PROFIT-ORIENTED DISASSEMBLY LINE BALANCING WITH STOCHASTIC TASK TIMES IN HYBRID LINES

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VOLKAN GÜMÜŞKAYA

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Approval of the thesis:

Submitted by **VOLKAN GÜMÜŞKAYA** in partial fulfillment of the requirements for the degree of **Master of Science in Industrial Engineering Department, Middle East Technical University** by,

Prof. Dr. Canan Özgen ________________
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. Murat Köksalan ________________
Head of Department, **Industrial Engineering**

Assoc. Prof. Dr. Z. Pelin Bayındır ________________
Supervisor, **Industrial Engineering Dept., METU**

Assist. Prof. Dr. Tevhide Altekin ________________
Co-Supervisor, **School of Management, Sabancı University**

Examining Committee Members:

Prof. Dr. Nur Evin Özdemirel ____________________
Industrial Engineering Dept., METU

Assist. Prof. Dr. İ. Serdar Bakal ____________________
Industrial Engineering Dept., METU

Assist. Prof. Dr. Sinan Gürel ____________________
Industrial Engineering Dept., METU

Assoc. Prof. Dr. Z. Pelin Bayındır ____________________
Industrial Engineering Dept., METU

Assist. Prof. Dr. Tevhide Altekin ____________________
School of Management, Sabancı University

Date: 25.06.2013

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: VOLKAN GÜMÜŞKAYA

Signature :

ABSTRACT

PROFIT-ORIENTED DISASSEMBLY LINE BALANCING

WITH STOCHASTIC TASK TIMES IN HYBRID LINES

Gümüşkaya, Volkan

M.Sc., Department of Industrial Engineering

Supervisor: Assoc. Prof. Dr. Z. Pelin Bayındır

Co-Supervisor: Assist. Prof. Dr. Tevhide Altekin

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We offer a solution approach for profit-oriented disassembly line balancing problem in hybrid lines with stochastic task times. When task times are stochastic, there is a probability that some of the tasks are not completed within the predefined cycle time. For task incompletions, the most commonly used remedial actions are stopping the line or offline repairs. Stopping the line is to stop the line until the incomplete tasks are completed, while in offline repair, incomplete tasks are completed in an offline area after the workpiece leaves the line. In a hybrid line, both of the remedial actions are implemented for two task classes: (F)inish and (P)ass tasks. The classification of tasks have significant effect on the costs incurred by line stoppages or offline repairs, which together make up incompletion costs. In this thesis, we propose a greedy algorithm, which makes this classification for a given cycle time and task assignment so as to maximize the expected profit of one product disassembled. We also propose a cost calculation method to calculate expected incompletion costs.

Keywords: Stochastic Task Times, Disassembly, Hybrid Lines

ÖZ

DEĞİŞKEN İŞ ZAMANLI KÂR AMAÇLI HİBRİT HATLARDA DEMONTAJ HAT DENGELENMESİ

Gümüşkaya, Volkan

Yüksek Lisans, Endüstri Mühendisliği Bölümü

Tez Yöneticisi: Doç. Dr. Z. Pelin Bayındır

Ortak Tez Yöneticisi: Yrd. Doç. Dr. Tevhide Altekin

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Bu çalışmada değişken iş süreli hibrit hatlarda kar amaçlı demontaj hat dengelemesi problemi için bir çözüm yaklaşımı öneriyoruz. İş süreleri değişken olduğunda, tüm işlerin gerekli süre içinde yapılmaması ihtimali bulunmaktadır. Yetişmeyen işler için kulanılan en yaygın iki yöntem hattı durdurmak ve hat dışı tamirlerdir. Hattı durdurma, yetişmeyen işler için hattı durdurarak bu işlerin tamamlanmasını ifade ederken, hat dışı tamirlerde, çalışılan ürün hattı terk ettiğinde ayrı bir bölüme alınır ve yetişmeyen işler tamamlanır. Hibrit hatlarda ise her iki yöntem şu iki iş sınıfı için uygulanmaktadır: F ve P işler. İşlerin sınıflandırma şekli hat durdurulması ve hat dışı tamir maliyetleri üzerinde ciddi bir öneme sahiptir. Biz bu tezde, belirli bir devir süresi ve iş dağılımı için beklenen kârı ençoklayarak bu sınıflandırmayı yapan bir açgözlü algoritma öneriyoruz. Buna ek olarak yetişmeyen işlerden doğan maliyetleri hesaplayabilmek için ayrı bir maliyet hesaplama yöntemi öneriyoruz.

Anahtar Kelimeler: Stokastik iş zamanı, Demontaj hat dengelemesi, Hibrit hat

To My Mother, Father and Sister...

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CHAPTER 1

INTRODUCTION

As average product lifetimes get shorter, total production and consumption grow and natural resources are depleted more rapidly leading to sustainability problems. Moreover, total waste amount increases in parallel to the total consumption leading to environmental problems due to landfills. Recovery of materials and products provide that natural resources are utilized more efficiently due to the reuse and recycling and so the total waste amount is decreased. As a result, public awareness arises and governments enforce legislations promoting product and material recovery. For automotive industry, for instance, the directive of European Parliament and of the Council declared in 2000 required that recycle and reuse rates for end-of-life vehicles should be over 85% until 2005 and 95% until 2015 in average weight. In addition to the pressure by the legislation, companies promote recycling as end-of-life products have economic value. IBM reports that 37,950 metric tons of products are processed by IBM's product end-of-life management operations in 2011 [12]. Similarly, in 2011, TOSHIBA has collected 125,000 tons of end-of-life products of which 119,000 has been recycled. TOSHIBA also reports that worldwide recycle rates of TVs are 45% in 2011 in weight [13]. End-of life-products' economic value as well as environmental and social value are recognized by the public and industry, and an increasing effort has been made in this area (Gungor and Gupta 1999). According to the report published by U.S. Environmental Protection Agency in 2001, in U.S. recycling and reuse establishments generated more than 236 billion dollars in gross and employed about 1.1 million people.

The end-of-life products are not usually reusable as the product loses its functionality; the parts, subassemblies, components or modules can be reused, recycled or remanufactured making disassembly a crucial step in product recovery. Disassembly can be defined as the separation of parts or subassemblies of products that are made of. Disassembly systems can be classified as single workstation, disassembly cell and disassembly lines (Wiendahl *et al.* 1998). Among these, disassembly lines are considered to be the most efficient way to disassemble large quantities of products (Das and Caudill 1999, Gungor and Gupta 2002). Wiendahl *et al.* (1998) claim that efficiency improvements up to 70% are possible by using workstations that are linked instead of a single workstation. Das and Caudill (1999) also point out that high productivity rates can be achieved in disassembly lines through economies of scale, division of labor and higher disassembly rate.

Disassembly is different from assembly in a number of aspects: Variability in task times and the quality in incoming parts are higher in disassembly. In assembly, precedence relations are typically AND precedence relations, whereas other types of precedence relations exist in disassembly, such as OR precedence, OR successor, AND within OR and OR within AND precedence relations. Disassembly is a divergent process while assembly process is convergent. Assembly is complete, i.e. all tasks have to be performed, while disassembly may be partial, i.e. all of the tasks are not necessarily performed. Due to these differences, Gungor and Gupta (1999) state that special techniques should be developed for disassembly problems.

Disassembly line balancing problem (DLBP) can be defined as assigning tasks to an ordered number of stations so that an objective function is optimized and precedence relations are met. Various objectives are considered in disassembly: minimizing the number of stations, balancing the total workcontents of stations, minimizing total idle times, minimizing cost, maximizing profit, minimizing the probability of line stoppage. DLBP can be separated into two classes depending on the nature of task times: Deterministic DLBP and stochastic DLBP.

In stochastic line balancing problems, since the task durations are not deterministic, there is a probability that some of the tasks are not finished within the predetermined cycle time. For the same problem occurring in assembly lines, several remedial actions have been proposed in the literature: Stopping the line, offline repair, hybrid lines, multiple manning and using inspection and repair points between stations. Among these, the two commonly used ones are stopping the line and offline repair. Stopping the line refers to the case, where in the case that the workcontent on a workstation is exceeded, the line is stopped and the cycle time is extended to finish all of the tasks. As soon as no incomplete task remains, end of the cycle is reached and workpieces are sent to next stations. On the other hand, offline repair refers to finishing incomplete task in an offline area after workpiece leaves the line. These remedial actions lead to additional costs as more time and labor should be spent, which are called as incompletion costs. In a hybrid line, proposed by Lau and Shtub (1987), in case of a task incompletion, both line stoppage or offline repair may be used as the remedial action depending on which task is incomplete. The tasks are classified into two: (F)inish tasks and (P)ass tasks. In case of task incompletions, for F-tasks, the line is stopped while offline repair is performed for P- tasks. Therefore, in a hybrid line, classification of the tasks as F-task and P-task is also required in addition to the determination of cycle time, the number of stations and the assignment of tasks to stations. Lau and Shtub (1987), which is the only study that discusses hybrid lines, show that cost savings are possible by implementing hybrid lines compared to the case where all incomplete tasks are completed by offline repair on a given example line balance.

We believe that hybrid lines may be suitable for disassembly lines for the following reasons: In disassembly, uncertainty in task times are higher (Guide, 2000; Gungor and Gupta, 2001; Ilgın and Gupta, 2010; Lambert, 2003; Tani and Guner, 1997) leading to higher costs due to incomplete tasks. Thus, higher cost savings and profit improvements can be possible. Hybrid lines offer operational flexibility in task incompletions as both offline repair and line stoppages are possible. It is also possible to avoid the disadvantages of both actions in terms of incompletion costs: High costs due to frequent line stoppages (or offline costs) can be avoided by implementing offline repair (or by stopping the line). However, in literature, hybrid lines are only studied by Lau and Shtub (1987) for the case of assembly. In this thesis, we want to investigate the operational characteristics of hybrid lines in disassembly lines and their relationship with uncertainty in task times. We formulate the problem of determining F-tasks and P-tasks for a given line balance so as to maximize the expected profit as an Mixed Integer Programming model and propose a greedy algorithm to solve this problem. We perform a computational analysis in different settings in terms of uncertainty in task times, and discuss the effect of uncertainty on incompletion costs and profit improvements by hybrid lines. We evaluate hybrid lines by expected profit and also by other performance measures such as expected profit per unit time, expected cycle time and cycle time variance. For calculating expected incompletion costs, rather than using approximations or simulation, we combine the cost models by Silverman and Carter (1986) and Kottas and Lau (1973) and propose a method for exact calculation of the incompletion costs. Typically, in all studies adopting offline repair, it is assumed that, in offline area all of the incomplete tasks are completed, no task can be skipped. This is mainly due to the fact that all of these studies involve assembly, where all of the tasks have to be completed. However, as partial disassembly is possible, for a workpiece that comes to the offline area with a number of incomplete tasks, it may be possible to improve expected profit by skipping some of the tasks. For this purpose, we allow selection of tasks to be completed by offline repair, which we refer to as offline task selection problem, and formulate it as a Linear Programming model. We also discuss the effect of offline task selection in expected profit.

The rest of the thesis is organized as follows: In Chapter 2, the literature on disassembly in general, disassembly line balancing and stochastic assembly line balancing problems are reviewed. In Chapter 3, profit oriented stochastic disassembly line balancing problem in hybrid lines is formulated and proposed cost calculation method, general solution approach, the greedy algorithm and the formulation of offline task selection problem are given. In Chapter 4, the main characteristics of hybrid lines are explored in terms of expected profit, expected cycle time and cycle time variation. The profit improvements by hybrid lines and offline task selection is also provided in Chapter 4. Finally, we give conclusions and directions for further research in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

Disassembly is the process of removing parts, subassemblies or modules from the product that reaches its end-of-life. Disassembly is defined by Brennan *et al.* (1994) as "the process of systematic removal of desirable constituent parts from an assembly while ensuring that there is no impairment of the parts due to the process". Gungor and Gupta (1999) define disassembly as a systematic method of separating a product into its composing parts by removing parts, subassemblies or components.

Disassembly can be carried out by various disassembly systems: single workstation, disassembly cell or disassembly line (Wiendahl *et al.* 1998). The classification of disassembly systems is similar to that of assembly systems. Single workstation and disassembly cell layout offer high level of flexibility while disassembly lines offer high level of productivity. Das and Caudill (1999) state that by using disassembly lines, economies of scale and division of labor are possible, which decreases costs, and a greater degree of disassembly is possible, by which more parts or material can be recovered. Moreover, they claim that existing assembly technologies can be implemented easily to disassembly. Das and Caudill (1999) conclude that due to these advantages, high productivity rates can be achieved in disassembly lines. Gungor and Gupta (1999) assert that in a problem environment, where a high number of products are processed, disassembly lines are the most convenient setting as high cost savings are possible due to high productivity rates.

A disassembly line involves workstations, where disassembly operations are performed, and a conveyor system that is used to transport the workpieces between workstations. Depending on the movement of the line, disassembly lines can be separated into two groups as paced and unpaced lines (Gungor and Gupta, 1999). In a paced line, the speed of the conveyor system is the same for all workstations; each workstation simultaneously sends the processed workpiece to the next station and receives the workpiece from the previous workstation. In an unpaced line, a workpiece is sent to the next station or buffer as soon as its processing is finished, leading to different line speeds between each workstation. Gungor and Gupta

(2002) state that paced line offers less work in process, less space requirements, high throughput rates and less probability of blocking and starvation.

In a typical paced disassembly line, the process of disassembly involves a set of *disassembly tasks*. Each *workstation* involves operators, machines or both, and is assigned an ordered set of disassembly tasks to be performed. A discarded product, referred to as *workpiece*, visits each workstation from the beginning to the end of the line, where disassembly tasks are performed. A disassembly task may result in the release of *parts*, which may have a positive or negative revenue. A disassembly task is performed by an operator or machine within a time period called *task time*. In a paced line, the conveyor system moves and the workpiece at each station is sent to the next one when the time period, called *cycle time,* passes. The disassembly tasks are performed within the cycle time and as soon as the end of the cycle time is reached, workpieces are sent from one workstation to the other and a new cycle starts.

Disassembly and assembly have significant differences. First, disassembly is a divergent process while assembly is convergent, which requires a different approach in production planning (Brennan *et al*. 1994). Disassembly is not performed to its full extent allowing *partial disassembly* while assembly is naturally *complete* (Gungor and Gupta, 1999; Lambert, 2003). Disassembly can be performed up to a point where parts, subassemblies or modules of interest are released; therefore, typically, disassembly is partial. Due to this possibility, in disassembly problems, the level of disassembly must also be determined. In disassembly systems, the uncertainty in task times and incoming part qualities are higher than assembly systems (Gungor and Gupta, 2001; Ilgın and Gupta, 2010; Lambert, 2003; Tani and Guner, 1997). Guide (2000) notes that the disassembly times are highly variable with coefficient of variances (CoV) up to five. In assembly, precedence relationships typically include *AND* precedence relations while in disassembly a number of other precedence relation types exist. This is mainly due to the fact that in assembly, physical as well as functional considerations play role as the interactions between parts are important, while in disassembly only physical considerations are taken into account. Therefore apart from the typical *AND precedence* relationship in assembly, Gungor and Gupta (2001) define *OR precedence*, *AND within OR* and *Complex AND/OR* relationships between parts. OR precedence relationship implies that a task can be performed only if at least one of its OR predecessors is finished, while AND precedence require all of the AND predecessors of the task to be finished. AND within OR and Complex AND/OR relationships involve both AND predecessors and OR predecessors. Unlike Gungor and Gupta (2001), Altekin *et al.* (2008) include precedence relationships between tasks, which are *OR successor, AND within OR* and *OR within AND*, which we also adopt in this thesis. The types of precedence relationships in their study and the explanations are provided as follows:

1) ***AND Precedence:*** Task i_1 and task i_2 AND precede i_6, if task i_1 and task i_2 must be completed to perform i_6 (See Figure 2.1 (a)).

2) ***OR Precedence:*** Task i_3 and task i_4 OR precede i_5, if at least one of the tasks i_3 and i_4 must be completed to perform i_5 (See Figure 2.1 (a)).

3) ***OR Successor:*** Task i_6 and task i_7 are OR successors of i_5, as at most one of the tasks i_6 and i_7 can be performed after having completed i_5 (See Figure 2.1 (a)).

4) ***AND within OR:*** In this relationship type, a task is preceded by a number of task sets, at least one of whose elements must all be completed. In Figure 2.1 (b), tasks i_1, i_2, i_3 and i_4, i_5 form two task sets. Before starting task i_6, either tasks i_1, i_2, i_3 or tasks i_4, i_5 must be finished. To represent this relationship, two dummy tasks with no cost and no task time is created for each task set, namely *A1* and *A2*. Using these dummy nodes, every relationship can be represented by the three main types mentioned: AND precedence, OR precedence and OR successor.

5) ***OR within AND:*** In this relationship type, again, a task is preceded by a number of task sets. In each of these task sets, at least one task should be completed to start the task that is preceded. For instance, in Figure 2.1 (c), at least one of the tasks i_1, i_2, i_3 and at least one of the tasks i_4, i_5 must be completed to perform i_6. For this relationship type, similar to AND within OR precedence relation, dummy tasks are created for each task set, namely A3 and A4 in Figure 2.1 (c). It should be noted that Complex AND/OR relationship in Gungor and Gupta (2001) is a special case of OR within AND.

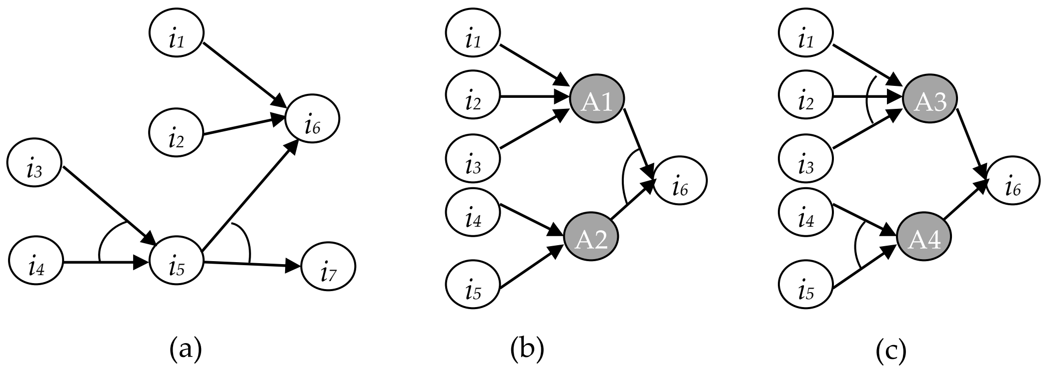

Figure 2-1 (a) Main types: AND precedence, OR Precedence, OR Successor, (b) AND within OR, (c) OR within AND (Altekin et al. 2008)

Due to the differences between assembly and disassembly mentioned, although disassembly may be seen as the reverse of the assembly, disassembly and assembly have different characteristics, which are summarized in Table 2.1. Therefore, special techniques should be developed to deal with disassembly problems (Gungor and Gupta, 1999).

Table 2-1 Comparison of assembly and disassembly lines (Gungor and Gupta, 2001)

Line Considerations	**Assembly Line**	**Disassembly Line**
Demand	Dependent	Dependent
Demand sources	Single	Multiple
Demanded entity	End Product	Individual parts/ subassemblies
Complexity related to precedence relationships	High (includes physical and functional precedence constraints)	Moderate (mostly physical constraints)
Uncertainty related to quality of parts	Low	High
Uncertainty related to quantity of parts	Low	High
Uncertainty related to workstations and the material handling system	Low to moderate	High
Reliability of the WSs and the material handling system	High	Low
Multiple products	Yes	Yes
Flow process	Convergent	Divergent
Line flexibility	Low to moderate	High
Layout alternatives	Multiple	Multiple
Complexity of performance measures	Moderate	High
Complexity of "between workstation inventory" handling	Moderate	High
Problem complexity of line balancing problems	NP-hard	NP-hard

There are various problems related to disassembly. Disassembly scheduling is the ordering of the end-of-life products so that the demands for parts and subassemblies will be satisfied (Ilgin and Gupta, 2010). Disassembly planning is defined as determining the sequence of disassembly operations so that a given set of objectives will be fulfilled and the constraints will be satisfied (Lee *et al.*, 2001). Gungor and Gupta (1999) study disassembly planning under two main topics: *Disassembly leveling* and *disassembly process planning*. Disassembly leveling involves determining the level to which a discarded product will be disassembled while disassembly process planning, also known as disassembly sequencing, involves finding the best sequence of disassembly tasks. Apart from these problems, disassembly line balancing problem is also an important issue in disassembly literature with disassembly lines used, which is the focus of this thesis.

Disassembly line balancing problem (DLBP) can be defined as the problem of assigning disassembly tasks to workstations so as to optimize a predefined performance measure under the given precedence relations. Profit oriented DLBP seeks feasible assignment of tasks to stations so as to maximize the total profit generated for a discarded product that is disassembled, while cost oriented DLBP aims at minimizing the cost of disassembling a discarded product. DLBP can be divided into two classes depending on task times as: Deterministic DLBP and Stochastic DLBP. Deterministic DLBP assumes task times to be known and constant while stochastic DLBP assumes task times to be random variates with known problem distributions. While deterministic DLBP has been studied by several authors (Altekin *et al.* 2008, Ding *et al.* 2010, Gungor and Gupta 2001, 2002, Koc *et al.* 2009, McGovern and Gupta 2003a, 2003b, 2006, 2007a, 2007b), to the best of our knowledge, stochastic DLBP has only been studied by Agrawal and Tiwari (2008). Hence, in our thesis, we will also review stochastic assembly line balancing problem (ALBP) literature as well as stochastic DLBP and deterministic DLBP literature.

The rest of this chapter is organized as follows: In Section 2.1, DLBP related literature, and in Section 2.2, stochastic ALBP is presented. The cost models adopted are given in Section 2.3. Finally, the objectives of this thesis and research questions are discussed in Section 2.4.

2.1 Disassembly Line Balancing Problem

Disassembly line balancing problem is studied with single objective such as minimizing number of workstations and maximizing profit (Altekin *et al.* 2008; Gungor and Gupta 2002; Koc *et al.* 2009), while it is also studied as a multi-objective problem including objectives such as minimizing number of stations, minimizing total idle times, recovering hazardous or highly demanded parts early on the line, minimizing probability of line stopping and minimizing the complications due to defective parts (Agrawal and Tiwari 2008, Ding *et al.* 2010, Gungor and Gupta 2001, McGovern and Gupta 2003a, 2003b, 2006, 2007a, 2007b). The studies on DLBP that will be reviewed assume different problem environments in terms of variability in task times, uncertainty in the quality of incoming products, whether or not partial disassembly is allowed, types of precedence relations included and the type of disassembly lines used (Straight or U-lines). In U-shaped layout, tasks are performed by stations, where the worker in a station works on both sides of the line. Since the tasks can be assigned both starting from the beginning or end of the line, different tasks in the precedence diagram can be assigned into the same station offering flexibility in task assignment.

Gungor and Gupta (2002) present a heuristic that solves DLBP on paced lines with the single objective of minimizing the number of stations under complete disassembly with deterministic task times and given cycle time. Precedence relations included are those defined in Gungor and Gupta (2001), namely AND precedence, OR precedence and Complex AND/OR precedence relations. The proposed heuristic DLBP-S involves assignment of tasks to stations, which are ordered according to their priority function values within the given cycle time. The priority function value involves the evaluation of a candidate task in terms of the idle time left on the station if the candidate task is assigned, the demand for the parts released by the candidate task (i.e. highly demanded parts are preferred), number of predecessors and successors, hazardous material content of the released parts, and finally, the number of movements in terms of direction changes on the workpiece necessary to perform the task. Hence, in addition to the single objective function of minimizing the number of stations, a number of other criteria are also considered as relevant to the performance of a solution and are included in the solution method.

Gungor and Gupta (2001) solve DLBP with task failures, DLBP-F, under the same problem environment as Gungor and Gupta (2002) in terms of deterministic task times, complete disassembly and precedence relations. However, they state that unlike assembly, where incoming products are inspected through various quality control stages, in disassembly there is a significant variability in the structure and quality of incoming parts, which may cause failure of some of the tasks. Due to precedence relations, failure of a single task can result in various complications on the workpiece. For instance, for a workpiece that arrives to a station, some of the tasks may be infeasible, none of the tasks may be feasible; while for a leaving work piece, none of the tasks in the next station may be feasible or none of the remaining tasks in the whole line may be feasible. These possibilities are enumerated and workpieces are classified as *"early leaving work pieces"*, *"self skipping work pieces"*, *"skipping work pieces"*, *"disappearing work pieces"*, *"revisiting work pieces", "exploding work pieces"* and *"normal flow"*. In a given solution, the probability and cost of each complication is calculated to find an overall expected cost term that incorporates the effect of task failures. The overall solution procedure basically involves generation of a network and generation of all states, where each state represents the tasks that are feasible according to precedence relationships. The states are linked with each other using directed arcs, the overall cost of complications are calculated for the paths and Dijkstra's algorithm is used to find the shortest path from the head node to the final node so that assignment of tasks to stations are made by minimizing the overall complications caused by incomplete tasks. The shortest path in terms of overall complication with the minimum number of stations is determined and proposed as the final solution (i.e. minimum number of stations is the primary objective).

Altekin *et al.* (2008) solve profit oriented DLBP with deterministic task times under partial disassembly. They develop a mixed integer programming formulation of the partial DLBP for the first time, and decide simultaneously on the number of stations, the cycle time, the tasks to be performed, parts released and the task assignments while the total profit is maximized. The objective function incorporates station operating costs, task costs and the revenue generated from the parts released. The part revenues, task costs and demand quantities are assumed to be deterministic and known. In addition to the precedence relationship types provided by Gungor and Gupta (2002), *"OR successor"* precedence relation is introduced in the study. The solution approach involves a lower and upper bounding scheme based on the linear relaxation of the problem. Upper bounding scheme involves solving the linear relaxation of the problem, to which two constraint sets are added to have a tighter upper bound for the objective function, while lower bounding scheme involves a construction and two improvement heuristics. The construction heuristic is run on the upper bound solution to have a starting solution and two improvement heuristics, namely *"task deletion"* and *"task insertion"* heuristics are applied to reach to the final solution.

Altekin and Akkan (2012) formulate the problem of rebalancing disassembly lines with task failure with the single objective of maximizing profit with precedence relations defined in Altekin *et al.* (2008). Similar to Gungor and Gupta (2001), it is assumed that during the disassembly of a specific product, a task may fail, which may lead to the infeasibility of the successors due to precedence relations. In that case, rather than skipping all of the infeasible tasks in downstream stations, it may be profitable to rebalance the rest of the line by determining the tasks to be performed in downstream stations and defining a new cycle time for that specific cycle. The main motivation of the study is to achieve improvements in profit by rebalancing the line when a task fails so as to maximize the profits earned by disassembling a product, referred to as "core". The solution approach involves mainly two phases: In the first phase, the deterministic problem is solved to find the "*predictive balance*". This first model, referred to as predictive disassembly line balancing (PDLB) model is similar to the model in Altekin *et al.* (2008) in terms of objective function, decision variables and precedence relations. The only difference is that number of stations is assumed to be given and demand considerations are held out of scope, i.e. each part released has a corresponding demand. In the second phase, given a failing task and the predictive balance, rebalancing the line is formulated as a MIP where new cycle time and task assignments in downstream stations are decision variables, and the objective function is to maximize the profit per product. Two approaches are adopted for determining the predictive balance: *Integrated* and *hierarchical approach.* In the integrated approach, the tasks to be performed and the assignment of the tasks to stations are determined at a single step. In hierarchical approach, at first stage, the tasks to be performed are selected by solving PDLB with the number of stations is equal to *one*. In the second step, the profit per core is maximized by determining the line balance for the desired number of stations. The possible improvements in profit by rebalancing the line when a task fails and the performances of two hierarchical and integrated approach are discussed by a simulation study, where profit per product and cycle times are considered as performance criteria.

Koc *et al.* (2009) give two formulations of DLBP with deterministic task times under complete disassembly using a modified version of AND/OR graph (AOG), named as *"Transformed AND/OR Graph" (TAOG)*. TAOG's main difference from AOG is that it contains information on the precedence relations between tasks. It is shown that using an AOG rather than a task precedence diagram results in better solutions in ALB problems. In their study, DLBP is formulated and solved as dynamic and integer programming problems with the objective of minimizing the number of stations using TAOG.

McGovern and Gupta (2003a, 2003b, 2006, 2007a, 2007b) formulate DLBP with deterministic task times under precedence relations between parts, no variability in incoming products and complete disassembly as a multi-objective problem. The objectives included have priorities over each other and the ones with lower priorities act as tie breaking rules. The objective functions in the order of decreasing priorities are: *"the number of stations"* (McGovern and Gupta 2003a, 2003b, 2006, 2007a, 2007b), *"the balance measure"* by which the number of stations are minimized while idle times at stations are kept similar (McGovern and Gupta 2003a, 2003b, 2006, 2007a, 2007b), *“hazardous part measure”* rewarding the positioning of hazardous parts early (McGovern and Gupta 2003a, 2003b, 2006, 2007a, 2007b), *“demand measure”* rewarding the positioning of high-demand parts early (McGovern and Gupta 2003a, 2003b, 2006, 2007a, 2007b), and *“the number of direction changes”* that is related with the added handling efforts (McGovern and Gupta 2006, 2007a, 2007b). In this problem context, McGovern and Gupta (2003a, 2003b) develop a two-phase solution approach where the first phase seeks a feasible solution with minimum number of stations by a greedy algorithm. The second phase improves the balance measure by a hill climbing algorithm by McGovern and Gupta (2003a) and by a 2-opt local search algorithm by McGovern and Gupta (2003b). Whereas McGovern and Gupta (2006) propose an ant colony optimization (ACO) method, McGovern and Gupta (2007b) propose a genetic algorithm. In computational analysis in McGovern and Gupta (2003a, 2003b, 2006, 2007a, 2007b), to make sure that the solution space involves a large number of feasible solutions; the number of parts demanded and the number of hazardous parts are assumed to be one, the direction changes on workpiece is different for only one task and precedence relations are ignored. As the main purpose is to compare the solution approaches with each other and with the optimal solution, task times are set to prime numbers so that the summation of any task time combination cannot be equal and thus the number of optimal solutions is reduced.

McGovern and Gupta (2007b) compare the performances of various solution approaches for DLBP for the same problem environment in their other studies ((2003a, 2003b, 2006, 2007a, 2007b). Exhaustive search, a genetic algorithm, an ant colony optimization (ACO), a hill climbing heuristic, greedy/2 opt hybrid algorithm (a tour improvement procedure where nodes are exchanged rather than edges), and Hunter-Killer heuristic (a technique where the solution space is sampled), and a greedy algorithm are implemented and the computational results are discussed.

Ding *et al.* (2010) propose a multi-objective ant colony optimization method for multi objective DLBP with deterministic task times under complete disassembly and AND type precedence relations. The proposed algorithm involves ant colony optimization to generate the solutions and Pareto filtering to determine Pareto optimal solutions. The performance of the algorithm is tested based on the comparisons made on the single objective functions, *“minimizing the number of stations”*, *“minimizing the measure of balance”* and *“demand rating”* since there is no general benchmark for multi-objective DLBP.

Sarin *et al.* (2006) formulate the disassembly optimization problem as a precedence constrained asymmetric travelling salesman problem (TSP), where the disassembly level and the disassembly sequence are both determined, and propose a three stage iterative solution method using a network representation. The single objective function includes the revenues generated from parts, the sequence dependent and independent costs. The three stages of solution approach involve; firstly, solving the Lagrangian relaxation of the model; secondly, identifying the sub-tours or constraint violations of the solution to the relaxation of the problem and adding the required constraints to avoid these violations; and finally, solving the mixed integer programming model with all of the added constraints.

All of the studies discussed so far assume disassembly task times to be deterministic and known. Carter and Silverman (1984) note that in assembly, where uncertainty in task times are much lower compared to disassembly, deterministic task time assumption is not realistic. The literature on DLBP, with stochastic task times is very limited. To the best of our knowledge, Agrawal and Tiwari (2008) are the only authors to study DLBP with stochastic task times. They simultaneously solve DLBP and model sequencing problem in U-lines under complete disassembly and AND type precedence relations with a novel ACO algorithm. The proposed algorithm, *"Collaborative Ant Colony Optimization (CACO)"*, involves the use of two ant colonies with different roles: First colony aims at finding optimal model sequence while the other seeks optimal line balance in terms of the objective functions, which are minimizing the balance measure (McGovern and Gupta 2003) and minimizing the probability of line failure, which implies the probability that the cycle time is exceeded by at least one station. The balance measure is the primary objective, while the other objective acts as tie breaking rule. At each iteration, if the balance measure of a found solution is not equal to the balance measure of the current best solution, secondary objective is ignored. Otherwise, i.e. when both balance measure values of the found solution and best solution are equal, the best solution is updated if the probability of line failure of the found solution is lower. Therefore, the effect of stochastic task times is observed only when balance measures are equal in the calculation of the probability of line failure; the additional costs incurred or the operational problems due to line failures are not covered explicitly. Task assignments are made so that the mean total task time of a station cannot exceed the cycle time just as the deterministic case.

The uncertainty in task times in disassembly or assembly lines lead to operational problems: Since the task times are stochastic, there is a probability that the cycle time is exceeded by one or more stations, and consequently, some of the tasks will not be completed within the cycle time. In disassembly literature, this problem is not addressed, while in assembly, there exist some studies proposing a number of remedial actions proposed. In assembly, in the case that the cycle time is exceeded, the most common two remedial actions are:

1. Stopping the line
2. Offline repair

Apart from these two remedial actions, a hybrid of these two remedial actions (Lau and Shtub 1987), multiple manning of stations (Shtub 1984, Vrat and Virani 1976) using a skilled worker or a repair team to support stations, using strategically positioned inspection and repair stations along the line are among other remedial actions proposed in the literature (Shtub 1984, Silverman and Carter 1986).

It should be noted that all of the remedial actions require significant additional effort in terms of time and labor. Hence additional costs are incurred, which should be taken into account. In stochastic ALBP literature, there are a number of approaches that incorporate these costs into the solution methods, and thus will be reviewed in next section. In the context of this thesis, stopping the line, offline repair and hybrid lines will be reviewed.

2.2 Remedial Actions in Stochastic Assembly Line Balancing Literature

The effect of stochasticity in ALBP is handled mainly in two ways: The effect of stochasticity and incompletions is controlled by imposing some form of a constraint or its costs are directly included in the objective function.

For the case of controlling the effect of stochasticity as a form of imposing a constraint, Ignall (1965) proposes that in each station the total mean workcontent should be within 90% of the cycle time. Moodie and Young (1965), on the other hand, propose keeping the probability of task incompletion in a station under a specific level so as to decrease the effects of stochasticity. Both Ignall (1965) and Moodie and Young (1965) do not explicitly cover the costs associated with not completing a task on the line within cycle time. Rather, they limit the impact of stochasticity by keeping the probability of task incompletions at low levels.

The inclusion of the costs related to stochastic task times in the objective function brings other complexities. First, exact calculation of the probability and/or the cost of task incompletions is only possible for a given line balance. Second, each remedial action has its own characteristics and cost terms, which may require special formulations. Third, the precedence relations between tasks further complicate the situation as an incomplete task leads to the successor of the task to be skipped. In the following section of this chapter, the three remedial actions, namely stopping the line, offline repair and hybrid line, and the cost structures proposed for each are studied in detail.

2.2.1 Stopping the Line

In this remedial action, in the case that all of the tasks are completed within the cycle time, the line is moved as soon as the end of the cycle time is reached. When the cycle time is exceeded when performing a task in any station, the line is stopped and cycle time is extended so long as all of the tasks are performed. The line is moved and workpieces are sent to the next station as soon as all of the tasks in all stations are completed. Therefore, in case of a task incompletion, cycle time is longer than the predefined value, which leads to additional costs, since for the products on the line during that time, the line is operated for more time.

Lyu (1997) solves stochastic ALBP with line stoppages. The proposed solution approach involves the use of stochastic optimization algorithm, PARMSR (Perturbation-Analysis-Robbins-Monro-Single-Run) by Suri and Leung (1989). The proposed algorithm mainly involves generating line balances with a heuristic, and then finding the expected total cost by simulation. If the stopping criteria, which include deriving an expression and calculating the deviation of the objective function value from an upper bound, are not met, the cycle time and iteration count is updated and heuristic is re-run. Lyu (1997) does not formulate the expected cost function, for each solution, the objective function value is found by simulation.

Silverman and Carter (1986) propose a cost model for stochastic ALBP with line stoppages, where task times are Normal random variables. The authors argue that incompletion costs are opportunity costs due to the lost production as the output rate decreases when cycle time increases. Assuming that the lost production due to the lower output rate will be realized by overtime, per unit time costs for task incompletions are assumed to be higher than regular operation. A cost model is proposed to calculate the expected amount of time the line is stopped and the expected incompletion costs. Three heuristics, deterministic, industrial and stochastic heuristics, are compared based on their total expected costs calculated by the cost model. As we adopt the cost model to calculate the expected cycle time, further details will be explained in detail in Section 2.3.1. The heuristics proposed can be summarized as; given cycle time, the tasks that satisfy precedence relations are randomly selected and assigned to stations until all of the tasks are assigned and a final line balance is reached. This procedure is repeated for a number of iterations and the solution with minimum total expected cost is selected as the best solution. The main difference between the heuristics are the constraints imposed on the total mean work contents: In stochastic method, the probability of exceeding the cycle times cannot exceed a given percentage value; in industrial method, the total mean work content cannot exceed a specified percentage of the cycle time, and in deterministic method, the cycle time is considered as the upper bound for total mean work content.

2.2.2 Offline Repair

Under this remedial action, when a station cannot complete any task(s) within the cycle time, the task is left incomplete and the workpiece is sent to the next station once cycle time is elapsed. In downstream stations, the tasks whose precedence relations are already satisfied are performed as usual, while the tasks that cannot be performed due to precedence relations are skipped. After the workpiece leaves the line, it is brought to an offline area, where all of the incomplete tasks are completed. The common assumptions of the studies focusing on offline repair are (Carter and Silverman 1984, Kottas and Lau 1976, 1981, Sarin and Erel 1990, Sarin *et al.* 1999, Shin 1990): (i) Offline repair of a task is more costly than performing the task on the line. (ii) The offline cost of a task is independent of the amount of time already spent for the task on the line. (iii) The task times are assumed to follow Normal distribution.

Kottas and Lau (1976) propose a cost evaluation model involving the effect of task incompletions, which is also adopted by various authors afterwards. It is assumed that performing a task offline, costs more than performing it on the line. Moreover, the offline cost of a task is deterministic and independent of the time spent on the task previously on the line. Kottas and Lau (1976), propose a cost model that evaluates the incompletion costs of a given line balance. As we will be adopting their offline cost calculation scheme, further details are provided in Section 2.3.2.

Kottas and Lau (1981) propose a heuristic algorithm for stochastic ALBP by using the cost model by Kottas and Lau (1976). The heuristic involves forming a fit list with the tasks, whose marginal expected incompletion cost is lower than the saving in labor cost. If there are more than one tasks in the fit list, they propose a collection of rules based on the duration and incompletion cost of the tasks.

Sarin and Erel (1990) propose a different approach to calculate the offline costs. The approach involves developing an enumeration tree to find the task incompletion probabilities. They propose a dynamic programming approach to solve the stochastic assembly line balancing problem.

Sarin *et al.* (1999) present a method to solve assembly line balancing under stochastic task times. The solution approach involves generating an initial solution by dynamic programming and improving it with a branch and bound algorithm. The objective function includes the overall expected cost, which is calculated by the cost model proposed by Sarin and Erel (1990).

Shin (1990) presents a heuristic to solve assembly line balancing under stochastic task times. In this study, if a station cannot complete all of the assigned tasks within the cycle time, the workpiece is directly sent to offline area rather than waiting until the workpiece leaves the line. The incompletion costs are calculated based on the probability that cycle time will be exceeded by each station. This probability is then multiplied by the total mean task time of the tasks assigned in the station and all of the downstream stations, and summed for all stations to find overall expected incompletion cost. The proposed heuristic involves solving deterministic problem given the cycle time and calculating the total expected cost for the line balance found. At each iteration, the cycle time is decreased and the procedure is repeated until the cycle time is less than target level. When the stopping criteria are met, the expected total costs found are compared and the solution with the lowest total expected cost is selected.

Carter and Silverman (1984) implement a cost structure that is used to calculate expected offline costs. They state that the costs due to task incompletions arise for two reasons: offline repair and cost of ill will for the defective products shipped to the customer. This cost is named as composite cost off ill will and offline repair, and represents the cost of a defective product, which is assumed to be proportional to the total mean work content. This term is then multiplied by the probability that cycle time is exceeded at least one station (the probability of a defective product) to calculate the expected offline cost of a product assembled. The three heuristics proposed by Silverman and Carter (1986), which are briefly explained in Section 2.3.1, are implemented and the results are compared.

2.2.3 Hybrid Lines

Lau and Shtub (1987) propose a hybrid strategy where stopping the line and offline repairs are both considered. In a hybrid line, the tasks are divided into two groups: P-tasks and F-tasks. P-tasks, as an abbreviation of “Pass” tasks, are those for which, offline repair is performed when the cycle time is exceeded. Whereas, for the second group of tasks, called F-tasks, which is an abbreviation of “Finish” tasks, if the cycle time is exceeded while or before performing the task, the line will be stopped until the task is finished. The cycle time is extended as long as F-tasks are performed and a new cycle starts when there are no incomplete F-tasks left. The calculation of incompletion costs in hybrid lines is complicated as in case of a task incompletion, different actions are taken for P-tasks and F-tasks. Therefore, both line stoppage costs and offline repair costs have to be calculated. Lau and Shtub (1987) do not provide a method for calculating the incompletion costs. Instead, they use simulation to estimate these costs. An example instance is solved assuming task times to be Normal random variables with known means and variances. The cost of the best solution is calculated with simulation and compared with the line where all tasks are P-tasks, as it is the case in Kottas and Lau (1976). Lau and Shtub (1987), apply the proposed hybrid line on a given line balance and compare the total expected cost of the line with the case where all incomplete tasks are completed by offline repair.

Determining how to categorize tasks as F-tasks or P-tasks is another issue for hybrid lines. Lau and Shtub (1987) determine P-tasks and F-tasks by enumerating all combinations and selecting the one which minimizes the expected cost of disassembling a product. They set two basic rules that limit the combinations and ordering of tasks in a station: First, a successor of a P-task cannot be labeled as F-task. Second, in a given station an F-task cannot be performed later than a P-task. Both rules are related with the basic definition of P-tasks and F-tasks. For instance, for the first rule, if a certain P-task is incomplete, its successors as well as the P-task itself will be completed by offline repair due to precedence relations. However, if one of these successors is an F-task, it will be completed by offline repair, which is not possible by definition. A similar problem occurs when an F-task is performed later than a P-task in a given station. After all of the combinations are generated, the one with the lowest total expected cost is selected and the solution is compared with the cost of offline repair.

2.3 Cost Evaluation Models

In this study, a cost calculation method is developed to calculate the incompletion costs in hybrid lines based on the studies Silverman and Carter (1986) and Kottas and Lau (1976). The cost models are modified to handle the distinction between F-tasks and P-tasks, which is discussed in Chapter 3. The details of the original cost models are discussed in sections 2.3.1 and 2.3.2 in detail.

2.3.1 Silverman and Carter (1986) Cost Model

Silverman and Carter (1986) study assembly line balancing problem under stochastic task times, where in the case of task incompletion, the line is stopped until the task is finished. Therefore, incompletion costs include only the costs due to the line stoppages, which is referred to as *"expected cost of exceeding the cycle time"* by Silverman and Carter (1986). In this part, formulation of *"expected cost of exceeding the cycle time",* $E[C]$, will be provided for a given line balance and cycle time. Note that task times are assumed to be Normal random variables with known means and variances.

I : # of tasks
K : # of stations
i : Task index, $i=1,2,..,I$
k : Station index, $k=1,2,\ldots, K$
μ_i : The mean task time of task i
σ_i : Standard deviation of task time of task i

A_k	:	Set of tasks assigned to station k
W_k	:	Random variable denoting the sum of task times in station k
$F(W_k)$	:	The cumulative distribution function of W_k.
W	:	Random variable denoting maximum time required for all stations to complete their tasks in a particular cycle, i.e. $W = \max_k \{W_k\}$
$G(W)$	:	Cumulative distribution function of W
$g(W)$	:	The probability density function of W
CT	:	Cycle time
l_c	:	Unit labor cost
e	:	Random variable denoting the amount of the time that the line stops, $e = \max\{0, W - CT\}$
$E[e]$	:	Expected amount of the time that the line stops
$E[C]$	:	Expected cost of exceeding the cycle time

By definition,

$$G(W) = \prod_k F(W_k),\ k = 1, 2, ..., K \tag{2.2}$$

where $W_k \sim N(m_k, s_k^2)$ and $m_k = \sum_{i \in A_k} \mu_i,\ s_k^2 = \sum_{i \in A_k} \sigma_i^2,\ k = 1, 2, ..., K.$

As,

$$E(W \mid W > CT) = \frac{\int_{CT}^{\infty} Wg(W)dw}{[1 - G(CT)]} \tag{2.3}$$

applying integration by parts,

$$E(W \mid W > CT) = CT + \int_{CT}^{\infty} \left[1 - G(W)\right] dw \tag{2.4}$$

Thus,

$$E[e] = \int_{CT}^{\infty} [1 - G(W)] dw \tag{2.5}$$

$$E\left[C\right] = K\ l_c\ E\left[e\right] \tag{2.6}$$

According to the formulation above, by (2.5) the expected amount of time that the line is stopped, and by (2.6), $E[C]$ can be calculated. Note that as (2.6) involves the integration of cumulative distribution function of a Normal random variable, numerical integration is used.

2.3.2 Kottas and Lau (1976) Cost Model

Kottas and Lau (1976) propose a cost model for the assembly line balancing problem with stochastic task times, where offline repair is applied. As only offline repair is implemented, the incompletion costs only include the costs incurred by offline repairs. Note that the task times are assumed to be Normal random variables with known means and variances.

2.3.2.1 An overview of Kottas and Lau (1976)

The calculation of the costs incurred by offline repairs is not straightforward due to precedence relations. If a task is not completed, the successors of the incomplete task cannot be performed due to precedence relations. Depending on the reason of incompletion, incomplete tasks may be classified as time related or precedence related incomplete tasks. A precedence related incomplete task is a task, which cannot be performed since its predecessors in previous stations are not completed. Therefore, even if unlimited time is allowed for performing the tasks in the current station, it cannot be performed. Whereas, precedence constraints are satisfied for time related incomplete tasks, but the cycle time is exceeded in the workstation that the task is being performed.

A unit may leave the disassembly line in many different ways in terms of complete and incomplete tasks named as an incompletion combination *(IC)*. For a given incompletion combination, complete tasks, time related incomplete tasks and time related incomplete tasks are known. An *IC* is represented uniquely by a K-tuple, $(n_1\ n_2\ \ldots\ n_K)$, where K is the number of stations and n_i is the number of time related incomplete tasks. N_k is the number of precedence feasible tasks at station k, which is the upper limit value for n_k. Each incompletion combination has a different expected cost and probability of occurrence. Hence, the overall cost model of Kottas and Lau (1976) involves generation of every possible *IC*, calculation of the cost and the probability of occurrence of each *IC*, finding the expected incompletion cost for *IC* and summing all to find the overall expected incompletion cost, *EIC*.

2.3.2.2 Generation of Incompletion Combinations

If there were no precedence constraints, the total number of *IC*'s would be $\left[\prod_k \left(|A_k|+1\right)\right]-1$, where $|A_k|$ is the number of tasks at station k. Due to precedence relations, some of the combinations are not possible. Therefore, the total number of *IC*'s is reduced to a plausible number (Kottas and Lau, 1976).

The following algorithm describes how all IC's, i.e. k-tuples are generated for a given line balance. As a result of this algorithm, all of the IC are generated and probability of occurrences and expected offline cost of each *IC* is calculated.

1. Start
2. *WHILE* $n_1 \leq N_1$ *DO*

   Determine N_2, set $n_2 = 0$

   WHILE $n_2 \leq N_2$ *DO*

   Determine N_3, set $n_3 = 0$

   .

   .

   WHILE $n_K \leq N_K$ *DO*

   Calculate $P(n_1\ n_2\ n_3\ ...\ n_k)$ and offline cost of the *IC*

   Set $n_K = n_K + 1$

   END WHILE

   .

   .

   Set $n_2 = n_2 + 1$

   END WHILE

   Set $n_3 = n_3 + 1$

   END WHILE
3. STOP

2.3.2.3 Calculating Offline Cost (OC) of an Incompletion Combination

After an *IC* is generated, as the incomplete tasks are known, the expected time of offline repair and expected offline costs can be calculated. The expected time of offline repair can now be determined by summing the expected time of offline repair of each individual incomplete task. The expected offline repair time is multiplied by the unit labor cost to calculate the expected offline cost of the *IC*.

2.3.2.4 *Calculating the Probability of Occurrence of an IC*

Let;

P	:	Probability of occurrence of *IC*
p_k	:	Probability that there are n_k time related incomplete tasks in station *k* given $n_1, n_2, ... n_{k-1}$
C_k	:	The set of completed tasks in station *k*
I_k	:	The set of time related incomplete tasks in station *k*
j_k	:	The first task in I_k, i.e. the task which is being performed when the cycle time is exceeded
J_k	:	$C_k \cup \{j_k\}$, the set of all completed tasks and the task while which is being performed when the cycle time is exceeded
t_i	:	Random variable denoting the task time *i*, $t_i \sim N(\mu_i, \sigma_i^2)$

As task times are assumed to be independent Normal random variables, station workcontents are also independent and therefore;

$$P = \prod_k p_k,\ k = 1, 2, ..., K \tag{2.7}$$

$$If\ \ I_k = \varnothing,\ p_k = P\left[\sum_{i \in C_k} t_i \le CT\right] \tag{2.8}$$

$$\text{else}\ \ p_k = P\left[\left(\sum_{i \in C_k} t_i \le CT\right), \left(\sum_{i \in J_k} t_i > CT\right)\right] \tag{2.9}$$

Using the rules of probability, the above equations (2.8) and (2.9) are equivalent to (2.10) and (2.11), respectively.

$$p_k = \bar{F}\left[\left(CT - \sum_{i \in C_k} \mu_i\right) \Big/ \left(\sqrt{\sum_{i \in C_k} \sigma_i^2}\right)\right] \tag{2.10}$$

$$p_k = \bar{F}\left[\left(CT - \sum_{i \in C_k} \mu_i\right) \Big/ \left(\sqrt{\sum_{i \in C_k} \sigma_i^2}\right)\right] - \bar{F}\left[\left(CT - \sum_{i \in J_k} \mu_i\right) \Big/ \left(\sqrt{\sum_{i \in J_k} \sigma_i^2}\right)\right] \tag{2.11}$$

where $\bar{F}[x]$, is the standard normal cumulative distribution function of *x*.

From (2.10) and (2.11), p_k 's can be calculated and used in (2.7) to find the probability of occurrence, *P*, of an *IC*.

2.3.2.5 Evaluation of Total Offline Cost

The expected offline cost of an IC is found by multiplying the probability of occurrence with its offline cost. Then, expected offline costs of all of the *IC*'s are summed to find the total expected offline cost (TOC).

$$TOC = \sum_q OC_q P_q \text{ , for } \forall q$$

where q denotes the index of incompletion combinations, OC_q is the offline cost and P_q is the probability of occurrence of incompletion combination q.

2.4 Discussion

Although deterministic DLBP has been studied by various authors, stochastic DLBP is only studied by Agrawal and Tiwari (2008), where costs due to stochastic task times are not calculated explicitly. The proposed solution approach primarily aims to optimize the balance measure, while minimizing the probability of line failure acts as tie breaking rule. Therefore, task incompletions, remedial actions and incompletion costs are not explicitly covered. In stochastic ALBP, other than the two common remedial actions, stopping the line and offline repair, hybrid lines are proposed by Lau and Shtub (1987) for assembly. The hybrid line concept is suitable for disassembly on disassembly lines for the following reasons:

1. Implementing offline repair for a task with many successors may lead to high offline costs as the idle time on the line will increase and the additional costs will be incurred for completing all of these incomplete tasks. It is even possible that due to precedence relations, none of the remaining tasks are feasible, and so all tasks have to be completed by offline repair. On the other hand, stopping the whole line for a task with low incompletion cost may lead to high line stoppage costs, especially with high number of stations. In a hybrid line, as both remedial actions are allowed, the disadvantages of each type of remedial actions can be avoided if the classification of tasks as P-tasks and F-tasks is done properly.
2. Higher uncertainty in task times may lead to more frequent task incompletions, which increase incompletion costs. Therefore, incompletion costs can have more impact in disassembly, where task time uncertainty is higher and hybrid lines may offer higher cost savings.
3. Hybrid lines offer operational flexibility since both stopping the line and offline repair are possible. In a disassembly line, there may be some tasks which require special equipment and can be performed only on the line. For instance, during the disassembly of refrigerators, hazardous gases are released which require special equipment. In a hybrid line, such tasks can be forced to be F-tasks so that they will always be completed on the line.

In stochastic ALBP, cost models that calculate incompletion costs are proposed when either offline repair (Kottas and Lau 1976) or line stoppage (Silverman and Carter 1986) is allowed. To the best of our knowledge, incompletion costs are not yet explicitly covered in hybrid lines. Lau and Shtub (1987), the only study that implements hybrid lines, calculate incompletion costs by simulation. Hence, a need for a method that calculates incompletion costs in hybrid lines arises. Calculation of the incompletion costs in hybrid line for disassembly require special attention since;

1. The precedence relations included in assembly is typically AND precedence relations whereas disassembly mainly may involve additional precedence relations such as OR precedence and OR successor relations. Due to these precedence relations, an incomplete task affects its successors in a more complicated way: While an AND successor of an incomplete task is always precedence infeasible, the same is not true for OR precedence.
2. Disassembly can be partial while assembly has to be complete. Due to this fact, in stochastic ALBP, all of the incomplete tasks are completed by implementing a remedial action. However, in disassembly one or more tasks may be left as incomplete to decrease incompletion costs and maximize profit.
3. Cycle time can be extended due to an incomplete F-task in a station. When that occurs, there will be more time to complete other P-tasks in other stations and so the probability that these tasks are completed increase. Hence, as offline costs depend on the probability that these P-tasks are completed, existing calculation methods need to be modified so that the interaction between line stoppages and offline costs are taken into account.

Lau and Shtub (1987) introduce hybrid lines, and show that cost savings are possible compared to the case where all incomplete tasks are completed by offline repair on one example instance. The results are not compared to the case where all tasks are completed by line stoppages. Hence, it may be interesting to compare hybrid lines with both remedial actions with different with precedence diagrams and task parameters. Moreover, the determination of P-tasks and F-tasks is made by enumerating all possible combinations. To the best of our knowledge, this problem is not mathematically formulated nor a solution approach is proposed. In DLBP, the classification of F-tasks and P-tasks are further complicated as additional type of precedence relations exist.

In our study, we focus on four issues on disassembly line balancing with stochastic task times in hybrid lines.

- *Cost evaluation method:* We propose a method that formulates the exact calculation of expected incompletion costs in hybrid lines, by modifying the cost evaluation models by Silverman and Carter (1986) and Kottas and Lau (1976). Therefore, we can evaluate the significance of incompletion costs and their interaction with the magnitude of uncertainty in task times.
- *Exploring the characteristics of hybrid lines:* Lau and Shtub (1987) is an exploratory study, which shows that cost savings are possible by hybrid lines on an example line balance. Our main motivation is to investigate the conditions under which hybrid lines provide profit improvement. By a numerical study, we evaluate hybrid lines with respect to expected profit, expected cycle time and variance of the cycle time. We compare hybrid lines with the two common remedial actions and try

to explain the effect of the uncertainty in task times on these performance measures.

- *Formulation of profit oriented stochastic DLBP in hybrid lines:* We formulate the problem of determining P-tasks and F-tasks in hybrid lines as a mixed integer problem that maximizes expected profit of a given line balance and cycle time. We propose a two phased greedy algorithm, which determines P-tasks and F-tasks for a given line balance and cycle time.
- *Offline repair optimization:* In the studies that incorporate offline repair, all of the incomplete tasks that are not completed on the line are completed by offline repair. However, in disassembly lines, it is possible that performing offline repair may become unprofitable depending on the state of the workpiece in terms of complete and incomplete tasks. Due to increased costs in offline repair, a task may incur higher costs than the revenue generated by the released parts, which causes performing offline repair for the specific task to be undesirable. We formulate the problem of selecting which of the incomplete tasks to be performed as an LP, for a given workpiece that arrives to offline area.

CHAPTER 3

OPERATING HYBRID DISASSEMBLY LINES WITH STOCHASTIC TASK TIMES

In the context of this thesis, disassembly is carried out on a disassembly line. A discarded product, which will be referred to shortly as *workpiece*, enters the line and visits each station from the first station to the end. The assigned tasks are performed in a predefined order at each station. At the end of each cycle, the workpieces are simultaneously sent to the next stations and a new cycle begins. In a given cycle, as a result of performing a task, *task cost* is incurred and *parts* are released, which are associated with *part revenues*, which may be positive or negative. The tasks have precedence relations between each other, which are *AND precedence, OR precedence, OR successor, AND within OR* and *OR within AND* precedence relations, defined by Altekin *et al.* (2008), explained in Section 2 in detail. *Task times* are assumed to be Normal random variables with known means an variances, while part revenues and task costs are deterministic.

As task times are stochastic, it is possible that one or more tasks are not completed within the predefined cycle time. For task incompletions, hybrid line concept introduced by Lau and Shtub (1987), is adopted. Following their definitions, in a hybrid line, there are two task classes, F-tasks and P-tasks, and a *base cycle time* value. Base cycle time is the predefined time duration, which is allotted to each station regardless of the status of incomplete tasks at each station. After this time duration is elapsed, if all of the tasks are completed, cycle ends as it is the case in deterministic case. Otherwise, if any task is incomplete, remedial action applied depends on the class of the incomplete task: If an F-task is incomplete, the line is stopped and cycle time is extended until all F-tasks are completed. Therefore, in a given cycle, if any F-task in any station is not completed within the base cycle time; cycle time is longer than the base cycle time value; otherwise, cycle time is equal to the base cycle time. When a P-task is not completed within cycle time (which can be greater than base cycle time due to incomplete F-tasks), it is left as incomplete and the workpiece is sent to the next station. In downstream stations, due to incomplete tasks, there may be tasks that are not feasible to perform due to precedence relations. In this case, the precedence feasible tasks are performed as usual while infeasible ones are skipped. This procedure is repeated at all downstream stations until the workpiece reaches the end of the line. After the workpiece leaves the line, it is brought to the offline area for offline processing for incomplete P-tasks.

Note that for a given line balance, it is possible to set base cycle time to any nonnegative value. However, one has to take into account that lower base cycle time values may lead to high probability of task incompletions while higher base cycle time values may lead to higher idle times. Therefore, base cycle time can be set to any value to operate a hybrid line.

Stopping the line and offline repair both require additional time and effort incurring additional costs. Due to the line stoppages in a cycle, the line is operated longer than the base cycle time leading to more time to disassemble a product. In the excess time the line is operated, additional costs are incurred per unit time, referred to as *line stoppage costs*. Similarly, performing offline repair for completing incomplete tasks requires additional labor and time in offline area referred to as *offline costs,* also incurred per unit time. These two terms together make up the additional costs of task incompletions when disassembling a product called *incompletion costs*. The disassembly of a product is associated with an expected profit including the terms: *total revenue* from the disassembled parts, *total task cost, station operating cost* and *incompletion costs*. Total revenue and total task costs are associated with completing certain tasks. Only when a task is completed, the task cost is incurred and part revenues are generated. When a task is started but not completed, these terms are not realized to avoid double counting. At each cycle, independent of the status of incomplete tasks, the line is operated for at least base cycle time incurring station operating costs, which can be calculated by multiplying number of stations, base cycle time and unit station operating cost. Hence, the expected profit of disassembling a product can be calculated by subtracting total task cost, station operating cost and expected incompletion costs from total revenue.

Studies involving offline repair in assembly lines typically assume all incomplete tasks to be completed by offline repair for a given line balance. However, in the case of disassembly lines, partial disassembly, i.e. skipping certain tasks, is possible and it may be possible that the revenue generated by the task is less than the offline cost of performing the task. Moreover, due to precedence relations, profitability of performing a task also depends on the status of other incomplete tasks. As a result, for a given incomplete task combination, profits can be increased by deciding on which of the incomplete tasks to be completed by offline repair and which of them to be left incomplete, which will be referred to as *offline task selection*.

In this problem context, in a hybrid disassembly line, main decisions involve: line balance (i.e. task assignments and ordering of tasks), classification of P-tasks and F-tasks (referred to hereafter as *P/F scheme)*, base cycle time and offline task selection.

Significant effort has already been spent on deterministic line balancing problems both in assembly and disassembly. Our main motivation in this thesis is to investigate hybrid lines in terms of various performance measures, and propose a solution approach, which determines P/F scheme and base cycle time so as to maximize the expected profit. Therefore, we assume line balance to be given to rule out the effect of selection and assignment of tasks to stations, and to evaluate merely the advantages of implementing hybrid lines compared to the common remedial actions proposed in the literature. Therefore, in our problem, the number of stations, the tasks to be performed, parts to release and the assignment and ordering of tasks at stations are given. Our main focus is to operate the given line balance as a hybrid line in an efficient way by determining P/F scheme and base cycle time so as to maximize the expected profit of a product.

In Section 3.1, we formulate the problem of determining the P/F scheme of a given line balance and base cycle time is formulated as a MIP problem. In Section 3.2, we develop a method to calculate the incompletion costs in hybrid lines using the cost models by Silverman and Carter (1986) and Kottas and Lau (1976). In Section 3.3, the overall solution approach is provided; and the greedy algorithm is explained, which determines P/F scheme of a given line balance and base cycle time so as to maximize the expected profit of a product. At the end of Section 3.3, offline task selection problem is formulated as an LP.

3.1 Operating Hybrid Disassembly Lines with Stochastic Task Times

3.1.1 Assumptions

The following assumptions are made:

(1) Number of stations, task assignments and internal ordering of tasks at each station, i.e. the line balance, are given.
(2) A single type of product is disassembled and partial disassembly is allowed. Each incoming product have the same number and type of parts. There are no missing or unusable parts in any product.
(3) Supply of products is infinite.
(4) One or more parts with one or more types can be released as a result of performing a task.
(5) Part revenues are deterministic and can have positive or negative values, where negative values imply that disposal costs are incurred.
(6) Task costs are deterministic, and independent of the station in which the task is performed or whether it is performed on the line or offline. Task cost is incurred once in any of the following cases: If it is completed on the line, if it is started and completed in offline area or if it is started on the line but could not be finished and completed offline.
(7) Task times are independent Normal random variables with known means and variances.
(8) All parts released are demanded and there is no explicit cost of not satisfying a demand (other than lost profit margin).
(9) The time necessary for completing a task offline is independent of the time the task has already spent on the line. It is assumed that the task is started from scratch and performing it offline takes longer than performing it on the line.
(10) Unit station operating cost is the same for regular operation within base cycle time and for the period the line is stopped to complete F-tasks.
(11) An upper limit for expected cycle time is given.
(12) For an arriving workpiece to offline area, all incomplete tasks are not necessarily completed. Some or all of the incomplete tasks may be left incomplete as partial disassembly is allowed.

Assumptions (2)-(5) are taken from Altekin *et al.* (2008) and describe problem environment.

Assumption (6) is also included in Altekin *et al.* (2008) for deterministic case where offline repair does not take place. It is modified to take offline repair into account.

Assumption (7) reflects the stochasticity aspect of the problem. Hicks and Young (1962) show that task times in assembly can be represented as Normal random variables and this assumption is employed by several authors in the literature (Carter and Silverman 1984, Kottas and Lau, 1973, 1976, 1981, Lau and Shtub 1987, McGovern and Gupta 2006, 2007b, Sarin *et al.* 1999, Silverman and Carter 1986). The only disassembly line balancing problem with stochastic task times, Agrawal and Tiwari (2008), also employ this assumption.

By assumption (8), it assumed that there is sufficient demand for each part, hence demand considerations are held out of the scope. Note that as not satisfying a demand is not penalized, the additional time spent to catch up demand is ignored. Therefore, in some cases we may prefer to not perform some tasks.

Assumption (9) is taken from Kottas and Lau (1976) and Lau and Shtub (1987). By this assumption, it is assured that the offline cost of a task is higher than completing it on the line.

Assumption (10) implies that extending cycle time for F-tasks does not incur additional costs. It can be modified easily if a penalty rate is to be imposed on extending cycle time.

Assumption (11) is the result of the output rate target given by problem owner.

3.1.2 Problem Formulation

The notation is as follows;

i : Task index, $i = 0, 1, 2, ..., n$, A1, A2,..., D

DMY : Index set of all dummy tasks, DMY = {0, A1, A2, A3,..., D}. Task 0 is the first dummy task which AND precedes all tasks, task D is the last dummy task such that all tasks are its OR predecessors, and task Ay is the y^{th} dummy task, $y = 1, 2, \ldots$

P : The number of part types

K : The number of stations

p : Part index, $p = 1, 2, ..., P$

k : Station index, $k=1,2,\ldots,K$

A : Set of all assigned tasks

S_k Set of tasks assigned to station k

t_i Random variable denoting task time i

s_i	:	The task that is performed just prior to task *i* at the same station (when task *i* is the first task assigned, it is empty)
c_i	:	Cost of disassembly task *i*
l_c	:	Station operating cost per unit time
r_p	:	Revenue realized for fulfilling per unit demand of part *p*
CT_b	:	Base cycle time
CT_u	:	Upper limit for expected cycle time
$m_{i,p}$	:	Number of units of part *p* released by task *i*. $m_{i,p} \geq 1$ if task *i* releases part *p* for potential sale. $m_{i,p} = -1$ if part *p* is in fact a subassembly which might be further disassembled (used up) by subsequent task *i* (if part *p* is disassembled further, part *p* itself cannot generate revenue; instead, the further disassembled parts generate revenue)
PE_i	:	Set of all tasks that are performed earlier on the line than task *i*
PAND(*i*)	:	Index set of AND predecessors of task *i*
POR(*i*)	:	Index set of OR predecessors of task *i*
SOR(*i*)	:	Index set of OR successors of task *i*

Decision variables are;

$$X_i = \begin{cases} 1 & \text{if task } i \text{ is assigned as F-task, } i \in A; \\ 0 & \text{otherwise} \end{cases}$$

$G(CT_b, \overline{X})$	:	The total expected offline cost as a function of CT_b and $\overline{X}$
$f_{CT}(CT_b, \overline{X})$	:	Random variable denoting the time the line is stopped, $f_{CT}(CT_b, \overline{X}) = \max_{k=1,..,K} \left\{ 0, \sum_{i \in S_k} t_i X_i - CT_b \right\}$
$f_{ORT}(CT_b, \overline{X})$	:	Random variable denoting the offline repair time

The problem is to determine the P/F scheme for a given line balance and base cycle time so as to maximize the expected profit. Note that even if this model assumes base cycle time to be given, our overall solution approach involves solving this model for a range of base cycle times to determine base cycle time, which will be explained in Section 3.3. The mathematical model for the described problem is as follows;

$$Max\ Z=\sum_{p=1}^{P} r_p \sum_{i\in A} m_{i,p} - \sum_{i\in A} c_i - l_c\ CT_b\ K - l_c\ \mathrm{E}\left[f_{CT}(CT_b, \overline{X}) \right] K - G(CT_b, \overline{X}) \tag{3.1}$$

s.to

$$X_i \le X_j \ , \quad \forall i \in A \text{ and } j = s_i \tag{3.2}$$

$$X_i \le X_j \ , \quad \forall i, j \in A \text{ and } j \in PAND(i) \tag{3.3}$$

$$X_j \le X_i \ , \quad \forall i, j \in A \text{ and } j \in SOR(i) \tag{3.4}$$

$$X_i \le \sum_{\substack{j\in PE_i \\ j\in POR(i)}} X_j \ , \quad \forall i \in A \text{ and } POR(i) \ne \varnothing \tag{3.5}$$

$$\mathrm{E}\left[f_{CT}(CT_b, \overline{X}) \right] + CT_b \le CT_u \tag{3.6}$$

$$\mathrm{E}\left[f_{ORT}(CT_b, \overline{X}) \right] \le \mathrm{E}\left[f_{CT}(CT_b, \overline{X}) \right] + CT_b \tag{3.7}$$

$$X_i \in \{0,1\}, \quad \forall i \in A \tag{3.8}$$

The objective function (3.1) represents the expected profit gained from disassembling one discarded product. The first term in the objective function represents the total revenue generated from the parts released by the tasks. The second term is the total task cost. The third term is the station operating cost, which is the product of the number of stations, base cycle time and unit station operating cost. These three terms can be calculated directly for a given line balance and base cycle time. The fourth and fifth terms express expected line stoppage and total expected offline cost. Note that the total revenue is formulated such that all tasks are completed either on the line or by offline repair. Both of the lost revenue and cost savings due to not completing an incomplete task offline is included in the fifth term. The details of the calculation of expected line stoppage and offline cost will be discussed in Section 3.2.

Constraint set (3.2) makes sure that a task *i* which is performed after task *j* at the same station can be F-task only if task *j* is an F-task. This constraint is a direct consequence of the definitions of F-tasks and P-tasks. If a P task *j* is not completed within actual cycle time, the workpiece has to be sent to next station, which means that task *i* will not be completed. However, if task *i* is an F-task it has to be completed on the line. Hence, either task *j* (P-task) has to be completed on the line or task *i* (F-task) has to be completed offline, which is a contradiction. To avoid such a case, this constraint set is imposed. As a result, in a station, the set of F-tasks are performed earlier than the set of P-tasks as in Lau and Shtub (1987).

Similar to the case in constraint set (3.2), constraint sets (3.3)-(3.5) are included. If task *i* is an F-task and is precedence infeasible due to an incomplete P-task *j*, task *i* cannot be performed due to precedence relations. However, as in the case in constraint set (3.2), either the F-task *i* will be completed offline or P-task *j* has to be completed on the line so that task *i* will be feasible. Again, to avoid such a case, constraint sets (3.3)-(3.5) are also included when generating a P/F scheme as in Lau and Shtub (1987).

Constraint set (3.3) assures that a task *i* can be assigned as F-task only if all of its AND predecessors are assigned as F-task.

Constraint set (3.4) allows the assignment of an OR successor of task *i* as F-task only if task *i* is assigned as F-task.

Constraint set (3.5) allows the assignment of task *i* as F-task only if at least one of the OR predecessors of task *i* that is performed earlier on the line is assigned as F-task.

Constraint (3.6) assures that the expected actual cycle time is less than or equal to the upper limit for actual cycle time.

Constraint (3.7) limits expected offline repair time to the expected cycle time. Without this constraint, we observed that in some problem instances base cycle time is set so low that nearly all of the tasks are selected as P-tasks and completed by offline repair. This is not desired for the following reasons: (i) Practically no task is completed on the line and offline area is used as a job shop disassembly layout. (ii) When the expected offline repair time is higher than expected actual cycle time, workpieces will accumulate and output rate will decrease. Hence, the output rate will rely on the performance of offline area. (iii) The whole disassembly line has practically no use. To avoid such cases, the expected cycle time is set as the upper limit for expected offline repair time. In literature, constraints are imposed on total workcontents of each station so that a service level is satisfied for line operation (Ignall 1965, Moodie and Young 1965). This has a similar effect as total workcontents cannot exceed cycle time much and most of the tasks are completed on the line. As we calculate explicit cost of task incompletions and remedial actions, rather than imposing a service level at each station, we restrict the expected offline repair time so that the expected output rate is within desired range.

The calculation of incompletion costs is further complicated as: (i) The calculation of line stoppage cost involves integration of terms that include cumulative distribution functions of Normal random variables. (ii) Due to precedence relations, the probability of completing a task *i* within cycle time depends on the status of many other tasks: The tasks that share the same station with task *i* (as they all have to be completed within cycle time), the predecessors of task *i* (as its precedence relations have to be satisfied), the predecessors of tasks that share the same station with task *i* (as some tasks are not feasible, less number of tasks will share the same cycle time with task *i*). (iii) The actual cycle time is determined by the elapsed time of the last F-task completed, as a result of which more time will be available for incomplete P-tasks at other stations to be completed. To our knowledge, there is no analytical method to calculate incompletion costs in hybrid lines in the literature. For these reasons, we develop a method to calculate incompletion costs for a given line balance, P/F scheme and base cycle time.

In addition to the complications related to the calculation of objective function, Constraints (3.6) and (3.7) require the calculation of expected actual cycle time, which requires numerical integration of cumulative distribution functions of Normal random variables, which further complicates the situation. Due to the fact that we cannot express these terms as closed form functions of decision variables, we propose an approximate solution method including a greedy algorithm to determine P/F scheme and base cycle time, while offline task selection problem is solved implicitly.

3.2 Calculation of Incompletion Costs

In hybrid lines, incompletion costs involve line stoppage costs and offline costs as both remedial actions are implemented. Line stoppage costs and offline costs are calculated by the cost models in Silverman and Carter (1986) and Kottas and Lau (1976), respectively. However, it is not possible to use these methods in hybrid lines directly as in hybrid lines both type of remedial actions are implemented. Line stoppage costs are calculated by Silverman and Carter (1986) in a problem environment where each task must be finished on line. On the other hand, Kottas and Lau (1976) assume that any task will be finished offline if it is not completed within cycle time. In hybrid lines, calculation of offline cost is further complicated for two reasons: First, the cycle time is not fixed. The actual cycle time can be longer than base cycle time if there is any incomplete F-task. Second, even if P-tasks share the same station with F-tasks, they are treated differently in case of incompletion. Therefore, the probability calculations should be made with special care taking these differences into account. As a result, it is necessary to modify existing cost models to calculate incompletion costs in hybrid lines. For this reason, we combine both cost models by Silverman and Carter (1986) and Kottas and Lau (1976) to calculate line stoppage costs and offline costs.

The calculation of expected line stoppage costs and total expected offline costs, which together make up incompletion costs, are explained in Sections 3.2.1 and 3.2.2.

3.2.1 Expected Line Stoppage Costs

Line stoppage costs are incurred due to the excess amount of time the line is operated beyond base cycle time. The expected amount of time the line is stopped is multiplied by unit station operating cost and number of stations to find the expected line stoppage cost. The method by Silverman and Carter (1986) is modified so that only F-tasks are taken into account. Since by constraint set (3.2), all F-tasks are performed earlier than P-tasks, P-tasks have no effect on actual cycle time. Thus, we simply ignore P-tasks and calculate the expected amount of time the line is stopped correspondingly.

AF_k	:	Set of F-tasks assigned to station k
T_k	:	Random variable denoting the sum of task times of F-tasks at station k
w	:	Random variable denoting actual cycle time, i.e. $w = \underset{k}{Max}\{T_k\}$
$G(w)$	:	The cumulative distribution function of w
$g(w)$	:	The probability density function of w
$f_{CT}(CT_b, \overline{X})$	:	Random variable denoting the time the line is stopped.

By definition,

$$w = \max_k \{T_k\},\ k = 1,2,..,K \qquad (3.9)$$

As task times are independent, station workcontents are also independent;

$$G(w) = \prod_k F_{T_k}(w),\ k = 1,2,...,K \qquad (3.10)$$

where $T_k \sim N(m_k, s_k^2),\ F_{T_k}$:Cumulative distribution function of T_k,
$m_k = \sum_{i \in AF_k} \mu_i,\ s_k^2 = \sum_{i \in AF_k} \sigma_i^2,\ k = 1,2,...,K$

As,

$$E\left[w \mid w > CT_b\right] = \frac{\int_{CT_b}^{\infty} wg(w)dw}{[1 - G(CT_b)]} \qquad (3.11)$$

applying integration by parts,

$$E\left[w \mid w > CT_b\right] = CT_b + \int_{CT_b}^{\infty} \left[1 - G(w)\right]dw \qquad (3.12)$$

$$E\left[f_{CT}(CT_b, \overline{X})\right] = \int_{CT_b}^{\infty} [1 - G(w)]dw \qquad (3.13)$$

where $E\left[f_{CT}(CT_b, \overline{X})\right]$ is the expected time the line is stopped.

According to the formulation above, by (3.13) the expected amount of time that the line is stopped, $E\left[f_{CT}(CT_b, \overline{X})\right]$, can be found for given set of F-tasks, AF_k and base cycle time value. Expected line stoppage cost is finally calculated by replacing $E\left[f_{CT}(CT_b, \overline{X})\right]$ in the objective function. Note that as (3.13) involves the integration of cumulative distribution function of a Normal random variable, numerical integration is used, as in Silverman and Carter (1986). The numerical integration is implemented by using the trapezoid rule. The details of the implementation of the trapezoid rule is given in Appendix A.

3.2.2 Offline Costs

We adopt Kottas and Lau (1976) cost model to calculate offline costs. As they assume all tasks as P-tasks, a number of modifications are made so that the method fits to hybrid lines. In a hybrid line a task can be incomplete for two reasons: Time or precedence relations. When a workpiece arrives at a station, the tasks at that station can be precedence feasible or infeasible depending on the previous incomplete tasks. If a precedence feasible task cannot be completed within actual cycle time, the task is called time related incomplete task. Whereas, the tasks that are precedence infeasible cannot be performed as they are successors of incomplete tasks, and therefore are called precedence related incomplete tasks.

The overall procedure can be summarized as follows: The incompletion combinations (IC) are generated, offline cost and probability of occurrences of each incompletion combination are calculated and the total expected offline cost is found. The notation is as follows:

Q		The number of incompletion combinations
q	:	Index for incompletion combination, $q=1,2,...,Q$
$OC(q)$	:	Offline cost of incompletion combination q
$P(q)$	:	Probability of occurrence of the incompletion combination q
$OT(q)$	:	Offline repair time of the incompletion combination q
$IT(q)$	:	Set of incomplete tasks in incompletion combination q

3.2.2.1 Generating Incompletion Combinations

Kottas and Lau (1976) treat each task as P-task and generate incompletion combinations accordingly. However, for hybrid lines, the generation of incompletion combinations is modified so that no F-task is incomplete. Therefore, when determining the tasks that are candidate to be time related incomplete, only P-tasks are considered. Hence, N_k represents the number of precedence feasible P-tasks in station *k*. Recall that, Kottas and Lau (1976) claim that theoretically the total number of *IC*'s would be $\left[\prod_k \left(|A_k|+1\right)\right]-1$, where $|A_k|$ is the number of tasks assigned to station *k*. However, in practice the total number of *IC*'s is lower due to precedence relations. In hybrid lines, as F-tasks are completed with certainty and cannot be incomplete, the total number of *IC*'s is decreased further. An *IC* is represented by a K-tuple, $(n_1\ n_2 ...\ n_k)$, as in Kottas and Lau (1976), where n_k represents the number of time related incomplete tasks from the first station to the last. Therefore, given n_k values, the complete tasks, time related and precedence related incomplete tasks are all known.

The following algorithm is the modified version of the algorithm by Kottas and Lau (1976), which generates all *IC*'s by enumerating all n_k combinations, and calculates the probability of occurrence of each *IC*.

```
Start
WHILE n_1 ≤ N_1 DO
        Determine N_2 , set  n_2 = 0
        WHILE n_2 ≤ N_2 DO
            Determine N_3 , set  n_3 = 0
                    .
                    .
                    WHILE n_K ≤ N_K DO
                            Calculate P(n_1 n_2 n_3 ... n_k) and offline cost of the IC
                            Set n_K = n_K + 1
                    END WHILE
                    .
                    .
            Set n_2 = n_2 + 1
        END WHILE
    Set n_3 = n_3 + 1
    END WHILE
STOP
```

3.2.2.2 Calculating Offline Cost of an Incompletion Combination

Offline cost of an incompletion combination depends on offline tasks selection (i.e. which of the incomplete tasks are finished and which of them are left incomplete). As total revenue is formulated as if all assigned tasks are completed either on the line or by offline repair, offline cost of an IC includes the cost of performing offline repair and the revenue lost due to not performing the tasks at all.

The offline cost of an incomplete task that is finished by offline repair is assumed to be the mean task time of the task multiplied by unit station operating cost and the offline cost rate, $coef_o$, which is greater than 1. As additional handling is required due to moving the unit to the offline area, and the specialized equipment and personnel on the line is not available in offline area, performing a task offline takes longer time. Hence, we assume that offline repair of a task is longer in offline area while station operating cost per unit time is the same as online operation (Kottas and Lau 1973, Lau and Shtub 1987).

On the other hand, the offline cost of an incomplete task that is not completed by offline repair is the lost profits, which is equal to the task revenue minus task cost and station operating cost associated with task time. The problem of selecting which tasks to perform by offline repair and which tasks to leave as incomplete is referred to as *offline task selection*, and solved at this stage. The details of offline task selection is given in Section 3.3.3.

For a given IC, the offline costs of incomplete tasks are summed to find *OC(q)*, of an incompletion combination *q*. Similar to *OC(q)*, offline repair time of an incompletion combination q, $OT(q)$ is found by summing the mean task times of the incomplete tasks that are completed by offline repair.

3.2.2.3 Calculating the Probability of Occurrence of an IC

Let,

$P(n_1\ n_1\ ...n_k)$	:	Probability of occurrence of K-tuple
T_k	:	Random variable denoting the sum of task times of F-tasks at station k
P_k	:	Probability that there are n_k time related incomplete tasks in station k
C_k	:	The set of complete tasks in station k
I_k	:	The set of time related incomplete tasks in station k
j_k		The first task in I_k, i.e. the task which is being performed when the cycle time is exceeded
J_k	:	$C_k \cup j_k$, the set of all completed tasks and the task while which is being performed the cycle time is exceeded
t_i	:	Random variable denoting task time i, $t_i \sim N(\mu_i, \sigma_i^2)$
Z_k	:	Random variable denoting the sum of the task times of complete tasks
Y_k	:	Random variable denoting the sum of task times of the tasks in J_k

As task times are assumed to be independent Normal random variables, station workcontents are independent. Then,

$$P(n_1\ n_2\ ...\ n_K) = \prod_{k}^{K} P_k \tag{3.14}$$

Recall that to calculate P_k, there are two formulations included in Kottas and Lau (1976) depending on whether there are time related incomplete tasks in station k or not. In addition to this factor, in hybrid lines, P_k also depends on whether the last task completed is an F-task or the last task completed is P-task or there is no task completed. These two factors lead to six different cases and for each case, an expression is developed to calculate P_k .

i. Last task completed is P-task, No time related incomplete task exists

$$P_k = P(Z_k < \max_j \{CT_b, T_j \mid \forall j \neq k\}) \tag{3.15}$$

From the rules of probability, (4.8) can be written as;

$$P_k = 1 - P(Z_k > CT_b, Z_k > T_j),\ \ j = 1,2,..,K,\quad j \neq k \tag{3.16}$$

(3.16) can be formulized as

$$P_k = 1 - \int_{CT_b}^{\infty} F_{T_1}(x) F_{T_2}(x) ... f_{Z_k}(x) dx \tag{3.17}$$

where $T_k \sim N(m_k, s_k^2)$, F_{T_k}: Cumulative distribution function of T_k,

f_{Z_k} : Probability distribution function of Z_k, $m_k = \sum_{i \in AF_k} \mu_i$, $s_k^2 = \sum_{i \in AF_k} \sigma_i^2$, $k = 1, 2, ..., K$

ii. Last task completed is P-task, One or more time-related incomplete tasks exist

$$P_k = P(Z_k < \max\{CT_b, T_i \mid i \neq k\}, Y_k > \max\{CT_b, T_i \mid i \neq k\}) \tag{3.18}$$

$$\begin{aligned} P\left(Y_k > \max\left\{CT_b, T_i \mid i \neq k\right\}\right) = {} & P\left(Y_k > \max\left\{CT_b, T_i \mid i \neq k\right\} \mid Z_k > \max\left\{CT_b, T_i \mid i \neq k\right\}\right) \\ & P\left(Z_k > \max\left\{CT_b, T_i \mid i \neq k\right\}\right) \\ & + P\left(Y_k > \max\left\{CT_b, T_i \mid i \neq k\right\} \mid Z_k \leq \max\left\{CT_b, T_i \mid i \neq k\right\}\right) \\ & P\left(Z_k \leq \max\left\{CT_b, T_i \mid i \neq k\right\}\right) \end{aligned} \tag{3.19}$$

$$P\left(Y_k > \max\left\{CT_b, T_i \mid i \neq k\right\} \mid Z_k > \max\left\{CT_b, T_i \mid i \neq k\right\}\right) = 1 \tag{3.20}$$

Replacing (3.20) in (3.19), (3.18) can be written as;

$$P_k = P\left(Y_k > \max\left\{CT_b, T_i \mid i \neq k\right\}\right) - P\left(Z_k > \max\left\{CT_b, T_i \mid i \neq k\right\}\right) \tag{3.21}$$

$$P_k = P\left(Y_k > CT_b, Y_k > T_j\right) - P\left(Z_k > CT_b, Z_k > T_j\right),\ j = 1,..,K,\ j \neq k \tag{3.22}$$

$$P_k = \int_{CT_b}^{\infty} F_{T_1}(x) F_{T_2}(x) ... f_{Y_k}(x) dx - \int_{CT_b}^{\infty} F_{T_1}(x) F_{T_2}(x) ... f_{Z_k}(x) dx \tag{3.23}$$

where $T_k \sim N(m_k, s_k^2)$, F_{T_k}: Cumulative distribution function of T_k,

f_{Z_k}, f_{Y_k} : Probability distribution function of Z_k, Y_k, $m_k = \sum_{i \in AF_k} \mu_i$, $s_k^2 = \sum_{i \in AF_k} \sigma_i^2$, $k = 1, 2, ..., K$

iii. Last task completed is F-task, No time related incomplete task exists

$$P_k = 1 \tag{3.24}$$

Since F-tasks have to be finished and there are no more tasks to be considered.

iv. Last task completed is F-task, One or more time related incomplete tasks exist

$$P_k = P(Y_k > \max\{CT_b, T_i \mid i \neq k\}) \tag{3.25}$$

$$P_k = P(Y_k > CT_b, Y_k > T_i \mid i \neq k) \tag{3.26}$$

$$P_k = \int_{CT_b}^{\infty} F_{T_1}(x)F_{T_2}(x)..f_{Y_k}(x)dx \tag{3.27}$$

where $T_k \sim N(m_k, s_k^2)$, F_{T_k}: Cumulative distribution function of T_k,
f_{Y_k} : Probability distribution function of Y_k, $m_k = \sum_{i \in AF_k} \mu_i$, $s_k^2 = \sum_{i \in AF_k} \sigma_i^2$, $k = 1,2,...,K$

v. ***No complete task, One or more time related incomplete task exist***

$$P_k = P(Y_k > \max\{CT_b, T_i \mid i \neq k\}) \tag{3.28}$$

$$P_k = P(Y_k > CT_b, Y_k > T_i \mid i \neq k) \tag{3.29}$$

$$P_k = \int_{CT_b}^{\infty} F_{T_1}(x)F_{T_2}(x)..f_{Y_k}(x)dx \tag{3.30}$$

where $T_k \sim N(m_k, s_k^2)$, F_{T_k}: Cumulative distribution function of T_k,
f_{Y_k} : Probability distribution function of Y_k, $m_k = \sum_{i \in AF_k} \mu_i$, $s_k^2 = \sum_{i \in AF_k} \sigma_i^2$, $k = 1,2,...,K$

vi. ***No complete task, No time related incomplete task exists***

$$P_k = 1 \tag{3.31}$$

Since there are no precedence feasible tasks.

3.2.2.4 Evaluation of Total Expected Offline Cost

Up to this stage, all *IC*'s are listed, their corresponding probability of occurrences and offline costs are calculated. The expected offline cost of an *IC* is found by multiplying the probability of occurrence and the offline cost, $OC(q)$. Then, expected offline costs of all of the *IC*'s are summed to find the total expected offline cost, $G(CT_b, \overline{X})$. Expected offline repair time, $\mathrm{E}\left[f_{ORT}(CT_b, \overline{X}) \right]$ is also calculated at this stage by multiplying probability of occurrences of each *IC* with offline repair time $OC(q)$ and summing all.

$$G(CT_b, \overline{X}) = \sum_q P(q)OC(q) \tag{3.32}$$

$$\mathrm{E}\left[f_{ORT}(CT_b, \overline{X}) \right] = \sum_q P(q)OT(q) \tag{3.33}$$

3.3 Solution Approach

We propose a greedy algorithm, which determines P/F scheme for a given base cycle time to maximize expected profit. Our main motivation in developing greedy algorithm is that we want to give an approximate method as a starting step other than complete enumeration, which may perform well in terms of both solution quality and computational time. The greedy algorithm is run for a range of base cycle time values so that the P/F scheme and base cycle time combination which maximizes the expected profit is found. The offline task selection problem is solved implicitly within greedy algorithm, whenever the expected profit for a given P/F scheme and base cycle time is calculated. The overall solution approach is illustrated in Figure 3.1.

3.3.1 Determination of Base Cycle Time Range

The greedy algorithm is run for the integer values within a range of base cycle time values determined for a given line balance. The upper limit for base cycle time, U_{CT_b}, is set to the upper limit for actual cycle time, CT_u, since if the base cycle time value is higher than, CT_u, each cycle time exceeds CT_u. The determination of lower limit, L_{CT_b}, depends on the task assignments and is found as follows: For each station, the CT_b values, for which the probability that the total task time in the station exceeds base cycle time is equal to 0.1, is calculated. L_{CT_b} is then set as the integer value of the following expression;

$$L_{CT_b} = \min_{k=1,..,K} \mathrm{c_k} : \left\{ c_k \middle| \mathrm{P}\left(\sum_{\forall A_i} t_i > c_k \right) = 0.1 \right\}, \qquad (3.34)$$

where A_i : set of all tasks assigned to station i

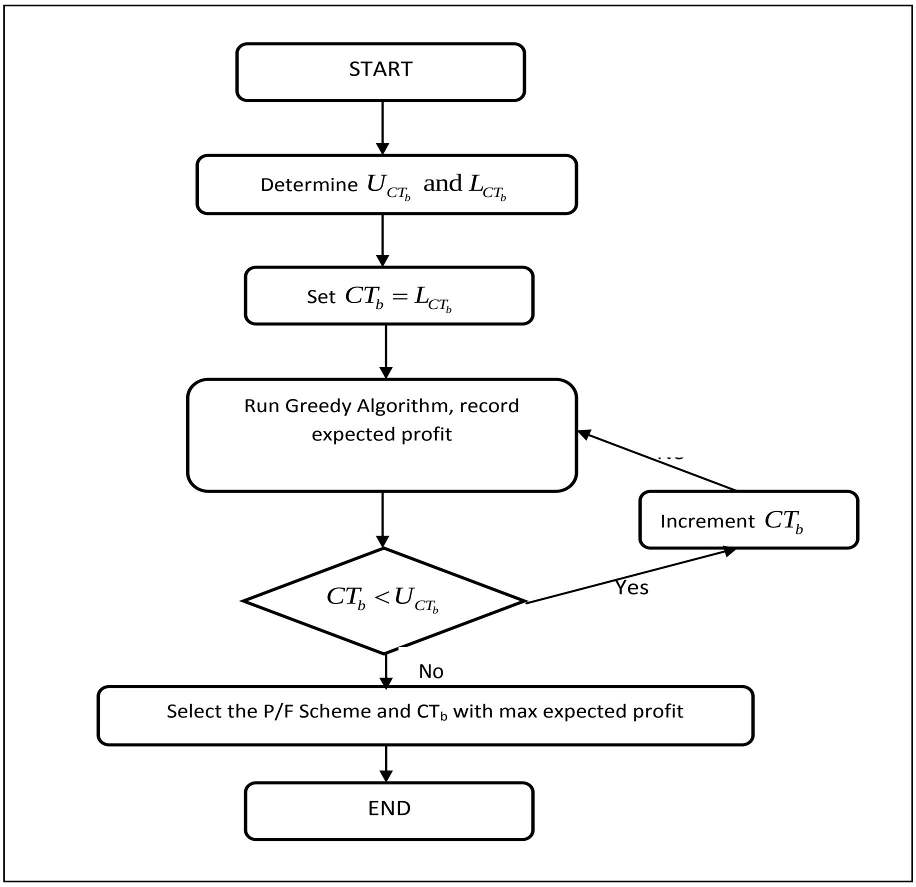

Figure 3-1 Overall Solution Approach

3.3.2 Greedy Algorithm

The greedy algorithm involves two phases: Forward and backward phase. In forward phase, profit improvements are sought by labeling F-tasks as P-tasks temporarily, while in backward phase, profit improvements are sought by labeling P-tasks as F-tasks. After the backward phase is run, the final P/F scheme is reached.

3.3.2.1 Forward Phase

Initially, all tasks are marked as F-task and the associated expected profit is recorded as the initial best known objective function value. In the beginning a candidate list (CL) is formed by the F-tasks. At each iteration, an F-task is picked from CL and marked as P-task temporarily to calculate profit improvements compared to the best known objective function value. To satisfy constraints (3.2)-(3.5) explained in Section 3.1.2, the successors of the candidate task and the F-tasks that are performed later than the candidate task in the same station are marked as P-task, temporarily. The profit improvement of the candidate task is recorded and temporary P-tasks are marked as F-tasks again. The profit improvements of each and every task is recorded in this manner and the one with the maximum profit improvement is marked as P-task permanently and best known objection function value is updated. After a candidate task is marked as P-task permanently, to satisfy constraints (3.2)-(3.5) the necessary changes are made and the procedure is repeated until there is no nonnegative improvement in expected profit.

In forward phase, constraint (3.6), which implies that expected actual cycle time has to be less than upper limit, and constraint (3.7), which imposes expected offline repair time to be less than the expected actual cycle time, are ignored. Therefore, we allow infeasibility at each iteration. These constraints are taken into account in backward phase; hence, feasibility is provided at the end of the run.

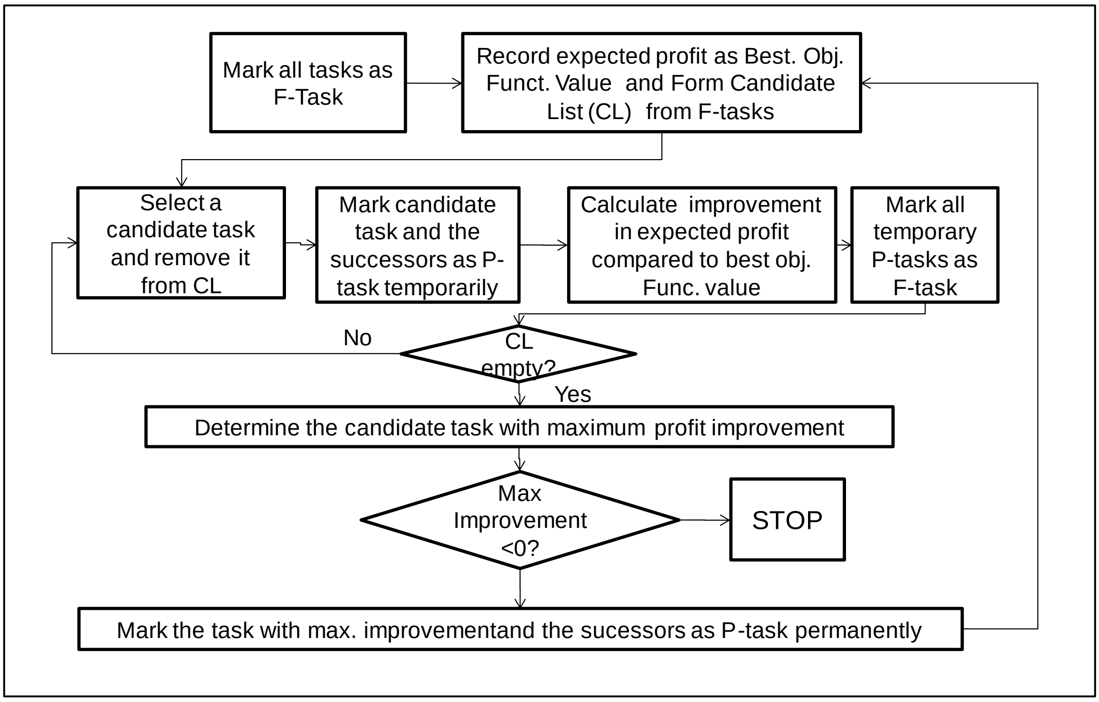

Figure 3-2 Greedy Algorithm (Forward Phase)

3.3.2.2 Backward Phase

In backward phase, the P/F scheme from the forward phase is kept and the P-tasks in that solution form the candidate task set. This time, candidate P-tasks are marked as F-tasks temporarily, and the predecessors of the candidate task and the P-tasks that are performed earlier than the candidate task in the same station are temporarily made F-task to obey constraints (3.2)-(3.5). Different from forward phase, in backward phase, constraints (3.6) and (3.7) are taken into account, and a solution, which violates any of these two constraints, is considered as invalid and ignored. If the initial solution that comes from forward phase is invalid, the P/F scheme is kept as the initial P/F scheme but the best known objective function value is set to a small number. Therefore, it is aimed that the solution at the end of the backward phase obeys all of the constraints in Section 3.2.2. At each iteration, the profit improvements of valid solutions are recorded, the candidate P-task with maximum nonnegative profit improvement is marked as F-task and the best known objective function value is updated. The algorithm ends when there is no candidate task with nonnegative profit improvement. See Figure 3.3. for the steps of backward phase.

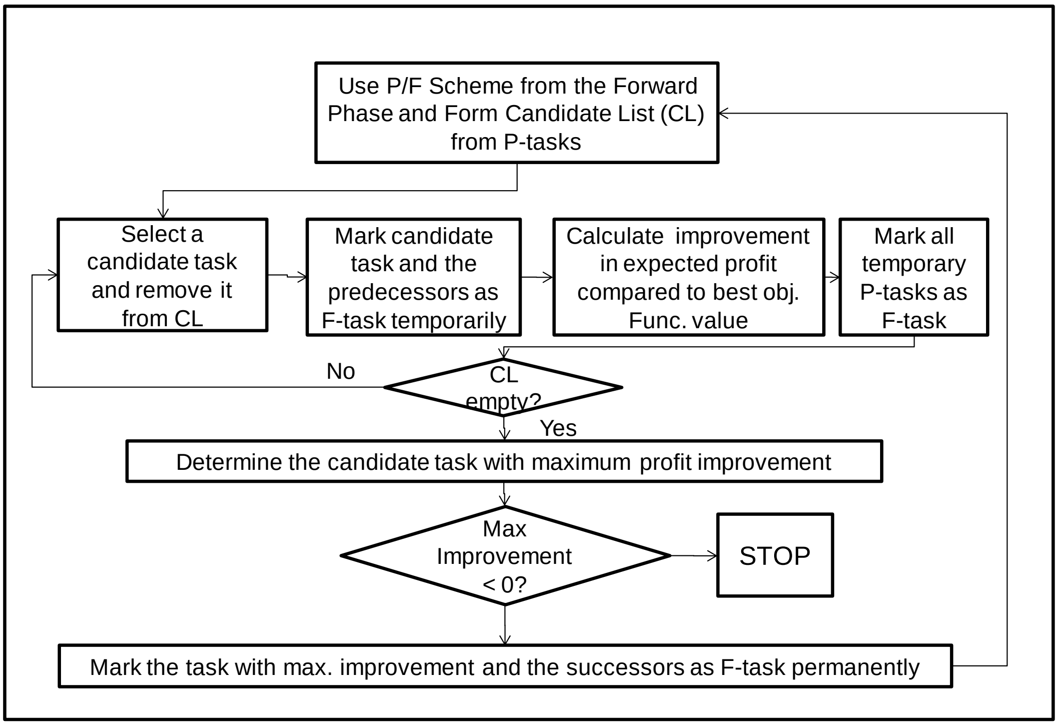

Figure 3-3 Greedy Algorithm (Backward Phase)

3.3.3 Offline Task Selection Problem

A workpiece comes to the offline area with a number of incomplete tasks. In some cases, it is possible that the completion of the task is too costly as total revenue generated by the parts released by the task is less than offline cost of the task. In those cases, not completing the task may be more profitable. Recalling that we assume partial disassembly, the incomplete tasks will not necessarily be completed by offline repair for each incompletion combination. Therefore, a task may be completed by offline repair in an incompletion combination while the same task is left incomplete in another.

For a given incompletion combination, the problem is to determine which of the incomplete tasks to be finished offline. The problem can be formulated as follows:

Decision variables are;

X_i : The decision variable denoting the incomplete task i is completed by offline repair, where $i \in IT(q)$ which is the set of all incomplete tasks in incompletion combination q

Note that X_i is not defined as a binary variable for the following reason: Lambert (1999) propose a mathematical model that determines which disassembly actions (tasks) to be performed to maximize net revenue. They define a decision variable for each action representing whether the action is performed or not, as a continuous variable, which takes values between 0 and 1. They state that as the calculation always results in a solution with all decision variables 0 or 1, defining them as continuous variables rather than binary variables is more computationally efficient. Therefore, we also define the decision variables as continuous variables.

$$Max\ Z = \sum_{i \in IT(q)} X_i \left[\left(\sum_{p=1}^{P} r_p\ m_{i,p} \right) - t_i l_c coef_o - c_i \right] \tag{3.35}$$

s.to

$$X_i \le X_j\ , \quad \forall i, j \in IT(q) \text{ and } j \in PAND(i) \tag{3.36}$$

$$X_j \le X_i\ , \quad \forall i, j \in IT(q) \text{ and } j \in SOR(i) \tag{3.37}$$

$$X_i \le \sum_{\substack{j \in IT(q) \\ j \in POR(i)}} X_j + \sum_{\substack{j \in A - IT(q) \\ j \in POR(i)}} 1\ , \quad \forall i \in IT(q) \text{ and } POR(i) \ne \varnothing \tag{3.38}$$

$$X_i \le 1\ , \quad \forall i \in IT(q) \tag{3.39}$$

$$X_i \ge 0\ , \quad \forall i \in IT(q) \tag{3.40}$$

The objective function maximizes the profit generated by offline repair of a given incompletion combination. The first term in the inner parenthesis is the revenue generated by completing the task. The second term is the labor cost of performing the task offline and the last term is the task cost.

Constraint sets (3.36)-(3.38) impose precedence constraints.

Constraint set (3.36) assures that a task *i* can be completed by offline repair if all of its incomplete AND predecessors are completed offline

Constraint set (3.37) allows the completion of an OR successor of task *i* only if task *i* is completed by offline repair. Note that the fact that at most one OR successor of a task can be performed is not considered in this model. The reason is that as the tasks which belong to , the set of all incomplete tasks, already obeys this rule as the given line balance already satisfies this constraint.

Constraint set (3.38) implies that task *i* can be completed by offline repair only if at least one of the OR predecessors of task *i* is completed either on the line or by offline repair.

Constraint set (3.39) and (3.40) are imposed to be able to model the problem as an LP instead of MIP for computational time concerns. However, as decision variables have to be either 0 or 1, these constraint sets are necessary.

Recall that when calculating the expected profit of a given line balance, P/F scheme and base cycle time, all incompletion combinations are generated and their offline costs are evaluated. When the probability of occurrence of an IC is calculated, the above model is solved to determine the tasks that will receive offline repair and the tasks that will be left incomplete. Having determined the incomplete tasks to be completed by offline repair, offline cost of an incompletion combination can be found as explained in Section 3.2.2 (II). The offline cost of an *IC* is multiplied by its probability of occurrence to calculate the total expected offline cost. As a result, offline task selection problem is solved simultaneously when the offline cost of an incompletion combination is calculated.

CHAPTER 4

COMPUTATIONAL STUDY

The objectives of the computational study are to; (i) Evaluate the performance of our solution approach in finding the best P/F scheme (ii) assess the significance of incompletion costs and the impact of stochastic task times in expected profit (iii) evaluate improvements in expected profit by hybrid lines compared to the two common remedial actions: stopping the line or offline repair (iv) discuss the effect of base cycle time and task time variability on performance measures. To our knowledge, Agrawal and Tiwari (2008) are the only authors to discuss DLBP with stochastic task times, in which neither cost nor profit is calculated explicitly. Lau and Shtub (1987) is the only study that implements hybrid lines, in which only one instance of a given line balance is solved in assembly. Therefore, there is no benchmark study for profit oriented stochastic DLBP in hybrid lines to compare our results and evaluate our solution approach. For this reason, we compare our results with complete enumeration and with those of common remedial actions, which represent either stopping the line or offline repair for each and every incomplete task. For each problem instance, these solution approaches are evaluated in terms of expected profit, expected cycle time and cycle time variance. In addition to the expected profit, the other two terms are also considered as performance measures since they have significant effect on the expected output rate and its variability.

1. ***Greedy Solution:*** Greedy solution refers to the solution found by the proposed greedy algorithm. Note that the greedy algorithm is run for a range of base cycle time values; hence given the line balance, for each base cycle time value, there is an associated P/F scheme determined by the greedy algorithm. Among these P/F scheme-base cycle time combinations, the one with the maximum expected profit is chosen. Therefore, a greedy solution refers to the P/F scheme and base cycle time value , CT_b , which maximizes the expected profit of a given instance.
2. ***Best P/F Scheme:*** Lau and Shtub (1987) determine P/F scheme of a given line balance by generating all feasible P/F schemes. Similarly, for a given line balance, we generate all feasible P/F schemes and select the P/F scheme and base cycle time value with the maximum expected profit and refer to this solution as best P/F scheme solution.

3. ***F-Solution:*** Here, all tasks are F-tasks as in Silverman and Carter (1986). Therefore in practice there is no need to determine the P/F scheme, the problem is to determine CT_b. For this reason, the expected profits are recorded for each integer CT_b and the one maximizing the expected profit is selected. Note that F-solution corresponds to stopping the line for any task incompletion.
4. ***P-Solution:*** Similar to F-solution, P-solution is the solution with maximum expected profit where all tasks are P-tasks and all incomplete tasks are completed offline as in Kottas and Lau (1976). As in F-solution , the only problem is to determine CT_b. Hence, expected profits are recorded for each CT_b, and the one that maximizes the expected profit is selected.

Note that offline task selection problem is solved implicitly for Greedy solution, Best P/F Scheme solution and P-Solution. Offline repair is not available in F-solution as all tasks are F-tasks.

It should be noted that our main focus is to determine P/F scheme and base cycle time to operate the given line balance so as to maximize expected profit. In neither of the solution approaches, "do nothing" option is not considered when negative expected profits are observed.

Computational study is conducted on five precedence diagrams, four of which are adopted from Altekin *et al.* (2008). The last problem is the cell phone example in Lambert and Gupta (2005). As in Altekin *et al.* (2008), the precedence diagrams are named using the name of the author, the number of actual tasks and number of type of parts. For instance, LAM30T10 represents the radio example in Lambert (1999) with 30 tasks and 10 parts. The key features of the problems are summarized in Table 4.1.

Table 4-1 Key features of the precedence diagrams

Precedence Diagram	Actual Tasks	Total Tasks	Total Parts	# of AND prec.	# of OR prec.	# of OR succ.
GUN8T8	8	8	8	10	2	0
AKO29T4-A	20	22	4	15	6	1
LAM20T10	20	25	10	5	8	5
LAM30T10	30	49	10	16	11	10
LAM25T25	25	27	25	45	0	0

Altekin *et al.* (2008) generate ten problem datasets for each precedence diagram, which are identical in terms of number and type of parts released by each task, and differ in terms of task costs, task times and part revenues. The generation of these datasets is as follows: Task times are generated from discrete uniform distribution between one and twenty. Task costs are generated from discrete uniform distribution between one and twice of the total mean task time. Total part revenues are assumed to be equal to the sum of task costs and station operating costs considering task times. Part revenues are generated from discrete uniform distribution taking into the mean and the variance of task costs into account. For each part, a probability of having a negative revenue value is set to 5%.

For the first four precedence diagrams, we use the same problem datasets as Altekin *et al.* (2008). However, as they assume deterministic task times, original task times are used as mean task times in our study. Since such datasets are not available for cell phone example of Lambert and Gupta (2005), we first create an initial dataset and generate 10 datasets from this initial dataset. Lambert and Gupta (2005) assumes that the profit generated from a task *k* depends on the previous task performed before task *k* on the precedence diagram, and define $\pi_{j,k}$ as the profit generated by task *k* if it is performed after task *j* on the precedence diagram. However, in our problem context, each task releases a fixed number of parts of known types independent of the task sequence and generates a fixed revenue. Hence, for the initial dataset, we assigned a fixed revenue for each task *k*, which is equal to the average of all positive $\pi_{j,k}$ values over all *j*. For convenience, we assume that each task releases a unique part with a revenue equal to this assigned value. As Lambert and Gupta (2005) only include task profits, task costs are assumed to be equal to task times and task times are used as mean task times for the initial dataset. From this initial dataset, we generate ten datasets by the same method in Altekin *et al.* (2008) explained above. The problem datasets and precedence diagrams are given in Appendix B.

The standard deviations of task times are generated by controlling the coefficient of variations of task times (CoV), where CoV is expressed as the ratio of standard deviation to the mean. For each precedence diagram and problem dataset, standard deviations of the tasks are determined by four CoV settings: Two include identical CoV values while the other two include non-identical CoV values across tasks. For each identical and non-identical CoV settings, two sets are generated for low variation and high variation cases. As a result, four CoV settings are generated for each precedence diagram and problem dataset: Identical low, non-identical low, identical high and non-identical high CoV settings. Identical CoV values are taken as 0.15 for low variation and 0.45 for high variation cases, respectively. Non-identical CoV's are created by taking random values from uniform distribution for the range [0; 0.3] for low variation, and [0.3; 0.6] for high variation case so that their means are equal to identical CoV values (See Table 4.2). The upper bound for CoV values is set to 0.6 to set the maximum probability of a negative task time at 5%. Finally, an instance refers to a given line balance of a precedence diagram, a dataset involving task costs, mean task times, part revenues and a CoV setting, making it 200 instances in total. For each instance, the station operating cost is assumed to be unity. However, when we solve the deterministic problem of LAM25T25, we observe that at most a few tasks are assigned due to low profit values. Therefore, for only LAM25T25, we use station operating cost as the half and task revenues as the double of their original values. Also note that we use the same offline cost rate as Kottas and Lau (1976) which is 1.4, implying that performing a task offline is 40% more costly.

Table 4-2 CoV Settings for each precedence diagram and dataset

	Low variation	High variation
Identical	0.15	0.45
Non Identical	U[0;0.3]	Uniform[0.3;0.6]

Implementation of the Proposed Algorithm

Our solution approach assumes line balances to be given. While conducting computational study, for each precedence diagram and problem dataset, we generate line balances using the method described in Altekin *et al.* (2008): For a given cycle time, the mathematical model of profit oriented deterministic DLBP is formulated as MIP. For a given cycle time, the linear relaxation of the model is strengthened by two constraint sets and solved to determine initial candidate tasks to be assigned. After candidate tasks are determined, these tasks are assigned to stations by Ranked Positional Weight (RPW) method. After an initial line balance is generated, two improvement heuristics "Task Deletion" and "Task Insertion" heuristics are applied. In task deletion heuristic, initially a deletion list (DL) is formed by the tasks having partial assignment values. In first trial, while DL is not empty, tasks are selected in forward breadth-first search order starting from Task 0. The selected task is deleted from selected task list and the RPW method is implemented. If the profit of the new solution is higher than that of the incumbent solution, the task is deleted from the selected task list; otherwise it is put back on the selected task list. In second trial, all procedure is the same as first trial except that the tasks are selected from DL, in backward breadth-first search order. The best solutions of both trials are compared and the one with higher profit is selected.

Overall procedure in task insertion is similar to task deletion. This time an insertion list, IL, is formed from the tasks that are not selected. In first and second trials, while IL is not empty, the tasks are selected and added to selected task list in forward breadth-first search order and backward breadth-first search order, respectively. As in task deletion, both trials are compared and the best solution is the final solution. As a result of task insertion and task deletion heuristics, a solution is found for deterministic DLBP problem for a given cycle time.

We adopted the procedure in Altekin *et al.* (2008) described above when generating line balances of a given precedence diagram an problem dataset: For a given instance, a range of cycle time is defined where the lower limit is the lowest task time of the tasks with no predecessors and the upper limit is the given upper limit value specified by the decision maker due to the output rate target. For each cycle time value, the deterministic problem is solved for five RPW criteria defined in Altekin *et al.* (2008) with the method explained above. Among these five line balances, the best line balance is selected primarily by "profit" and then by the "measure of balance" defined by McGovern and Gupta (2003), which is defined as the sum squares of the difference between cycle time and station workcontent. Hence, for a given cycle time the line balance is selected. This procedure is repeated for each integer cycle time value between the lower and upper limits defined for each precedence diagram and dataset. Note that the given upper limits for cycle times are taken from Altekin *et al.* (2008) for each corresponding precedence diagram and problem dataset. The same limits are used as the upper limits for expected cycle time when applying our greedy algorithm. For LAM25T25 the upper cycle time limit is taken as 50. The overall solution approach is coded and run on Visual Studio 2010. CPLEX 12.0 is called from C to solve LP relaxation of the deterministic problem to generate line balance and to solve offline task selection problem.

The rest of the chapter is organized as follows: In Section 4.1, the significance of incompletion costs and the effect of the variability in task times on incompletion costs are discussed. The findings related with the improvements in expected profit by hybrid lines are given in Section 4.2. Performance of the greedy algorithm is evaluated and four solution approaches are compared in terms of expected profit per product, expected profit per unit time, expected cycle time and cycle time variance in Section 4.3.

4.1 Significance of Incompletion Costs

In a problem environment with deterministic task times, incompletion costs are ignored, although they have an effect on the performance of line balance in real life. Therefore, we compare total task cost and station operating costs with expected incompletion costs to show that incompletion costs constitute a significant portion of the total costs.

Our findings show that the magnitude of incompletion costs depends on the variability in task times. We see that compared to low variation, in high variation cases, probability of task incompletions increases, and hence incompletion costs increase. Table 4.3 illustrates the average of percentages of expected incompletion costs, station operating costs and total task costs within the total cost of each solution approach for each precedence diagram and CoV setting. Note that each value represents the average percentage values over all problem datasets for a given precedence diagram and CoV setting.

Table 4-3 Average of percentage values of cost terms in total cost for each solution approach

PROBLEM	CoV Setting	Average % Total Expected Incompletion Cost			Average % Station Operating Cost			Average % Total Task Cost		
		Best P/F Solution	F-solution	P-solution	Best P/F Solution	F-solution	P-solution	Best P/F Solution	F-solution	P-solution
AKO20T4-A	Identical Low	15.13%	15.17%	3.14%	39.31%	39.29%	54.52%	45.57%	45.54%	42.34%
	Identical High	31.94%	34.08%	8.73%	26.01%	24.48%	53.47%	42.05%	41.45%	37.80%
	Nonidentical low	17.24%	16.48%	3.93%	37.45%	38.52%	54.16%	45.31%	45.00%	41.91%
	Nonidentical high	32.14%	34.43%	8.67%	25.67%	23.99%	53.25%	42.19%	41.58%	38.08%
GUN8T8	Identical Low	10.37%	10.41%	3.02%	36.92%	36.90%	48.29%	52.71%	52.69%	48.69%
	Identical High	25.65%	25.71%	11.96%	22.25%	22.23%	42.71%	52.10%	52.06%	45.33%
	Nonidentical low	14.78%	14.84%	5.55%	32.59%	32.57%	47.01%	52.62%	52.60%	47.44%
	Nonidentical high	20.24%	20.29%	7.86%	27.50%	27.48%	45.95%	52.26%	52.23%	46.19%
LAM20T10	Identical Low	11.68%	12.05%	2.87%	37.32%	36.21%	49.24%	51.00%	51.74%	47.89%
	Identical High	27.15%	27.59%	9.74%	24.45%	23.47%	46.36%	48.39%	48.94%	43.90%
	Nonidentical low	12.80%	12.43%	4.08%	36.31%	35.86%	48.37%	50.89%	51.71%	47.55%
	Nonidentical high	28.39%	28.72%	10.69%	23.37%	22.54%	45.58%	48.23%	48.74%	43.73%
LAM30T10	Identical Low	15.25%	15.31%	3.54%	37.21%	37.18%	52.65%	47.54%	47.51%	43.81%
	Identical High	29.97%	30.76%	9.66%	24.71%	23.47%	50.68%	45.32%	45.78%	39.66%
	Nonidentical low	16.81%	16.87%	5.30%	35.92%	35.89%	51.60%	47.27%	47.24%	43.09%
	Nonidentical high	30.05%	31.18%	10.25%	24.65%	23.08%	50.02%	45.30%	45.74%	39.74%
LAM25T25	Identical Low	20.59%	20.63%	1.54%	19.23%	19.22%	41.64%	60.19%	60.15%	56.82%
	Identical High	37.01%	37.30%	4.61%	8.70%	8.65%	46.22%	54.30%	54.04%	49.17%
	Nonidentical low	19.83%	21.03%	2.81%	20.68%	19.54%	41.95%	59.49%	59.44%	55.24%
	Nonidentical high	34.47%	36.00%	4.44%	9.96%	9.42%	44.60%	55.57%	54.59%	50.96%

Similar to Table 4.3, Table 4.4 shows the average of percentages of the same cost terms for each CoV setting over all precedence diagrams.

Table 4-4 Average of percentage values of cost terms in total cost for three solution approaches

CoV Setting	Average of % Total Expected Incompletion Cost			Average of % Station Operating Cost			Average of % Total Task Cost		
	Best P/F Solution	F-solution	P-solution	Best P/F Solution	F-solution	P-solution	Best P/F Solution	F-solution	P-solution
Identical Low	14.31%	14.48%	2.89%	34.90%	34.61%	49.68%	50.80%	50.92%	47.42%
Identical High	30.01%	30.80%	9.17%	22.02%	21.01%	47.99%	47.97%	48.19%	42.84%
Nonidentical low	16.25%	16.24%	4.35%	32.84%	32.84%	48.68%	50.91%	50.92%	46.97%
Nonidentical high	28.89%	29.99%	8.65%	22.92%	21.57%	48.02%	48.19%	48.44%	43.33%

Table 4.3 and Table 4.4 show that incompletion costs constitute a significant portion of total task costs in Best P/F Scheme and F-solutions, especially in high variation settings. For P-solutions, the share of incompletion costs within total costs are relatively lower due to the following: In P-solutions, the base cycle time is set considerably higher than the maximum total mean workcontent of stations and idle times are increased so as to limit the probability of task incompletions and to avoid high offline costs. Therefore, station operating costs can also be considered to involve the costs related to task incompletions. As a result, for P-solutions, station operating costs and task costs comprise the most of the total costs. In low variation cases, although incompletion costs are less effective, they still form a significant portion of total revenue for Best P/F scheme and F-solutions. The average percentage value

of incompletion costs in total cost is around 15% for Best P/F Scheme and F-solutions, and around 30% for high variation cases. In P-solutions the average of percentage values of incompletion costs are as low as 2.8% for low variation case and 8% for high variation case.

The effect of CoV settings on incompletion costs are mostly related to the magnitude of variation, rather than whether the CoV's are identical across the tasks or not. Figure 4.1, shows total expected incompletion costs of Best P/F scheme solutions for each instance of LAM30T10 with respect to the setting on CoV. We can observe that there is a significant gap between high variation and low variation cases, while we cannot observe such a pattern between identical and non-identical CoV settings.

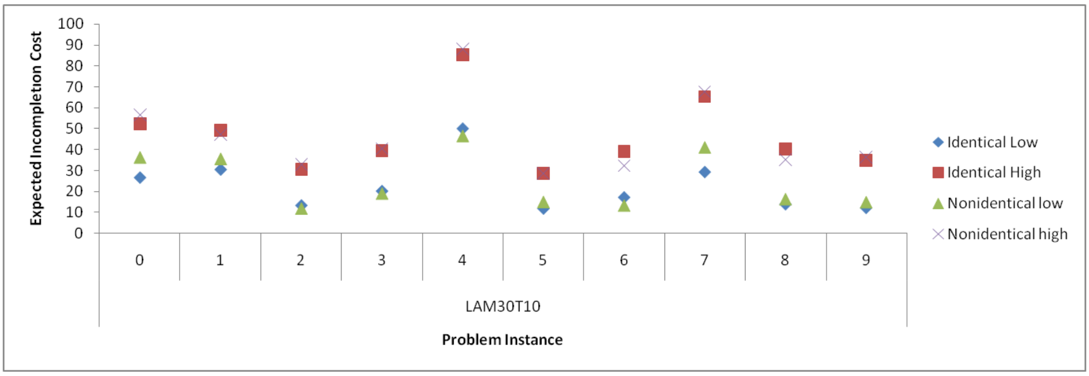

Figure 4-1 Total expected incompletion costs of Best P/F scheme solutions for each of ten instances of LAM30T10 and CoV dataset.

4.2 Improvements in Expected Profit by Hybrid Lines

Lau and Shtub (1987) show that it is possible to improve the total cost of disassembling a product by implementing hybrid lines compared to the case where all incomplete tasks are completed by offline repair on one example line balance. Similarly, according to the results of 200 instances, we also observe that the expected profit of a given line balance can be increased by hybrid lines depending on the CoV setting. Table 4.5 shows the average of expected profits and improvements over all ten problem datasets for the given precedence graphs and CoV setting. A single improvement in expected profit of two solution approaches is formulated as follows:

$$\%\ improvement = \frac{E[\text{Profit}]_F - E[\text{Profit}]_L}{E[\text{Profit}]_L} x100$$

where $E[\text{Profit}]_F$ and $E[\text{Profit}]_L$ are the expected profits of the former and the latter solution approaches, respectively.

The three solution approaches, F-solution, P-solution and Best P/F scheme solution are compared in terms of expected profit. The last three columns show the averages of percentage improvements of pair wise comparisons of three solution types, where a single improvement value refers to the difference of the expected profits divided by the absolute value of expected profit of the latter solution approach. Note that in some of the instances, there may be no valid F-solutions, P-Solutions or Best P/F scheme solutions due to the constraints imposed on expected offline repair time and expected actual cycle time. According to our results, out of 200 instances, no valid solution is found for 9, 14, and 7 instances for P-solution, F-solution and greedy solution, respectively. Such solutions are not considered when making pairwise comparisons. Also note that the expected profit may be negative due to the high costs and low part revenues as "do nothing" is not an option.

Table 4-5 Average of expected profits and pairwise improvements

Problem	CoV Setting	Average Expected Profits			Average % Improvements in Pairwise Comparisons		
		F-Solution	P-Solution	Best P/F Scheme	Best P/F vs F	Best P/F vs P	F vs P
AKO20T4-A	Identical Low	153.53	150.37	153.66	0.09%	11.25%	11.14%
	Identical High	146.24	123.99	149.19	2.52%	31.01%	27.57%
	Nonidentical Low	162.93	148.59	152.66	0.23%	12.30%	12.04%
	Nonidentical High	147.68	127.65	150.68	2.60%	27.08%	23.62%
GUN8T8	Identical Low	12.99	9.36	13.06	1.18%	57.82%	56.58%
	Identical High	11.18	4.26	11.33	1.68%	76.55%	76.07%
	Nonidentical Low	12.86	8.22	12.96	1.91%	62.98%	61.72%
	Nonidentical High	11.65	5.47	11.78	2.69%	62.56%	62.05%
LAM20T10	Identical Low	229.52	217.92	228.76	0.05%	5.38%	5.00%
	Identical High	219.35	201.12	219.27	0.43%	9.96%	9.78%
	Nonidentical Low	229.26	216.41	228.28	0.01%	6.09%	5.83%
	Nonidentical High	218.69	200.38	218.77	0.51%	10.22%	10.01%
LAM25T25	Identical Low	201.32	181.20	201.48	0.07%	13.07%	12.99%
	Identical High	161.17	123.72	162.77	1.11%	54.37%	52.19%
	Nonidentical Low	200.40	173.67	200.80	0.14%	18.23%	18.07%
	Nonidentical High	160.00	129.07	161.85	1.08%	47.56%	45.86%
LAM30T10	Identical Low	354.80	342.15	354.88	0.03%	4.16%	4.14%
	Identical High	347.13	325.19	347.47	0.28%	7.79%	7.38%
	Nonidentical Low	353.96	339.47	354.04	0.03%	4.74%	4.71%
	Nonidentical High	347.12	325.82	347.51	0.27%	7.46%	7.04%

As expected, the Best P/F Scheme solution is at least as good as F-solution and P-solution since F-solutions and P-solutions are also generated when finding the Best P/F Scheme solution. Note that in Table 4.5, for some of the values (Ex: LAM20T10, identical low), the reverse is observed, i.e. average of F-solutions are higher than that of Best P/F scheme solutions. The reason for this situation is that the averages are taken for different number and type of instances. Hence, even if each and every Best P/F scheme solution is at least as good as F-solutions for the same instance, the average of F-solutions might be higher. Best P/F Scheme solutions offer improvements in expected profit over P-solutions as much as 76%, while the improvements over F-solutions is 2.69% at maximum. We observe that in most of the instances, F-solutions yield better expected profit values than P-solutions. Maximum of average improvements by F-solutions over P-solutions is 62% for high variability and 61% for low variability. As seen in Table 4.3, CoV setting has a significant effect on the amount of expected incompletion costs, which affect the percentage of improvements. Table 4.5 shows that average percentage improvements for high variability cases are higher than low variability cases for all precedence diagrams.

For the same precedence graph, improvement values may differ for each instance as each may involve different number of stations, total revenue, total task cost and base cycle time. Table 4.6 shows the individual improvement values for different instances of AKO20T4-A in identical high CoV setting. In Table 4.6, we observe that the improvement by Best P/F scheme compared to P-solution is 89.65% for the fourth instance, while this value is 7.8% for the sixth instance. If we look at the Best P/F scheme vs F comparison, we see that the improvements are highest for fifth instance with 7%, while it is as low as 0.39% for the third instance. Note that the row for seventh instance is blank, as there is no F-solution or P-solutions for all base cycle time values due to the constraints on expected cycle time and expected offline repair time.

Table 4-6 % Improvement values for different instances of AKO20T4-A for identical high CoV setting

Instance	# of Stations	% Improvements		
		Best P/F vs F	Best P/F vs P	F vs P
0	**4**	0.84%	20.75%	19.75%
1	**2**	0.48%	9.78%	9.26%
2	**2**	0.80%	27.95%	26.93%
3	**3**	0.39%	27.28%	26.79%
4	**4**	6.21%	89.65%	78.57%
5	**3**	7.01%	25.76%	17.52%
6	**3**	1.63%	7.80%	6.07%
7	**3**			
8	**3**	3.06%	13.54%	10.18%
9	**6**	2.31%	56.57%	53.04%

The Effect of Offline Repair Time Constraint on Expected Profits

In our model, we include constraint (3.7), which assures that the expected offline repair time is less than or equal to the expected cycle time. The main reason to include this constraint is to avoid the cases where (i) Base cycle time is set very low and nearly all of the tasks are completed by offline repair, and offline area operates like a job shop layout (ii) Workpieces accumulate in offline area as output rate will be limited by expected offline repair time. We want to see the effect of imposing this constraint on the expected profit and so we rerun the computational study for P-solutions, as we expect that the difference would be the biggest for P-solutions, as all of the incomplete tasks can be completed only by offline repair. Table 4.7 illustrates the comparison of the expected profits when constraint (3.7) is included and ignored. Each value in the table refers to the average of percentage deviations in expected profits of these two cases among the problem datasets of a given precedence diagram and

CoV setting. Note that a single percentage deviation is calculated by the differences of expected profits, divided by the expected profit of the solution without constraint (3.7). Table 4.7 shows that the overall average percentage deviation is 0.59%, which can be interpreted as a minor effect. The highest average deviation is for GUN8T8 in identical high CoV setting with 11.6%. In Table 4.8, the instances where percentage deviations greater than 1% are listed. In the table, we see that the deviaitions are greater than 1% in 7 out of 191 instances. We also observe that in these instances, the expected offline repair time is very high compared to the base cycle time (which is also the expected cycle time as there is no F-task). In these solutions, the offline area practically acts like a job shop layout with significantly less output rate.

Table 4-7 The effect of offline repair time constraint on expected profit

Precedence Diagram	CoV Setting	%Deviation E[Profit]
GUN8T8	Identical High	11.60%
	Identical Low	0.00%
	Nonidentical High	0.00%
	Nonidentical Low	0.00%
AKO20T4-A	Identical High	0.60%
	Identical Low	0.00%
	Nonidentical High	0.00%
	Nonidentical Low	0.00%
LAM20T10	Identical High	0.15%
	Identical Low	0.00%
	Nonidentical High	0.05%
	Nonidentical Low	0.00%
LAM30T10	Identical High	1.00%
	Identical Low	0.00%
	Nonidentical High	1.00%
	Nonidentical Low	0.00%
LAM25T25	Identical High	0.00%
	Identical Low	0.00%
	Nonidentical High	0.00%
	Nonidentical Low	0.00%
Grand Total		**0.59%**

Table 4-8 The instances where the percentage deviations due to offline repair time constraint is greater than 1%

Problem	Instance	CoV Setting	With Offline Repair Time Constraint			Without Offline Repair Time Constraint			% Deviation
			Base Cycle Time	E[Profit]	E[Offline time]	Base Cycle Time	E[Profit]	E[Offline time]	
GUN8T8	8	Identical High	10	-4.96	8.93	4.00	-3.06	14.19	62.36%
GUN8T8	6	Identical High	36	-31.03	13.68	15.00	-27.22	22.57	14.02%
LAM30T10	4	Identical High	31	181.12	20.88	6.00	201.29	100.71	10.02%
LAM30T10	4	Nonidentical High	30	187.07	18.93	5.00	203.94	102.06	8.27%
AKO20T4-A	9	Identical High	30	74.60	27.40	8.00	78.83	155.17	5.36%
GUN8T8	4	Identical High	9	6.43	2.58	2.00	6.75	9.25	4.84%
LAM20T10	4	Identical High	30	215.36	28.64	8.00	218.59	135.41	1.48%

4.3 Properties of The Best P/F Scheme Solutions

A line balance may be evaluated based on a number of performance criteria such as expected profit per product, expected profit per unit time, expected cycle time, number of stations, variance of actual cycle time and probability of line stoppages. While our main focus is the expected profit, we will also analyze greedy solutions in terms of the remaining criteria.

4.3.1 P/F Scheme Patterns

Other than the performance measures, we also investigate if there exists patterns in P/F Schemes. For each instance, we record the number of P-tasks and F-tasks and try to see if there are any patterns in P/F schemes of the Best P/F Scheme solutions. In Figure 4.2 and Figure 4.3, we plot the percentage of the number of P-tasks in total actual tasks for each CoV setting to see if there is any relation. Note that GUN8T8 is not included as in all of the corresponding instances, all tasks are F-tasks, which gives no information in terms of the comparison between CoV settings (in GUN8T8, the number of stations is one in 9 out of 10 instances, hence all tasks are labeled as F-task and the idle time becomes zero). We observe that the number of P-tasks increase for high CoV settings and get close to 50%. As high CoV leads to high incompletion costs, it is possible to improve expected profit by implementing hybrid lines. Therefore, in high CoV settings, we can observe P/F schemes in which both P-tasks and F-tasks are included. For low CoV settings, as hybrid lines cannot improve the expected profits significantly, most of the tasks are F-tasks.

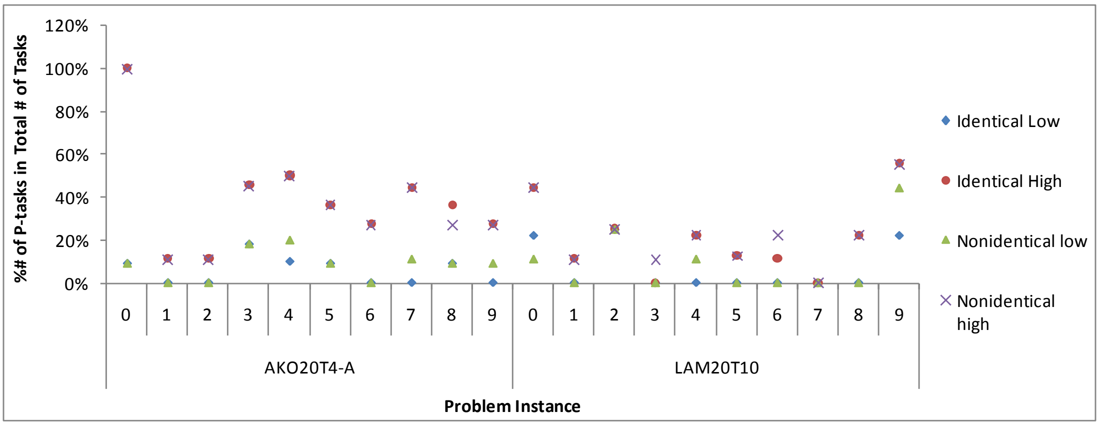

Figure 4-2 Percentage of the number of P-tasks in total number of actual tasks for different CoV settings in AKO20T4-A and LAM20T10

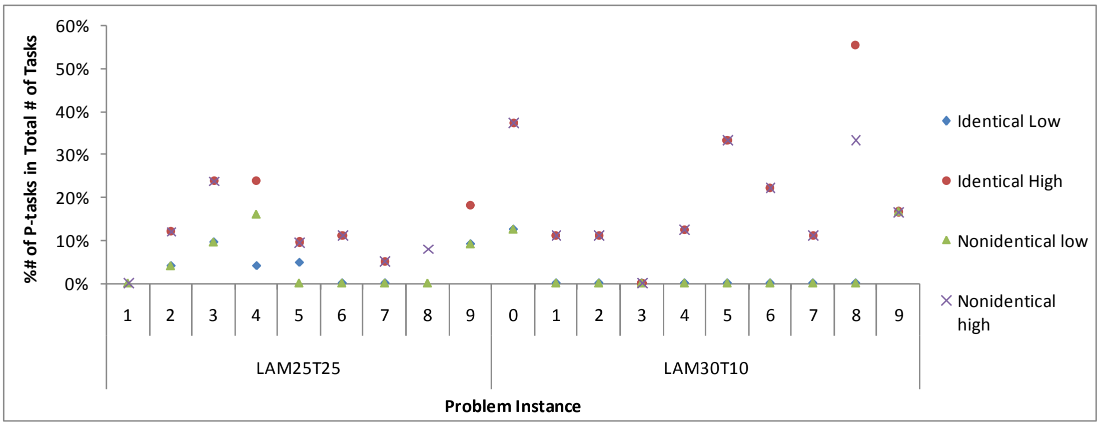

Figure 4-3 Percentage of the number of P-tasks in total number of actual tasks for different CoV settings in LAM25T25 and LAM30T10

According to our observations, there are a number of factors which may cause a task to be labeled as P-task. In most of the cases the selection of a task as P-task occurs when one or several of the following cases happen:

i. Total mean task time of task *i* and the previous tasks in the same station is significantly higher than the total task times of F-tasks in other stations
ii. The number of successors of the task is not high
iii. The task is performed last or lately on the station
iv. Task *i*, its successors and the tasks that are performed later than task *i* have low offline costs

These cases are determined depending on our overall observations on the instances. Mostly, a task satisfies some of the conditions, while it fails the others. To prove the validity of these observations, it is necessary to design experimental frame so that the individual effects of the conditions can be analyzed analytically. In that case, conditions need to be defined such that a rule has to be defined that determines whether the condition holds or not. For instance, it should be clear that the number of successors of a task is high or low depending on problem dataset. Due to these complications, we present the above statements as subjective evaluations and leave the analytical proof as a future work.

4.3.2 Expected Profit Analysis

4.3.2.1 Greedy vs Best P/F Scheme Solutions

Out of the 200 problem instances solved, 193 comparisons can be made between greedy solutions and Best P/F Scheme solutions, since no valid solution can be found in seven instances due to the constraints imposed on expected cycle time and expected offline repair time. For these 193 instances, percentage deviations in expected profit are calculated by subtracting the expected profit of Best P/F Scheme solution from that of the greedy solution, and dividing the difference by the absolute value of the expected profit of the Best P/F scheme solution. Results show that out of the 193 comparisons, in 174 instances the Best P/F Scheme solution is found by the greedy algorithm. The average deviation in expected profit is 0.046%, while the maximum deviation 1.65%. Table 4.9 shows the maximum and average deviations in expected profit of the greedy solutions compared to the Best P/F Scheme solutions over all problem datasets for given precedence diagrams.

Table 4-9 Average and maximum percentage deviations of greedy solutions compared to Best P/F scheme solutions

Problem	CoV Setting	Maximum of Greedy % Deviations	Average of Greedy % Deviations	# of Best P/F Scheme Found by Greedy	# of Comparisons
AKO20T4-A	Identical High	0.05%	0.01%	8	9
	Identical Low	0.00%	0.00%	10	10
	Nonidentical High	1.65%	0.19%	7	9
	Nonidentical Low	0.00%	0.00%	10	10
GUN8T8	Identical High	0.00%	0.00%	9	9
	Identical Low	0.00%	0.00%	9	9
	Nonidentical High	0.00%	0.00%	9	9
	Nonidentical Low	0.00%	0.00%	9	9
LAM20T10	Identical High	0.05%	0.00%	9	10
	Identical Low	0.00%	0.00%	10	10
	Nonidentical High	0.06%	0.01%	9	10
	Nonidentical Low	0.00%	0.00%	10	10
LAM25T25	Identical High	1.51%	0.36%	6	10
	Identical Low	0.00%	0.00%	10	10
	Nonidentical High	1.20%	0.25%	5	9
	Nonidentical Low	0.63%	0.12%	8	10
LAM30T10	Identical High	0.00%	0.00%	10	10
	Identical Low	0.00%	0.00%	10	10
	Nonidentical High	0.00%	0.00%	10	10
	Nonidentical Low	0.00%	0.00%	10	10
Overall				**178**	**193**

4.3.2.2 Greedy vs F-Solutions and P-Solutions

Greedy solutions offer improvements over F-solutions and P-Solutions depending on the problem instance and CoV setting. Over 200 instances, for 186,191 and 193 instances valid F-solutions, P-solutions and greedy solutions can be found, respectively. For some instances and CoV settings, even if no valid P-solution or F-solution is found, it is possible to find valid greedy solutions due to the flexibility of hybrid lines. The pairwise comparisons are made between only the instances with valid solutions.

As is the case for Best P/F Scheme solutions, improvements in expected profit by greedy solutions are higher for high variation cases compared to low variation cases. Table 4.10 shows the average and maximum percentage improvements over F-solutions and P-solutions.

We observe that higher improvements are achieved compared to P-solutions than F-solutions. According to Table 4.10, average improvements over F-solutions range from 0.03% to 2.69% for low variation, and from 4.16% to 76.55% for high variation.

Table 4-10 Average and maximum percentage improvements in expected profit by greedy solutions over P-solutions and F-solutions for different problems and CoV settings.

Problem	Variability In Task Times	Average % Improvement		Maximum % Improvement		# of Comparisons	
		Greedy vs F	Greedy vs P	Greedy vs F	Greedy vs P	F	P
AKO20T4-A	Identical Low	0.09%	11.25%	0.31%	20.36%	10	9
	Identical High	2.52%	31.00%	7.01%	89.65%	9	9
	Nonidentical Low	0.23%	12.30%	1.15%	26.80%	9	9
	Nonidentical High	2.39%	26.84%	6.89%	84.44%	9	9
GUN8T8	Identical Low	1.18%	57.82%	10.62%	216.22%	9	9
	Identical High	1.68%	76.55%	15.15%	162.58%	9	9
	Nonidentical Low	1.91%	62.98%	17.22%	177.04%	9	9
	Nonidentical High	2.69%	62.56%	24.23%	118.66%	9	9
LAM20T10	Identical Low	0.05%	5.38%	0.47%	10.01%	9	10
	Identical High	0.42%	9.95%	1.19%	21.88%	9	10
	Nonidentical Low	0.01%	6.09%	0.05%	14.83%	9	10
	Nonidentical High	0.51%	10.22%	1.38%	23.67%	9	10
LAM25T25	Identical Low	0.07%	13.07%	0.30%	26.41%	10	10
	Identical High	1.11%	54.37%	3.86%	225.47%	10	10
	Nonidentical Low	0.14%	18.23%	0.55%	40.93%	10	10
	Nonidentical High	1.08%	47.56%	1.95%	206.33%	9	9
LAM30T10	Identical Low	0.03%	4.16%	0.18%	8.91%	10	10
	Identical High	0.28%	7.79%	0.56%	19.65%	9	10
	Nonidentical Low	0.03%	4.74%	0.15%	8.64%	10	10
	Nonidentical High	0.27%	7.46%	0.74%	16.50%	9	10
OVERALL						**186**	**191**

The improvements over F-solutions and P-solutions are not directly inline; for a certain instance, it is possible that the improvement over F-solution may be the highest while the improvement over P-solution is. Figure 4.4 and Figure 4.5 illustrate this observation: In Figure 4.4, we see that in instances 0 and 6, the improvement over F-solutions are the highest among all instances, while the improvements over P-solutions in the same instances are below average. Similarly, while the improvements over P-solutions are the highest in instance 2 in Figure 4.3, the improvements over F-solutions are among the lowest in Figure 4.4.

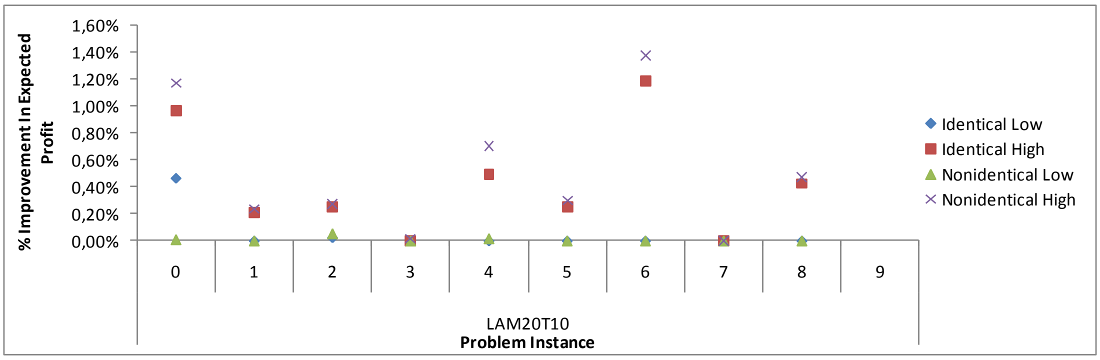

Figure 4-4 Percentage improvements in expected profit by greedy solutions over F-solutions for LAM20T10 for given ten instances and CoV settings

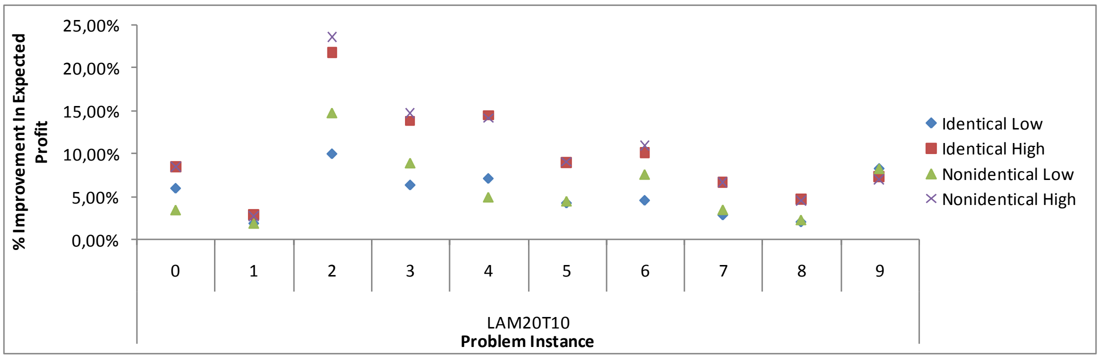

Figure 4-5 Percentage improvements in expected profit by greedy solutions over P-solutions for LAM20T10 for given ten instances and CoV settings

4.3.2.3 Computational Time

Given the task assignments and ordering of tasks, without precedence relations, the number of possible P/F schemes for a given station k is $n_k + 1$, where n_k is the number of tasks. This is due to the fact that determining P/F scheme in a given station can be simplified to the problem of determining the boundary that separates F-tasks and P-tasks, since all F-tasks are performed earlier than P-Solutions. Hence, if there are K stations, theoretically the maximum number of P/F schemes in total would be $\prod_{k}^{K}(n_k + 1)$. In practice, the total number of feasible P/F schemes, however, are lower than the theoretical maximum due to the precedence relations.Therefore, it might be possible that complete enumeration does not require excess computational time effort for the line balances with less number of stations. Assuming each station is assigned the same number of tasks n and there are K number of stations, the overall time requirement for generating all feasible P/F schemes would be $O(n^K)$.

The greedy algorithm's time requirement depends on the number of trials of each candidate task in the candidate list for seeking profit improvement. In forward phase, initially each task is marked as F-task and then labelled as P-task temporarily to calculate profit improvements.

Therefore, assuming the total number of tasks assigned is *N*, the number of trials are N in the first iteration. At the end of the iteration, the candidate task with maximum profit improvement, and the successors of the task, will be marked as P-task permanently so that constraints (3.2)-(3.5) will be satisfied. In second iteration, the candidate list will be formed by the remaining F-tasks, and again each candidate task will be marked as P-task to calculate profit improvements. Note that at each iteration the number of candidate tasks will depend on the number of tasks marked as P-task permanently. In worst case scenario, at each iteration, the number of candidate tasks (which is equal to number of P/F schemes generated and evaluated) will be one less than the previous iteration. Hence, there will be N number of P/F schemes in the first iteration, $(N-1)$ number of P/F schemes in the second iteration, $(N-k+1)$ number of P/F schemes in k th iteration and so on. As a result, in forward phase the total number of P/F schemes generated is formulated by $\frac{N(N+1)}{2}$. Hence, the time complexity of the generation of P/F schemes in forward phase will be $O(n^2)$. As backward phase is run after the forward phase is over, and as the algorithm is very similar to that of backward phase, the overall time complexity of the greedy algorithm is $O(n^2)$.Here it should be noted that the mentioned time complexities merely involves the comparison of the algorithms in generating P/F schemes. The processes such as calculation and evaluation of each P/F scheme (including the generation of all incompletion combinations and the numerical integrations), the determination of temporary tasks to be labelled as P-task in forward phase (or F-task in backward phase) to satisfy the feasibility conditions are ignored since these processes are conducted in the same manner for both approaches and have nothing to do with the generation of P/F schemes. Our main purpose, here, is to compare the time effort required to generate the P/F schemes by greedy algorithm and complete enumeration.

In Table 4.11, average CPU times for each precedence diagram and problem instance, the number of P/F schemes generated for each solution approach and the theoretical maximum number of P/F schemes are illustrated. Note that the number of P/F schemes generated are the total number of P/F schemes generated for each precedence diagram and problem dataset in identical low CoV setting given base cycle time is equal to the lower limit for base cycle time. We set base cycle time to the lower limit due to the following: (i) When base cycle time value is very high, no improvements are possible, and so the number of P/F schemes generated in greedy algorithm only depends on the number of tasks (ii) In most of the instances, base cycle time is set to the lower limit, hence it makes sense to make the comparison in this setting. We observe that, in general, the computational times increase with number of P/F schemes generated and the total number of P/F schemes are significantly lower than the theoretical maximum as claimed by Kottas and Lau (1976). Especially in LAM25T25, where only AND precedence relations are included, the ratio of number of P/F schemes generated to the theoretical maximum is close to 0%. When the precedence relations involve AND precedence and OR successor relationship, the total number of P/F schemes get lower as labeling a task as P-task leads to all of its AND successors and OR successors to be P-tasks. Hence, the number of feasible P/F schemes decrease significantly in LAM25T25, where only AND precedence relationship is included. Also note that although a more sophisticated analysis would be more reliable, in overall, we can claim that the number of P/F schemes generated increases with number of stations and number of tasks with less number of AND precedence and OR successor relationships.

The proposed algorithm performs the best when the total number of P/F schemes is large as in LAM25T25, otherwise complete enumeration performs similarly or better. Fortunately, greedy algorithm performs better when the computational time of complete enumeration is very high as in most instances of LAM25T25. Therefore, time savings are possible by implementing greedy algorithm for the problems that require considerable computational effort (when heuristics or metaheuristics are supposed to perform better). Here, we should remind that our main motivation is to explore hybrid lines, and to propose an approach other than complete enumeration as a starting point for further research. Our aim is not to develop a novel heuristic that solve a commonly known hard problem. We want to show that efficient methods can be developed instead of complete enumeration and that much more efficient algorithms can be developed for this specific problem.

Table 4-11 Computational times and number of P/F schemes for different solution approaches and problem instances

Problem	Instance	Number of Stations	Number of Tasks	CPU Time (in sec.)		Number of schemes generated (% value within Theoretical Max)		Theoretical Max.
				Greedy	Best P/F	Greedy	Best P/F	
AKO20T4-A	1	4	9	2,154.6	1,172.6	9 (32%)	12 (42%)	28
	2	2	9	2,829.1	1,958.6	9 (30%)	14 (46%)	30
	3	2	11	4,820.4	2,422.0	22 (26%)	18 (21%)	84
	4	3	10	3,221.6	1,690.8	20 (13%)	15 (10%)	144
	5	3	11	4,644.9	3,608.1	22 (22%)	33 (34%)	96
	6	3	11	1,243.8	1,516.6	11 (11%)	26 (26%)	100
	7	3	9	1,136.4	198.0	9 (14%)	10 (15%)	64
	8	3	11	2,382.4	1,833.0	22 (24%)	24 (26%)	90
	9	6	11	5,493.5	4,208.7	11 (2%)	40 (9%)	432
LAM20T10	0	3	9	2,097.4	1,178.5	26 (61%)	24 (57%)	42
	1	2	9	485.6	386.5	9 (30%)	13 (43%)	30
	2	2	8	286.8	135.2	16 (64%)	9 (36%)	25
	3	2	9	298.0	233.2	9 (32%)	10 (35%)	28
	4	5	9	925.3	1,089.7	9 (6%)	27 (18%)	144
	5	2	8	333.1	151.7	8 (38%)	9 (42%)	21
	6	3	9	536.3	503.0	9 (16%)	21 (38%)	54
	7	2	9	113.2	92.7	9 (32%)	10 (35%)	28
	8	2	9	471.2	376.8	9 (30%)	17 (56%)	30
	9	2	9	355.9	89.0	18 (64%)	10 (35%)	28
LAM30T10	0	3	8	507.3	281.9	16 (40%)	14 (35%)	40
	1	3	9	326.3	157.7	9 (15%)	11 (18%)	60
	2	2	9	103.3	81.6	9 (32%)	10 (35%)	28
	3	2	8	86.5	56.8	8 (32%)	9 (36%)	25
	4	4	8	189.4	87.2	8 (11%)	9 (12%)	72
	5	2	9	111.6	58.0	9 (30%)	10 (33%)	30
	6	2	9	57.4	61.2	9 (30%)	10 (33%)	30
	7	3	9	70.6	66.2	9 (15%)	12 (20%)	60
	8	2	9	63.2	23.8	9 (32%)	10 (35%)	28
	9	2	6	34.6	24.1	12 (75%)	7 (43%)	16
LAM25T25	0	12	25	6,897.2	45,321.0	25 (0%)	206 (0%)	373,248
	1	2	7	154.0	298.0	7 (35%)	14 (70%)	20
	2	11	25	1,685.3	28,521.0	50 (0%)	489 (0%)	279,936
	3	8	21	12,002.3	43,035.3	62 (0%)	211 (0%)	23,328
	4	16	25	7,321.8	50,349.0	50 (0%)	641 (0%)	1,990,656
	5	9	21	461.8	528.2	42 (0%)	52 (0%)	38,880
	6	9	18	6,964.5	8,832.5	18 (0%)	67 (0%)	9,600
	7	12	20	21,038.8	30,386.4	40 (0%)	99 (0%)	104,976
	8	14	25	4,669.2	32,967.8	50 (0%)	591 (0%)	1,119,744
	9	11	22	30,122.1	46,559.5	65 (0%)	288 (0%)	116,640

4.3.3 Cycle Time Analysis

4.3.3.1 Base Cycle Time vs Profit Analysis

Base cycle time has a significant effect on expected profit and expected cycle time of a given P/F scheme. The three solution approaches, F-solutions, P-solutions and greedy solutions propose different base cycle time values. Lau and Shtub (1987) show that, if P/F scheme is carefully selected, expected total costs decrease as base cycle time decreases. We also observe the same behavior: For a large base cycle time value, due to different workcontents across stations, idle times lead to additional costs increasing total costs. When base cycle time is decreased, these idle times are decreased in the expense of higher offline costs. At this point, the advantage of hybrid lines is that the tasks with high offline costs are labeled as F-tasks and therefore high offline costs are avoided in the expense of relatively less line stoppage costs. On the other hand, the tasks which have lower offline costs compared to line stoppage costs, are labeled as P-tasks and therefore high lines stoppage costs are avoided. As a result, as the base cycle time decreases, even if offline costs of P-tasks increase, this increase is compensated by lower idle times and lower expected cycle time.

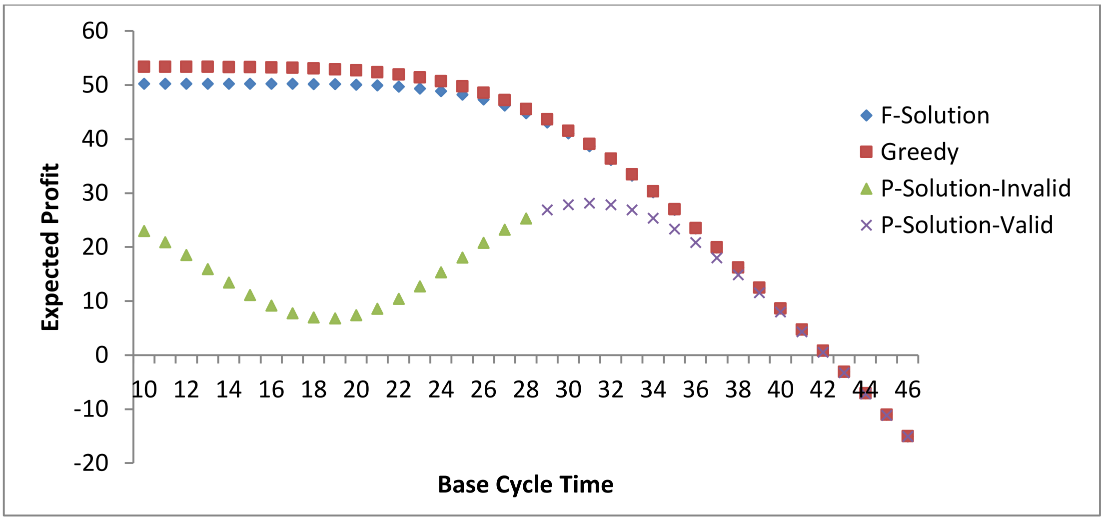

Figure 4-6 Expected profit versus base cycle time for different solution approaches in LAM20T10, instance 4, identical high CoV setting

Figure 4.6 illustrates the typical behavior of three solution types with respect to base cycle time for the fourth instance of LAM20T10 and identical high CoV setting. According to the figure, we see that expected profit of the P-solution is maximum when base cycle time is 31. To the right of 31, the expected profit decreases as the increase in station operating costs is more rapid than the decrease in offline costs. To the left of 31, expected profit first decreases till base cycle time is 18, as offline costs increase more rapidly than station operating costs decrease. After this point, as all of the tasks are almost always completed by offline repair, the expected profit increases as station operating costs decrease. Even if the expected profits increase, these solutions are infeasible as offline repair time is much higher than expected cycle time. Another observation in this figure is that, the maximum expected value of P-solution is at the valid part (i.e. expected offline repair time is less than expected cycle time, which is equal to base cycle time for P-solutions).

F-solution and greedy solutions behave similarly: For high base cycle time values, there is so much idle time that all tasks are always completed on the line, hence greedy solution performs similar to F-solution. Beyond base cycle time value of 28, by labeling some of the F-tasks as P-tasks, cost savings are achieved by greedy solution as the sum of station operating costs and line stoppage costs decrease more rapidly than offline costs increase.

After base cycle time is decreased to 20, no change occurs in expected profit in F-solution and Greedy solution since changing base cycle time does not affect expected cycle time any more as the cycle time is almost always determined by F-tasks.

Due to this characteristics, base cycle time for F-solutions and Best P/F scheme solutions are set to the lower base cycle time limit. The same is not always true for greedy solutions: In some rare cases, greedy solution cannot find the best P/F scheme when base cycle time is set to the lower limit; however, it finds the best P/F scheme for a higher base cycle time value. Therefore, other than such rare cases, base cycle time of the greedy solution is also set to the lower limit.

4.3.3.2 Expected Cycle Time Comparison

Labeling an F-task as P-task may decrease the expected cycle time since the task can no longer be the task that is the one last completed. Hence, for a given line balance CoV setting and base cycle time, expected cycle time decreases or stays constant as number of P-tasks increase. Since base cycle time of the greedy solutions are almost always equal to that of F-solutions, and since greedy solutions may include one or more P-tasks while F-solution cannot, expected cycle time of a greedy solution is less than or equal to that of F-solution for a given line balance and CoV setting. Therefore, greedy solutions improve not only the expected profit but also improve the expected cycle time.

For P-solutions, expected cycle time is equal to the base cycle time value as no task is F-task. The base cycle time value, which maximizes the expected profit, may be lower or higher than the expected cycle time of F-solution or greedy solution. The graph in Figure 4.7 illustrates the change in expected profit versus the change in expected cycle time of greedy solutions compared to F-solutions and P-solutions. Note that the chart is plotted for all instances except the ones including improvements in expected profits greater than 50% (In the instances for which the expected profits are near zero, very high percentage improvements are realized. When these instances are included, most of the F-solutions focus in a very small region due to the wider X-axis that makes it hard for the reader to follow). In Figure 4.7, we see that for some instances, even if expected profit of F-solutions are improved for a relatively small amount, expected cycle times are improved significantly. Moreover, we see that while expected profits of P-solutions are increased significantly, expected actual cycle time may or may not be improved.

Figure 4-7 The percentage changes of expected cycle times plotted against the percentage changes in expected profits of greedy solutions compared to F-solutions and P-solutions. Negative values in Y-axis imply an improvement in expected cycle time.

In this thesis, our main concern is to explore the characteristics of hybrid lines in disassembly lines so that a given product can be disassembled more efficiently as in many studies in ALBP and DLBP. This makes sense as the scarce resources of time and labor are utilized efficiently. However, from the point of view of the industry, when all parts released have a corresponding demand, one might want to maximize the profits earned per unit time. Therefore, we also want to compare these solution approaches in terms of expected profit per unit time. Expected profit per unit time is formulated as expected profit per product divided by expected cycle time as the output rate of a line is expected to be determined by the expected cycle time.

We rerun the computational study by adopting expected profit per unit time instead of the expected profit and select base cycle time value based on the expected profit per unit time rather than the expected profit. Figure 4.7 and the discussion in 4.3.2.2. suggest that when greedy solutions and F-solutions are compared, greedy solutions outperform F-solutions in both expected profit per product and expected cycle time. Recalling that when base cycle time decreases, the expected profit per product increases and expected cycle time decreases, we can claim that greedy solutions will outperform F-solutions in expected profit per unit time. However, for P-solutions the same may not be true. For P-solutions, when base cycle time decreases, expected profit per product may increase or decrease for specific base cycle time values. Hence, for each instance, new P-solutions with new base cycle time values are determined that maximizes the expected profit per unit time. The table below is prepared for greedy solutions, F-solutions already found and for the new P-solutions. Table 4.12 shows that the improvements in expected profit per unit time is higher over F-solutions compared to the improvements in expected profit as expected (see Table 4.5). On the other hand, in overall, we observe that P-solutions perform better in expected profit per unit time than expected profit. The improvements over P-solutions are lower in expected profit per unit time compared to the improvements in expected profit. We also observe that in LAM20T10 and LAM30T10, P-solutions outperform F-solutions in high CoV settings. In these problems, the profit gains by F-solutions are lower than the losses in output rate due to the higher expected cycle times in F-solutions.

Table 4-12 Average expected profit per unit time and the improvements over all problem datasets for different precedence diagrams and CoV settings

Problem	CoV Setting	Average of Expected Profit per Unit Time			Average of % Improvements in Pairwise Comparisons		
		F-Solution	P-Solution	Greedy	Greedy vs P	Greedy vs F	F vs P
AKO20T4-A	Identical Low	4.46	4.14	4.49	12.59%	0.50%	11.90%
	Identical High	3.65	3.26	4.12	39.68%	14.82%	21.83%
	Nonidentical Low	4.73	4.19	4.45	15.26%	1.23%	13.84%
	Nonidentical High	3.75	3.43	4.18	32.00%	12.57%	16.77%
GUN8T8	Identical Low	1.61	1.01	1.61	76.35%	1.49%	74.63%
	Identical High	1.51	0.76	1.52	96.01%	1.43%	95.60%
	Nonidentical Low	1.59	0.93	1.60	83.07%	2.31%	81.43%
	Nonidentical High	1.55	0.83	1.55	82.20%	2.47%	81.71%
LAM20T10	Identical Low	7.61	7.11	7.40	5.93%	0.54%	5.80%
	Identical High	6.41	6.49	6.61	4.27%	5.81%	-0.31%
	Nonidentical Low	7.60	7.30	7.36	4.00%	0.17%	4.71%
	Nonidentical High	6.34	6.46	6.66	6.07%	8.34%	-0.81%
LAM25T25	Identical Low	7.77	1.56	7.82	38.31%	0.55%	37.30%
	Identical High	4.79	3.31	4.98	74.79%	3.61%	68.32%
	Nonidentical Low	7.70	5.67	7.83	31.45%	1.27%	29.99%
	Nonidentical High	4.85	3.78	5.08	63.37%	3.99%	57.67%
LAM30T10	Identical Low	11.32	10.83	11.43	6.16%	0.90%	5.21%
	Identical High	10.25	10.05	10.74	7.88%	7.18%	1.11%
	Nonidentical Low	11.16	10.83	11.26	4.22%	0.87%	3.31%
	Nonidentical High	10.23	10.13	10.71	6.51%	7.10%	-0.20%

Variability in cycle time is also another performance criterion that should be taken into account as high variability may lead to high fluctuations in cycle time and output rate. Standard deviation of cycle time of P-solutions is zero as cycle time is always equal to base cycle time. For F-solutions and greedy solutions, due to the existence of one or more F-tasks, actual cycle time may differ from cycle to cycle. Figure 4.8 shows the standard deviations of cycle time of three problems and ten instances for identical low CoV setting. It is observed that that the variability in actual cycle time of greedy solutions are higher than F-solutions in almost all cases.

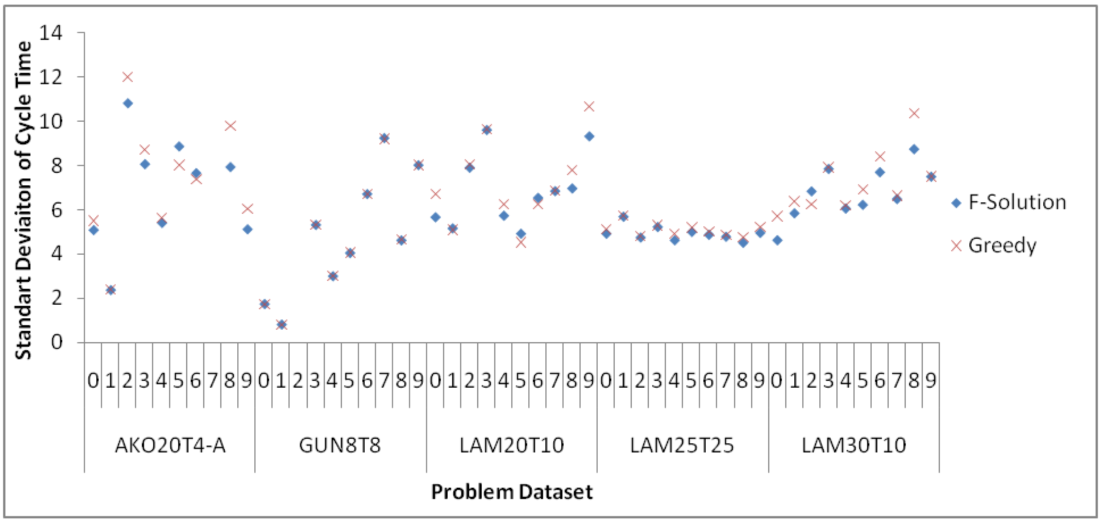

Figure 4-8 The standart deviaitions for each precedence diagram and problem dataset for identical low CoV setting

The closed form calculation of the standard deviation of the cycle time is complicated as the cycle time is a maximum of base cycle time (a constant number) and Normal random variates that represent station workcontents at each cycle. Therefore, Monte Carlo simulation is used in calculating the standard deviation of cycle time. The procedure is as follows: For one iteration, random variates for the total task of F-tasks at each station are generated, and the cycle time is calculated by taking the maximum of the random variates and the base cycle time. 10^5 iterations are generated and the standard deviation of all is recorded as the standard deviation of the given P/F scheme and base cycle time value.

4.3.4 Smoothness of Line Operation

For a given base cycle time and line balance, greedy solutions improve expected profit by finding a balance point between offline repair costs and line stoppage costs to maximize the total expected incompletion cost. Therefore, if greedy solution improves P-solution or F-solution, either probability of line stoppage or probability of offline repair should be increased, since zero offline cost is equivalent to F-solution and zero line stoppage cost is equivalent to P-solution. Our observations show that greedy solutions tend to have very high probability of line stoppages as high as 1, which leads to frequent line stoppages, which may not be desired. This is due to the characteristic of greedy solution with respect to base cycle time discussed in Section 4.3.2.1. Since our solution approach seeks even slight profit improvements, the base cycle time is decreased so as to capture these slight profit improvements leading to low base cycle times and very high probability of line stoppages. If lower probability of line stoppages is sought for smoother operations, expected profit decreases as some of the F-tasks have to be labeled as P-task and we move away from the balance point between line stoppage costs and offline costs. We investigate the effect of limiting probability of line stoppages on expected profit by setting various upper limits for probability of line stoppages. Just as we imposed limits for expected cycle time and expected offline repair time, we modified our algorithm so that solutions with probability of line stoppages exceeding the upper limit for probability of line stoppage are considered as invalid. Figure 4.9 shows the expected profit values achieved for different upper limits for probability of line stoppages of eighth instance of LAM30T10 for identical low CoV setting. In the figure, we see that decreasing the level of upper limit decreases the expected profit.

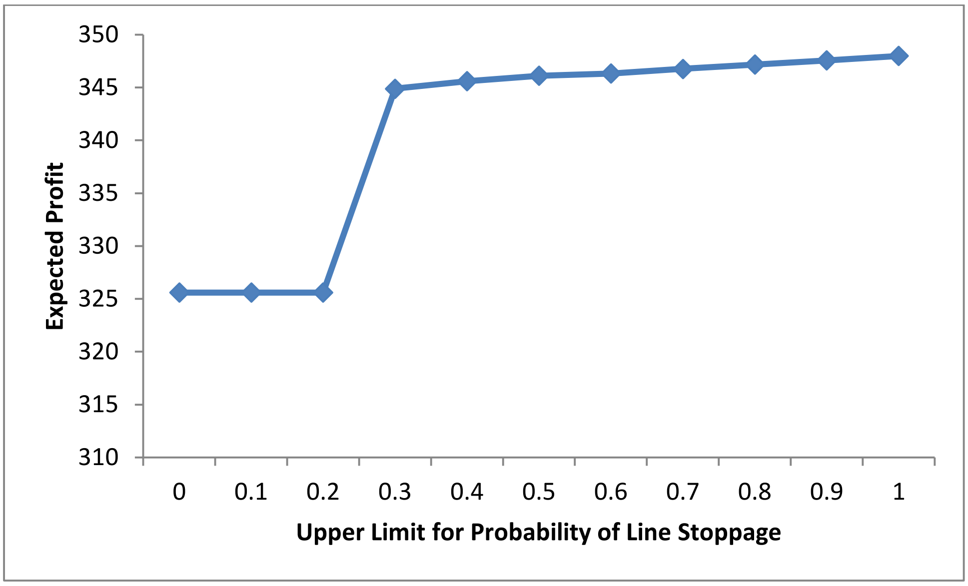

Figure 4-9 The expected profit versus various upper limits imposed on line stoppage probability for LAM30T10, instance 8, identical low CoV setting

CHAPTER 5

CONCLUSION

Due to the increasing amount of total production and consumption, environmental and sustainability issues arise leading to the increased importance of product and material recovery. As products are usually not reusable as a whole, and parts, modules or subassemblies have to be separated from the product; disassembly has gained greater attention. Disassembly lines are considered as one of the most efficient disassembly setting. Disassembly line balancing problem (DLBP) involves the assignment of tasks to stations so that an objective function is optimized and precedence relations are met. Profit oriented DLBP aims to maximize the profit of one unit disassembled. DLBP can be classified into two classes as deterministic DLBP and stochastic DLBP.

In stochastic DLBP, as task times are stochastic, it is possible that tasks are not completed within cycle time. In this case, hybrid lines offer profit improvements compared to the pure remedial actions, where either offline repair or line stoppages are applied. In hybrid lines, tasks are classified into two as F-tasks or P-tasks, depending on which remedial action is taken in case of a task incompletion. If an F-task is not completed within the base cycle time, line is stopped so long as all F-tasks are completed. Hence, in actual cycle time may be longer than base cycle time. If a P-task is incomplete, the task is left incomplete and the workpiece is sent to next station. After the workpiece leaves the line, workpiece is brought to the offline area for offline disassembly. Mostly, studies involving offline repair involve assembly and so all incomplete tasks are completed either on the line or by offline repair. However, in disassembly, all tasks are not necessarily completed. Hence, selection of tasks to be completed by offline repair may improve profit, which is called as offline task selection problem.

In this thesis, we formulate the problem of determining P/F scheme of a given line balance and base cycle time so as to maximize expected profit and propose a greedy algorithm for the aforementioned problem. We propose a method that calculates incompletion costs by adopting the cost models of Silverman and Carter (1986) and Kottas and Lau (1976). Our overall solution approach involves running the greedy algorithm for a range of base cycle time values and determining P/F scheme and base cycle time value. We also formulate offline task selection problem and solve it implicitly while calculating expected profit.

Our computational results show that incompletion costs have significant effect on total costs depending on the CoV setting. Therefore, it is possible to improve the expected profit of a line balance by implementing hybrid lines compared to the common remedial actions. This improvement is more obvious when all incomplete tasks are completed by offline repair. We also evaluate the performance of greedy algorithm in terms of the number of the Best P/F scheme is found, the average and maximum deviations and computational time. Our results show that greedy algorithm is pretty successful in finding the best P/F scheme solution, while it is not so successful in computational time. We observe that in the cases where total number of P/F schemes is high, greedy algorithm requires significantly less time than complete enumeration while the inverse may be true for less number of P/F schemes. We also analyze greedy solutions in terms of expected cycle time, expected profit per unit time and cycle time variance. Our results show that greedy solutions outperform F-solutions in all performance measures except the cycle time variance. P-solutions are better than greedy solutions in cycle time variance, as the cycle time is always fixed for P-solutions. Expected cycle time of P-solutions are better than greedy solutions in some instances, while the inverse is true for some others. We observed that P-solutions perform better in the expected profit per unit time than expected profit and outperform F-solutions in some of the instances. The characteristics of each solution approach differ in terms of the change of expected profit versus base cycle time. We observed that for greedy, best P/F scheme and F-solutions, expected profit increases as base cycle time decreases, which is also stated in Lau and Shtub (1987). On the other hand, there is a specific base cycle time value for P-solutions, where the total expected cost is minimized and expected profit is maximized. We also showed that the probability of line stoppages are very high in hybrid lines where improvements in expected profits exist. This is mainly due to the fact that in a solution where the best P/F scheme is selected, the idle times among stations are minimized by decreasing base cycle time. Here, even if the probability of offline repair for P-tasks increase, the savings in idle times are higher than the losses due to offline repairs.

Further research directions may include:

- Uncertainty in incoming products: We assume all incoming products are identical. However, as end-of-life products are disposed products they may include missing or nonworking parts.
- Higher CoV settings: We believe that the advantages of hybrid lines can be better observed for higher CoV settings. As discussed in Chapter 2, variability in tasks times in disassembly is much higher than assembly. Guide (2000) claims that the CoV values can be as high as five. However, in the computational study, the maximum CoV allowed is set to 0.6, by which the maximum probability of negative task times is held below 5%. When the CoV values are increased, the probability of negative task times increase, which leads to inaccuracy in probability calculations. Therefore, it is not possible to work with higher CoV under Normal distribution assumption and we tested using Lognormal random variates to denote the task times. The main problem we faced with Lognormal distribution is that the existing

formulations by Silverman and Carter (1986) and Kottas and Lau (1976) require the sum of Normal random variables to be Normal random variable. Even if there is no such a characteristic of Lognormal distribution, it is widely accepted that the sum of Lognormal random variables can be approximated by another Lognormal random variable (Fenton, 1960, Schwartz and Yeh 1982). The main problem is to estimate the mean and variance of the sum Lognormal random variables. Schwartz and Yeh (1982) give a formulation to calculate the mean and variance of two Lognormal random variables in system performance studies such as shadowing in mobile radio. When we tested Schwartz and Yeh (1982)'s formula to estimate the mean of the sum of the Lognormal random variables, we observed that in some cases the estimated means were very sensitive to the changes in standard deviations of the terms. This problem is not observed in Schwartz and Yeh (1982) since they work with signals which are measured in decibels (A number is converted to a decibel by taking logarithm with base 10). Hence, we preferred to use Normal random variables and kept CoV values to be 0.6 at maximum. We believe that our findings in computational study can be observed more obviously for higher CoV values.

- Due to the above complications, it is not convenient to illustrate task times with Normal random variables. Therefore, different probability distributions can be utilized to allow higher CoV settings. As a further research topic, it may be worthwhile to test other distributions such as exponential or gamma distribution to represent task times in disassembly
- Dynamic P/F scheme: In our problem environment, a task is either F-task or P-task independent of the status of other tasks at other stations. It is possible that stopping the whole line for only one task is costly, but it may not be so, if there are many such incomplete tasks on the line at the same cycle. Hence, a decision support system, which decides on line stoppages and offline repair can be developed.
- Improving Greedy Solution: Our greedy solution involves seeking profit improvements by labeling all F-tasks as P-task and vice versa. Greedy solution turns out to be ineffective in terms of computational time. A more efficient algorithm remains to be developed.
- Determining P/F scheme and line balance simultaneously: With an algorithm which performs well in terms of the computational time, it may be possible to propose a method such that line balance is determined while determining P/F scheme.

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APPENDIX A

IMPLEMENTATION OF TRAPEZOID RULE

For calculating both probability of occurrence of an incompletion combination and expected line stoppage time, the following equations (3.13), (3.18), (3.24), (3.28), (3.31) are evaluated by numerical integration. The number of trapezoids is taken as 100, as the error in the expected cycle time is around %0.001 compared to the case where number of increments are 10^6. As the upper limit is infinity, we approximate the integral by taking the upper limit high enough that beyond this upper limit, the added integral value approaches zero. The lower limit is CT_b in all equations. The upper limit, U , is formulated below:

$$U = \max\{CT_b + 4s_{\max}, m_{\max} + 4s_{\max}\}$$
where $m_{\max} = \max_k\{m_k\}$ and $s_{\max} = \max_k\{s_k^2\}$ for $\forall k = 1, 2, ..K,\ m_k = \sum_{i \in A_k} \mu_i,\ s_k^2 = \sum_{i \in A_k} \sigma_i^2$

1. Assume the integrals are in the form of $\int_{CT_b}^{\infty} f(x)dx$
2. The increment, $e = \dfrac{U - CT_b}{100}$
3. Set $x = CT_b$, $F = 0$; where x is the current point and F is the total sum of the integral
4. Add the region of the incremental trapezoid by;
   $F = F + \left(\dfrac{f(x) + f(x+e)}{2} \right) e$
5. If $x + e \leq U$ STOP, the integral value is F . Else set $x = x + e$ and return to Step 3.

APPENDIX B

PRECEDENCE DIAGRAMS

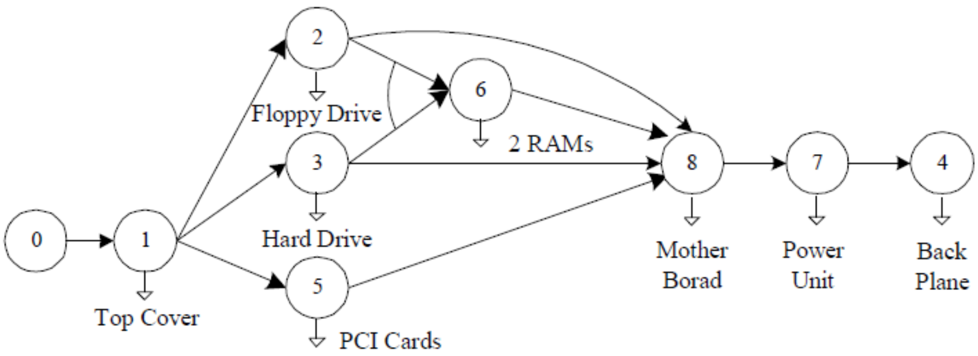

Figure B-1 Precedence diagram of Gungor and Gupta's (2002) 8 Task 8 Part PC example

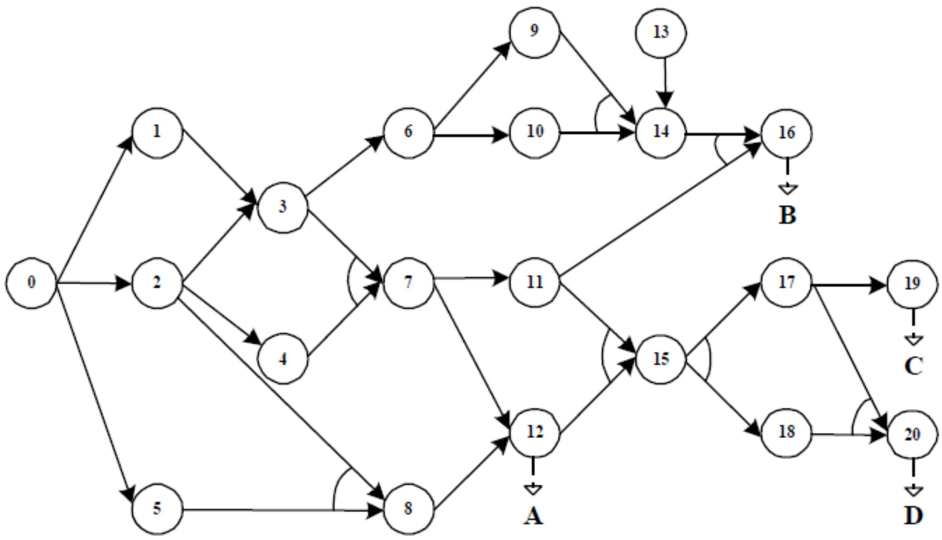

Figure B-2 Precedence diagram of 20 Task 4 Part problem

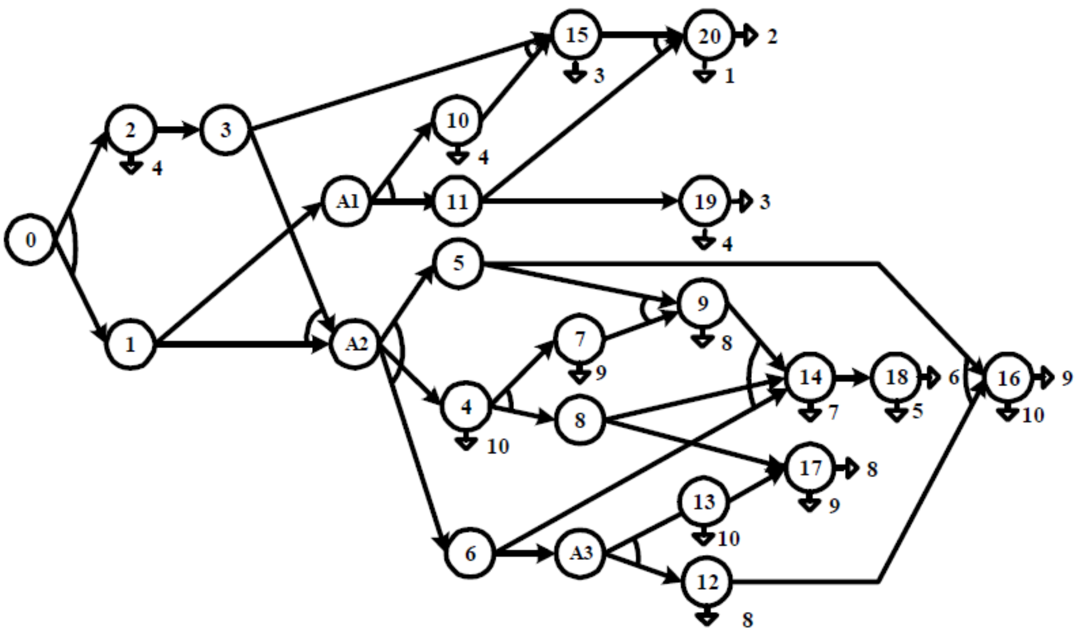

Figure B-3 Precedence diagram of Lambert (1997) 20 Task 10 Part ball point pen example

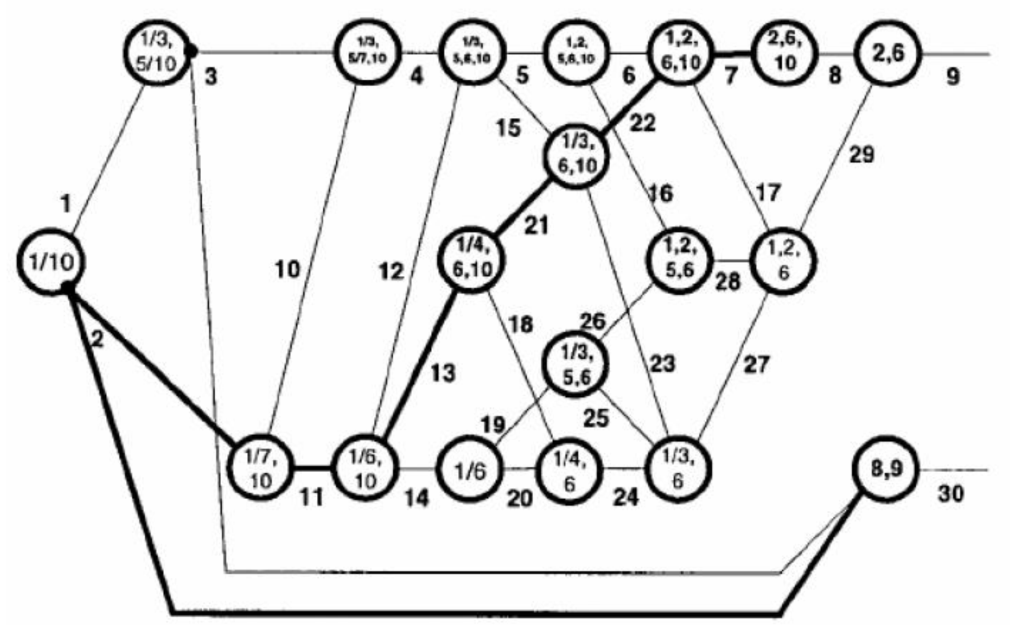

Figure B-4 Disassembly graph of Lambert (1999) 30-Task 10-Part radio example

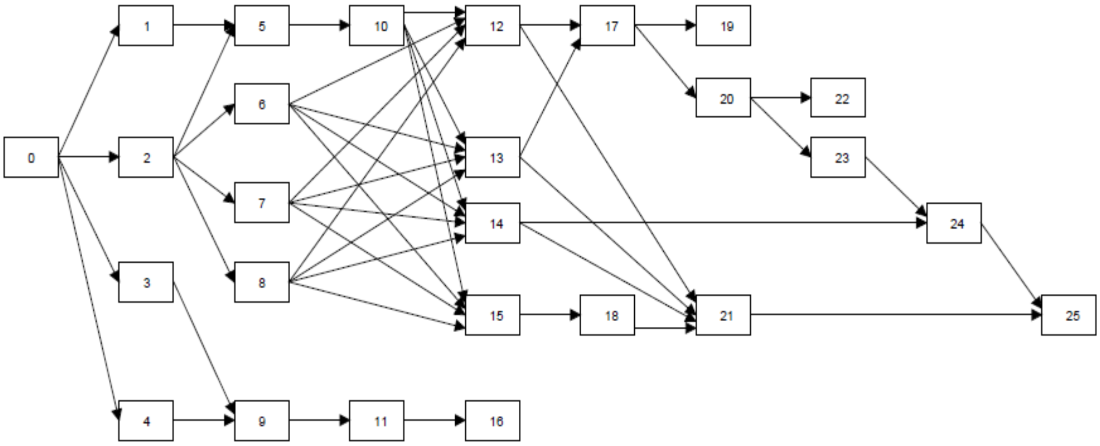

Figure B-5 Disassembly precedence graph of Lambert (2005) 25-Task cell phone example

APPENDIX C

DETAILS OF PROBLEM DATASETS

Table C.1 Details of Problem datasets for 10 instances of GUN8T8

Mean Task Times (GUN8T8)										
Problem dataset	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	4	2	20	12	7	6	12	15	11	18
2	20	16	16	18	15	3	6	7	20	5
3	14	1	5	17	18	7	10	17	20	3
4	3	20	13	2	12	1	12	15	14	13
5	16	20	19	4	18	10	16	9	19	7
6	5	13	12	8	11	16	17	12	1	3
7	12	12	15	15	1	3	3	7	7	1
8	14	14	20	19	6	2	19	4	6	3
Task Costs (GUN8T8)										
1	19	10	14	6	2	3	14	7	7	10
2	20	15	13	9	13	11	15	16	9	9
3	13	16	8	10	5	7	14	19	20	11
4	11	4	6	16	10	10	16	10	13	9
5	9	8	23	6	19	8	5	6	19	13
6	8	15	15	20	16	12	9	4	14	10
7	12	10	23	16	14	4	18	18	7	10
8	5	4	18	20	10	13	4	16	13	3
Part Revenues (GUN8T8)										
A	9	8	8	6	9	3	5	2	8	1
B	7	2	4	0	8	9	5	6	0	3
C	8	5	3	4	2	2	7	8	2	5
D	0	2	6	2	0	2	1	4	0	4
E	10	8	8	8	3	0	4	4	6	0
F	4	2	0	7	9	6	7	2	8	2
G	8	1	4	7	0	6	8	4	5	0
H	8	8	3	5	5	3	0	8	1	3

Table C.2 Details of Problem datasets for 10 instances of AKO20T4-A

Mean Task Times (AKO20T4-A)										
Problem dataset	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1	10	18	2	20	7	11	12	15	11
2	20	10	6	16	7	15	5	6	7	20
3	5	5	9	1	18	4	18	10	17	20
4	14	3	12	20	14	19	9	12	15	14
5	6	20	5	20	2	14	20	16	9	19
6	1	14	7	13	13	10	20	17	12	1
7	1	1	4	12	1	1	12	3	7	7
8	6	12	13	14	6	5	19	19	4	6
9	18	6	9	8	1	5	13	14	8	6
10	7	14	1	14	2	19	1	15	17	7
11	2	2	18	15	17	16	12	13	20	19
12	10	8	15	2	3	4	9	16	10	11
13	19	13	1	6	1	13	17	5	7	18
14	5	1	17	14	14	1	8	9	5	13
15	6	12	16	9	16	16	6	18	19	5
16	11	17	13	2	17	14	5	3	17	11
17	2	7	1	1	3	20	19	18	6	6
18	17	7	13	19	4	1	9	15	17	4
19	8	12	20	9	5	10	10	15	4	6
20	1	5	18	1	3	15	12	3	14	8
Task Costs (AKO20T4-A)										
1	17	10	7	10	15	6	11	10	15	17
2	8	1	3	1	11	19	10	10	16	14
3	3	12	2	12	12	5	8	2	7	14
4	15	15	5	6	8	7	6	9	6	5
5	16	17	8	8	12	18	9	16	17	9
6	13	15	19	8	1	19	20	12	18	19
7	7	12	13	11	9	1	3	13	4	12
8	9	10	16	9	8	8	9	15	2	1
9	2	5	12	18	16	11	13	12	19	4
10	13	11	12	14	1	3	9	18	5	5
11	14	15	9	1	5	5	8	6	5	8
12	11	15	2	7	2	16	20	19	16	18
13	9	13	15	15	7	1	18	12	6	12
14	2	12	10	5	7	4	2	12	14	2
15	17	2	9	10	17	4	4	16	18	6
16	8	6	18	5	9	3	7	4	11	1
17	8	17	1	16	4	12	4	11	9	13

Table C.2 Details of Problem datasets for 10 instances of AKO20T4-A (continued)

Task Costs (AKO20T4-A)										
18	6	16	2	3	5	15	8	17	4	16
19	5	13	4	5	7	16	15	16	10	11
20	17	12	2	17	7	18	6	3	18	3
Part Revenues (AKO20T4-A)										
A	96	107	-81	96	86	95	141	101	107	89
B	97	109	92	93	74	93	130	-90	112	88
C	105	111	81	99	-83	96	146	102	114	99
D	102	112	84	83	89	88	144	90	105	98
A	7	2	0	6	4	2	7	2	6	2
B	1	1	2	4	5	1	6	0	3	2
C	2	4	0	2	0	4	7	10	7	1
D	6	6	4	4	8	6	8	8	6	8

Table C.3 Details of Problem datasets for 10 instances of LAM20T10

Mean Task Times (LAM20T10)										
Problem dataset	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1	10	18	6	16	6	10	12	11	7
2	20	10	6	3	1	3	5	6	20	15
3	5	5	9	7	19	7	3	3	20	4
4	14	3	12	2	19	1	20	8	14	19
5	6	20	5	17	1	10	14	9	19	14
6	1	14	7	16	11	16	1	9	1	10
7	1	1	4	15	15	3	12	9	7	1
8	6	12	13	9	11	2	6	15	6	5
9	18	6	9	16	4	4	14	8	6	5
10	7	14	1	16	19	15	2	16	7	19
11	2	2	18	20	20	9	8	9	19	16
12	10	8	15	19	1	14	13	11	11	4
13	19	13	1	9	20	10	1	17	18	13
14	5	1	17	14	17	16	12	11	13	1
15	6	12	16	19	12	5	17	8	5	16
16	11	17	13	18	20	18	7	19	11	14
17	2	7	1	2	19	11	7	16	6	20
18	17	7	13	16	6	5	12	16	4	1
19	8	12	20	6	8	5	5	18	6	10
20	1	5	18	1	20	20	20	5	8	15
Task Costs (LAM20T10)										
1	17	10	7	8	6	15	15	17	17	6
2	8	1	3	3	15	13	6	16	14	19

Table C.3 Details of Problem datasets for 10 instances of LAM20T10 (continued)

Task Costs (LAM20T10)										
3	3	12	2	2	12	3	18	8	14	5
4	15	15	5	8	20	9	13	7	5	7
5	16	17	8	4	8	18	8	14	9	18
6	13	15	19	14	9	5	9	18	19	19
7	7	12	13	2	17	3	2	20	12	1
8	9	10	16	14	9	11	13	15	1	8
9	2	5	12	10	12	3	7	13	4	11
10	13	11	12	11	18	14	12	20	5	3
11	14	15	9	7	11	4	11	8	8	5
12	11	15	2	5	7	2	2	14	18	16
13	9	13	15	15	18	6	8	15	12	1
14	2	12	10	11	13	17	13	13	2	4
15	17	2	9	10	18	5	13	2	6	4
16	8	6	18	15	13	5	8	19	1	3
17	8	17	1	16	14	4	5	17	13	12
18	6	16	2	12	3	11	5	6	16	15
19	5	13	4	14	14	12	17	18	11	16
20	17	12	2	12	3	7	13	19	3	18
Part Revenues (LAM20T10)										
A	36	38	-30	44	40	33	39	57	32	38
B	37	40	41	40	52	-34	39	46	31	36
C	45	42	30	35	50	38	38	62	42	39
D	42	43	33	36	45	24	37	60	41	31
E	33	41	33	43	48	25	47	58	37	31
F	43	42	41	43	51	28	39	61	42	40
G	33	49	38	40	41	28	31	60	33	33
H	-36	45	33	39	52	41	46	53	34	46
I	48	38	37	36	56	37	47	53	33	39
J	42	44	30	42	56	41	40	54	30	45

Table C.4 Details of Problem datasets for 10 instances of LAM30T10

Mean Task Times (LAM30T10)										
Problem Dataset	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1	10	18	6	16	6	4	12	11	7
2	20	10	6	3	1	3	6	6	20	15
3	5	5	9	7	19	7	12	3	20	4
4	14	3	12	2	19	1	13	8	14	19
5	6	20	5	17	1	10	5	9	19	14
6	1	14	7	16	11	16	18	9	1	10
7	1	1	4	15	15	3	20	9	7	1
8	6	12	13	9	11	2	14	15	6	5
9	18	6	9	16	4	4	5	8	6	5
10	7	14	1	16	19	15	3	16	7	19
11	2	2	18	20	20	9	18	9	19	16
12	10	8	15	19	1	14	4	11	11	4
13	19	13	1	9	20	10	6	17	18	13
14	5	1	17	14	17	16	18	11	13	1
15	6	12	16	19	12	5	6	8	5	16
16	11	17	13	18	20	18	17	19	11	14
17	2	7	1	2	19	11	20	16	6	20
18	17	7	13	16	6	5	7	16	4	1
19	8	12	20	6	8	5	3	18	6	10
20	1	5	18	1	20	20	3	5	8	15
21	20	12	7	7	4	17	16	17	18	7
22	10	2	3	2	14	14	7	16	15	20
23	3	13	2	1	10	3	19	7	15	6
24	18	17	5	8	19	10	14	6	6	7
25	19	19	9	3	6	20	9	14	10	19
26	15	17	20	13	7	6	9	18	20	20
27	8	14	13	1	16	3	2	20	13	1
28	10	12	17	14	7	12	13	14	1	9
29	3	6	12	10	10	3	7	12	4	12
30	15	13	13	11	17	15	12	20	5	3
Task Costs (LAM30T10)										
1	15	5	9	6	11	4	11	9	8	5
2	12	9	2	4	7	2	2	15	18	16
3	9	3	15	14	18	6	8	16	12	1
4	2	8	10	10	13	17	13	14	2	4
5	18	7	9	9	18	5	13	3	6	4
6	9	7	18	14	13	5	8	20	1	3
7	8	1	1	15	14	4	5	18	13	12

Table C.4 Details of Problem datasets for 10 instances of LAM30T10 (continued)

Task Costs (LAM30T10)										
8	7	4	2	11	3	11	5	7	16	15
9	5	5	4	13	14	12	17	19	11	16
10	18	13	2	11	3	7	13	20	3	18
11	1	18	19	13	18	10	12	11	7	6
12	5	15	7	16	4	10	10	14	4	10
13	4	24	13	9	19	18	12	7	1	3
14	7	23	18	12	16	11	10	3	3	8
15	3	21	15	12	12	3	17	18	8	14
16	14	18	7	7	14	14	9	19	14	11
17	7	25	2	18	7	6	15	6	7	15
18	12	13	10	8	9	1	8	17	13	3
19	13	11	9	6	13	5	12	17	12	5
20	3	6	10	15	12	2	18	15	9	3
21	5	1	17	15	4	6	6	16	4	8
22	13	7	18	15	15	5	10	18	14	12
23	1	9	19	8	10	3	2	15	13	2
24	3	14	15	12	5	5	2	17	5	5
25	18	9	6	14	4	6	1	19	10	16
26	6	10	10	11	16	17	17	10	6	18
27	3	9	4	9	6	17	2	7	16	8
28	17	3	14	8	20	14	18	10	5	11
29	7	14	2	16	9	5	9	12	8	18
30	11	9	7	14	20	17	11	11	2	17
Part Revenues (LAM30T10)										
A	60	58	67	67	-66	57	55	83	44	-58
B	58	52	55	69	73	48	54	82	54	60
C	52	51	53	60	67	48	61	78	42	62
D	51	55	51	64	61	58	68	81	42	65
E	55	-50	65	62	66	47	65	77	50	-61
F	-50	50	60	60	73	49	68	87	41	64
G	50	55	52	67	67	53	66	87	59	52
H	55	60	51	-75	-67	51	53	83	48	59
I	60	55	57	68	69	48	65	84	59	60
J	55	15	-60	72	65	44	65	84	53	65

Table C.5 Details of Problem datasets for 10 instances of LAM25T25

Mean Task Times (LAM25T25)										
Problem dataset	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	1	10	18	6	16	6	4	12	11	7
2	20	10	6	3	1	3	6	6	20	15
3	5	5	9	7	19	7	12	3	20	4
4	14	3	12	2	19	1	13	8	14	19
5	6	20	5	17	1	10	5	9	19	14
6	1	14	7	16	11	16	18	9	1	10
7	1	1	4	15	15	3	20	9	7	1
8	6	12	13	9	11	2	14	15	6	5
9	18	6	9	16	4	4	5	8	6	5
10	7	14	1	16	19	15	3	16	7	19
11	2	2	18	20	20	9	18	9	19	16
12	10	8	15	19	1	14	4	11	11	4
13	19	13	1	9	20	10	6	17	18	13
14	5	1	17	14	17	16	18	11	13	1
15	6	12	16	19	12	5	6	8	5	16
16	11	17	13	18	20	18	17	19	11	14
17	2	7	1	2	19	11	20	16	6	20
18	17	7	13	16	6	5	7	16	4	1
19	8	12	20	6	8	5	3	18	6	10
20	1	5	18	1	20	20	3	5	8	15
21	20	12	7	7	4	17	16	17	18	7
22	10	2	3	2	14	14	7	16	15	20
23	3	13	2	1	10	3	19	7	15	6
24	18	17	5	8	19	10	14	6	6	7
25	19	19	9	3	6	20	9	14	10	19
Task Costs (LAM25T25)										
1	15	5	9	6	11	4	11	9	8	5
2	12	9	2	4	7	2	2	15	18	16
3	9	3	15	14	18	6	8	16	12	1
4	2	8	10	10	13	17	13	14	2	4
5	18	7	9	9	18	5	13	3	6	4
6	9	7	18	14	13	5	8	20	1	3
7	8	1	1	15	14	4	5	18	13	12
8	7	4	2	11	3	11	5	7	16	15
9	5	5	4	13	14	12	17	19	11	16
10	18	13	2	11	3	7	13	20	3	18
11	1	18	19	13	18	10	12	11	7	6
12	5	15	7	16	4	10	10	14	4	10

Table C.5 Details of Problem datasets for 10 instances of LAM25T25 (continued)

Task Costs (LAM25T25)										
13	4	24	13	9	19	18	12	7	1	3
14	7	23	18	12	16	11	10	3	3	8
15	3	21	15	12	12	3	17	18	8	14
16	14	18	7	7	14	14	9	19	14	11
17	7	25	2	18	7	6	15	6	7	15
18	12	13	10	8	9	1	8	17	13	3
19	13	11	9	6	13	5	12	17	12	5
20	3	6	10	15	12	2	18	15	9	3
21	5	1	17	15	4	6	6	16	4	8
22	13	7	18	15	15	5	10	18	14	12
23	1	9	19	8	10	3	2	15	13	2
24	3	14	15	12	5	5	2	17	5	5
25	18	9	6	14	4	6	1	19	10	16
Part Revenues (LAM25T25)										
A	7	6	9	8	5	8	2	1	1	5
B	0	9	6	4	5	0	9	2	1	7
C	9	7	0	6	6	6	3	1	0	6
D	5	8	6	7	9	4	8	2	9	6
E	2	6	2	9	1	8	8	8	0	15
F	4	8	9	8	8	8	12	7	3	19
G	17	5	7	17	13	3	16	11	4	12
H	12	3	18	13	12	8	16	16	5	17
I	19	7	11	0	18	3	0	12	12	17
J	16	9	17	16	15	5	12	0	13	0
K	14	5	12	11	17	4	17	15	16	14
L	15	9	14	19	12	1	11	19	19	15
M	13	3	17	19	16	0	17	17	11	14
N	11	8	15	15	15	7	19	14	13	17
O	17	7	19	19	12	7	16	12	14	0
Q	11	7	17	16	17	2	11	0	18	12
P	16	1	11	0	11	2	0	15	19	15
R	0	4	11	18	18	6	11	11	11	17
S	15	5	19	24	30	22	14	17	19	11
T	12	13	26	14	14	25	22	19	21	16
U	24	18	27	30	15	9	29	22	8	-15
V	20	15	21	23	29	10	17	23	16	27
X	13	-24	23	17	28	24	-25	23	23	25
Y	15	23	15	25	32	23	19	18	11	18
Z	26	21	29	18	14	10	25	32	18	11

APPENDIX D

DETAILS OF ALL SOLUTIONS

Table D.1 Details of all solutions

Problem	Instance	CoV Setting	Solution Type	CT Deterministic Problem	RPW Criterion	# of Stations	# F-tasks	# P-tasks	Base Cycle Time	Expected Profit	Total Expected Cost	Total Revenue	Total Task cost	Station Operating Cost	E[Line Stoppage Cost]	E[Offline Cost]	E[CT]	Expected Offline Repair Time
GUN8T8	0	Identical Low	F	4	0	1	1	0	3	4.99	22.00	28	19	3	1.01	0.00	4.01	0.00
GUN8T8	0	Identical Low	P	4	0	1	0	1	5	3.73	24.00	28	19	5	0.00	0.27	5.00	0.27
GUN8T8	0	Identical Low	Best P/F	4	0	1	1	0	3	4.99	22.00	28	19	3	1.01	0.00	4.01	0.00
GUN8T8	0	Identical Low	Greedy	4	0	1	1	0	3	4.99	22.00	28	19	3	1.01	0.00	4.01	0.00
GUN8T8	0	Identical High	F	4	0	1	1	0	1	4.96	20.00	28	19	1	3.04	0.00	4.04	0.00
GUN8T8	0	Identical High	P	4	0	1	0	1	5	2.38	24.00	28	19	5	0.00	1.62	5.00	1.62
GUN8T8	0	Identical High	Best P/F	4	0	1	1	0	1	4.96	20.00	28	19	1	3.04	0.00	4.04	0.00
GUN8T8	0	Identical High	Greedy	4	0	1	1	0	1	4.96	20.00	28	19	1	3.04	0.00	4.04	0.00
GUN8T8	0	Nonidentical low	F	4	0	1	1	0	2	4.98	21.00	28	19	2	2.02	0.00	4.02	0.00
GUN8T8	0	Nonidentical low	P	4	0	1	0	1	5	2.97	24.00	28	19	5	0.00	1.03	5.00	1.03
GUN8T8	0	Nonidentical low	Best P/F	4	0	1	1	0	2	4.98	21.00	28	19	2	2.02	0.00	4.02	0.00
GUN8T8	0	Nonidentical low	Greedy	4	0	1	1	0	2	4.98	21.00	28	19	2	2.02	0.00	4.02	0.00
GUN8T8	0	Nonidentical high	F	4	0	1	1	0	2	4.96	21.00	28	19	2	2.04	0.00	4.04	0.00
GUN8T8	0	Nonidentical high	P	4	0	1	0	1	5	2.71	24.00	28	19	5	0.00	1.29	5.00	1.29
GUN8T8	0	Nonidentical high	Best P/F	4	0	1	1	0	2	4.96	21.00	28	19	2	2.04	0.00	4.04	0.00
GUN8T8	0	Nonidentical high	Greedy	4	0	1	1	0	2	4.96	21.00	28	19	2	2.04	0.00	4.04	0.00
GUN8T8	1	Identical Low	F	2	0	1	1	0	1	16.00	11.00	28	10	1	1.00	0.00	2.00	0.00
GUN8T8	1	Identical Low	P	2	0	1	0	1	3	15.00	13.00	28	10	3	0.00	0.00	3.00	0.00
GUN8T8	1	Identical Low	Best P/F	2	0	1	1	0	1	16.00	11.00	28	10	1	1.00	0.00	2.00	0.00
GUN8T8	1	Identical Low	Greedy	2	0	1	1	0	1	16.00	11.00	28	10	1	1.00	0.00	2.00	0.00
GUN8T8	1	Identical High	F	2	0	1	1	0	1	15.94	11.00	28	10	1	1.06	0.00	2.06	0.00
GUN8T8	1	Identical High	P	2	0	1	0	1	3	14.63	13.00	28	10	3	0.00	0.37	3.00	0.37
GUN8T8	1	Identical High	Best P/F	2	0	1	1	0	1	15.94	11.00	28	10	1	1.06	0.00	2.06	0.00
GUN8T8	1	Identical High	Greedy	2	0	1	1	0	1	15.94	11.00	28	10	1	1.06	0.00	2.06	0.00
GUN8T8	1	Nonidentical low	F	2	0	1	1	0	1	15.99	11.00	28	10	1	1.01	0.00	2.01	0.00
GUN8T8	1	Nonidentical low	P	2	0	1	0	1	3	14.90	13.00	28	10	3	0.00	0.10	3.00	0.10
GUN8T8	1	Nonidentical low	Best P/F	2	0	1	1	0	1	15.99	11.00	28	10	1	1.01	0.00	2.01	0.00

Table D.1 Details of all solutions (continued)

GUN8T8	1	Nonidentic al low	Gree dy	2	0	1	1	0	1	15.99	11.00	28	10	1	1.01	0.00	2.01	0.00
GUN8T8	1	Nonidentic al high	F	2	0	1	1	0	1	15.98	11.00	28	10	1	1.02	0.00	2.02	0.00
GUN8T8	1	Nonidentic al high	P	2	0	1	0	1	3	14.80	13.00	28	10	3	0.00	0.20	3.00	0.20
GUN8T8	1	Nonidentic al high	Best P/F	2	0	1	1	0	1	15.98	11.00	28	10	1	1.02	0.00	2.02	0.00
GUN8T8	1	Nonidentic al high	Gree dy	2	0	1	1	0	1	15.98	11.00	28	10	1	1.02	0.00	2.02	0.00
GUN8T8	3	Identical Low	F	16	0	1	2	0	13	9.95	25.00	38	12	13	3.05	0.00	16.05	0.00
GUN8T8	3	Identical Low	P	16	0	1	0	2	17	7.28	29.00	38	12	17	0.00	1.72	17.00	1.72
GUN8T8	3	Identical Low	Best P/F	16	0	1	2	0	13	9.95	25.00	38	12	13	3.05	0.00	16.05	0.00
GUN8T8	3	Identical Low	Gree dy	16	0	1	2	0	13	9.95	25.00	38	12	13	3.05	0.00	16.05	0.00
GUN8T8	3	Identical High	F	16	0	1	2	0	8	9.79	20.00	38	12	8	8.21	0.00	16.21	0.00
GUN8T8	3	Identical High	P	16	0	1	0	2	18	3.73	30.00	38	12	18	0.00	4.27	18.00	4.27
GUN8T8	3	Identical High	Best P/F	16	0	1	2	0	8	9.79	20.00	38	12	8	8.21	0.00	16.21	0.00
GUN8T8	3	Identical High	Gree dy	16	0	1	2	0	8	9.79	20.00	38	12	8	8.21	0.00	16.21	0.00
GUN8T8	3	Nonidentic al low	F	16	0	1	2	0	11	9.90	23.00	38	12	11	5.10	0.00	16.10	0.00
GUN8T8	3	Nonidentic al low	P	16	0	1	0	2	18	5.85	30.00	38	12	18	0.00	2.15	18.00	2.15
GUN8T8	3	Nonidentic al low	Best P/F	16	0	1	2	0	11	9.90	23.00	38	12	11	5.10	0.00	16.10	0.00
GUN8T8	3	Nonidentic al low	Gree dy	16	0	1	2	0	11	9.90	23.00	38	12	11	5.10	0.00	16.10	0.00
GUN8T8	3	Nonidentic al high	F	16	0	1	2	0	10	9.83	22.00	38	12	10	6.17	0.00	16.17	0.00
GUN8T8	3	Nonidentic al high	P	16	0	1	0	2	18	5.01	30.00	38	12	18	0.00	2.99	18.00	2.99
GUN8T8	3	Nonidentic al high	Best P/F	16	0	1	2	0	10	9.83	22.00	38	12	10	6.17	0.00	16.17	0.00
GUN8T8	3	Nonidentic al high	Gree dy	16	0	1	2	0	10	9.83	22.00	38	12	10	6.17	0.00	16.17	0.00
GUN8T8	4	Identical Low	F	7	0	1	1	0	5	10.99	7.00	20	2	5	2.01	0.00	7.01	0.00
GUN8T8	4	Identical Low	P	7	0	1	0	1	9	8.72	11.00	20	2	9	0.00	0.28	9.00	0.28
GUN8T8	4	Identical Low	Best P/F	7	0	1	1	0	5	10.99	7.00	20	2	5	2.01	0.00	7.01	0.00
GUN8T8	4	Identical Low	Gree dy	7	0	1	1	0	5	10.99	7.00	20	2	5	2.01	0.00	7.01	0.00
GUN8T8	4	Identical High	F	7	0	1	1	0	2	10.92	4.00	20	2	2	5.08	0.00	7.08	0.00
GUN8T8	4	Identical High	P	7	0	1	0	1	9	6.42	11.00	20	2	9	0.00	2.58	9.00	2.58
GUN8T8	4	Identical High	Best P/F	7	0	1	1	0	2	10.92	4.00	20	2	2	5.08	0.00	7.08	0.00
GUN8T8	4	Identical High	Gree dy	7	0	1	1	0	2	10.92	4.00	20	2	2	5.08	0.00	7.08	0.00
GUN8T8	4	Nonidentic al low	F	7	0	1	1	0	4	10.95	6.00	20	2	4	3.05	0.00	7.05	0.00
GUN8T8	4	Nonidentic al low	P	7	0	1	0	1	9	7.51	11.00	20	2	9	0.00	1.49	9.00	1.49
GUN8T8	4	Nonidentic al low	Best P/F	7	0	1	1	0	4	10.95	6.00	20	2	4	3.05	0.00	7.05	0.00
GUN8T8	4	Nonidentic al low	Gree dy	7	0	1	1	0	4	10.95	6.00	20	2	4	3.05	0.00	7.05	0.00
GUN8T8	4	Nonidentic al high	F	7	0	1	1	0	3	10.96	5.00	20	2	3	4.04	0.00	7.04	0.00
GUN8T8	4	Nonidentic al high	P	7	0	1	0	1	9	7.04	11.00	20	2	9	0.00	1.96	9.00	1.96
GUN8T8	4	Nonidentic al high	Best P/F	7	0	1	1	0	3	10.96	5.00	20	2	3	4.04	0.00	7.04	0.00
GUN8T8	4	Nonidentic al high	Gree dy	7	0	1	1	0	3	10.96	5.00	20	2	3	4.04	0.00	7.04	0.00
GUN8T8	5	Identical Low	F	16	0	1	3	0	14	21.94	35.00	59	21	14	2.06	0.00	16.06	0.00
GUN8T8	5	Identical Low	P	16	0	1	0	3	17	19.95	38.00	59	21	17	0.00	1.05	17.00	1.05
GUN8T8	5	Identical Low	Best P/F	16	0	1	3	0	14	21.94	35.00	59	21	14	2.06	0.00	16.06	0.00
GUN8T8	5	Identical Low	Gree dy	16	0	1	3	0	14	21.94	35.00	59	21	14	2.06	0.00	16.06	0.00
GUN8T8	5	Identical High	F	16	0	1	3	0	10	21.83	31.00	59	21	10	6.17	0.00	16.17	0.00

Table D.1 Details of all solutions (continued)

GUN8T8	5	Identical High	P	16	0	1	0	3	17	17.64	38.00	59	21	17	0.00	3.36	17.00	3.36
GUN8T8	5	Identical High	Best P/F	16	0	1	3	0	10	21.83	31.00	59	21	10	6.17	0.00	16.17	0.00
GUN8T8	5	Identical High	Greedy	16	0	1	3	0	10	21.83	31.00	59	21	10	6.17	0.00	16.17	0.00
GUN8T8	5	Nonidentical low	F	16	0	1	3	0	13	21.96	34.00	59	21	13	3.04	0.00	16.04	0.00
GUN8T8	5	Nonidentical low	P	16	0	1	0	3	17	19.69	38.00	59	21	17	0.00	1.31	17.00	1.31
GUN8T8	5	Nonidentical low	Best P/F	16	0	1	3	0	13	21.96	34.00	59	21	13	3.04	0.00	16.04	0.00
GUN8T8	5	Nonidentical low	Greedy	16	0	1	3	0	13	21.96	34.00	59	21	13	3.04	0.00	16.04	0.00
GUN8T8	5	Nonidentical high	F	16	0	1	3	0	11	21.84	32.00	59	21	11	5.16	0.00	16.16	0.00
GUN8T8	5	Nonidentical high	P	16	0	1	0	3	17	18.02	38.00	59	21	17	0.00	2.98	17.00	2.98
GUN8T8	5	Nonidentical high	Best P/F	16	0	1	3	0	11	21.84	32.00	59	21	11	5.16	0.00	16.16	0.00
GUN8T8	5	Nonidentical high	Greedy	16	0	1	3	0	11	21.84	32.00	59	21	11	5.16	0.00	16.16	0.00
GUN8T8	6	Identical Low	F	29	3	3	7	0	23	6.26	148.00	176	79	69	21.74	0.00	30.25	0.00
GUN8T8	6	Identical Low	P	29	3	3	0	7	33	-5.96	178.00	176	79	99	0.00	3.96	33.00	2.46
GUN8T8	6	Identical Low	Best P/F	29	3	3	6	1	23	6.92	148.00	176	79	69	19.49	1.59	29.50	1.59
GUN8T8	6	Identical Low	Greedy	29	3	3	6	1	23	6.92	148.00	176	79	69	19.49	1.59	29.50	1.59
GUN8T8	6	Identical High	F	29	3	3	7	0	15	-8.86	124.00	176	79	45	60.86	0.00	35.29	0.00
GUN8T8	6	Identical High	P	29	3	3	0	7	36	-31.03	187.00	176	79	108	0.00	20.03	36.00	13.68
GUN8T8	6	Identical High	Best P/F	29	3	3	6	1	15	-7.51	124.00	176	79	45	58.04	1.47	34.35	1.47
GUN8T8	6	Identical High	Greedy	29	3	3	6	1	15	-7.51	124.00	176	79	45	58.04	1.47	34.35	1.47
GUN8T8	6	Nonidentical low	F	29	3	3	7	0	22	5.46	145.00	176	79	66	25.54	0.00	30.51	0.00
GUN8T8	6	Nonidentical low	P	29	3	3	0	7	33	-8.31	178.00	176	79	99	0.00	6.31	33.00	3.18
GUN8T8	6	Nonidentical low	Best P/F	29	3	3	6	1	22	6.40	145.00	176	79	66	22.86	1.75	29.62	1.75
GUN8T8	6	Nonidentical low	Greedy	29	3	3	6	1	22	6.40	145.00	176	79	66	22.86	1.75	29.62	1.75
GUN8T8	6	Nonidentical high	F	29	3	3	7	0	17	-5.01	130.00	176	79	51	51.01	0.00	34.00	0.00
GUN8T8	6	Nonidentical high	P	29	3	3	0	7	36	-26.27	187.00	176	79	108	0.00	15.27	36.00	10.63
GUN8T8	6	Nonidentical high	Best P/F	29	3	3	6	1	17	-3.80	130.00	176	79	51	48.33	1.46	33.11	1.46
GUN8T8	6	Nonidentical high	Greedy	29	3	3	6	1	17	-3.80	130.00	176	79	51	48.33	1.46	33.11	1.46
GUN8T8	7	Identical Low	F	43	0	1	4	0	38	18.90	71.00	95	33	38	5.10	0.00	43.10	0.00
GUN8T8	7	Identical Low	P	43	0	1	0	4	46	13.66	79.00	95	33	46	0.00	2.34	46.00	2.34
GUN8T8	7	Identical Low	Best P/F	43	0	1	4	0	38	18.90	71.00	95	33	38	5.10	0.00	43.10	0.00
GUN8T8	7	Identical Low	Greedy	43	0	1	4	0	38	18.90	71.00	95	33	38	5.10	0.00	43.10	0.00
GUN8T8	7	Identical High	F	43	0	1	4	0	30	18.54	63.00	95	33	30	13.46	0.00	43.46	0.00
GUN8T8	7	Identical High	P	43	0	1	0	4	42	9.94	75.00	95	33	42	0.00	10.06	42.00	10.07
GUN8T8	7	Identical High	Best P/F	43	0	1	4	0	30	18.54	63.00	95	33	30	13.46	0.00	43.46	0.00
GUN8T8	7	Identical High	Greedy	43	0	1	4	0	30	18.54	63.00	95	33	30	13.46	0.00	43.46	0.00
GUN8T8	7	Nonidentical low	F	43	0	1	4	0	37	18.80	70.00	95	33	37	6.20	0.00	43.20	0.00
GUN8T8	7	Nonidentical low	P	43	0	1	0	4	45	12.74	78.00	95	33	45	0.00	4.26	45.00	4.26
GUN8T8	7	Nonidentical low	Best P/F	43	0	1	4	0	37	18.80	70.00	95	33	37	6.20	0.00	43.20	0.00
GUN8T8	7	Nonidentical low	Greedy	43	0	1	4	0	37	18.80	70.00	95	33	37	6.20	0.00	43.20	0.00
GUN8T8	7	Nonidentical high	F	43	0	1	4	0	32	18.70	65.00	95	33	32	11.30	0.00	43.30	0.00
GUN8T8	7	Nonidentical high	P	43	0	1	0	4	44	10.96	77.00	95	33	44	0.00	7.04	44.00	7.04
GUN8T8	7	Nonidentical high	Best P/F	43	0	1	4	0	32	18.70	65.00	95	33	32	11.30	0.00	43.30	0.00

Table D.1 Details of all solutions (continued)

GUN8T8	7	Nonidentical high	Greedy	43	0	1	4	0	32	18.70	65.00	95	33	32	11.30	0.00	43.30	0.00
GUN8T8	8	Identical Low	F	11	0	1	1	0	8	0.98	15.00	19	7	8	3.02	0.00	11.02	0.00
GUN8T8	8	Identical Low	P	11	0	1	0	1	13	-2.35	20.00	19	7	13	0.00	1.35	13.00	1.74
GUN8T8	8	Identical Low	Best P/F	11	0	1	1	0	8	0.98	15.00	19	7	8	3.02	0.00	11.02	0.00
GUN8T8	8	Identical Low	Greedy	11	0	1	1	0	8	0.98	15.00	19	7	8	3.02	0.00	11.02	0.00
GUN8T8	8	Identical High	F	11	0	1	1	0	4	0.82	11.00	19	7	4	7.18	0.00	11.18	0.00
GUN8T8	8	Identical High	P	11	0	1	0	1	10	-4.96	17.00	19	7	10	0.00	6.96	10.00	8.93
GUN8T8	8	Identical High	Best P/F	11	0	1	1	0	4	0.82	11.00	19	7	4	7.18	0.00	11.18	0.00
GUN8T8	8	Identical High	Greedy	11	0	1	1	0	4	0.82	11.00	19	7	4	7.18	0.00	11.18	0.00
GUN8T8	8	Nonidentical low	F	11	0	1	1	0	7	0.86	14.00	19	7	7	4.14	0.00	11.14	0.00
GUN8T8	8	Nonidentical low	P	11	0	1	0	1	14	-3.95	21.00	19	7	14	0.00	1.95	14.00	2.51
GUN8T8	8	Nonidentical low	Best P/F	11	0	1	1	0	7	0.86	14.00	19	7	7	4.14	0.00	11.14	0.00
GUN8T8	8	Nonidentical low	Greedy	11	0	1	1	0	7	0.86	14.00	19	7	7	4.14	0.00	11.14	0.00
GUN8T8	8	Nonidentical high	F	11	0	1	1	0	6	0.84	13.00	19	7	6	5.16	0.00	11.16	0.00
GUN8T8	8	Nonidentical high	P	11	0	1	0	1	14	-4.53	21.00	19	7	14	0.00	2.53	14.00	3.24
GUN8T8	8	Nonidentical high	Best P/F	11	0	1	1	0	6	0.84	13.00	19	7	6	5.16	0.00	11.16	0.00
GUN8T8	8	Nonidentical high	Greedy	11	0	1	1	0	6	0.84	13.00	19	7	6	5.16	0.00	11.16	0.00
GUN8T8	9	Identical Low	F	29	0	1	4	0	25	26.89	65.00	96	40	25	4.11	0.00	29.11	0.00
GUN8T8	9	Identical Low	P	29	0	1	0	4	29	24.18	69.00	96	40	29	0.00	2.82	29.00	2.82
GUN8T8	9	Identical Low	Best P/F	29	0	1	4	0	25	26.89	65.00	96	40	25	4.11	0.00	29.11	0.00
GUN8T8	9	Identical Low	Greedy	29	0	1	4	0	25	26.89	65.00	96	40	25	4.11	0.00	29.11	0.00
GUN8T8	9	Identical High	F	29	0	1	4	0	17	26.68	57.00	96	40	17	12.32	0.00	29.32	0.00
GUN8T8	9	Identical High	P	29	0	1	0	4	30	19.59	70.00	96	40	30	0.00	6.41	30.00	6.41
GUN8T8	9	Identical High	Best P/F	29	0	1	4	0	17	26.68	57.00	96	40	17	12.32	0.00	29.32	0.00
GUN8T8	9	Identical High	Greedy	29	0	1	4	0	17	26.68	57.00	96	40	17	12.32	0.00	29.32	0.00
GUN8T8	9	Nonidentical low	F	29	0	1	4	0	22	26.80	62.00	96	40	22	7.20	0.00	29.20	0.00
GUN8T8	9	Nonidentical low	P	29	0	1	0	4	29	22.56	69.00	96	40	29	0.00	4.45	29.00	4.45
GUN8T8	9	Nonidentical low	Best P/F	29	0	1	4	0	22	26.80	62.00	96	40	22	7.20	0.00	29.20	0.00
GUN8T8	9	Nonidentical low	Greedy	29	0	1	4	0	22	26.80	62.00	96	40	22	7.20	0.00	29.20	0.00
GUN8T8	9	Nonidentical high	F	29	0	1	4	0	20	26.75	60.00	96	40	20	9.25	0.00	29.25	0.00
GUN8T8	9	Nonidentical high	P	29	0	1	0	4	30	21.48	70.00	96	40	30	0.00	4.52	30.00	4.52
GUN8T8	9	Nonidentical high	Best P/F	29	0	1	4	0	20	26.75	60.00	96	40	20	9.25	0.00	29.25	0.00
GUN8T8	9	Nonidentical high	Greedy	29	0	1	4	0	20	26.75	60.00	96	40	20	9.25	0.00	29.25	0.00
AKO20T4-A	0	Identical Low	F	21	0	4	11	0	12	180.57	167.00	400	119	48	52.43	0.00	25.11	0.00
AKO20T4-A	0	Identical Low	P	21	0	4	0	11	28	156.98	231.00	400	119	112	0.00	12.02	28.00	12.02
AKO20T4-A	0	Identical Low	Best P/F	21	0	4	10	1	12	181.16	167.00	400	119	48	51.46	0.38	24.87	0.38
AKO20T4-A	0	Identical Low	Greedy	21	0	4	10	1	12	181.16	167.00	400	119	48	51.46	0.38	24.87	0.38
AKO20T4-A	0	Identical High	F	21	0	4	11	0	1	142.66	123.00	400	119	4	134.34	0.00	34.59	0.00
AKO20T4-A	0	Identical High	P	21	0	4	0	11	34	111.75	255.00	400	119	136	0.00	33.25	34.00	33.25
AKO20T4-A	0	Identical High	Best P/F	21	0	4	0	11	1	150.84	123.00	400	119	4	102.46	23.70	26.61	23.70
AKO20T4-A	0	Identical High	Greedy	21	0	4	4	7	1	150.84	123.00	400	119	4	102.46	23.70	26.61	23.70
AKO20T4-A	0	Nonidentical low	F	21	0	4	11	0	16	178.52	183.00	400	119	64	38.48	0.00	25.62	0.00

Table D.1 Details of all solutions (continued)

AKO20T4-A	0	Nonidentical low	P	21	0	4	0	11	28	149.68	231.00	400	119	112	0.00	19.32	28.00	19.32
AKO20T4-A	0	Nonidentical low	Best P/F	21	0	4	10	1	10	179.15	159.00	400	119	40	61.45	0.40	25.36	0.40
AKO20T4-A	0	Nonidentical low	Greedy	21	0	4	10	1	10	179.15	159.00	400	119	40	61.45	0.40	25.36	0.40
AKO20T4-A	0	Nonidentical high	F	21	0	4	11	0	1	140.67	123.00	400	119	4	136.33	0.00	35.08	0.00
AKO20T4-A	0	Nonidentical high	P	21	0	4	0	11	35	108.72	259.00	400	119	140	0.00	32.28	35.00	32.28
AKO20T4-A	0	Nonidentical high	Best P/F	21	0	4	0	11	1	149.46	123.00	400	119	4	104.16	23.39	27.04	23.39
AKO20T4-A	0	Nonidentical high	Greedy	21	0	4	4	7	1	149.46	123.00	400	119	4	104.16	23.39	27.04	23.39
AKO20T4-A	1	Identical Low	F	35	0	2	9	0	29	166.59	151.00	332	93	58	14.41	0.00	36.20	0.00
AKO20T4-A	1	Identical Low	P	35	0	2	0	9	39	158.45	171.00	332	93	78	0.00	2.55	39.00	2.55
AKO20T4-A	1	Identical Low	Best P/F	35	0	2	9	0	29	166.59	151.00	332	93	58	14.41	0.00	36.20	0.00
AKO20T4-A	1	Identical Low	Greedy	35	0	2	9	0	29	166.59	151.00	332	93	58	14.41	0.00	36.20	0.00
AKO20T4-A	1	Identical High	F	35	0	2	9	0	21	160.02	135.00	332	93	42	36.98	0.00	39.49	0.00
AKO20T4-A	1	Identical High	P	35	0	2	0	9	39	146.46	171.00	332	93	78	0.00	14.54	39.00	14.54
AKO20T4-A	1	Identical High	Best P/F	35	0	2	8	1	21	160.78	135.00	332	93	42	32.95	3.27	37.47	3.27
AKO20T4-A	1	Identical High	Greedy	35	0	2	8	1	21	160.78	135.00	332	93	42	32.95	3.27	37.47	3.27
AKO20T4-A	1	Nonidentical low	F	35	0	2	9	0	28	165.06	149.00	332	93	56	17.94	0.00	36.97	0.00
AKO20T4-A	1	Nonidentical low	P	35	0	2	0	9	40	154.70	173.00	332	93	80	0.00	4.30	40.00	4.30
AKO20T4-A	1	Nonidentical low	Best P/F	35	0	2	9	0	28	165.06	149.00	332	93	56	17.94	0.00	36.97	0.00
AKO20T4-A	1	Nonidentical low	Greedy	35	0	2	9	0	28	165.06	149.00	332	93	56	17.94	0.00	36.97	0.00
AKO20T4-A	1	Nonidentical high	F	35	0	2	9	0	21	159.73	135.00	332	93	42	37.27	0.00	39.64	0.00
AKO20T4-A	1	Nonidentical high	P	35	0	2	0	9	39	145.79	171.00	332	93	78	0.00	15.21	39.00	15.21
AKO20T4-A	1	Nonidentical high	Best P/F	35	0	2	8	1	21	160.50	135.00	332	93	42	33.23	3.27	37.62	3.27
AKO20T4-A	1	Nonidentical high	Greedy	35	0	2	8	1	21	160.50	135.00	332	93	42	33.23	3.27	37.62	3.27
AKO20T4-A	2	Identical Low	F	56	3	2	9	0	47	79.85	158.00	257	64	94	19.15	0.00	56.58	0.00
AKO20T4-A	2	Identical Low	P	56	3	2	0	9	59	68.31	182.00	257	64	118	0.00	6.69	59.00	6.69
AKO20T4-A	2	Identical Low	Best P/F	56	3	2	9	0	47	79.85	158.00	257	64	94	19.15	0.00	56.58	0.00
AKO20T4-A	2	Identical Low	Greedy	56	3	2	9	0	47	79.85	158.00	257	64	94	19.15	0.00	56.58	0.00
AKO20T4-A	2	Identical High	F	56	3	2	9	0	36	70.20	136.00	257	64	72	50.80	0.00	61.40	0.00
AKO20T4-A	2	Identical High	P	56	3	2	0	9	59	55.30	182.00	257	64	118	0.00	19.70	59.00	19.70
AKO20T4-A	2	Identical High	Best P/F	56	3	2	8	1	36	70.76	136.00	257	64	72	41.99	8.24	57.00	8.24
AKO20T4-A	2	Identical High	Greedy	56	3	2	8	1	36	70.76	136.00	257	64	72	41.99	8.24	57.00	8.24
AKO20T4-A	2	Nonidentical low	F	56	3	2	9	0	47	79.32	158.00	257	64	94	19.68	0.00	56.84	0.00
AKO20T4-A	2	Nonidentical low	P	56	3	2	0	9	59	67.23	182.00	257	64	118	0.00	7.77	59.00	7.77
AKO20T4-A	2	Nonidentical low	Best P/F	56	3	2	9	0	47	79.32	158.00	257	64	94	19.68	0.00	56.84	0.00
AKO20T4-A	2	Nonidentical low	Greedy	56	3	2	9	0	47	79.32	158.00	257	64	94	19.68	0.00	56.84	0.00
AKO20T4-A	2	Nonidentical high	F	56	3	2	9	0	34	69.81	132.00	257	64	68	55.19	0.00	61.59	0.00
AKO20T4-A	2	Nonidentical high	P	56	3	2	0	9	57	57.28	178.00	257	64	114	0.00	21.72	57.00	21.72
AKO20T4-A	2	Nonidentical high	Best P/F	56	3	2	8	1	34	70.35	132.00	257	64	68	46.34	8.30	57.17	8.30
AKO20T4-A	2	Nonidentical high	Greedy	56	3	2	8	1	34	70.35	132.00	257	64	68	46.34	8.30	57.17	8.30
AKO20T4-A	3	Identical Low	F	36	0	3	11	0	25	169.00	163.00	371	88	75	39.00	0.00	38.00	0.00
AKO20T4-A	3	Identical Low	P	36	0	3	0	11	42	150.33	214.00	371	88	126	0.00	6.67	42.00	6.67
AKO20T4-A	3	Identical Low	Best P/F	36	0	3	9	2	25	169.00	163.00	371	88	75	38.97	0.02	37.99	0.02

Table D.1 Details of all solutions (continued)

AKO20T4-A	3	Identical Low	Greedy	36	0	3	9	2	25	169.00	163.00	371	88	75	38.97	0.02	37.99	0.02
AKO20T4-A	3	Identical High	F	36	0	3	11	0	19	154.90	145.00	371	88	57	71.10	0.00	42.70	0.00
AKO20T4-A	3	Identical High	P	36	0	3	0	11	46	122.17	226.00	371	88	138	0.00	22.83	46.00	22.83
AKO20T4-A	3	Identical High	Best P/F	36	0	3	6	5	19	155.50	145.00	371	88	57	68.96	1.55	41.99	1.55
AKO20T4-A	3	Identical High	Greedy	36	0	3	6	5	19	155.50	145.00	371	88	57	68.96	1.55	41.99	1.55
AKO20T4-A	3	Nonidentical low	F	36	0	3	11	0	25	169.14	163.00	371	88	75	38.86	0.00	37.95	0.00
AKO20T4-A	3	Nonidentical low	P	36	0	3	0	11	42	150.21	214.00	371	88	126	0.00	6.79	42.00	6.79
AKO20T4-A	3	Nonidentical low	Best P/F	36	0	3	9	2	25	169.15	163.00	371	88	75	38.82	0.04	37.94	0.04
AKO20T4-A	3	Nonidentical low	Greedy	36	0	3	9	2	25	169.15	163.00	371	88	75	38.82	0.04	37.94	0.04
AKO20T4-A	3	Nonidentical high	F	36	0	3	11	0	19	156.91	145.00	371	88	57	69.09	0.00	42.03	0.00
AKO20T4-A	3	Nonidentical high	P	36	0	3	0	11	45	124.37	223.00	371	88	135	0.00	23.63	45.00	23.63
AKO20T4-A	3	Nonidentical high	Best P/F	36	0	3	6	5	19	157.34	145.00	371	88	57	67.34	1.32	41.45	1.32
AKO20T4-A	3	Nonidentical high	Greedy	36	0	3	6	5	19	157.34	145.00	371	88	57	67.34	1.32	41.45	1.32
AKO20T4-A	4	Identical Low	F	23	0	4	10	0	16	70.43	144.00	249	80	64	34.57	0.00	24.64	0.00
AKO20T4-A	4	Identical Low	P	23	0	4	0	10	26	58.85	184.00	249	80	104	0.00	6.15	26.00	6.15
AKO20T4-A	4	Identical Low	Best P/F	23	0	4	9	1	16	70.51	144.00	249	80	64	34.15	0.33	24.54	0.33
AKO20T4-A	4	Identical Low	Greedy	23	0	4	9	1	16	70.51	144.00	249	80	64	34.15	0.33	24.54	0.33
AKO20T4-A	4	Identical High	F	23	0	4	10	0	10	50.26	120.00	249	80	40	78.74	0.00	29.68	0.00
AKO20T4-A	4	Identical High	P	23	0	4	0	10	31	28.15	204.00	249	80	124	0.00	16.85	31.00	16.85
AKO20T4-A	4	Identical High	Best P/F	23	0	4	5	5	10	53.38	120.00	249	80	40	61.79	13.83	25.45	13.83
AKO20T4-A	4	Identical High	Greedy	23	0	4	5	5	10	53.38	120.00	249	80	40	61.79	13.83	25.45	13.83
AKO20T4-A	4	Nonidentical low	F	23	0	4	10	0	14	67.94	136.00	249	80	56	45.06	0.00	25.27	0.00
AKO20T4-A	4	Nonidentical low	P	23	0	4	0	10	26	57.84	184.00	249	80	104	0.00	7.16	26.00	7.16
AKO20T4-A	4	Nonidentical low	Best P/F	23	0	4	8	2	14	68.72	136.00	249	80	56	40.71	3.57	24.18	3.57
AKO20T4-A	4	Nonidentical low	Greedy	23	0	4	8	2	14	68.72	136.00	249	80	56	40.71	3.57	24.18	3.57
AKO20T4-A	4	Nonidentical high	F	23	0	4	10	0	9	50.89	116.00	249	80	36	82.11	0.00	29.53	0.00
AKO20T4-A	4	Nonidentical high	P	23	0	4	0	10	30	29.49	200.00	249	80	120	0.00	19.51	30.00	19.51
AKO20T4-A	4	Nonidentical high	Best P/F	23	0	4	5	5	9	54.40	116.00	249	80	36	63.04	15.57	24.76	15.57
AKO20T4-A	4	Nonidentical high	Greedy	23	0	4	5	5	9	54.40	116.00	249	80	36	63.04	15.57	24.76	15.57
AKO20T4-A	5	Identical Low	F	46	0	3	11	0	39	117.67	226.00	372	109	117	28.33	0.00	48.44	0.00
AKO20T4-A	5	Identical Low	P	46	0	3	0	11	48	108.81	253.00	372	109	144	0.00	10.19	48.00	10.19
AKO20T4-A	5	Identical Low	Best P/F	46	0	3	10	1	39	117.98	226.00	372	109	117	26.76	1.26	47.92	1.26
AKO20T4-A	5	Identical Low	Greedy	46	0	3	10	1	39	117.98	226.00	372	109	117	26.76	1.26	47.92	1.26
AKO20T4-A	5	Identical High	F	46	0	3	11	0	29	97.92	196.00	372	109	87	78.08	0.00	55.03	0.00
AKO20T4-A	5	Identical High	P	46	0	3	0	11	53	83.32	268.00	372	109	159	0.00	20.68	53.00	20.68
AKO20T4-A	5	Identical High	Best P/F	46	0	3	7	4	29	104.79	196.00	372	109	87	43.08	28.14	43.36	28.14
AKO20T4-A	5	Identical High	Greedy	46	0	3	7	4	29	104.79	196.00	372	109	87	43.08	28.14	43.36	28.14
AKO20T4-A	5	Nonidentical low	F	46	0	3	11	0	38	116.76	223.00	372	109	114	32.24	0.00	48.75	0.00
AKO20T4-A	5	Nonidentical low	P	46	0	3	0	11	48	109.31	253.00	372	109	144	0.00	9.69	48.00	9.69
AKO20T4-A	5	Nonidentical low	Best P/F	46	0	3	10	1	38	117.07	223.00	372	109	114	30.63	1.30	48.21	1.30
AKO20T4-A	5	Nonidentical low	Greedy	46	0	3	10	1	38	117.07	223.00	372	109	114	30.63	1.30	48.21	1.30
AKO20T4-A	5	Nonidentical high	F	46	0	3	11	0	27	97.15	190.00	372	109	81	84.86	0.00	55.29	0.00

Table D.1 Details of all solutions (continued)

AKO20T4-A	5	Nonidentical high	P	46	0	3	0	11	53	83.34	268.00	372	109	159	0.00	20.66	53.00	20.66
AKO20T4-A	5	Nonidentical high	Best P/F	46	0	3	7	4	27	104.22	190.00	372	109	81	49.95	27.83	43.65	27.83
AKO20T4-A	5	Nonidentical high	Greedy	46	0	3	7	4	40	102.57	229.00	372	109	120	16.26	24.17	45.42	24.17
AKO20T4-A	6	Identical Low	F	40	1	3	11	0	34	341.92	194.00	561	92	102	25.08	0.00	42.36	0.00
AKO20T4-A	6	Identical Low	P	40	1	3	0	11	44	331.14	224.00	561	92	132	0.00	5.86	44.00	5.86
AKO20T4-A	6	Identical Low	Best P/F	40	1	3	11	0	34	341.92	194.00	561	92	102	25.08	0.00	42.36	0.00
AKO20T4-A	6	Identical Low	Greedy	40	1	3	11	0	34	341.92	194.00	561	92	102	25.08	0.00	42.36	0.00
AKO20T4-A	6	Identical High	F	40	1	3	11	0	26	325.19	170.00	561	92	78	65.81	0.00	47.94	0.00
AKO20T4-A	6	Identical High	P	40	1	3	0	11	48	306.60	236.00	561	92	144	0.00	18.40	48.00	18.40
AKO20T4-A	6	Identical High	Best P/F	40	1	3	8	3	26	330.51	170.00	561	92	78	42.95	17.55	40.32	17.55
AKO20T4-A	6	Identical High	Greedy	40	1	3	8	3	26	330.51	170.00	561	92	78	42.95	17.55	40.32	17.55
AKO20T4-A	6	Nonidentical low	F	40	1	3	11	0	34	342.75	194.00	561	92	102	24.25	0.00	42.08	0.00
AKO20T4-A	6	Nonidentical low	P	40	1	3	0	11	43	334.26	221.00	561	92	129	0.00	5.74	43.00	5.74
AKO20T4-A	6	Nonidentical low	Best P/F	40	1	3	11	0	34	342.75	194.00	561	92	102	24.25	0.00	42.08	0.00
AKO20T4-A	6	Nonidentical low	Greedy	40	1	3	11	0	34	342.75	194.00	561	92	102	24.25	0.00	42.08	0.00
AKO20T4-A	6	Nonidentical high	F	40	1	3	11	0	24	326.10	164.00	561	92	72	70.90	0.00	47.63	0.00
AKO20T4-A	6	Nonidentical high	P	40	1	3	0	11	47	310.78	233.00	561	92	141	0.00	17.22	47.00	17.22
AKO20T4-A	6	Nonidentical high	Best P/F	40	1	3	8	3	24	331.62	164.00	561	92	72	47.32	18.06	39.77	18.06
AKO20T4-A	6	Nonidentical high	Greedy	40	1	3	8	3	24	331.62	164.00	561	92	72	47.32	18.06	39.77	18.06
AKO20T4-A	7	Identical Low	F	37	4	3	9	0	31	61.85	205.00	293	112	93	26.15	0.00	39.72	0.00
AKO20T4-A	7	Identical Low	Best P/F	37	4	3	9	0	31	61.85	205.00	293	112	93	26.15	0.00	39.72	0.00
AKO20T4-A	7	Identical Low	Greedy	37	4	3	9	0	31	61.85	205.00	293	112	93	26.15	0.00	39.72	0.00
AKO20T4-A	7	Identical High	Best P/F	37	4	3	5	4	33	24.19	211.00	293	112	99	19.54	38.27	39.51	38.27
AKO20T4-A	7	Identical High	Greedy	37	4	3	5	4	33	24.19	211.00	293	112	99	19.54	38.27	39.51	38.27
AKO20T4-A	7	Nonidentical low	Best P/F	37	4	3	8	1	30	57.90	202.00	293	112	90	29.12	3.98	39.71	3.98
AKO20T4-A	7	Nonidentical low	Greedy	37	4	3	6	3	30	57.90	202.00	293	112	90	29.12	3.98	39.71	3.98
AKO20T4-A	7	Nonidentical high	Best P/F	37	4	3	5	4	34	24.22	214.00	293	112	102	16.29	38.49	39.43	38.49
AKO20T4-A	7	Nonidentical high	Greedy	37	4	3	5	4	34	24.22	214.00	293	112	102	16.29	38.49	39.43	38.49
AKO20T4-A	8	Identical Low	F	43	0	3	11	0	33	189.70	214.00	438	115	99	34.30	0.00	44.43	0.00
AKO20T4-A	8	Identical Low	P	43	0	3	0	11	46	179.41	253.00	438	115	138	0.00	5.59	46.00	5.59
AKO20T4-A	8	Identical Low	Best P/F	43	0	3	10	1	33	190.06	214.00	438	115	99	32.37	1.56	43.79	1.56
AKO20T4-A	8	Identical Low	Greedy	43	0	3	10	1	33	190.06	214.00	438	115	99	32.37	1.56	43.79	1.56
AKO20T4-A	8	Identical High	F	43	0	3	11	0	23	172.32	184.00	438	115	69	81.68	0.00	50.23	0.00
AKO20T4-A	8	Identical High	P	43	0	3	0	11	47	156.40	256.00	438	115	141	0.00	25.60	47.00	25.60
AKO20T4-A	8	Identical High	Best P/F	43	0	3	7	4	23	177.59	184.00	438	115	69	55.88	20.53	41.63	20.53
AKO20T4-A	8	Identical High	Greedy	43	0	3	7	4	23	177.59	184.00	438	115	69	55.88	20.53	41.63	20.53
AKO20T4-A	8	Nonidentical low	F	43	0	3	11	0	31	187.98	208.00	438	115	93	42.02	0.00	45.01	0.00
AKO20T4-A	8	Nonidentical low	P	43	0	3	0	11	47	175.73	256.00	438	115	141	0.00	6.27	47.00	6.27
AKO20T4-A	8	Nonidentical low	Best P/F	43	0	3	10	1	31	188.63	208.00	438	115	93	39.68	1.69	44.23	1.69
AKO20T4-A	8	Nonidentical low	Greedy	43	0	3	10	1	31	188.63	208.00	438	115	93	39.68	1.69	44.23	1.69
AKO20T4-A	8	Nonidentical high	F	43	0	3	11	0	22	172.60	181.00	438	115	66	84.40	0.00	50.13	0.00
AKO20T4-A	8	Nonidentical high	P	43	0	3	0	11	47	156.50	256.00	438	115	141	0.00	25.50	47.00	25.50

Table D.1 Details of all solutions (continued)

AKO20T4-A	8	Nonidentical high	Best P/F	43	0	3	8	3	22	177.55	181.00	438	115	66	69.14	10.31	45.05	10.31
AKO20T4-A	8	Nonidentical high	Greedy	43	0	3	8	3	22	177.55	181.00	438	115	66	69.14	10.31	45.05	10.31
AKO20T4-A	9	Identical Low	F	20	0	6	11	0	14	148.51	176.00	374	92	84	49.49	0.00	22.25	0.00
AKO20T4-A	9	Identical Low	P	20	0	6	0	11	25	123.39	242.00	374	92	150	0.00	8.61	25.00	8.61
AKO20T4-A	9	Identical Low	Best P/F	20	0	6	11	0	14	148.51	176.00	374	92	84	49.49	0.00	22.25	0.00
AKO20T4-A	9	Identical Low	Greedy	20	0	6	11	0	14	148.51	176.00	374	92	84	49.49	0.00	22.25	0.00
AKO20T4-A	9	Identical High	F	20	0	6	11	0	8	114.17	140.00	374	92	48	119.83	0.00	27.97	0.00
AKO20T4-A	9	Identical High	P	20	0	6	0	11	30	74.60	272.00	374	92	180	0.00	27.40	30.00	27.40
AKO20T4-A	9	Identical High	Best P/F	20	0	6	8	3	8	116.80	140.00	374	92	48	112.00	5.19	26.67	5.19
AKO20T4-A	9	Identical High	Greedy	20	0	6	6	5	8	116.74	140.00	374	92	48	111.91	5.35	26.65	5.35
AKO20T4-A	9	Nonidentical low	F	20	0	6	11	0	13	148.93	170.00	374	92	78	55.07	0.00	22.18	0.00
AKO20T4-A	9	Nonidentical low	P	20	0	6	0	11	25	117.48	242.00	374	92	150	0.00	14.52	25.00	14.52
AKO20T4-A	9	Nonidentical low	Best P/F	20	0	6	10	1	13	148.96	170.00	374	92	78	54.40	0.64	22.07	0.64
AKO20T4-A	9	Nonidentical low	Greedy	20	0	6	10	1	13	148.96	170.00	374	92	78	54.40	0.64	22.07	0.64
AKO20T4-A	9	Nonidentical high	F	20	0	6	11	0	10	122.30	152.00	374	92	60	99.70	0.00	26.62	0.00
AKO20T4-A	9	Nonidentical high	P	20	0	6	0	11	29	90.01	266.00	374	92	174	0.00	17.99	29.00	17.99
AKO20T4-A	9	Nonidentical high	Best P/F	20	0	6	8	3	10	125.05	152.00	374	92	60	91.25	5.70	25.21	5.70
AKO20T4-A	9	Nonidentical high	Greedy	20	0	6	7	4	10	124.97	152.00	374	92	60	91.11	5.92	25.19	5.92
LAM20T10	0	Identical Low	F	19	0	3	9	0	15	169.70	136.00	323	91	45	17.30	0.00	20.77	0.00
LAM20T10	0	Identical Low	P	19	0	3	0	9	22	160.81	157.00	323	91	66	0.00	5.19	22.00	5.19
LAM20T10	0	Identical Low	Best P/F	19	0	3	7	2	15	170.49	136.00	323	91	45	14.87	1.64	19.96	1.64
LAM20T10	0	Identical Low	Greedy	19	0	3	7	2	15	170.49	136.00	323	91	45	14.87	1.64	19.96	1.64
LAM20T10	0	Identical High	F	19	0	3	9	0	8	157.84	115.00	323	91	24	50.16	0.00	24.72	0.00
LAM20T10	0	Identical High	P	19	0	3	0	9	22	146.92	157.00	323	91	66	0.00	19.08	22.00	19.08
LAM20T10	0	Identical High	Best P/F	19	0	3	5	4	8	159.37	115.00	323	91	24	44.05	4.59	22.68	4.59
LAM20T10	0	Identical High	Greedy	19	0	3	5	4	8	159.37	115.00	323	91	24	44.05	4.59	22.68	4.59
LAM20T10	0	Nonidentical low	F	19	0	3	9	0	16	173.08	139.00	323	91	48	10.92	0.00	19.64	0.00
LAM20T10	0	Nonidentical low	P	19	0	3	0	9	21	167.18	154.00	323	91	63	0.00	1.82	21.00	1.82
LAM20T10	0	Nonidentical low	Best P/F	19	0	3	8	1	16	173.10	139.00	323	91	48	10.74	0.16	19.58	0.16
LAM20T10	0	Nonidentical low	Greedy	19	0	3	8	1	16	173.10	139.00	323	91	48	10.74	0.16	19.58	0.16
LAM20T10	0	Nonidentical high	F	19	0	3	9	0	7	156.56	112.00	323	91	21	54.44	0.00	25.15	0.00
LAM20T10	0	Nonidentical high	P	19	0	3	0	9	22	145.97	157.00	323	91	66	0.00	20.03	22.00	20.03
LAM20T10	0	Nonidentical high	Best P/F	19	0	3	5	4	7	158.40	112.00	323	91	21	47.99	4.61	23.00	4.61
LAM20T10	0	Nonidentical high	Greedy	19	0	3	5	4	7	158.40	112.00	323	91	21	47.99	4.61	23.00	4.61
LAM20T10	1	Identical Low	F	25	0	2	9	0	22	282.63	131.00	422	87	44	8.37	0.00	26.18	0.00
LAM20T10	1	Identical Low	P	25	0	2	0	9	28	277.18	143.00	422	87	56	0.00	1.82	28.00	1.82
LAM20T10	1	Identical Low	Best P/F	25	0	2	9	0	22	282.63	131.00	422	87	44	8.37	0.00	26.18	0.00
LAM20T10	1	Identical Low	Greedy	25	0	2	9	0	22	282.63	131.00	422	87	44	8.37	0.00	26.18	0.00
LAM20T10	1	Identical High	F	25	0	2	9	0	16	277.89	119.00	422	87	32	25.11	0.00	28.55	0.00
LAM20T10	1	Identical High	P	25	0	2	0	9	26	270.73	139.00	422	87	52	0.00	12.27	26.00	12.27
LAM20T10	1	Identical High	Best P/F	25	0	2	8	1	16	278.47	119.00	422	87	32	21.04	3.48	26.52	3.48
LAM20T10	1	Identical High	Greedy	25	0	2	8	1	16	278.47	119.00	422	87	32	21.04	3.48	26.52	3.48

Table D.1 Details of all solutions (continued)

LAM20T10	1	Nonidentical low	F	25	0	2	9	0	20	281.72	127.00	422	87	40	13.28	0.00	26.64	0.00
LAM20T10	1	Nonidentical low	P	25	0	2	0	9	28	276.26	143.00	422	87	56	0.00	2.74	28.00	2.74
LAM20T10	1	Nonidentical low	Best P/F	25	0	2	9	0	20	281.72	127.00	422	87	40	13.28	0.00	26.64	0.00
LAM20T10	1	Nonidentical low	Greedy	25	0	2	9	0	20	281.72	127.00	422	87	40	13.28	0.00	26.64	0.00
LAM20T10	1	Nonidentical high	F	25	0	2	9	0	14	277.39	115.00	422	87	28	29.61	0.00	28.81	0.00
LAM20T10	1	Nonidentical high	P	25	0	2	0	9	26	270.72	139.00	422	87	52	0.00	12.28	26.00	12.28
LAM20T10	1	Nonidentical high	Best P/F	25	0	2	8	1	14	278.05	115.00	422	87	28	25.45	3.50	26.73	3.50
LAM20T10	1	Nonidentical high	Greedy	25	0	2	8	1	14	278.05	115.00	422	87	28	25.45	3.50	26.73	3.50
LAM20T10	2	Identical Low	F	38	3	2	8	0	27	137.63	115.00	275	61	54	22.37	0.00	38.18	0.00
LAM20T10	2	Identical Low	P	38	3	2	0	8	43	125.14	147.00	275	61	86	0.00	2.86	43.00	2.86
LAM20T10	2	Identical Low	Best P/F	38	3	2	6	2	27	137.67	115.00	275	61	54	22.13	0.21	38.06	0.21
LAM20T10	2	Identical Low	Greedy	38	3	2	6	2	27	137.67	115.00	275	61	54	22.13	0.21	38.06	0.21
LAM20T10	2	Identical High	F	38	3	2	8	0	19	132.27	99.00	275	61	38	43.73	0.00	40.86	0.00
LAM20T10	2	Identical High	P	38	3	2	0	8	43	108.80	147.00	275	61	86	0.00	19.20	43.00	19.32
LAM20T10	2	Identical High	Best P/F	38	3	2	6	2	19	132.61	99.00	275	61	38	42.52	0.88	40.26	0.88
LAM20T10	2	Identical High	Greedy	38	3	2	6	2	19	132.61	99.00	275	61	38	42.52	0.88	40.26	0.88
LAM20T10	2	Nonidentical low	F	38	3	2	8	0	28	137.26	117.00	275	61	56	20.74	0.00	38.37	0.00
LAM20T10	2	Nonidentical low	P	38	3	2	0	8	43	119.60	147.00	275	61	86	0.00	8.40	43.00	8.41
LAM20T10	2	Nonidentical low	Best P/F	38	3	2	6	2	28	137.33	117.00	275	61	56	20.34	0.32	38.17	0.32
LAM20T10	2	Nonidentical low	Greedy	38	3	2	6	2	28	137.33	117.00	275	61	56	20.34	0.32	38.17	0.32
LAM20T10	2	Nonidentical high	F	38	3	2	8	0	18	131.23	97.00	275	61	36	46.77	0.00	41.39	0.00
LAM20T10	2	Nonidentical high	P	38	3	2	0	8	43	106.40	147.00	275	61	86	0.00	21.60	43.00	21.77
LAM20T10	2	Nonidentical high	Best P/F	38	3	2	6	2	18	131.59	97.00	275	61	36	45.49	0.92	40.75	0.92
LAM20T10	2	Nonidentical high	Greedy	38	3	2	6	2	18	131.59	97.00	275	61	36	45.49	0.92	40.75	0.92
LAM20T10	3	Identical Low	F	47	4	2	9	0	40	230.52	150.00	398	70	80	17.48	0.00	48.74	0.00
LAM20T10	3	Identical Low	P	47	4	2	0	9	54	216.65	178.00	398	70	108	0.00	3.35	54.00	3.35
LAM20T10	3	Identical Low	Best P/F	47	4	2	9	0	40	230.52	150.00	398	70	80	17.48	0.00	48.74	0.00
LAM20T10	3	Identical Low	Greedy	47	4	2	9	0	40	230.52	150.00	398	70	80	17.48	0.00	48.74	0.00
LAM20T10	3	Identical High	F	47	4	2	9	0	30	221.71	130.00	398	70	60	46.29	0.00	53.14	0.00
LAM20T10	3	Identical High	P	47	4	2	0	9	59	194.70	188.00	398	70	118	0.00	15.30	59.00	15.30
LAM20T10	3	Identical High	Best P/F	47	4	2	9	0	30	221.71	130.00	398	70	60	46.29	0.00	53.14	0.00
LAM20T10	3	Identical High	Greedy	47	4	2	9	0	30	221.71	130.00	398	70	60	46.29	0.00	53.14	0.00
LAM20T10	3	Nonidentical low	F	47	4	2	9	0	39	229.92	148.00	398	70	78	20.08	0.00	49.04	0.00
LAM20T10	3	Nonidentical low	P	47	4	2	0	9	55	210.94	180.00	398	70	110	0.00	7.06	55.00	7.06
LAM20T10	3	Nonidentical low	Best P/F	47	4	2	9	0	39	229.92	148.00	398	70	78	20.08	0.00	49.04	0.00
LAM20T10	3	Nonidentical low	Greedy	47	4	2	9	0	39	229.92	148.00	398	70	78	20.08	0.00	49.04	0.00
LAM20T10	3	Nonidentical high	F	47	4	2	9	0	30	220.90	130.00	398	70	60	47.10	0.00	53.55	0.00
LAM20T10	3	Nonidentical high	P	47	4	2	0	9	59	192.53	188.00	398	70	118	0.00	17.47	59.00	17.47
LAM20T10	3	Nonidentical high	Best P/F	47	4	2	8	1	30	220.94	130.00	398	70	60	36.47	10.60	48.23	10.60
LAM20T10	3	Nonidentical high	Greedy	47	4	2	8	1	30	220.94	130.00	398	70	60	36.47	10.60	48.23	10.60
LAM20T10	4	Identical Low	F	21	1	5	9	0	15	276.38	172.00	491	97	75	42.62	0.00	23.52	0.00
LAM20T10	4	Identical Low	P	21	1	5	0	9	26	257.93	227.00	491	97	130	0.00	6.07	26.00	6.07

Table D.1 Details of all solutions (continued)

LAM20T10	4	Identical Low	Best P/F	21	1	5	9	0	15	276.38	172.00	491	97	75	42.62	0.00	23.52	0.00
LAM20T10	4	Identical Low	Greedy	21	1	5	9	0	15	276.38	172.00	491	97	75	42.62	0.00	23.52	0.00
LAM20T10	4	Identical High	F	21	1	5	9	0	8	245.46	137.00	491	97	40	108.54	0.00	29.71	0.00
LAM20T10	4	Identical High	P	21	1	5	0	9	30	215.36	247.00	491	97	150	0.00	28.64	30.00	28.64
LAM20T10	4	Identical High	Best P/F	21	1	5	7	2	8	246.66	137.00	491	97	40	99.67	7.67	27.93	7.67
LAM20T10	4	Identical High	Greedy	21	1	5	7	2	8	246.66	137.00	491	97	40	99.67	7.67	27.93	7.67
LAM20T10	4	Nonidentical low	F	21	1	5	9	0	13	274.79	162.00	491	97	65	54.21	0.00	23.84	0.00
LAM20T10	4	Nonidentical low	P	21	1	5	0	9	24	261.67	217.00	491	97	120	0.00	12.33	24.00	12.33
LAM20T10	4	Nonidentical low	Best P/F	21	1	5	8	1	13	274.83	162.00	491	97	65	53.43	0.74	23.69	0.74
LAM20T10	4	Nonidentical low	Greedy	21	1	5	8	1	13	274.83	162.00	491	97	65	53.43	0.74	23.69	0.74
LAM20T10	4	Nonidentical high	F	21	1	5	9	0	8	246.21	137.00	491	97	40	107.79	0.00	29.56	0.00
LAM20T10	4	Nonidentical high	P	21	1	5	0	9	30	217.20	247.00	491	97	150	0.00	26.80	30.00	26.80
LAM20T10	4	Nonidentical high	Best P/F	21	1	5	7	2	8	247.95	137.00	491	97	40	97.94	8.11	27.59	8.11
LAM20T10	4	Nonidentical high	Greedy	21	1	5	7	2	8	247.95	137.00	491	97	40	97.94	8.11	27.59	8.11
LAM20T10	5	Identical Low	F	23	3	2	8	0	17	151.12	98.00	262	64	34	12.88	0.00	23.44	0.00
LAM20T10	5	Identical Low	P	23	3	2	0	8	26	144.87	116.00	262	64	52	0.00	1.13	26.00	1.13
LAM20T10	5	Identical Low	Best P/F	23	3	2	8	0	17	151.12	98.00	262	64	34	12.88	0.00	23.44	0.00
LAM20T10	5	Identical Low	Greedy	23	3	2	8	0	17	151.12	98.00	262	64	34	12.88	0.00	23.44	0.00
LAM20T10	5	Identical High	F	23	3	2	8	0	11	146.73	86.00	262	64	22	29.27	0.00	25.64	0.00
LAM20T10	5	Identical High	P	23	3	2	0	8	28	134.91	120.00	262	64	56	0.00	7.09	28.00	7.09
LAM20T10	5	Identical High	Best P/F	23	3	2	7	1	11	147.11	86.00	262	64	22	26.02	2.88	24.01	2.88
LAM20T10	5	Identical High	Greedy	23	3	2	7	1	11	147.11	86.00	262	64	22	26.02	2.88	24.01	2.88
LAM20T10	5	Nonidentical low	F	23	3	2	8	0	18	151.21	100.00	262	64	36	10.79	0.00	23.39	0.00
LAM20T10	5	Nonidentical low	P	23	3	2	0	8	26	144.61	116.00	262	64	52	0.00	1.39	26.00	1.39
LAM20T10	5	Nonidentical low	Best P/F	23	3	2	8	0	18	151.21	100.00	262	64	36	10.79	0.00	23.39	0.00
LAM20T10	5	Nonidentical low	Greedy	23	3	2	8	0	18	151.21	100.00	262	64	36	10.79	0.00	23.39	0.00
LAM20T10	5	Nonidentical high	F	23	3	2	8	0	11	146.66	86.00	262	64	22	29.34	0.00	25.67	0.00
LAM20T10	5	Nonidentical high	P	23	3	2	0	8	28	134.83	120.00	262	64	56	0.00	7.17	28.00	7.17
LAM20T10	5	Nonidentical high	Best P/F	23	3	2	7	1	11	147.10	86.00	262	64	22	26.02	2.88	24.01	2.88
LAM20T10	5	Nonidentical high	Greedy	23	3	2	7	1	11	147.10	86.00	262	64	22	26.02	2.88	24.01	2.88
LAM20T10	6	Identical Low	F	27	0	3	9	0	20	226.57	150.00	403	90	60	26.43	0.00	28.81	0.00
LAM20T10	6	Identical Low	P	27	0	3	0	9	31	216.56	183.00	403	90	93	0.00	3.44	31.00	3.44
LAM20T10	6	Identical Low	Best P/F	27	0	3	9	0	20	226.57	150.00	403	90	60	26.43	0.00	28.81	0.00
LAM20T10	6	Identical Low	Greedy	27	0	3	9	0	20	226.57	150.00	403	90	60	26.43	0.00	28.81	0.00
LAM20T10	6	Identical High	F	27	0	3	9	0	14	212.97	132.00	403	90	42	58.03	0.00	33.34	0.00
LAM20T10	6	Identical High	P	27	0	3	0	9	33	195.71	189.00	403	90	99	0.00	18.29	33.00	18.29
LAM20T10	6	Identical High	Best P/F	27	0	3	8	1	14	215.50	132.00	403	90	42	51.61	3.88	31.20	3.88
LAM20T10	6	Identical High	Greedy	27	0	3	8	1	14	215.50	132.00	403	90	42	51.61	3.88	31.20	3.88
LAM20T10	6	Nonidentical low	F	27	0	3	9	0	20	224.76	150.00	403	90	60	28.24	0.00	29.41	0.00
LAM20T10	6	Nonidentical low	P	27	0	3	0	9	32	208.75	186.00	403	90	96	0.00	8.25	32.00	8.25
LAM20T10	6	Nonidentical low	Best P/F	27	0	3	9	0	20	224.76	150.00	403	90	60	28.24	0.00	29.41	0.00
LAM20T10	6	Nonidentical low	Greedy	27	0	3	9	0	20	224.76	150.00	403	90	60	28.24	0.00	29.41	0.00

Table D.1 Details of all solutions (continued)

LAM20T10	6	Nonidentical high	F	27	0	3	9	0	13	210.56	129.00	403	90	39	63.44	0.00	34.15	0.00
LAM20T10	6	Nonidentical high	P	27	0	3	0	9	32	192.40	186.00	403	90	96	0.00	24.60	32.00	24.60
LAM20T10	6	Nonidentical high	Best P/F	27	0	3	7	2	13	213.47	129.00	403	90	39	50.36	10.18	29.79	10.18
LAM20T10	6	Nonidentical high	Greedy	27	0	3	7	2	13	213.47	129.00	403	90	39	50.36	10.18	29.79	10.18
LAM20T10	7	Identical Low	F	39	3	2	9	0	30	381.32	164.00	564	104	60	18.68	0.00	39.34	0.00
LAM20T10	7	Identical Low	P	39	3	2	0	9	43	370.48	190.00	564	104	86	0.00	3.52	43.00	3.52
LAM20T10	7	Identical Low	Best P/F	39	3	2	9	0	30	381.32	164.00	564	104	60	18.68	0.00	39.34	0.00
LAM20T10	7	Identical Low	Greedy	39	3	2	9	0	30	381.32	164.00	564	104	60	18.68	0.00	39.34	0.00
LAM20T10	7	Identical High	F	39	3	2	9	0	22	375.84	148.00	564	104	44	40.16	0.00	42.08	0.00
LAM20T10	7	Identical High	P	39	3	2	0	9	43	352.33	190.00	564	104	86	0.00	21.67	43.00	21.67
LAM20T10	7	Identical High	Best P/F	39	3	2	9	0	22	375.84	148.00	564	104	44	40.16	0.00	42.08	0.00
LAM20T10	7	Identical High	Greedy	39	3	2	9	0	22	375.84	148.00	564	104	44	40.16	0.00	42.08	0.00
LAM20T10	7	Nonidentical low	F	39	3	2	9	0	32	381.56	168.00	564	104	64	14.44	0.00	39.22	0.00
LAM20T10	7	Nonidentical low	P	39	3	2	0	9	43	368.43	190.00	564	104	86	0.00	5.57	43.00	5.57
LAM20T10	7	Nonidentical low	Best P/F	39	3	2	9	0	32	381.56	168.00	564	104	64	14.44	0.00	39.22	0.00
LAM20T10	7	Nonidentical low	Greedy	39	3	2	9	0	32	381.56	168.00	564	104	64	14.44	0.00	39.22	0.00
LAM20T10	7	Nonidentical high	F	39	3	2	9	0	22	375.42	148.00	564	104	44	40.58	0.00	42.29	0.00
LAM20T10	7	Nonidentical high	P	39	3	2	0	9	43	351.97	190.00	564	104	86	0.00	22.03	43.00	22.03
LAM20T10	7	Nonidentical high	Best P/F	39	3	2	9	0	22	375.42	148.00	564	104	44	40.58	0.00	42.29	0.00
LAM20T10	7	Nonidentical high	Greedy	39	3	2	9	0	22	375.42	148.00	564	104	44	40.58	0.00	42.29	0.00
LAM20T10	8	Identical Low	F	37	0	2	9	0	33	209.80	134.00	355	68	66	11.20	0.00	38.60	0.00
LAM20T10	8	Identical Low	P	37	0	2	0	9	39	205.43	146.00	355	68	78	0.00	3.57	39.00	3.57
LAM20T10	8	Identical Low	Best P/F	37	0	2	9	0	33	209.80	134.00	355	68	66	11.20	0.00	38.60	0.00
LAM20T10	8	Identical Low	Greedy	37	0	2	9	0	33	209.80	134.00	355	68	66	11.20	0.00	38.60	0.00
LAM20T10	8	Identical High	F	37	0	2	9	0	25	203.39	118.00	355	68	50	33.61	0.00	41.80	0.00
LAM20T10	8	Identical High	P	37	0	2	0	9	39	195.12	146.00	355	68	78	0.00	13.88	39.00	13.88
LAM20T10	8	Identical High	Best P/F	37	0	2	7	2	25	204.36	118.00	355	68	50	23.55	9.09	36.77	9.09
LAM20T10	8	Identical High	Greedy	37	0	2	7	2	27	204.28	122.00	355	68	54	19.76	8.96	36.88	8.96
LAM20T10	8	Nonidentical low	F	37	0	2	9	0	32	209.07	132.00	355	68	64	13.93	0.00	38.97	0.00
LAM20T10	8	Nonidentical low	P	37	0	2	0	9	39	204.20	146.00	355	68	78	0.00	4.80	39.00	4.80
LAM20T10	8	Nonidentical low	Best P/F	37	0	2	9	0	32	209.07	132.00	355	68	64	13.93	0.00	38.97	0.00
LAM20T10	8	Nonidentical low	Greedy	37	0	2	9	0	32	209.07	132.00	355	68	64	13.93	0.00	38.97	0.00
LAM20T10	8	Nonidentical high	F	37	0	2	9	0	25	203.30	118.00	355	68	50	33.70	0.00	41.85	0.00
LAM20T10	8	Nonidentical high	P	37	0	2	0	9	39	195.30	146.00	355	68	78	0.00	13.70	39.00	13.70
LAM20T10	8	Nonidentical high	Best P/F	37	0	2	7	2	25	204.39	118.00	355	68	50	23.53	9.08	36.77	9.08
LAM20T10	8	Nonidentical high	Greedy	37	0	2	7	2	27	204.31	122.00	355	68	54	19.74	8.95	36.87	8.95
LAM20T10	9	Identical Low	P	42	4	2	0	9	43	204.14	155.00	378	69	86	0.00	18.86	43.00	18.86
LAM20T10	9	Identical Low	Best P/F	42	4	2	7	2	37	221.10	143.00	378	69	74	12.62	1.28	43.31	1.28
LAM20T10	9	Identical Low	Greedy	42	4	2	7	2	37	221.10	143.00	378	69	74	12.62	1.28	43.31	1.28
LAM20T10	9	Identical High	P	42	4	2	0	9	42	196.61	153.00	378	69	84	0.00	28.39	42.00	28.39
LAM20T10	9	Identical High	Best P/F	42	4	2	4	5	27	211.10	123.00	378	69	54	31.11	12.80	42.55	12.80
LAM20T10	9	Identical High	Greedy	42	4	2	4	5	27	211.10	123.00	378	69	54	31.11	12.80	42.55	12.80

Table D.1 Details of all solutions (continued)

LAM20T10	9	Nonidentical low	P	42	4	2	0	9	43	202.46	155.00	378	69	86	0.00	20.54	43.00	20.54
LAM20T10	9	Nonidentical low	Best P/F	42	4	2	5	4	32	219.33	133.00	378	69	64	21.30	4.37	42.65	4.37
LAM20T10	9	Nonidentical low	Greedy	42	4	2	5	4	32	219.33	133.00	378	69	64	21.30	4.37	42.65	4.37
LAM20T10	9	Nonidentical high	P	42	4	2	0	9	38	196.49	145.00	378	69	76	0.00	36.51	38.00	36.51
LAM20T10	9	Nonidentical high	Best P/F	42	4	2	4	5	25	210.36	119.00	378	69	50	35.31	13.33	42.65	13.33
LAM20T10	9	Nonidentical high	Greedy	42	4	2	4	5	25	210.36	119.00	378	69	50	35.31	13.33	42.65	13.33
LAM30T10	0	Identical Low	F	20	3	3	8	0	12	323.65	87.00	438	51	36	27.35	0.00	21.12	0.00
LAM30T10	0	Identical Low	P	20	3	3	0	8	23	313.60	120.00	438	51	69	0.00	4.40	23.00	4.40
LAM30T10	0	Identical Low	Best P/F	20	3	3	7	1	12	324.23	87.00	438	51	36	24.70	2.07	20.23	2.07
LAM30T10	0	Identical Low	Greedy	20	3	3	7	1	12	324.23	87.00	438	51	36	24.70	2.07	20.23	2.07
LAM30T10	0	Identical High	F	20	3	3	8	0	6	315.05	69.00	438	51	18	53.95	0.00	23.98	0.00
LAM30T10	0	Identical High	P	20	3	3	0	8	25	298.81	126.00	438	51	75	0.00	13.19	25.00	13.19
LAM30T10	0	Identical High	Best P/F	20	3	3	5	3	6	316.83	69.00	438	51	18	47.45	4.72	21.82	4.72
LAM30T10	0	Identical High	Greedy	20	3	3	5	3	6	316.83	69.00	438	51	18	47.45	4.72	21.82	4.72
LAM30T10	0	Nonidentical low	F	20	3	3	8	0	9	323.29	78.00	438	51	27	36.71	0.00	21.24	0.00
LAM30T10	0	Nonidentical low	P	20	3	3	0	8	23	314.75	120.00	438	51	69	0.00	3.25	23.00	3.25
LAM30T10	0	Nonidentical low	Best P/F	20	3	3	7	1	9	323.74	78.00	438	51	27	34.33	1.93	20.44	1.93
LAM30T10	0	Nonidentical low	Greedy	20	3	3	7	1	9	323.74	78.00	438	51	27	34.33	1.93	20.44	1.93
LAM30T10	0	Nonidentical high	F	20	3	3	8	0	5	313.15	66.00	438	51	15	58.85	0.00	24.62	0.00
LAM30T10	0	Nonidentical high	P	20	3	3	0	8	24	296.98	123.00	438	51	72	0.00	18.02	24.00	18.02
LAM30T10	0	Nonidentical high	Best P/F	20	3	3	5	3	5	315.47	66.00	438	51	15	51.68	4.85	22.23	4.85
LAM30T10	0	Nonidentical high	Greedy	20	3	3	5	3	5	315.47	66.00	438	51	15	51.68	4.85	22.23	4.85
LAM30T10	1	Identical Low	F	25	3	3	9	0	15	262.42	108.00	401	63	45	30.58	0.00	25.19	0.00
LAM30T10	1	Identical Low	P	25	3	3	0	9	28	248.03	147.00	401	63	84	0.00	5.97	28.00	5.97
LAM30T10	1	Identical Low	Best P/F	25	3	3	9	0	15	262.42	108.00	401	63	45	30.58	0.00	25.19	0.00
LAM30T10	1	Identical Low	Greedy	25	3	3	9	0	15	262.42	108.00	401	63	45	30.58	0.00	25.19	0.00
LAM30T10	1	Identical High	F	25	3	3	9	0	11	254.62	96.00	401	63	33	50.38	0.00	27.79	0.00
LAM30T10	1	Identical High	P	25	3	3	0	9	27	235.85	144.00	401	63	81	0.00	21.16	27.00	21.16
LAM30T10	1	Identical High	Best P/F	25	3	3	8	1	11	255.78	96.00	401	63	33	46.82	2.40	26.61	2.40
LAM30T10	1	Identical High	Greedy	25	3	3	8	1	11	255.78	96.00	401	63	33	46.82	2.40	26.61	2.40
LAM30T10	1	Nonidentical low	F	25	3	3	9	0	14	260.44	105.00	401	63	42	35.56	0.00	25.85	0.00
LAM30T10	1	Nonidentical low	P	25	3	3	0	9	28	241.29	147.00	401	63	84	0.00	12.71	28.00	12.71
LAM30T10	1	Nonidentical low	Best P/F	25	3	3	9	0	14	260.44	105.00	401	63	42	35.56	0.00	25.85	0.00
LAM30T10	1	Nonidentical low	Greedy	25	3	3	9	0	14	260.44	105.00	401	63	42	35.56	0.00	25.85	0.00
LAM30T10	1	Nonidentical high	F	25	3	3	9	0	12	253.79	99.00	401	63	36	48.21	0.00	28.07	0.00
LAM30T10	1	Nonidentical high	P	25	3	3	0	9	26	236.54	141.00	401	63	78	0.00	23.46	26.00	23.46
LAM30T10	1	Nonidentical high	Best P/F	25	3	3	8	1	12	254.84	99.00	401	63	36	44.74	2.42	26.91	2.42
LAM30T10	1	Nonidentical high	Greedy	25	3	3	8	1	12	254.84	99.00	401	63	36	44.74	2.42	26.91	2.42
LAM30T10	2	Identical Low	F	34	0	2	9	0	28	325.54	112.00	451	56	56	13.46	0.00	34.73	0.00
LAM30T10	2	Identical Low	P	34	0	2	0	9	37	318.43	130.00	451	56	74	0.00	2.57	37.00	2.57
LAM30T10	2	Identical Low	Best P/F	34	0	2	9	0	28	325.54	112.00	451	56	56	13.46	0.00	34.73	0.00
LAM30T10	2	Identical Low	Greedy	34	0	2	9	0	28	325.54	112.00	451	56	56	13.46	0.00	34.73	0.00

Table D.1 Details of all solutions (continued)

LAM30T10	2	Identical High	F	34	0	2	9	0	22	319.68	100.00	451	56	44	31.32	0.00	37.66	0.00
LAM30T10	2	Identical High	P	34	0	2	0	9	38	307.00	132.00	451	56	76	0.00	12.00	38.00	12.00
LAM30T10	2	Identical High	Best P/F	34	0	2	8	1	22	320.41	100.00	451	56	44	23.45	7.13	33.73	7.13
LAM30T10	2	Identical High	Greedy	34	0	2	8	1	22	320.41	100.00	451	56	44	23.45	7.13	33.73	7.13
LAM30T10	2	Nonidentical low	F	34	0	2	9	0	29	325.20	114.00	451	56	58	11.80	0.00	34.90	0.00
LAM30T10	2	Nonidentical low	P	34	0	2	0	9	36	318.45	128.00	451	56	72	0.00	4.55	36.00	4.55
LAM30T10	2	Nonidentical low	Best P/F	34	0	2	9	0	29	325.20	114.00	451	56	58	11.80	0.00	34.90	0.00
LAM30T10	2	Nonidentical low	Greedy	34	0	2	9	0	29	325.20	114.00	451	56	58	11.80	0.00	34.90	0.00
LAM30T10	2	Nonidentical high	F	34	0	2	9	0	21	319.42	98.00	451	56	42	33.58	0.00	37.79	0.00
LAM30T10	2	Nonidentical high	P	34	0	2	0	9	38	306.80	132.00	451	56	76	0.00	12.20	38.00	12.20
LAM30T10	2	Nonidentical high	Best P/F	34	0	2	8	1	21	320.14	98.00	451	56	42	25.74	7.12	33.87	7.12
LAM30T10	2	Nonidentical high	Greedy	34	0	2	8	1	21	320.14	98.00	451	56	42	25.74	7.12	33.87	7.12
LAM30T10	3	Identical Low	F	34	3	2	8	0	24	364.69	136.00	521	88	48	20.31	0.00	34.15	0.00
LAM30T10	3	Identical Low	P	34	3	2	0	8	39	351.18	166.00	521	88	78	0.00	3.82	39.00	3.82
LAM30T10	3	Identical Low	Best P/F	34	3	2	8	0	24	364.69	136.00	521	88	48	20.31	0.00	34.15	0.00
LAM30T10	3	Identical Low	Greedy	34	3	2	8	0	24	364.69	136.00	521	88	48	20.31	0.00	34.15	0.00
LAM30T10	3	Identical High	F	34	3	2	8	0	17	359.68	122.00	521	88	34	39.32	0.00	36.66	0.00
LAM30T10	3	Identical High	P	34	3	2	0	8	43	334.90	174.00	521	88	86	0.00	12.10	43.00	12.10
LAM30T10	3	Identical High	Best P/F	34	3	2	8	0	17	359.68	122.00	521	88	34	39.32	0.00	36.66	0.00
LAM30T10	3	Identical High	Greedy	34	3	2	8	0	17	359.68	122.00	521	88	34	39.32	0.00	36.66	0.00
LAM30T10	3	Nonidentical low	F	34	3	2	8	0	25	363.97	138.00	521	88	50	19.03	0.00	34.52	0.00
LAM30T10	3	Nonidentical low	P	34	3	2	0	8	41	343.45	170.00	521	88	82	0.00	7.55	41.00	7.55
LAM30T10	3	Nonidentical low	Best P/F	34	3	2	8	0	25	363.97	138.00	521	88	50	19.03	0.00	34.52	0.00
LAM30T10	3	Nonidentical low	Greedy	34	3	2	8	0	25	363.97	138.00	521	88	50	19.03	0.00	34.52	0.00
LAM30T10	3	Nonidentical high	F	34	3	2	8	0	17	358.59	122.00	521	88	34	40.41	0.00	37.20	0.00
LAM30T10	3	Nonidentical high	P	34	3	2	0	8	41	331.93	170.00	521	88	82	0.00	19.07	41.00	19.07
LAM30T10	3	Nonidentical high	Best P/F	34	3	2	8	0	17	358.59	122.00	521	88	34	40.41	0.00	37.20	0.00
LAM30T10	3	Nonidentical high	Greedy	34	3	2	8	0	17	358.59	122.00	521	88	34	40.41	0.00	37.20	0.00
LAM30T10	4	Identical Low	F	22	1	4	8	0	11	231.88	124.00	406	80	44	50.12	0.00	23.53	0.00
LAM30T10	4	Identical Low	P	22	1	4	0	8	27	212.90	188.00	406	80	108	0.00	5.10	27.00	5.10
LAM30T10	4	Identical Low	Best P/F	22	1	4	8	0	11	231.88	124.00	406	80	44	50.12	0.00	23.53	0.00
LAM30T10	4	Identical Low	Greedy	22	1	4	8	0	11	231.88	124.00	406	80	44	50.12	0.00	23.53	0.00
LAM30T10	4	Identical High	F	22	1	4	8	0	6	216.55	104.00	406	80	24	85.45	0.00	27.36	0.00
LAM30T10	4	Identical High	P	22	1	4	0	8	31	181.12	204.00	406	80	124	0.00	20.88	31.00	20.88
LAM30T10	4	Identical High	Best P/F	22	1	4	7	1	6	216.72	104.00	406	80	24	85.05	0.23	27.26	0.23
LAM30T10	4	Identical High	Greedy	22	1	4	7	1	6	216.72	104.00	406	80	24	85.05	0.23	27.26	0.23
LAM30T10	4	Nonidentical low	F	22	1	4	8	0	12	231.46	128.00	406	80	48	46.54	0.00	23.63	0.00
LAM30T10	4	Nonidentical low	P	22	1	4	0	8	25	213.05	180.00	406	80	100	0.00	12.95	25.00	12.95
LAM30T10	4	Nonidentical low	Best P/F	22	1	4	8	0	12	231.46	128.00	406	80	48	46.54	0.00	23.63	0.00
LAM30T10	4	Nonidentical low	Greedy	22	1	4	8	0	12	231.46	128.00	406	80	48	46.54	0.00	23.63	0.00
LAM30T10	4	Nonidentical high	F	22	1	4	8	0	5	217.80	100.00	406	80	20	88.20	0.00	27.05	0.00
LAM30T10	4	Nonidentical high	P	22	1	4	0	8	30	187.07	200.00	406	80	120	0.00	18.93	30.00	18.93

Table D.1 Details of all solutions (continued)

LAM30T10	4	Nonidentical high	Best P/F	22	1	4	7	1	5	217.94	100.00	406	80	20	87.84	0.21	26.96	0.21
LAM30T10	4	Nonidentical high	Greedy	22	1	4	7	1	5	217.94	100.00	406	80	20	87.84	0.21	26.96	0.21
LAM30T10	5	Identical Low	F	29	3	2	9	0	24	364.05	127.00	503	79	48	11.95	0.00	29.97	0.00
LAM30T10	5	Identical Low	P	29	3	2	0	9	33	354.65	145.00	503	79	66	0.00	3.35	33.00	3.35
LAM30T10	5	Identical Low	Best P/F	29	3	2	9	0	24	364.05	127.00	503	79	48	11.95	0.00	29.97	0.00
LAM30T10	5	Identical Low	Greedy	29	3	2	9	0	24	364.05	127.00	503	79	48	11.95	0.00	29.97	0.00
LAM30T10	5	Identical High	F	29	3	2	9	0	18	358.43	115.00	503	79	36	29.57	0.00	32.78	0.00
LAM30T10	5	Identical High	P	29	3	2	0	9	37	340.28	153.00	503	79	74	0.00	9.72	37.00	9.72
LAM30T10	5	Identical High	Best P/F	29	3	2	6	3	18	359.52	115.00	503	79	36	24.02	4.45	30.01	4.45
LAM30T10	5	Identical High	Greedy	29	3	2	6	3	18	359.52	115.00	503	79	36	24.02	4.45	30.01	4.45
LAM30T10	5	Nonidentical low	F	29	3	2	9	0	23	363.07	125.00	503	79	46	14.93	0.00	30.47	0.00
LAM30T10	5	Nonidentical low	P	29	3	2	0	9	35	349.15	149.00	503	79	70	0.00	4.85	35.00	4.85
LAM30T10	5	Nonidentical low	Best P/F	29	3	2	9	0	23	363.07	125.00	503	79	46	14.93	0.00	30.47	0.00
LAM30T10	5	Nonidentical low	Greedy	29	3	2	9	0	23	363.07	125.00	503	79	46	14.93	0.00	30.47	0.00
LAM30T10	5	Nonidentical high	F	29	3	2	9	0	18	358.53	115.00	503	79	36	29.47	0.00	32.74	0.00
LAM30T10	5	Nonidentical high	P	29	3	2	0	9	37	339.38	153.00	503	79	74	0.00	10.62	37.00	10.62
LAM30T10	5	Nonidentical high	Best P/F	29	3	2	6	3	18	359.53	115.00	503	79	36	24.04	4.43	30.02	4.43
LAM30T10	5	Nonidentical high	Greedy	29	3	2	6	3	18	359.53	115.00	503	79	36	24.04	4.43	30.02	4.43
LAM30T10	6	Identical Low	F	40	1	2	9	0	32	463.70	139.00	620	75	64	17.30	0.00	40.65	0.00
LAM30T10	6	Identical Low	P	40	1	2	0	9	43	454.90	161.00	620	75	86	0.00	4.10	43.00	4.10
LAM30T10	6	Identical Low	Best P/F	40	1	2	9	0	32	463.70	139.00	620	75	64	17.30	0.00	40.65	0.00
LAM30T10	6	Identical Low	Greedy	40	1	2	9	0	32	463.70	139.00	620	75	64	17.30	0.00	40.65	0.00
LAM30T10	6	Identical High	F	40	1	2	9	0	24	457.17	123.00	620	75	48	39.83	0.00	43.92	0.00
LAM30T10	6	Identical High	P	40	1	2	0	9	43	440.40	161.00	620	75	86	0.00	18.60	43.00	18.60
LAM30T10	6	Identical High	Best P/F	40	1	2	7	2	24	457.96	123.00	620	75	48	27.66	11.39	37.83	11.39
LAM30T10	6	Identical High	Greedy	40	1	2	7	2	24	457.96	123.00	620	75	48	27.66	11.39	37.83	11.39
LAM30T10	6	Nonidentical low	F	40	1	2	9	0	34	463.73	143.00	620	75	68	13.27	0.00	40.64	0.00
LAM30T10	6	Nonidentical low	P	40	1	2	0	9	40	456.27	155.00	620	75	80	0.00	8.73	40.00	8.73
LAM30T10	6	Nonidentical low	Best P/F	40	1	2	9	0	34	463.73	143.00	620	75	68	13.27	0.00	40.64	0.00
LAM30T10	6	Nonidentical low	Greedy	40	1	2	9	0	34	463.73	143.00	620	75	68	13.27	0.00	40.64	0.00
LAM30T10	6	Nonidentical high	F	40	1	2	9	0	27	458.13	129.00	620	75	54	32.87	0.00	43.43	0.00
LAM30T10	6	Nonidentical high	P	40	1	2	0	9	43	443.55	161.00	620	75	86	0.00	15.45	43.00	15.45
LAM30T10	6	Nonidentical high	Best P/F	40	1	2	7	2	27	458.70	129.00	620	75	54	21.07	11.24	37.53	11.24
LAM30T10	6	Nonidentical high	Greedy	40	1	2	7	2	27	458.70	129.00	620	75	54	21.07	11.24	37.53	11.24
LAM30T10	7	Identical Low	F	32	4	3	9	0	24	607.61	189.00	826	117	72	29.39	0.00	33.80	0.00
LAM30T10	7	Identical Low	P	32	4	3	0	9	37	595.26	228.00	826	117	111	0.00	2.74	37.00	2.74
LAM30T10	7	Identical Low	Best P/F	32	4	3	9	0	24	607.61	189.00	826	117	72	29.39	0.00	33.80	0.00
LAM30T10	7	Identical Low	Greedy	32	4	3	9	0	24	607.61	189.00	826	117	72	29.39	0.00	33.80	0.00
LAM30T10	7	Identical High	F	32	4	3	9	0	16	593.42	165.00	826	117	48	67.58	0.00	38.53	0.00
LAM30T10	7	Identical High	P	32	4	3	0	9	41	569.86	240.00	826	117	123	0.00	16.14	41.00	16.14
LAM30T10	7	Identical High	Best P/F	32	4	3	8	1	16	595.70	165.00	826	117	48	61.10	4.19	36.37	4.19
LAM30T10	7	Identical High	Greedy	32	4	3	8	1	16	595.70	165.00	826	117	48	61.10	4.19	36.37	4.19

Table D.1 Details of all solutions (continued)

LAM30T10	7	Nonidentical low	F	32	4	3	9	0	21	604.95	180.00	826	117	63	41.05	0.00	34.68	0.00
LAM30T10	7	Nonidentical low	P	32	4	3	0	9	38	588.30	231.00	826	117	114	0.00	6.70	38.00	6.70
LAM30T10	7	Nonidentical low	Best P/F	32	4	3	9	0	21	604.95	180.00	826	117	63	41.05	0.00	34.68	0.00
LAM30T10	7	Nonidentical low	Greedy	32	4	3	9	0	21	604.95	180.00	826	117	63	41.05	0.00	34.68	0.00
LAM30T10	7	Nonidentical high	F	32	4	3	9	0	15	594.74	162.00	826	117	45	69.26	0.00	38.09	0.00
LAM30T10	7	Nonidentical high	P	32	4	3	0	9	41	570.97	240.00	826	117	123	0.00	15.03	41.00	15.03
LAM30T10	7	Nonidentical high	Best P/F	32	4	3	8	1	15	596.43	162.00	826	117	45	63.57	4.00	36.19	4.00
LAM30T10	7	Nonidentical high	Greedy	32	4	3	8	1	15	596.43	162.00	826	117	45	63.57	4.00	36.19	4.00
LAM30T10	8	Identical Low	F	41	0	2	9	0	36	347.98	130.00	492	58	72	14.02	0.00	43.01	0.00
LAM30T10	8	Identical Low	P	41	0	2	0	9	43	325.61	144.00	492	58	86	0.00	22.39	43.00	22.39
LAM30T10	8	Identical Low	Best P/F	41	0	2	9	0	36	347.98	130.00	492	58	72	14.02	0.00	43.01	0.00
LAM30T10	8	Identical Low	Greedy	41	0	2	9	0	36	347.98	130.00	492	58	72	14.02	0.00	43.01	0.00
LAM30T10	8	Identical High	P	41	0	2	0	9	43	314.01	144.00	492	58	86	0.00	33.99	43.00	33.99
LAM30T10	8	Identical High	Best P/F	41	0	2	4	5	26	341.75	110.00	492	58	52	31.37	8.88	41.69	8.88
LAM30T10	8	Identical High	Greedy	41	0	2	4	5	26	341.75	110.00	492	58	52	31.37	8.88	41.69	8.88
LAM30T10	8	Nonidentical low	F	41	0	2	9	0	35	347.70	128.00	492	58	70	16.30	0.00	43.15	0.00
LAM30T10	8	Nonidentical low	P	41	0	2	0	9	43	323.76	144.00	492	58	86	0.00	24.24	43.00	24.24
LAM30T10	8	Nonidentical low	Best P/F	41	0	2	9	0	35	347.70	128.00	492	58	70	16.30	0.00	43.15	0.00
LAM30T10	8	Nonidentical low	Greedy	41	0	2	9	0	35	347.70	128.00	492	58	70	16.30	0.00	43.15	0.00
LAM30T10	8	Nonidentical high	P	41	0	2	0	9	43	315.56	144.00	492	58	86	0.00	32.44	43.00	32.44
LAM30T10	8	Nonidentical high	Best P/F	41	0	2	6	3	28	342.81	114.00	492	58	56	27.83	7.36	41.92	7.36
LAM30T10	8	Nonidentical high	Greedy	41	0	2	6	3	28	342.81	114.00	492	58	56	27.83	7.36	41.92	7.36
LAM30T10	9	Identical Low	F	31	0	2	6	0	26	256.46	94.00	363	42	52	12.54	0.00	32.27	0.00
LAM30T10	9	Identical Low	P	31	0	2	0	6	36	247.00	114.00	363	42	72	0.00	2.00	36.00	2.00
LAM30T10	9	Identical Low	Best P/F	31	0	2	5	1	26	256.69	94.00	363	42	52	9.83	2.47	30.92	2.47
LAM30T10	9	Identical Low	Greedy	31	0	2	5	1	26	256.69	94.00	363	42	52	9.83	2.47	30.92	2.47
LAM30T10	9	Identical High	F	31	0	2	6	0	18	249.61	78.00	363	42	36	35.39	0.00	35.69	0.00
LAM30T10	9	Identical High	P	31	0	2	0	6	40	229.66	122.00	363	42	80	0.00	11.34	40.00	11.34
LAM30T10	9	Identical High	Best P/F	31	0	2	5	1	18	250.33	78.00	363	42	36	32.45	2.21	34.23	2.21
LAM30T10	9	Identical High	Greedy	31	0	2	5	1	18	250.33	78.00	363	42	36	32.45	2.21	34.23	2.21
LAM30T10	9	Nonidentical low	F	31	0	2	6	0	25	255.76	92.00	363	42	50	15.24	0.00	32.62	0.00
LAM30T10	9	Nonidentical low	P	31	0	2	0	6	36	246.25	114.00	363	42	72	0.00	2.75	36.00	2.75
LAM30T10	9	Nonidentical low	Best P/F	31	0	2	5	1	25	256.16	92.00	363	42	50	12.43	2.41	31.22	2.41
LAM30T10	9	Nonidentical low	Greedy	31	0	2	5	1	25	256.16	92.00	363	42	50	12.43	2.41	31.22	2.41
LAM30T10	9	Nonidentical high	F	31	0	2	6	0	17	249.90	76.00	363	42	34	37.10	0.00	35.55	0.00
LAM30T10	9	Nonidentical high	P	31	0	2	0	6	40	229.38	122.00	363	42	80	0.00	11.62	40.00	11.62
LAM30T10	9	Nonidentical high	Best P/F	31	0	2	5	1	17	250.64	76.00	363	42	34	34.13	2.22	34.07	2.22
LAM30T10	9	Nonidentical high	Greedy	31	0	2	5	1	17	250.64	76.00	363	42	34	34.13	2.22	34.07	2.22
LAM25T25	1	Nonidentical low	P	25	0	2	0	7	28	32.44	66.00	100	38	28	0.00	1.56	28.00	1.62
LAM25T25	1	Nonidentical low	Best P/F	25	0	2	7	0	19	36.06	57.00	100	38	19	6.94	0.00	25.94	0.00
LAM25T25	1	Nonidentical low	Greedy	25	0	2	7	0	19	36.06	57.00	100	38	19	6.94	0.00	25.94	0.00
LAM25T25	1	Nonidentical high	F	25	0	2	7	0	17	34.32	55.00	100	38	17	10.68	0.00	27.68	0.00

Table D.1 Details of all solutions (continued)

LAM25T25	1	Nonidentical high	P	25	0	2	0	7	30	28.72	68.00	100	38	30	0.00	3.28	30.00	3.40
LAM25T25	1	Nonidentical high	Best P/F	25	0	2	7	0	17	34.32	55.00	100	38	17	10.68	0.00	27.68	0.00
LAM25T25	1	Nonidentical high	Greedy	25	0	2	7	0	17	34.32	55.00	100	38	17	10.68	0.00	27.68	0.00
LAM25T25	2	Identical Low	F	24	0	11	25	0	12	316.16	323.00	722	257	66	82.84	0.00	27.06	0.00
LAM25T25	2	Identical Low	P	24	0	11	0	25	30	294.85	422.00	722	257	165	0.00	5.15	30.00	5.15
LAM25T25	2	Identical Low	Best P/F	24	0	11	24	1	12	316.54	323.00	722	257	66	81.98	0.48	26.91	0.48
LAM25T25	2	Identical Low	Greedy	24	0	11	24	1	12	316.54	323.00	722	257	66	81.98	0.48	26.91	0.48
LAM25T25	2	Identical High	F	24	0	11	25	0	6	273.42	290.00	722	257	33	158.58	0.00	34.83	0.00
LAM25T25	2	Identical High	P	24	0	11	0	25	38	236.11	466.00	722	257	209	0.00	19.89	38.00	19.89
LAM25T25	2	Identical High	Best P/F	24	0	11	22	3	6	275.09	290.00	722	257	33	151.81	5.10	33.60	5.10
LAM25T25	2	Identical High	Greedy	24	0	11	22	3	6	275.09	290.00	722	257	33	151.81	5.10	33.60	5.10
LAM25T25	2	Nonidentical low	F	24	0	11	25	0	10	313.56	312.00	722	257	55	96.44	0.00	27.53	0.00
LAM25T25	2	Nonidentical low	P	24	0	11	0	25	32	276.26	433.00	722	257	176	0.00	12.74	32.00	12.74
LAM25T25	2	Nonidentical low	Best P/F	24	0	11	24	1	10	313.93	312.00	722	257	55	95.61	0.46	27.38	0.46
LAM25T25	2	Nonidentical low	Greedy	24	0	11	24	1	10	313.93	312.00	722	257	55	95.61	0.46	27.38	0.46
LAM25T25	2	Nonidentical high	F	24	0	11	25	0	3	277.01	273.50	722	257	17	171.49	0.00	34.18	0.00
LAM25T25	2	Nonidentical high	P	24	0	11	0	25	36	247.89	455.00	722	257	198	0.00	19.11	36.00	18.88
LAM25T25	2	Nonidentical high	Best P/F	24	0	11	22	3	3	278.84	273.50	722	257	17	164.31	5.35	32.87	5.35
LAM25T25	2	Nonidentical high	Greedy	24	0	11	22	3	3	278.84	273.50	722	257	17	164.31	5.35	32.87	5.35
LAM25T25	3	Identical Low	F	26	0	8	21	0	14	290.71	296.00	646	240	56	59.29	0.00	28.82	0.00
LAM25T25	3	Identical Low	P	26	0	8	0	21	32	274.08	368.00	646	240	128	0.00	3.92	32.00	3.92
LAM25T25	3	Identical Low	Best P/F	26	0	8	19	2	14	291.57	296.00	646	240	56	56.82	1.61	28.20	1.61
LAM25T25	3	Identical Low	Greedy	26	0	8	19	2	14	291.57	296.00	646	240	56	56.82	1.61	28.20	1.61
LAM25T25	3	Identical High	F	26	0	8	21	0	8	261.72	272.00	646	240	32	112.28	0.00	36.07	0.00
LAM25T25	3	Identical High	P	26	0	8	0	21	41	228.79	404.00	646	240	164	0.00	13.21	41.00	13.21
LAM25T25	3	Identical High	Best P/F	26	0	8	16	5	8	265.36	272.00	646	240	32	104.20	4.44	34.05	4.44
LAM25T25	3	Identical High	Greedy	26	0	8	16	5	8	265.36	272.00	646	240	32	104.20	4.44	34.05	4.44
LAM25T25	3	Nonidentical low	F	26	0	8	21	0	12	290.89	288.00	646	240	48	67.11	0.00	28.78	0.00
LAM25T25	3	Nonidentical low	P	26	0	8	0	21	32	273.17	368.00	646	240	128	0.00	4.83	32.00	4.83
LAM25T25	3	Nonidentical low	Best P/F	26	0	8	19	2	12	292.50	288.00	646	240	48	62.63	2.87	27.66	2.87
LAM25T25	3	Nonidentical low	Greedy	26	0	8	19	2	12	292.50	288.00	646	240	48	62.63	2.87	27.66	2.87
LAM25T25	3	Nonidentical high	F	26	0	8	21	0	8	261.66	272.00	646	240	32	112.34	0.00	36.09	0.00
LAM25T25	3	Nonidentical high	P	26	0	8	0	21	39	235.35	396.00	646	240	156	0.00	14.65	39.00	14.65
LAM25T25	3	Nonidentical high	Best P/F	26	0	8	16	5	8	266.75	272.00	646	240	32	101.83	5.41	33.46	5.41
LAM25T25	3	Nonidentical high	Greedy	26	0	8	16	5	8	266.75	272.00	646	240	32	101.83	5.41	33.46	5.41
LAM25T25	4	Identical Low	F	22	2	16	25	0	12	268.96	372.00	744	276	96	103.04	0.00	24.88	0.00
LAM25T25	4	Identical Low	P	22	2	16	0	25	27	242.63	492.00	744	276	216	0.00	9.37	27.00	8.84
LAM25T25	4	Identical Low	Best P/F	22	2	16	24	1	12	268.96	372.00	744	276	96	102.73	0.31	24.84	0.31
LAM25T25	4	Identical Low	Greedy	22	2	16	24	1	12	268.96	372.00	744	276	96	102.73	0.31	24.84	0.31
LAM25T25	4	Identical High	F	22	2	16	25	0	6	195.84	324.00	744	276	48	224.16	0.00	34.02	0.00
LAM25T25	4	Identical High	P	22	2	16	0	25	36	147.22	564.00	744	276	288	0.00	32.78	36.00	30.46
LAM25T25	4	Identical High	Best P/F	22	2	16	19	6	6	198.79	324.00	744	276	48	213.25	7.96	32.66	7.54

Table D.1 Details of all solutions (continued)

LAM25T25	4	Identical High	Greedy	22	2	16	19	6	6	198.79	324.00	744	276	48	213.25	7.96	32.66	7.54
LAM25T25	4	Nonidentical low	F	22	2	16	25	0	12	261.49	372.00	744	276	96	110.51	0.00	25.81	0.00
LAM25T25	4	Nonidentical low	P	22	2	16	0	25	28	226.43	500.00	744	276	224	0.00	17.57	28.00	18.00
LAM25T25	4	Nonidentical low	Best P/F	22	2	16	21	4	12	262.52	372.00	744	276	96	101.05	8.43	24.63	10.02
LAM25T25	4	Nonidentical low	Greedy	22	2	16	21	4	12	262.52	372.00	744	276	96	101.05	8.43	24.63	10.02
LAM25T25	5	Identical Low	F	25	1	9	21	0	16	85.96	197.00	338	125	72	55.04	0.00	28.23	0.00
LAM25T25	5	Identical Low	P	25	1	9	0	21	31	68.10	264.50	338	125	140	0.00	5.40	31.00	4.44
LAM25T25	5	Identical Low	Best P/F	25	1	9	20	1	16	86.08	197.00	338	125	72	53.62	1.30	27.91	1.30
LAM25T25	5	Identical Low	Greedy	25	1	9	20	1	16	86.08	197.00	338	125	72	53.62	1.30	27.91	1.30
LAM25T25	5	Identical High	F	25	1	9	21	0	8	52.10	161.00	338	125	36	124.90	0.00	35.75	0.00
LAM25T25	5	Identical High	P	25	1	9	0	21	40	16.63	305.00	338	125	180	0.00	16.37	40.00	11.60
LAM25T25	5	Identical High	Best P/F	25	1	9	19	2	8	54.11	161.00	338	125	36	120.14	2.75	34.70	3.43
LAM25T25	5	Identical High	Greedy	25	1	9	19	2	8	54.11	161.00	338	125	36	120.14	2.75	34.70	3.43
LAM25T25	5	Nonidentical low	F	25	1	9	21	0	16	88.34	197.00	338	125	72	52.66	0.00	27.70	0.00
LAM25T25	5	Nonidentical low	P	25	1	9	0	21	32	62.68	269.00	338	125	144	0.00	6.32	32.00	5.51
LAM25T25	5	Nonidentical low	Best P/F	25	1	9	21	0	16	88.34	197.00	338	125	72	52.66	0.00	27.70	0.00
LAM25T25	5	Nonidentical low	Greedy	25	1	9	21	0	16	88.34	197.00	338	125	72	52.66	0.00	27.70	0.00
LAM25T25	5	Nonidentical high	F	25	1	9	21	0	5	53.43	147.50	338	125	23	137.07	0.00	35.46	0.00
LAM25T25	5	Nonidentical high	P	25	1	9	0	21	39	17.74	300.50	338	125	176	0.00	19.76	39.00	16.02
LAM25T25	5	Nonidentical high	Best P/F	25	1	9	19	2	5	54.34	147.50	338	125	23	134.09	2.06	34.80	2.64
LAM25T25	5	Nonidentical high	Greedy	25	1	9	19	2	5	54.34	147.50	338	125	23	134.09	2.06	34.80	2.64
LAM25T25	6	Identical Low	F	21	1	9	18	0	12	180.47	237.00	468	183	54	50.53	0.00	23.23	0.00
LAM25T25	6	Identical Low	P	21	1	9	0	18	26	161.61	300.00	468	183	117	0.00	6.39	26.00	6.39
LAM25T25	6	Identical Low	Best P/F	21	1	9	18	0	12	180.47	237.00	468	183	54	50.53	0.00	23.23	0.00
LAM25T25	6	Identical Low	Greedy	21	1	9	18	0	12	180.47	237.00	468	183	54	50.53	0.00	23.23	0.00
LAM25T25	6	Identical High	F	21	1	9	18	0	6	149.34	210.00	468	183	27	108.66	0.00	30.15	0.00
LAM25T25	6	Identical High	P	21	1	9	0	18	35	111.26	340.50	468	183	158	0.00	16.24	35.00	16.25
LAM25T25	6	Identical High	Best P/F	21	1	9	16	2	6	149.52	210.00	468	183	27	107.79	0.69	29.95	0.69
LAM25T25	6	Identical High	Greedy	21	1	9	16	2	6	149.52	210.00	468	183	27	107.79	0.69	29.95	0.69
LAM25T25	6	Nonidentical low	F	21	1	9	18	0	14	184.01	246.00	468	183	63	37.99	0.00	22.44	0.00
LAM25T25	6	Nonidentical low	P	21	1	9	0	18	25	164.61	295.50	468	183	113	0.00	7.89	25.00	7.89
LAM25T25	6	Nonidentical low	Best P/F	21	1	9	18	0	14	184.01	246.00	468	183	63	37.99	0.00	22.44	0.00
LAM25T25	6	Nonidentical low	Greedy	21	1	9	18	0	14	184.01	246.00	468	183	63	37.99	0.00	22.44	0.00
LAM25T25	6	Nonidentical high	F	21	1	9	18	0	6	152.96	210.00	468	183	27	105.04	0.00	29.34	0.00
LAM25T25	6	Nonidentical high	P	21	1	9	0	18	33	121.69	331.50	468	183	149	0.00	14.81	33.00	14.82
LAM25T25	6	Nonidentical high	Best P/F	21	1	9	16	2	6	153.18	210.00	468	183	27	103.98	0.84	29.11	0.84
LAM25T25	6	Nonidentical high	Greedy	21	1	9	16	2	6	153.18	210.00	468	183	27	103.98	0.84	29.11	0.84
LAM25T25	7	Identical Low	F	24	2	12	20	0	11	141.32	340.00	574	274	66	92.68	0.00	26.45	0.00
LAM25T25	7	Identical Low	P	24	2	12	0	20	30	116.07	454.00	574	274	180	0.00	3.93	30.00	3.74
LAM25T25	7	Identical Low	Best P/F	24	2	12	20	0	11	141.32	340.00	574	274	66	92.68	0.00	26.45	0.00
LAM25T25	7	Identical Low	Greedy	24	2	12	20	0	11	141.32	340.00	574	274	66	92.68	0.00	26.45	0.00
LAM25T25	7	Identical High	F	24	2	12	20	0	5	99.83	304.00	574	274	30	170.17	0.00	33.36	0.00

Table D.1 Details of all solutions (continued)

LAM25T25	7	Identical High	P	24	2	12	0	20	37	56.37	496.00	574	274	222	0.00	21.63	37.00	20.71
LAM25T25	7	Identical High	Best P/F	24	2	12	19	1	5	100.14	304.00	574	274	30	168.97	0.89	33.16	1.31
LAM25T25	7	Identical High	Greedy	24	2	12	19	1	5	100.14	304.00	574	274	30	168.97	0.89	33.16	1.31
LAM25T25	7	Nonidentical low	F	24	2	12	20	0	11	139.17	340.00	574	274	66	94.83	0.00	26.80	0.00
LAM25T25	7	Nonidentical low	P	24	2	12	0	20	30	105.58	454.00	574	274	180	0.00	14.42	30.00	13.97
LAM25T25	7	Nonidentical low	Best P/F	24	2	12	20	0	11	139.17	340.00	574	274	66	94.83	0.00	26.80	0.00
LAM25T25	7	Nonidentical low	Greedy	24	2	12	20	0	11	139.17	340.00	574	274	66	94.83	0.00	26.80	0.00
LAM25T25	7	Nonidentical high	F	24	2	12	20	0	3	100.76	292.00	574	274	18	181.24	0.00	33.21	0.00
LAM25T25	7	Nonidentical high	P	24	2	12	0	20	36	62.15	490.00	574	274	216	0.00	21.85	36.00	21.30
LAM25T25	7	Nonidentical high	Best P/F	24	2	12	19	1	3	101.58	292.00	574	274	18	179.11	1.32	32.85	1.95
LAM25T25	7	Nonidentical high	Greedy	24	2	12	19	1	3	101.58	292.00	574	274	18	179.11	1.32	32.85	1.95
LAM25T25	8	Identical Low	F	21	0	14	25	0	14	184.63	312.00	570	214	98	73.37	0.00	24.48	0.00
LAM25T25	8	Identical Low	P	21	0	14	0	25	27	160.10	403.00	570	214	189	0.00	6.90	27.00	5.44
LAM25T25	8	Identical Low	Best P/F	21	0	14	24	1	14	184.77	312.00	570	214	98	72.19	1.04	24.31	1.04
LAM25T25	8	Identical Low	Greedy	21	0	14	24	1	14	184.77	312.00	570	214	98	72.19	1.04	24.31	1.04
LAM25T25	8	Identical High	F	21	0	14	25	0	7	126.65	263.00	570	214	49	180.35	0.00	32.76	0.00
LAM25T25	8	Identical High	P	21	0	14	0	25	36	79.61	466.00	570	214	252	0.00	24.39	36.00	19.74
LAM25T25	8	Identical High	Best P/F	21	0	14	22	3	7	128.99	263.00	570	214	49	173.61	4.40	31.80	4.40
LAM25T25	8	Identical High	Greedy	21	0	14	22	3	7	128.99	263.00	570	214	49	173.61	4.40	31.80	4.40
LAM25T25	8	Nonidentical low	F	21	0	14	25	0	14	184.40	312.00	570	214	98	73.60	0.00	24.52	0.00
LAM25T25	8	Nonidentical low	P	21	0	14	0	25	27	152.68	403.00	570	214	189	0.00	14.32	27.00	10.60
LAM25T25	8	Nonidentical low	Best P/F	21	0	14	25	0	14	184.40	312.00	570	214	98	73.60	0.00	24.52	0.00
LAM25T25	8	Nonidentical low	Greedy	21	0	14	25	0	14	184.40	312.00	570	214	98	73.60	0.00	24.52	0.00
LAM25T25	8	Nonidentical high	F	21	0	14	25	0	7	136.39	263.00	570	214	49	170.61	0.00	31.37	0.00
LAM25T25	8	Nonidentical high	P	21	0	14	0	25	34	98.48	452.00	570	214	238	0.00	19.52	34.00	15.57
LAM25T25	8	Nonidentical high	Best P/F	21	0	14	23	2	7	139.05	263.00	570	214	49	165.46	2.50	30.64	2.50
LAM25T25	8	Nonidentical high	Greedy	21	0	14	23	2	7	139.05	263.00	570	214	49	165.46	2.50	30.64	2.50
LAM25T25	9	Identical Low	F	24	0	11	22	0	12	238.83	252.00	574	186	66	83.17	0.00	27.12	0.00
LAM25T25	9	Identical Low	P	24	0	11	0	22	30	216.92	351.00	574	186	165	0.00	6.08	30.00	4.79
LAM25T25	9	Identical Low	Best P/F	24	0	11	20	2	12	238.90	252.00	574	186	66	83.06	0.04	27.10	0.04
LAM25T25	9	Identical Low	Greedy	24	0	11	20	2	12	238.90	252.00	574	186	66	83.06	0.04	27.10	0.04
LAM25T25	9	Identical High	F	24	0	11	22	0	6	196.51	219.00	574	186	33	158.49	0.00	34.82	0.00
LAM25T25	9	Identical High	P	24	0	11	0	22	38	155.30	395.00	574	186	209	0.00	23.70	38.00	19.79
LAM25T25	9	Identical High	Best P/F	24	0	11	18	4	6	198.80	219.00	574	186	33	153.42	2.77	33.90	2.77
LAM25T25	9	Identical High	Greedy	24	0	11	18	4	6	198.80	219.00	574	186	33	153.42	2.77	33.90	2.77
LAM25T25	9	Nonidentical low	F	24	0	11	22	0	11	234.33	246.50	574	186	61	93.17	0.00	27.94	0.00
LAM25T25	9	Nonidentical low	P	24	0	11	0	22	31	202.68	356.50	574	186	171	0.00	14.82	31.00	13.15
LAM25T25	9	Nonidentical low	Best P/F	24	0	11	20	2	11	234.39	246.50	574	186	61	93.08	0.03	27.92	0.03
LAM25T25	9	Nonidentical low	Greedy	24	0	11	20	2	11	234.39	246.50	574	186	61	93.08	0.03	27.92	0.03
LAM25T25	9	Nonidentical high	F	24	0	11	22	0	4	197.32	208.00	574	186	22	168.68	0.00	34.67	0.00
LAM25T25	9	Nonidentical high	P	24	0	11	0	22	37	158.18	389.50	574	186	204	0.00	26.32	37.00	21.54

Table D.1 Details of all solutions (continued)

LAM25T25	9	Nonidentical high	Best P/F	24	0	11	17	5	4	200.06	208.00	574	186	22	162.07	3.87	33.47	4.03
LAM25T25	9	Nonidentical high	Greedy	24	0	11	17	5	4	200.06	208.00	574	186	22	162.07	3.87	33.47	4.03