS for different size-STR combination.

Table 7. 2 Best TS based on problem size and STR

Size	STR	TS1	TS2	TS3	TS4	TS5	TS6	TS7	TS8	TS9	TS10
Small	2			x			x				
	5			x							
	10				x				x		
Medium	2			x			x				
	5			x							
	10				x				x		
Large	2			x			x				
	5			x							
	10			x					x		

Tukey's test shows that TS3 (C LTM-Max Fixed) is outperforming the other TSs in most cases. TS4 (C LTM-Min Fixed) and TS8 (NC LTM-Min Fixed) are the best TSs when solving problems with setup time ratio equal to 10 for small and medium problems. When solving large problem with STR equal to 10, TS3 (C LTM-Max Fixed) and TS8 (NC LTM-Min Fixed) are outperforming the others. It is interesting to discover that NC LTM is not out performing C LTM in any problem. IS2 outperforms IS1 when problem size varies from small to medium. IS1 and IS2 perform the same in solving large problems. The only difference between IS1 and IS2 is that IS2 puts weight into consideration on the tardiness side; however, it results in significant difference of their performances in solving small and medium problems.

Although the computational time by TSs for this problem is very short compared to the computational time by branch-and-bound algorithm implemented in CPLEX, ANOVA is still performed for computational time (CT) to analyze the difference between TSs and ISs. The result is shown in Table 7.3. The inversed CT is used to make the distribution of the response variable close to normal distribution. Figures 8 and 9 give the normal probability plot of CT and inversed CT.

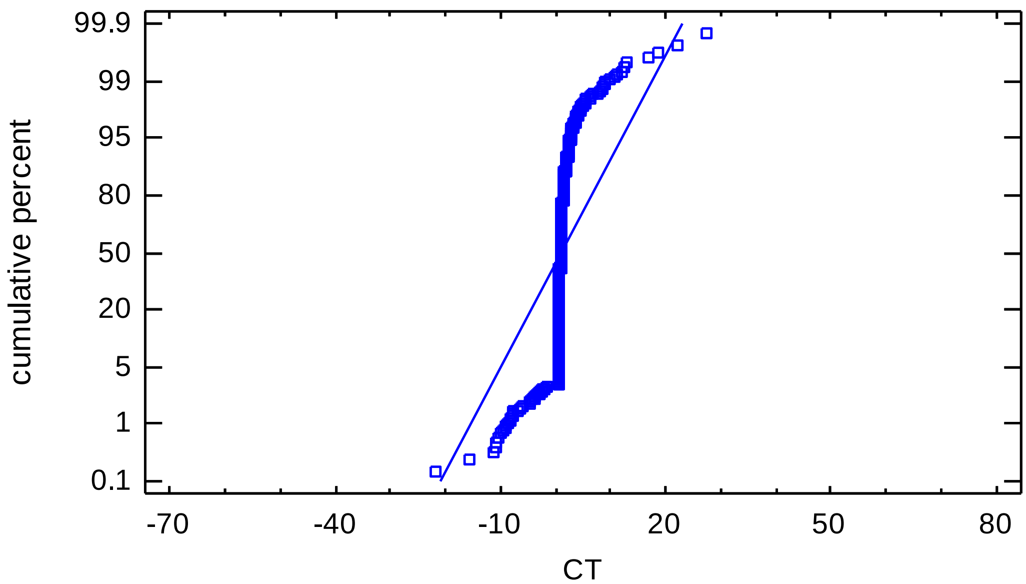

Figure 8 Normal probability plot for CT

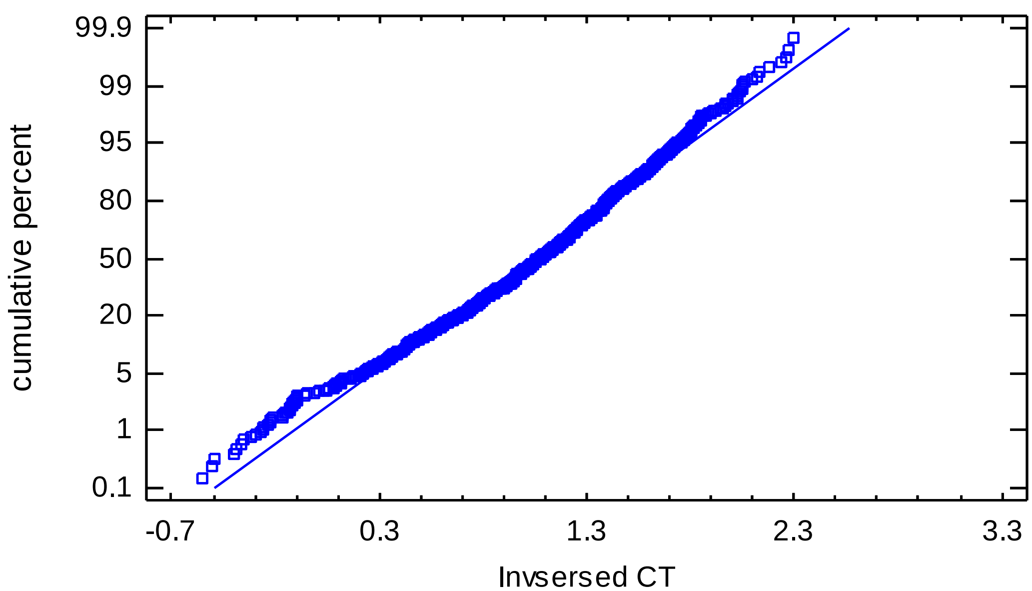

Figure 9 Normal probability plot for inversed CT

With CT as the response variable, three different hypotheses need to be tested and they can be stated as follows:

Hypothesis 1

H0: There is no difference in the computational time spent for the problem instances using the two initial solutions.

H1: One of the initial solution generation methods tends to yield a smaller computational time than the others.

Hypothesis 2

H0: There is no difference in computational time spent for the problem instances using the ten tabu search heuristics.

H1: At least one of the tabu search heuristics tends to yield a smaller computational time than the others.

Hypothesis 3

H0: There is no interaction between initial solution and tabu search heuristic.

In this table only algorithm and setup time ratio*algorithm are showing significance at 5% level. To identify the difference between the speeds of algorithms, Tukey's test is performed. The results show that TS1 and TS2 are the two fastest TSs, which is reasonable because LTM is not implemented in those TSs. TS4 is the fastest algorithm with LTM when STR is equal to 2 and 5, TS5 is the fastest algorithm with LTM when STR is equal to 10. In the TSs with LTM implemented, the TSs with C LTM shows smaller CT than the TSs with NC LTM. Table 7.4 shows the average difference in CT reported by Tukey's test.

The difference between C LTM and NC LTM is very big compared to the average time spent by C LTM. Recall that NC LTM is not showing better performance with its objective function value. Thus, the use of NC LTM is not benefiting in solving this bi-criteria problem.

Table 7. 3 ANOVA of computational time in split-plot design

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Size	1.54E+01	2	7.68E+00	6.24E+00	0.00
Replicate	1.16E+00	1	1.16E+00	9.45E-01	0.25
Scenario	1.04E+00	2	5.18E-01	4.21E-01	0.64
Setup Time Ratio	9.37E+00	2	4.68E+00	3.81E+00	0.03
Size*Scenario	6.24E+00	4	1.56E+00	1.27E+00	0.38
Size*Setup Time Ratio	2.14E+01	4	5.34E+00	4.34E+00	0.01
Scenario*Setup Time Ratio	2.43E+00	4	6.07E-01	4.93E-01	0.71
Size*Scenario*Setup Time Ratio	5.95E+00	8	7.44E-01	6.04E-01	0.79
Main plot error	3.20E+01	26	1.23E+00		
Algorithm	1.23E+01	9	1.36E+00	3.18E+00	0.00
Initial Solution	9.49E-01	1	9.49E-01	2.21E+00	0.09
Size*Algorithm	1.12E+01	18	6.24E-01	1.46E+00	0.40
Scenario*Algorithm	9.35E+00	18	5.20E-01	1.21E+00	0.81
Setup Time Ratio*Algorithm	1.63E+01	18	9.04E-01	2.11E+00	0.02
Size*Scenario*Algorithm	2.25E+01	36	6.25E-01	1.46E+00	0.28
Size*Setup Time Ratio*Algorithm	2.05E+01	36	5.70E-01	1.33E+00	0.58
Scenario*Setup Time Ratio*Algorithm	2.34E+01	36	6.49E-01	1.52E+00	0.20
Size*Initial Solution	2.93E-01	2	1.46E-01	3.42E-01	0.71
Scenario*Initial Solution	3.62E-01	2	1.81E-01	4.23E-01	0.65
Initial Solution*Setup Time Ratio	3.17E-01	2	1.59E-01	3.70E-01	0.69
Size*Scenario*Initial Solution	3.60E-01	4	9.00E-02	2.10E-01	0.55
Scenario*Initial Solution*Setup Time Ratio	7.72E-01	4	1.93E-01	4.50E-01	0.73
Size*Initial Solution*Setup Time Ratio	1.29E-01	4	3.23E-02	7.54E-02	0.26
Initial Solution*Algorithm	7.35E-01	9	8.17E-02	1.91E-01	0.10
Sub-plot error	3.54E+02	827	4.28E-01		

Table 7. 4 Difference in CT between C LTM and NC LTM (in seconds)

	Average CT with C LTM	Average CT with NC LTM	Difference
Small	0.132	0.548	0.416
Medium	1.268	15.391	14.123
Large	8.255	52.139	43.884

CHAPTER 8: CONCLUSIONS AND FUTURE RESEARCH

A flow shop group scheduling problem with sequence-dependent setup time and dynamic assumptions has been addressed in this research. The machines considered in this research have dynamic availability time, which means that each machine may become available at a different time than the start of the planning horizon. Accumulated machine availability is developed to further mimic the real manufacturing environment. The jobs are also assumed to be released dynamically. Each job in the scheduling problem considered in this research has a job release time, due date, and weight associated with it. A sequence-dependent setup time has also been considered in this research, which implies that a considerable amount of time can be spent to change over between two jobs from different groups. The release time can be viewed as a customer's order placement date, the due date can be considered as the shipment date and the weights can be considered as the priority of each job. Notice that although in this research group technology is assumed, which means that the jobs within each group should be processed consecutively without getting preempted by jobs from other groups, the jobs in each group can still have different weights, release times and due dates. The reason for this is that customers can place orders for similar jobs at different times with different priorities and different demands.

The goal is to minimize two objectives at the same time, one from the customer side (total weighted tardiness), and the other from the supplier side (total weighted completion time). Normalized weight is introduced to represent the trade-off between the two objectives.

The research problem is formulated as a mixed (binary) integer-linear programming model with the objective function focused on minimizing the combination of the two objectives. Because either of the two objectives is proven to be strongly NP-hard by the previous works, the computational complexity of the research problem is also strongly NP-hard. Thus, an implicit enumeration technique such as the branch-and-bound technique can only be used to solve small problem instances in a reasonable computation time. For medium and large problem instances, the branch-and-bound technique would not only be very time consuming, but in some cases may never find the optimal solution even after spending an extremely large computation time. Knowing the inefficiency of the implicit enumeration method, a higher-level search heuristic, based on the concept of tabu search (TS), is developed and applied to solve the research problem.

The use of long-term memory (LTM) has been examined thoroughly in this research. Ten different tabu-search based heuristics are developed by incorporating the different features of tabu search such as short-term and long-term memory with fixed and variable tabu-list size. An important part of this research is that C LTM and NC LTM are compared by their ability to find the best solutions. Two different methods are developed to generate the IS that can be used as starting sequences by tabu search. The sequence of an IS is obtained by combining two sequences, each focusing on minimizing one objective. The two ISs use the same mechanism to sequence the groups/jobs to minimize total weighted completion time. On total weighted tardiness minimization, IS1 uses EDD sequence and IS2 uses wEDD sequence. Normalized weights are used to combine the sequences from both sides together.

In order to assess the quality of the final solutions obtained from tabu-search based heuristics, twelve small problem instances were generated and solved using the branch-and-bound technique embedded in CPLEX 9.0 and the tabu search based heuristics. Using the branch-and-bound technique, 9 out of 12 problem instances were solved optimally. The optimal solutions are then compared with the solutions obtained from the tabu-search based heuristics. The heuristics have an average of 1.77% deviation from the optimal solution, speaking highly in favor of the effectiveness of the search heuristics. Moreover, the average time cost by the heuristics is equal to 0.09 second, compared to 8190 seconds by CPLEX. This strongly supports the fact that the use of heuristic search algorithms is very time-efficient.

A multi-factor split-plot design is developed to reveal the significance in the performance (objective function as well as computational time) of the TS-based heuristics, aided by IS generation methods. Factors that define a particular problem (size, setup time ratio, replicate (block), and scenario) stay in the main plot. IS and TS are put in the subplot. The reason for this design is that with the problem characteristic parameters staying in the main plot, the effect of ISs and TSs (all 20 (2 levels of IS * 10 levels of TS) combinations of factors) can be tested without the influence of problem parameters. The result shows that TS4 (C LTM-Min Fixed) and TS8 (NC LTM-Min Fixed) are the best TSs when solving problems with setup time ratio (STR) equal to 10 for small and medium problems. When solving large problems with STR equal to 10, TS3 (C LTM-Max Fixed) and TS8 (NC LTM-Min Fixed) are outperforming the others. It is interesting to discover that NC LTM is not out performing C LTM in any problem. IS2 outperforms IS1 when problem size varies from small to medium. IS1 and IS2 perform the same in solving large problems. The result also shows that C LTM spends less time than NC LTM.

Future research could focus on adding complexity to the flow shop. Flexible flow shops are becoming increasingly popular in industry, primarily due to large workload requirements imposed by jobs on machines representing one or more stages of a multi-stage flow shop scheduling problem. Logendran et al. (2006) studied a group scheduling problem in flexible flow shop with static assumptions, which is a solid and constructive starting point. Machine skipping is another popular feature that is implemented in numerous flow shops in different manufacturing plants, due to customer requirements or budgetary constraints (Pandya and Logendran (2010)). Thus, the focus of future research may include introducing machine skipping in the problem investigated in this research and considering parallel machines in one or more stages of the flow shop with or without machine skipping.

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APPENDIX

Appendix A: Pseudo Code of the proposed algorithm

```
Find the IS
Current solution ← IS
Inside search:
Seed ← Current solution
IAL ← Current solution's objective function value
Calculate ITL size, IEIL, IIWI
While (restart≤2)
{
    While (IIL size<IEIL||IIT<IIWI)
    {
        Do
        {
            Perform the perturbation (Exchange moves) only on the job sequence
            ITCL ← new solution
        }
        Find the best entry among ITCL
        If (best move ≠ tabu move)
        {
            ICL ← best solution
            Tabu move ← best move
            Initialize ITCL
        }
        Else
        {
            Find the next best solution in ITCL
            ICL ← next best solution
            Tabu move ← next best move
            Initialize ITCL
        }
        If (ICL is better than seed)
        {
            Assign a star (*) to the ICL
            Seed ← ICL
            OAL←ICL
            Update frequency matrix
        }
        Else
        {
            If (Seed has a star)
            {
                Assign another star to the seed (**)
                IIL ← seed
                Seed ← ICL
```

```
                Update frequency matrix
            }
            Else
            {
                Seed ← ICL
                Update frequency matrix
            }
        }
    }
    Identify restart point using frequency matrix
    Initialize IIT, IIL, ICL, and frequency matrix
}
Return best solution
Outside search:
Seed ← Current solution
OAL← Current solution's objective function value
Calculate OTL size, OEIL, OIWI
While (restart≤2)
{
    While (OIL size<OEIL||OIT<OIWI)
    {
        Do
        {
            Perform the perturbation (Exchange moves) only on the group
            sequence
            Within each neighborhood, invoke inside search to find best job
            sequence
            OTCL ← new solution
        }
        Find the best entry among OTCL
        If (best move ≠ tabu move)
        {
            OCL ← best solution
            Tabu move ← best move
            Initialize OTCL
        }
        Else
        {
            Find the next best solution in OTCL
            OCL ← next best solution
            Tabu move ← next best move
            Initialize OTCL
        }
        If (OCL is better than seed)
        {
            Assign a star (*) to the OCL
```

```
            Seed ← OCL
            OAL←OCL
            Update frequency matrix
        }
        Else
        {
            If (Seed has a star)
            {
                Assign another star to the seed (**)
                OIL ← seed
                Seed ← OCL
                Update frequency matrix
            }
            Else
            {
                Seed ← OCL
                Update frequency matrix
            }
        }
    }
    Identify restart point using frequency matrix
    Initialize OIT, OIL, OCL, and frequency matrix
}
Return best solution
```

ITCL: Inside temporary candidate list, a list that stores and sorts neighborhood solutions during inside search
OTCL: Outside temporary candidate list, a list that stores and sorts neighborhood solutions during outside search

Appendix B: Results from the generated problems

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	1	0.4	IS2	2	STM-Fixed	1452.2	0.003
Small	1	0.4	IS2	2	STM-Var	1452.2	0.007
Small	1	0.4	IS2	2	LTM-Max Fixed	1452.2	0.006
Small	1	0.4	IS2	2	LTM-Min Fixed	1452.2	0.004
Small	1	0.4	IS2	2	LTM-Max Var	1452.2	0.004
Small	1	0.4	IS2	2	LTM-Min Var	1452.2	0.003
Small	1	0.4	IS2	2	NC LTM-Max Fixed	1452.2	0.006
Small	1	0.4	IS2	2	NC LTM-Min Fixed	1445.6	0.004
Small	1	0.4	IS2	2	NC LTM-Max Var	1452.2	0.003
Small	1	0.4	IS2	2	NC LTM-Min Var	1445.6	0.003
Small	1	0.4	IS1	2	STM-Fixed	1595.8	0.005
Small	1	0.4	IS1	2	STM-Var	1608.8	0.009
Small	1	0.4	IS1	2	LTM-Max Fixed	1595.8	0.013
Small	1	0.4	IS1	2	LTM-Min Fixed	1595.8	0.016
Small	1	0.4	IS1	2	LTM-Max Var	1608.8	0.018
Small	1	0.4	IS1	2	LTM-Min Var	1608.8	0.021
Small	1	0.4	IS1	2	NC LTM-Max Fixed	1595.8	0.024
Small	1	0.4	IS1	2	NC LTM-Min Fixed	1595.8	0.028
Small	1	0.4	IS1	2	NC LTM-Max Var	1608.8	0.032
Small	1	0.4	IS1	2	NC LTM-Min Var	1521.4	0.036
Small	2	0.4	IS2	2	STM-Fixed	1929.4	0.017
Small	2	0.4	IS2	2	STM-Var	1973.8	0.015
Small	2	0.4	IS2	2	LTM-Max Fixed	1929.4	0.012
Small	2	0.4	IS2	2	LTM-Min Fixed	1929.4	0.015
Small	2	0.4	IS2	2	LTM-Max Var	1973.8	0.011

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	2	0.4	IS2	2	NC LTM-Min Fixed	1929.4	0.012
Small	2	0.4	IS2	2	NC LTM-Max Var	1973.8	0.008
Small	2	0.4	IS2	2	NC LTM-Min Var	1920.4	0.014
Small	2	0.4	IS1	2	STM-Fixed	1938.6	0.024
Small	2	0.4	IS1	2	STM-Var	1971.8	0.036
Small	2	0.4	IS1	2	LTM-Max Fixed	1938.6	0.05
Small	2	0.4	IS1	2	LTM-Min Fixed	1938.6	0.063
Small	2	0.4	IS1	2	LTM-Max Var	1942.4	0.077
Small	2	0.4	IS1	2	LTM-Min Var	1971.8	0.086
Small	2	0.4	IS1	2	NC LTM-Max Fixed	1925.4	0.104
Small	2	0.4	IS1	2	NC LTM-Min Fixed	1938.6	0.115
Small	2	0.4	IS1	2	NC LTM-Max Var	1964.8	0.129
Small	2	0.4	IS1	2	NC LTM-Min Var	1920.4	0.143
Small	1	0.4	IS2	5	STM-Fixed	3146.4	0.005
Small	1	0.4	IS2	5	STM-Var	3138.2	0.018
Small	1	0.4	IS2	5	LTM-Max Fixed	3145.4	0.015
Small	1	0.4	IS2	5	LTM-Min Fixed	3146.4	0.011
Small	1	0.4	IS2	5	LTM-Max Var	3138.2	0.012
Small	1	0.4	IS2	5	LTM-Min Var	3089.8	0.012
Small	1	0.4	IS2	5	NC LTM-Max Fixed	3050.6	0.011
Small	1	0.4	IS2	5	NC LTM-Min Fixed	3052.4	0.011
Small	1	0.4	IS2	5	NC LTM-Max Var	3050.6	0.012
Small	1	0.4	IS2	5	NC LTM-Min Var	3138.2	0.01
Small	1	0.4	IS1	5	STM-Fixed	3191.8	0.021
Small	1	0.4	IS1	5	STM-Var	3183	0.036
Small	1	0.4	IS1	5	LTM-Max Fixed	3107	0.053

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	1	0.4	IS1	5	LTM-Min Fixed	3191.8	0.066
Small	1	0.4	IS1	5	LTM-Max Var	3113.8	0.079
Small	1	0.4	IS1	5	LTM-Min Var	3093.2	0.093
Small	1	0.4	IS1	5	NC LTM-Max Fixed	3052.4	0.108
Small	1	0.4	IS1	5	NC LTM-Min Fixed	3084	0.124
Small	1	0.4	IS1	5	NC LTM-Max Var	3133.6	0.139
Small	1	0.4	IS1	5	NC LTM-Min Var	3183	0.152
Small	2	0.4	IS2	5	STM-Fixed	1663.6	0
Small	2	0.4	IS2	5	STM-Var	1602.6	0.001
Small	2	0.4	IS2	5	LTM-Max Fixed	1512.6	0.001
Small	2	0.4	IS2	5	LTM-Min Fixed	1534.6	0
Small	2	0.4	IS2	5	LTM-Max Var	1512.6	0.001
Small	2	0.4	IS2	5	LTM-Min Var	1534.6	0.001
Small	2	0.4	IS2	5	NC LTM-Max Fixed	1640.6	0.001
Small	2	0.4	IS2	5	NC LTM-Min Fixed	1554.6	0
Small	2	0.4	IS2	5	NC LTM-Max Var	1602.6	0.001
Small	2	0.4	IS2	5	NC LTM-Min Var	1554.6	0.001
Small	2	0.4	IS1	5	STM-Fixed	1560.6	0.001
Small	2	0.4	IS1	5	STM-Var	1560.6	0.002
Small	2	0.4	IS1	5	LTM-Max Fixed	1512.6	0.003
Small	2	0.4	IS1	5	LTM-Min Fixed	1534.6	0.004
Small	2	0.4	IS1	5	LTM-Max Var	1512.6	0.005
Small	2	0.4	IS1	5	LTM-Min Var	1534.6	0.005
Small	2	0.4	IS1	5	NC LTM-Max Fixed	1560.6	0.006
Small	2	0.4	IS1	5	NC LTM-Min Fixed	1554.6	0.007
Small	2	0.4	IS1	5	NC LTM-Max Var	1560.6	0.007

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	2	0.4	IS1	5	NC LTM-Min Var	1554.6	0.008
Small	1	0.4	IS2	10	STM-Fixed	3388.8	0.002
Small	1	0.4	IS2	10	STM-Var	3388.8	0.004
Small	1	0.4	IS2	10	LTM-Max Fixed	3353.6	0.003
Small	1	0.4	IS2	10	LTM-Min Fixed	3348.4	0.002
Small	1	0.4	IS2	10	LTM-Max Var	3353.6	0.002
Small	1	0.4	IS2	10	LTM-Min Var	3348.4	0.004
Small	1	0.4	IS2	10	NC LTM-Max Fixed	3316.4	0.002
Small	1	0.4	IS2	10	NC LTM-Min Fixed	3316.4	0.002
Small	1	0.4	IS2	10	NC LTM-Max Var	3316.4	0.002
Small	1	0.4	IS2	10	NC LTM-Min Var	3316.4	0.003
Small	1	0.4	IS1	10	STM-Fixed	5831.2	0.004
Small	1	0.4	IS1	10	STM-Var	5864.2	0.006
Small	1	0.4	IS1	10	LTM-Max Fixed	5827.2	0.008
Small	1	0.4	IS1	10	LTM-Min Fixed	3459.6	0.011
Small	1	0.4	IS1	10	LTM-Max Var	4672.2	0.014
Small	1	0.4	IS1	10	LTM-Min Var	3315.6	0.016
Small	1	0.4	IS1	10	NC LTM-Max Fixed	5619.4	0.02
Small	1	0.4	IS1	10	NC LTM-Min Fixed	5831.2	0.022
Small	1	0.4	IS1	10	NC LTM-Max Var	5827.2	0.024
Small	1	0.4	IS1	10	NC LTM-Min Var	3445.6	0.026
Small	2	0.4	IS2	10	STM-Fixed	5987.4	0.015
Small	2	0.4	IS2	10	STM-Var	5786.4	0.023
Small	2	0.4	IS2	10	LTM-Max Fixed	5987.4	0.017
Small	2	0.4	IS2	10	LTM-Min Fixed	5987.4	0.014
Small	2	0.4	IS2	10	LTM-Max Var	5786.4	0.015
Small	2	0.4	IS2	10	LTM-Min Var	5786.4	0.017

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	2	0.4	IS2	10	NC LTM-Max Fixed	5987.4	0.014
Small	2	0.4	IS2	10	NC LTM-Min Fixed	5987.4	0.008
Small	2	0.4	IS2	10	NC LTM-Max Var	5786.4	0.01
Small	2	0.4	IS2	10	NC LTM-Min Var	5786.4	0.012
Small	2	0.4	IS1	10	STM-Fixed	6791.8	0.025
Small	2	0.4	IS1	10	STM-Var	5791.6	0.043
Small	2	0.4	IS1	10	LTM-Max Fixed	6262.4	0.055
Small	2	0.4	IS1	10	LTM-Min Fixed	6211.4	0.075
Small	2	0.4	IS1	10	LTM-Max Var	5791.6	0.088
Small	2	0.4	IS1	10	LTM-Min Var	5765.8	0.105
Small	2	0.4	IS1	10	NC LTM-Max Fixed	5775.8	0.122
Small	2	0.4	IS1	10	NC LTM-Min Fixed	6034.4	0.139
Small	2	0.4	IS1	10	NC LTM-Max Var	5791.6	0.155
Small	2	0.4	IS1	10	NC LTM-Min Var	5775.8	0.169
Medium	1	0.4	IS2	2	STM-Fixed	13090.8	5.148
Medium	1	0.4	IS2	2	STM-Var	13375.6	1.56
Medium	1	0.4	IS2	2	LTM-Max Fixed	13090.8	2.072
Medium	1	0.4	IS2	2	LTM-Min Fixed	12698.2	2.106
Medium	1	0.4	IS2	2	LTM-Max Var	13108.2	2.187
Medium	1	0.4	IS2	2	LTM-Min Var	12840.7	1.688
Medium	1	0.4	IS2	2	NC LTM-Max Fixed	12567.3	2.067
Medium	1	0.4	IS2	2	NC LTM-Min Fixed	12698.2	1.493
Medium	1	0.4	IS2	2	NC LTM-Max Var	12974.4	9.367
Medium	1	0.4	IS2	2	NC LTM-Min Var	12840.7	1.486
Medium	1	0.4	IS1	2	STM-Fixed	13028.6	5.812
Medium	1	0.4	IS1	2	STM-Var	13180.8	7.549

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	1	0.4	IS1	2	LTM-Max Fixed	12247	9.639
Medium	1	0.4	IS1	2	LTM-Min Fixed	12377.3	11.628
Medium	1	0.4	IS1	2	LTM-Max Var	12785.5	13.78
Medium	1	0.4	IS1	2	LTM-Min Var	12917.3	15.541
Medium	1	0.4	IS1	2	NC LTM-Max Fixed	12768.1	24.157
Medium	1	0.4	IS1	2	NC LTM-Min Fixed	13028.6	33.865
Medium	1	0.4	IS1	2	NC LTM-Max Var	12653.7	42.367
Medium	1	0.4	IS1	2	NC LTM-Min Var	13180.8	44.528
Medium	2	0.4	IS2	2	STM-Fixed	15758.2	7.983
Medium	2	0.4	IS2	2	STM-Var	16048.2	2.097
Medium	2	0.4	IS2	2	LTM-Max Fixed	14497.6	4.135
Medium	2	0.4	IS2	2	LTM-Min Fixed	15443.1	2.747
Medium	2	0.4	IS2	2	LTM-Max Var	15245.9	3.767
Medium	2	0.4	IS2	2	LTM-Min Var	15085.4	2.888
Medium	2	0.4	IS2	2	NC LTM-Max Fixed	15285.6	2.924
Medium	2	0.4	IS2	2	NC LTM-Min Fixed	15285.6	2.977
Medium	2	0.4	IS2	2	NC LTM-Max Var	15245.9	3.108
Medium	2	0.4	IS2	2	NC LTM-Min Var	15566.9	2.644
Medium	2	0.4	IS1	2	STM-Fixed	16220.6	8.387
Medium	2	0.4	IS1	2	STM-Var	16011.4	10.388
Medium	2	0.4	IS1	2	LTM-Max Fixed	14598.6	13.536
Medium	2	0.4	IS1	2	LTM-Min Fixed	15409.7	15.865
Medium	2	0.4	IS1	2	LTM-Max Var	15050.8	20.418
Medium	2	0.4	IS1	2	LTM-Min Var	15210.9	23.834
Medium	2	0.4	IS1	2	NC LTM-Max Fixed	15409.7	40.989
Medium	2	0.4	IS1	2	NC LTM-Min Fixed	15571.9	57.704

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	2	0.4	IS1	2	NC LTM-Max Var	15531.2	73.965
Medium	2	0.4	IS1	2	NC LTM-Min Var	15691.3	92.796
Medium	1	0.4	IS2	5	STM-Fixed	28621.4	18.624
Medium	1	0.4	IS2	5	STM-Var	29284	4.499
Medium	1	0.4	IS2	5	LTM-Max Fixed	28335.3	4.118
Medium	1	0.4	IS2	5	LTM-Min Fixed	28621.4	3.939
Medium	1	0.4	IS2	5	LTM-Max Var	27234.2	3.937
Medium	1	0.4	IS2	5	LTM-Min Var	28112.7	3.941
Medium	1	0.4	IS2	5	NC LTM-Max Fixed	27476.6	3.928
Medium	1	0.4	IS2	5	NC LTM-Min Fixed	27762.9	4.315
Medium	1	0.4	IS2	5	NC LTM-Max Var	28698.4	34.161
Medium	1	0.4	IS2	5	NC LTM-Min Var	28698.4	3.973
Medium	1	0.4	IS1	5	STM-Fixed	29027	20.59
Medium	1	0.4	IS1	5	STM-Var	29455.6	38.524
Medium	1	0.4	IS1	5	LTM-Max Fixed	26995.2	66.939
Medium	1	0.4	IS1	5	LTM-Min Fixed	28156.3	110.077
Medium	1	0.4	IS1	5	LTM-Max Var	27982.9	138.399
Medium	1	0.4	IS1	5	LTM-Min Var	27099.3	143.333
Medium	1	0.4	IS1	5	NC LTM-Max Fixed	28736.8	171.289
Medium	1	0.4	IS1	5	NC LTM-Min Fixed	28446.6	203.446
Medium	1	0.4	IS1	5	NC LTM-Max Var	28572	212.098
Medium	1	0.4	IS1	5	NC LTM-Min Var	29161.1	243.731
Medium	2	0.4	IS2	5	STM-Fixed	23818	2.642
Medium	2	0.4	IS2	5	STM-Var	23867	3.131
Medium	2	0.4	IS2	5	LTM-Max Fixed	22865.4	3.617
Medium	2	0.4	IS2	5	LTM-Min Fixed	23579.9	3.281

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	2	0.4	IS2	5	LTM-Max Var	22196.4	2.649
Medium	2	0.4	IS2	5	LTM-Min Var	23151.1	3.18
Medium	2	0.4	IS2	5	NC LTM-Max Fixed	23103.6	3.657
Medium	2	0.4	IS2	5	NC LTM-Min Fixed	22865.4	3.292
Medium	2	0.4	IS2	5	NC LTM-Max Var	23151.1	3.664
Medium	2	0.4	IS2	5	NC LTM-Min Var	23151.1	3.358
Medium	2	0.4	IS1	5	STM-Fixed	23682.8	9.269
Medium	2	0.4	IS1	5	STM-Var	24443	12.393
Medium	2	0.4	IS1	5	LTM-Max Fixed	21788.3	15.317
Medium	2	0.4	IS1	5	LTM-Min Fixed	22498.8	19.019
Medium	2	0.4	IS1	5	LTM-Max Var	23709.8	22.533
Medium	2	0.4	IS1	5	LTM-Min Var	22732.1	25.432
Medium	2	0.4	IS1	5	NC LTM-Max Fixed	22498.8	28.475
Medium	2	0.4	IS1	5	NC LTM-Min Fixed	23209.2	32.351
Medium	2	0.4	IS1	5	NC LTM-Max Var	23221	35.38
Medium	2	0.4	IS1	5	NC LTM-Min Var	23954.2	39.249
Medium	1	0.4	IS2	10	STM-Fixed	52647.4	37.164
Medium	1	0.4	IS2	10	STM-Var	53539.6	6.93
Medium	1	0.4	IS2	10	LTM-Max Fixed	52121	11.908
Medium	1	0.4	IS2	10	LTM-Min Fixed	51068.1	9.405
Medium	1	0.4	IS2	10	LTM-Max Var	50327.3	12.061
Medium	1	0.4	IS2	10	LTM-Min Var	51933.5	11.139
Medium	1	0.4	IS2	10	NC LTM-Max Fixed	51594.6	10.075
Medium	1	0.4	IS2	10	NC LTM-Min Fixed	52121	8.812
Medium	1	0.4	IS2	10	NC LTM-Max Var	51398.1	8.25
Medium	1	0.4	IS2	10	NC LTM-Min Var	52468.9	12.95

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	1	0.4	IS1	10	STM-Fixed	54749.6	24.559
Medium	1	0.4	IS1	10	STM-Var	50389.2	35.303
Medium	1	0.4	IS1	10	LTM-Max Fixed	54749.6	46.06
Medium	1	0.4	IS1	10	LTM-Min Fixed	53107.2	56.418
Medium	1	0.4	IS1	10	LTM-Max Var	47365.9	68.363
Medium	1	0.4	IS1	10	LTM-Min Var	49381.5	77.394
Medium	1	0.4	IS1	10	NC LTM-Max Fixed	53107.2	87.631
Medium	1	0.4	IS1	10	NC LTM-Min Fixed	53654.7	98.232
Medium	1	0.4	IS1	10	NC LTM-Max Var	49885.4	205.751
Medium	1	0.4	IS1	10	NC LTM-Min Var	49885.4	216.196
Medium	2	0.4	IS2	10	STM-Fixed	21153.8	1.486
Medium	2	0.4	IS2	10	STM-Var	22197	0.88
Medium	2	0.4	IS2	10	LTM-Max Fixed	19461.6	0.973
Medium	2	0.4	IS2	10	LTM-Min Fixed	20519.3	0.971
Medium	2	0.4	IS2	10	LTM-Max Var	20643.3	0.669
Medium	2	0.4	IS2	10	LTM-Min Var	21087.3	0.981
Medium	2	0.4	IS2	10	NC LTM-Max Fixed	20096.2	4.741
Medium	2	0.4	IS2	10	NC LTM-Min Fixed	20519.3	3.955
Medium	2	0.4	IS2	10	NC LTM-Max Var	21309.2	0.69
Medium	2	0.4	IS2	10	NC LTM-Min Var	21531.2	3.472
Medium	2	0.4	IS1	10	STM-Fixed	22295.4	6.604
Medium	2	0.4	IS1	10	STM-Var	21289.6	7.558
Medium	2	0.4	IS1	10	LTM-Max Fixed	22295.4	8.74
Medium	2	0.4	IS1	10	LTM-Min Fixed	20957.8	9.583
Medium	2	0.4	IS1	10	LTM-Max Var	20225.2	10.531
Medium	2	0.4	IS1	10	LTM-Min Var	20225.2	11.37
Medium	2	0.4	IS1	10	NC LTM-Max Fixed	22295.4	12.206

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	2	0.4	IS1	10	NC LTM-Min Fixed	21626.6	13.243
Medium	2	0.4	IS1	10	NC LTM-Max Var	20438.1	14.29
Medium	2	0.4	IS1	10	NC LTM-Min Var	20863.9	15.11
Large	1	0.4	IS2	2	STM-Fixed	21992.6	14.605
Large	1	0.4	IS2	2	STM-Var	27821.2	21.188
Large	1	0.4	IS2	2	LTM-Max Fixed	21332.8	19.133
Large	1	0.4	IS2	2	LTM-Min Fixed	21332.8	28.18
Large	1	0.4	IS2	2	LTM-Max Var	26708.4	26.595
Large	1	0.4	IS2	2	LTM-Min Var	26708.4	36.916
Large	1	0.4	IS2	2	NC LTM-Max Fixed	21552.8	34.308
Large	1	0.4	IS2	2	NC LTM-Min Fixed	21772.6	54.636
Large	1	0.4	IS2	2	NC LTM-Max Var	27264.8	131.057
Large	1	0.4	IS2	2	NC LTM-Min Var	27821.2	207.617
Large	1	0.4	IS1	2	STM-Fixed	27360.2	18.87
Large	1	0.4	IS1	2	STM-Var	27416.2	17.99
Large	1	0.4	IS1	2	LTM-Max Fixed	27086.6	54.534
Large	1	0.4	IS1	2	LTM-Min Fixed	27086.6	48.573
Large	1	0.4	IS1	2	LTM-Max Var	27142	139.607
Large	1	0.4	IS1	2	LTM-Min Var	27416.2	162.72
Large	1	0.4	IS1	2	NC LTM-Max Fixed	27086.6	185.677
Large	1	0.4	IS1	2	NC LTM-Min Fixed	26813	294.523
Large	1	0.4	IS1	2	NC LTM-Max Var	27416.2	610.877
Large	1	0.4	IS1	2	NC LTM-Min Var	26867.8	951.309
Large	2	0.4	IS2	2	STM-Fixed	31201.2	18.314
Large	2	0.4	IS2	2	STM-Var	31775.4	12.274
Large	2	0.4	IS2	2	LTM-Max Fixed	30577.2	26.555

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	2	0.4	IS2	2	LTM-Min Fixed	29953.2	15.343
Large	2	0.4	IS2	2	LTM-Max Var	30504.4	37.708
Large	2	0.4	IS2	2	LTM-Min Var	30186.6	19.946
Large	2	0.4	IS2	2	NC LTM-Max Fixed	30265.2	66.366
Large	2	0.4	IS2	2	NC LTM-Min Fixed	30577.2	47.471
Large	2	0.4	IS2	2	NC LTM-Max Var	31140	191.134
Large	2	0.4	IS2	2	NC LTM-Min Var	31457.6	120.102
Large	2	0.4	IS1	2	STM-Fixed	26601.8	21.047
Large	2	0.4	IS1	2	STM-Var	28180.2	14.635
Large	2	0.4	IS1	2	LTM-Max Fixed	26601.8	56.827
Large	2	0.4	IS1	2	LTM-Min Fixed	26335.8	39.954
Large	2	0.4	IS1	2	LTM-Max Var	27616.6	163.662
Large	2	0.4	IS1	2	LTM-Min Var	28180.2	158.218
Large	2	0.4	IS1	2	NC LTM-Max Fixed	26335.8	209.487
Large	2	0.4	IS1	2	NC LTM-Min Fixed	26069.8	230.998
Large	2	0.4	IS1	2	NC LTM-Max Var	27616.6	806.525
Large	2	0.4	IS1	2	NC LTM-Min Var	27334.8	960.952
Large	1	0.4	IS2	5	STM-Fixed	48084	15.894
Large	1	0.4	IS2	5	STM-Var	50954.2	18.866
Large	1	0.4	IS2	5	LTM-Max Fixed	47603.2	19.868
Large	1	0.4	IS2	5	LTM-Min Fixed	47603.2	24.714
Large	1	0.4	IS2	5	LTM-Max Var	48916	27.219
Large	1	0.4	IS2	5	LTM-Min Var	50444.8	30.645
Large	1	0.4	IS2	5	NC LTM-Max Fixed	47603.2	47.361
Large	1	0.4	IS2	5	NC LTM-Min Fixed	47603.2	54.242
Large	1	0.4	IS2	5	NC LTM-Max Var	49425.6	135.452

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	1	0.4	IS2	5	NC LTM-Min Var	49935.2	98.72
Large	1	0.4	IS1	5	STM-Fixed	47604.4	20.012
Large	1	0.4	IS1	5	STM-Var	62446	9.982
Large	1	0.4	IS1	5	LTM-Max Fixed	47128.4	66.44
Large	1	0.4	IS1	5	LTM-Min Fixed	47128.4	28.349
Large	1	0.4	IS1	5	LTM-Max Var	61197	174.737
Large	1	0.4	IS1	5	LTM-Min Var	61821.4	126.437
Large	1	0.4	IS1	5	NC LTM-Max Fixed	46176.2	269.095
Large	1	0.4	IS1	5	NC LTM-Min Fixed	46176.2	225.058
Large	1	0.4	IS1	5	NC LTM-Max Var	61197	1079.071
Large	1	0.4	IS1	5	NC LTM-Min Var	60572.6	711.183
Large	2	0.4	IS2	5	STM-Fixed	48112.4	21.464
Large	2	0.4	IS2	5	STM-Var	47734	7.965
Large	2	0.4	IS2	5	LTM-Max Fixed	48112.4	27.689
Large	2	0.4	IS2	5	LTM-Min Fixed	47150.2	10.275
Large	2	0.4	IS2	5	LTM-Max Var	47256.8	35.165
Large	2	0.4	IS2	5	LTM-Min Var	46779.4	14.282
Large	2	0.4	IS2	5	NC LTM-Max Fixed	46669	49.583
Large	2	0.4	IS2	5	NC LTM-Min Fixed	45706.8	29.564
Large	2	0.4	IS2	5	NC LTM-Max Var	46302	127.428
Large	2	0.4	IS2	5	NC LTM-Min Var	47734	126.534
Large	2	0.4	IS1	5	STM-Fixed	41208.2	10.016
Large	2	0.4	IS1	5	STM-Var	46930.6	12.991
Large	2	0.4	IS1	5	LTM-Max Fixed	41208.2	32.953
Large	2	0.4	IS1	5	LTM-Min Fixed	40384	40.792
Large	2	0.4	IS1	5	LTM-Max Var	45992	79.746
Large	2	0.4	IS1	5	LTM-Min Var	46461.4	153.378

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	2	0.4	IS1	5	NC LTM-Max Fixed	40384	119.619
Large	2	0.4	IS1	5	NC LTM-Min Fixed	40796	277.614
Large	2	0.4	IS1	5	NC LTM-Max Var	46461.4	377.996
Large	2	0.4	IS1	5	NC LTM-Min Var	46461.4	866.156
Large	1	0.4	IS2	10	STM-Fixed	103189	12.493
Large	1	0.4	IS2	10	STM-Var	95300.6	12.839
Large	1	0.4	IS2	10	LTM-Max Fixed	102157	17.115
Large	1	0.4	IS2	10	LTM-Min Fixed	101125	17.076
Large	1	0.4	IS2	10	LTM-Max Var	92441.6	23.276
Large	1	0.4	IS2	10	LTM-Min Var	91488.6	21.003
Large	1	0.4	IS2	10	NC LTM-Max Fixed	101125	41.664
Large	1	0.4	IS2	10	NC LTM-Min Fixed	101125	48.097
Large	1	0.4	IS2	10	NC LTM-Max Var	93394.6	77.495
Large	1	0.4	IS2	10	NC LTM-Min Var	93394.6	216.917
Large	1	0.4	IS1	10	STM-Fixed	90884.4	11.922
Large	1	0.4	IS1	10	STM-Var	95739.6	13.681
Large	1	0.4	IS1	10	LTM-Max Fixed	89975.6	34.335
Large	1	0.4	IS1	10	LTM-Min Fixed	89975.6	38.854
Large	1	0.4	IS1	10	LTM-Max Var	95739.6	76.91
Large	1	0.4	IS1	10	LTM-Min Var	93824.8	130.161
Large	1	0.4	IS1	10	NC LTM-Max Fixed	89975.6	109.212
Large	1	0.4	IS1	10	NC LTM-Min Fixed	89975.6	216.067
Large	1	0.4	IS1	10	NC LTM-Max Var	95739.6	203.134
Large	1	0.4	IS1	10	NC LTM-Min Var	90952.6	384.599
Large	2	0.4	IS2	10	STM-Fixed	36807.6	16.312
Large	2	0.4	IS2	10	STM-Var	43506.2	9.089

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	2	0.4	IS2	10	LTM-Max Fixed	36807.6	22.021
Large	2	0.4	IS2	10	LTM-Min Fixed	35703.4	12.543
Large	2	0.4	IS2	10	LTM-Max Var	42201	32.151
Large	2	0.4	IS2	10	LTM-Min Var	43071	16.431
Large	2	0.4	IS2	10	NC LTM-Max Fixed	36071.4	58.193
Large	2	0.4	IS2	10	NC LTM-Min Fixed	36807.6	32.04
Large	2	0.4	IS2	10	NC LTM-Max Var	41766	224.625
Large	2	0.4	IS2	10	NC LTM-Min Var	42201	99.644
Large	2	0.4	IS1	10	STM-Fixed	42807.2	13.813
Large	2	0.4	IS1	10	STM-Var	34915	12.477
Large	2	0.4	IS1	10	LTM-Max Fixed	42379.2	46.274
Large	2	0.4	IS1	10	LTM-Min Fixed	42807.2	27.824
Large	2	0.4	IS1	10	LTM-Max Var	34915	128.642
Large	2	0.4	IS1	10	LTM-Min Var	34915	122.704
Large	2	0.4	IS1	10	NC LTM-Max Fixed	42379.2	223.837
Large	2	0.4	IS1	10	NC LTM-Min Fixed	42379.2	200.008
Large	2	0.4	IS1	10	NC LTM-Max Var	34565.8	729.709
Large	2	0.4	IS1	10	NC LTM-Min Var	33867.6	524.021
Small	1	0	IS2	2	STM-Fixed	1452.2	0.002
Small	1	0	IS2	2	STM-Var	1452.2	0.006
Small	1	0	IS2	2	LTM-Max Fixed	1452.2	0.005
Small	1	0	IS2	2	LTM-Min Fixed	1452.2	0.003
Small	1	0	IS2	2	LTM-Max Var	1452.2	0.004
Small	1	0	IS2	2	LTM-Min Var	1452.2	0.003
Small	1	0	IS2	2	NC LTM-Max Fixed	1452.2	0.005
Small	1	0	IS2	2	NC LTM-Min Fixed	1445.6	0.005

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	1	0	IS2	2	NC LTM-Max Var	1452.2	0.003
Small	1	0	IS2	2	NC LTM-Min Var	1445.6	0.003
Small	1	0	IS1	2	STM-Fixed	1595.8	0.006
Small	1	0	IS1	2	STM-Var	1608.8	0.01
Small	1	0	IS1	2	LTM-Max Fixed	1595.8	0.011
Small	1	0	IS1	2	LTM-Min Fixed	1595.8	0.014
Small	1	0	IS1	2	LTM-Max Var	1608.8	0.021
Small	1	0	IS1	2	LTM-Min Var	1608.8	0.025
Small	1	0	IS1	2	NC LTM-Max Fixed	1595.8	0.026
Small	1	0	IS1	2	NC LTM-Min Fixed	1595.8	0.02
Small	1	0	IS1	2	NC LTM-Max Var	1608.8	0.028
Small	1	0	IS1	2	NC LTM-Min Var	1521.4	0.025
Small	2	0	IS2	2	STM-Fixed	1929.4	0.013
Small	2	0	IS2	2	STM-Var	1973.8	0.016
Small	2	0	IS2	2	LTM-Max Fixed	1929.4	0.012
Small	2	0	IS2	2	LTM-Min Fixed	1929.4	0.014
Small	2	0	IS2	2	LTM-Max Var	1973.8	0.014
Small	2	0	IS2	2	LTM-Min Var	1970.2	0.013
Small	2	0	IS2	2	NC LTM-Max Fixed	1929.4	0.016
Small	2	0	IS2	2	NC LTM-Min Fixed	1929.4	0.009
Small	2	0	IS2	2	NC LTM-Max Var	1973.8	0.007
Small	2	0	IS2	2	NC LTM-Min Var	1920.4	0.013
Small	2	0	IS1	2	STM-Fixed	1938.6	0.028
Small	2	0	IS1	2	STM-Var	1971.8	0.031
Small	2	0	IS1	2	LTM-Max Fixed	1938.6	0.06
Small	2	0	IS1	2	LTM-Min Fixed	1938.6	0.047

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	2	0	IS1	2	LTM-Max Var	1942.4	0.055
Small	2	0	IS1	2	LTM-Min Var	1971.8	0.07
Small	2	0	IS1	2	NC LTM-Max Fixed	1925.4	0.104
Small	2	0	IS1	2	NC LTM-Min Fixed	1938.6	0.091
Small	2	0	IS1	2	NC LTM-Max Var	1964.8	0.135
Small	2	0	IS1	2	NC LTM-Min Var	1920.4	0.17
Small	1	0	IS2	5	STM-Fixed	3146.4	0.005
Small	1	0	IS2	5	STM-Var	3138.2	0.018
Small	1	0	IS2	5	LTM-Max Fixed	3145.4	0.016
Small	1	0	IS2	5	LTM-Min Fixed	3146.4	0.011
Small	1	0	IS2	5	LTM-Max Var	3138.2	0.014
Small	1	0	IS2	5	LTM-Min Var	3089.8	0.009
Small	1	0	IS2	5	NC LTM-Max Fixed	3050.6	0.011
Small	1	0	IS2	5	NC LTM-Min Fixed	3052.4	0.008
Small	1	0	IS2	5	NC LTM-Max Var	3050.6	0.01
Small	1	0	IS2	5	NC LTM-Min Var	3138.2	0.012
Small	1	0	IS1	5	STM-Fixed	3191.8	0.021
Small	1	0	IS1	5	STM-Var	3183	0.036
Small	1	0	IS1	5	LTM-Max Fixed	3107	0.044
Small	1	0	IS1	5	LTM-Min Fixed	3191.8	0.074
Small	1	0	IS1	5	LTM-Max Var	3113.8	0.074
Small	1	0	IS1	5	LTM-Min Var	3093.2	0.083
Small	1	0	IS1	5	NC LTM-Max Fixed	3052.4	0.121
Small	1	0	IS1	5	NC LTM-Min Fixed	3084	0.141
Small	1	0	IS1	5	NC LTM-Max Var	3133.6	0.143
Small	1	0	IS1	5	NC LTM-Min Var	3183	0.158

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	2	0	IS2	5	STM-Fixed	1663.6	0
Small	2	0	IS2	5	STM-Var	1602.6	0.001
Small	2	0	IS2	5	LTM-Max Fixed	1512.6	0.001
Small	2	0	IS2	5	LTM-Min Fixed	1534.6	0
Small	2	0	IS2	5	LTM-Max Var	1512.6	0.001
Small	2	0	IS2	5	LTM-Min Var	1534.6	0.001
Small	2	0	IS2	5	NC LTM-Max Fixed	1640.6	0.001
Small	2	0	IS2	5	NC LTM-Min Fixed	1554.6	0
Small	2	0	IS2	5	NC LTM-Max Var	1602.6	0.001
Small	2	0	IS2	5	NC LTM-Min Var	1554.6	0.001
Small	2	0	IS1	5	STM-Fixed	1560.6	0.001
Small	2	0	IS1	5	STM-Var	1560.6	0.002
Small	2	0	IS1	5	LTM-Max Fixed	1512.6	0.003
Small	2	0	IS1	5	LTM-Min Fixed	1534.6	0.003
Small	2	0	IS1	5	LTM-Max Var	1512.6	0.006
Small	2	0	IS1	5	LTM-Min Var	1534.6	0.004
Small	2	0	IS1	5	NC LTM-Max Fixed	1560.6	0.004
Small	2	0	IS1	5	NC LTM-Min Fixed	1554.6	0.005
Small	2	0	IS1	5	NC LTM-Max Var	1560.6	0.006
Small	2	0	IS1	5	NC LTM-Min Var	1554.6	0.005
Small	1	0	IS2	10	STM-Fixed	3388.8	0.003
Small	1	0	IS2	10	STM-Var	3388.8	0.004
Small	1	0	IS2	10	LTM-Max Fixed	3353.6	0.002
Small	1	0	IS2	10	LTM-Min Fixed	3348.4	0.001
Small	1	0	IS2	10	LTM-Max Var	3353.6	0.002
Small	1	0	IS2	10	LTM-Min Var	3348.4	0.004
Small	1	0	IS2	10	NC LTM-Max Fixed	3316.4	0.003

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	1	0	IS2	10	NC LTM-Min Fixed	3316.4	0.002
Small	1	0	IS2	10	NC LTM-Max Var	3316.4	0.002
Small	1	0	IS2	10	NC LTM-Min Var	3316.4	0.004
Small	1	0	IS1	10	STM-Fixed	5831.2	0.005
Small	1	0	IS1	10	STM-Var	5864.2	0.005
Small	1	0	IS1	10	LTM-Max Fixed	5827.2	0.01
Small	1	0	IS1	10	LTM-Min Fixed	3459.6	0.013
Small	1	0	IS1	10	LTM-Max Var	4672.2	0.016
Small	1	0	IS1	10	LTM-Min Var	3315.6	0.013
Small	1	0	IS1	10	NC LTM-Max Fixed	5619.4	0.02
Small	1	0	IS1	10	NC LTM-Min Fixed	5831.2	0.027
Small	1	0	IS1	10	NC LTM-Max Var	5827.2	0.022
Small	1	0	IS1	10	NC LTM-Min Var	3445.6	0.027
Small	2	0	IS2	10	STM-Fixed	5987.4	0.019
Small	2	0	IS2	10	STM-Var	5786.4	0.024
Small	2	0	IS2	10	LTM-Max Fixed	5987.4	0.018
Small	2	0	IS2	10	LTM-Min Fixed	5987.4	0.016
Small	2	0	IS2	10	LTM-Max Var	5786.4	0.012
Small	2	0	IS2	10	LTM-Min Var	5786.4	0.02
Small	2	0	IS2	10	NC LTM-Max Fixed	5987.4	0.011
Small	2	0	IS2	10	NC LTM-Min Fixed	5987.4	0.01
Small	2	0	IS2	10	NC LTM-Max Var	5786.4	0.012
Small	2	0	IS2	10	NC LTM-Min Var	5786.4	0.015
Small	2	0	IS1	10	STM-Fixed	6791.8	0.025
Small	2	0	IS1	10	STM-Var	5791.6	0.046
Small	2	0	IS1	10	LTM-Max Fixed	6262.4	0.06

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	2	0	IS1	10	LTM-Min Fixed	6211.4	0.089
Small	2	0	IS1	10	LTM-Max Var	5791.6	0.099
Small	2	0	IS1	10	LTM-Min Var	5765.8	0.11
Small	2	0	IS1	10	NC LTM-Max Fixed	5775.8	0.106
Small	2	0	IS1	10	NC LTM-Min Fixed	6034.4	0.122
Small	2	0	IS1	10	NC LTM-Max Var	5791.6	0.122
Small	2	0	IS1	10	NC LTM-Min Var	5775.8	0.155
Medium	1	0	IS2	2	STM-Fixed	13090.8	5.148
Medium	1	0	IS2	2	STM-Var	13375.6	1.56
Medium	1	0	IS2	2	LTM-Max Fixed	13090.8	2.072
Medium	1	0	IS2	2	LTM-Min Fixed	12698.2	2.106
Medium	1	0	IS2	2	LTM-Max Var	13108.2	2.187
Medium	1	0	IS2	2	LTM-Min Var	12840.7	1.688
Medium	1	0	IS2	2	NC LTM-Max Fixed	12567.3	2.067
Medium	1	0	IS2	2	NC LTM-Min Fixed	12698.2	1.493
Medium	1	0	IS2	2	NC LTM-Max Var	12974.4	9.367
Medium	1	0	IS2	2	NC LTM-Min Var	12840.7	1.486
Medium	1	0	IS1	2	STM-Fixed	13028.6	5.812
Medium	1	0	IS1	2	STM-Var	13180.8	7.549
Medium	1	0	IS1	2	LTM-Max Fixed	12247	9.639
Medium	1	0	IS1	2	LTM-Min Fixed	12377.3	11.628
Medium	1	0	IS1	2	LTM-Max Var	12785.5	13.78
Medium	1	0	IS1	2	LTM-Min Var	12917.3	15.541
Medium	1	0	IS1	2	NC LTM-Max Fixed	12768.1	24.157
Medium	1	0	IS1	2	NC LTM-Min Fixed	13028.6	33.865
Medium	1	0	IS1	2	NC LTM-Max Var	12653.7	42.367

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	1	0	IS1	2	NC LTM-Min Var	13180.8	44.528
Medium	2	0	IS2	2	STM-Fixed	15758.2	7.983
Medium	2	0	IS2	2	STM-Var	16048.2	2.097
Medium	2	0	IS2	2	LTM-Max Fixed	14497.6	4.135
Medium	2	0	IS2	2	LTM-Min Fixed	15443.1	2.747
Medium	2	0	IS2	2	LTM-Max Var	15245.9	3.767
Medium	2	0	IS2	2	LTM-Min Var	15085.4	2.888
Medium	2	0	IS2	2	NC LTM-Max Fixed	15285.6	2.924
Medium	2	0	IS2	2	NC LTM-Min Fixed	15285.6	2.977
Medium	2	0	IS2	2	NC LTM-Max Var	15245.9	3.108
Medium	2	0	IS2	2	NC LTM-Min Var	15566.9	2.644
Medium	2	0	IS1	2	STM-Fixed	16220.6	8.387
Medium	2	0	IS1	2	STM-Var	16011.4	10.388
Medium	2	0	IS1	2	LTM-Max Fixed	14598.6	13.536
Medium	2	0	IS1	2	LTM-Min Fixed	15409.7	15.865
Medium	2	0	IS1	2	LTM-Max Var	15050.8	20.418
Medium	2	0	IS1	2	LTM-Min Var	15210.9	23.834
Medium	2	0	IS1	2	NC LTM-Max Fixed	15409.7	40.989
Medium	2	0	IS1	2	NC LTM-Min Fixed	15571.9	57.704
Medium	2	0	IS1	2	NC LTM-Max Var	15531.2	73.965
Medium	2	0	IS1	2	NC LTM-Min Var	15691.3	92.796
Medium	1	0	IS2	5	STM-Fixed	28621.4	18.624
Medium	1	0	IS2	5	STM-Var	29284	4.499
Medium	1	0	IS2	5	LTM-Max Fixed	28335.3	4.118
Medium	1	0	IS2	5	LTM-Min Fixed	28621.4	3.939
Medium	1	0	IS2	5	LTM-Max Var	27234.2	3.937
Medium	1	0	IS2	5	LTM-Min Var	28112.7	3.941

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	1	0	IS2	5	NC LTM-Max Fixed	27476.6	3.928
Medium	1	0	IS2	5	NC LTM-Min Fixed	27762.9	4.315
Medium	1	0	IS2	5	NC LTM-Max Var	28698.4	34.161
Medium	1	0	IS2	5	NC LTM-Min Var	28698.4	3.973
Medium	1	0	IS1	5	STM-Fixed	29027	20.59
Medium	1	0	IS1	5	STM-Var	29455.6	38.524
Medium	1	0	IS1	5	LTM-Max Fixed	26995.2	66.939
Medium	1	0	IS1	5	LTM-Min Fixed	28156.3	110.077
Medium	1	0	IS1	5	LTM-Max Var	27982.9	138.399
Medium	1	0	IS1	5	LTM-Min Var	27099.3	143.333
Medium	1	0	IS1	5	NC LTM-Max Fixed	28736.8	171.289
Medium	1	0	IS1	5	NC LTM-Min Fixed	28446.6	203.446
Medium	1	0	IS1	5	NC LTM-Max Var	28572	212.098
Medium	1	0	IS1	5	NC LTM-Min Var	29161.1	243.731
Medium	2	0	IS2	5	STM-Fixed	23818	2.642
Medium	2	0	IS2	5	STM-Var	23867	3.131
Medium	2	0	IS2	5	LTM-Max Fixed	22865.4	3.617
Medium	2	0	IS2	5	LTM-Min Fixed	23579.9	3.281
Medium	2	0	IS2	5	LTM-Max Var	22196.4	2.649
Medium	2	0	IS2	5	LTM-Min Var	23151.1	3.18
Medium	2	0	IS2	5	NC LTM-Max Fixed	23103.6	3.657
Medium	2	0	IS2	5	NC LTM-Min Fixed	22865.4	3.292
Medium	2	0	IS2	5	NC LTM-Max Var	23151.1	3.664
Medium	2	0	IS2	5	NC LTM-Min Var	23151.1	3.358
Medium	2	0	IS1	5	STM-Fixed	23682.8	9.269
Medium	2	0	IS1	5	STM-Var	24443	12.393

Structure	Replicate	$\alpha-\beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	2	0	IS1	5	LTM-Max Fixed	21788.3	15.317
Medium	2	0	IS1	5	LTM-Min Fixed	22498.8	19.019
Medium	2	0	IS1	5	LTM-Max Var	23709.8	22.533
Medium	2	0	IS1	5	LTM-Min Var	22732.1	25.432
Medium	2	0	IS1	5	NC LTM-Max Fixed	22498.8	28.475
Medium	2	0	IS1	5	NC LTM-Min Fixed	23209.2	32.351
Medium	2	0	IS1	5	NC LTM-Max Var	23221	35.38
Medium	2	0	IS1	5	NC LTM-Min Var	23954.2	39.249
Medium	1	0	IS2	10	STM-Fixed	52647.4	37.164
Medium	1	0	IS2	10	STM-Var	53539.6	6.93
Medium	1	0	IS2	10	LTM-Max Fixed	52121	11.908
Medium	1	0	IS2	10	LTM-Min Fixed	51068.1	9.405
Medium	1	0	IS2	10	LTM-Max Var	50327.3	12.061
Medium	1	0	IS2	10	LTM-Min Var	51933.5	11.139
Medium	1	0	IS2	10	NC LTM-Max Fixed	51594.6	10.075
Medium	1	0	IS2	10	NC LTM-Min Fixed	52121	8.812
Medium	1	0	IS2	10	NC LTM-Max Var	51398.1	8.25
Medium	1	0	IS2	10	NC LTM-Min Var	52468.9	12.95
Medium	1	0	IS1	10	STM-Fixed	54749.6	24.559
Medium	1	0	IS1	10	STM-Var	50389.2	35.303
Medium	1	0	IS1	10	LTM-Max Fixed	54749.6	46.06
Medium	1	0	IS1	10	LTM-Min Fixed	53107.2	56.418
Medium	1	0	IS1	10	LTM-Max Var	47365.9	68.363
Medium	1	0	IS1	10	LTM-Min Var	49381.5	77.394
Medium	1	0	IS1	10	NC LTM-Max Fixed	53107.2	87.631
Medium	1	0	IS1	10	NC LTM-Min Fixed	53654.7	98.232

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	1	0	IS1	10	NC LTM-Max Var	49885.4	205.751
Medium	1	0	IS1	10	NC LTM-Min Var	49885.4	216.196
Medium	2	0	IS2	10	STM-Fixed	21153.8	1.486
Medium	2	0	IS2	10	STM-Var	22197	0.88
Medium	2	0	IS2	10	LTM-Max Fixed	19461.6	0.973
Medium	2	0	IS2	10	LTM-Min Fixed	20519.3	0.971
Medium	2	0	IS2	10	LTM-Max Var	20643.3	0.669
Medium	2	0	IS2	10	LTM-Min Var	21087.3	0.981
Medium	2	0	IS2	10	NC LTM-Max Fixed	20096.2	4.741
Medium	2	0	IS2	10	NC LTM-Min Fixed	20519.3	3.955
Medium	2	0	IS2	10	NC LTM-Max Var	21309.2	0.69
Medium	2	0	IS2	10	NC LTM-Min Var	21531.2	3.472
Medium	2	0	IS1	10	STM-Fixed	22295.4	6.604
Medium	2	0	IS1	10	STM-Var	21289.6	7.558
Medium	2	0	IS1	10	LTM-Max Fixed	22295.4	8.74
Medium	2	0	IS1	10	LTM-Min Fixed	20957.8	9.583
Medium	2	0	IS1	10	LTM-Max Var	20225.2	10.531
Medium	2	0	IS1	10	LTM-Min Var	20225.2	11.37
Medium	2	0	IS1	10	NC LTM-Max Fixed	22295.4	12.206
Medium	2	0	IS1	10	NC LTM-Min Fixed	21626.6	13.243
Medium	2	0	IS1	10	NC LTM-Max Var	20438.1	14.29
Medium	2	0	IS1	10	NC LTM-Min Var	20863.9	15.11
Large	1	0	IS2	2	STM-Fixed	20893	21.851
Large	1	0	IS2	2	STM-Var	26708.4	17.151
Large	1	0	IS2	2	LTM-Max Fixed	18559.6	22.102
Large	1	0	IS2	2	LTM-Min Fixed	19626.2	21.896

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	1	0	IS2	2	LTM-Max Var	24304.6	36.468
Large	1	0	IS2	2	LTM-Min Var	26441.4	23.538
Large	1	0	IS2	2	NC LTM-Max Fixed	20475.2	53.317
Large	1	0	IS2	2	NC LTM-Min Fixed	19160	96.987
Large	1	0	IS2	2	NC LTM-Max Var	28355.4	273.464
Large	1	0	IS2	2	NC LTM-Min Var	23369.8	152.814
Large	1	0	IS1	2	STM-Fixed	27360.2	16.926
Large	1	0	IS1	2	STM-Var	27690.4	17.339
Large	1	0	IS1	2	LTM-Max Fixed	24648.8	40.733
Large	1	0	IS1	2	LTM-Min Fixed	26274	30.863
Large	1	0	IS1	2	LTM-Max Var	23342.2	134.82
Large	1	0	IS1	2	LTM-Min Var	24126.4	165.923
Large	1	0	IS1	2	NC LTM-Max Fixed	26545	259.798
Large	1	0	IS1	2	NC LTM-Min Fixed	20646	174.665
Large	1	0	IS1	2	NC LTM-Max Var	27142	990.021
Large	1	0	IS1	2	NC LTM-Min Var	23643.8	389.636
Large	2	0	IS2	2	STM-Fixed	32449.2	11.417
Large	2	0	IS2	2	STM-Var	29551.2	22.804
Large	2	0	IS2	2	LTM-Max Fixed	28131	10.376
Large	2	0	IS2	2	LTM-Min Fixed	26658.4	24.554
Large	2	0	IS2	2	LTM-Max Var	23488.4	13.701
Large	2	0	IS2	2	LTM-Min Var	31092.2	46.062
Large	2	0	IS2	2	NC LTM-Max Fixed	28146.6	36.343
Large	2	0	IS2	2	NC LTM-Min Fixed	31188.8	99.021
Large	2	0	IS2	2	NC LTM-Max Var	31140	50.269
Large	2	0	IS2	2	NC LTM-Min Var	24222.4	537.993

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	2	0	IS1	2	STM-Fixed	21281.4	16.238
Large	2	0	IS1	2	STM-Var	22544.2	24.74
Large	2	0	IS1	2	LTM-Max Fixed	26867.8	59.755
Large	2	0	IS1	2	LTM-Min Fixed	24229	75.502
Large	2	0	IS1	2	LTM-Max Var	24302.6	121.835
Large	2	0	IS1	2	LTM-Min Var	26207.6	316.687
Large	2	0	IS1	2	NC LTM-Max Fixed	25019	159.06
Large	2	0	IS1	2	NC LTM-Min Fixed	24766.4	517.41
Large	2	0	IS1	2	NC LTM-Max Var	25407.4	694.021
Large	2	0	IS1	2	NC LTM-Min Var	23234.6	2451.447
Large	1	0	IS2	5	STM-Fixed	36543.8	13.672
Large	1	0	IS2	5	STM-Var	42292	9.781
Large	1	0	IS2	5	LTM-Max Fixed	41414.8	28.609
Large	1	0	IS2	5	LTM-Min Fixed	45699.2	13.602
Large	1	0	IS2	5	LTM-Max Var	40600.4	35.861
Large	1	0	IS2	5	LTM-Min Var	41869.2	24.696
Large	1	0	IS2	5	NC LTM-Max Fixed	38558.6	79.434
Large	1	0	IS2	5	NC LTM-Min Fixed	37130.6	40.703
Large	1	0	IS2	5	NC LTM-Max Var	50908.4	206.541
Large	1	0	IS2	5	NC LTM-Min Var	48936.6	140.388
Large	1	0	IS1	5	STM-Fixed	37131.4	17.192
Large	1	0	IS1	5	STM-Var	57450.4	10.76
Large	1	0	IS1	5	LTM-Max Fixed	45714.6	49.19
Large	1	0	IS1	5	LTM-Min Fixed	44772	24.118
Large	1	0	IS1	5	LTM-Max Var	47733.8	268.963
Large	1	0	IS1	5	LTM-Min Var	57494	136.007
Large	1	0	IS1	5	NC LTM-Max Fixed	37864.6	333.029

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	1	0	IS1	5	NC LTM-Min Fixed	38326.2	183.642
Large	1	0	IS1	5	NC LTM-Max Var	51405.6	1140.986
Large	1	0	IS1	5	NC LTM-Min Var	57544	662.656
Large	2	0	IS2	5	STM-Fixed	36565.4	9.808
Large	2	0	IS2	5	STM-Var	36277.8	10.747
Large	2	0	IS2	5	LTM-Max Fixed	40414.4	12.329
Large	2	0	IS2	5	LTM-Min Fixed	47621.8	15.625
Large	2	0	IS2	5	LTM-Max Var	42531.2	17.708
Large	2	0	IS2	5	LTM-Min Var	45843.8	15.5
Large	2	0	IS2	5	NC LTM-Max Fixed	43402.2	30.168
Large	2	0	IS2	5	NC LTM-Min Fixed	35651.4	19.544
Large	2	0	IS2	5	NC LTM-Max Var	36578.6	134.771
Large	2	0	IS2	5	NC LTM-Min Var	40096.6	150.033
Large	2	0	IS1	5	STM-Fixed	36263.2	21.98
Large	2	0	IS1	5	STM-Var	45053.4	19.919
Large	2	0	IS1	5	LTM-Max Fixed	36675.4	53.223
Large	2	0	IS1	5	LTM-Min Fixed	38364.8	47.989
Large	2	0	IS1	5	LTM-Max Var	40933	165.905
Large	2	0	IS1	5	LTM-Min Var	37633.8	171.631
Large	2	0	IS1	5	NC LTM-Max Fixed	33518.8	189.94
Large	2	0	IS1	5	NC LTM-Min Fixed	33044.8	269.307
Large	2	0	IS1	5	NC LTM-Max Var	43209.2	856.29
Large	2	0	IS1	5	NC LTM-Min Var	38563	948.188
Large	1	0	IS2	10	STM-Fixed	98029.6	15.13
Large	1	0	IS2	10	STM-Var	81958.6	21.753
Large	1	0	IS2	10	LTM-Max Fixed	80704	18.269

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	1	0	IS2	10	LTM-Min Fixed	85956.4	27.814
Large	1	0	IS2	10	LTM-Max Var	73029	20.72
Large	1	0	IS2	10	LTM-Min Var	70446.2	33.687
Large	1	0	IS2	10	NC LTM-Max Fixed	86967.8	42.754
Large	1	0	IS2	10	NC LTM-Min Fixed	81911.4	61.847
Large	1	0	IS2	10	NC LTM-Max Var	88725	149.002
Large	1	0	IS2	10	NC LTM-Min Var	96196.4	153.016
Large	1	0	IS1	10	STM-Fixed	79978.4	18.941
Large	1	0	IS1	10	STM-Var	89995.2	13.134
Large	1	0	IS1	10	LTM-Max Fixed	68381.6	47.775
Large	1	0	IS1	10	LTM-Min Fixed	68381.6	37.199
Large	1	0	IS1	10	LTM-Max Var	76591.8	149.504
Large	1	0	IS1	10	LTM-Min Var	92886.6	202.379
Large	1	0	IS1	10	NC LTM-Max Fixed	89975.6	118.491
Large	1	0	IS1	10	NC LTM-Min Fixed	70181	261.79
Large	1	0	IS1	10	NC LTM-Max Var	80421.4	347.349
Large	1	0	IS1	10	NC LTM-Min Var	83676.4	611.305
Large	2	0	IS2	10	STM-Fixed	34231.2	8.382
Large	2	0	IS2	10	STM-Var	43506.2	10.936
Large	2	0	IS2	10	LTM-Max Fixed	30550.4	15.511
Large	2	0	IS2	10	LTM-Min Fixed	32847.2	14.764
Large	2	0	IS2	10	LTM-Max Var	32494.8	20.062
Large	2	0	IS2	10	LTM-Min Var	37471.8	27.4
Large	2	0	IS2	10	NC LTM-Max Fixed	32825	31.807
Large	2	0	IS2	10	NC LTM-Min Fixed	29078	32.836
Large	2	0	IS2	10	NC LTM-Max Var	38007.2	82.143

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	2	0	IS2	10	NC LTM-Min Var	37559	114.832
Large	2	0	IS1	10	STM-Fixed	43663.4	19.583
Large	2	0	IS1	10	STM-Var	35962.6	20.077
Large	2	0	IS1	10	LTM-Max Fixed	35598.6	41.312
Large	2	0	IS1	10	LTM-Min Fixed	33817.8	51.225
Large	2	0	IS1	10	LTM-Max Var	27583	111.724
Large	2	0	IS1	10	LTM-Min Var	34216.8	140.627
Large	2	0	IS1	10	NC LTM-Max Fixed	37717.6	112.769
Large	2	0	IS1	10	NC LTM-Min Fixed	44074.4	310.084
Large	2	0	IS1	10	NC LTM-Max Var	29381	395.395
Large	2	0	IS1	10	NC LTM-Min Var	29464.8	877.854
Small	1	-0.4	IS2	2	STM-Fixed	1379.6	0.002
Small	1	-0.4	IS2	2	STM-Var	1263.4	0.005
Small	1	-0.4	IS2	2	LTM-Max Fixed	1190.8	0.005
Small	1	-0.4	IS2	2	LTM-Min Fixed	1263.4	0.005
Small	1	-0.4	IS2	2	LTM-Max Var	1365.2	0.004
Small	1	-0.4	IS2	2	LTM-Min Var	1190.8	0.003
Small	1	-0.4	IS2	2	NC LTM-Max Fixed	1161.8	0.006
Small	1	-0.4	IS2	2	NC LTM-Min Fixed	1257.8	0.004
Small	1	-0.4	IS2	2	NC LTM-Max Var	1060.2	0.004
Small	1	-0.4	IS2	2	NC LTM-Min Var	1171	0.004
Small	1	-0.4	IS1	2	STM-Fixed	1516	0.006
Small	1	-0.4	IS1	2	STM-Var	1512.4	0.007
Small	1	-0.4	IS1	2	LTM-Max Fixed	1212.8	0.014
Small	1	-0.4	IS1	2	LTM-Min Fixed	1436.2	0.017
Small	1	-0.4	IS1	2	LTM-Max Var	1528.4	0.013
Small	1	-0.4	IS1	2	LTM-Min Var	1158.4	0.023

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	1	-0.4	IS1	2	NC LTM-Max Fixed	1181	0.021
Small	1	-0.4	IS1	2	NC LTM-Min Fixed	1388.4	0.023
Small	1	-0.4	IS1	2	NC LTM-Max Var	1512.4	0.028
Small	1	-0.4	IS1	2	NC LTM-Min Var	1156.4	0.043
Small	2	-0.4	IS2	2	STM-Fixed	1505	0.017
Small	2	-0.4	IS2	2	STM-Var	1421.2	0.013
Small	2	-0.4	IS2	2	LTM-Max Fixed	1505	0.013
Small	2	-0.4	IS2	2	LTM-Min Fixed	1736.6	0.018
Small	2	-0.4	IS2	2	LTM-Max Var	1835.6	0.009
Small	2	-0.4	IS2	2	LTM-Min Var	1714.2	0.019
Small	2	-0.4	IS2	2	NC LTM-Max Fixed	1485.6	0.013
Small	2	-0.4	IS2	2	NC LTM-Min Fixed	1389.2	0.009
Small	2	-0.4	IS2	2	NC LTM-Max Var	1618.6	0.009
Small	2	-0.4	IS2	2	NC LTM-Min Var	1786	0.016
Small	2	-0.4	IS1	2	STM-Fixed	1783.6	0.028
Small	2	-0.4	IS1	2	STM-Var	1636.6	0.032
Small	2	-0.4	IS1	2	LTM-Max Fixed	1686.6	0.049
Small	2	-0.4	IS1	2	LTM-Min Fixed	1725.4	0.079
Small	2	-0.4	IS1	2	LTM-Max Var	1398.6	0.095
Small	2	-0.4	IS1	2	LTM-Min Var	1419.8	0.082
Small	2	-0.4	IS1	2	NC LTM-Max Fixed	1598.2	0.099
Small	2	-0.4	IS1	2	NC LTM-Min Fixed	1473.4	0.143
Small	2	-0.4	IS1	2	NC LTM-Max Var	1434.4	0.155
Small	2	-0.4	IS1	2	NC LTM-Min Var	1747.6	0.159
Small	1	-0.4	IS2	5	STM-Fixed	2800.4	0.006
Small	1	-0.4	IS2	5	STM-Var	2793	0.019

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	1	-0.4	IS2	5	LTM-Max Fixed	2579.2	0.015
Small	1	-0.4	IS2	5	LTM-Min Fixed	2517.2	0.01
Small	1	-0.4	IS2	5	LTM-Max Var	2322.4	0.015
Small	1	-0.4	IS2	5	LTM-Min Var	2719	0.012
Small	1	-0.4	IS2	5	NC LTM-Max Fixed	2715	0.014
Small	1	-0.4	IS2	5	NC LTM-Min Fixed	2289.4	0.012
Small	1	-0.4	IS2	5	NC LTM-Max Var	2318.6	0.008
Small	1	-0.4	IS2	5	NC LTM-Min Var	2447.8	0.01
Small	1	-0.4	IS1	5	STM-Fixed	3032.2	0.02
Small	1	-0.4	IS1	5	STM-Var	3024	0.033
Small	1	-0.4	IS1	5	LTM-Max Fixed	2299.2	0.064
Small	1	-0.4	IS1	5	LTM-Min Fixed	2904.6	0.07
Small	1	-0.4	IS1	5	LTM-Max Var	2553.4	0.068
Small	1	-0.4	IS1	5	LTM-Min Var	2876.8	0.115
Small	1	-0.4	IS1	5	NC LTM-Max Fixed	2564	0.089
Small	1	-0.4	IS1	5	NC LTM-Min Fixed	2775.6	0.15
Small	1	-0.4	IS1	5	NC LTM-Max Var	2444.2	0.175
Small	1	-0.4	IS1	5	NC LTM-Min Var	3024	0.112
Small	2	-0.4	IS2	5	STM-Fixed	1514	0
Small	2	-0.4	IS2	5	STM-Var	1218	0.001
Small	2	-0.4	IS2	5	LTM-Max Fixed	1195	0.001
Small	2	-0.4	IS2	5	LTM-Min Fixed	1319.8	0
Small	2	-0.4	IS2	5	LTM-Max Var	1134.6	0.001
Small	2	-0.4	IS2	5	LTM-Min Var	1458	0.001
Small	2	-0.4	IS2	5	NC LTM-Max Fixed	1378.2	0.001
Small	2	-0.4	IS2	5	NC LTM-Min Fixed	1477	0

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	2	-0.4	IS2	5	NC LTM-Max Var	1186	0.001
Small	2	-0.4	IS2	5	NC LTM-Min Var	1383.6	0.001
Small	2	-0.4	IS1	5	STM-Fixed	1435.8	0.001
Small	2	-0.4	IS1	5	STM-Var	1264.2	0.002
Small	2	-0.4	IS1	5	LTM-Max Fixed	1255.6	0.004
Small	2	-0.4	IS1	5	LTM-Min Fixed	1350.4	0.004
Small	2	-0.4	IS1	5	LTM-Max Var	1300.8	0.005
Small	2	-0.4	IS1	5	LTM-Min Var	1365.8	0.004
Small	2	-0.4	IS1	5	NC LTM-Max Fixed	1279.8	0.006
Small	2	-0.4	IS1	5	NC LTM-Min Fixed	1150.4	0.008
Small	2	-0.4	IS1	5	NC LTM-Max Var	1435.8	0.007
Small	2	-0.4	IS1	5	NC LTM-Min Var	1181.6	0.006
Small	1	-0.4	IS2	10	STM-Fixed	3117.8	0.002
Small	1	-0.4	IS2	10	STM-Var	2643.4	0.004
Small	1	-0.4	IS2	10	LTM-Max Fixed	2817	0.003
Small	1	-0.4	IS2	10	LTM-Min Fixed	2913.2	0.002
Small	1	-0.4	IS2	10	LTM-Max Var	2716.4	0.001
Small	1	-0.4	IS2	10	LTM-Min Var	2611.8	0.004
Small	1	-0.4	IS2	10	NC LTM-Max Fixed	3051.2	0.002
Small	1	-0.4	IS2	10	NC LTM-Min Fixed	3117.4	0.002
Small	1	-0.4	IS2	10	NC LTM-Max Var	2421	0.001
Small	1	-0.4	IS2	10	NC LTM-Min Var	3183.8	0.003
Small	1	-0.4	IS1	10	STM-Fixed	4665	0.005
Small	1	-0.4	IS1	10	STM-Var	4222.2	0.005
Small	1	-0.4	IS1	10	LTM-Max Fixed	5244.6	0.006
Small	1	-0.4	IS1	10	LTM-Min Fixed	2560.2	0.008

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Small	1	-0.4	IS1	10	LTM-Max Var	3457.4	0.012
Small	1	-0.4	IS1	10	LTM-Min Var	2553	0.017
Small	1	-0.4	IS1	10	NC LTM-Max Fixed	5113.8	0.02
Small	1	-0.4	IS1	10	NC LTM-Min Fixed	5073.2	0.026
Small	1	-0.4	IS1	10	NC LTM-Max Var	4778.4	0.02
Small	1	-0.4	IS1	10	NC LTM-Min Var	2515.4	0.02
Small	2	-0.4	IS2	10	STM-Fixed	5328.8	0.014
Small	2	-0.4	IS2	10	STM-Var	4455.6	0.02
Small	2	-0.4	IS2	10	LTM-Max Fixed	5089.4	0.014
Small	2	-0.4	IS2	10	LTM-Min Fixed	4849.8	0.017
Small	2	-0.4	IS2	10	LTM-Max Var	5497.2	0.019
Small	2	-0.4	IS2	10	LTM-Min Var	5439.2	0.016
Small	2	-0.4	IS2	10	NC LTM-Max Fixed	4909.8	0.012
Small	2	-0.4	IS2	10	NC LTM-Min Fixed	4610.4	0.01
Small	2	-0.4	IS2	10	NC LTM-Max Var	4455.6	0.01
Small	2	-0.4	IS2	10	NC LTM-Min Var	4860.6	0.015
Small	2	-0.4	IS1	10	STM-Fixed	5841	0.029
Small	2	-0.4	IS1	10	STM-Var	5154.6	0.037
Small	2	-0.4	IS1	10	LTM-Max Fixed	5761.4	0.037
Small	2	-0.4	IS1	10	LTM-Min Fixed	4845	0.084
Small	2	-0.4	IS1	10	LTM-Max Var	5502	0.092
Small	2	-0.4	IS1	10	LTM-Min Var	5074	0.118
Small	2	-0.4	IS1	10	NC LTM-Max Fixed	4736.2	0.149
Small	2	-0.4	IS1	10	NC LTM-Min Fixed	5310.4	0.096
Small	2	-0.4	IS1	10	NC LTM-Max Var	5212.4	0.161
Small	2	-0.4	IS1	10	NC LTM-Min Var	4620.6	0.147

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	1	-0.4	IS2	2	STM-Fixed	13090.8	4.53
Medium	1	-0.4	IS2	2	STM-Var	13375.6	1.42
Medium	1	-0.4	IS2	2	LTM-Max Fixed	13090.8	1.761
Medium	1	-0.4	IS2	2	LTM-Min Fixed	12698.2	1.58
Medium	1	-0.4	IS2	2	LTM-Max Var	13108.2	2.209
Medium	1	-0.4	IS2	2	LTM-Min Var	12840.7	1.992
Medium	1	-0.4	IS2	2	NC LTM-Max Fixed	12567.3	2.212
Medium	1	-0.4	IS2	2	NC LTM-Min Fixed	12698.2	1.09
Medium	1	-0.4	IS2	2	NC LTM-Max Var	12974.4	7.213
Medium	1	-0.4	IS2	2	NC LTM-Min Var	12840.7	1.516
Medium	1	-0.4	IS1	2	STM-Fixed	13028.6	6.568
Medium	1	-0.4	IS1	2	STM-Var	13180.8	4.982
Medium	1	-0.4	IS1	2	LTM-Max Fixed	12247	11.76
Medium	1	-0.4	IS1	2	LTM-Min Fixed	12377.3	8.954
Medium	1	-0.4	IS1	2	LTM-Max Var	12785.5	17.363
Medium	1	-0.4	IS1	2	LTM-Min Var	12917.3	13.365
Medium	1	-0.4	IS1	2	NC LTM-Max Fixed	12768.1	24.882
Medium	1	-0.4	IS1	2	NC LTM-Min Fixed	13028.6	43.347
Medium	1	-0.4	IS1	2	NC LTM-Max Var	12653.7	47.027
Medium	1	-0.4	IS1	2	NC LTM-Min Var	13180.8	48.536
Medium	2	-0.4	IS2	2	STM-Fixed	15758.2	7.584
Medium	2	-0.4	IS2	2	STM-Var	16048.2	2.642
Medium	2	-0.4	IS2	2	LTM-Max Fixed	14497.6	3.019
Medium	2	-0.4	IS2	2	LTM-Min Fixed	15443.1	3.351
Medium	2	-0.4	IS2	2	LTM-Max Var	15245.9	4.596
Medium	2	-0.4	IS2	2	LTM-Min Var	15085.4	2.599
Medium	2	-0.4	IS2	2	NC LTM-Max Fixed	15285.6	3.099

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	2	-0.4	IS2	2	NC LTM-Min Fixed	15285.6	3.781
Medium	2	-0.4	IS2	2	NC LTM-Max Var	15245.9	3.201
Medium	2	-0.4	IS2	2	NC LTM-Min Var	15566.9	2.142
Medium	2	-0.4	IS1	2	STM-Fixed	16220.6	6.626
Medium	2	-0.4	IS1	2	STM-Var	16011.4	9.038
Medium	2	-0.4	IS1	2	LTM-Max Fixed	14598.6	16.514
Medium	2	-0.4	IS1	2	LTM-Min Fixed	15409.7	15.072
Medium	2	-0.4	IS1	2	LTM-Max Var	15050.8	20.622
Medium	2	-0.4	IS1	2	LTM-Min Var	15210.9	26.456
Medium	2	-0.4	IS1	2	NC LTM-Max Fixed	15409.7	41.399
Medium	2	-0.4	IS1	2	NC LTM-Min Fixed	15571.9	71.553
Medium	2	-0.4	IS1	2	NC LTM-Max Var	15531.2	88.758
Medium	2	-0.4	IS1	2	NC LTM-Min Var	15691.3	75.165
Medium	1	-0.4	IS2	5	STM-Fixed	28621.4	16.203
Medium	1	-0.4	IS2	5	STM-Var	29284	3.824
Medium	1	-0.4	IS2	5	LTM-Max Fixed	28335.3	5.271
Medium	1	-0.4	IS2	5	LTM-Min Fixed	28621.4	3.978
Medium	1	-0.4	IS2	5	LTM-Max Var	27234.2	3.937
Medium	1	-0.4	IS2	5	LTM-Min Var	28112.7	3.744
Medium	1	-0.4	IS2	5	NC LTM-Max Fixed	27476.6	3.26
Medium	1	-0.4	IS2	5	NC LTM-Min Fixed	27762.9	4.401
Medium	1	-0.4	IS2	5	NC LTM-Max Var	28698.4	32.111
Medium	1	-0.4	IS2	5	NC LTM-Min Var	28698.4	4.132
Medium	1	-0.4	IS1	5	STM-Fixed	29027	24.708
Medium	1	-0.4	IS1	5	STM-Var	29455.6	33.516
Medium	1	-0.4	IS1	5	LTM-Max Fixed	26995.2	71.625

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	1	-0.4	IS1	5	LTM-Min Fixed	28156.3	139.798
Medium	1	-0.4	IS1	5	LTM-Max Var	27982.9	175.767
Medium	1	-0.4	IS1	5	LTM-Min Var	27099.3	140.466
Medium	1	-0.4	IS1	5	NC LTM-Max Fixed	28736.8	159.299
Medium	1	-0.4	IS1	5	NC LTM-Min Fixed	28446.6	238.032
Medium	1	-0.4	IS1	5	NC LTM-Max Var	28572	159.074
Medium	1	-0.4	IS1	5	NC LTM-Min Var	29161.1	255.918
Medium	2	-0.4	IS2	5	STM-Fixed	23818	2.246
Medium	2	-0.4	IS2	5	STM-Var	23867	2.536
Medium	2	-0.4	IS2	5	LTM-Max Fixed	22865.4	3.581
Medium	2	-0.4	IS2	5	LTM-Min Fixed	23579.9	4.134
Medium	2	-0.4	IS2	5	LTM-Max Var	22196.4	3.364
Medium	2	-0.4	IS2	5	LTM-Min Var	23151.1	3.212
Medium	2	-0.4	IS2	5	NC LTM-Max Fixed	23103.6	3.328
Medium	2	-0.4	IS2	5	NC LTM-Min Fixed	22865.4	3.16
Medium	2	-0.4	IS2	5	NC LTM-Max Var	23151.1	2.858
Medium	2	-0.4	IS2	5	NC LTM-Min Var	23151.1	3.19
Medium	2	-0.4	IS1	5	STM-Fixed	23682.8	11.401
Medium	2	-0.4	IS1	5	STM-Var	24443	11.154
Medium	2	-0.4	IS1	5	LTM-Max Fixed	21788.3	11.641
Medium	2	-0.4	IS1	5	LTM-Min Fixed	22498.8	20.921
Medium	2	-0.4	IS1	5	LTM-Max Var	23709.8	20.505
Medium	2	-0.4	IS1	5	LTM-Min Var	22732.1	27.212
Medium	2	-0.4	IS1	5	NC LTM-Max Fixed	22498.8	36.163
Medium	2	-0.4	IS1	5	NC LTM-Min Fixed	23209.2	24.263
Medium	2	-0.4	IS1	5	NC LTM-Max Var	23221	32.903

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	2	-0.4	IS1	5	NC LTM-Min Var	23954.2	29.437
Medium	1	-0.4	IS2	10	STM-Fixed	52647.4	30.474
Medium	1	-0.4	IS2	10	STM-Var	53539.6	7.623
Medium	1	-0.4	IS2	10	LTM-Max Fixed	52121	12.146
Medium	1	-0.4	IS2	10	LTM-Min Fixed	51068.1	8.747
Medium	1	-0.4	IS2	10	LTM-Max Var	50327.3	9.528
Medium	1	-0.4	IS2	10	LTM-Min Var	51933.5	12.142
Medium	1	-0.4	IS2	10	NC LTM-Max Fixed	51594.6	12.695
Medium	1	-0.4	IS2	10	NC LTM-Min Fixed	52121	8.812
Medium	1	-0.4	IS2	10	NC LTM-Max Var	51398.1	9.818
Medium	1	-0.4	IS2	10	NC LTM-Min Var	52468.9	15.799
Medium	1	-0.4	IS1	10	STM-Fixed	54749.6	29.962
Medium	1	-0.4	IS1	10	STM-Var	50389.2	28.595
Medium	1	-0.4	IS1	10	LTM-Max Fixed	54749.6	53.43
Medium	1	-0.4	IS1	10	LTM-Min Fixed	53107.2	72.215
Medium	1	-0.4	IS1	10	LTM-Max Var	47365.9	52.64
Medium	1	-0.4	IS1	10	LTM-Min Var	49381.5	74.298
Medium	1	-0.4	IS1	10	NC LTM-Max Fixed	53107.2	69.228
Medium	1	-0.4	IS1	10	NC LTM-Min Fixed	53654.7	76.621
Medium	1	-0.4	IS1	10	NC LTM-Max Var	49885.4	248.959
Medium	1	-0.4	IS1	10	NC LTM-Min Var	49885.4	175.119
Medium	2	-0.4	IS2	10	STM-Fixed	21153.8	1.62
Medium	2	-0.4	IS2	10	STM-Var	22197	1.056
Medium	2	-0.4	IS2	10	LTM-Max Fixed	19461.6	0.905
Medium	2	-0.4	IS2	10	LTM-Min Fixed	20519.3	0.806
Medium	2	-0.4	IS2	10	LTM-Max Var	20643.3	0.816
Medium	2	-0.4	IS2	10	LTM-Min Var	21087.3	1.246

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Medium	2	-0.4	IS2	10	NC LTM-Max Fixed	20096.2	4.457
Medium	2	-0.4	IS2	10	NC LTM-Min Fixed	20519.3	4.706
Medium	2	-0.4	IS2	10	NC LTM-Max Var	21309.2	0.662
Medium	2	-0.4	IS2	10	NC LTM-Min Var	21531.2	3.437
Medium	2	-0.4	IS1	10	STM-Fixed	22295.4	6.34
Medium	2	-0.4	IS1	10	STM-Var	21289.6	8.087
Medium	2	-0.4	IS1	10	LTM-Max Fixed	22295.4	8.653
Medium	2	-0.4	IS1	10	LTM-Min Fixed	20957.8	7.954
Medium	2	-0.4	IS1	10	LTM-Max Var	20225.2	8.109
Medium	2	-0.4	IS1	10	LTM-Min Var	20225.2	14.099
Medium	2	-0.4	IS1	10	NC LTM-Max Fixed	22295.4	10.985
Medium	2	-0.4	IS1	10	NC LTM-Min Fixed	21626.6	10.594
Medium	2	-0.4	IS1	10	NC LTM-Max Var	20438.1	16.576
Medium	2	-0.4	IS1	10	NC LTM-Min Var	20863.9	17.83
Large	1	-0.4	IS2	2	STM-Fixed	16505.6	21.851
Large	1	-0.4	IS2	2	STM-Var	24571.8	17.151
Large	1	-0.4	IS2	2	LTM-Max Fixed	19302	22.102
Large	1	-0.4	IS2	2	LTM-Min Fixed	17663.6	21.896
Large	1	-0.4	IS2	2	LTM-Max Var	24061.6	36.468
Large	1	-0.4	IS2	2	LTM-Min Var	26441.4	23.538
Large	1	-0.4	IS2	2	NC LTM-Max Fixed	21294.2	53.317
Large	1	-0.4	IS2	2	NC LTM-Min Fixed	19543.2	96.987
Large	1	-0.4	IS2	2	NC LTM-Max Var	28639	273.464
Large	1	-0.4	IS2	2	NC LTM-Min Var	21500.2	152.814
Large	1	-0.4	IS1	2	STM-Fixed	24897.8	16.926
Large	1	-0.4	IS1	2	STM-Var	24921.4	17.339

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	1	-0.4	IS1	2	LTM-Max Fixed	21444.6	40.733
Large	1	-0.4	IS1	2	LTM-Min Fixed	26274	30.863
Large	1	-0.4	IS1	2	LTM-Max Var	19841	134.82
Large	1	-0.4	IS1	2	LTM-Min Var	23644	165.923
Large	1	-0.4	IS1	2	NC LTM-Max Fixed	24421.4	259.798
Large	1	-0.4	IS1	2	NC LTM-Min Fixed	17342.6	174.665
Large	1	-0.4	IS1	2	NC LTM-Max Var	21170.8	990.021
Large	1	-0.4	IS1	2	NC LTM-Min Var	22225.2	389.636
Large	2	-0.4	IS2	2	STM-Fixed	28230.8	11.417
Large	2	-0.4	IS2	2	STM-Var	29551.2	22.804
Large	2	-0.4	IS2	2	LTM-Max Fixed	27568.4	10.376
Large	2	-0.4	IS2	2	LTM-Min Fixed	27191.6	24.554
Large	2	-0.4	IS2	2	LTM-Max Var	18790.8	13.701
Large	2	-0.4	IS2	2	LTM-Min Var	23941	46.062
Large	2	-0.4	IS2	2	NC LTM-Max Fixed	25050.6	36.343
Large	2	-0.4	IS2	2	NC LTM-Min Fixed	23703.6	99.021
Large	2	-0.4	IS2	2	NC LTM-Max Var	26157.6	50.269
Large	2	-0.4	IS2	2	NC LTM-Min Var	21558	537.993
Large	2	-0.4	IS1	2	STM-Fixed	21919.8	16.238
Large	2	-0.4	IS1	2	STM-Var	18486.2	24.74
Large	2	-0.4	IS1	2	LTM-Max Fixed	23912.4	59.755
Large	2	-0.4	IS1	2	LTM-Min Fixed	18898.6	75.502
Large	2	-0.4	IS1	2	LTM-Max Var	23573.6	121.835
Large	2	-0.4	IS1	2	LTM-Min Var	24373.2	316.687
Large	2	-0.4	IS1	2	NC LTM-Max Fixed	25019	159.06
Large	2	-0.4	IS1	2	NC LTM-Min Fixed	20308.4	517.41

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	2	-0.4	IS1	2	NC LTM-Max Var	24899.4	694.021
Large	2	-0.4	IS1	2	NC LTM-Min Var	18820	2451.447
Large	1	-0.4	IS2	5	STM-Fixed	31062.2	13.672
Large	1	-0.4	IS2	5	STM-Var	37640	9.781
Large	1	-0.4	IS2	5	LTM-Max Fixed	33131.8	28.609
Large	1	-0.4	IS2	5	LTM-Min Fixed	41586.4	13.602
Large	1	-0.4	IS2	5	LTM-Max Var	32886.4	35.861
Large	1	-0.4	IS2	5	LTM-Min Var	36007.6	24.696
Large	1	-0.4	IS2	5	NC LTM-Max Fixed	35859.6	79.434
Large	1	-0.4	IS2	5	NC LTM-Min Fixed	33788.8	40.703
Large	1	-0.4	IS2	5	NC LTM-Max Var	39199.6	206.541
Large	1	-0.4	IS2	5	NC LTM-Min Var	47468.6	140.388
Large	1	-0.4	IS1	5	STM-Fixed	30819.2	17.192
Large	1	-0.4	IS1	5	STM-Var	50556.4	10.76
Large	1	-0.4	IS1	5	LTM-Max Fixed	41600.4	49.19
Large	1	-0.4	IS1	5	LTM-Min Fixed	35817.6	24.118
Large	1	-0.4	IS1	5	LTM-Max Var	41051.2	268.963
Large	1	-0.4	IS1	5	LTM-Min Var	45995.2	136.007
Large	1	-0.4	IS1	5	NC LTM-Max Fixed	34078.2	333.029
Large	1	-0.4	IS1	5	NC LTM-Min Fixed	34493.6	183.642
Large	1	-0.4	IS1	5	NC LTM-Max Var	49349.4	1140.986
Large	1	-0.4	IS1	5	NC LTM-Min Var	54666.8	662.656
Large	2	-0.4	IS2	5	STM-Fixed	33640.2	9.808
Large	2	-0.4	IS2	5	STM-Var	29747.8	10.747
Large	2	-0.4	IS2	5	LTM-Max Fixed	38393.8	12.329
Large	2	-0.4	IS2	5	LTM-Min Fixed	36668.8	15.625

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	2	-0.4	IS2	5	LTM-Max Var	39979.4	17.708
Large	2	-0.4	IS2	5	LTM-Min Var	45385.4	15.5
Large	2	-0.4	IS2	5	NC LTM-Max Fixed	35155.8	30.168
Large	2	-0.4	IS2	5	NC LTM-Min Fixed	34582	19.544
Large	2	-0.4	IS2	5	NC LTM-Max Var	36944.4	134.771
Large	2	-0.4	IS2	5	NC LTM-Min Var	38492.8	150.033
Large	2	-0.4	IS1	5	STM-Fixed	30461.2	21.98
Large	2	-0.4	IS1	5	STM-Var	45504	19.919
Large	2	-0.4	IS1	5	LTM-Max Fixed	27873.4	53.223
Large	2	-0.4	IS1	5	LTM-Min Fixed	39515.8	47.989
Large	2	-0.4	IS1	5	LTM-Max Var	33565.2	165.905
Large	2	-0.4	IS1	5	LTM-Min Var	34246.8	171.631
Large	2	-0.4	IS1	5	NC LTM-Max Fixed	27150.2	189.94
Large	2	-0.4	IS1	5	NC LTM-Min Fixed	27757.6	269.307
Large	2	-0.4	IS1	5	NC LTM-Max Var	34999.6	856.29
Large	2	-0.4	IS1	5	NC LTM-Min Var	40105.6	948.188
Large	1	-0.4	IS2	10	STM-Fixed	75482.8	15.13
Large	1	-0.4	IS2	10	STM-Var	84417.4	21.753
Large	1	-0.4	IS2	10	LTM-Max Fixed	80704	18.269
Large	1	-0.4	IS2	10	LTM-Min Fixed	80799	27.814
Large	1	-0.4	IS2	10	LTM-Max Var	56962.6	20.72
Large	1	-0.4	IS2	10	LTM-Min Var	57061.4	33.687
Large	1	-0.4	IS2	10	NC LTM-Max Fixed	85228.4	42.754
Large	1	-0.4	IS2	10	NC LTM-Min Fixed	72901.2	61.847
Large	1	-0.4	IS2	10	NC LTM-Max Var	70980	149.002
Large	1	-0.4	IS2	10	NC LTM-Min Var	98120.4	153.016

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	1	-0.4	IS1	10	STM-Fixed	79178.6	18.941
Large	1	-0.4	IS1	10	STM-Var	92695.2	13.134
Large	1	-0.4	IS1	10	LTM-Max Fixed	66330.2	47.775
Large	1	-0.4	IS1	10	LTM-Min Fixed	62227.4	37.199
Large	1	-0.4	IS1	10	LTM-Max Var	59741.6	149.504
Large	1	-0.4	IS1	10	LTM-Min Var	75238.2	202.379
Large	1	-0.4	IS1	10	NC LTM-Max Fixed	87276.4	118.491
Large	1	-0.4	IS1	10	NC LTM-Min Fixed	68777.4	261.79
Large	1	-0.4	IS1	10	NC LTM-Max Var	73183.6	347.349
Large	1	-0.4	IS1	10	NC LTM-Min Var	81166.2	611.305
Large	2	-0.4	IS2	10	STM-Fixed	27042.6	8.382
Large	2	-0.4	IS2	10	STM-Var	44376.4	10.936
Large	2	-0.4	IS2	10	LTM-Max Fixed	24440.4	15.511
Large	2	-0.4	IS2	10	LTM-Min Fixed	32518.8	14.764
Large	2	-0.4	IS2	10	LTM-Max Var	25671	20.062
Large	2	-0.4	IS2	10	LTM-Min Var	29602.8	27.4
Large	2	-0.4	IS2	10	NC LTM-Max Fixed	31840.4	31.807
Large	2	-0.4	IS2	10	NC LTM-Min Fixed	22680.8	32.836
Large	2	-0.4	IS2	10	NC LTM-Max Var	34586.6	82.143
Large	2	-0.4	IS2	10	NC LTM-Min Var	36432.2	114.832
Large	2	-0.4	IS1	10	STM-Fixed	37114	19.583
Large	2	-0.4	IS1	10	STM-Var	35603	20.077
Large	2	-0.4	IS1	10	LTM-Max Fixed	35598.6	41.312
Large	2	-0.4	IS1	10	LTM-Min Fixed	26716.2	51.225
Large	2	-0.4	IS1	10	LTM-Max Var	27031.4	111.724
Large	2	-0.4	IS1	10	LTM-Min Var	32506	140.627
Large	2	-0.4	IS1	10	NC LTM-Max Fixed	36963.2	112.769

Structure	Replicate	$\alpha - \beta$	IS	Setup Time Ratio	Alogorithm	Solution	Soving Time
Large	2	-0.4	IS1	10	NC LTM-Min Fixed	34378	310.084
Large	2	-0.4	IS1	10	NC LTM-Max Var	22329.6	395.395
Large	2	-0.4	IS1	10	NC LTM-Min Var	22982.6	877.854