

DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

**MULTI-PROJECT SCHEDULING WITH SKILL-
AND CAPABILITY-BASED RESOURCE
CONSTRAINTS: A CASE STUDY FOR R&D
PROJECTS IN HEATING INDUSTRY**

by
Tuğba BADUR

April, 2021
İZMİR

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AND CAPABILITY-BASED RESOURCE
CONSTRAINTS: A CASE STUDY FOR R&D
PROJECTS IN HEATING INDUSTRY**

**A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Master of Science
in Industrial Engineering, Industrial Engineering Program**

**by
Tuğba BADUR**

**April, 2021
İZMİR**

M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled “**MULTI-PROJECT SCHEDULING WITH SKILL- AND CAPABILITY-BASED RESOURCE CONSTRAINTS: A CASE STUDY FOR R&D PROJECTS IN HEATING INDUSTRY**” completed by **TUĞBA BADUR** under the supervision of **PROF. DR. ŞEYDA TOPALOĞLU YILDIZ**, and we certify that in our opinion, it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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ACKNOWLEDGEMENTS

First and foremost, I would like to express my most profound appreciation to my advisor, Prof. Dr. Şeyda TOPALOĞLU YILDIZ, for her continuous support, guidance, patience, and encouragement throughout my M.Sc. study. This dissertation could not have been completed without her active interest in my work, valuable insights, inspiring advice, and constructive feedback.

I take this opportunity to thank my supervisor, my colleagues and my friends for their encouragement and support during my graduate study. Their insightful feedback, support and all of the opportunities I was given brought my study to a higher level.

Last but not least, I would like to give special thanks to my parents and my sister for the invaluable support they provided me throughout my entire life and their confidence in me. Without their encouragement, this dissertation would not have been completed.

Tuğba BADUR

MULTI-PROJECT SCHEDULING WITH SKILL- AND CAPABILITY-BASED RESOURCE CONSTRAINTS: A CASE STUDY FOR R&D PROJECTS IN HEATING INDUSTRY

ABSTRACT

The resource-constrained multi-project scheduling problem (RCMPSP) considers more than one project and its task executions, precedence relations, availability of shared resources with limited total working capacity. The RCMPSP belongs to the class of hard optimization problems. Companies' intensive research and development activities require multiple projects to be started and performed simultaneously with resources with different skills, which resemble the RCMPSP with shared resources. In this problem, resources with different skills are assigned to the project tasks according to their skill and capability.

We have developed discrete-time mixed-integer linear programming, continuous-time event-based mixed-integer linear programming, and constraint programming models for the considered problem. We have developed our models with three objectives: minimizing projects' tardiness, minimizing the total project development cost of projects, and maximizing the total quality score of projects, respectively. We have conducted a computational study of the proposed models with a series of test instances. The results show that the constraint programming model reduces computational time and improves solution quality, with an average of fifty-six percent on sixty test instances relative to the mixed-integer linear programming models due to the reduction in the number of constraints and variables.

Finally, constraint programming is applied to a real-life problem, as it shows the best performance in computational study. The real-life problem is solved using goal programming and goal attainment techniques as multi-objective approaches. The changes in objective weights, number of resources, and capability values are analyzed.

Keywords: Multi-project scheduling, multi-skill resource constraints, constraint programming, mixed-integer linear programming, case study



BECERİ VE YETKİNLİĞE DAYALI KAYNAK KISITLAMALARI İLE ÇOKLU PROJE ÇİZELGELEME: ISITMA ENDÜSTRİSİNDEKİ AR-GE PROJELERİ İÇİN BİR VAKA ÇALIŞMASI

ÖZ

Kaynak kısıtlı çoklu proje çizelgeleme problemi (KKÇPÇP) birden fazla projeyi ve bunların görev yürütmelerini, öncelik ilişkilerini ve kaynakların kullanılabilirliğini dikkate alır. KKÇPÇP, zor optimizasyon problemleri sınıfına aittir. Şirketlerin yoğun araştırma ve geliştirme faaliyetleri, farklı becerilere sahip kaynaklarla aynı anda birden fazla projenin başlatılmasını ve yürütülmesini gerektirir; bu da paylaşılan kaynakların olduğu KKÇPÇP'yi andırmaktadır. Bu problemde, farklı yeteneklere sahip kaynaklar, becerilerine ve kapasitelerine göre proje görevlerine atanır.

Ele alınan problem için ayrık zamanlı karma tamsayılı doğrusal programlama, sürekli zamanlı olay tabanlı karma tamsayılı doğrusal programlama ve kısıt programlama formülasyonlarını geliştirdik. Formülasyonlarımızı sırasıyla projelerin gecikmesini enküçükleyen, tüm projelerin toplam geliştirme maliyetini enküçükleyen ve projelerin toplam kalite puanını enbüyükleyen üç hedef ile geliştirdik. Bir dizi test örneğiyle önerilen formülasyonların karşılaştırmalı bir çalışmasını gerçekleştirdik. Sonuçlar, kısıt programlamanın hesaplama süresini azalttığını ve kısıtların ve değişkenlerin sayısındaki azalma nedeniyle karma tamsayılı doğrusal programlamaya göre altmış test örneğinde ortalama yüzde elli altı oranında çözüm kalitesini iyileştirdiğini göstermektedir.

Son olarak, karşılaştırmalı çalışmada en iyi performansı gösterdiği için kısıt programlama gerçek hayattaki bir probleme uygulanmıştır. Gerçek hayat problemi, çok amaçlı yaklaşımlardan olan hedef programlama ve hedefe ulaşma teknikleri kullanılarak çözülmüştür. Amaç ağırlıkları, kaynak sayısı ve yetkinlik değerlerindeki değişiklikler analiz edilmiştir.

Anahtar Kelimeler: Çoklu proje çizelgeleme, çok becerili kaynak kısıtlamaları, kısıt programlama, karma tamsayılı doğrusal programlama, vaka çalışması



CONTENTS

	Page
M.Sc THESIS EXAMINATION RESULT FORM.....	ii
ACKNOWLEDGEMENTS	iii
ABSTRACT.....	iv
ÖZ	vi
LIST OF FIGURES	x
LIST OF TABLES	xi
CHAPTER ONE – INTRODUCTION	1
CHAPTER TWO – LITERATURE REVIEW	5
2.1 Resource-Constrained Single-Project Scheduling Problem (RCPSP)	8
2.2 Resource-Constrained Multi-Project Scheduling Problem (RCMPSP)	12
2.3 Research Gap and Contributions of Proposed Study	17
CHAPTER THREE – PROBLEM STATEMENT AND MATHEMATICAL FORMULATIONS.....	20
3.1 Problem Description and Assumptions	20
3.2 Overview of Mathematical Programming Approaches	22
3.2.1 Mixed-Integer Linear Programming (MILP).....	23
3.2.1.1 Multi-Objective Programming	25
3.2.1.1.1 Weighted Goal Programming and Analytical Hierarchy Process	26
3.2.1.1.2 Goal Attainment Technique	28
3.2.2 Proposed Mixed-Integer Linear Programming Models.....	29
3.2.2.1 Discrete-Time Mixed-Integer Linear Programming Model	30
3.2.2.2 Continuous-Time Event-Based Mixed-Integer Linear Programming Model.....	35
3.2.3 Constraint Programming (CP)	40

3.2.4 Proposed Constraint Programming Model	41
CHAPTER FOUR – TEST INSTANCES AND COMPUTATIONAL STUDY	46
4.1 Overview of Existing Benchmark Datasets.....	46
4.2 Data Generation for Proposed Formulations.....	48
4.3 Verification and Validation of Proposed Models on Three Test Instances.....	60
4.4 Variable and Value Ordering	67
4.5 Search Strategies	76
4.6 Computational Study of Developed Models Using Generated Test Instances	81
CHAPTER FIVE – REAL-LIFE PROBLEM AND MANAGERIAL IMPLICATIONS	91
5.1 Overview of Real-Life Problem	91
5.2 Managerial Implications for Real-Life Problem	100
5.2.1 Changes in the Objective Function Weights	101
5.2.2 Changes in the Total Resource Capability.....	104
5.2.3 Changes in the Number of Resources.....	107
5.2.4 Changes in the Objective Function Weights in Goal Attainment Technique	110
CHAPTER SIX – CONCLUSIONS	114
REFERENCES	116
APPENDICES	126

LIST OF FIGURES

	Page
Figure 4.1 The project and task schedule for the first test instance	63
Figure 4.2 The resources' loading for the first test instance	64
Figure 5.1 Precedence relationships in finished product (a), subassembly (b) and spare parts (c) projects.....	97
Figure 5.2 Total percentage deviations for the changes in objective function weights	103
Figure 5.3 Total percentage deviations for the changes in the total resource capability	106
Figure 5.4 Total percentage deviations for the changes in the number of resources	109
Figure 5.5 Total percentage deviations for the changes in the objective function weights in goal attainment technique	113

LIST OF TABLES

	Page
Table 2.1 Overview of resource-constrained single-project scheduling problem in the literature.....	11
Table 2.2 Overview of resource-constrained multi-project scheduling problem in the literature.....	15
Table 3.1 Saaty numerical scale.....	27
Table 4.1 Summary of existing benchmark datasets in the literature	49
Table 4.2 Overview of resource-constrained single-project scheduling problem test instances in the literature	50
Table 4.3 Overview of resource-constrained multi-project scheduling problem test instances in the literature	51
Table 4.4 Pairwise comparisons between business objectives concerning the management satisfaction.....	56
Table 4.5 Relative importance values of business objectives.....	56
Table 4.6 Normalized relative importance values of business objectives	56
Table 4.7 Overview of the sixty test instances.....	58
Table 4.8 Summary of the first test instance parameters	61
Table 4.9 Computational results for the three test instances.....	66
Table 4.10 The summary and results of variable and value ordering strategies for the large-size test instance.....	75
Table 4.11 Summary of the tree search strategy results.....	78
Table 4.12 Computational results of small-size test instances	85
Table 4.13 Computational results of mid-size test instances	87
Table 4.14 Computational results of large-size test instances	89
Table 5.1 Summary of the project parameters in the real-life problem	92
Table 5.2 Summary of the task parameters in the real-life problem.....	94
Table 5.3 Summary of the resource parameters in the real-life problem.....	96
Table 5.4 Summary of the skill parameters in the real-life problem	97
Table 5.5 CP model solution results for the task start (S) and finish (F) times	99
Table 5.6 CP model results for the amount of resource capacity consumed and their excessive use.....	100

Table 5.7 Computational results for the changes in objective function weights	102
Table 5.8 Computational results for the changes in total resource capability	105
Table 5.9 Computational results for the changes in the number of resources	108
Table 5.10 Computational results for the changes in objective function weights in goal attainment technique.....	112



CHAPTER ONE

INTRODUCTION

Project scheduling is a decision-making process used in project management. It requires defining tasks or work packages to be accomplished and resources to be allocated to achieve project outcomes within a specified time frame. Only 2.5 percent of companies complete their project with a hundred percent success rate, according to research on more than 10,640 projects conducted by PwC, a company providing audit and assurance, consulting, and tax services, while all the rest are unable to meet targets (Andriole, 2020). In today's business world, these failures result in high costs that need to be covered by organizations. The importance of project scheduling increases to ensure successful project completion by meeting the customer requirements within aligned acceptance levels of cost, quality, and time.

A project is a temporary activity that requires careful planning to accomplish an objective to provide service or present product on a specified due date. Each project consists of several tasks to be completed within an exact time frame defined as the project life cycle. It is aimed to provide a unique outcome during a project life cycle. Thus, routine activities cannot be considered as a project.

A task is a piece of work that needs to be completed on time. Each task can be considered a standalone work or grouped work with other related tasks to build a work package that is a sub-project within a mid- or large-size project. Therefore, a task is the smallest unit of a small-size project, while a work package is the smallest unit of a mid- or large-size project.

As part of the work package or project, a task has a duration defined in advance by the project manager or project team based on experience and company project management procedures. According to Cadle & Yeates (2008), task duration can be calculated as a difference between the latest finish time (LFT) and the earliest start time (EST). Alternatively, the difference between the earliest finish time (EFT) and the earliest start time or between the latest finish time and latest start time (LST) can

be considered in the task duration calculation as well. A task can be temporarily interrupted until resuming it at a later stage (*preemptive task*) or continued without interruption (*non-preemptive task*). In both cases, the project is ended after the completion time of the final task, considering precedence relations between each task. Therefore, it is crucial to define project completion time considering task duration, task interruption, and precedence relations.

Today, many organizations execute projects with the support of shared resources. A resource is a supply of money, employee, material and other assets which can be provided to meet the demand of a person or organization. According to the availability during different project periods, a resource can be renewable, nonrenewable, or doubly constrained (Besikci, Bilge & Ulusoy, 2012). A *renewable resource*, such as a machine or employee, is used in each time period while performing a task. On the other hand, a *nonrenewable resource* such as a budget cannot be used in each time period due to its consumption. A resource can also be constrained both at each time period and over the project lifecycle (*doubly constrained resource*).

The project scheduling problem constrained with specific resources is named resource-constrained single-project scheduling problem (RCPSP). It considers scheduling of a task within a project under limited resource availability. As an extended variant of RCPSP, the resource-constrained multi-project scheduling problem (RCMPSP) is developed by taking multiple projects into account with scarce resources in today's business world. Accordingly, a project scheduling formulation can help project managers balance their resources' capacity considering the hardness of executing tasks in projects on time.

To ensure that resources are not overextended and used inefficiently, project managers should consider a more realistic view on resource demand (or requirement), resource supply (or capacity), and the skill and capability of resources required to perform a task. The RCMPSP can be extended with resources having one or more than one skill from a given pool of skills. Each task demands one or more skills from all available resources in such a multi-skilled problem. On the other hand, the resources

with the required skills cannot have the capability to perform a task if they have skill levels at a lower level than demanded. For this reason, the skill and capability of resources and each task's demand concerning the skill and capability requirements should be considered in the project constraints. It is required to optimally allocate the right resources' capacity to the right tasks for such a problem since resource management affects the project success a great deal.

Alternatively, in the real world RCPSP and RCMPSP, it is observed that tasks are assigned to resources with the required skill and capability regardless of their availability. This situation results in an excessive amount of resource capacity that needs to be allocated. However, there must be a maximum limitation for excessive resource usage since it has an additional load on the company's budget or is restricted to a certain capacity level due to legal constraints.

The RCMPSP is the sub-class of the project scheduling problems that consider more than one project and their task execution, precedence relations, shared resources availability, capability, and skills. Similar to the RCPSP, the RCMPSP is classified as an NP-hard optimization problem as well (Chakraborty, Rahman, Haque, Paul & Ryan, 2020). This thesis studies the multi-project scheduling problem with skill- and capability-based resource constraints. Employees and machines are assigned to tasks in different projects according to their skill and capability under limited capacity.

The organization of the thesis is as follows: In Chapter 2, the literature review is performed for the RCPSP and RCMPSP in detail to address the research gap and explain our methodology. The considered problem and proposed models are given in Chapter 3. Discrete-time and continuous-time event-based mixed-integer linear programming (MILP) formulations of the proposed models are presented. The variables are indexed by time periods in the discrete-time formulation, whereas the continuous-time event-based MILP formulation consists of variables indexed by events that refer to the start or finish time of tasks. A new constraint programming (CP) has also been developed for the problem. As multi-objective optimization methods, three goals that minimize projects' tardiness, minimize the total development

cost of projects, and maximize the total quality score of projects using goal programming and goal attainment techniques are discussed. These methods are also described in Chapter 3.

The computational study is given in Chapter 4. Existing benchmark data sets are analyzed, and new data sets are generated to evaluate developed models' performance. Accordingly, sixty test instances of the small, medium and large-size problems are generated and solved. CP model is improved with variable and value ordering and search strategies to provide better performance than the pure formulation. Finally, the computational results are analyzed and discussed.

In Chapter 5, a real-life multi-objective multi-project scheduling problem with skill- and capability-based resource constraints is explained and solved with improved CP formulation. Then, how the real-life problem produces solutions with different parameters, the effects of these changes on the solution, and the managerial experiences obtained from these results are explained. Consequently, concluding remarks and contributions of this study are represented, and future directions of the proposed research are identified in Chapter 6.

CHAPTER TWO

LITERATURE REVIEW

The project scheduling problem (PSP) under a resource constraint is classified as either a resource-constrained single-project or resource-constrained multi-project scheduling problem. According to the computational complexity theory, which classifies and compares the inherent difficulty of solving problems that find an optimal objective from a finite set, the RCPSP can be viewed as a combinatorial optimization problem. Thus, the RCPSP is defined as a non-deterministic polynomial-time hard (NP-hard) problem by Blazewicz, Lenstra & Rinnooy Kan (1983) in the field of project scheduling.

Every project consists of a task or a group of tasks called work-package. Pritsker, Watters & Wolfe (1969) present a zero-one linear programming formulation considering that each task can also be split into subtasks. Patterson (1984) proposes that a task can be split only at specific periods when different resource levels are assigned to the task. Similarly, Nubtasomboon & Randhawa (1997) assume that tasks can be preempted any number of times using active time variables.

Any task requires at least one resource to support the completion of a project. According to Slowinski (1980), resources can be defined as renewable, nonrenewable, and doubly constrained based on their availability. A renewable resource, such as a machine or employee, is used in each time period while performing a task. A limited or nonrenewable resource such as a budget cannot be used in each time period due to its consumption level over the project life cycle. Alternatively, a doubly constrained resource can be constrained both at each time period and over the project lifecycle.

In the RCPSP literature, many researchers examined human resources. Alfares & Bailey (1995) present a project scheduling algorithm that determines the start time and processing time for each task as a labor level function. However, instead of considering the demand for human resources, Bassett (2000) focuses on their availability, location, skill level, and expertise to assign them to a specific role. On the other hand, many

researchers consider skill levels of human resources while defining resource constraints. Campbell & Diaby (2001) develop a heuristic approach and a MILP model to allocate employees who work in different departments and have different skill levels. Yoshimura, Fujimi, Izui & Nishiwaki (2006) prepare a skill matrix for human resources considering that each employee can have more than one skill. Drezet & Billaut (2007) propose a linear programming (LP) model for a project scheduling problem where employees are resources that have different skills. They define the minimum and maximum skill requirements for an activity as the minimum and the maximum number of available employees that can perform an activity. The additional constraints are added for activity changes, assignment moves, and workforce legislation. According to these studies, the multi-skill RCPSP is defined as a variant of RCPSP considering that each resource excels in one or more skills during the project lifecycle.

In the literature, the RCPSPs can be classified according to the combination of resources as well. Many researchers have developed heuristic algorithms and heuristic-based priority rules in order to solve problems in which tasks are processed in more than one operating mode having different duration and renewable resource constraints (e.g., Alcaraz, Maroto & Ruiz, 2003; Lova, Tormos & Barber, 2006) instead of developing mathematical models. Tao & Dong (2018) state that each task in multi-mode RCPSP (MRCPSP) is implemented in one of the multiple execution modes that present a combination of resource requirements and a processing time for that task.

Today, many organizations require multiple projects which are started and performed simultaneously with shared resources. In the RCMPSPs, one of the crucial constraints for project managers is the limited availability of resources and their concurrency. Patterson (1984) examines bounded enumeration, branch and bound, and implicit enumeration procedures for resource conflict resolution decisions that occur on a project's conflicting tasks and exceed the maximum available resource capacity. The proposed bounded enumeration procedure is found superior on RCPSPs compared to branch and bound and implicit enumeration procedures since it provides an optimal solution in less computational time. According to Kara, Kayis & Kaebernick (2001),

executing tasks in parallel requires careful project planning and implementation due to complexities and uncertainties in the process.

In the literature, it is common to use time-based formulations and heuristic approaches for the RCMPSPs. Discrete-time models use time-indexed decision variables for events that occur at specific predefined time points considering all feasible activities. On the other hand, continuous-time event-based formulations include event points as the start of each task. As an alternative to discrete-time formulations, time periods are not shown in continuous-time event-based formulations, but they are identified with a time variable that corresponds to event points. It leads practitioners to track the start and end time of tasks according to task processing times and event time variables and allows using time-variant resource capacity by introducing additional variables into the formulation. Event-based formulations are applied mostly on single project scheduling problems depending on the instance characteristics in the literature (Kone, Artigues, Lopez & Mongeau, 2009; Kopanos, Kyriakidis & Georgiadis, 2014; Correia, Lourenco & Saldanha-da-Gama, 2012; H. Zheng, Wang & X. Zheng, 2015) and only a few papers consider event-based formulations in multi-project scheduling problems (Edwards, Baatar, Smith-Miles & Ernst, 2019).

One of the most significant limitations of the MILP solution procedure is the number of constraints and variables that make the solution procedure too challenging to solve real-life problems. Many studies (e.g., Demeulemeester & Herroelen, 1997; Kone et al., 2009; Chakraborty, Ruhul & Daryl, 2018) state that RCPSP is still unable to be solved for problems dealing with more than 60 tasks with exact methods. Therefore, some researchers propose different mathematical model formulations by using LP relaxation (Heimerl & Kolisch, 2010) and valid inequalities (Kone et al., 2009) to reduce complexity and solve RCPSPs with 60 tasks within a reasonable time. Other than that, Demassey, Artigues & Michelon (2005) propose a cooperative methodology between CP and integer programming to reduce lower bounds for the RCPSP with 60, 90, and 120 tasks. They apply constraint propagation to derive cutting planes to strengthen the linear formulations.

2.1 Resource-Constrained Single-Project Scheduling Problem (RCPSP)

The resource-constrained single project scheduling problem (RCPSP) deals with scheduling preemptive or non-preemptive tasks within a project under precedence constraints and limited resource availability. Many researchers started searching for the RCPSPs in the early 1970s since tasks cannot be completed on time, and project objectives cannot be met under the lack of resources.

Kopanos et al. (2014) define an event-based MILP formulation considering precedence-based decision variables for the single-objective RCPSP. According to their comparative study, the event-based models perform better than discrete-time models for problems with a high number of tasks due to event points considered. This feature of the event-based formulation allows fewer variables than formulations indexed by time and reduces complexity. Another event-based MILP formulation is proposed by Correia et al. (2012), considering flexible multi-skilled resources, each with more than one skill. In addition to the other event-based models, their study provides simplified formulations to reach an optimal solution using inequalities requiring a valid upper bound. On the other hand, Drezet et al. (2007) propose a time-based linear programming (LP) model, greedy algorithm, and tabu search algorithm to minimize the maximum lateness for the single-objective RCPSP where employees are resources with different skills.

Following, Zheng et al. (2015) solve the multi-skill RCPSP considering each task can be processed with a skill equal to or greater than a specific level defined from a set $\{1, 2\}$. Their study contributes to the multi-skill RCPSP literature by applying teaching and learning-based optimization algorithms for event-based MILP models. Polo-Mejia, Artigues, Lopez & Basini (2019) develop the CP and time-based MILP models and a greedy algorithm to tackle the multi-skill RCPSP with preemptive, partially preemptive, and non-preemptive tasks. In their study, MILP and CP models are applied to solve real-life industry problems; however, proposed formulations are not fast enough for presenting high-quality solutions in a limited computation time, mainly caused by task preemption.

A few researchers propose CP to solve large-scale single-mode and multi-mode RCPSPs (Liess & Michelon, 2007; Menesi & Hegazy, 2014; Kreter, Schutt & Stuckey, 2017). Kyriakidis, Kopanos & Georgiadis (2012) define a time-based MILP model for single- and multi-mode RCPSP considering task preemption and renewable and nonrenewable resources. The single-mode RCPSP contains one execution mode with specific time and resource requirements for each task. On the other hand, the multi-mode RCPSP includes various execution modes that determine different task duration and resource requirements in each execution. The proposed multi-mode RCPSP formulation performs less computational effort for large-size problems due to the reduced number of integer and binary variables. In the literature, various integer and MILP models are developed as time-based formulations that divide the planning horizon into time intervals with equal durations for the multi-mode RCPSP. On the other hand, recent studies consider event-based formulations that include event points to indicate each task's beginning and ending without reflecting time periods. Kone et al. (2009) propose two continuous-time MILP formulations using the variables indexed by events that correspond to the task start time and task finish time. A start and end event-based formulation takes two types of binary variables into account to set start-end times of tasks by introducing a continuous variable to represent the event time. Alternatively, an on-off event-based formulation is also introduced in their study, which includes only one type of binary variable to set the start and processing of activity at an event.

In today's business world, customers raise more than one requirement that needs to be provided for project completion, such as moderate product/service cost, high quality, and market readiness. Therefore, project managers must consider more than one objective during the project life cycle to successfully meet these requirements. An evolutionary algorithm is developed by Yannibelli & Amandi (2013) to solve the multi-skill RCPSP where resources have skill levels from a set $\{0, 1\}$. They contribute to the literature by maximizing the assignment of the most useful resources to the tasks besides minimizing project makespan as model objectives. Myszkowski, Skowronski, Olech & Oslizlo (2014) proposes a weighted sum method for hybrid ant colony optimization to solve the multi-skill RCPSP to minimize project schedule duration and

performance cost. First, they identify the weights of the objectives. Then, the objective function is formulated as a single objective to find a solution by using weights. Kia, Shahnazari-Shahrezaei & Zabihi (2016) proposes the ε -constraint method to solve the multi-objective non-linear mixed-integer programming model, which minimizes the project completion time, the idle time of resources, and penalty of allocating resources with low capability. Maghsoudlou, Afshar-Nadjafi, Taghi & Niaki (2016) develop invasive weeds optimization algorithm, non-dominated sorting genetic algorithm (NSGA-II), and finally, particle swarm optimization algorithm (MOPSO) to solve the multi-skill multi-mode RCPSP for three business objectives: minimizing maximum project completion time, minimizing total cost of allocating human resources, maximizing total quality of processing activities. The RCPSP literature published in the 2000s is summarized in Table 2.1 in detail.

Table 2.1 Overview of resource-constrained single-project scheduling problem in the literature

Author (s)	Year	Objective		Method		Schedule		Task		Resource		Mode		Skill		
		Single	Multiple	Exact	Heuristic	Time-based	Event-based	Preemptive	Nonpreemptive	Renewable	Nonrenewable	Single	Multiple	Single	Multiple	Level
Liess & Michelon	2007	✓		CP	✓	✓			✓	✓			✓	✓		
Drezet & Billaut	2007	✓		LP	✓	✓			✓	✓		✓			✓	
Kone et al.	2009	✓		MILP		✓	✓		✓	✓			✓	✓		
Kyriakidis et al.	2012	✓		MILP		✓		✓		✓	✓	✓	✓	✓		
Correia et al.	2012	✓		MILP			✓		✓	✓		✓			✓	
Yannibelli & Amandi	2013		✓		✓	✓			✓	✓		✓			✓	[0, 1]
Menesi & Hegazy	2014		✓	CP		✓			✓	✓			✓	✓		
Kopanos et al.	2014	✓		MILP		✓	✓		✓	✓		✓		✓		
Myszkowski et al.	2014		✓		✓	✓			✓	✓		✓			✓	
Zheng et al.	2015	✓			✓		✓		✓	✓		✓			✓	[1, 2]
Maghsoudlou et al.	2016		✓		✓	✓			✓	✓			✓		✓	
Kia et al.	2016		✓	MINLP		✓			✓	✓		✓			✓	[1, 3]
Kreter et al.	2017	✓		MILP, CP		✓			✓	✓		✓		✓		
Polo-Mejia et al.	2019	✓		MILP, CP	✓	✓		✓	✓	✓		✓			✓	

2.2 Resource-Constrained Multi-Project Scheduling Problem (RCMPSP)

The resource-constrained multi-project scheduling problem is an extension of the RCPSP and considers more than one project to be conducted and performed simultaneously with scarce resources. According to Payne (1995), 90% of all projects performed by companies have a multi-project framework. A questionnaire performed by Lova & Tormos (2001) among 202 Spanish companies has shown that 84% of them run more than one project simultaneously in a particular time horizon.

Krueger & Scholl (2009) present priority-based parallel scheduling heuristics for solving the single-objective RCMPSP with sequence- and resource-type dependent setup times to minimize the average project duration. Homberger (2012) develops an agent-based heuristic with (μ, λ) -coordination mechanism regarding the use of scarce resources. Similarly, a two-phase priority rule heuristic and a genetic algorithm are developed by Suresh, Dutta & Jain (2015) for the RCMPSP with transfer times since resources moved between projects organized in different locations maximizing the net present value from time and cost perspectives. Similarly, Song, Kang, Zhang & Xi (2017) propose a multi-unit combinatorial auction with greedy and branch-and-bound heuristics and Li & Xu (2018) develop a multi-agent system for distributed multi-project scheduling with a two-stage decomposition approach for decentralized RCMPSP.

On the other hand, Villafanez, Poza, Lopez-Paredes, Pajares & Olmo (2019) develop a novel algorithm that demonstrates better results than published algorithms in the multi-project scheduling problem library (MPSPLIB) with parallel schedule generation via minimum total slack priority rule in order to minimize total makespan. Eynde & Vanhoucke (2020) provide priority-rule heuristic and genetic algorithm for the RCMPSP to minimize the average percentage of the delay and the portfolio delay objectives separately. Their paper presents a multi-project approach resulting in decoupled versions of the single-project schedule generation schemes to provide better quality solutions and more advanced algorithms. On the other hand, Edwards et al. (2019) develop discrete-time MILP, continuous-time on-off event-based MILP, and

CP to minimize total makespan and average project delay objectives separately. Many researchers take into account the multi-objective approach for the RCMPSPs by using the weighted sum method. Chiu & Tsai (2002) propose a non-linear mixed-integer programming and critical ratio search method using a weighted sum method to minimize project delay penalty and maximize early completion bonus. On the other hand, many researchers (e.g., Browning & Yassine, 2010; Perez, Posada & Lorenzana, 2015; Asta, Karapetyan, Kheiri, Ozcan & Parkes, 2016; Geiger, 2016; Chakraborty, Sarker & Essam, 2017) apply a weighted sum method in their papers considering proposed heuristic and metaheuristic approaches such as priority rule heuristic, genetic algorithm, hyper-heuristic approach, and variable neighborhood search.

Zapata, Hodge & Reklaitis (2008) propose three alternative formulations for the multi-mode RCMPSP to maximize the total non-discounted profit obtained from the projects: discrete-time formulation, precedence-based continuous-time formulation, continuous-time event-based formulation. Their study aims to overcome the limitations of indexes of multi-modes, time periods, and discrete nature of resources by using an event-based formulation which also causes a reduction in the number of variables. However, the reduction achieved with the continuous variables is compensated by the increase in the number of constraints and negative impacts of LP relaxation. Unlike the other multi-project scheduling problems, Besikci, Bilge & Ulusoy (2014) propose a genetic algorithm for a project portfolio and renewable and nonrenewable resource portfolio scheduling problem to minimize total weighted lateness. Can & Ulusoy (2014) develop a two-stage decomposition for binary integer programming and a genetic algorithm for the macro-activity scheduling problem considering maximization of net present value and minimization of makespan in two consecutive decision stages separately. On the other hand, Toffolo, Santos, Carvalho & Soares (2015) propose a time-based integer programming to minimize the sum of project completion times and makespan with a weighted sum approach for a multi-mode RCMPSP. Kucuksayacigil & Ulusoy (2020) define a hybrid genetic algorithm for the multi-objective resource-constrained project scheduling problem to pair minimization of makespan, mean completion time and mean flow time, and maximization of net present value objectives with a single-objective approach.

Other than heuristic and metaheuristic approaches widely used in the RCMPSP, Heimerl et al. (2010) propose a MILP model considering human resources from inside and outside the company as source skills. Their study indicates an efficiency notation for resource allocation to perform a task requiring skill at a specific time period. Kazemipoor, Tavakkoli-Moghaddam, Shahnazari-Shahrezaei & Azaron (2013) develop non-linear mixed-integer programming and differential evaluation algorithms using the weighted mean of deviation method with a single-objective approach. Certa, Enea, Galante & La Fata (2009), Heimerl et al. (2010), and Kazemipoor et al. (2013) propose models where resources' skills are assigned to the projects. Chen, Liang, Gu & Leung (2017) consider a non-linear mixed-integer programming and non-dominated sorting genetic algorithm using a weighted sum method to maximize skill efficiency increase, minimize product development cycle time, and minimize product development costs. Gutjahr, Katzensteiner, Reiter, Stummer & Denk (2010) propose a linear asymptotic approximation to maximize economic and competence benefit using genetic algorithm and ant colony optimization. On the other hand, Florez, Castro-Lacouture & Medaglia (2013) propose the multi-objective multi-mode RCMPSP with renewable and non-renewable resources. The RCMPSP literature published in the 2000s is summarized in Table 2.2, including the current RCMPSP study proposed.

Table 2.2 Overview of resource-constrained multi-project scheduling problem in the literature

Author (s)	Year	Objective		Method		Schedule		Task		Resource		Mode		Skill		
		Single	Multiple	Exact	Heuristic	Time-based	Event-based	Preemptive	Nonpreemptive	Renewable	Nonrenewable	Single	Multiple	Single	Multiple	Level
Chiu & Tsai	2002		✓	MINLP	✓	✓			✓	✓		✓		✓		
Zapata et al.	2008	✓		MILP		✓	✓		✓	✓			✓	✓		
Krueger & Scholl	2009	✓			✓	✓			✓	✓		✓		✓		
Certa et al.	2009		✓	MINLP		✓				✓		✓			✓	[0, 1]
Browning & Yassine	2010		✓		✓	✓			✓	✓		✓		✓		
Heimerl & Kolisch	2010	✓		MILP		✓				✓		✓			✓	
Gutjahr et al.	2010		✓		✓	✓				✓		✓			✓	[0, 1]
Homberger	2012	✓			✓	✓			✓	✓		✓		✓		
Kazemipoor et al.	2013		✓	MILP	✓	✓			✓	✓		✓			✓	
Florez et al.	2013		✓	MILP		✓				✓	✓		✓		✓	
Besikci et al.	2014	✓			✓	✓			✓	✓	✓		✓	✓		
Can & Ulusoy	2014	✓			✓	✓			✓	✓	✓		✓	✓		
Suresh et al.	2015	✓		MILP	✓	✓			✓	✓		✓		✓		

Table 2.2 continues

Author (s)	Year	Objective		Method		Schedule		Task		Resource		Mode		Skill		
		Single	Multiple	Exact	Heuristic	Time-based	Event-based	Preemptive	Nonpreemptive	Renewable	Nonrenewable	Single	Multiple	Single	Multiple	Level
Perez et al.	2015		✓		✓	✓			✓	✓		✓		✓		
Toffolo et al.	2015		✓	MILP		✓			✓	✓	✓		✓	✓		
Asta et al.	2016		✓		✓	✓			✓	✓	✓		✓	✓		
Geiger	2016		✓		✓	✓			✓	✓	✓		✓	✓		
Song et al.	2017	✓			✓	✓			✓	✓		✓		✓		
Chakraborty et al.	2017		✓		✓	✓			✓	✓		✓		✓		
Chen et al.	2017		✓	MINLP	✓	✓			✓	✓		✓			✓	[0, 1]
Li & Xu	2018	✓			✓	✓			✓	✓		✓		✓		
Villafanez et al.	2019	✓			✓	✓			✓	✓		✓		✓		
Edwards et al.	2019	✓		MILP, CP		✓	✓		✓	✓		✓		✓		
Eynde & Vanhoucke	2020	✓			✓	✓			✓	✓		✓		✓		
Kucuksayacigil & Ulusoy	2020		✓		✓	✓			✓	✓	✓		✓	✓		
Current study	2020		✓	MILP, CP		✓	✓		✓	✓		✓			✓	{0, 1}

2.3 Research Gap and Contributions of Proposed Study

The contributions of this thesis are summarized as follows:

- The time-based mathematical programming formulations are widely used in the RCMPSP (e.g., Chiu et al., 2002; Zapata et al., 2008; Certa et al., 2009; Heimerl et al., 2010; Kazemipoor et al., 2013; Toffolo et al., 2015; Chen et al., 2017; Edwards et al., 2019). Alternatively, only a few researchers developed event-based mathematical programming formulations (e.g., Zapata et al., 2008; Edwards et al., 2019). On the other hand, constraint programming formulation is only proposed by Edwards et al. (2019) in RCMPSP literature. In this thesis, time-based and event-based MILP models and a CP model are proposed for the studied RCMPSP within the framework of multi-objective programming. Thus, the proposed model is different from the RCMPSPs (Liess et al., 2007; Kone et al., 2009; Kyriakidis et al., 2012; Correia et al., 2012; Menesi et al., 2014; Kreter et al., 2017; Polo-Meija et al., 2019).
- The multi-objective techniques used in RCMPSP literature are the weighted sum method, lexicographic goal programming method, and the ϵ -constraint method (e.g., Chiu et al., 2002; Certa et al., 2009; Gutjahr et al., 2010; Kazemipoor et al., 2013; Toffolo et al., 2015; Perez et al., 2015; Geiger, 2016; Asta, 2016; Chen et al., 2017). A goal programming and goal attainment method are used to solve the models in this thesis. Therefore, the proposed model varies from single-objective RCMPSPs (e.g., Zapata et al., 2008; Krueger et al., 2009; Heimerl et al., 2010; Can et al., 2014; Song et al., 2017; Edwards et al., 2019; Eynde et al., 2020).
- Practitioners can more accurately track project and task schedules using the task start time variable and time index. The binary variables represent task start and finish times in this thesis, as opposed to Chiu et al. (2002) introducing binary variables for task processing time. This thesis proposes a time index that differs from Certa et al. (2009) using time as a parameter, which is a fraction of the planning period.

- On the other hand, this thesis uses the task finish time variable to find project completion time and tardiness compared to Kazemipoor et al. (2013), defining variables only for task start time and processing time.
- The big-M constraints used to reflect the planning horizon into the model by Zapata et al. (2008) are not considered to simplify the proposed discrete-time MILP model.
- In contrast to Zapata et al. (2008), the proposed continuous-time event-based MILP model has fewer event constraints since time variables corresponding to the event points are not included to improve computational efficiency.
- The constraint programming model is improved with value and variable ordering and search strategies to improve solution performance and quality.
- Most of the RCMPSP studies define a constraint, which assigns resources to the tasks without exceeding the total number of resources or the total capacity unit of resources available (e.g., Edwards et al., 2019; Chiu et al., 2002; Can et al., 2014; Toffolo et al., 2015; Kazemipoor et al., 2013; Chen et al., 2017; Certa et al., 2009; Florez et al., 2013). The decision variables for regular and excessive resource capacity usage are introduced into the proposed models different than Heimerl et al. (2010) using a parameter.
- The excessive resource capacity usage is introduced for the proposed CP model, different from Edwards et al. (2019), considering only regular resource capacity usage.
- Excluding a few papers (Besikci et al., 2014; Can et al., 2014; Toffolo et al., 2015; Asta et al., 2016; Geiger, 2016; Kucuksayacigil et al., 2020), all studies take renewable resources into account and mainly refer to human resources. Moreover, there are very limited RCMPSPs that consider tasks requiring skilled human resources while developing exact solution methodologies. Here in this thesis, human resources with skills and capabilities and machines with skills and different capabilities are taken into account as renewable resources.
- Human resources may differ from each other, considering their capability, and may not be assigned to the same task even if they have the same skill

(Heimerl et al., 2010). On the other hand, machines have the skill and the capability to perform each task requiring their specific skill.

- This thesis presents small, mid, and large-size datasets for the studied problem with inspiration from the existing benchmark sets and additional literature studies. A computational study is conducted for the proposed formulations with a series of presented datasets.



CHAPTER THREE

PROBLEM STATEMENT AND MATHEMATICAL FORMULATIONS

The research gap in the RCPSP and RCMPSP literature clearly shows that discrete-time MILP, continuous-time event-based MILP, and CP models need to be investigated further. In this chapter, first, problem description and assumptions for the baseline of all model formulations are explained. Second, an overview of the mathematical programming approaches to compare MILP and CP techniques are presented. Finally, MILP and CP models are provided in detail.

3.1 Problem Description and Assumptions

The considered problem is driven by a case that arises in a combi boiler company of a leading manufacturer in the heating industry. A product on the market for several years may no longer meet the requirements, or competitors may provide better alternatives. As a result, the heating industry's competition drives product managers to conduct market research for existing trends and customer needs. Based on this market research analysis, each project idea is presented to the Executive Committee (sponsors) by the product managers. The selected projects are shared with the R&D department at the beginning of every year. These projects are carried out simultaneously and are classified under three major product categories:

- *The finished product project* category consists of the design and development of a combi boiler. A finished product project is carried out either for new design development or an upgrade of the existing combi boiler. It varies according to customer, regulatory, or technology requirements and lasts up to 2 years starting from market requirements' gathering until product delivery release to the market. The projects P1, P2, and P3 are in this project category.
- *The subassembly project* category consists of designing and developing a subassembly part such as a hydraulic unit, manifold, fan motor, heat pump, heat exchanger, etc. A subassembly project is performed to upgrade existing subassembly parts that can be used in finished product projects in the next

years. It is part of the patent application and lasts up to 1.5 years from the technical design review to internal use release. As such, it is managed as a stand-alone project to avoid delay on the finished product project. The projects P4, P5, and P6 are in this project category.

- *The spare part project* category consists of the design and development of a spare part such as a pressure sensor, energy-saving pump, control panel, and valves. A spare parts project is carried out based on customer complaints and comments from after-sales services after introducing the final product on the market. It lasts up to 6 months, depending on the design and packaging complexity. The projects P7, P8, and P9 are in this project category.

The R&D department implements an internal project management process with predefined tasks and priority relationships. Each project is executed with specific tasks listed in the process based on their product category. Each project is assigned to project managers based on their expertise by the R&D project management team leader. Project managers require specific resources from team leaders in other departments depending on each task's requirements in their Project. These resources include office employees with skills in quality management, primary product design, subcomponent design, spare parts design, R&D test management, purchasing management, production planning, simulation, supply chain design, cost control, and technical documentation. Also, machines with sample management and direct testing skills must be assigned to some of the tasks as well. The product manager, project manager, and selected project team members have a kick-off meeting to align with the project's scope. The resource allocation and project planning process take up to 1 month before the project officially begins. The significant characteristics of the problems are summarized as follows:

- A task is mandatory or optional, and an optional task has a predefined quality score to satisfy market requirements when completed. Optional tasks are not essential for project completion; however, they have project quality benefits once completed.

- Each task requires one or more skills; one or more resources provide each skill. In other words, each task is started and handled in an environment where several skills are needed to perform the task.
- Human resources acquire individual skills. A human resource may have the same skills as other human resources but may not have the capability to carry out a task. In other words, human resources may differ from each other based on their capability and may not be assigned to the same task even if they have the same skills.
- Machine resources acquire individual skills; all machines with the appropriate skills have the capability to perform tasks requiring that skill.
- The project planning horizon is broken up into weekly planning periods. A resource has a maximum capacity that can be consumed throughout the planning period. A resource can work on more than one task weekly.
- A resource capacity can be used in excess of its maximum capacity at an additional cost; however, it has a limit.
- Each project cost includes costs incurred by proponents in carrying out optional project tasks, the cost of regular resource use, and over-consumption of resources.

The company aims to allocate resources with the skills and capabilities needed for projects while optimizing conflicting goals: minimizing total tardiness of projects, minimizing total cost of projects, and maximizing the qualities of projects.

3.2 Overview of Mathematical Programming Approaches

Mathematical programming or optimization is a quantitative decision-making approach that searches for an optimal solution from a set of feasible alternatives regarding evaluation criteria. It is widely used in operations research, a discipline dealing with the optimization of advanced analytical problems.

A programming or optimization problem includes an objective function that is subject to certain constraints. The mathematical programming chooses input values

from domains with systematic search methods to find the best available solutions to minimize or maximize an objective function in the optimization problem. It attempts to solve problems with known input values (*parameters*) and values to be determined during the solution process (*decision variables*).

3.2.1 Mixed-Integer Linear Programming (MILP)

MILP is a variant of integer programming in which only certain variables are restricted to be integers. In other words, some other variables are allowed to be non-integers (Lepenioti, Bousdekis, Apostolou & Mentzas, 2020). The MILP can be formulated as follows:

$$\text{Minimize } A * x + B * y \quad (3.1)$$

$$C * x + D * y \leq E \quad (3.2)$$

$$F * x + G * y \leq H \quad (3.3)$$

$$x \geq 0 \quad (3.4)$$

$$y \geq 0, \text{integer} \quad (3.5)$$

The linear objective function (3.1) is represented to be minimized, and the following Constraints (3.2) and (3.3) present linear constraints. This example requires decision variable x to be greater or equal to zero, as shown in Constraint (3.4), and decision variable y should be greater than or equal to zero and be an integer as shown in Constraint (3.5).

The MILP considers objective functions as a guide for optimization and evaluates all constraints simultaneously. However, it has NP-hard nature since some elements of the solution vector contain both integer and non-integer solution values, which may need to be separated via linear programming relaxation (Abaffy & Fodor, 2013). The

linear programming relaxation removes each variable's integrality constraint in the MILP formulation and results in linear programming (LP) formulation. Then, LP formulation is solved optimally with a simplex method, an efficient algorithm proposed by Dantzig (1963).

The following methods are used for solving MILP problems:

- *The branch and bound method* solves the problem as a pure linear programming problem by exploring the solutions where x is required to take integer values. It performs tree search until the best available solution is found.
- *The cutting planes method* aims to cut off solutions by adding extra constraints to the problem. The process continues until the solution satisfies integer requirements by relaxing the integrality constraints.

Among the research trends observed in the study of RCMPSPs, the mathematical formulations are developed mostly with discrete-time formulations consisting of binary time-indexed variables and divide time horizon into smaller portions represented by time units as day, week, month. The discrete-time mixed-integer linear programming formulation considers a predefined grid onto which projects, tasks, resources, and other problem characteristics are embedded (Merchan, Lee & Maravelias, 2016). It divides the time horizon into time intervals with uniform durations in which the start and finish times of tasks are associated with boundaries of intervals. The time horizon is split into specific periods with fixed lengths in discrete-time formulations. Thus, the discrete-time formulation size grows linearly with the length of time horizon and number of periods (Lee & Maravelias, 2017). It causes a large number of constraints and variables and increases the tightness of formulations.

Alternatively, continuous-time formulations, which use continuous variables to represent the tasks' precedence relationships, are limited in the past research. Another class of continuous-time formulations, which is named event-based formulation, is developed with a set of events representing the start time and finish time of the tasks by Kone et al. (2009). In this formulation, time periods are not shown, but they are

identified with a time variable that corresponds to event points to track the start and finish time of tasks. This formulation reduces the number of constraints and variables significantly comparing to the discrete-time formulations. Therefore, most researchers (Kone et al., 2009; Kopanos et al., 2014) conclude that continuous-time event-based formulation provides better solution performance for mid and large-size problems.

3.2.1.1 Multi-Objective Programming

Multi-objective programming is a variant of multiple criteria decision-making concerning problems that simultaneously have more than one conflicting objective. A solution may be optimal for one objective function but not optimal for another (Pike-Burke, 2019). Thus, typically, there is not only one feasible solution to meet all goals. Different solutions are achieving most of the objective functions that can tolerate others, and such solutions (Pareto optimal solution) may not be improved further without degrading at least one of the objective functions. The multi-objective programming can be formulated as follows:

$$\text{Minimize } A * x + B * y \quad (3.6)$$

$$\text{Minimize } C * x + D * y \quad (3.7)$$

$$\text{Maximize } E * x + F * y \quad (3.8)$$

$$G * x + H * y \leq I \quad (3.9)$$

$$J * x + K * y \geq L \quad (3.10)$$

$$x \geq 0 \quad (3.11)$$

$$y \geq 0, \text{integer} \quad (3.12)$$

The objective function (3.6) and (3.7) are represented to be minimized, and the objective function (3.8) is aimed to be maximized. Following, Constraints (3.9) and

(3.10) present linear constraints. The decision variable x is greater or equal to zero, as shown in Constraint (3.11). The decision variable y should be greater than or equal to zero and be an integer as shown in Constraint (3.12).

In this thesis, first, a goal programming approach is used to solve the models, in which deviations of goals from target values are weighted based on the analytical hierarchy process. Second, the goal attainment method is applied.

3.2.1.1.1 Weighted Goal Programming and Analytical Hierarchy Process. Goal programming is a technique used in multi-objective programming to find a solution minimizing the deviations from prespecified goals within a given set of constraints. There are hard constraints that must be satisfied by any feasible solution and soft constraints that are allowed to be violated in mathematical programming. An equation is developed for such constraints by adding deviation variables. The positive deviation variable is added into constraints to reflect overachievement of the specified goal. Similarly, the negative deviation variable is introduced into constraints to reflect underachievement of the specified goal. The goal programming minimizes the positive and negative deviations of the objective functions from specified goals as follows:

$$\text{Minimize } DP1 + DP2 + DN3 \quad (3.13)$$

$$A * x + B * y - DP1 = G1 \quad (3.14)$$

$$C * x + D * y - DP2 = G2 \quad (3.15)$$

$$E * x + F * y + DN3 = G3 \quad (3.16)$$

$$G * x + H * y \leq I \quad (3.17)$$

$$J * x + K * y \geq L \quad (3.18)$$

$$x \geq 0 \quad (3.19)$$

$$y \geq 0, \text{integer} \quad (3.20)$$

The objective function (3.13) consisting of positive (DP1, DP2) and negative (DN3) deviational variables are represented to be minimized. Following, Constraints (3.14), (3.15), and (3.16) present linear constraints that are introduced with prespecified goals and deviational variables. Following, Constraints (3.17) and (3.18) present linear constraints. The decision variable x to be greater or equal to zero, as shown in Constraint (3.19), and the decision variable y should be greater than or equal to zero and be an integer as shown in Constraint (3.20).

A goal can be more important than other specified goals; therefore, weight coefficients are assigned to positive and negative deviation variables. The deviations of goals from target values are weighted using the analytical hierarchy process (AHP). The pairwise comparison approach from the AHP is used to calculate the objective weights for project tardiness minimization, total project development cost minimization, and project quality score maximization. The decision-maker defines each objective function weight coefficient based on the objectives' relative importance, using the Saaty scale (Saaty, 1994) in Table 3.1. Percentage deviation values found by proportioning each goal's deviation variable to the target value enable the objectives with different units to be considered together.

Table 3.1 Saaty numerical scale (Saaty, 1994)

Rating Scale	Verbal Scale	Explanation
1	Equal importance	Two objectives contribute equally
3	Moderate importance	Experience and judgment favor one objective over another
5	Strong importance	An objective is strongly favored
7	Very strong importance	An objective is very strongly favored
9	Extreme importance	At least an order of magnitude favors an objective
2, 4, 6, 8	Intermediate importance values	Used to compromise between two judgments

Pairwise comparisons between each business objective are performed concerning the management satisfaction, and the relative importance factor of business objectives are normalized. The pairwise comparisons should maintain reasonable consistency, calculated using consistency ratio (CR) and random index (RI) as in Equation 3.21.

$$CR = \frac{(\lambda - n)}{RI * (n - 1)} \quad (3.21)$$

According to these calculations, if CR takes a value less than or equal to 0.1, it shows that pairwise comparisons are consistent. The goal programming technique is used only by a few researchers in RCPSPs (Aouni, Avignon & Gagnon, 2015; Amirian & Sahraeian, 2018).

3.2.1.1.2 Goal Attainment Technique. One of the multi-objective approaches, goal attainment, deals with the expectations of the decision-maker that must be gathered before solving a model. The Pareto-optimal solutions, which are highly sensitive to goal and weight values provided by the decision-maker, are the best results obtained using this technique. It has the advantage of having fewer variables in contrast to other multi-objective approaches and solving the model easily. In this technique, the goal b_0 and weight w_0 values must be determined before solving the model. The goal b_0 can be found by solving the model for each objective function separately. The weight w_0 is provided by the decision-maker initially. The sum of all weight values must be equal to one. The relative under-achievement and over-achievement of a goal are measured by deviational variable G multiplied by weight as follows:

$$\text{Min } G \quad (3.22)$$

$$F_1 - w_1 * G \leq b_1 \quad (3.23)$$

$$F_2 - w_2 * G \leq b_2 \quad (3.24)$$

$$F_3 + w_3 * G \geq b_3 \quad (3.25)$$

$$G * x + H * y \leq I \quad (3.26)$$

$$J * x + K * y \geq L \quad (3.27)$$

$$G, x \geq 0 \quad (3.28)$$

$$y \geq 0, \text{integer} \quad (3.29)$$

The objective function (3.22) consisting G deviational variable is represented to be minimized. Following, Constraints (3.23), (3.24), and (3.25) present linear constraints that are introduced with prespecified goals and deviational variables. Following, Constraints (3.26) and (3.27) present linear constraints. The decision variable G and x to be greater or equal to zero, as shown in Constraint (3.28) and decision variable y should be greater than or equal to zero and be an integer as shown in Constraint (3.29).

In the goal attainment technique, the goal b_0 and weight w_0 values are changed manually to create a set of Pareto-optimal solutions. Once parameter b_0 or w_0 is changed by keeping the other parameter in its same value, the optimal solution shows high sensitivity concerning the changed parameter. Therefore, Pareto-optimal solutions are highly responsive to changes. After building a certain number of Pareto-optimal solutions, the decision maker's final decision is to choose one of them. Mohammadipour et al. (2016) develop a time-based mixed-integer programming model to minimize project total excessive cost, risk enhancement, and quality reduction. To perform cost – quality – risk tradeoff analysis, they transform the multi-objective model into the single-objective model using the goal attainment technique.

3.2.2 Proposed Mixed-Integer Linear Programming Models

The three mathematical models are developed to address multi-objective multi-project scheduling problems with skill- and capability-based resource constraints in the following sections.

3.2.2.1 Discrete-Time Mixed-Integer Linear Programming Model

The binary variables indicating task i in project p are started and finished at time t are introduced in this thesis. The usage of task start time variable and time index t enable practitioners to track project and task schedules more precisely. Alternatively, in this thesis, using the task finish time variable allows finding project completion time and tardiness directly. In contrast to the proposed formulation, Chiu et al. (2002) introduce a binary variable for task j in project i processing during time period t . Certa et al. (2009) define time t as a parameter, which is a fraction of the planning period. On the other hand, Kazemipoor et al. (2013) define $(X_{ik}^m)^l$ decision variable for the start time of task i in project l by resource m with skill k and $(Y_{ik}^m)^l$ a binary variable for task i in project l is performed using resource m with skill.

The big-M constraints are used to reflect the planning horizon into the model by Zapata et al. (2008). However, such constraints are not taken into account in our model to simplify the discrete-time MILP formulation. There is no observed negative impact of excluding these constraints from the model since planning horizon is already defined by an index of time t and restricted with the earliest start and finish times of tasks.

In this thesis, the decision variables for regular and excessive resource capacity usage are introduced to find resource capacity during the project horizon. Only two decision variables indexed by time t for regular and excessive resource k capacity usage during the planning horizon are proposed in our model to simplify resource flow constraints. In comparison to the proposed formulation, Heimerl et al. (2010) introduce two types of resource capacity parameter: $(R_{kt})^r$ for internal human resource k performing work with regular capacity r at time period t and $(R_{kt})^o$ for internal human resource k performing work with overtime capacity o at time period t . On the other hand, Kyriakidis et al. (2012) have used $(R_r)^{initial}$, $(R_r)^{min}$, $(R_r)^{max}$, $(R_{r,final})^{min}$, and $(R_{r,final})^{max}$ parameters to define the initial available capacity of resource r , the minimum and maximum available capacity of resource r during the planning horizon,

and the minimum and maximum excessive capacity of resource r at the end of the project for the RCPSP, respectively.

The following notation is used for the discrete-time MILP model:

Indices

- p index for projects ($p = 1, \dots, P$).
- i index for tasks ($i = 1, \dots, I$).
- t index for time periods ($t = 1, \dots, T$).
- k index for resources ($k = 1, \dots, K$).
- s index for skills ($s = 1, \dots, S$).

Subsets

- $AllTaskSet_p$ The set of tasks for project p .
- $ManTaskSet_p$ The set of mandatory tasks for project p .
- $OptTaskSet_p$ The set of optional tasks for project p .
- $PreTaskSet_{pi}$ The set of tasks that precede task i in project p .
- $SkillSet_k$ The set of skills acquired by resource k .

Parameters

- $InvCost_{pi}$ The cost invested by sponsors for the execution of optional task i in project p .
- $FixedCost_k$ The cost spent for one unit regular capacity of resource k .
- $OverCapCost_k$ The cost spent for one unit above the maximum capacity of resource k .
- $RMAX_k$ The maximum capacity of resource k .
- $BRatio_{piks}$ The amount of capacity required of resource k with skill s to perform task i of project p .
- $Capability_{piks}$ 1, if resource k with skill s is capable of performing task i of project p ; 0, otherwise.
- PT_{pi} The processing time of task i of project p .
- EST_{pi} The earliest start time of task i of project p .

EFT_{pi}	The earliest finish time of task i of project p .
$QRatio_{pi}$	The quality score of optional task i of project p .
DT_p	The due date of project p .
$G1_p$	The target value for the tardiness of project p .
$G2$	The target value for the total project development cost.
$G3_p$	The target value for the quality score of project p .
$W1$	The objective weight coefficient for project tardiness minimization.
$W2$	The objective weight coefficient for total project development cost minimization.
$W3$	The objective weight coefficient for project quality score maximization.
WP_p	The relative importance value of project p .

Binary variables

XS_{pit}	1, if task i in project p is started at time t ; 0, otherwise.
XF_{pit}	1, if task i in project p is finished at time t ; 0, otherwise.

Continuous variables

$Tardiness_p$	The tardiness of project p .
$MaxCompTime_p$	The maximum completion time of project p .
$PQRatio_p$	The quality score of project p .
R_{kt}	The amount of capacity of resource k consumed at time t .
$Ssurp_{kt}$	The excessive amount of capacity of resource k consumed at time t .
$DP1_p$	The positive deviation from the tardiness target of project p .
$DP2$	The positive deviation from the total development cost target of all projects.
$DN3_p$	The negative deviation from the quality score target of project p .

Using this notation, the model developed is as follows:

Minimize

$$W1 * \sum_{p=1}^P \frac{WP_p * DP1_p}{G1_p} + W2 * \frac{DP2}{G2} + W3 * \sum_{p=1}^P \frac{WP_p * DN3_p}{G3_p} \quad (3.30)$$

subject to:

$$Tardiness_p - DP1_p \leq G1_p, \forall p \quad (3.31)$$

$$Tardiness_p \geq MaxCompTime_p - DT_p, \forall p \quad (3.32)$$

$$MaxCompTime_p \geq t * XF_{pit}, \forall t, \forall p, \forall i \in AllTaskSet_p \quad (3.33)$$

$$\sum_{p=1}^P \sum_{i=1}^I \sum_{t=1}^T InvCost_{pi} * XS_{pit} + \sum_{k=1}^K \sum_{t=1}^T FixedCost_k * R_{kt} + \sum_{k=1}^K \sum_{t=1}^T OverCapCost_k * Ssurp_{kt} - DP2 \leq G2 \quad (3.34)$$

$$PQRatio_p + DN3_p \geq G3_p, \forall p \quad (3.35)$$

$$PQRatio_p = \sum_{i=1}^I \sum_{t=1}^T QRatio_{pi} * XS_{pit}, \forall p, \forall i \in OptTaskSet_p \quad (3.36)$$

$$\sum_{t \geq EST_{pi}}^T XS_{pit} = 1, \forall p, \forall i \in ManTaskSet_p \quad (3.37)$$

$$\sum_{t \geq EFT_{pi}}^T XF_{pit} = 1, \forall p, \forall i \in ManTaskSet_p \quad (3.38)$$

$$\sum_{t \geq EST_{pi}}^T XS_{pit} \leq 1, \forall p, \forall i \in OptTaskSet_p \quad (3.39)$$

$$\sum_{t \geq EFT_{pi}}^T XF_{pit} \leq 1, \forall p, \forall i \in OptTaskSet_p \quad (3.40)$$

$$\sum_{t \geq EST_{pi}}^T (t * XS_{pit} + PT_{pi} * XS_{pit}) = \sum_{t \geq EFT_{pi}}^T t * XF_{pit}, \quad (3.41)$$

$$\begin{aligned}
& \forall p, \forall i \in AllTaskSet_p \\
& \sum_{t \geq EST_{pi}}^T t * XS_{pit} \geq \sum_{t \geq EST_{pj}}^T t * XS_{pjt} + PT_{pj} * XS_{pjt} \quad , \\
& \forall p, \forall j \in PreTaskSet_{pi}
\end{aligned} \tag{3.42}$$

$$\begin{aligned}
R_{kt} - R_{k(t-1)} &= \left(\sum_{p=1}^P \sum_{s=1}^S BRatio_{piks} * XS_{pit} * Capability_{piks} \right) - \\
&\left(\sum_{p=1}^P \sum_{s=1}^S BRatio_{piks} * XF_{pi(t-1)} * Capability_{piks} \right) \quad , \forall k, \forall t > 1
\end{aligned} \tag{3.43}$$

$$R_{kt} - Ssurp_{kt} \leq RMAX_k \quad , \forall t, \forall k \tag{3.44}$$

$$XS_{pit}, XF_{pit} \in \{0,1\} \quad , \forall t, \forall p, \forall i \tag{3.45}$$

$$R_{kt}, Ssurp_{kt} \geq 0 \quad , \forall t, \forall k \tag{3.46}$$

$$Tardiness_p, MaxCompTime_p, PQRatio_p, DP1_p, DN3_p \geq 0 \quad , \forall p \tag{3.47}$$

The objective function (3.30) minimizes the weighted sum of the percentage deviations of the goals from the target values. The proposed objective function is built based on the AHP method, which is widely used in the literature to calculate objective weights related to each objective target value. The decision-maker defines each objective function weight coefficient based on the objectives' relative importance, using the Saaty scale (Saaty, 1994). Percentage deviation values found by proportioning each goal's deviation variable to the target value enable the objectives with different units to be considered together.

Constraint (3.31) computes the positive deviations from each project's tardiness target value, which requires minimization. Constraints (3.32) and (3.33) allow each project's tardiness to be calculated as the difference between the predefined project completion date and the project's maximum completion time. Constraint (3.34) calculates that positive deviation from the total product development cost target. The development cost is equal to the sum of cost invested by sponsors to execute optional tasks, cost spent for the amount of regular capacity consumed, and cost spent for

exceeding resource capacity usage to complete the projects. Constraint (3.35) computes the negative deviations from each project's target quality score, which requires minimization. Constraint (3.36) ensures that the project quality score is equal to the sum of the quality score of optional tasks performed. Constraints (3.37) and (3.38) ensure that a mandatory task is started and finished at only one time period after its earliest start time and earliest finish time, respectively. Constraints (3.39) and (3.40) ensure that the optional task can be started and finished at only one time period after its earliest start time and earliest finish time, respectively. Constraint (3.41) ensures that the finish time of task i of project p is equal to the sum of its start time at time t and its processing time. Constraint (3.42) ensures that the start time of task i in project p is greater than or equal to the finish time of its preceding task j . Constraint (3.43) ensures resource capacity consumption between consecutive times $(t-1)$ and t for each resource. It guarantees that the regular amount of capacity of resource k consumed at time t is equal to the sum of the amount of capacity consumed at time $(t-1)$ and the difference between resource requirements of tasks starting at time t and finishing at $(t-1)$. Constraint (3.44) ensures that the excessive amount of capacity of resource k consumed at time t can be found when the regular amount of capacity consumed is higher than the maximum amount of resource capacity. Finally, Constraint (3.45) declares the 0-1 variables, and Constraints (3.46) - (3.47) require that the rest of the variables are greater than or equal to zero.

3.2.2.2 Continuous-Time Event-Based Mixed-Integer Linear Programming Model

It is highlighted by Zapata et al. (2008) that a discrete-time mixed-integer programming formulation has limitations to solve problems, where time period and time horizon is long due to the exponential growth on the problem size. Alternatively, Zapata et al. (2008) propose a continuous-time event-based mixed-integer programming formulation for the RCMPSP using three binary variables for task i in project p to indicate whether it is started, finished, and being processed at event point e . Additionally, the decision variable T_{pie} is used to denote the finish time of task i in project p at event point e and the decision variable T_e is used to denote the time corresponding to event point e . However, these decision variables and in-process binary variables used to identify task start and finish times add more complexity to the

model. Consequently, the slight reduction in the number of variables used in event-based formulation causes a huge increase in the number of constraints, and it impacts model performance negatively by requiring more relaxation on the model. In this thesis, the binary variables indicating task i in project p are started and finished at event point e are introduced. Additionally, task finish time variable and time variable corresponding to event point are not introduced to provide better computational performance reducing the number of variables.

A few studies (e.g., Kone et al., 2009; Kopanos et al., 2014) develop continuous-time event-based formulations using only two binary variables for task start and end (start/end event-based) for RCPSP. Additionally, they propose binary variables for task start and processing (on/off event-based) to solve RCPSPs. The start/end event-based and on/off event-based formulations are considered variants of Zapata et al. (2008) that use binary variables showing start/end and on/off characteristics. Alternatively, Edwards et al. (2019) provide symmetry-breaking constraints and develop an on/off event-based model for the RCMPSP as a variant of Kone et al. (2009). Unlike Edwards et al. (2019), an improved start/end event-based model is proposed in this thesis to provide better computational performance.

The same indices, sets, and parameters are used. The additional notation required for continuous-time event-based MILP model is as follows:

Indices

e index for event ($e = 1, \dots, E$).

Binary variables

XS_{pie} 1, if task i in project p is started at event point e ; 0, otherwise.

XF_{pie} 1, if task i in project p is finished at event point e ; 0, otherwise.

Continuous variables

$Tardiness_p$ The tardiness of project p .

$MaxCompTime_p$ The maximum completion time of project p .

$PQRatio_p$	The quality score of project p .
TS_{pie}	The start time of task i in project p at event point e .
TF_{pie}	The finish time of task i in project p at event point e .
R_{ke}	The amount of capacity of resource k consumed at event point e .
$Ssurp_{ke}$	The excessive amount of capacity of resource k consumed at event point e .
$DP1_p$	The positive deviation from the tardiness target of project p .
$DP2$	The positive deviation from the total project development cost target.
$DN3_p$	The negative deviation from the quality score target of project p .

Using this notation, the model developed is as follows:

Minimize

$$W1 * \sum_{p=1}^P \frac{WP_p * DP1_p}{G1_p} + W2 * \frac{DP2}{G2} + W3 * \sum_{p=1}^P \frac{WP_p * DN3_p}{G3_p} \quad (3.48)$$

subject to:

$$Tardiness_p - DP1_p \leq G1_p, \forall p \quad (3.49)$$

$$Tardiness_p \geq MaxCompTime_p - DT_p, \forall p \quad (3.50)$$

$$MaxCompTime_p \geq TF_{pie}, \forall e, \forall p, \forall i \in AllTaskSet_p \quad (3.51)$$

$$\sum_{p=1}^P \sum_{i=1}^I \sum_{e=1}^E InvCost_{pi} * XS_{pie} + \sum_{k=1}^K \sum_{e=1}^E FixedCost_k * R_{ke} + \sum_{k=1}^K \sum_{e=1}^E OverCapCost_k * Ssurp_{ke} - DP2 \leq G2 \quad (3.52)$$

$$PQRatio_p + DN3_p \geq G3_p, \forall p \quad (3.53)$$

$$PQRatio_p = \sum_{i=1}^I \sum_{e=1}^E QRatio_{pi} * XS_{pie} , \forall p, \forall i \in OptTaskSet_p \quad (3.54)$$

$$\sum_{e=1}^E XS_{pie} = 1 , \forall p, \forall i \in ManTaskSet_p \quad (3.55)$$

$$\sum_{e=1}^E XF_{pie} = 1 , \forall p, \forall i \in ManTaskSet_p \quad (3.56)$$

$$\sum_{e=1}^E XS_{pie} \leq 1 , \forall p, \forall i \in OptTaskSet_p \quad (3.57)$$

$$\sum_{e=1}^E XF_{pie} \leq 1 , \forall p, \forall i \in OptTaskSet_p \quad (3.58)$$

$$\sum_{v < e} XS_{piv} - \sum_{v \leq e} XF_{piv} = 0 , \forall e, \forall p, \forall i \in AllTaskSet_p \quad (3.59)$$

$$TS_{pie} \geq EST_{pi} , \forall e, \forall p, \forall i \in AllTaskSet_p \quad (3.60)$$

$$TF_{pie} \geq EFT_{pi} , \forall e, \forall p, \forall i \in AllTaskSet_p \quad (3.61)$$

$$TS_{pie} + PT_{pi} * XS_{pie} = TF_{pie} , \forall e, \forall p, \forall i \in AllTaskSet_p \quad (3.62)$$

$$\sum_e TS_{pie} \geq \sum_e TS_{pje} + PT_{pj} * XS_{pje} , \forall p, \forall i, \forall j \in PreTaskSet_{pi} \quad (3.63)$$

$$XS_{pie} - \sum_{v \leq e} XF_{piv} \leq 1 - XS_{pie} , \forall e, \forall p, \forall i, \forall j \in PreTaskSet_{pi} \quad (3.64)$$

$$R_{ke} - R_{k(e-1)} = \left(\sum_{p=1}^P \sum_{s=1}^S BRatio_{piks} * XS_{pie} * Capability_{piks} \right) - \left(\sum_{p=1}^P \sum_{s=1}^S BRatio_{piks} * XF_{pi(e-1)} * Capability_{piks} \right) , \forall k, e > 1 \quad (3.65)$$

$$R_{ke} - Ssurp_{ke} \leq RMAX_k , \forall e, \forall k \quad (3.66)$$

$$XS_{pie}, XF_{pie} \in \{0,1\} , \forall e, \forall p, \forall i \quad (3.67)$$

$$R_{ke}, Ssurp_{ke} \geq 0 , \forall t, \forall k \quad (3.68)$$

$$TS_{pie}, TF_{pie} \geq 0, \forall e, \forall p, \forall i \quad (3.69)$$

$$Tardiness_p, MaxCompTime_p, PQRatio_p, DP1_p, DN3_p \geq 0, \forall p \quad (3.70)$$

The proposed objective function (3.48) and Constraints (3.49)-(3.54) have the same functioning. Constraint (3.55) and (3.56) ensure that a mandatory task is started and finished only at one event point, e . Constraint (3.57) and (3.58) ensure that the optional task is started and finished at most one event point, e . Constraint (3.59) ensures that task i starting earlier than event point e must finish at or after e . Constraint (3.60) ensures that the start time of task i of project p at event point e is greater than or equal to its earliest start time. Similarly, Constraint (3.61) ensures that the finish time of task i of project p at event point e is greater than or equal to its earliest finish time.

Constraint (3.62) ensures that the finish time of task i in project p at event point e is equal to the sum of its start time and processing time. Constraint (3.63) ensures that the start time of current task i in project p is greater than or equal to the finish time of its preceding task j . Constraint (3.64) ensures that preceding task j is completed at a specific event point, e . Constraint (3.65) ensures resource capacity consumption between consecutive event points ($e-1$) and e for each resource. It guarantees that the regular amount of capacity of resource k consumed at event point e is equal to the sum of the amount of capacity consumed at event point ($e-1$) and the difference between resource requirements of tasks starting at event point e and finishing ($e-1$). Constraint (3.66) ensures that the excessive amount of capacity of resource k consumed at time t is found when the regular amount of capacity consumed is higher than the maximum amount of resource capacity. Finally, Constraint (3.67) declares the 0-1 variables, and Constraints (3.68), (3.69), and (3.70) require that the rest of the variables are greater than or equal to zero.

3.2.3 Constraint Programming (CP)

CP is a solution approach for declarative description and solves large-size combinatorial optimization problems efficiently, especially in the scheduling area (Bartak, 1999). In the last few years, CP has attracted attention and has been used as an alternative solution method to MILP to solve real-life scheduling problems. The decision variables have a finite domain consisting of their potential values. The constraints restrict the possible assignment of values to the variables, eliminating specific values within the domain. The constraint propagation is a process of reducing the domain of decision variables until all domains are reduced or become empty (Bockmayr & Hooker, 2003). CP is used to solve such problems defined over finite domains by finding an assignment to the variables that satisfy all constraints. It finds a feasible solution by performing a constructive search with a branching strategy that fixes a chosen variable to the chosen value.

CP allows a variable to be used as an index of other variables to reduce the number of decision variables required in the formulation compared to MILP formulations. CP uses constraints to handle modeling quickly and continuously produce solutions for challenging combinatorial problems. Additionally, it considers efficient solution procedures to solve problems quickly. As an alternative to MILP, it considers constraints as a guide for optimization, evaluates all constraints sequentially, and has a problem-based influence on search. Mızrak Ozfirat, Edis & Ozkarahan (2006) state that CP requires less computation time besides fewer variables than the MILP approach. On the other hand, as a limitation of CP, Lustig & Puget (2001) present that CP may fail to provide optimal solutions since a lower bound does not exist. Also, Bartak (1999) states that even small changes in the formulation may lead to a dramatic change in CP solution performance; therefore, a CP model's stability is lower than MILP.

CP formulation requires no enumeration of time periods for scheduling problems. It can be developed and solved efficiently, regardless of which relevant time scale

describes a scheduling problem compared to MILP formulations. CP Optimizer provides specific features for modeling scheduling problems as follows:

- *Interval variable* is a time interval that defines a task having a start, an end, a length and a size to be completed. It also states whether a task is optional or mandatory to be performed.
- *Cumul function expression* is a function that calculates the cumulated usage of renewable resources over a fixed interval of time. It is used together with an elementary cumul function expression such as *pulse function* that shows cumulated resource usage increased by the required amount of a task at its start time and decreased by the same amount at its finish time (International Business Machines [IBM], 2017).
- *Precedence constraints* define precedence relationships and transfer times between tasks. In other words, it shows the position of interval variables in a solution.
- *Logical constraints* restrict the presence status of interval variables, and they are used with *presenceOf* to show that an interval variable is present.

3.2.4 Proposed Constraint Programming Model

A few researchers propose CP to solve large-scale single-mode and multi-mode RCPSPs (Liess et al., 2007; Menesi et al., 2014; Kreter et al., 2017). In this thesis, CP formulation is developed for RCMPSPs. The resources with specific skills are considered in our models similar to Polo-Mejia et al. (2019) developing CP for RCPSP with task preemption. However, in this thesis, task preemption is not allowed; thus *span constraint* stating interval variables span over all present variables are not considered.

Edwards et al. (2019) define symmetry-breaking constraints for the CP formulation to provide better solutions to the RCMPSP. In this thesis, the CP formulation is developed with multi-objective approaches using goal programming and goal attainment techniques compared to Edwards et al. (2019). The resources with skills are introduced in this thesis, and they may differ from each other considering their

capability. These resources may not be assigned to the same task even if they have the same skill set. On the other hand, machines with skills and capability to perform the task are considered different from Edwards et al. (2019). Additionally, the excessive resource capacity usage constraints and optional tasks are also introduced in our model. The CP formulation is improved with value and variable ordering and search strategies for better solution performance and quality, comparing Edwards et al. (2019).

The same indices, sets, and parameters are used. The additional notation required for the CP model is as follows:

Decision expressions and variables

$itvs_{pi}$	Interval variable to define the start and finish time of task i in project p with the earliest start time EST_{pi} and earliest finish time EFT_{pi} and size PT_{pi} .
$Tardiness_p$	The tardiness of project p .
$MaxCompTime_p$	The maximum completion time of project p .
$PQRatio_p$	The quality score of project p .
R_k	The amount of capacity of resource k consumed.
$Ssurp_k$	The excessive amount of capacity of resource k consumed.
$DP1_p$	The positive deviation from the tardiness target of project p .
$DP2$	The positive deviation from the total project development cost target.
$DN3_p$	The negative deviation from the quality score target of project p .

Cumulative function

$ResourceUsage_k$ equals to the amount of capacity of resource k consumed over time.

Using this notation, the CP model is developed as follows:

$$ResourceUsage_k = \sum_{p=1}^P \sum_{i=1}^I \sum_{s=1}^S pulse(itvs_{pi}, BRatio_{piks} * Capability_{piks}) , \forall k \quad (3.71)$$

Minimize

$$W1 * \sum_{p=1}^P \frac{WP_p * DP1_p}{G1_p} + W2 * \frac{DP2}{G2} + W3 * \sum_{p=1}^P \frac{WP_p * DN3_p}{G3_p} \quad (3.72)$$

subject to:

$$Tardiness_p - DP1_p \leq G1_p , \forall p \quad (3.73)$$

$$Tardiness_p \geq MaxCompTime_p - DT_p , \forall p \quad (3.74)$$

$$MaxCompTime_p \geq endOf(itvs_{pi}) , \forall p, \forall i \in AllTaskSet_p \quad (3.75)$$

$$\begin{aligned} & \sum_{p=1}^P \sum_{i=1}^I InvCost_{pi} * presenceOf(itvs_{pi}) + \\ & \sum_{p=1}^P \sum_{i=1}^I \sum_{k=1}^K FixedCost_k * \\ & heightAtStart(itvs_{pi}, ResourceUsage_k) + \sum_{k=1}^K OverCapCost_k * \\ & Ssurp_k - DP2 \leq G2 \end{aligned} \quad (3.76)$$

$$PQRatio_p + DN3_p \geq G3_p , \forall p \quad (3.77)$$

$$\begin{aligned} PQRatio_p &= \sum_{i=1}^I QRatio_{pi} * presenceOf(itvs_{pi}) , \\ &\forall p, \forall i \in OptTaskSet_p \end{aligned} \quad (3.78)$$

$$presenceOf(itvs_{pi}) = 1 , \forall p, \forall i \in ManTaskSet_p \quad (3.79)$$

$$presenceOf(itvs_{pi}) \leq 1 , \forall p, \forall i \in OptTaskSet_p \quad (3.80)$$

$$endBeforeStart(itvs_{pj}, itvs_{pi}) , \forall p, \forall i, \forall j \in PreTaskSet_{pi} \quad (3.81)$$

$$R_k \geq ResourceUsage_k , \forall k \quad (3.82)$$

$$R_k - Ssurp_k \leq RMAX_k , \forall k \quad (3.83)$$

$$R_k, Ssurp_k \geq 0 , \forall k \quad (3.84)$$

$$Tardiness_p, MaxCompTime_p, PQRatio_p, DP1_p, DN3_p \geq 0 , \forall p \quad (3.85)$$

The *cumul function expression* is a function that calculates the cumulated usage of renewable resources over a fixed interval of time. It is used together with an *elementary cumul function expression* to build an equation depending on the resource usage approach. In the proposed model, *pulse function* is used by which cumulated resource usage is increased by the required amount of a task at its start time and decreased by the same amount at its finish time (IBM, 2017). The cumulative function (3.71) ensures resource capacity consumption during the planning horizon for each resource. The proposed objective function (3.72) is the same as in the MILP models. Constraint (3.73) computes the positive deviations from each project's tardiness target value, which requires minimization. Constraints (3.74) and (3.75) allow each project's tardiness to be calculated as the difference between the predefined project completion date and the project's maximum completion time that is calculated by the integer expression *endOf* . This expression is used to reflect the finish time of the interval variable *itvs_{pi}* to the model directly. The integer expression value is considered 1 if the optional task related to the interval variable is performed. Constraint (3.76) calculates a positive deviation from the total product development cost target. The *presenceOf* expression is used to reflect the presence of interval variable *itvs_{pi}* to the final schedule by taking the value 1. The *heightAtStart* expression takes the value of the cumulative *ResourceUsage_k* function expression at the start point of the interval variable *itvs_{pi}*. The development cost is equal to the sum of cost invested by sponsors

to execute optional tasks, the cost spent for the amount of regular capacity consumed, and the cost spent for exceeding resource capacity usage to complete the projects. Constraint (3.77) computes the negative deviations from each project's target quality score, which requires minimization. Constraint (3.78) ensures that the project quality score is equal to the sum of the quality score of optional tasks performed.

Constraint (3.79) ensures that a mandatory task is started and finished, considering the earliest start time and its processing time. Constraint (3.80) ensures that the optional task can be started and finished at only one time period after its earliest start time and earliest finish time, respectively. Constraint (3.81) ensures with the *endBeforeStart* constraint that the start time of task i is greater than or equal to the finish time of its preceding task j . Constraint (3.82) ensures that the renewable resources' cumulated usage should be smaller than or equal to the amount of resource capacity consumed over the planning horizon. Constraint (3.83) ensures that the excessive amount of resource capacity consumed should not be higher than the maximum amount allowed. Lastly, Constraints (3.84) and (3.85) state all decision expressions and variables.

CHAPTER FOUR

TEST INSTANCES AND COMPUTATIONAL STUDY

The baseline for evaluating the discrete-time MILP, continuous-time event-based MILP, and CP models is provided by generating test instances in the light of benchmark datasets in project scheduling literature. First, three simple test instances are described and solved in order to verify and validate the formulations. Second, sixty test instances consisting of the small, medium, and large-size problems are generated and solved to make a comparative study of the formulations based on their performances. Third, the CP model is improved with variable and value ordering and search strategies to provide better performance than the pure formulation. Finally, the computational results obtained with solving the models, including the improved CP model, are analyzed and discussed.

4.1 Overview of Existing Benchmark Datasets

In the project scheduling literature, nine datasets have been used for benchmarking the models. The datasets are generated considering network and resource measures to define the chosen parametric characterization (Vanhoucke & Coelho, 2018) on the problems. These measures are described as in the following:

- Resource factor or actual resource factor (abbr., RF, ARF) is the average number of resources demanded by each task in a project (Kolish et al., 1995; Pascoe, 1966). The case where each task requests all resources is shown as $RF=1$. If none of the tasks requires a resource, it is shown as $RF=0$.
- Resource strength (abbr., RS) is the division of the available resource capacity into the total amount of each task's resource capacity demand (Cooper, 1976). If RS is closer to 1, then the capacity of resources is large enough to execute tasks. If RS is closer to 0, it represents the smallest feasible resource availability, which causes a very tight scheduling environment. Alternatively, the average resource utilization factor (abbr., AUF) is proposed as the division

of the total amount of resource capacity consumed into the maximum available resource capacity (Browning et al., 2010).

- Network complexity (abbr., NC, C, NCF, OS, CI) is the number of successors or predecessors of each task, reflecting precedence network complexity (Davis, 1975).

Researchers use the network and resource metrics described above to generate benchmark sets with specific problem characteristics. Kolisch, Sprecher & Drexl (1995) develop ProGen, a data generator for single and multi-mode RCPSPs. The generator and 1,216 instances show that the parameters have a significant impact on distinguishing easy and difficult instances. Following this, Kolisch & Sprecher (1997) publish benchmark instances generated with ProGen in a project scheduling problem library (PSPLIB) to evaluate single and multi-mode solution procedures further. The PSPLIB is extensively used in the project scheduling problem literature to include new problems with similar characteristics to the library's existing ones.

Similar to ProGen, Demeulemeester, Vanhoucke & Herroelen (2003) develop RanGen, which is a random generator for a wide variety of activity-on-node networks for single and multi-mode RCPSPs. The RanGen uses network order strength (OS) and complexity index (CI) to generate more efficient networks and predict the hardness of different types of problems. Peteghem & Vanhoucke (2014) create a new library MMLIB50, MMLIB100, and MMLIB+ by using RanGen to extend multi-mode RCPSPs with repair functions for resource factor and strength measures and inefficient modes. Myszkowski, Laszczyk, Nikulin & Skowronski (2018) develop a data generator and library for bi-criteria optimization of the multi-skill RCPSP.

Alternatively, Homberger (2007) create a resource-constrained multi-project scheduling problem library (MPSPLIB), which is the generalization of PSPLIB instances with arrival dates corresponding to the project's earliest start time and with a set of renewable shared resources. The 140 problem instances are created by selecting the number of projects, jobs, and resources from sets of {2, 5, 10, 20}, {30, 90, 120} and {1, 2, 3, 4} respectively and solved by the proposed restart evolution

strategy. Another new data generator for the RCMPSP is proposed by Browning et al. (2010) with 12,320 instances. The procedure generates a single project with the desired value for the normalized network complexity and resource factor values. Wauters et al. (2014) provide a new library for the multi-mode RCMPSP by combining multiple instances from PSPLIB for MISTA 2013 challenge. Similarly, Perez et al. (2015) aim to overcome the limitations of existing libraries, which cannot provide the best solutions for the RCMPSP due to randomly generated instances.

An overview of the previously discussed existing benchmark datasets in the literature is provided in Table 4.1. The number of instances in the datasets is denoted in column ‘#Inst.’ while the number of projects is indicated in column $|P|$, the number of tasks per project in column $|I|$, the number of resources in column $|K|$, the number of skills per resource in column $|S|$ and the number of modes in column $|M|$. The instance details of RCPSPs are summarized in Table 4.2 and the instance details of RCMPSPs are listed in Table 4.3.

4.2 Data Generation for Proposed Formulations

The new datasets are generated for the computational study considering large-size real-life RCMPSP problems to increase practical relevance. The use of RCPSP’s benchmark datasets (Kolisch et al., 1995; Demeulemeester et al., 2003; Peteghem et al., 2014; Myszkowski et al., 2018) is not considered in this thesis in order not to cause any misleading conclusions. The human resources and machines with skills and capabilities are taken into account as renewable resources in the considered problem. Additionally, in this thesis, the proposed models are developed with a multi-objective mathematical programming approach. However, the resource and objective characteristics proposed in the RCMPSP’s benchmark datasets are presented without multi-skill, capability, and multi-objective approaches. Thus, existing benchmark sets’ capabilities and limitations are found inadequate to solve considered real-life multi-objective, multi-project, and multi-skill resource-constrained scheduling problems.

Table 4.1 Summary of existing benchmark datasets in the literature

Author (s)	Year	Problem	Benchmark Dataset	Type		P	I	K	S	M	# Inst.
				Data Generator	Library						
Kolisch et al.	1995	RCPSP	ProGen	✓		1	[10, 30]	4	–	[1, 3]	1,216
Kolisch et al.	1997	RCPSP	PSPLIB		✓	1	[30, 120]	4	–	[1, 4]	480
Demeulemeester et al.	2003	RCPSP	RanGen	✓		1	[5, 120]	3	–	[1, 3]	–
Homberger	2007	RCMPSP	MPSPLIB		✓	[2, 20]	[30, 120]	[1, 4]	–	–	140
Browning & Yassine	2010	RCMPSP	BY10	✓		3	20	4	–	–	12,320
Peteghem et al.	2014	RCPSP	MMLIB		✓	1	[50, 100]	4	–	[3, 9]	3,240
Wauters et al.	2014	RCMPSP	MISTA		✓	[2, 20]	[20, 600]	[1, 2]	–	3	30
Perez et al.	2015	RCMPSP	RCMPSP LIB		✓	3	[10, 120]	[4, 6]	–	–	27
Myszkowski et al.	2018	RCPSP	iMOPSE	✓	✓	1	[100, 200]	[5, 40]	[9, 15]	–	36

Table 4.2 Overview of resource-constrained single-project scheduling problem test instances in the literature

Author (s)	Year	# Objective	# Task	# Resource	# Mode	# Skill	Dataset	# Test Instance	Time Limit (seconds)
Liess & Michelon	2007	1	[30, 90]	[1, 4]	–	–	PSPLIB	480	900 – 6,000
Drezet & Billaut	2007	1	[30, 60]	[1, 4]	–	[0, 1]	PSPLIB	110	300 – 600
Kone et al.	2009	1	[30]	[1, 4]	–	–	PSPLIB	480	500
Kyriakidis et al.	2012	1	[10, 16]	4	[1, 3]	–	PSPLIB	10	145 – 1,000
Correia et al.	2012	1	[20]	[10, 30]	–	[1, 4]	PSPLIB	216	18,000
Yannibelli & Amandi	2013	2	[30, 120]	[1, 15]	–	[1, 4]	PSPLIB	360	10 – 194
Menesi & Hegazy	2014	3	[10, 2000]	7	3	–	Own Set	1	10,800
Kopanos et al.	2014	1	[30, 90]	4	–	–	PSPLIB	3,240	600 – 1,200
Myszkowski et al.	2014	2	[100, 200]	[5, 40]	–	[9, 15]	iMOPSE	36	7 – 270
Zheng et al.	2015	1	[100, 200]	[5, 40]	–	[9, 15]	iMOPSE	36	5 – 25
Maghsoudlou et al.	2016	3	[3, 100]	[6, 12]	[3, 8]	[2, 10]	Own Set	30	–
Kia et al.	2016	3	[5, 100]	[4, 10]	–	[3, 5]	Own Set	10	271 – 51,744
Kreter et al.	2017	1	[20, 100]	[1, 6]	–	–	Own Set	1	600 – 10,800
Polo-Mejia et al.	2019	1	[30, 100]	[1, 8]	–	[5, 10]	Own Set	180	300 – 600

Table 4.3 Overview of resource-constrained multi-project scheduling problem test instances in the literature

Author (s)	Year	# Objective	# Project	# Task	# Resource	# Mode	# Skill	Dataset	# Test Instance	Time Limit (seconds)
Chiu & Tsai	2002	2	[2, 4]	7	3	–	–	Own Set	[42, 7,280]	192 – 27,173
Zapata et al.	2008	1	3	10	6	10	–	Own Set	4	60 – 36,000
Krueger & Scholl	2009	1	[1, 5]	[60, 204]	[1, 4]	–	–	PSPLIB	[100, 480]	3,600
Certa et al.	2009	3	5	–	8	–	5	Own Set	1	–
Browning & Yassine	2010	2	3	20	4	–	–	BY10	12,320	–
Heimerl & Kolisch	2010	1	20	–	100	–	25	Own Set	210	92
Gutjahr et al.	2010	[2, 8]	[12, 18]	–	28	–	[20, 80]	Own Set	80	120 - 240
Homberger	2012	1	[2, 20]	[30, 120]	[1, 4]	–	–	MPSPLIB	140	440
Kazemipoor et al.	2013	2	[2, 25]	[10, 40]	[40, 150]	–	[2, 6]	Own Set	10	36,000
Florez et al.	2013	3	10	–	14	[1, 2]	[1, 3]	Own Set	1	52 - 630
Besikci et al.	2014	1	6	[20, 30]	4	4	–	PSPLIB	10	10,800
Can & Ulusoy	2014	1	[2, 20]	[10, 30]	[1, 4]	4	–	PSPLIB	[27, 84]	120
Suresh et al.	2015	1	[2, 4]	32	[1, 4]	–	–	PSPLIB	[108, 324]	–

Table 4.3 continues

Author (s)	Year	# Objective	# Project	# Task	# Resource	# Mode	# Skill	Dataset	# Test Instance	Time Limit (seconds)
Perez et al.	2015	2	[2, 10]	[10, 120]	[4, 6]	–	–	RCMPSPLIB	23	–
Toffolo et al.	2015	2	[2, 20]	[24, 640]	[1, 40]	3	–	MISTA	30	300
Asta et al.	2016	2	[2, 20]	[20, 600]	[1, 2]	3	–	MISTA	30	300
Geiger	2016	2	[2, 20]	[24, 640]	[1, 40]	[3, 9]	–	MISTA MMLIB	[30, 3,240]	389
Song et al.	2017	1	[2, 20]	[30, 120]	[1, 4]	–	–	MPSPLIB	140	730
Chakraborty et al.	2017	2	3	20	4	–	–	BY10	77	500
Chen et al.	2017	3	4	10	40	–	8	Own Set	1	600
Villafanez et al.	2019	1	[2, 20]	[30, 120]	[1, 4]	–	–	MPSPLIB	140	–
Li & Xu	2018	1	[2, 20]	[30, 120]	[1, 4]	–	–	MPSPLIB	140	1,230
Edwards et al.	2019	1	[2, 20]	[10, 90]	[4, 5]	–	–	PSPLIB; MPSPLIB	[140, 365]	600
Eynde & Vanhoucke	2020	1	[6, 24]	60	4	–	–	BY10	[833, 2,254]	30
Kucuksayacigil & Ulusoy	2020	3	[2, 20]	[100, 300]	[1, 4]	–	–	PSPLIB	[27, 84]	11,857
Current study	2020	3	[2, 10]	[10, 40]	[2, 80]	–	[2, 4]	Own Set	60	36,000

First of all, several preliminary computational tests are performed with randomly generated large-size instances to understand all models' performance limitations. The number of projects $|P|$ is determined to be selected from a range $[2, 10]$, while the number of tasks $|I|$ is selected from a set $[10, 40]$ for new data generation. Second, parametric characterization of the new datasets is defined following specific measures such as skill factor (SF), modified resource strength (MRS), and network complexity (NC) in the project scheduling literature.

In addition to the resource factor defined as the average number of resources demanded by each task, Correia et al. (2012) propose skill factor (SF). Similarly, the skill factor is defined as the average number of skills required by each task. If $SF=1$, all skills are required by each task. The case where $SF=0$ shows that no skill is required. According to the skill factor, the number of skills per resource $|S|$ is randomly generated from a range $[1, 4]$. For $SF=1$, all tasks require all four available skills. For $SF=0.5$, all tasks require two skills which are randomly selected among all four available skills.

Correia et al. (2012) propose modified resource strength (MRS) as an alternative measure for resource strength. This measure is equal to the total maximum amount of resource capacity divided by the amount of resource capacity required to perform all tasks with the required skill and capability. According to MRS, the below characteristics are defined for the proposed study:

- The maximum amount of capacity of resource k , $RMAX_k$ is defined as 100 units as in our real-life problem.
- The amount of capacity of resource k with skill s required to perform task i in project p , $BRatio_{piks}$ is drawn randomly from a range $[0, 25]$.
- The capability of resource k with skill s to perform task i in project p , $Capability_{piks}$ is taken value from $\{0, 1\}$ randomly.
- The total resource capability is the sum of $Capability_{piks}$ parameter values of all multi-skilled resources that are capable of performing tasks in projects. It is calculated as follows:

$$\sum_{p=1}^P \sum_{i=1}^I \sum_{k=1}^K \sum_{s=1}^S Capability_{piks} \quad (4.1)$$

- In order to increase the hardness of test instances, $BRatio_{piks}$ is increased from 0 to 25. The total resource capability is reduced from the initial sum of $Capability_{piks}$ values as 10%, 20%, 30% and 40%, respectively.
- MRS also takes 1, 0.56, 0.42, 0.36, and 0.33 values respectively for each five case.
- The number of skills is chosen from a set $\{1\}$ for each resource.

On the other hand, network complexity (NC) measure is reflected into datasets as follows:

- The number of predecessors is randomly chosen from a range $[0, 3]$ for each task, and the final network is built as a connected graph accordingly.
- The mandatory and optional tasks are selected randomly from the set $\{0, 1\}$ without disrupting precedence relationships among tasks. The total number of optional tasks is randomly defined for each project from a range from zero to 25% of the number of tasks in a project. The optional tasks are determined by counting backward from the network graph until reaching the randomly defined number.

Kone et al. (2009) stated that discrete-time mixed-integer programming formulation is highly sensitive to the time horizon. Similar to Heimerl et al. (2010), the time horizon is defined based on the earliest start time EST_{pi} and earliest finish time EFT_{pi} in the datasets. These time-related parameters are calculated in LINGO 18.0, and the time horizon is defined according to the length of the longest path. On the other hand, the number of events is equal to the sum of the number of tasks in projects plus one, and it is reduced further step by step by trial and error on small, mid and large-size problems (Kone et al., 2009).

The processing time of each task i in project p , PT_{pi} is randomly generated from a range $[1, 10]$ similar to the ProGen instances (Kolisch et al., 1997). The due date of project p , DT_p is calculated as 30% more at the earliest due time of the last task of the

project. The quality score of task i in project p , $QRatio_{pi}$ is selected randomly from a range $[1, 3]$. The cost spent for one unit regular capacity of resource k , $FixedCost_k$ is defined as \$58. Similarly, the cost spent for one excessive unit capacity of resource k , $OverCapCost_k$ is defined as \$9. On the other hand, the cost invested by sponsors for the execution of optional task i in project p , $InvCost_{pi}$ is randomly selected from $[\$1,000, \$5,000]$ considering the values used in the real-life problem.

The target value of project p tardiness $G1_p$, is defined as 0 for each project since any delay in the project finish time may cause a loss on the company's market share. The sum of the cost invested by sponsors to execute optional tasks is calculated as the sum of $InvCost_{pi}$ values assuming all optional tasks in projects are executed. The cost spent for the amount of regular capacity consumed is estimated as fixed cost multiplied by task processing time, resource demand, and resource capability. The cost spent for excessive resource capacity usage to complete the projects is considered as 0. The target value of the total project development cost $G2$, is estimated to be 10% above than the sum of the cost invested by sponsors to execute optional tasks, spent for the amount of regular capacity consumed and for exceeding resource capacity usage complete the projects. The target value of quality score for project p , $G3_p$, is estimated as the sum of the quality score of optional tasks in each project. The relative importance factor of project p , WP_p , is calculated randomly between $[0, 1]$ and the sum of all project weights is equal to one.

On the other hand, the pairwise comparison approach from the analytical hierarchy process (AHP) described in Chapter 3 is defines objective weights $W1$, $W2$, and $W3$. The management makes the pairwise comparisons between each business objective shown in Table 4.4. Accordingly, the grand sum of the management satisfaction values is found for the relative importance factor of business objectives as listed in Table 4.5, and they are normalized as shown in Table 4.6.

Table 4.4 Pairwise comparisons between business objectives concerning the management satisfaction

Management Satisfaction	<i>Obj₁</i>	<i>Obj₂</i>	<i>Obj₃</i>
<i>Obj₁</i>	1	2	3
<i>Obj₂</i>	1/2	1	2
<i>Obj₃</i>	1/3	1	1

Table 4.4 continues

Management Satisfaction	<i>Obj₁</i>	<i>Obj₂</i>	<i>Obj₃</i>
<i>Obj₁</i>	1.00	2.00	3.00
<i>Obj₂</i>	0.50	1.00	2.00
<i>Obj₃</i>	0.33	0.50	1.00
Grand Sum	1.83	3.50	6.00

Table 4.5 Relative importance values of business objectives

Management Satisfaction	<i>Obj₁</i>	<i>Obj₂</i>	<i>Obj₃</i>	Average
<i>Obj₁</i>	0.55	0.57	0.50	0.54
<i>Obj₂</i>	0.27	0.29	0.33	0.30
<i>Obj₃</i>	0.18	0.14	0.17	0.16

Table 4.6 Normalized relative importance values of business objectives

Normalized Importance	<i>Obj₁</i>	<i>Obj₂</i>	<i>Obj₃</i>
<i>Obj₁</i>	0.54	0.59	0.49
<i>Obj₂</i>	0.27	0.30	0.33
<i>Obj₃</i>	0.18	0.15	0.16
Grand Sum	0.99	1.04	0.98

The results of pairwise comparisons should maintain reasonable consistency as described in Chapter 3. Following, the total grand sum of normalized relative importance factors λ is found as 3.01. The number of business objectives n equals to 3. The random index RI is found from a specific table provided by Saaty (1994) as

0.58. According to these calculations, CR is found as 0.01, which is $CR \leq 0.1$ showing that pairwise comparisons are consistent. Consequently, objective weights are noted as $W1 = 0.54$, $W2 = 0.30$, and $W3 = 0.16$ from Table 4.5.

According to the data generation procedure, sixty test instances consisting of small, mid-, and large-size problems are generated as in Table 4.7. The first twenty test instances are considered small-size instances considering $P = [2]$, $I = [10, 40]$, $K = [2, 16]$ and $S = [2, 4]$. The second twenty test instances are considered mid-size instances considering $P = [5]$ and $K = [5, 40]$, and the third twenty test instances are considered large-size instances considering $P = [10]$ and $K = [10, 80]$. The hardness of test instances is increased in every five cases considering the increase in $B\text{Ratio}_{piks}$ parameter and reduced total resource capability. For example, the amount of resource capacity required to perform tasks is drawn from a range $[0, 25]$ instead of a range $[0, 5]$ while proceeding from Problem 1 to Problem 5. On the other hand, the total resource capability is reduced from the initial value like 10%, 20%, 30%, and 40%.

The discrete-time MILP and continuous-time event-based MILP are implemented using the CPLEX engine, and CP models are performed using the CP Optimizer of IBM ILOG CPLEX Optimization Studio 12.6.1. The computation time is limited to 10 h, and model details are listed in Appendix 3.1 – 3.3.

Table 4.7 Overview of the sixty test instances

#	P	I	K	S	BRatio _{piks}	Reduction From The Total Resource Capability (%)	MRS
1	2	10	2	2	5	0	1.00
2	2	10	2	2	10	10	0.56
3	2	10	2	2	15	20	0.42
4	2	10	2	2	20	30	0.36
5	2	10	2	2	25	40	0.33
6	2	20	4	2	5	0	1.00
7	2	20	4	2	10	10	0.56
8	2	20	4	2	15	20	0.42
9	2	20	4	2	20	30	0.36
10	2	20	4	2	25	40	0.33
11	2	30	12	4	5	0	1.00
12	2	30	12	4	10	10	0.56
13	2	30	12	4	15	20	0.42
14	2	30	12	4	20	30	0.36
15	2	30	12	4	25	40	0.33
16	2	40	16	4	5	0	1.00
17	2	40	16	4	10	10	0.56
18	2	40	16	4	15	20	0.42
19	2	40	16	4	20	30	0.36
20	2	40	16	4	25	40	0.33
21	5	10	5	2	5	0	1.00
22	5	10	5	2	10	10	0.56
23	5	10	5	2	15	20	0.42
24	5	10	5	2	20	30	0.36
25	5	10	5	2	25	40	0.33
26	5	20	10	2	5	0	1.00
27	5	20	10	2	10	10	0.56
28	5	20	10	2	15	20	0.42
29	5	20	10	2	20	30	0.36
30	5	20	10	2	25	40	0.33

Table 4.7 continues

#	P	I	K	S	BRatio _{piks}	Reduction From The Total Resource Capability (%)	MRS
31	5	30	30	4	5	0	1.00
32	5	30	30	4	10	10	0.56
33	5	30	30	4	15	20	0.42
34	5	30	30	4	20	30	0.36
35	5	30	30	4	25	40	0.33
36	5	40	40	4	5	0	1.00
37	5	40	40	4	10	10	0.56
38	5	40	40	4	15	20	0.42
39	5	40	40	4	20	30	0.36
40	5	40	40	4	25	40	0.33
41	10	10	10	2	5	0	1.00
42	10	10	10	2	10	10	0.56
43	10	10	10	2	15	20	0.42
44	10	10	10	2	20	30	0.36
45	10	10	10	2	25	40	0.33
46	10	20	20	2	5	0	1.00
47	10	20	20	2	10	10	0.56
48	10	20	20	2	15	20	0.42
49	10	20	20	2	20	30	0.36
50	10	20	20	2	25	40	0.33
51	10	30	60	4	5	0	1.00
52	10	30	60	4	10	10	0.56
53	10	30	60	4	15	20	0.42
54	10	30	60	4	20	30	0.36
55	10	30	60	4	25	40	0.33
56	10	40	80	4	5	0	1.00
57	10	40	80	4	10	10	0.56
58	10	40	80	4	15	20	0.42
59	10	40	80	4	20	30	0.36
60	10	40	80	4	25	40	0.33

4.3 Verification and Validation of Proposed Models on Three Test Instances

According to the data generation procedure explained, first, three simple test instances are described as in the following:

- The first test instance includes two projects and ten tasks for each project, with parameters provided in Table 4.8. A machine resource ($K=1$) with a direct testing skill ($S=1$) and a human resource ($K=2$) with project management skill ($S=2$) are considered. The resource-related parameters are generated as $RMAX_{1,2} = 30$, $FixedCost_{1,2} = \$111$ and $OverCapCost_{1,2} = \$22$. According to Table 4.11, for example, Task 5 ($I=5$) is a mandatory task that has precedence relation with Task 2 ($I=2$). Its processing time is equal to 4 weeks, and it can be started earliest at the fourth week and finished at eighth week of the planning horizon. As a mandatory task, it does not have any quality score. Thus, there is also no cost invested by sponsors for its execution additionally. Task 5 requires 9 units weekly capacity of machine resource ($K=1$) and 8 units weekly capacity of human resource ($K=2$) for completion before the project due date, which is 28 weeks.
- The second test instance consists of two projects and fifteen tasks for each project, with parameters provided in Appendix 4.1 - 4.2. A machine resource ($K=1$) with a direct testing skill ($S=1$) and two human resources ($K=2, K=3$) with project management skills ($S=2$) are taken into account. The resource-related parameters are generated as $RMAX_{1,2} = 30$, $RMAX_3 = 40$, $FixedCost_{1,2,3} = \$111$ and $OverCapCost_{1,2,3} = \$22$.
- The third test instance includes three projects and fifteen tasks for each project with parameters provided in Appendix 4.3 - 4.5. Two machine resources ($K=1, K=2$) with a direct testing skill ($S=1$) and two human resources ($K=3, K=4$) with project management skills ($S=2$) are considered. The resource-related parameters are generated as $RMAX_{1,2} = 30$, $RMAX_{3,4} = 40$, $FixedCost_{1,2,3,4} = \$111$ and $OverCapCost_{1,2,3,4} = \22 .

Table 4.8 Summary of the first test instance parameters

P	I	J (Pred.) ¹	Type	PT_{pi}	EST_{pi}	EFT_{pi}	DT_{pi}	QRatio_{pi}	InvCost_{pi}	BRatio_{pi11}	BRatio_{pi22}
1	1	–	M	5	0	7	28	–	–	5	7
	2	–	M	4	0	7		–	–	6	9
	3	–	M	5	1	7		–	–	7	10
	4	1	M	2	7	11		–	–	9	9
	5	2	M	4	4	8		–	–	9	8
	6	2	M	3	6	11		–	–	7	9
	7	3	O	4	6	11		3	3,111	4	9
	8	4, 5, 6	M	3	8	15		–	–	7	9
	9	8	O	4	13	20		1	2,557	9	2
	10	7, 9	O	4	15	19		2	3,821	7	1
2	1	–	M	3	2	7	28	–	–	3	10
	2	1	M	6	5	11		–	–	6	7
	3	2	M	3	14	19		–	–	8	10
	4	2	M	4	11	17		–	–	3	8
	5	3	M	3	14	20		–	–	1	8
	6	3	M	4	14	20		–	–	4	3
	7	4	M	2	16	21		–	–	1	1
	8	7	M	2	17	21		–	–	4	9
	9	7	M	2	17	21		–	–	8	2
	10	5, 6, 7, 8, 9	O	1	23	24		1	4,275	2	10

¹ The column shows the task *J* precedes task *I* according to the precedence relationships.

The three test instances are solved to verify and validate MILP and CP models. First, the project and task schedules for the first test instance are drawn in Figure 4.1. According to this figure, all mandatory and optional tasks in both projects are started and finished within their earliest start and latest finish time. All tasks are processed without any interruption during their processing time. The precedence relationships between tasks are respected. The final tasks in projects are completed before the specified project due dates. The second test instances' project and task schedules are provided in Appendix 4.6 – 4.7, and for the third test instance in Appendix 4.11 – 4.13.

The resource loading is equal to the total amount of resource capacity consumption divided by the maximum available resource capacity over the planning horizon. Accordingly, the resource loading level shows the percentage value of the resource loading. First, the resources' loading for the first test instance is drawn in Figure 4.2. The maximum available resource capacity is 30 units for each resource over 28 weeks planning horizon. According to this figure, the total amount of machine resource capacity consumption is equal to 398 units. Similarly, the total amount of human resource capacity consumption is equal to 479 units over the planning horizon. Thus, the resources' loading level is found 52.20% considering $(398+479)$ units divided by $(2*30*28)$ capacity. The increase in resources' loading level shows that resources are in high demand. On the other hand, the lower resources' loading level presents an environment where the number of resources is higher than required. The resources' loading for the second test instance is presented in Appendix 4.8 – 4.10, and for the third test instance, it is presented in Appendix 4.14 – 4.17.

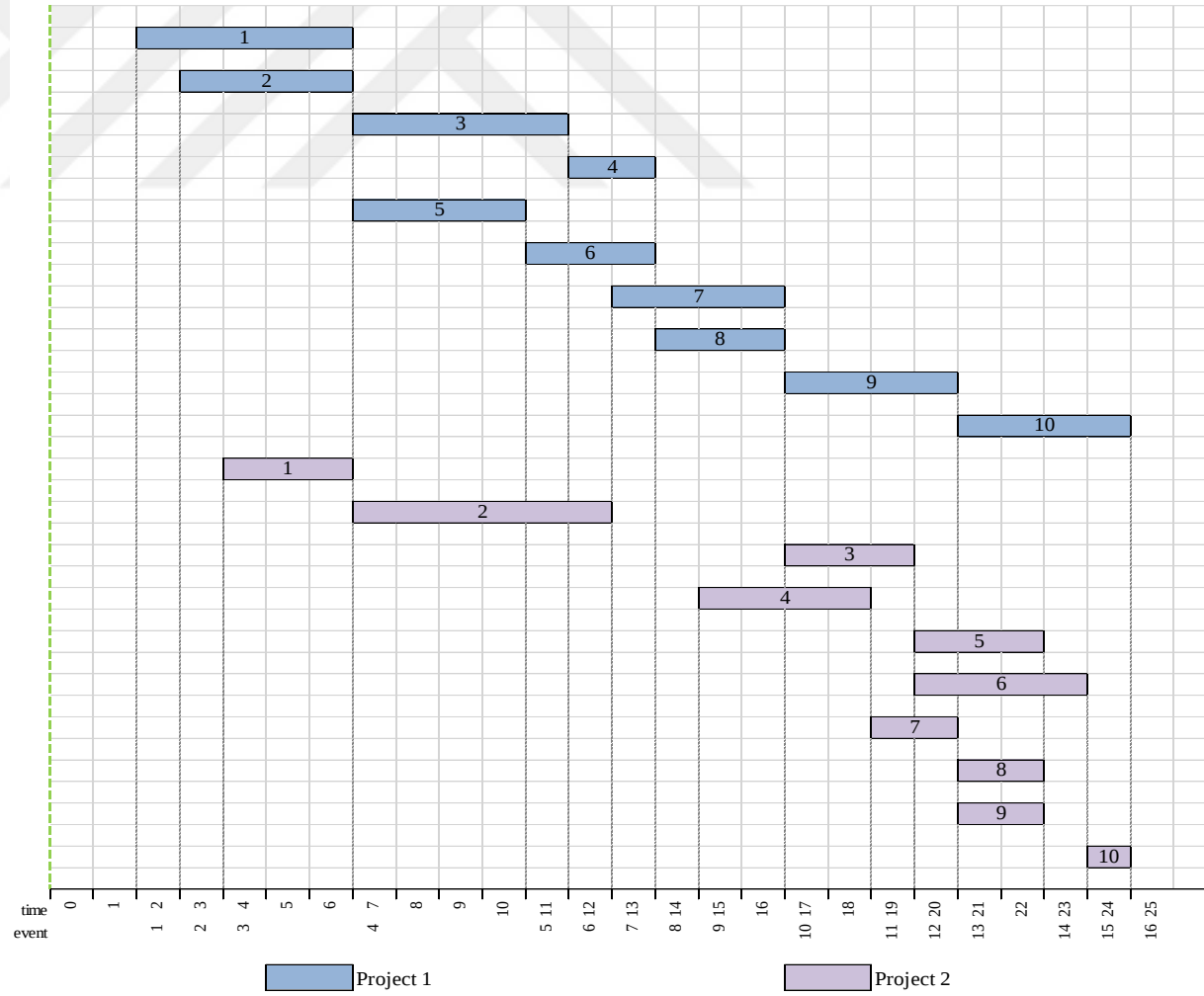


Figure 4.1 The project and task schedule for the first test instance

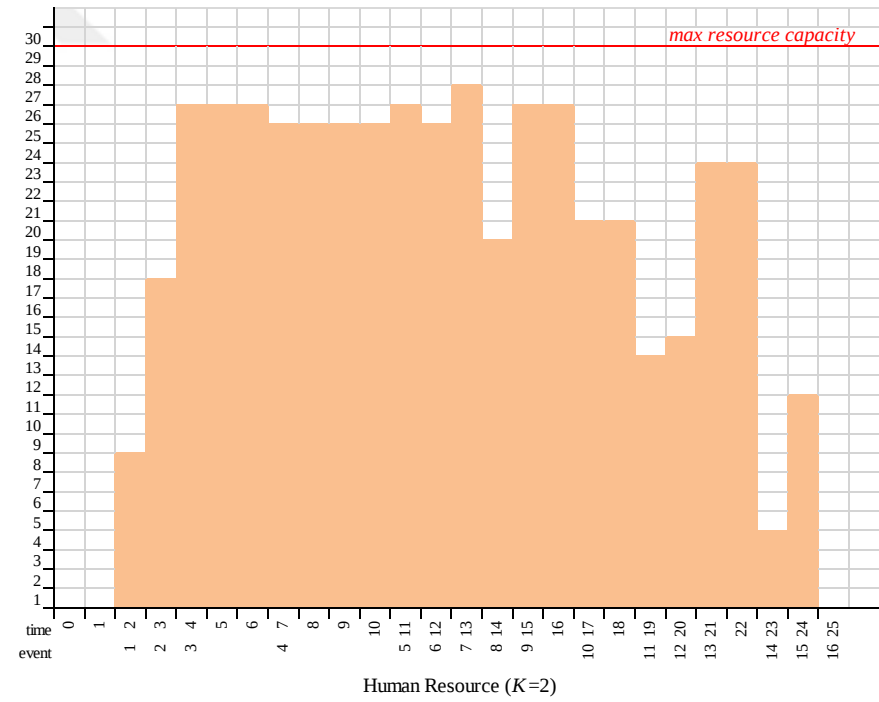
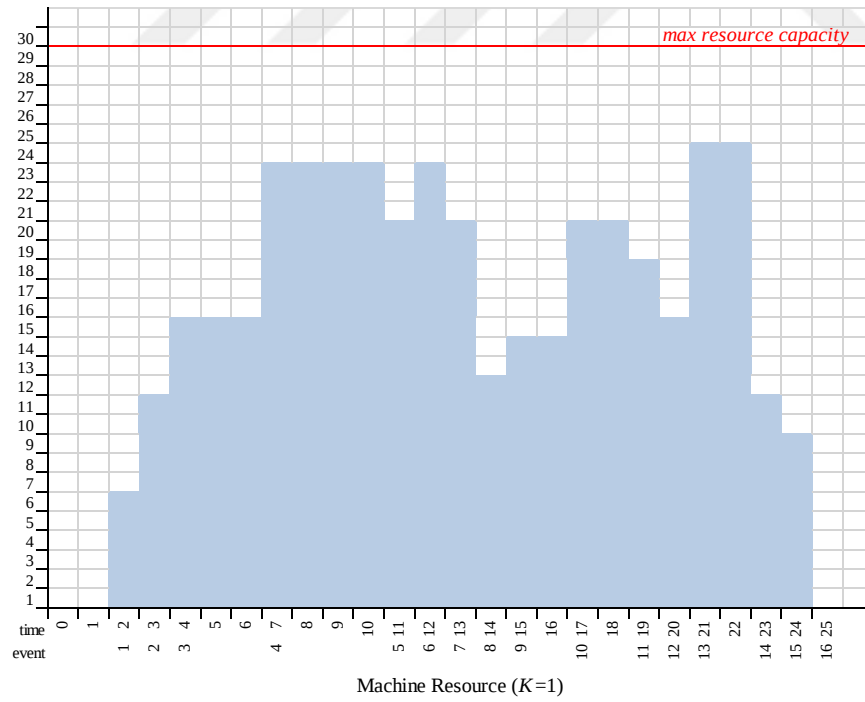


Figure 4.2 The resources' loading for the first test instance

For the first test instance, the target value of project tardiness $G1_1$, is defined as 0. The sum of the cost invested by sponsors to execute optional tasks is calculated as \$13,764. The cost spent for the amount of regular capacity consumed is estimated to be \$39,496. The cost spent for excessive resource capacity usage to complete the projects is considered as 0. Following, the target value of the total project development cost $G2$, is estimated to be 10% above than \$53,260, which equals \$59,178. The target value of project quality score $G3_1$ is defined as the sum of the quality score of optional tasks 6 and 1. Similarly, all target values are calculated and presented in Table 4.9 for each test instance.

The computational study results for three test instances are listed in Table 4.9. All models provide the same results for the project and task scheduling, resource loading, objective function, and deviational variables. They present the optimum solution with an objective function value of 0 for three test instances. According to each business objective's target values, the deviations from target values are found as 0. The model CP provides the results 83.34% faster than the discrete-time MILP model and 43.95% faster than the continuous-time event-based MILP model with fewer variables and constraints used in the formulation. However, all three test instances are small, and all models provide solutions in less than two seconds. Therefore, it can be stated that the CP and MILP models solve small-size RCMPSPs efficiently. All models provided are verified and validated considering their computational results.

Table 4.9 Computational results for the three test instances

#	# Constraints			# Variables			Solution Time			Obj.	Resource Loading Level (%)	Deviation Variables			Target Values		
	DT ¹	CT ²	CP ³	DT	CT	CP	DT	CT	CP			DP1	DP2	DN3	G1	G2	G3
1	690	1,467	86	990	936	35	0.34	0.09	0.05	0	52.20	[0, 0]	0	[0, 0]	[0, 0]	59,178	[6, 1]
2	1,390	3,140	119	2,162	2,028	47	0.91	0.31	0.19	0	46.11	[0, 0]	0	[0, 0]	[0, 0]	123,662	[6, 12]
3	2,842	4,675	170	4,604	3,025	69	1.39	0.39	0.20	0	50.63	[0, 0, 0]	0	[0, 0, 0]	[0, 0, 0]	246,170	[6, 12, 7]

¹ DT: Discrete-time MILP model² CT: Continuous-time event-based MILP model³ CP: Constraint programming model

4.4 Variable and Value Ordering

Certain search phases guide the search by ordering the search moves and values tested in CP (Baykasoglu, Topaloglu & Senyuzluler, 2017), and define branching strategies to help the prespecified algorithm. CP starts the search from a point and solves the model by creating alternative solutions. This search strategy is similar to a tree and search which is advanced from the tree's root to its branches with alternative solutions (Alagas, 2017). CP solves a model using constraint propagation and search strategies. The constraint propagation reduces the domain of decision variables until all domains are reduced or become empty. CP is used to solve such problems defined over finite domains by finding an assignment to the variables that satisfy all constraints. It finds a feasible solution by performing a constructive search with a branching strategy that fixes a chosen variable to the chosen value (IBM, 2017).

The variable ordering provides a decision on which variables to be chosen for instantiation, and value ordering deals with the order in which the values are assigned to the variable. The variable ordering is selected for instantiation and impacts search complexity, while the value ordering has a critical impact on the first solution time (Bartak, 2005). The search phase consists of a variable and a value selector to identify which variable should be instantiated to which value (*single-criteria search phase*). Alternatively, it includes ordering of more than one search phase or variable (*multi-criteria search phase*). CP allows users to order where the values in the domain of a decision variable are tried during the search for a solution using search phases (*variable and value evaluators*). Users can change search phases to find the right order of variables and values to improve computational efficiency.

This section analyzes specific variable and value ordering strategies that may give efficient search strategies for the considered problem. First, a script statement is written to execute a search phase in the CP Optimizer engine. The search instantiates variables starting from the first one and moves step by step. The 14 strategies are developed and tested with the large-size problem instance using specific functions as follows:

- *domainSize* is a function selecting the number of possible values of a variable's existing domain.
- *impactofLastBranch* is a function selecting variables according to a domain reduction completing the last instantiation. The values are assigned from a range [0,1], showing that domain reduction is made successfully if it takes a value closer to one.
- *selectLargest* is a function selecting variables or values with the largest evaluation.
- *selectRandomValue* is a function selecting a random value among all available value assignments.
- *selectRandomVar* is a function selecting only one variable randomly among all available variables.
- *selectSmallest* is a function selecting variables or values with the smallest evaluation.
- *value* is a function selecting a value to define instantiation strategy choosing the minimum or maximum value in a domain.
- *valueImpact* is a function selecting a value that has impact on variable instantiation. The values with minimum effect on the variables cause better strategy.
- *valueSuccessRate* is a function selecting value with success rate calculated as the difference between the number of instantiation and failures, divided by the number of instantiation (IBM, 2017).

In branching strategy 1, the variables with the smallest domain size are selected, and a variable is randomly selected from this set. The smallest value is selected from the value set randomly and assigned to the variable.

Branching Strategy 1:

```
execute{
var f= cp.factory;
var multiPhaseVar=new Array(f.selectSmallest(f.domainSize()),f.selectRandomVar());
var multiPhaseValue=new Array(f.selectSmallest(f.value()),f.selectRandomValue());
var phase=f.searchPhase(multiPhaseVar,multiPhaseValue);
```

```
cp.setSearchPhases(phase);}
```

In branching strategy 2, the same variable and value ordering strategy in branching strategy 1 is applied by adding the *FailLimit* parameter to reduce the search time.

Branching Strategy 2:

```
execute{
var f= cp.factory;
var multiPhaseVar=new Array(f.selectSmallest(f.domainSize()),f.selectRandomVar());
var multiPhaseValue=new Array(f.selectSmallest(f.value()),f.selectRandomValue());
var phase=f.searchPhase(multiPhaseVar,multiPhaseValue);
cp.setSearchPhases(phase);
var p=cp.param;
cp.param.FailLimit=4000;}
```

In branching strategy 3, the variables with the largest impact on the search tree are selected, and a variable is randomly selected from this set. Afterward, the value with the largest impact is then selected from the value set randomly and assigned to the variable.

Branching Strategy 3:

```
execute{
var f= cp.factory;
var multiPhaseVar=new Array(f.selectLargest(f.impactofLastBranch()),
f.selectRandomVar());
var multiPhaseValue=new Array(f.selectLargest(f.valueImpact()),
f.selectRandomValue());
var phase=f.searchPhase(multiPhaseVar,multiPhaseValue);
cp.setSearchPhases(phase);}
```

In branching strategy 4, the same variable and value ordering strategy in branching strategy 3 is applied by adding the *FailLimit* parameter to decrease the search time.

Branching Strategy 4:

```
execute{
var f= cp.factory;
```

```

var multiPhaseVar=new Array(f.selectLargest(f.impactofLastBranch()),
f.selectRandomVar());
var multiPhaseValue=new Array(f.selectLargest(f.valueImpact()),
f.selectRandomValue());
var phase=f.searchPhase(multiPhaseVar,multiPhaseValue);
cp.setSearchPhases(phase);
var p=cp.param;
cp.param.FailLimit=4000;}

```

In branching strategy 5, the variables with the largest impact on the last branch are selected, and a variable with the largest value among them is selected. Then, the largest impact value is selected from the largest value set and assigned to the variable.

Branching Strategy 5:

```

execute{
var f= cp.factory;
var multiPhaseVar=new Array(f.selectLargest(f.impactofLastBranch()),
f.selectLargest(f.value()));
var multiPhaseValue=new Array(f.selectLargest(f.valueImpact()),
f.selectLargest(f.value()));
var phase=f.searchPhase(multiPhaseVar,multiPhaseValue);
cp.setSearchPhases(phase);}

```

In branching strategy 6, the same variable and value ordering strategy in branching strategy 5 is applied by adding the *FailLimit* parameter to decrease the search time.

Branching Strategy 6:

```

execute{
var f= cp.factory;
var multiPhaseVar=new Array(f.selectLargest(f.impactofLastBranch()),
f.selectLargest(f.value()));
var multiPhaseValue=new Array(f.selectLargest(f.valueImpact()),
f.selectLargest(f.value()));
var phase=f.searchPhase(multiPhaseVar,multiPhaseValue);
cp.setSearchPhases(phase);
var p=cp.param;

```

```
cp.param.FailLimit=4000;}
```

Branching strategy 7 is defined as follows. The variables with the smallest domain size are selected. Then, the smallest success rate value is selected from the value set and assigned to the variable. The variable ordering in search phase 1 schedules tasks in each project before any other decision is implemented. After deciding on the schedule, search phase 2 guarantees that project tardiness with the smallest domain size is selected. Following, search phase 3 ensures that the project quality score with the smallest domain size is selected. Search phase 1 is used before the other search phases in branching strategy 7, considering that it is essential to define the schedule before deciding on other variables.

Branching Strategy 7:

```
execute{  
var f= cp.factory;  
var phase1=f.searchPhase(itvs,f.selectSmallest(f.domainSize()),  
f.selectSmallest(f.valueSuccessRate()));  
var phase2= f.searchPhase(Tardiness,f.selectSmallest(f.domainSize()),  
f.selectSmallest(f.valueSuccessRate()));  
var phase3=f.searchPhase(PQRatio,f.selectSmallest(f.domainSize()),  
f.selectSmallest(f.valueSuccessRate()));  
cp.setSearchPhases(phase1, phase2, phase3);}
```

In branching strategy 8, the same search phases employed in branching strategy 7 are used, but their sequence is changed by giving more priority to search phase 2 than the other phases.

Branching Strategy 8:

```
execute{  
var f= cp.factory;  
var phase7=f.searchPhase(itvs,f.selectSmallest(f.domainSize()),  
f.selectSmallest(f.valueSuccessRate()));  
var phase8=f.searchPhase(Tardiness,f.selectSmallest(f.domainSize()),  
f.selectSmallest(f.valueSuccessRate()));  
var phase9=f.searchPhase(PQRatio,f.selectSmallest(f.domainSize()),
```

```
f.selectSmallest(f.valueSuccessRate()));
cp.setSearchPhases(phase2, phase1, phase3);}
```

Branching strategy 9 is defined as follows. The variables with the smallest domain size are selected. Afterward, the smallest success rate value is selected from the value set and assigned to the variable. The variable ordering in search phase 1 schedules tasks in each project before any other decision is implemented. After deciding on the schedule, search phase 2 guarantees that project tardiness with the smallest domain size is selected. Following, search phase 3 ensures that the amount of resource capacity consumed with the smallest domain size is selected. Finally, search phase 1 is used before the other search phases, considering that it is crucial to define the schedule before deciding on other variables. Also, the *FailLimit* parameter is added to decrease the time spent in the search.

Branching Strategy 9:

```
execute{
var f= cp.factory;
var phase1=f.searchPhase(itvs,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
var phase2=f.searchPhase(Tardiness,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
var phase3=f.searchPhase(R,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
cp.setSearchPhases(phase1, phase2, phase3);
var p=cp.param;
cp.param.FailLimit = 4000;}
```

In branching strategy 10, the same search phases are employed in branching strategy 9 by changing their sequence and giving more priority to search phase 2 than the other phases.

Branching Strategy 10:

```
execute{
var f= cp.factory;
var phase1=f.searchPhase(itvs,f.selectSmallest(f.domainSize()),
```

```

f.selectSmallest(f.valueSuccessRate()));
var phase2=f.searchPhase(Tardiness,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
var phase3=f.searchPhase(R,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
cp.setSearchPhases(phase2, phase1, phase3);
var p=cp.param;
cp.param.FailLimit = 4000;}

```

In branching strategy 11, the same search phases are employed in branching strategy 9 and 10 by changing their sequence and giving more priority to search phase 3 than the other phases.

Branching Strategy 11:

```

execute{
var f= cp.factory;
var phase1=f.searchPhase(itvs,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
var phase2=f.searchPhase(Tardiness,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
var phase3=f.searchPhase(R,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
cp.setSearchPhases(phase3, phase1, phase2);
var p=cp.param;
cp.param.FailLimit = 4000;}

```

In branching strategy 12, the same search phases are employed in branching strategies 9, 10, and 11 by changing their sequence and giving more priority to search phase 3 and then 2.

Branching strategy 12:

```

execute{
var f=cp.factory;
var phase1=f.searchPhase(itvs,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));

```

```

var phase2=f.searchPhase(Tardiness,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
var phase3=f.searchPhase(R,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
cp.setSearchPhases(phase3, phase2, phase1);
var p=cp.param;
cp.param.FailLimit = 4000;}

```

In branching strategy 13, the variables with the smallest domain size are selected. Afterward, the largest value is selected from the value set and assigned to the variable.

Branching strategy 13:

```

execute{
var f=cp.factory;
var phase=f.searchPhase(itvs,f.selectSmallest(f.domainSize()),
f.selectLargest(f.value()));
cp.setSearchPhases(phase);}

```

In branching strategy 14, the variables with the smallest domain size are selected. The value with the smallest success rate is selected from the value set and assigned to the variable.

Branching strategy 14:

```

execute{
var f=cp.factory;
var phase=f.searchPhase(itvs,f.selectSmallest(f.domainSize()),
f.selectSmallest(f.valueSuccessRate()));
cp.setSearchPhases(phase);}

```

The 14 strategies are tested on the large-size Problem 50 with the computation time limited to 3 h. The results of the mentioned strategies are listed in Table 4.10.

Table 4.10 The summary and results of variable and value ordering strategies for the large-size test instance

#	Variable Ordering				Value Ordering					Search Phases				Fail Limit	Objective	First Solution Time	Solution Time
	<i>selectSmallest(domainSize())</i>	<i>selectLargest(impactofLastBranch())</i>	<i>selectLargest(value())</i>	<i>selectRandomVar()</i>	<i>selectSmallest(value())</i>	<i>selectLargest(valueImpact())</i>	<i>selectLargest(value())</i>	<i>selectSmallest(valueSuccessRate())</i>	<i>selectRandomValue()</i>	<i>itvs</i>	<i>Tardiness</i>	<i>PQRatio</i>	<i>ResourceUsage</i>				
0															58.32	10,721.67	10,800.00
1	✓			✓	✓				✓						108.43	10,699.14	10,800.00
2	✓			✓	✓				✓					4,000	127.67	9,922.02	10,800.00
3		✓		✓		✓			✓						6.22	6,812.48	10,800.00
4		✓		✓		✓			✓					4,000	38.51	10,292.10	10,800.00
5		✓	✓			✓	✓								14.03	9,110.22	10,800.00
6		✓	✓			✓	✓							4,000	8.86	9,328.38	10,800.00
7	✓							✓		1	2	3			5.58	7,476.16	10,800.00
8	✓							✓		2	1	3			6.53	9,664.80	10,800.00
9	✓							✓		1	2		3	4,000	47.12	8,233.01	10,800.00
10	✓							✓		2	1		3	4,000	31.66	8,698.92	10,800.00
11	✓							✓		2	3		1	4,000	7.92	8,091.02	10,800.00
12	✓							✓		3	2		1	4,000	14.85	8,885.98	10,800.00
13	✓						✓			1					4.64	6,971.58	10,699.15
14	✓							✓		1					50.16	10,119.48	10,800.00

According to the objective values, branching strategies 3, 7, 8, 11, and 13 have provided better results. On the other hand, branching strategy 3, 7, 9, 11, and 13 have outperformed other strategies according to the first solution time. Branching strategy 13 shows better solution performance since the problem is solved under a predefined time limit. Consequently, branching strategies 3, 7, 11, and 13 provide good performance among other strategies considering all three aspects listed in Table 4.10. Accordingly, we aim to use these four selected strategies and different tree search strategies to improve the CP model's performance further.

4.5 Search Strategies

Variable and value ordering strategies aim to find the right order of variables and values to improve computational efficiency; however, it may require tuning to provide even better results. CP Optimizer enables users to tune the search by setting parameters for different tree search types to find better solutions and reduce the search time (IBM, 2017).

The depth-first search is one of the tree search algorithms and exists in CP Optimizer as a specific search type for tuning the search. The search considers the instantiation of a decision variable as a search tree branch. It applies constructive search and considers the sub-tree of one branch until it finds a solution or proves no feasible solution. The search does not consider another sub-tree until the current one is thoroughly investigated; therefore, it may be inefficient for some problems.

On the other hand, the restart search type is the default, and it is a constructive search initiated from time to time and leads to an optimal solution. A depth-first search is re-initiated after a certain number of fails on a branch in such a search type. The multi-point search type generates different solutions and combines them to produce even better solutions. It enables the search to continue until the best solution found cannot be improved. Auto search type chooses the appropriate search method and may define different searches over the search tree randomly (IBM, 2017).

Following the selected four variable and value ordering strategies, depth-first, restart, multi-point, and auto search types are applied to improve the CP model's performance. The search strategies are implemented into ten mid-and large-size test instances selected from sixty test instances. The time limit is set as 10,800 seconds for each instance. The computational results for these strategies are listed in Table 4.11.

According to the objective values, the first solution time and completion time, *branching strategy 3 with multi-point* search type, provides better performance in eight test instances out of ten. The remaining two test instances #44 and #45, in which *branching strategy 1 with multi-point* search type perform well, include fewer constraints and variables than other instances. According to the results, *branching strategy 3 with multi-point* search type performs 2.4% faster than *branching strategy 1 with multi-point* search type in larger size instances. Alternatively, *branching strategy 1 with multi-point* search type performs 1.3% faster than *branching strategy 3 with multi-point* search type only on test instances #44 and #45 by providing objective function value 1.349 with global optimum.

As a result of the search strategies analysis, *branching strategy 3 with multi-point* search type is selected as the main search strategy to improve the CP model's performance. Accordingly, all ten instances are tested further with *branching strategy 3 with multi-point* search type considering the *FailLimit* parameter. Based on the preliminary analysis using the CP Optimizer, it is decided to set the *FailLimit* as 1000, 2500, and 4000 to improve performance by decreasing solution time.

The *FailLimit* parameter's impact results are listed in 4.11. Consequently, when the *FailLimit* parameter is taken as 4000, the CP model provides better performance in eight test instances. Alternatively, when the *FailLimit* parameter is taken as 2,500, the CP model performs better than the other *FailLimit* values only for test instances #44 and #45. The CP model with *branching strategy 3 with multi-point* search type and the *FailLimit* parameter taken as 4,000 is selected to be analyzed further with all sixty test instances.

Table 4.11 Summary of the tree search strategy results

Variable & Value Ordering Strategy	Search Strategy		#39			#40			#44			#45		
			Objective	First Solution Time	Solution Time	Objective	First Solution Time	Solution Time	Objective	First Solution Time	Solution Time	Objective	First Solution Time	Solution Time
3	DepthFirst		0,00	32,49	14,29	0,00	30,16	13,61	0,00	21,75	20,04	0,00	20,98	6,88
	Restart		0,00	30,51	19,90	0,00	32,64	20,43	0,00	14,13	18,70	0,00	12,68	3,79
	MultiPoint		0,00	24,67	4,12	0,00	22,62	7,14	0,00	12,28	10,48	0,00	11,56	3,25
	Auto		0,00	35,52	22,02	0,00	35,23	21,44	0,00	21,12	14,26	0,00	21,30	4,16
7	DepthFirst		0,00	42,33	18,80	0,00	42,58	20,77	0,00	4,08	16,05	0,00	6,61	12,73
	Restart		0,00	31,41	11,97	0,00	34,11	20,55	0,00	21,13	19,57	0,00	22,88	16,26
	MultiPoint		0,00	28,96	8,92	0,00	36,74	8,68	0,00	3,31	10,13	0,00	1,64	1,09
	Auto		0,00	34,37	14,41	0,00	37,50	25,05	0,00	4,71	11,98	0,00	2,87	4,19
11	DepthFirst		0,00	28,34	20,00	0,00	26,17	27,49	0,00	6,48	21,31	0,00	10,07	16,15
	Restart		0,00	27,25	14,68	0,00	27,67	23,30	0,00	10,97	19,85	0,00	16,38	14,05
	MultiPoint		0,00	25,79	13,26	0,00	25,96	17,09	0,00	13,71	24,19	0,00	20,52	21,59
	Auto		0,00	34,41	29,47	0,00	32,94	28,34	0,00	15,94	11,57	0,00	18,87	12,32
13	DepthFirst		0,00	38,61	29,53	0,00	37,08	28,38	0,00	6,86	10,80	0,00	10,40	12,72
	Restart		0,00	32,73	4,71	0,00	30,56	10,96	0,00	12,71	23,74	0,00	17,32	24,86
	MultiPoint		0,00	33,97	25,04	0,00	36,91	24,04	0,00	12,28	25,82	0,00	20,78	28,16
	Auto		0,00	37,99	25,03	0,00	36,90	25,41	0,00	16,66	14,58	0,00	15,50	6,49
3	MultiPoint	FailLimit=1,000	0,00	9,18	4,06	0,00	18,84	6,97	0,00	2,69	5,59	0,00	1,09	0,71
	MultiPoint	FailLimit=2,500	0,00	4,60	1,91	0,00	4,49	2,88	0,00	0,00	0,00	0,00	0,00	0,00
	MultiPoint	FailLimit=4,000	0,00	0,00	0,00	0,00	0,00	0,00	0,00	1,01	7,19	0,00	1,39	0,44

Table 4.11 continues

Variable & Value Ordering Strategy	Search Strategy		#55			#59			#60			AVERAGE		
			Objective	First Solution Time	Solution Time	Objective	First Solution Time	Solution Time	Objective	First Solution Time	Solution Time	Objective	First Solution Time	Solution Time
3	DepthFirst		11,05	7,05	0,00	12,30	1,55	0,00	-	-	0,00	10,29	17,34	6,51
	Restart		9,30	4,67	0,00	7,24	1,66	0,00	-	-	0,00	9,44	13,60	7,31
	MultiPoint		0,78	2,50	0,00	0,00	0,30	0,00	0,00	0,26	0,00	0,09	9,68	2,90
	Auto		-	-	0,00	-	-	0,00	-	-	0,00	8,26	22,56	7,22
7	DepthFirst		-	-	0,00	-	-	0,00	-	-	0,00	9,57	26,69	7,86
	Restart		9,30	5,41	0,00	27,33	0,39	0,00	-	-	0,00	12,91	26,41	7,86
	MultiPoint		3,49	5,08	0,00	21,55	0,90	0,00	-	-	0,00	4,09	13,25	3,70
	Auto		-	-	0,00	-	-	0,00	-	-	0,00	10,17	24,22	6,59
11	DepthFirst		13,06	6,98	0,00	7,24	0,63	0,00	12,88	0,32	0,00	11,64	12,61	9,52
	Restart		-	-	0,00	-	-	0,00	-	-	0,00	12,82	24,38	8,22
	MultiPoint		3,45	3,46	0,00	-	-	0,00	-	-	0,00	3,79	17,17	8,25
	Auto		-	-	0,00	-	-	0,00	-	-	0,00	13,46	25,69	9,20
13	DepthFirst		-	-	0,00	-	-	0,00	-	-	0,00	10,30	17,95	9,17
	Restart		-	-	0,00	-	-	0,00	-	-	0,00	11,03	22,73	7,45
	MultiPoint		0,78	4,54	0,00	0,00	1,62	0,00	-	-	0,00	0,12	15,48	10,83
	Auto		-	-	0,00	-	-	0,00	-	-	0,00	8,38	25,04	8,18
3	MultiPoint	FailLimit=1000	0,78	1,79	0,00	0,00	0,21	0,00	0,00	0,25	0,00	0,36	6,84	2,10
	MultiPoint	FailLimit=2500	0,78	1,05	0,00	0,00	0,18	0,00	0,00	0,19	0,00	0,12	2,89	0,50
	MultiPoint	FailLimit=4000	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	1,08	0,93

4.6 Computational Study of Developed Models Using Generated Test Instances

The performance of the developed models is done by solving the generated test instances. They are implemented using ILOG's concert technology and solved with CPLEX 12.6.1 in the Intel Core environment with 2.27 GHz i5-430M processors and 4 GB in RAM. The computation time is limited to 10 h. The computational study results are presented in Tables 4.12 to 4.14.

The first twenty test instances are considered small-size instances. The parameters of these instances have been defined as: $P = [2]$, $I = [10, 40]$, $K = [2, 16]$ and $S = [2, 4]$. The computational results for these problems are given in Table 4.12. The number of constraints is denoted in column '#Constraints' while the number of variables is indicated in column '#Variables' and the objective function value in column 'Obj.' The column 'First Solution Time' shows the time that the best solution is first found while 'Solution Time' indicates the time (seconds) that optimal or near-optimal solution is found. The column '%Gap (Time)' shows the percentage deviation between models' solution times. It is calculated as a difference between the discrete-time MILP and CP solution times divided by discrete-time MILP solution time in column 'CP-DT.' Similarly; it is indicated as a difference between continuous-time event-based MILP and CP solution times divided by continuous-time event-based MILP solution time in column 'CP-DT.' For example, Problem #1 objective function value is found zero by discrete-time MILP model (DT) in 0.38 seconds, by continuous-time event-based MILP model (CT) in 0.31 seconds and by CP model (CP) in 0.03 seconds. The gap between CP and DT solution times is calculated as $(DT - CP)/DT$, and found 92%. Similarly, the gap between CP and CT solution times is calculated as $(CT - CP)/CT$, and found 90%. The gap values that are closer to 100% refer to a significant improvement in the solution time.

All test problems are solved to optimality for the first twenty test instances. The objective values of 60% of problems are 0, whereas the remaining have objective values greater than 0 due to deviations from the goals' target values. The solution time gradually increases from Problem #1 to #20. The CP model (CP) solves 78.32% faster

than discrete-time MILP (DT) and 73.29% faster than continuous-time event-based MILP (CT) models. The CP model's solution time is shorter than the DT and CT models; however, these models are also in an acceptable performance range for small-size instances and can find global optimum solutions. The solution results and target values are given in Table 4.12. For example, for Problem #1, the resource loading level is calculated as 4.2% considering resource demand ranging from 0 to 5 for two resources having 100 units maximum available capacity during the planning horizon. The deviational variables for Problem #1 show no deviation from target values. The deviational variable DP1 shows a different value than zero if a project is not completed within the due date. The deviational variable DP2 shows a different value than zero if the number of regular and excessive resource capacity consumptions increases, or some optional tasks are started to be processed. Finally, the deviational variable DN3 shows a different value than zero if some optional tasks are not processed during the planning horizon.

The second twenty test instances are considered mid-size instances. The parameters of these instances have been defined as: $P = [5]$, $I = [10, 40]$, $K = [5, 40]$ and $S = [2, 4]$. The computational results for these problems are given in Table 4.13. All test problems are solved to optimality. The objective values of 60% of problems are 0, whereas the remaining have objective values greater than 0 due to deviations from the goals' target values. The solution time gradually increases from Problem #21 to #40. The CP model solves 61.79% faster than the DT and 34.91%. The solution results and target values are given in Table 4.20. On the other hand, compared to the computational results on small-size instances, it is clear that the CT model performs 43% faster than the DT model for mid-size instances. Thus, the CP and CT models are relatively preferred over the DT model for solving mid-size instances.

Finally, the third set of test instances is regarded as large instances, and they offer a behavior closer to the real-life problem. The parameters of these instances have been defined as: $P = [10]$, $I = [10, 40]$, $K = [10, 80]$ and $S = [2, 4]$. The computational results for these problems are given in Table 4.14. The CP model has solved all problems optimally within the specified runtime limit. The objective values of 20% of

the problems are 0, while the remaining 80% have objective values exceeding 0 due to deviations from the objectives' target values. The solution time gradually increases from Problem #41 to #60. The CP model solves 50.63% faster than the DT and 38.38% faster than the CT models. The solution results and target values for the objectives are given in Table 4.14. The column '%Gap (Obj)' shows the percentage deviation between models' objective function values. It is calculated as a difference between discrete-time MILP and CP objective function values divided by discrete-time MILP objective function value in column 'CP-DT.' Similarly; it is indicated as a difference between continuous-time event-based MILP and CP objective function values divided by continuous-time event-based MILP objective function value in column 'CP-DT.' For example, Problem #51 objective function value is found 0.239 by discrete-time MILP model (DT). On the other hand, its objective value is found 0.218 by continuous-time event-based MILP model (CT) and CP model (CP). The gap between CP and DT solution times is calculated as $(DT - CP)/DT$, and found as 9%. Similarly, the gap between CP and CT solution times is calculated as $(CT - CP)/CT$, and found as 0%. The gap values that are closer to 100% refer to a significant improvement in the objective function value.

In the DT model, 10 out of 20 problems are optimally solved. For the other ten problems, only three feasible solutions were found within the time limit, and no feasible solutions could be found for the rest. Moreover, the feasible solutions of the DT model deviate by 8.46 % from the optimal objective values. In the CT model, the optimum solution is found for 14 out of 20 problems. For the other six problems, five feasible solutions were found within the time limit, and no solution could be found for Problem #60. The feasible solutions of the CT model deviate by 14.66% from the optimal objective values. The CT model performs 7.79% better objective values given the feasible solutions of the DT model. Also, The CT model is 12.86 % faster than the DT model for large-sized instances.

The DT model contains 18% more constraints and 42% more variables than the CT model on average. The difference in the number of constraints and variables between the two models mainly depends on the number of time points and event

indexes. Therefore, the more there are differences between the time point and event point values, the more the difference is reflected in the number of constraints and variables. Among all models, the CP model clearly has far fewer constraints and variables than the DT and CT models. The CT model provides optimal solutions for large problems with ten projects up to 30 tasks, 60 resources, and four skills. On the other hand, the CP model finds the optimal solution for all large cases. Given the size of the case problem with nine projects, 44 tasks, 44 resources, 15 skills, and the CP model's high performance, the improved CP model with the selected branching and search strategy is decided to solve the real problem.

Both MILP formulations provide feasible and infeasible results for large-size instances with ten projects up to 40 tasks, 80 resources, and four skills. The real-life problem size is also large-size with nine projects, 44 tasks, 44 resources, and 15 skills. As it is stated that CP provides better solution performance and quality compared to MILP formulations, the improved CP model with the suggested branching and search strategies is selected as the most efficient model and decided to apply it to the actual problem.

Table 4.12. Computational results of small-size test instances

#	P	I	K	S	# Constraints			# Variables			Obj	First Solution Time*			Solution Time (s)			%Gap (Time)		
					DT	CT	CP	DT	CT	CP		DT	CT	CP	DT	CT	CP	CP-DT	CP-CT	
1	2	10	2	2	2,489	2,715	85	4,064	1,776	33	0	0.36	0.31	0.03	0.38	0.31	0.03	92.11	90.32	
2	2	10	2	2	2,489	2,715	85	4,064	1,776	33	0	0.50	0.42	0.04	0.52	0.42	0.04	92.31	90.48	
3	2	10	2	2	2,489	2,715	85	4,064	1,776	33	0	0.59	0.56	0.07	0.61	0.56	0.07	88.52	87.50	
4	2	10	2	2	2,489	2,715	85	4,064	1,776	33	0	0.77	0.78	0.18	0.77	0.78	0.18	76.62	76.92	
5	2	10	2	2	2,489	2,715	85	4,064	1,776	33	0.004	0.78	0.84	0.19	0.80	0.84	0.19	76.25	77.38	
6	2	20	4	2	5,933	10,629	155	9,189	6,900	57	0	1.55	0.95	0.24	1.55	0.95	0.24	84.52	74.74	
7	2	20	4	2	5,933	10,629	155	9,189	6,900	57	0	1.33	1.33	0.36	1.34	1.33	0.36	73.13	72.93	
8	2	20	4	2	5,933	10,629	155	9,189	6,900	57	0	2.19	2.03	0.44	2.19	2.03	0.44	79.91	78.33	
9	2	20	4	2	5,933	10,629	155	9,189	6,900	57	0.003	2.31	2.22	0.54	2.31	2.22	0.54	76.62	75.68	
10	2	20	4	2	5,933	10,629	155	9,189	6,900	57	0	3.05	3.01	1.53	3.05	3.01	1.53	49.84	49.17	
11	2	30	12	4	14,527	24,221	233	20,837	16,116	93	0	22.36	12.48	2.00	22.36	12.48	2.00	91.06	83.97	
12	2	30	12	4	14,527	24,221	233	20,837	16,116	93	0	33.26	15.83	3.45	33.28	15.83	3.45	89.63	78.21	
13	2	30	12	4	14,527	24,221	233	20,837	16,116	93	0	30.31	20.47	5.73	30.31	20.47	5.73	81.10	72.01	
14	2	30	12	4	14,527	24,221	233	20,837	16,116	93	0	47.55	32.80	8.92	47.55	32.80	8.92	81.24	72.80	
15	2	30	12	4	14,527	24,221	233	20,837	16,116	93	1.475	48.50	43.53	12.98	58.52	43.53	12.98	77.82	70.18	
16	2	40	16	4	27,210	41,965	301	40,459	28,524	121	0.086	98.87	87.28	19.48	99.06	87.28	19.48	80.34	77.68	
17	2	40	16	4	27,210	41,965	301	40,459	28,524	121	2.313	110.23	98.42	24.15	120.31	98.42	24.15	79.93	75.46	
18	2	40	16	4	27,210	41,965	301	40,459	28,524	121	2.313	123.12	103.94	32.38	124.55	103.94	32.38	74.00	68.85	
19	2	40	16	4	27,210	41,965	301	40,459	28,524	121	2.322	156.65	110.05	56.75	156.72	110.05	56.75	63.79	48.43	
20	2	40	16	4	27,210	41,965	301	40,459	28,524	121	2.322	174.71	133.76	74.00	174.85	133.76	74.00	57.68	44.68	
*The time the best solution is first found												Avg.	42.95	35.55	12.17	42.95	35.55	12.17	78.32	73.29

Table 4.12 continues

#	Resource Loading Level (%)	Deviational Variables			Target Values		
		DP1	DP2	DN3	G1	G2	G3
1	4.2	[0, 0]	0	[0, 0]	[0, 0]	144,878	[5, 8]
2	7.8	[0, 0]	0	[0, 0]	[0, 0]	144,878	[5, 8]
3	9.5	[0, 0]	0	[0, 0]	[0, 0]	144,878	[5, 8]
4	10.3	[0, 0]	6	[0, 0]	[0, 0]	144,878	[5, 8]
5	10.6	[0, 0]	1,859	[0, 0]	[0, 0]	144,878	[5, 8]
6	13.9	[0, 0]	1	[0, 0]	[0, 0]	575,783	[12, 13]
7	16.3	[0, 0]	0	[0, 0]	[0, 0]	575,783	[12, 13]
8	20.9	[0, 0]	1	[0, 0]	[0, 0]	575,783	[12, 13]
9	26.1	[0, 0]	5,778	[0, 0]	[0, 0]	575,783	[12, 13]
10	38.0	[0, 0]	0	[0, 0]	[0, 0]	575,783	[12, 13]
11	20.0	[0, 0]	4	[0, 0]	[0, 0]	2,229,062	[11, 8]
12	35.5	[0, 0]	0	[0, 0]	[0, 0]	2,229,062	[11, 8]
13	48.8	[0, 0]	4	[0, 0]	[0, 0]	2,229,062	[11, 8]
14	54.2	[0, 0]	1	[0, 0]	[0, 0]	2,229,062	[11, 8]
15	59.2	[0, 5]	127,090	[0, 0]	[0, 0]	2,229,062	[11, 8]
16	21.6	[0, 0]	95	[0, 9]	[0, 0]	3,749,158	[17, 10]
17	38.0	[9, 0]	145	[0, 9]	[0, 0]	3,749,158	[17, 10]
18	48.8	[9, 0]	275	[0, 9]	[0, 0]	3,749,158	[17, 10]
19	56.7	[9, 0]	377	[0, 10]	[0, 0]	3,749,158	[17, 10]
20	63.4	[9, 0]	486	[0, 10]	[0, 0]	3,749,158	[17, 10]

Table 4.13 Computational results of mid-size test instances

#	P	I	K	S	# Constraints			# Variables			Obj	First Solution Time			Solution Time (s)			%Gap (Time)	
					DT	CT	CP	DT	DT	CP		DT	CT	CP	DT	CT	CP	CP-DT	CP-CT
21	5	10	5	2	18,221	16,236	196	29,512	10,737	81	0	61.09	13.39	6.65	61.11	13.39	6.65	89.12	50.34
22	5	10	5	2	18,221	16,236	196	29,512	10,737	81	0	74.46	17.27	10.24	74.48	17.27	10.24	86.25	40.71
23	5	10	5	2	18,221	16,236	196	29,512	10,737	81	0	106.80	23.03	11.25	106.84	23.03	11.25	89.47	51.15
24	5	10	5	2	18,221	16,236	196	29,512	10,737	81	0	120.72	38.83	12.78	120.74	38.83	12.78	89.42	67.09
25	5	10	5	2	18,221	16,236	196	29,512	10,737	81	0	147.25	57.84	29.60	147.27	57.84	29.60	79.90	48.82
26	5	20	10	2	66,431	64,971	371	110,719	42,477	141	0	578.32	302.12	152.42	621.13	366.75	152.42	75.46	58.44
27	5	20	10	2	66,431	64,971	371	110,719	42,477	141	0	612.34	377.94	316.38	725.56	402.56	316.38	56.40	21.41
28	5	20	10	2	66,431	64,971	371	110,719	42,477	141	0	655.73	423.33	427.74	768.92	478.64	427.74	44.37	10.63
29	5	20	10	2	66,431	64,971	371	110,719	42,477	141	2.676	703.16	525.01	541.91	884.14	612.90	541.91	38.71	11.58
30	5	20	10	2	66,431	64,971	371	110,719	42,477	141	2.676	791.53	669.73	751.23	1,002.13	782.19	751.23	25.04	3.96
31	5	30	30	4	169,666	149,201	566	266,720	99,687	231	0	4,678.32	2,001.92	766.37	5,004.55	2,241.56	2,129.03	57.46	5.02
32	5	30	30	4	169,666	149,201	566	266,720	99,687	231	0	6,578.23	3,443.10	834.93	7,185.98	3,887.17	3,874.89	46.08	0.32
33	5	30	30	4	169,666	149,201	566	266,720	99,687	231	0	7,003.74	4,122.37	866.11	7,912.47	4,592.65	3,916.00	50.51	14.73
34	5	30	30	4	169,666	149,201	566	266,720	99,687	231	2.819	8,249.65	5,881.34	901.74	8,756.17	6,792.01	4,040.09	53.86	40.52
35	5	30	30	4	169,666	149,201	566	266,720	99,687	231	2.828	8,788.32	6,557.13	974.62	9,950.74	7,100.32	4,145.96	58.34	41.61
36	5	40	40	4	226,221	265,941	751	353,953	176,701	301	0	10,254.75	7,881.46	1,991.47	13,087.23	9,897.56	5,252.46	59.87	46.93
37	5	40	40	4	226,221	265,941	751	353,953	176,701	301	0.021	11,456.27	8,997.19	3,008.04	13,628.24	10,023.99	5,681.20	58.31	43.32
38	5	40	40	4	226,221	265,941	751	353,953	176,701	301	0.197	13,562.83	10,023.19	4,127.93	15,029.93	11,340.22	6,089.49	59.48	46.30
39	5	40	40	4	226,221	265,941	751	353,953	176,701	301	2.644	14,277.84	11,550.92	4,291.03	15,693.58	12,335.07	6,875.10	56.19	44.26
40	5	40	40	4	226,221	265,941	751	353,953	176,701	301	2.681	15,339.56	13,377.01	4,463.84	18,277.27	14,355.34	7,027.84	61.55	51.04
											Avg.	5,202.05	3,814.21	1,224.31	5,951.92	4,267.96	2,564.61	61.79	34.91

Table 4.13 continues

#	Resource Loading Level (%)	Deviational Variables			Target Values		
		DP1	DP2	DN3	G1	G2	G3
21	8.5	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	959,221	[5, 8, 11, 7, 7]
22	15.4	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	959,221	[5, 8, 11, 7, 7]
23	20.3	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	959,221	[5, 8, 11, 7, 7]
24	23.9	[0, 0, 0, 0, 0]	2	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	959,221	[5, 8, 11, 7, 7]
25	48.8	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	959,221	[5, 8, 11, 7, 7]
26	38.3	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	3,701,981	[12, 13, 12, 13, 14]
27	56.2	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	3,701,981	[12, 13, 12, 13, 14]
28	88.4	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	3,701,981	[12, 13, 12, 13, 14]
29	96.8	[10, 5, 0, 0, 3]	9,65	[12, 0, 6, 0, 10]	[0, 0, 0, 0, 0]	3,701,981	[12, 13, 12, 13, 14]
30	99.1	[10, 5, 0, 0, 3]	7,268	[12, 0, 6, 0, 10]	[0, 0, 0, 0, 0]	3,701,981	[12, 13, 12, 13, 14]
31	77.6	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	1,5208,501	[11, 8, 10, 8, 9]
32	99.2	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	1,5208,501	[11, 8, 10, 8, 9]
33	98.6	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	1,5208,501	[11, 8, 10, 8, 9]
34	94.2	[20, 0, 0, 9, 0]	147	[11, 2, 2, 0, 4]	[0, 0, 0, 0, 0]	1,5208,501	[11, 8, 10, 8, 9]
35	98.0	[20, 0, 0, 9, 0]	928	[10, 3, 2, 0, 5]	[0, 0, 0, 0, 0]	1,5208,501	[11, 8, 10, 8, 9]
36	43.6	[0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0]	[0, 0, 0, 0, 0]	2,6400,182	[14, 14, 16, 15, 13]
37	89.7	[0, 0, 0, 0, 0]	182	[4, 4, 0, 0, 1]	[0, 0, 0, 0, 0]	2,6400,182	[14, 14, 16, 15, 13]
38	89.7	[2, 0, 0, 0, 0]	9,870	[4, 4, 0, 0, 10]	[0, 0, 0, 0, 0]	2,6400,182	[14, 14, 16, 15, 13]
39	90.3	[10, 5, 0, 8, 0]	105,050	[4, 4, 0, 0, 10]	[0, 0, 0, 0, 0]	2,6400,182	[14, 14, 16, 15, 13]
40	94.5	[10, 5, 0, 8, 0]	700,129	[14, 4, 0, 5, 10]	[0, 0, 0, 0, 0]	2,6400,182	[14, 14, 16, 15, 13]

Table 4.14 Computational results of large-size test instances

#	P	I	K	S	# Constraints			# Variables			Obj			First Solution Time			Solution Time (s)			%Gap (Time)	
					DT	CT	CP	DT	CT	CP	DT	CT	CP	DT	CT	CP	DT	CT	CP	DT	CT
41	10	10	10	2	82,641	63,971	381	133,229	42,472	161	0	0	0	993.56	776.11	490.19	1,250.96	878.92	876.19	29.96	0.31
42	10	10	10	2	82,641	63,971	381	133,229	42,472	161	0	0	0	1,205.11	1,006.83	561.33	2,793.50	1,334.69	1,261.33	54.85	5.50
43	10	10	10	2	82,641	63,971	381	133,229	42,472	161	0	0	0	2,476.77	1,776.54	658.94	3,853.11	2,103.44	1,868.94	51.50	11.15
44	10	10	10	2	82,641	63,971	381	133,229	42,472	161	1.349	1.349	1.349	6,001.43	2,733.45	766.53	6,942.32	4,779.23	3,677.31	47.03	23.06
45	10	10	10	2	82,641	63,971	381	133,229	42,472	161	1.349	1.349	1.349	9,945.99	7,199.05	800.02	10,003.95	8,893.51	4,201.65	58.00	52.76
46	10	20	20	2	174,861	257,941	731	274,161	168,892	281	0	0	0	20,789.32	10,612.73	5,229.12	23,704.32	14,479.90	7,216.43	69.56	50.16
47	10	20	20	2	174,861	257,941	731	274,161	168,892	281	0.512	0.512	0.512	21,132.72	13,933.75	5,934.66	24,112.84	16,103.22	8,723.85	63.82	45.83
48	10	20	20	2	174,861	257,941	731	274,161	168,892	281	0.512	0.512	0.512	25,078.91	17,713.17	5,998.10	27,992.45	20,023.78	10,049.16	64.10	49.81
49	10	20	20	2	174,861	257,941	731	274,161	168,892	281	1.009	1.009	1.009	26,335.76	19,001.77	6,107.94	28,978.10	21,501.77	10,184.15	64.86	52.64
50	10	20	20	2	174,861	257,941	731	274,161	168,892	281	1.038	1.038	1.038	28,895.78	22,002.33	6,563.32	31,275.39	25,532.67	10,473.16	66.51	58.98
51	10	30	60	4	339,331	593,901	1,121	488,634	397,372	461	0.239	0.218	0.218	34,899.24	23,331.94	7,088.23	36,000.00	27,011.21	11,168.06	68.98	58.65
52	10	30	60	4	339,331	593,901	1,121	488,634	397,372	461	0.824	0.764	0.764	35,005.65	24,544.75	8,367.18	36,000.00	28,876.10	12,152.16	66.24	57.92
53	10	30	60	4	339,331	593,901	1,121	488,634	397,372	461	0.916	0.849	0.849	35,911.45	25,576.90	9,034.93	36,000.00	31,899.11	13,137.19	63.51	58.82
54	10	30	60	4	339,331	593,901	1,121	488,634	397,372	461	–	3.248	3.248	–	27,102.43	9,926.79	36,000.00	34,498.01	13,367.34	62.87	61.25
55	10	30	60	4	339,331	593,901	1,121	488,634	397,372	461	–	5.102	4.195	–	28,876.01	10,093.01	36,000.00	36,000.00	16,923.18	52.99	52.99
56	10	40	80	4	452,441	911,626	1,491	651,080	609,958	601	–	2.454	0.688	–	29,976.23	10,934.13	36,000.00	36,000.00	23,063.62	35.93	35.93
57	10	40	80	4	452,441	911,626	1,491	651,080	609,958	601	–	2.454	0.688	–	31,123.97	10,844.17	36,000.00	36,000.00	23,950.05	33.47	33.47
58	10	40	80	4	452,441	911,626	1,491	651,080	609,958	601	–	3.556	1.800	–	33,559.01	10,930.85	36,000.00	36,000.00	27,832.76	22.69	22.69
59	10	40	80	4	452,441	911,626	1,491	651,080	609,958	601	–	3.556	1.801	–	35,540.93	11,012.34	36,000.00	36,000.00	28,003.82	22.21	22.21
60	10	40	80	4	452,441	911,626	1,491	651,080	609,958	601	–	–	3.211	–	–	11,253.14	36,000.00	36,000.00	31,121.60	13.55	13.55
													Avg.	19,128.59	18,757.26	6,629.75	26,045.35	22,695.78	12,962.60	50.63	38.38

*Bolded numbers indicate optimal objective values

Table 4.14 continues

#	%Gap (Obj)		Resource Loading Level (%)	Deviation Variables			Target Values		
	CP-DT	CP-CT		DP1	DP2	DN3	G1	G2	G3
41	0	0	19.2	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	3,607,527	[7, 7, 9, 7, 6, 6, 7, 6, 5, 6]
42	0	0	20.0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	2	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	3,607,527	[7, 7, 9, 7, 6, 6, 7, 6, 5, 6]
43	0	0	28.3	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	3,607,527	[7, 7, 9, 7, 6, 6, 7, 6, 5, 6]
44	0	0	36.1	[10, 5, 10, 0, 0, 4, 0, 0, 0, 0]	879	[5, 5, 2, 0, 0, 6, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	3,607,527	[7, 7, 9, 7, 6, 6, 7, 6, 5, 6]
45	0	0	59.2	[10, 5, 10, 0, 0, 4, 0, 0, 0, 0]	6,885	[5, 5, 2, 0, 0, 6, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	3,607,527	[7, 7, 9, 7, 6, 6, 7, 6, 5, 6]
46	0	0	62.0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	13,826,896	[10, 13, 11, 13, 13, 12, 10, 13, 8, 16]
47	0	0	73.9	[20, 0, 0, 0, 0, 0, 0, 0, 3, 5]	10,345	[5, 3, 6, 0, 0, 0, 10, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	13,826,896	[10, 13, 11, 13, 13, 12, 10, 13, 8, 16]
48	0	0	96.2	[20, 0, 0, 0, 0, 0, 0, 0, 3, 5]	15,670	[5, 3, 6, 0, 0, 0, 10, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	13,826,896	[10, 13, 11, 13, 13, 12, 10, 13, 8, 16]
49	0	0	97.7	[20, 0, 0, 0, 0, 10, 0, 0, 5, 6]	22,356	[5, 3, 6, 0, 0, 0, 10, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	13,826,896	[10, 13, 11, 13, 13, 12, 10, 13, 8, 16]
50	0	0	99.9	[20, 0, 0, 0, 0, 10, 0, 0, 5, 6]	1,000,025	[5, 3, 11, 0, 0, 0, 10, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	13,826,896	[10, 13, 11, 13, 13, 12, 10, 13, 8, 16]
51	9	0	76.7	[10, 2, 0, 0, 0, 0, 0, 0, 0, 0]	55,670	[5, 3, 1, 0, 0, 0, 7, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	60,532,835	[11, 8, 10, 8, 9, 11, 8, 10, 8, 9]
52	7	0	94.4	[10, 10, 0, 0, 0, 0, 0, 0, 5, 0]	70,598	[5, 3, 1, 0, 0, 0, 7, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	60,532,835	[11, 8, 10, 8, 9, 11, 8, 10, 8, 9]
53	7	0	92.5	[10, 12, 0, 0, 0, 0, 0, 0, 5, 0]	235,075	[6, 3, 6, 0, 0, 0, 7, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	60,532,835	[11, 8, 10, 8, 9, 11, 8, 10, 8, 9]
54	-	0	93.9	[10, 25, 8, 0, 0, 0, 0, 0, 0, 15]	122,045	[5, 5, 0, 8, 0, 0, 0, 0, 0, 9]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	60,532,835	[11, 8, 10, 8, 9, 11, 8, 10, 8, 9]
55	-	18	94.5	[10, 25, 12, 0, 0, 0, 0, 7, 0, 15]	357,997	[5, 8, 10, 8, 0, 0, 0, 0, 0, 9]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	60,532,835	[11, 8, 10, 8, 9, 11, 8, 10, 8, 9]
56	-	72	95.1	[10, 5, 2, 0, 0, 0, 0, 0, 0, 0]	390,775	[4, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	105,079,359	[14, 14, 16, 15, 13, 14, 14, 16, 15, 13]
57	-	72	99.5	[10, 5, 2, 0, 0, 0, 0, 0, 0, 0]	475,904	[4, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	105,079,359	[14, 14, 16, 15, 13, 14, 14, 16, 15, 13]
58	-	49	95.6	[15, 7, 5, 0, 0, 0, 0, 10, 0, 0]	490,003	[10, 5, 5, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	105,079,359	[14, 14, 16, 15, 13, 14, 14, 16, 15, 13]
59	-	49	99.9	[15, 7, 5, 0, 0, 0, 0, 10, 0, 0]	575,020	[10, 5, 5, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	105,079,359	[14, 14, 16, 15, 13, 14, 14, 16, 15, 13]
60	-	-	95.6	[15, 10, 17, 0, 0, 0, 0, 10, 0, 5]	1,002,253	[14, 14, 6, 0, 0, 0, 0, 0, 0, 3]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	105,079,359	[14, 14, 16, 15, 13, 14, 14, 16, 15, 13]
Avg	1.76	13.68							

CHAPTER FIVE

REAL-LIFE PROBLEM AND MANAGERIAL IMPLICATIONS

The intensive research and development activities of enterprises require that multiple projects be initiated and carried out simultaneously with employees with different skills and limited capabilities. First, an overview of the real-life RCMPSP is explained in light of the description of the problem given in Chapter 3. Second, the real-life problem is solved with the improved CP model using goal programming and goal attainment techniques. Subsequently, the parameters of the problem are changed, and different solutions are obtained under different scenarios. Finally, managerial implications are derived, providing better insights to management.

5.1. Overview of Real-Life Problem

The considered company is the largest combi boiler factory of a leading manufacturer operating in the heating industry with its eighteen plants and more than 15000 employees. The company is based in Turkey and exports 70% of its production, which constitutes 1.5% of its total exports. It has around 600 employees working in production, quality, logistics, purchasing, human resources, research and development, and many other departments. The company's research and development (R&D) department designs new combi boilers, subassembly units, and spare parts due to the following reasons:

- Improve company's existing product portfolio with new product versions,
- Deliver the most profitable return for the company by strengthening its market position with high-quality services and products,
- Enter the market at an early phase to stay ahead of the competition,
- Meet customer needs more effectively with innovative and useful solutions.

There are nine projects presented to the R&D department of the company: P1, P2, and P3 projects are in the finished product project category, P4, P5, and P6 projects are in the subassembly project category, and P7, P8, and P9 projects are in the spare part project category. The executive committee defines each project's relative

importance WP_p according to AHP pairwise comparisons, taking into account their profitability. The project due dates DT_p refer to a weekly period, and they are defined as 15% more than the completion time of the final task in each project. The target value of project tardiness $G1_p$, is defined as 0 for each project since any delay in the projects' finish times may cause a loss on the company's market share. The sum of sponsors' cost to execute optional tasks is calculated as \$152,972 for a real-life problem. The cost spent for the amount of regular resource capacity usage is calculated as \$276,408. On the other hand, the cost spent for excessive resource capacity usage is considered as 0. The target value of the total project development cost $G2$, is equal to 429,380 \$ as the sum of all considered cost elements. The total cost for the remaining mandatory tasks is calculated as \$1,157,496; however, this cost is not included in models. The target value of project quality score $G3_p$ is defined according to the sum of the quality score of optional tasks in each project as 36, 33, 31, 33, 32, 32, 21, 25, and 22. The summary of the project parameters is shown in Table 5.1 in detail.

Table 5.1. Summary of the project parameters in the real-life problem

P	WP_p	DT_p	$G1_p$	$G2$	$G3_p$
P1	0.13	82	0	429,380	36
P2	0.18	136	0		33
P3	0.18	129	0		31
P4	0.11	78	0		33
P5	0.16	134	0		32
P6	0.14	181	0		32
P7	0.02	47	0		21
P8	0.07	60	0		25
P9	0.01	118	0		22

Project managers are responsible for supervising the tasks required in their projects and duration. The product manager, project manager, and selected project team members have a kick-off meeting to align with the project's scope. The resource allocation and project planning process take up to 1 month before the project officially begins. The company has seven milestones in its internal project management procedure that consists of predefined tasks listed in Table 5.2. The letter "M" shows mandatory tasks, and "O" shows optional tasks in the project. Each task has a different quality score that varies from one project to another. Optional tasks are not critical to perform, but they bring benefits to the project's quality once performed.

Every project is run with specific tasks listed in the procedure based on their project category. Each task has precedence relations with other tasks depending on the project category, as shown in Figure 5.1. Each task is available for processing at time and event point 0. The processing time, earliest start time, and earliest finish time of a task are deterministic and weekly duration and independent of the allocated resources. The processing time of a job and its earliest start and end times differ in each project.

Each task allocates at least one resource that can be either a human resource or a machine with some skill and capability, as shown in Table 5.3. The weekly working capacity is defined as 100 units. ' $FixedCost_k$ ' refers to the cost spent in USD dollars for one unit of human resource usage per week. The weekly cost spent for human resources is in the range from \$500 to \$1,000 per week. The portion of this spent for 1 unit of human resource usage varies between \$5 – \$10. On the other hand, the weekly cost spent for machine resources is in the range from \$20,000 to \$25,000 per week. The portion of this spent for 1 unit of machine resource usage varies between \$200 – \$250. The ' $OverCapCost_k$ ' refers to the cost spent in USD dollars for one unit above the maximum capacity of resources. This cost is set at a fixed price of \$11 for human resources, and it is in the range from \$245 to \$275 per week.

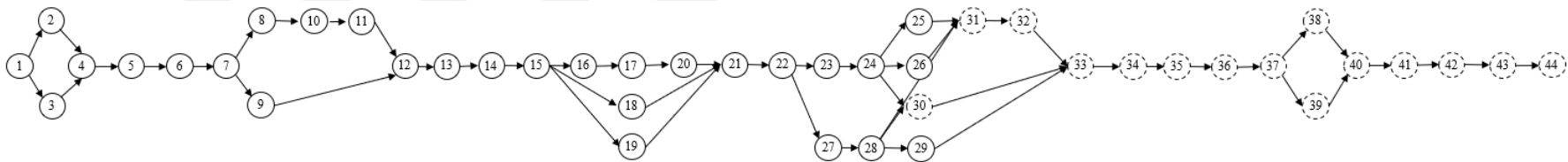
A task requires at least one skill, as indicated in Table 5.4. Each skill is owned by at least one resource. Each task is defined based on their demand for varying skills and resources for each project and task, as detailed in Appendix 5.1 – 5.30. Employees have different skills and capabilities to perform a task, and employees having the same skill may not be assigned to the same tasks due to different capabilities. On the other hand, machines have the skill and the capability to perform a task requiring that skill. Resource skills and capabilities do not change with time. A resource has a maximum capacity of 100 units weekly; however, it can be surpassed further to achieve project objectives.

The fixed cost spent for each resource unit and the cost of excess use spent for excess resource capacity impacts the project's development cost. The project lifecycle's time horizon is divided into equal periods as one week for the CP model. The time

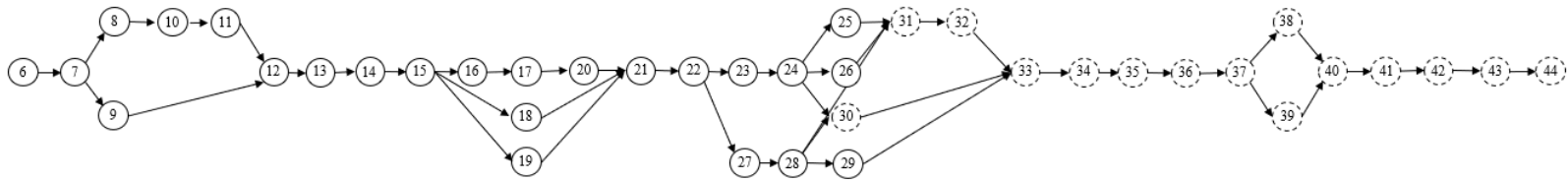
period starts from 0 and ends at 198 in a weekly horizon. Successful R&D projects involve planning multiple projects and tasks. It is planned by determining the start and finish times of tasks taking into account the precedence relations between them, amount of resource capacity used, and amount of excessive resource consumption considering the skill and capability of resources.

Table 5.2 Summary of the task parameters in the real-life problem

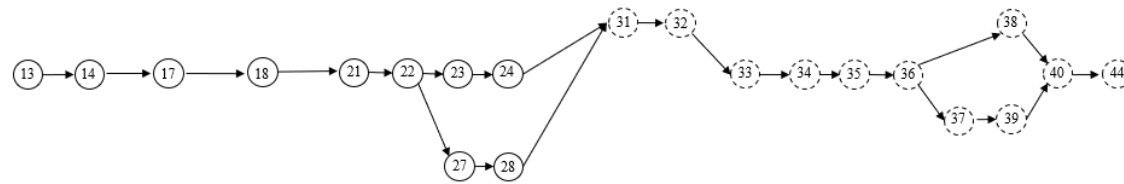
Task ID	Task Name	PT_{pt}	P1	P2	P3	P4	P5	P6	P7	P8	P9
1	Project Release Approval	1	M	M	M	–	–	–	–	–	–
2	Market Requirements Gathering	2	M	M	M	–	–	–	–	–	–
3	Project Team Build	2	M	M	M	–	–	–	–	–	–
4	Product Requirements Review	3	M	M	M	–	–	–	–	–	–
5	First Quality Control & Review	1	M	M	M	–	–	–	–	–	–
6	Project Start Approval	1	M	M	M	M	M	M	–	–	–
7	Technical Design Review	3	M	M	M	M	M	M	–	–	–
8	Product Sample Matrix Creation	1	M	M	M	M	M	M	–	–	–
9	Supplier Selection & Contracting	3	M	M	M	M	M	M	–	–	–
10	First Sample Build	2	M	M	M	M	M	M	–	–	–
11	Risk Assessment	1	M	M	M	M	M	M	–	–	–
12	Second Quality Control & Review	1	M	M	M	M	M	M	–	–	–
13	Project Confirmation Approval	1	M	M	M	M	M	M	M	M	M
14	BOM Preparation	2	M	M	M	M	M	M	M	M	M
15	Second Sample Build	2	M	M	M	M	M	M	–	–	–
16	Simulation Test	3	M	M	M	M	M	M	–	–	–
17	Risk Assessment	1	M	M	M	M	M	M	M	M	M
18	Supplier Quality Check	1	M	M	M	M	M	M	M	M	M
19	Production Concept Planning	1	M	M	M	M	M	M	–	–	–
20	Technical Documentation	1	M	M	M	M	M	M	–	–	–
21	Third Quality Control & Review	1	M	M	M	M	M	M	M	M	M
22	Technical Design Release Approval	1	M	M	M	M	M	M	M	M	M
23	Order Supplier Tools for Third Sample	3	M	M	M	M	M	M	M	M	M
24	Third Sample Build	2	M	M	M	M	M	M	M	M	M
25	Lifetime Test	12	M	M	M	M	M	M	–	–	–
26	Customer Acceptance Test	2	M	M	M	M	M	M	–	–	–
27	Order Supplier Tools for Spare Parts	1	M	M	M	M	M	M	M	M	M
28	Spare Parts Build	1	M	M	M	M	M	M	M	M	M
29	Serviceability Test	1	M	M	M	M	M	M	–	–	–
30	Supply Chain Design	1	O	O	O	O	O	O	–	–	–
31	Risk Assessment	2	O	O	O	O	O	O	O	O	O
32	Development Report Completion	2	O	O	O	O	O	O	O	O	O
33	Fourth Quality Control & Review	1	O	O	O	O	O	O	O	O	O
34	Start of Production	1	O	O	O	O	O	O	O	O	O
35	Order Stock for Forth Sample	3	O	O	O	O	O	O	O	O	O
36	Forth Sample Build	2	O	O	O	O	O	O	O	O	O
37	Qualification Test	2	O	O	O	O	O	O	O	O	O
38	Product Cost Control	1	O	O	O	O	O	O	O	O	O
39	Risk Assessment	3	O	O	O	O	O	O	O	O	O
40	Fifth Quality Control & Review	1	O	O	O	O	O	O	O	O	O
41	Delivery Release	4	O	O	O	O	O	O	–	–	–
42	Lessons Learnt	1	O	O	O	O	O	O	–	–	–
43	Archive Project Data	1	O	O	O	O	O	O	–	–	–
44	Project End	2	O	O	O	O	O	O	O	O	O



(a)



(b)



(c)

Figure 5.1 Precedence relationships in finished product (a), subassembly (b) and spare parts (c) projects

Table 5.3 Summary of the resource parameters in the real-life problem

Resource ID	Resource Name	Skill ID	Skill Name	FixedCost _k	OverCapCost _k
R1	Human Resource 1	S1	Product Management	10	11
R2	Human Resource 2	S1	Product Management	10	11
R3	Human Resource 3	S1	Product Management	10	11
R4	Human Resource 4	S1	Product Management	10	11
R5	Human Resource 5	S2	Project Management	10	11
R6	Human Resource 6	S2	Project Management	10	11
R7	Human Resource 7	S2	Project Management	10	11
R8	Human Resource 8	S2	Project Management	9	11
R9	Human Resource 9	S2	Project Management	9	11
R10	Human Resource 10	S3	Quality Management	7	11
R11	Human Resource 11	S3	Quality Management	7	11
R12	Human Resource 12	S3	Quality Management	6	11
R13	Human Resource 13	S4	Primary Product Design	9	11
R14	Human Resource 14	S4	Primary Product Design	9	11
R15	Human Resource 15	S4	Primary Product Design	8	11
R16	Human Resource 16	S4	Primary Product Design	8	11
R17	Human Resource 17	S5	Sub-component Design	8	11
R18	Human Resource 18	S5	Sub-component Design	8	11
R19	Human Resource 19	S5	Sub-component Design	9	11
R20	Human Resource 20	S5	Sub-component Design	9	11
R21	Human Resource 21	S6	Spare Part Design	7	11
R22	Human Resource 22	S6	Spare Part Design	8	11
R23	Human Resource 23	S7	R&D Test Management	7	11
R24	Human Resource 24	S7	R&D Test Management	7	11
R25	Human Resource 25	S7	R&D Test Management	9	11
R26	Human Resource 26	S8	Purchasing Management	8	11
R27	Human Resource 27	S8	Purchasing Management	7	11
R28	Human Resource 28	S8	Purchasing Management	7	11
R29	Human Resource 29	S9	Production Planning	6	11
R30	Human Resource 30	S9	Production Planning	6	11
R31	Human Resource 31	S9	Production Planning	6	11
R32	Human Resource 32	S9	Production Planning	6	11
R33	Human Resource 33	S10	Simulation	5	11
R34	Human Resource 34	S10	Simulation	5	11
R35	Human Resource 35	S11	Supply Chain Design	5	11
R36	Human Resource 36	S12	Cost Controlling	5	11
R37	Human Resource 37	S13	Technical Documentation	7	11
R38	Human Resource 38	S13	Technical Documentation	7	11
R39	Machine 1	S14	Sample Management	200	245
R40	Machine 2	S14	Sample Management	200	245
R41	Machine 3	S14	Sample Management	200	245
R42	Machine 4	S15	Direct Testing	250	275
R43	Machine 5	S15	Direct Testing	250	275
R44	Machine 6	S15	Direct Testing	250	275

Table 5.4 Summary of the skill parameters in the real-life problem

Task ID	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
1	✓	✓													
2	✓	✓													
3		✓													
4	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
5	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
6	✓	✓													
7				✓	✓	✓									
8				✓	✓	✓			✓						
9								✓							
10		✓		✓	✓	✓			✓						
11		✓		✓	✓	✓	✓								
12	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
13		✓													
14				✓	✓	✓			✓						
15		✓		✓	✓	✓									
16							✓			✓					✓
17		✓		✓	✓	✓	✓			✓					
18								✓							
19									✓						
20													✓		
21	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
22		✓													
23								✓							
24		✓							✓					✓	
25							✓								✓
26	✓														
27								✓							
28		✓							✓					✓	
29	✓														
30								✓			✓				
31		✓		✓	✓	✓	✓			✓					
32				✓	✓	✓	✓			✓			✓		
33	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
34		✓													
35								✓							
36		✓							✓					✓	
37			✓											✓	
38	✓							✓	✓			✓			
39		✓		✓	✓	✓	✓			✓					
40	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
41		✓													
42	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
43		✓													
44		✓													

The improved CP model is assessed for the actual problem of the R&D department. This problem with nine projects, 44 tasks, 44 resources, and 15 skills is addressed. The amount of resource capacity required to perform a task is considered in the range [0, 5], and resource capability taking value from a set {0, 1}. Each human resources have 51 workweeks to perform required tasks in actual problem in a year. Five weeks of vacation and three weeks of sick-leaves are estimated for every human resource by management; thus, available work weeks are equal to 44. Following, the human resources' loading level is calculated as 85%. On the other hand, machine resources have 52 work weeks and four weeks routine and deep maintenance periods in a year. Thus, available work weeks are equal to 48 weeks which leads to a 92% loading level. The average resources' loading level is 86%, considering 38 human and six machine resources.

The problem consists of 1,044 constraints and 521 variables using the CP model. The optimum solution is found in 11,706.48 seconds, while this solution is first found in 7,380.30 seconds. The objective function value is 0.029 with 2% deviation from the tardiness, 3.59% deviation from project development costs and 80.57% deviation from quality score targets listed in Table 5.1. The fewer capacity units required for each task, the higher the number of capable resources, providing an environment where sufficient resources are available to complete the tasks. The average resource utilization is found 70.93%, which is at an acceptable level of loading compared to the 86% target.

The solution results obtained by the CP model are given in Table 5.5 and Table 5.6. The task start and finish times of tasks for all projects are presented. The completion time for the final task in each project corresponds to the project's maximum completion time, and their values are less than the due date of each project. Therefore, it is clear that there is no deviation from the project tardiness target value. The amount of resource capacity consumed falls below the maximum capacity level of 100 units. Therefore, there is no excessive use of resources. According to these results, R19 and R20 with sub-component design skill and R23 with R&D test management skill have the lowest loading levels due to their low level of capability to perform required tasks.

On the other hand, R33 and R34 with simulation skills are the only resources with that skill; however, they are not loaded at the expected level as well.

Table 5.5 CP model solution results for the task start (S) and finish (F) times

Task ID	P1		P2		P3		P4		P5		P6		P7		P8		P9	
	S	F	S	F	S	F	S	F	S	F	S	F	S	F	S	F	S	F
1	0	1	58	59	53	54	–	–	–	–	–	–	–	–	–	–	–	–
2	1	3	59	61	55	57	–	–	–	–	–	–	–	–	–	–	–	–
3	2	4	59	61	54	56	–	–	–	–	–	–	–	–	–	–	–	–
4	4	7	64	67	58	61	–	–	–	–	–	–	–	–	–	–	–	–
5	9	10	68	69	62	63	–	–	–	–	–	–	–	–	–	–	–	–
6	10	11	70	71	63	64	4	5	70	71	125	126	–	–	–	–	–	–
7	11	14	72	75	66	69	5	8	72	75	127	130	–	–	–	–	–	–
8	14	15	75	76	70	71	8	9	76	77	130	131	–	–	–	–	–	–
9	15	18	76	79	69	72	8	11	75	78	130	133	–	–	–	–	–	–
10	17	19	77	79	71	73	11	13	77	79	133	135	–	–	–	–	–	–
11	19	20	80	81	74	75	14	15	79	80	135	136	–	–	–	–	–	–
12	20	21	82	83	76	77	16	17	81	82	137	138	–	–	–	–	–	–
13	21	22	83	84	78	79	18	19	83	84	138	139	19	20	33	34	96	97
14	22	24	85	87	79	81	20	22	85	87	141	143	20	22	34	36	97	99
15	24	26	87	89	81	83	22	24	87	89	143	145	–	–	–	–	–	–
16	27	30	90	93	84	87	24	27	90	93	146	149	–	–	–	–	–	–
17	31	32	93	94	88	89	28	29	94	95	150	151	22	23	36	37	99	100
18	27	28	90	91	84	85	24	25	90	91	145	146	23	24	37	38	101	102
19	26	27	90	91	83	84	24	25	90	91	146	147	–	–	–	–	–	–
20	34	35	95	96	89	90	30	31	96	97	152	153	–	–	–	–	–	–
21	35	36	97	98	90	91	32	33	98	99	154	155	24	25	38	39	104	105
22	38	39	98	99	91	92	34	35	100	101	156	157	25	26	40	41	105	106
23	39	42	101	104	93	96	36	39	102	105	160	163	26	29	41	44	107	110
24	43	45	105	107	97	99	39	41	106	108	163	165	31	33	44	46	110	112
25	47	59	109	121	99	111	41	53	109	121	165	177	–	–	–	–	–	–
26	45	47	109	111	99	101	41	43	109	111	167	169	–	–	–	–	–	–
27	40	41	100	101	93	94	36	37	102	103	159	160	26	27	42	43	107	108
28	41	42	102	103	95	96	38	39	104	105	162	163	28	29	43	44	108	109
29	42	43	103	104	96	97	40	41	106	107	163	164	–	–	–	–	–	–
30	46	47	109	110	100	101	42	43	108	109	166	167	–	–	–	–	–	–
31	61	63	123	125	112	114	55	57	123	125	177	179	35	37	46	48	113	115
32	63	65	125	127	115	117	57	59	126	128	180	182	37	39	48	50	116	118
33	66	67	128	129	118	119	60	61	128	129	182	183	40	41	51	52	118	119
34	68	69	130	131	120	121	62	63	130	131	184	185	42	43	52	53	119	120
35	71	74	131	134	122	125	64	67	132	135	186	189	43	46	53	56	120	123
36	75	77	134	136	125	127	67	69	135	137	189	191	47	49	56	58	124	126
37	77	79	137	139	129	131	71	73	137	139	191	193	49	51	58	60	127	129
38	78	79	137	138	131	132	70	71	138	139	191	192	49	50	58	59	127	128
39	80	83	140	143	132	135	74	77	140	143	194	197	52	55	61	64	129	132
40	84	85	144	145	136	137	78	79	144	145	198	199	50	51	65	66	133	134
41	85	89	145	149	138	142	79	83	145	149	199	203	–	–	–	–	–	–
42	89	90	150	151	142	143	84	85	150	151	203	204	–	–	–	–	–	–
43	90	91	152	153	144	145	86	87	151	152	204	205	–	–	–	–	–	–
44	92	94	154	156	147	149	87	89	152	154	206	208	51	53	66	68	134	136

Table 5.6 CP model results for the amount of resource capacity consumed and their excessive use

Resource ID	Resource Loading Level (%)	Ssurp _k	Resource ID	Resource Loading Level (%)	Ssurp _k
R1	83.8	0	R23	38.7	0
R2	72.6	0	R24	87.0	0
R3	91.0	0	R25	57.5	0
R4	84.4	0	R26	91.7	0
R5	94.2	0	R27	85.4	0
R6	90.2	0	R28	85.4	0
R7	83.0	0	R29	49.5	0
R8	83.0	0	R30	65.4	0
R9	65.4	0	R31	87.0	0
R10	94.2	0	R32	86.3	0
R11	83.8	0	R33	29.5	0
R12	65.4	0	R34	43.8	0
R13	65.4	0	R35	75.1	0
R14	58.2	0	R36	43.8	0
R15	79.8	0	R37	45.6	0
R16	71.9	0	R38	42.5	0
R17	90.2	0	R39	43.8	0
R18	72.6	0	R40	65.4	0
R19	51.0	0	R41	70.9	0
R20	51.0	0	R42	66.3	0
R21	99.4	0	R43	85.1	0
R22	79.8	0	R44	65.4	0

5.2 Managerial Implications for Real-Life Problem

The following changes are made to the CP model settings to observe changes to the solution. Based on the CP solution results, relative comparisons are made from which management implications are inferred:

- Changes in the objective function weights
- Changes in the total resource capability
- Changes in the number of resources
- Changes in the objective function weights in goal attainment technique

5.2.1 Changes in the Objective Function Weights

The CP model evaluates the twelve problem cases shown in Table 5.7 to analyze the objective weight changes, and total percentage deviations are drawn in Figure 5.2. Case C0 refers to the original settings. The problem cases are generated as follows:

- The objective weight is decreased by 0.01 from the delay ($W1$), and it is increased by 0.01 for the total cost target ($W2$) from C1 to C4.
- The objective weight is increased by 0.01 for the total cost target ($W2$), and it is decreased by 0.01 for the quality score target ($W3$) from C5 to C8.
- The objective weight is increased by 0.01 for the delay ($W1$), and it is decreased by 0.01 for the quality score target ($W3$) from C9 to C12.

The optimal objective function value is found as 0.029 for all ten cases. The deviation from the delay objective is 1.13% for all cases. The total cost deviation reduces from 3.59% up to 3.35%, while the quality score deviation increases from 80.57% up to 111.95%. A slight reduction is noted in Cases C2, C6, and C10, compromising the total cost deviation 3.49 – 3.52% with the quality score deviation of 89.67%. Here, the project quality score deviation has increased for the P9 project, which has the lowest relative importance weight among all projects. These case solutions might be seen as alternative solutions that compromise the company's total cost and the quality score targets; however, C0 can be preferable for the company not to reduce the quality score any further.

Table 5.7 Computational results for the changes in objective function weights

#	W1	W2	W3	Obj	First Solution Time	Solution Time (s)	Resource Loading Level (%)	Deviation Variables		
								<i>DP1_p</i>	<i>DP2</i>	<i>DN3_p</i>
C0	0.54	0.30	0.16	0.029	7,380.30	11,706.48	70.9	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13% ¹	\$15,420 3.59% ²	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73] , 80.57% ³
C1	0.53	0.31	0.16	0.029	7,369.42	11,701.93	70.9	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,389 3.58%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73] , 80.57%
C2	0.52	0.32	0.16	0.029	7,361.28	11,697.17	70.7	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,024 3.50%	[3, 0, 0, 3, 0, 3, 4, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 31.82] , 89.67%
C3	0.51	0.33	0.16	0.029	7,356.11	11,695.42	70.4	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$14,419 3.36%	[3, 0, 0, 3, 0, 3, 6, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 28.57, 12.00, 31.82] , 99.19%
C4	0.50	0.34	0.16	0.029	7,355.36	11,693.73	70.4	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$14,368 3.35%	[3, 0, 0, 3, 0, 3, 7, 5, 7] [8.33, 0, 0, 9.09, 0, 9.38, 33.33, 20.00, 31.82] , 111.95%
C5	0.54	0.31	0.15	0.029	7,357.75	11,696.52	70.9	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,362 3.58%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73] , 80.57%
C6	0.54	0.32	0.14	0.029	7,353.03	11,692.12	70.7	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,004 3.49%	[3, 0, 0, 3, 0, 3, 4, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 31.82] , 89.67%
C7	0.54	0.33	0.13	0.029	7,351.26	11,690.23	70.4	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$14,709 3.43%	[3, 0, 0, 3, 0, 3, 6, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 28.57, 12.00, 31.82] , 99.19%
C8	0.54	0.34	0.12	0.029	7,350.34	11,687.05	70.2	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$14,478 3.37%	[3, 0, 0, 3, 0, 3, 7, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 33.33, 12.00, 31.82] , 103.95%
C9	0.55	0.30	0.15	0.029	7,378.12	11,705.04	70.9	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,415 3.59%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73] , 80.57%
C10	0.56	0.30	0.14	0.029	7,349.98	11,690.73	70.6	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,108 3.52%	[3, 0, 0, 3, 0, 3, 4, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 31.82] , 89.67%
C11	0.57	0.30	0.13	0.029	7,348.34	11,688.65	70.4	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$14,765 3.44%	[3, 0, 0, 3, 0, 3, 6, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 28.57, 12.00, 31.82] , 99.19%
C12	0.58	0.30	0.12	0.029	7,345.67	11,686.29	70.1	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$14,461 3.37%	[3, 0, 0, 3, 0, 3, 7, 5, 7] [8.33, 0, 0, 9.09, 0, 9.38, 33.33, 20.00, 31.82] , 111.95%

¹ Percentage deviation from each project's delay objective and total percentage deviation² Percentage deviation from the total cost target³ Percentage deviation from each project's quality score target and total percentage deviation

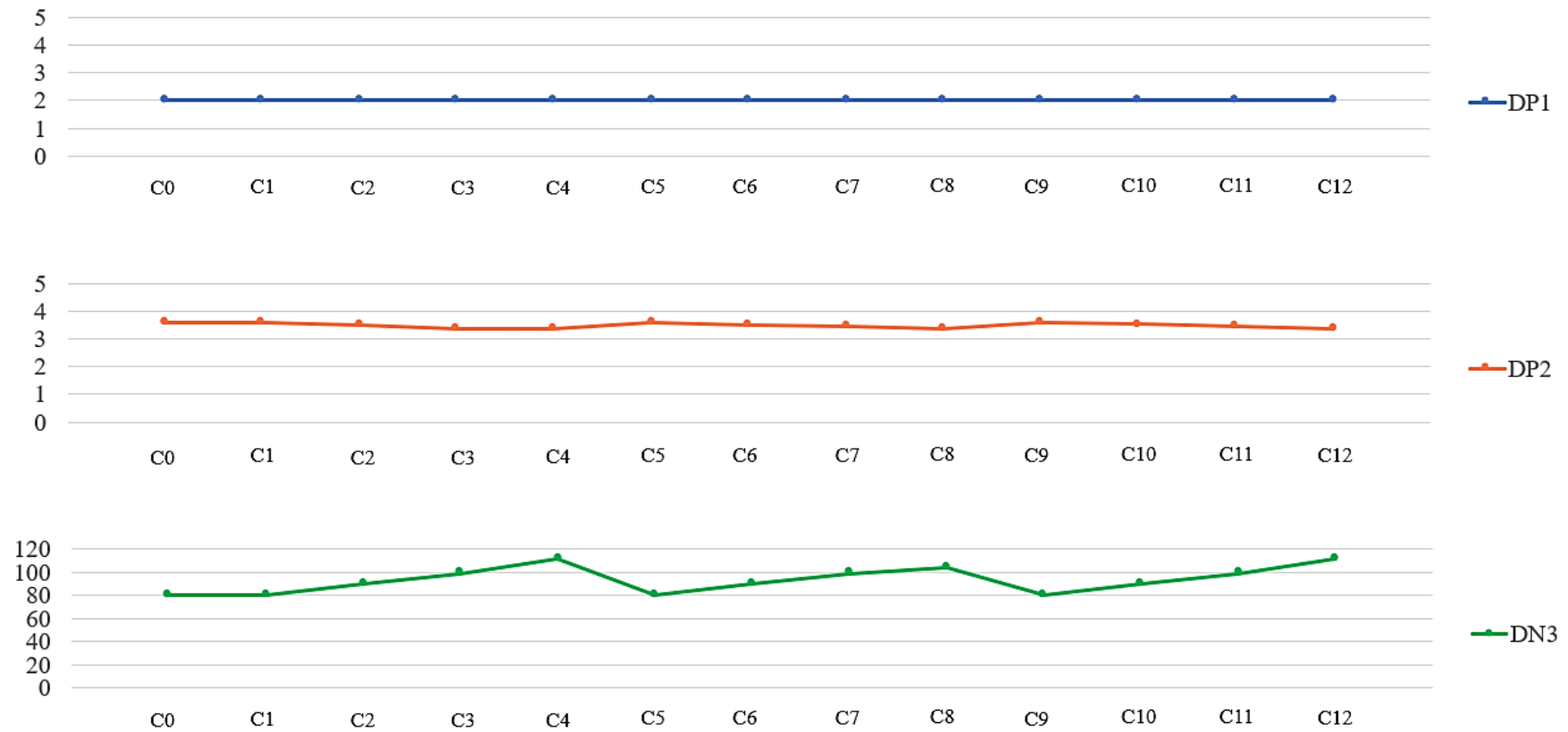


Figure 5.2 Total percentage deviations for the changes in objective function weights

5.2.2 Changes in the Total Resource Capability

The CP model is evaluated with nine problem cases shown in Table 5.8 to analyze the total resource capability (TRC) changes, and total percentage deviations are drawn in Figure 5.3. The problem cases are generated as follows:

- TRC is increased from the initial value in Case C0 with increases of 10%, 20%, 30%, and 40%, respectively, from C4 to C1.
- TRC is reduced from the initial value in Case C0 with decreases of 10%, 20%, 30%, and 40%, respectively, from C5 to C8

The CP solved all case problems optimally. As TRC decreases from cases C0 to C8, the deviations from the objectives increase with the increase of the optimal objective values. This situation can be attributed to the reduced capability, which reduces the overall capacity of available resources.

Note that as TRC increases from C0 to C1, the total cost deviation starts to improve. However, the improvement in the delay and quality score deviation can only be observed in C1, when TRC is 40% higher. The average level of resource loading also goes down in this direction. The company can analyze training and human resource development to increase its capacity to realize these potential improvements. It can provide the sharing of best practices among employees, on-the-job training, job shadowing, and senior employees' mentoring.

Table 5.8 Computational results for the changes in the total resource capability

#	Deviation From The Total Resource Capability (%)	Obj	First Solution Time	Solution Time (s)	Resource Loading Level (%)	Deviational Variables		
						$DP1_p$	$DP2$	$DN3_p$
C1	+ 40	0.026	7,348.09	11,561.83	62.5	[0, 0, 0, 0, 0, 0, 0, 0] wk [0, 0, 0, 0, 0, 0, 0, 0], 0% ¹	\$13,651 3.18% ²	[3, 0, 0, 3, 0, 3, 3, 0, 3] [8.33, 0, 0, 9.09, 0, 9.38, 14.29, 0, 13.64], 54.72% ³
C2	+ 30	0.027	7,356.55	11,571.20	65.6	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00], 1.13%	\$14,787 3.44%	[3, 0, 0, 3, 0, 3, 3, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 14.29, 12.00, 22.73], 75.81%
C3	+ 20	0.027	7,370.31	11,682.43	68.7	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00], 1.13%	\$15,124 3.52%	[3, 0, 0, 3, 0, 3, 3, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 14.29, 12.00, 22.73], 75.81%
C4	+ 10	0.028	7,376.24	11,701.91	70.6	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00], 1.13%	\$15,302 3.56%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73], 80.57%
C0	0	0.029	7,380.30	11,706.48	70.9	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00], 1.13%	\$15,420 3.59%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73], 80.57%
C5	- 10	0.029	7,387.51	11,734.72	70.9	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00], 1.13%	\$15,658 3.65%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73], 80.57%
C6	- 20	0.030	7,431.62	11,778.16	74.3	[0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 2.00], 1.13%	\$16,850 3.92%	[3, 0, 0, 3, 0, 3, 4, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 31.82], 89.67%
C7	- 30	0.042	7,483.59	12,043.67	78.6	[0, 0, 0, 0, 0, 0, 1, 2] wk [0, 0, 0, 0, 0, 0, 1.00, 2.00], 2.58%	\$17,489 4.07%	[3, 0, 0, 3, 0, 3, 4, 3, 10] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 45.45], 103.30%
C8	- 40	0.043	7,565.03	12,741.53	85.3	[0, 0, 0, 0, 0, 0, 1, 2] wk [0, 0, 0, 0, 0, 0, 1.00, 2.00], 2.58%	\$18,702 4.36%	[3, 0, 0, 3, 0, 3, 6, 3, 10] [8.33, 0, 0, 9.09, 0, 9.38, 28.57, 12.00, 45.45], 112.83%

¹ Percentage deviation from each project's delay objective and total percentage deviation² Percentage deviation from the total cost target³ Percentage deviation from each project's quality score target and total percentage deviation

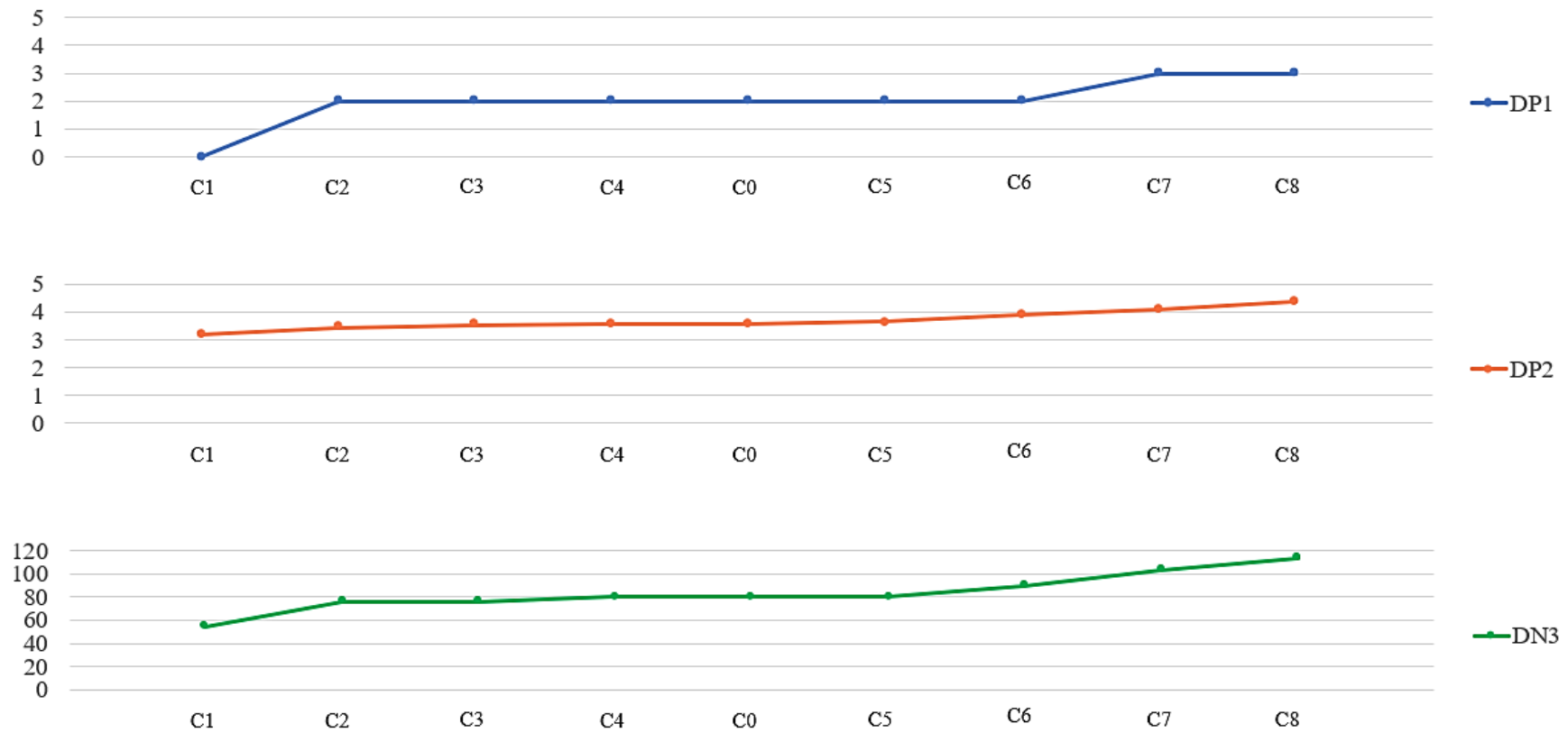


Figure 5.3 Total percentage deviations for the changes in the total resource capability

5.2.3 Changes in the Number of Resources

The CP model is evaluated using seven problem cases presented in Table 5.9 to analyze the changes in the number of resources, and total percentage deviations are drawn in Figure 5.4. The problem cases are generated by decreasing and increasing the number of resources with four increments relative to the original case C0. The resources with the most demanded skills are included, which are project management (S2), primary product design (S4), sub-component design (S5), and spare parts design (S6).

The change in the number of resources has a minor effect on the number of constraints and variables required. The objective function values improve from C0 to C6, while the average level of resource loading also goes down in this direction. This increase only affects the total cost deviation, except C6, with no delay for all projects. When we switch from C0 to C3, we can say that there is only a slight increase in the total cost, the other objectives being the same.

The resource loading level is acceptable in all cases compared to the 86% target. Thus, case C1 might be seen as alternative solutions that compromise resource loading and the company's tardiness, total cost, and quality score targets.

Table 5.9 Computational results for the changes in the number of resources

#	# Resources	# Constraints	# Variables	Obj	First Solution Time	Solution Time (s)	Resource Loading Level (%)	Deviational Variables		
								$DP1_p$	$DP2$	$DN3_p$
C1	32	1,020	497	0.030	7,411.74	11,729.12	75.6	[0, 0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$16,032 3.73%	[3, 0, 0, 3, 0, 3, 4, 3, 7] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 31.82] , 89.67%
C2	36	1,028	505	0.030	7,398.32	11,725.02	73.2	[0, 0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,679 3.65%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73] , 80.57%
C3	40	1,036	513	0.029	7,385.78	11,716.73	71.6	[0, 0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,445 3.60%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73] , 80.57%
C0	44	1,044	521	0.029	7,380.30	11,706.48	70.9	[0, 0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,420 3.59%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73] , 80.57%
C4	48	1,052	529	0.029	7,376.11	11,702.81	70.7	[0, 0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$15,326 3.57%	[3, 0, 0, 3, 0, 3, 4, 3, 3] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 13.64] , 71.48%
C5	52	1,060	537	0.028	7,361.95	11,645.92	67.9	[0, 0, 0, 0, 0, 0, 0, 0, 2] wk [0, 0, 0, 0, 0, 0, 0, 0, 2.00] , 1.13%	\$14,154 3.30%	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 19.05, 12.00, 22.73] , 80.57%
C6	56	1,068	545	0.017	7,355.83	11,641.17	64.2	[0, 0, 0, 0, 0, 0, 0, 0, 0] wk [0, 0, 0, 0, 0, 0, 0, 0, 0] , 0%	\$13,348 3.11%	[3, 0, 0, 3, 0, 3, 3, 3, 5] [8.33, 0, 0, 9.09, 0, 9.38, 14.29, 12.00, 22.73] , 75.81%

¹ Percentage deviation from each project's delay objective and total percentage deviation² Percentage deviation from the total cost target³ Percentage deviation from each project's quality score target and total percentage deviation

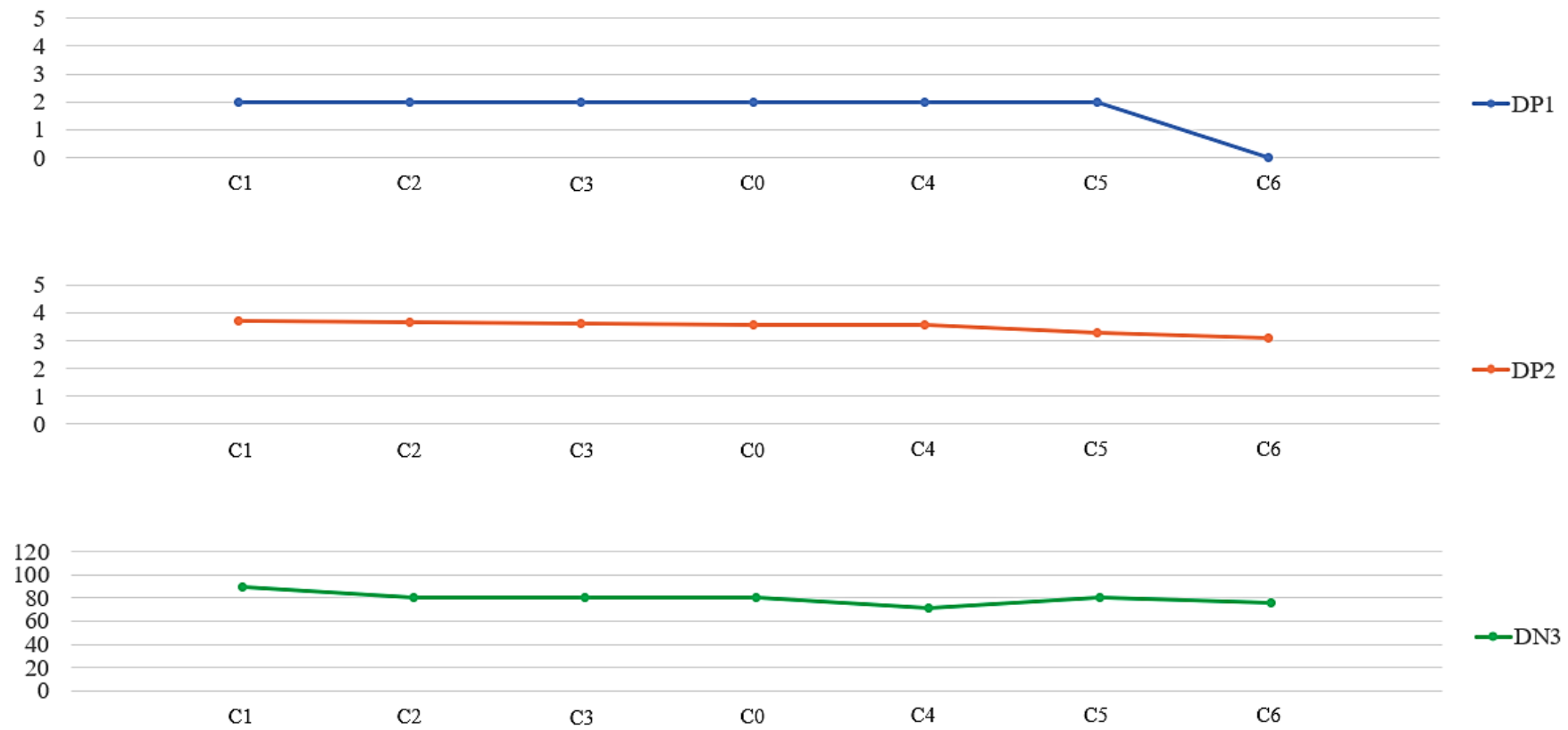


Figure 5.4 Total percentage deviations for the changes in the number of resources

5.2.4 Changes in the Objective Function Weights in Goal Attainment Technique

The goal attainment approach is applied for the problem as an alternative multi-objective solution technique. The objective weight coefficients are $W1 = 0.54$, $W2 = 0.30$ and $W3 = 0.16$ for project tardiness, project development cost, and project quality score. The project tardiness target value $G1$ equals the sum of all project tardiness values, which is zero. The targeted project development cost $G2$ is \$429,380. The targeted project quality score value $G3$ is the sum of all project quality scores equal to 265.

Second, the objective function G is minimized. Each objective function is entered into the constraints by multiplying the corresponding weights with the $G1$, $G2$, and $G3$ targets to reflect the deviation.

Minimize G

subject to:

$$Tardiness_p - W1 * G \leq G1, \forall p \quad (5.1)$$

$$\begin{aligned} & \sum_{p=1}^P \sum_{i=1}^I InvCost_{pi} * presenceOf(itvs_{pi}) + \\ & \sum_{p=1}^P \sum_{i=1}^I \sum_{k=1}^K FixedCost_k * \\ & heightAtStart(itvs_{pi}, ResourceUsage_k) + \sum_{k=1}^K OverCapCost_k * \\ & Ssurp_k - W2 * G \leq G2 \end{aligned} \quad (5.2)$$

$$PQRatio_p + W3 * G \geq G3, \forall p \quad (5.3)$$

The CP model is evaluated with twelve problem cases in Table 5.10 to analyze the objective weights' changes, and total percentage deviations are drawn in Figure 5.5. Case C0 refers to the real-life problem. The problem cases are generated in the same way according to changes in objective weights as in goal programming.

The percentage deviation from project development cost varies between 3.54-3.59% for all cases. The deviation from project tardiness reduces from 2 to 0 weeks from C7 to C12, while the deviation from the total project quality increases. Here, the deviation of project quality score increases for projects P7 and P9, which have low relative importance weight among all projects. The company can tolerate deviation from the total project quality score in C9 and C10 for the sake of a 2 weeks reduction in the deviation from project tardiness. Thus, the problem cases' objective function weights can be considered to reduce project tardiness and keep good quality in important projects.

According to the computational results, it is clear that the number of constraints and variables is slightly reduced with the goal attainment technique compared to the weighted goal programming method. The goal attainment technique solves the problem cases 10% faster than goal programming due to reduced constraints and variables. The deviations in the initial case C0 are found as same as in goal programming. The goal attainment technique is more sensitive to objective weight changes in tardiness than the goal programming technique which is sensitive to objective weight changes in project cost. The company can also consider the goal attainment technique to analyze the impact of changes on the objective weights.

Table 5.10 Computational results for the changes in objective function weights in goal attainment technique

#	W1	W2	W3	Obj (G)	First Solution Time	Solution Time (s)	Resource Loading Level (%)	Deviation Variables		
								$DP1_p$	$DP2$	$DN3_p$
C0	0.54	0.30	0.16	1,525	7,555.21	10,512.34	70.7	[0, 0, 0, 0, 0, 0, 0, 0, 2] [0, 0, 0, 0, 0, 0, 0, 0, 2], 2 ¹	15,420 3.6 ²	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8, 0, 0, 9, 0, 9, 19, 12, 23], 8 ³
C1	0.53	0.31	0.16	1,525	7,543.78	10,508.93	70.7	[0, 0, 0, 0, 0, 0, 0, 0, 2] [0, 0, 0, 0, 0, 0, 0, 0, 2], 2	15,326 3.6	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8, 0, 0, 9, 0, 9, 19, 12, 23], 8
C2	0.52	0.32	0.16	1,525	7,520.34	10,497.12	70.7	[0, 0, 0, 0, 0, 0, 0, 0, 2] [0, 0, 0, 0, 0, 0, 0, 0, 2], 2	15,291 3.6	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8, 0, 0, 9, 0, 9, 19, 12, 23], 8
C3	0.51	0.33	0.16	1,525	7,506.12	10,470.43	70.5	[0, 0, 0, 0, 0, 0, 0, 0, 2] [0, 0, 0, 0, 0, 0, 0, 0, 2], 2	15,277 3.6	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8, 0, 0, 9, 0, 9, 19, 12, 23], 8
C4	0.50	0.34	0.16	1,525	7,497.45	10,465.11	70.4	[0, 0, 0, 0, 0, 0, 0, 0, 2] [0, 0, 0, 0, 0, 0, 0, 0, 2], 2	15,251 3.6	[3, 0, 0, 3, 0, 3, 4, 3, 5] [8, 0, 0, 9, 0, 9, 19, 12, 23], 8
C5	0.54	0.31	0.15	1,525	7,547.13	10,506.83	70.5	[0, 0, 0, 0, 0, 0, 0, 0, 2] [0, 0, 0, 0, 0, 0, 0, 0, 2], 2	15,286 3.6	[3, 0, 0, 5, 0, 3, 7, 5, 10] [8, 0, 0, 15, 0, 9, 33, 20, 45], 12
C6	0.54	0.32	0.14	1,467	7,530.79	10,497.82	70.4	[0, 0, 0, 0, 0, 0, 0, 0, 2] [0, 0, 0, 0, 0, 0, 0, 0, 2], 2	15,214 3.6	[3, 0, 0, 5, 0, 3, 7, 5, 10] [8, 0, 0, 15, 0, 9, 33, 20, 45], 12
C7	0.54	0.33	0.13	1,373	7,512.56	10,485.38	70.4	[0, 0, 0, 0, 0, 0, 0, 0, 1] [0, 0, 0, 0, 0, 0, 0, 0, 1], 1	15,187 3.6	[3, 0, 0, 5, 0, 3, 7, 5, 10] [8, 0, 0, 15, 0, 9, 33, 20, 45], 12
C8	0.54	0.34	0.12	1,327	7,497.07	10,479.61	70.2	[0, 0, 0, 0, 0, 0, 0, 0, 1] [0, 0, 0, 0, 0, 0, 0, 0, 1], 1	15,157 3.6	[3, 0, 0, 5, 0, 3, 7, 5, 13] [8, 0, 0, 15, 0, 9, 33, 20, 59], 14
C9	0.55	0.30	0.15	1,467	7,502.73	10,495.28	70.6	[0, 0, 0, 0, 0, 0, 0, 0, 0] [0, 0, 0, 0, 0, 0, 0, 0, 0], 0	15,388 3.6	[3, 0, 0, 3, 0, 3, 4, 3, 7] [8, 0, 0, 9, 0, 9, 19, 12, 32], 9
C10	0.56	0.30	0.14	1,443	7,486.98	10,487.03	70.6	[0, 0, 0, 0, 0, 0, 0, 0, 0] [0, 0, 0, 0, 0, 0, 0, 0, 0], 0	15,375 3.6	[3, 0, 0, 3, 0, 3, 4, 3, 7] [8, 0, 0, 9, 0, 9, 19, 12, 32], 9
C11	0.57	0.30	0.13	1,437	7,470.37	10,472.34	70.4	[0, 0, 0, 0, 0, 0, 0, 0, 0] [0, 0, 0, 0, 0, 0, 0, 0, 0], 0	15,354 3.6	[3, 0, 0, 5, 0, 3, 7, 5, 10] [8, 0, 0, 15, 0, 9, 33, 20, 45], 12
C12	0.58	0.30	0.12	1,434	7,459.36	10,461.97	70.1	[0, 0, 0, 0, 0, 0, 0, 0, 0] [0, 0, 0, 0, 0, 0, 0, 0, 0], 0	15,332 3.6	[3, 0, 0, 5, 0, 3, 7, 5, 13] [8, 0, 0, 15, 0, 9, 33, 20, 59], 14

¹ Percentage deviations from project tardiness target, and total percentage deviation² Percentage deviation from project development costs target³ Percentage deviations from project quality score target, and average percentage deviation

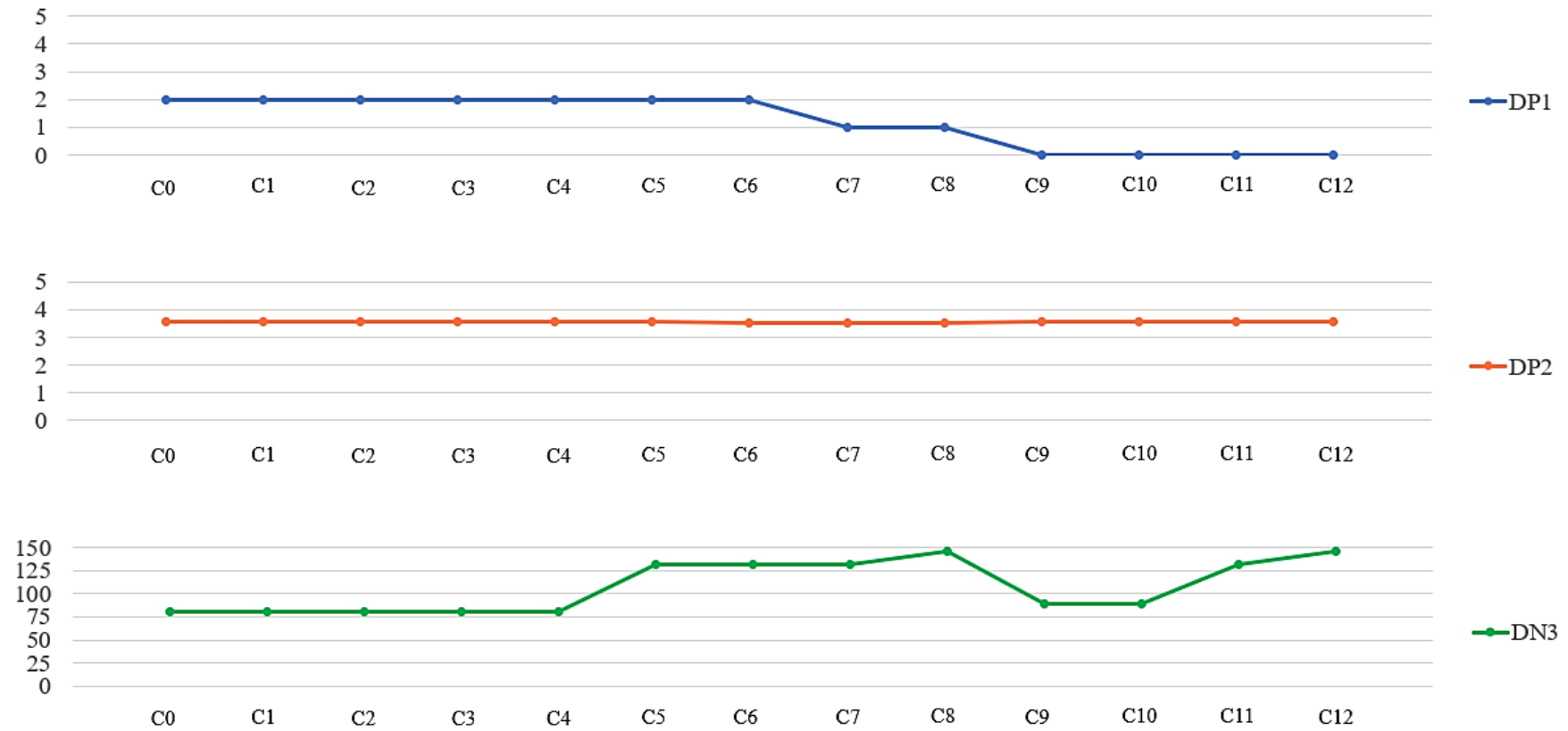


Figure 5.5 Total percentage deviations for the changes in the objective function weights in goal attainment technique

CHAPTER SIX

CONCLUSION

Most researchers have studied single-objective single-project resource-constrained scheduling problems. However, the companies' intensive research and development activities require the execution of multiple projects simultaneously to meet more than one business objective for customer requirements. There are not many studies that address multi-objective multi-project scheduling problems with skill- and capability-based resource constraints.

In this thesis, the following questions are investigated to find good-quality solutions (optimal or feasible) for multi-objective, multi-project, and multi-skill resource-constrained scheduling problems:

- What is the amount of resource capacity required to meet the project schedule based on the task start time and finish time, processing time, and precedence relationships?
- What is the excess amount of resources consumed while the project is running?
- How are resources assigned to the tasks based on their skills, capacity, and capability to substitute other resources and take more than one different task?
- How are the good-quality solutions impacted if managerial decisions would change based on resources, resources' capability, and selected multi-objective techniques?

RCMPSP is defined as a non-deterministic polynomial-time hard (NP-hard) project scheduling problem. It is mostly focused on developing heuristic approaches to this problem. A few researchers present mathematical programming models with discrete-time MILP and continuous-time event-based MILP formulations. Moreover, CP formulation is not developed for the multi-skill, multi-objective RCMPSP to date. The most significant limitation for the mentioned mathematical formulations is the number of constraints and variables, making the procedure too difficult to solve real-life problems.

In this thesis, discrete-time MILP, continuous-time event-based MILP and CP formulations are developed with simplified time and event constraints and extensions with an excessive resource usage constraint. Additionally, CP formulation is improved with variable ordering, value ordering, and search strategies to provide better performance than the pure formulation. The reduction in the number of variables and constraints results in optimum solutions, which increases the applicability of MILP and CP formulations for small, mid-and large-size problems.

All formulations are evaluated with test instances generated and solved to make a comparative study based on their performances. According to the computational results, it is clear that continuous-time event-based MILP provides better results than discrete-time MILP. Also, CP using fewer constraints and variables provides better results compared to the MILP formulations. Consequently, CP performs 63% faster than discrete-time MILP and 29% faster than event-based MILP formulation by finding optimum results for small, medium and large instances.

Finally, the real-life problem is solved with the improved CP model using goal programming and goal attainment as multi-objective approaches. The objective weights, the number of resources, and resource capabilities are changed, and managerial implications are driven to provide better management insight. According to the results, the company can reduce project development costs and project tardiness by compromising the total project quality score. Human resources' training needs can be analyzed to increase their capability, or hiring new employees can be considered alternatively. The company can use the goal attainment technique to analyze given managerial decisions quickly.

Future research may focus on developing heuristics and metaheuristic approaches for solving this problem. Additionally, learning and forgetting curves for resources, transfer times between tasks and projects, multi-mode characteristics, alternative multi-objective techniques such as preemptive goal programming, and different objective weights per project can be considered.

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APPENDICES

APPENDIX 3.1: Discrete-Time Mixed-Integer Linear Programming Model

```
using CPLEX;

int nbProjects =...;
int nbTasks    =...;
int nbTime     =...;
int nbResources =...;
int nbSkills   =...;

tuple AllTaskSets {
    key int projectid;
    key int alltaskid;}
{AllTaskSets} AllTaskSet=...;

tuple PreTaskSets {
    int precprojectid;
    int beforeid;
    int afterid;};
{PreTaskSets} PreTaskSet=...;

tuple ManTaskSets {
    key int manprojectid;
    key int  mantaskid;};
{ManTaskSets} ManTaskSet=...;

tuple OptTaskSets {
    key int optprojectid;
    key int  opttaskid;};
{OptTaskSets} OptTaskSet=...;

tuple SkillSets {
    key int resourceid;
    key int  skillid;};
{SkillSets} SkillSet=...;

int DueDate[1..nbProjects]=...;
int G1[1..nbProjects]=...;
float WP[1..nbProjects]=...;
float W1=...;
float W2=...;
float W3=...;
int G2=...;
int G3[1..nbProjects]=...;

int FixedCost[1..nbResources]=...;
int OverCapCost[1..nbResources]=...;
int RMAX[1..nbResources]=...;
int PT[1..nbProjects][1..nbTasks]=...;
int EST[1..nbProjects][1..nbTasks]=...;
int EFT[1..nbProjects][1..nbTasks]=...;

int InvCost[1..nbProjects][1..nbTasks]=...;
int QRatio[1..nbProjects][1..nbTasks]=...;
```

```

int
BRatio[1..nbProjects][1..nbTasks][1..nbResources][1..nbSkills]=...;
int
Capability[1..nbProjects][1..nbTasks][1..nbResources][1..nbSkills]=.
...;

dvar int+ Tardiness[P in 1..nbProjects];
dvar int+ MaxCompTime[P in 1..nbProjects];
dvar int+ DP1[P in 1..nbProjects];
dvar int+ DP2;
dvar int+ PQRatio[1..nbProjects];
dvar int+ DN3[P in 1..nbProjects];

dvar boolean XS[1..nbProjects][1..nbTasks][1..nbTime];
dvar boolean XF[1..nbProjects][1..nbTasks][1..nbTime];
dvar int+ R[1..nbResources][1..nbTime];
dvar int+ SSURP[1..nbResources][1..nbTime];

execute{cplex.tilim=36000;}

minimize W1*(sum(P in 1..nbProjects) WP[P]*DP1[P]) + W2*DP2/G2 +
W3*(sum(P in 1..nbProjects) WP[P]*DN3[P]/G3[P]);

subject to{

forall(P in 1..nbProjects)
    Tardiness[P]-DP1[P]==G1[P];
forall(P in 1..nbProjects)
    Tardiness[P]>= MaxCompTime[P]-DueDate[P];
forall(P in AllTaskSet, T in 1..nbTime)
    MaxCompTime[P.projectid]>=T*XF[P.projectid][P.alltaskid][T];

sum(P in OptTaskSet, T in 1..nbTime)
InvCost[P.optprojectid][P.opttaskid]*XS[P.optprojectid][P.opttaskid]
[T]+sum(K in 1..nbResources, T in 1..nbTime)
FixedCost[K]*R[K][T]+sum(K in 1..nbResources, T in 1..nbTime)
OverCapCost[K]*SSURP[K][T]-DP2==G2;

forall(P in 1..nbProjects)
    PQRatio[P]+DN3[P]==G3[P];
forall(P in 1..nbProjects)
    PQRatio[P]==sum(I in 1..nbTasks, T in 1..nbTime: T>=EST[P][I])
    QRatio[P][I]*XS[P][I][T];

forall(P in ManTaskSet) sum(T in 1..nbTime:
T>=EST[P.manprojectid][P.mantaskid])
XS[P.manprojectid][P.mantaskid][T]==1;
forall(P in ManTaskSet) sum(T in 1..nbTime:
T>=EFT[P.manprojectid][P.mantaskid])
XF[P.manprojectid][P.mantaskid][T]==1;
forall(P in OptTaskSet) sum(T in 1..nbTime:
T>=EST[P.optprojectid][P.opttaskid])
XS[P.optprojectid][P.opttaskid][T]<=1;
forall(P in OptTaskSet) sum(T in 1..nbTime:
T>=EFT[P.optprojectid][P.opttaskid])
XF[P.optprojectid][P.opttaskid][T]<=1;

forall(P in AllTaskSet) sum(T in 1..nbTime:
T>=EST[P.projectid][P.alltaskid])

```

```

(T*XS[P.projectid][P.alltaskid][T]+PT[P.projectid][P.alltaskid]*XS[P
.projectid][P.alltaskid][T])==sum(T in 1..nbTime:
T>=EFT[P.projectid][P.alltaskid])
(T*XF[P.projectid][P.alltaskid][T]);

forall(P in PreTaskSet) sum(T in 1..nbTime:
T>=EST[P.precprojectid][P.afterid]) (T*XS[P.precprojectid][P.afterid]
[T])>=sum(T in 1..nbTime:
T>=EST[P.precprojectid][P.beforeid]) (T*XS[P.precprojectid][P.beforei
d][T]+PT[P.precprojectid][P.beforeid]*XS[P.precprojectid][P.beforeid
][T]);

forall(K in 1..nbResources, T in 1..nbTime: T>1) (R[K][T]-R[K][T-
1])== sum(P in AllTaskSet, S in 1..nbSkills:
T>=EST[P.projectid][P.alltaskid])
(BRatio[P.projectid][P.alltaskid][K][S]*XS[P.projectid][P.alltaskid]
[T]*Capability[P.projectid][P.alltaskid][K][S])-sum(P in AllTaskSet,
S in 1..nbSkills: T>=EFT[P.projectid][P.alltaskid])
(BRatio[P.projectid][P.alltaskid][K][S]*XF[P.projectid][P.alltaskid]
[T-1]*Capability[P.projectid][P.alltaskid][K][S]);

forall(K in 1..nbResources, T in 1..nbTime) R[K][T]-
SSURP[K][T]<=RMAX[K];}

```

APPENDIX 3.2: Continuous-Time Event-Based Mixed-Integer Linear Programming Model

```
int nbProjects   =...;
int nbTasks      =...;
int nbEvent       =...;
int nbResources  =...;
int nbSkills     =...;

tuple AllTaskSets {
    key int projectid;
    key int alltaskid;}
{AllTaskSets} AllTaskSet=...;

tuple PreTaskSets {
    int precprojectid;
    int beforeid;
    int afterid;};
{PreTaskSets} PreTaskSet=...;

tuple ManTaskSets {
    key int manprojectid;
    key int mantaskid;}
{ManTaskSets} ManTaskSet=...;

tuple OptTaskSets {
    key int optprojectid;
    key int opttaskid;}
{OptTaskSets} OptTaskSet=...;

tuple SkillSets {
    key int resourceid;
    key int skillid;}
{SkillSets} SkillSet=...;

int DueDate[1..nbProjects]=...;
int G1[1..nbProjects]=...;
float WP[1..nbProjects]=...;
float W1=...;
float W2=...;
float W3=...;
int G2=...;
int G3[1..nbProjects]=...;

int FixedCost[1..nbResources]=...;
int OverCapCost[1..nbResources]=...;
int RMAX[1..nbResources]=...;
int PT[1..nbProjects][1..nbTasks]=...;
int EST[1..nbProjects][1..nbTasks]=...;
int EFT[1..nbProjects][1..nbTasks]=...;

int InvCost[1..nbProjects][1..nbTasks]=...;
int QRatio[1..nbProjects][1..nbTasks]=...;
int
BRatio[1..nbProjects][1..nbTasks][1..nbResources][1..nbSkills]=...;
```

```

int
Capability[1..nbProjects][1..nbTasks][1..nbResources][1..nbSkills]=.
...;

dvar int+ Tardiness[P in 1..nbProjects];
dvar int+ MaxCompTime[P in 1..nbProjects];
dvar int+ DP1[P in 1..nbProjects];
dvar int+ DP2;
dvar int+ PQRatio[1..nbProjects];
dvar int+ DN3[P in 1..nbProjects];

dvar boolean XS[1..nbProjects][1..nbTasks][1..nbEvent];
dvar boolean XF[1..nbProjects][1..nbTasks][1..nbEvent];
dvar int+ TS[1..nbProjects][1..nbTasks][1..nbEvent];
dvar int+ TF[1..nbProjects][1..nbTasks][1..nbEvent];
dvar int+ R[1..nbResources][1..nbEvent];
dvar int+ SSURP[1..nbResources][1..nbEvent];

execute{cplex.tilim=36000;}

minimize W1*(sum(P in 1..nbProjects) WP[P]*DP1[P]) + W2*DP2/G2 +
W3*(sum(P in 1..nbProjects) WP[P]*DN3[P]/G3[P]);

subject to{

forall(P in 1..nbProjects)
    Tardiness[P]-DP1[P]==G1[P];
forall(P in 1..nbProjects)
    Tardiness[P]>= MaxCompTime[P]-DueDate[P];
forall(P in AllTaskSet, E in 1..nbEvent)
    MaxCompTime[P.projectid]>=TF[P.projectid][P.alltaskid][E];

sum(P in OptTaskSet, E in 1..nbEvent)
InvCost[P.optprojectid][P.opttaskid]*XS[P.optprojectid][P.opttaskid]
[E]+sum(K in 1..nbResources, E in 1..nbEvent)
FixedCost[K]*R[K][E]+sum(K in 1..nbResources, E in 1..nbEvent)
OverCapCost[K]*SSURP[K][E]-DP2==G2;

forall(P in 1..nbProjects)
    PQRatio[P]+DN3[P]==G3[P];
forall(P in 1..nbProjects)
    PQRatio[P]==sum(I in 1..nbTasks, E in 1..nbEvent)
QRatio[P][I]*XS[P][I][E];

forall(P in ManTaskSet) sum(E in 1..nbEvent)
XS[P.manprojectid][P.mantaskid][E]==1;
forall(P in ManTaskSet) sum(E in 1..nbEvent)
XF[P.manprojectid][P.mantaskid][E]==1;
forall(P in OptTaskSet) sum(E in 1..nbEvent)
XS[P.optprojectid][P.opttaskid][E]<=1;
forall(P in OptTaskSet) sum(E in 1..nbEvent)
XF[P.optprojectid][P.opttaskid][E]<=1;

forall(P in AllTaskSet, E in 1..nbEvent) sum(V in 1..nbEvent: V<E)
XS[P.projectid][P.alltaskid][V]-sum(V in 1..nbEvent: V<=E)
XF[P.projectid][P.alltaskid][V]==0;

forall(P in AllTaskSet, E in 1..nbEvent)
TS[P.projectid][P.alltaskid][E]>=EST[P.projectid][P.alltaskid];

```

```

forall(P in AllTaskSet, E in 1..nbEvent)
TF[P.projectid][P.alltaskid][E]>=EFT[P.projectid][P.alltaskid];
forall(P in AllTaskSet, E in 1..nbEvent)
TS[P.projectid][P.alltaskid][E]+PT[P.projectid][P.alltaskid]*XS[P.pr
ojectid][P.alltaskid][E]==TF[P.projectid][P.alltaskid][E];

forall(P in PreTaskSet) sum(E in
1..nbEvent) (TS[P.precprojectid][P.afterid][E])>=sum(E in 1..nbEvent)
(TS[P.precprojectid][P.beforeid][E]+PT[P.precprojectid][P.beforeid]*
XS[P.precprojectid][P.beforeid][E]);
forall(P in PreTaskSet, E in
1..nbEvent) (XS[P.precprojectid][P.afterid][E])-sum(V in 1..nbEvent:
V<=E) (XF[P.precprojectid][P.beforeid][V])<=1-
XS[P.precprojectid][P.afterid][E];

forall(K in 1..nbResources, E in 1..nbEvent: E>1) (R[K][E]-R[K][E-
1])=sum(P in AllTaskSet, S in 1..nbSkills)
(BRatio[P.projectid][P.alltaskid][K][S]*XS[P.projectid][P.alltaskid]
[E-1]*Capability[P.projectid][P.alltaskid][K][S])-
sum(P in AllTaskSet, S in 1..nbSkills)
(BRatio[P.projectid][P.alltaskid][K][S]*XF[P.projectid][P.alltaskid]
[E-1]*Capability[P.projectid][P.alltaskid][K][S]);

forall(K in 1..nbResources, E in 1..nbEvent) R[K][E]-
SSURP[K][E]<=RMAX[K];}

```

APPENDIX 3.3: Constraint Programming Model

```
using CP;

int nbProjects =...;
int nbTasks =...;
int nbResources =...;
int nbSkills =...;

tuple AllTaskSets {
    key int projectid;
    key int alltaskid;}
{AllTaskSets} AllTaskSet=...;

tuple PreTaskSets {
    int precprojectid;
    int beforeid;
    int afterid;};
{PreTaskSets} PreTaskSet=...;

tuple ManTaskSets {
    key int manprojectid;
    key int mantaskid;}
{ManTaskSets} ManTaskSet=...;

tuple OptTaskSets {
    key int optprojectid;
    key int opttaskid;}
{OptTaskSets} OptTaskSet=...;

tuple SkillSets {
    key int resourceid;
    key int skillid;}
{SkillSets} SkillSet=...;

int DueDate[1..nbProjects]=...;
int G1[1..nbProjects]=...;
float WP[1..nbProjects]=...;
float W1=...;
float W2=...;
float W3=...;
int G2=...;
int G3[1..nbProjects]=...;

int FixedCost[1..nbResources]=...;
int OverCapCost[1..nbResources]=...;
int RMAX[1..nbResources]=...;
int PT[1..nbProjects][1..nbTasks]=...;
int EST[1..nbProjects][1..nbTasks]=...;
int EFT[1..nbProjects][1..nbTasks]=...;

int InvCost[1..nbProjects][1..nbTasks]=...;
int QRatio[1..nbProjects][1..nbTasks]=...;
int
BRatio[1..nbProjects][1..nbTasks][1..nbResources][1..nbSkills]=...;
```

```

int
Capability[1..nbProjects][1..nbTasks][1..nbResources][1..nbSkills]=.
..;

dvar int+ Tardiness[P in 1..nbProjects];
dvar int+ MaxCompTime[P in 1..nbProjects];
dvar int+ DP1[P in 1..nbProjects];
dvar int+ DP2;
dvar int+ PQRatio[1..nbProjects];
dvar int+ DN3[P in 1..nbProjects];

dvar interval itvs[P in 1..nbProjects][I in 1..nbTasks] in
EST[P][I]..EFT[P][I] size PT[P][I];
dvar int+ R[K in 1..nbResources];
dvar int+ SSURP[K in 1..nbResources];

cumulFunction ResourceUsage[K in 1..nbResources]=
sum(P in 1..nbProjects, I in 1..nbTasks, S in 1..nbSkills)
pulse(itvs[P][I], BRatio[P][I][K][S]*Capability[P][I][K][S]);

execute{cp.param.timelimit=36000;}

minimize W1*(sum(P in 1..nbProjects) WP[P]*DP1[P]) + W2*DP2/G2 +
W3*(sum(P in 1..nbProjects) WP[P]*DN3[P]/G3[P]);

subject to{

forall(P in 1..nbProjects)
    Tardiness[P]-DP1[P]==G1[P];
forall(P in 1..nbProjects)
    Tardiness[P]>= MaxCompTime[P]-DueDate[P];
forall(P in AllTaskSet)
    MaxCompTime[P.projectid]>=endOf(itvs[P.projectid][P.alltaskid]);

sum(P in OptTaskSet)
InvCost[P.optprojectid][P.opttaskid]*presenceOf(itvs[P.optprojectid]
[P.opttaskid])+sum(P in 1..nbProjects, I in 1..nbTasks, K in
1..nbResources)
FixedCost[K]*heightAtStart(itvs[P][I], ResourceUsage[K])+sum(P in
1..nbProjects, I in 1..nbTasks, K in 1..nbResources)
FixedCost[K]*PT[P][I]*heightAtStart(itvs[P][I], ResourceUsage[K])+sum
(K in 1..nbResources) OverCapCost[K]*SSURP[K]-DP2==G2;;

forall(P in 1..nbProjects)
    PQRatio[P]+DN3[P]==G3[P];
forall(P in 1..nbProjects)
    PQRatio[P]==sum(I in 1..nbTasks)
QRatio[P][I]*presenceOf(itvs[P][I]);

forall(P in ManTaskSet)
    presenceOf(itvs[P.manprojectid][P.mantaskid])==1;
forall(P in OptTaskSet)
    presenceOf(itvs[P.optprojectid][P.opttaskid])<=1;

forall(J in PreTaskSet)
endBeforeStart(itvs[J.precprojectid][J.beforeid], itvs[J.precprojecti
d][J.afterid]);

forall(K in 1..nbResources)

```

```

R[K]>=ResourceUsage[K];

forall(K in 1..nbResources)
  R[K]-SSURP[K]<=RMAX[K];}

execute {
var f = cp.factory;
var multiPhaseVar = new
Array(f.selectLargest(f.impactofLastBranch()),f.selectRandomVar());
var multiPhaseValue = new
Array(f.selectLargest(f.valueImpact()),f.selectRandomValue());
var phase4 = f.searchPhase(multiPhaseVar,multiPhaseValue);
cp.param.SearchType= 26;
var p = cp.param;
cp.param.FailLimit = 4000;}

```



APPENDIX 4.1: Summary of the second test instance parameters

P	I	J (Pred.)	Type	PT _{pi}	EST _{pi}	EFT _{pi}	DT _{pi}	QRatio _{pi}	InvCost _{pi}	BRatio _{pi11}	BRatio _{pi22}	BRatio _{pi32}
1	1	–	M	5	0	7	33	–	–	5	7	7
	2	–	M	4	0	7		–	–	6	9	5
	3	–	M	5	1	7		–	–	7	7	5
	4	1	M	2	7	11		–	–	9	6	10
	5	2	M	4	4	8		–	–	8	8	4
	6	2	M	3	6	11		–	–	7	9	2
	7	3	M	4	6	11		–	–	4	6	2
	8	4, 5, 6	M	3	8	15		–	–	7	9	10
	9	8	M	4	13	20		–	–	8	2	2
	10	7	M	4	15	19		–	–	7	1	7
	11	7	M	5	10	20		–	–	4	7	9
	12	9, 10	M	2	15	21		–	–	6	6	1
	13	10, 11	O	5	15	25		3	2,869	2	5	6
	14	12	O	5	17	27		2	2,554	2	4	1
	15	13, 14	O	2	22	28		1	1,874	4	4	1

APPENDIX 4.2: Summary of the second test instance parameters (cont.)

P	I	J (Pred.)	Type	PT _{pi}	EST _{pi}	EFT _{pi}	DT _{pi}	QRatio _{pi}	InvCost _{pi}	BRatio _{pi11}	BRatio _{pi22}	BRatio _{pi32}
2	1	–	M	3	2	7	35	–	–	3	10	4
	2	1	M	6	5	11		–	–	6	7	3
	3	2	M	3	14	19		–	–	8	10	6
	4	2	M	4	11	17		–	–	3	8	6
	5	3	M	3	14	22		–	–	1	8	5
	6	3	M	4	14	21		–	–	4	3	4
	7	4	M	2	16	21		–	–	1	1	10
	8	7	O	2	17	20		1	3,098	4	9	8
	9	7	O	6	17	25		3	4,870	8	2	1
	10	8, 9	O	2	23	26		1	4,275	2	10	2
	11	5	M	2	17	23		–	–	9	9	10
	12	6	O	4	18	25		1	3,166	5	8	6
	13	10, 11, 12	O	2	25	28		3	2,944	4	9	8
	14	13	O	2	23	30		1	2,967	5	7	7
	15	13	O	2	27	30		2	1,433	9	7	3

APPENDIX 4.3: Summary of the third test instance parameters

P	I	J (Pred.)	Type	PT _{pi}	EST _{pi}	EFT _{pi}	DT _{pi}	QRatio _{pi}	InvCost _{pi}	BRatio _{pi11}	BRatio _{pi21}	BRatio _{pi32}	BRatio _{pi42}
1	1	—	M	5	0	7	50	—	—	5	7	7	5
	2	—	M	4	0	7		—	—	6	9	4	6
	3	—	M	5	1	7		—	—	7	5	5	7
	4	1	M	2	7	11		—	—	9	9	10	9
	5	2	M	4	4	8		—	—	9	8	4	9
	6	2	M	3	6	11		—	—	7	4	2	7
	7	3	M	4	6	11		—	—	4	4	2	4
	8	4, 5, 6	M	3	8	15		—	—	7	9	10	7
	9	8	M	4	13	20		—	—	9	2	2	9
	10	7	M	4	15	19		—	—	7	1	8	7
	11	7	M	5	10	20		—	—	4	7	9	4
	12	9, 10	M	2	15	21		—	—	6	6	1	6
	13	10, 11	O	5	15	25		3	2,869	2	5	6	2
	14	12	O	5	17	27		2	2,554	2	4	1	2
	15	13, 14	O	2	22	28		1	1,874	4	4	1	4

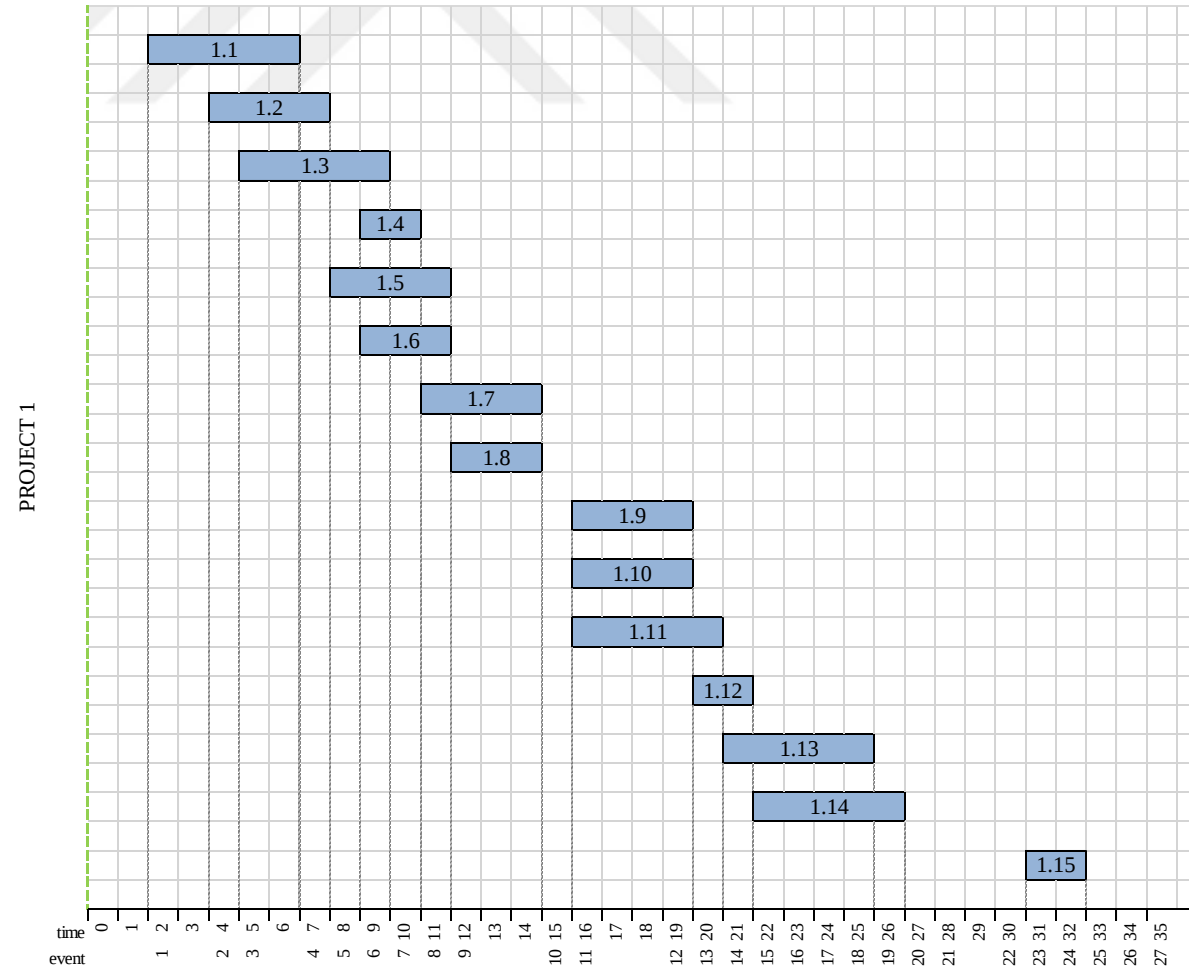
APPENDIX 4.4: Summary of the third test instance parameters (cont.)

P	I	J (Pred.)	Type	PT _{pi}	EST _{pi}	EFT _{pi}	DT _{pi}	QRatio _{pi}	InvCost _{pi}	BRatio _{pi11}	BRatio _{pi21}	BRatio _{pi32}	BRatio _{pi42}
2	1	—	M	3	2	7	50	—	—	3	4	4	10
	2	1	M	6	5	11		—	—	5	7	3	7
	3	2	M	3	14	19		—	—	8	4	6	10
	4	2	M	4	11	17		—	—	3	8	6	8
	5	3	M	3	14	22		—	—	1	8	5	8
	6	3	M	4	14	21		—	—	4	3	4	3
	7	4	M	2	16	21		—	—	1	1	10	1
	8	7	O	2	17	20		1	3,098	4	9	8	9
	9	7	O	6	17	25		3	4,870	8	2	1	2
	10	8, 9	O	2	23	26		1	4,275	2	10	2	10
	11	5	M	2	17	23		—	—	9	9	10	9
	12	6	O	4	18	25		1	3,166	5	8	6	8
	13	10, 11, 12	O	2	25	28		3	2,944	4	9	8	9
	14	13	O	2	23	30		1	2,967	5	7	7	7
	15	13	O	2	27	30		2	1,433	9	7	3	7

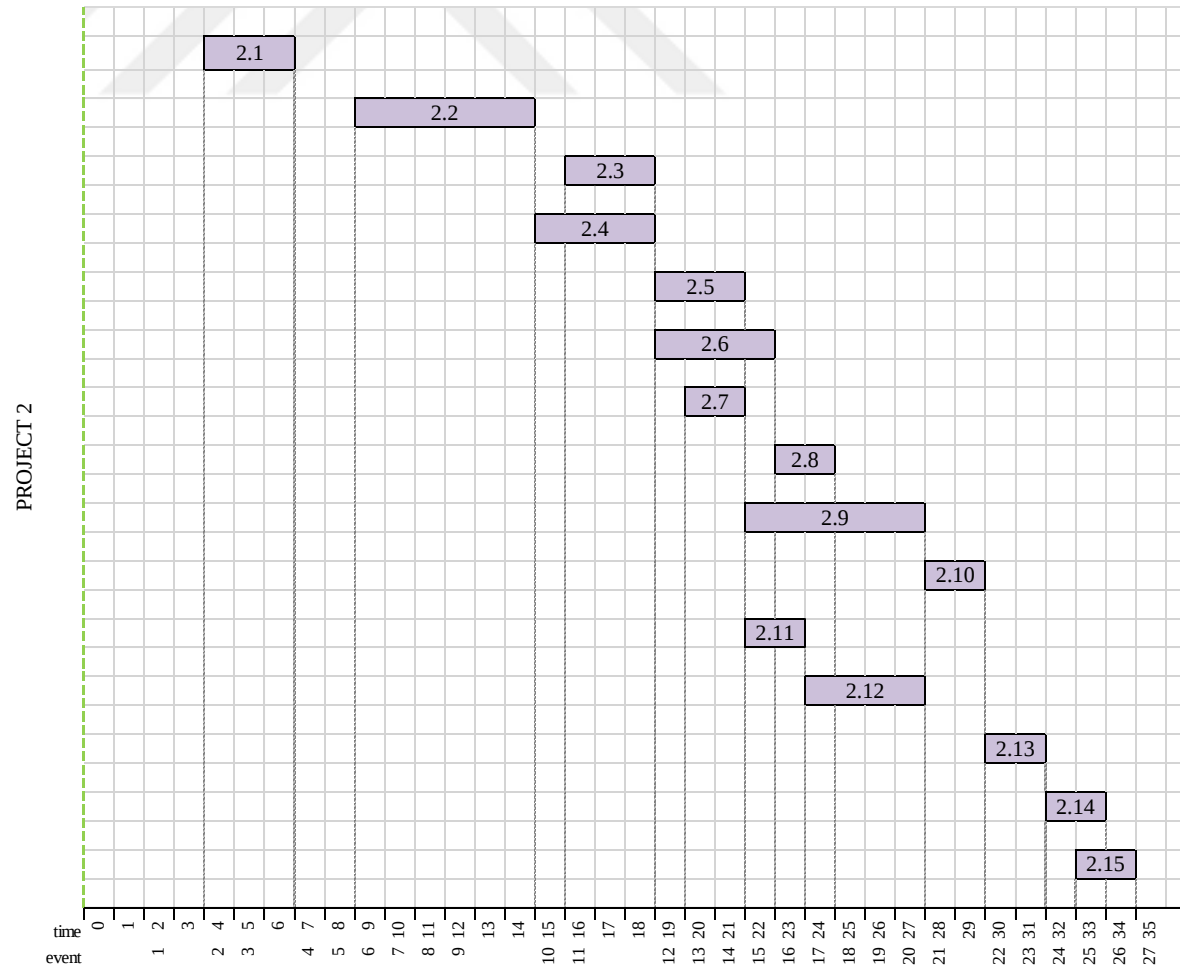
APPENDIX 4.5: Summary of the third test instance parameters (cont.)

P	I	J (Pred.)	Type	PT_{pi}	EST_{pi}	EFT_{pi}	DT_{pi}	QRatio_{pi}	InvCost_{pi}	BRatio_{pi11}	BRatio_{pi21}	BRatio_{pi32}	BRatio_{pi42}
3	1	–	M	5	0	5	50	–	–	5	7	7	7
	2	–	M	2	1	3		–	–	6	9	5	5
	3	1	M	2	6	8		–	–	7	6	5	5
	4	2	M	3	4	7		–	–	9	4	10	10
	5	3, 4	M	4	8	12		–	–	9	8	4	4
	6	5	M	6	13	19		–	–	7	9	2	2
	7	6	M	3	19	22		–	–	4	9	2	2
	8	6	M	2	19	21		–	–	3	1	10	10
	9	7, 8	M	6	25	31		–	–	9	2	2	2
	10	9	M	5	31	36		–	–	7	1	8	8
	11	10	M	4	37	41		–	–	4	7	9	9
	12	11	O	2	41	43		1	3,166	6	6	1	1
	13	11	O	2	41	43		3	2,944	2	5	6	6
	14	12	O	3	43	46		1	2,967	2	4	1	1
	15	13, 14	O	4	46	50		2	1,433	4	4	1	1

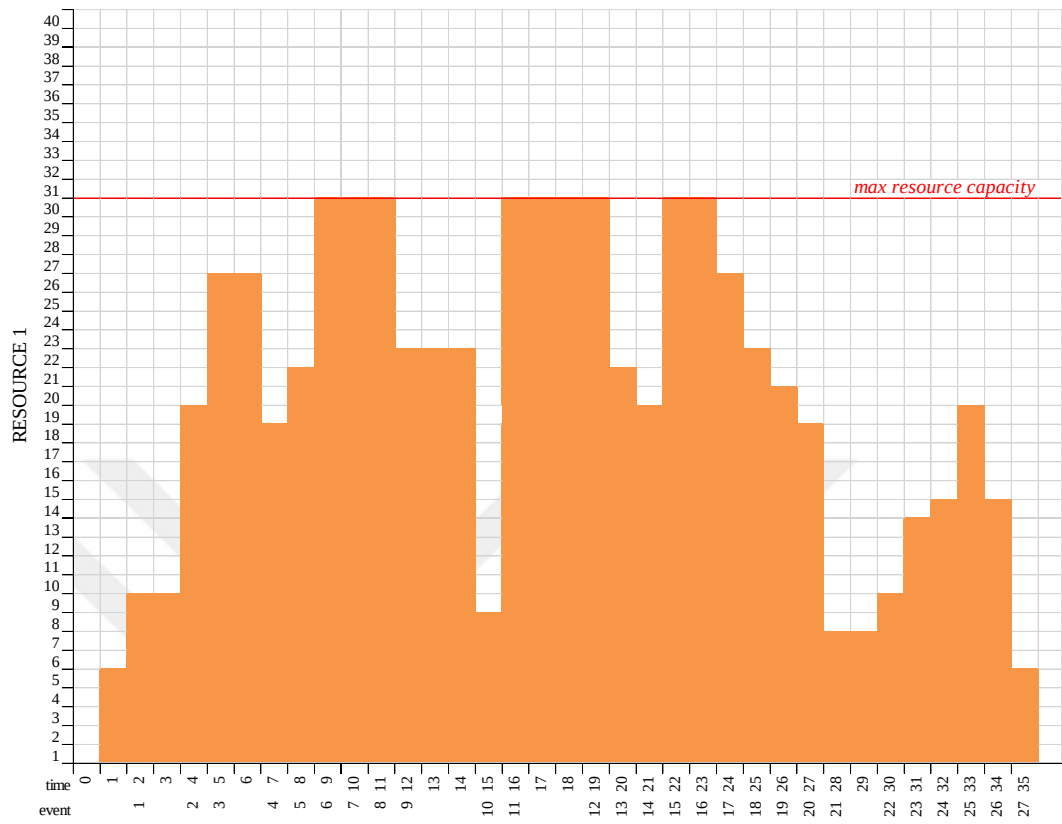
APPENDIX 4.6: The project and task schedule for the second test instance



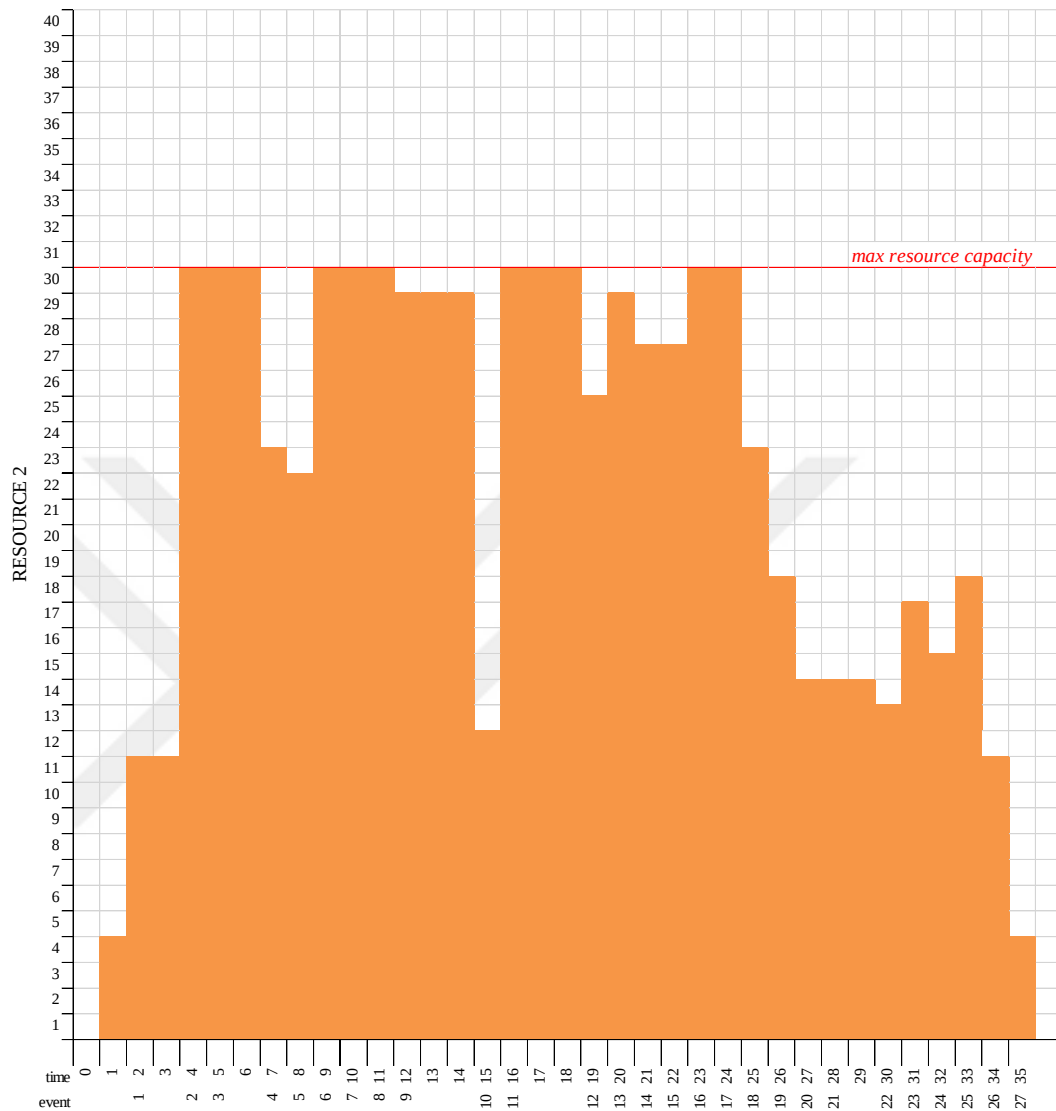
APPENDIX 4.7: The project and task schedule for the second test instance (cont.)



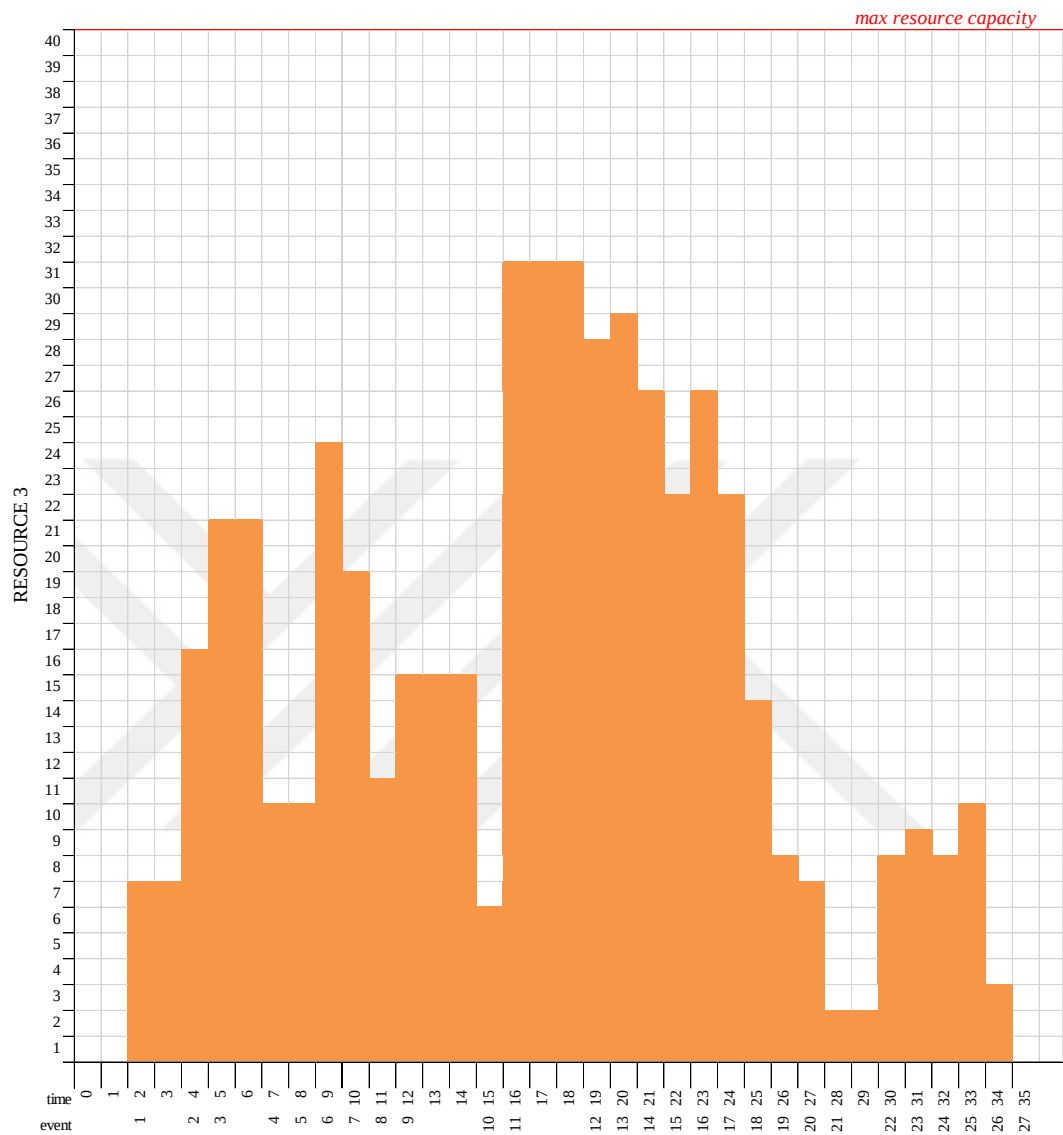
APPENDIX 4.8: The resources' loading for the second test instance



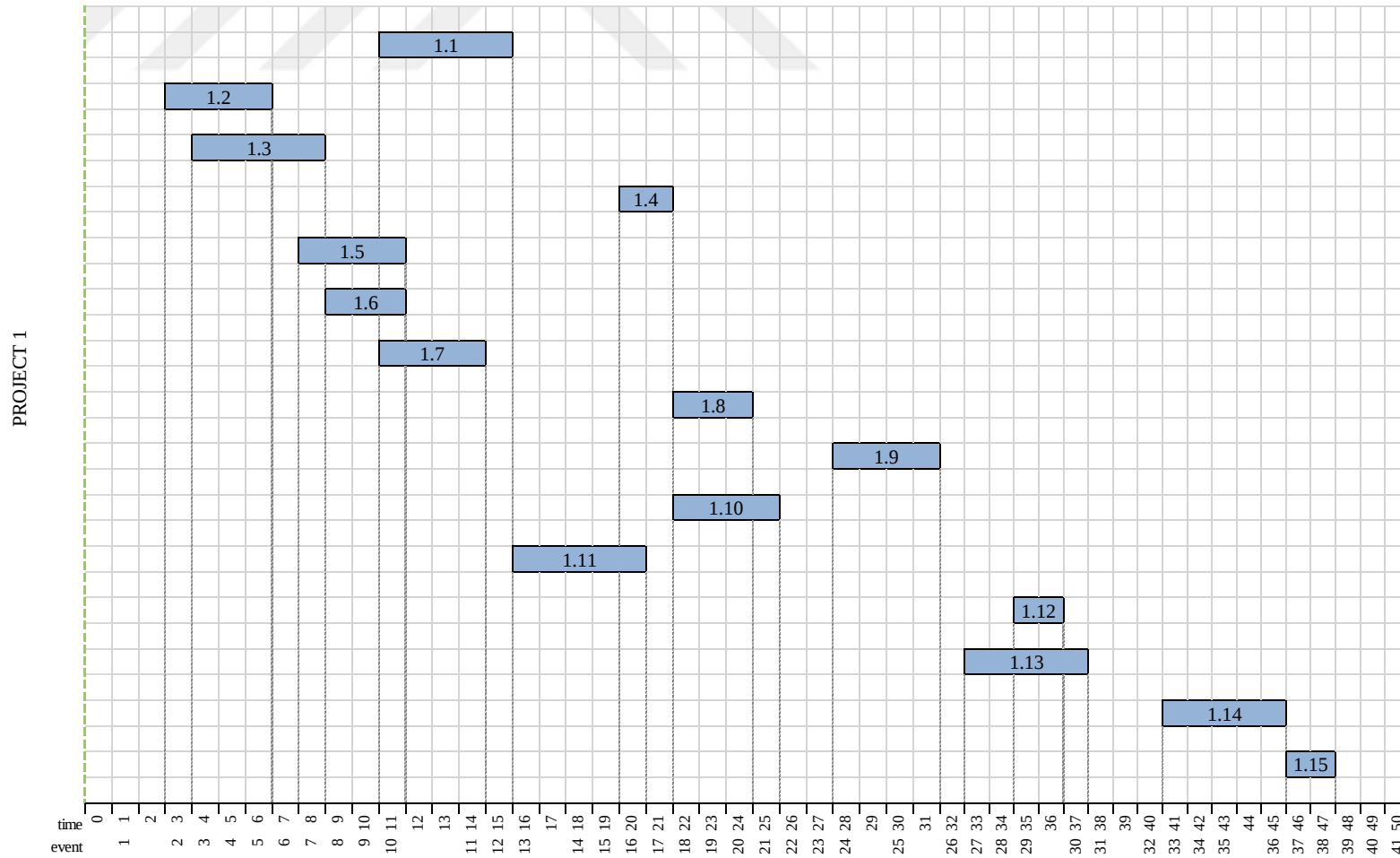
APPENDIX 4.9: The resources' loading for the second test instance (cont.)



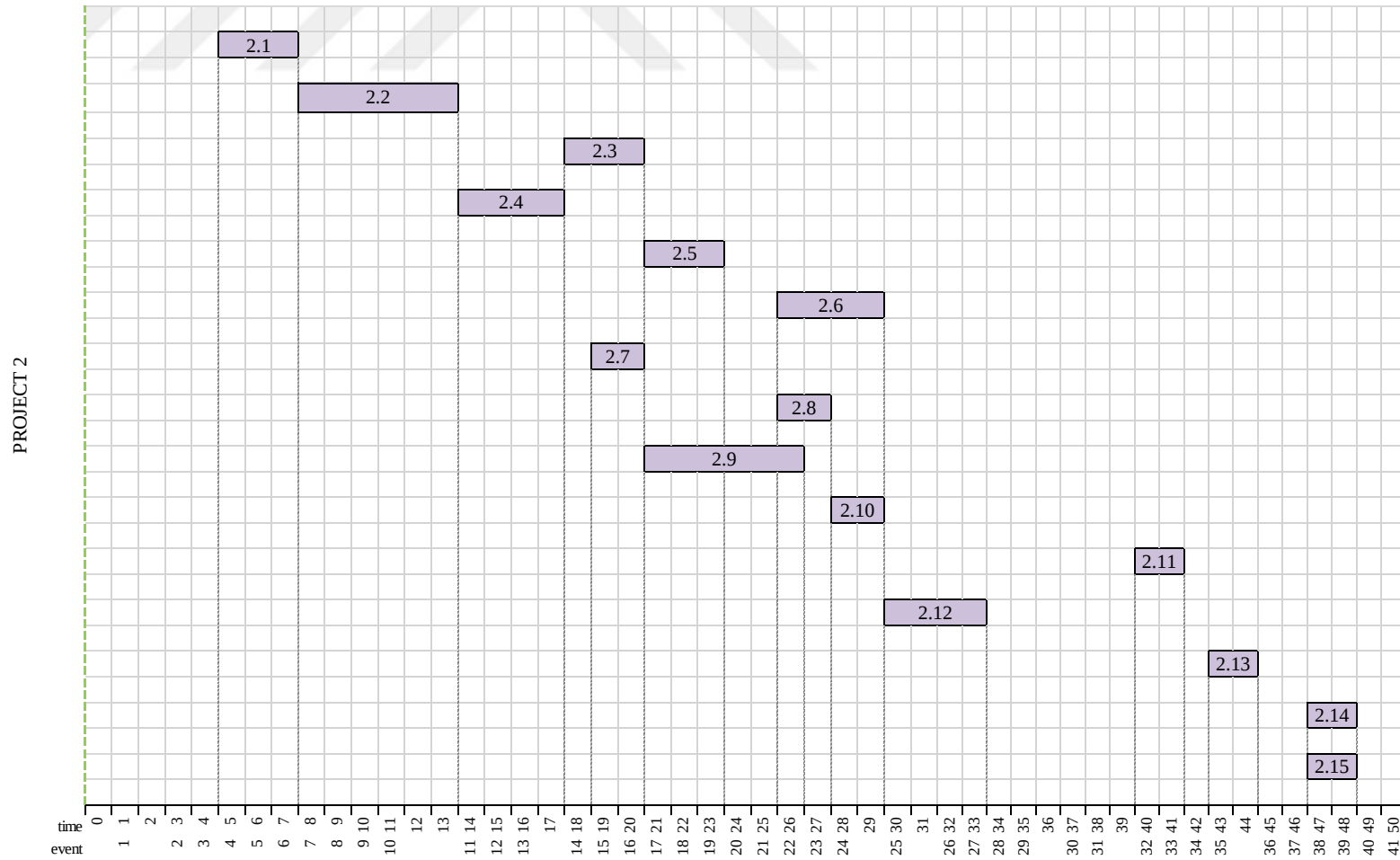
APPENDIX 4.10: The resources' loading for the second test instance (cont.)



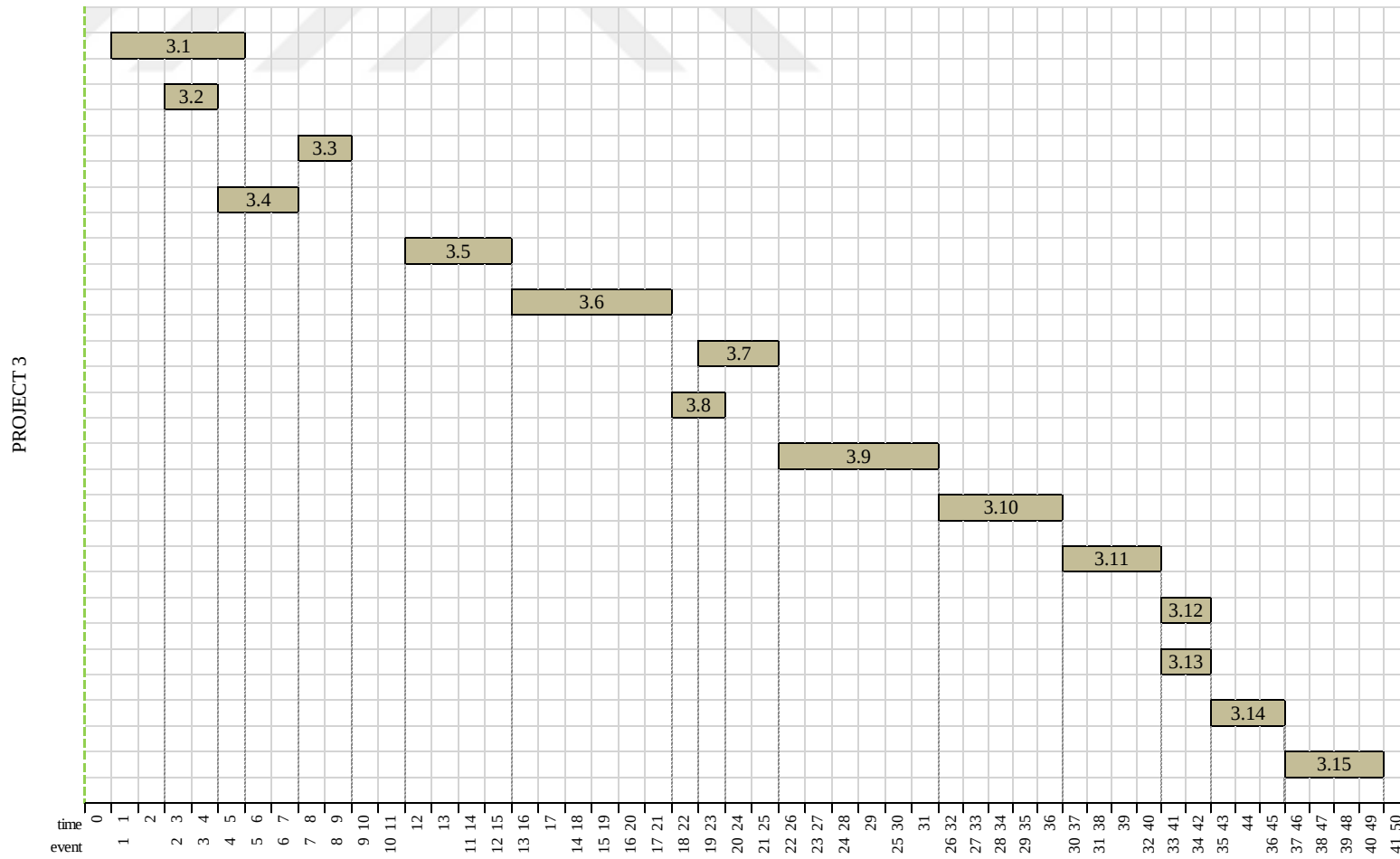
APPENDIX 4.11: The project and task schedule for the third test instance

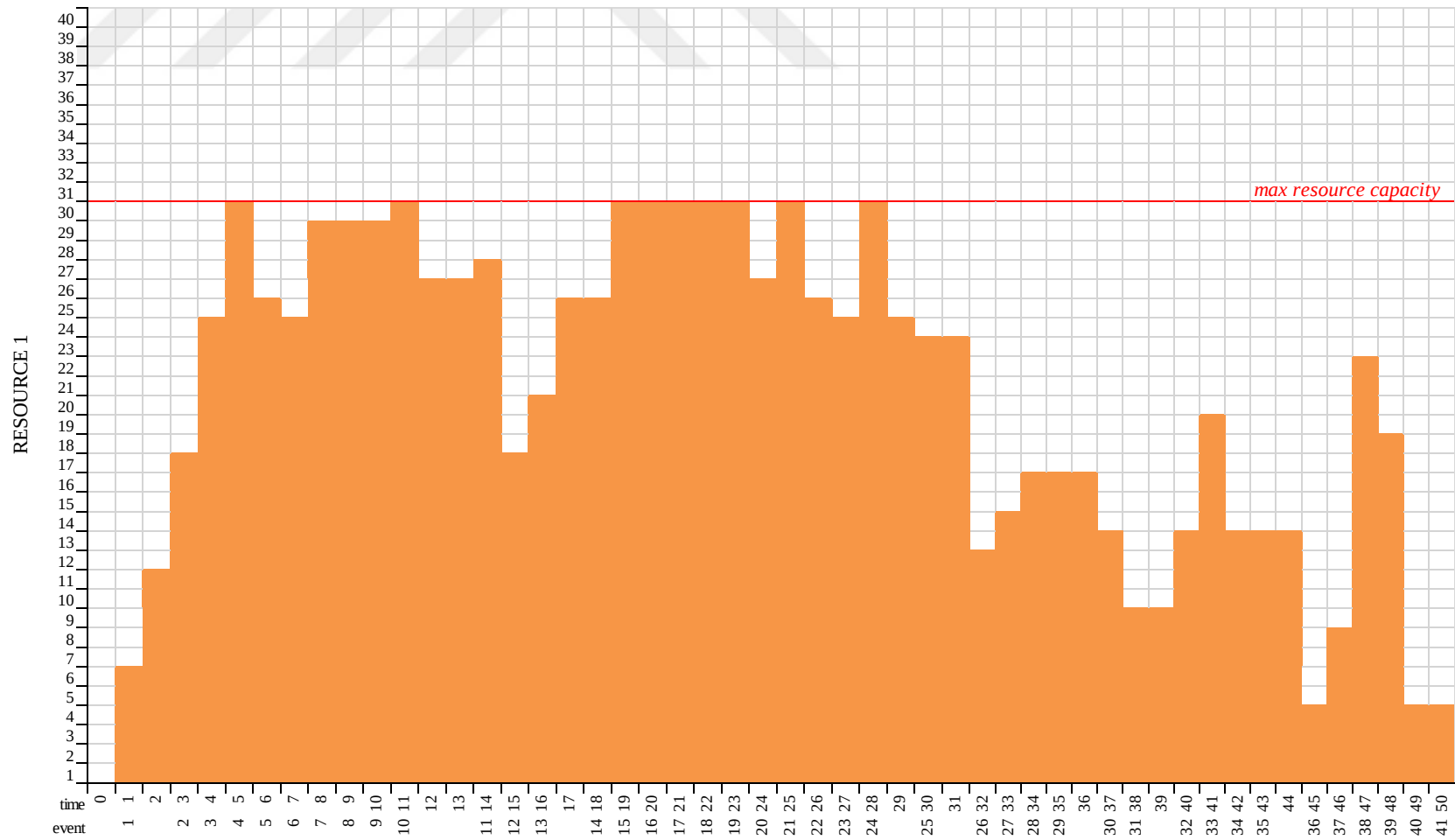


APPENDIX 4.12: The project and task schedule for the third test instance (cont.)

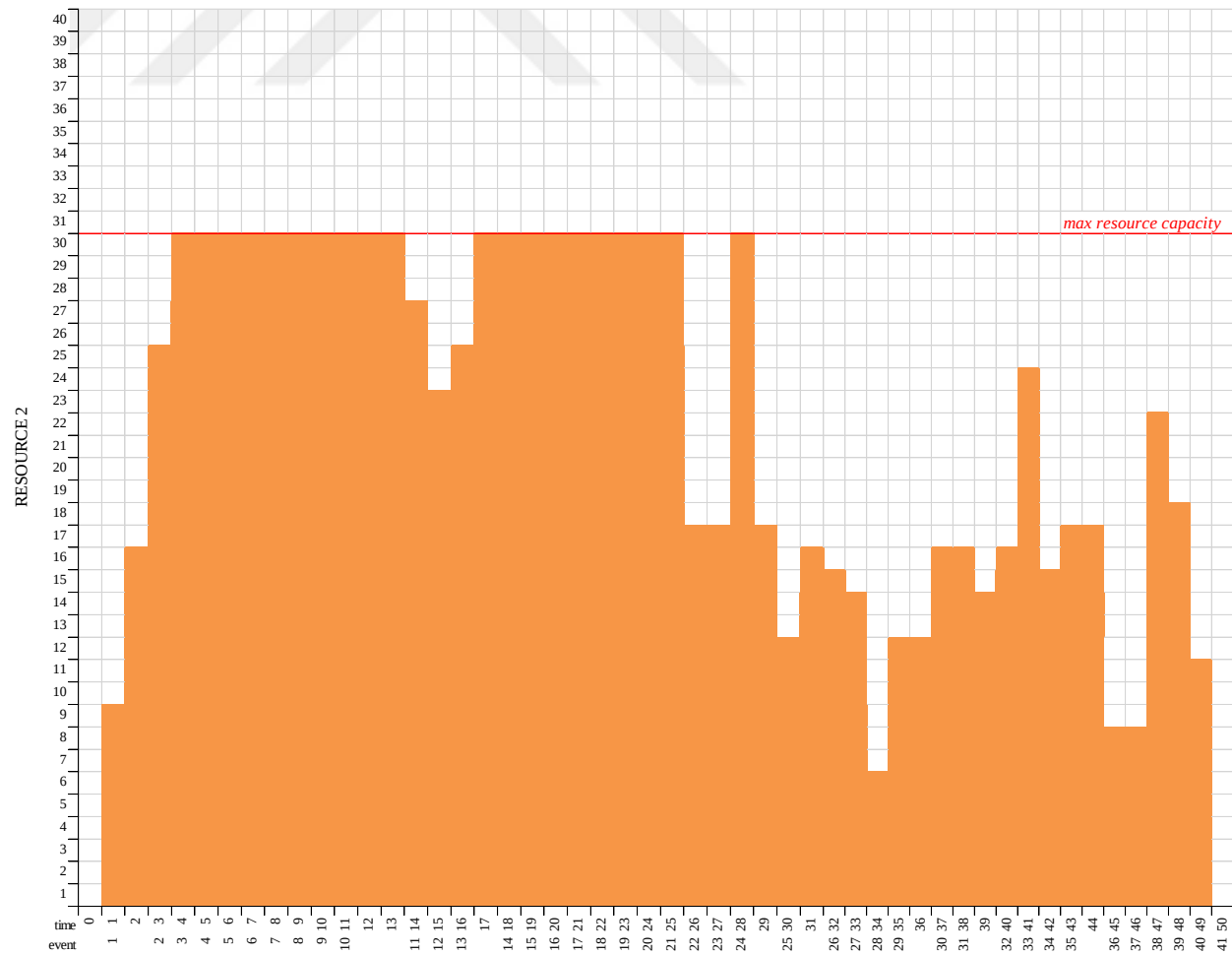


APPENDIX 4.13: The project and task schedule for the third test instance (cont.)

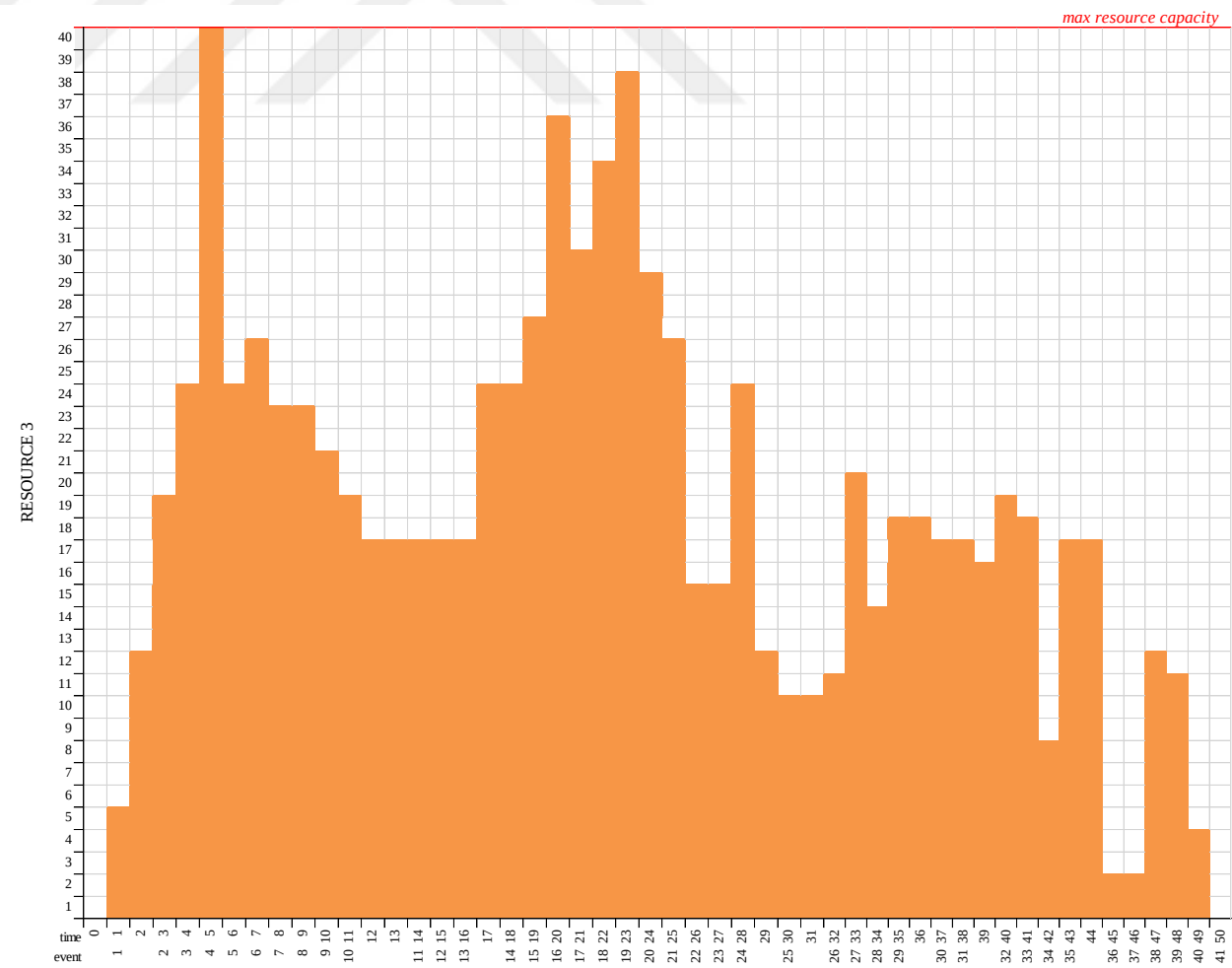


APPENDIX 4.14: The resources' loading for the third test instance

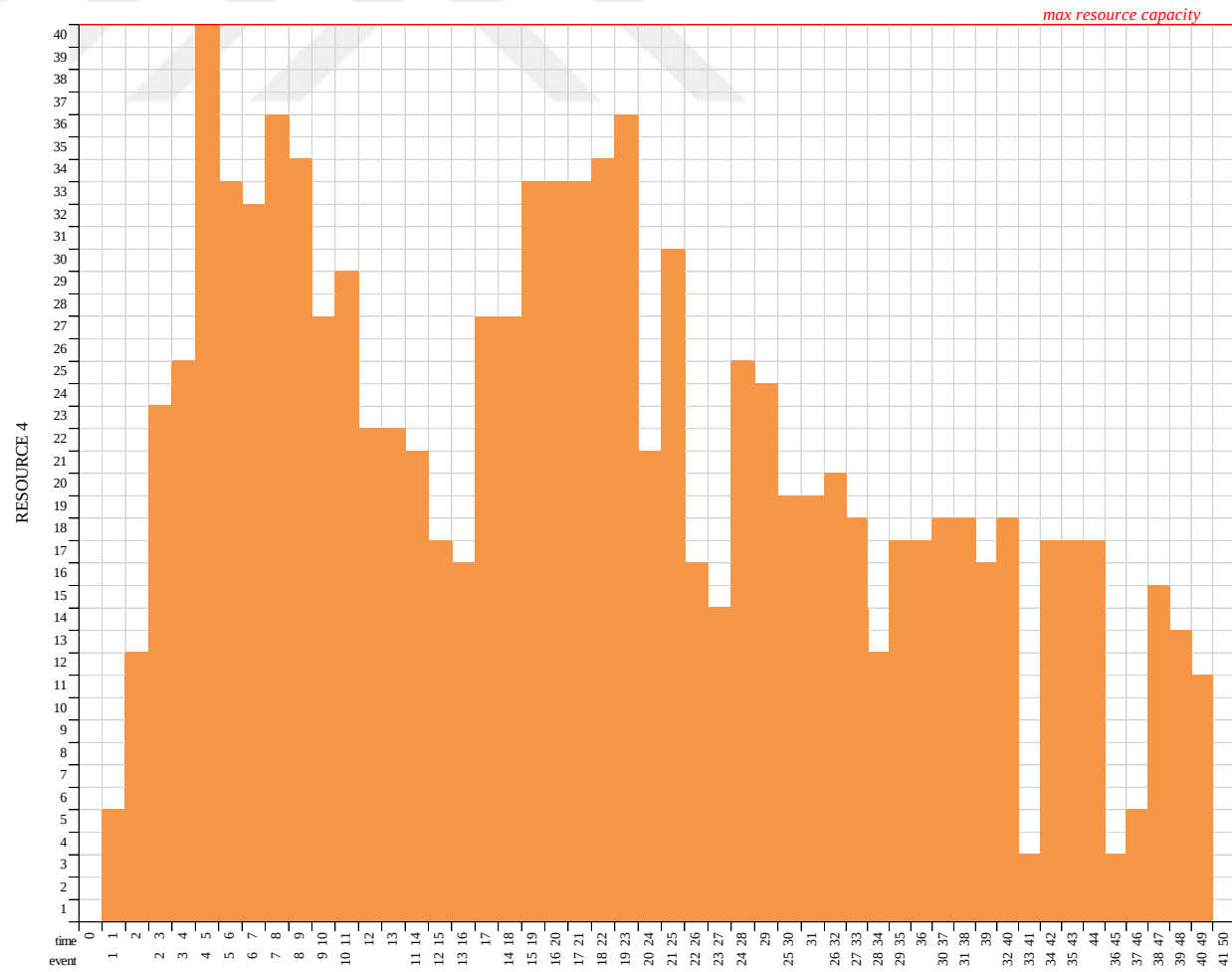
APPENDIX 4.15: The resources' loading for the third test instance (cont.)



APPENDIX 4.16: The resources’ loading for the third test instance (cont.)



APPENDIX 4.17: The resources' loading for the third test instance (cont.)



APPENDIX 5.2: Demand for Resources for P1 Project Tasks 23 through 44

[illegible]

APPENDIX 5.3: Resource Capability Values for P1 Project Tasks 1 through 22

[illegible]

APPENDIX 5.4: Resource Capability Values for P1 Project Tasks 23 through 44

[illegible]

APPENDIX 5.6: Demand for Resources for P2 Project Tasks 23 through 44

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
24	0	0	0	0	2	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	0	0	0	0	0	0	2	2	2	0	0	0	0	
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	
26	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	2	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	2	0	0	0	0	0	0	0	3	3	3	0	0	0	0
29	3	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	2	2	2	2	2	0	0	0	3	0	0	3	2	2	0	2	1	1	2	2	2	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	0	2	2	2	2	0	0	0	0	0	0	0	0	4	4	0	0	2	2	0	0	0	0	0	0	0	
33	5	0	0	5	2	0	0	2	2	2	2	0	2	2	2	2	2	0	2	0	2	2	0	2	2	0	4	4	0	2	2	0	1	1	4	5	4	4	0	0	0	0	0	0	0	0
34	0	0	0	0	2	0	0	2	2	0	0	0	2	2	2	2	0	2	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	4	4	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0
37	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	
38	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	4	4	4	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
39	0	0	0	0	2	2	2	2	0	0	0	0	4	4	4	0	0	2	2	2	2	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
40	2	2	2	0	0	0	2	2	2	0	2	2	1	1	1	0	0	0	2	2	1	1	2	2	2	2	0	2	1	1	1	1	1	1	2	2	1	1	0	0	0	0	0	0	0	0
41	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
42	2	2	0	0	0	1	0	1	0	0	1	1	0	2	2	0	0	0	3	3	2	2	0	2	2	2	2	2	2	2	2	2	0	4	4	4	4	5	5	0	0	0	0	0	0	0
43	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
44	0	0	0	0	1	1	1	1	1	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX 5.7: Resource Capability Values for P2 Project Tasks 1 through 22

[illegible]

APPENDIX 5.8: Resource Capability Values for P2 Project Tasks 23 through 44

[illegible]

APPENDIX 5.9: Demand for Resources for P3 Project Tasks 1 through 22

[illegible]

APPENDIX 5.10: Demand for Resources for P3 Project Tasks 23 through 44

[illegible]

APPENDIX 5.11: Resource Capability Values for P3 Project Tasks 1 through 22

[illegible]

APPENDIX 5.12: Resource Capability Values for P3 Project Tasks 23 through 44

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44				
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
24	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1	0	0	0	0	
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	
26	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
28	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	
29	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
30	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0		
31	0	0	0	0	1	1	1	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	
32	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0	0	0		
33	1	0	0	1	1	1	0	1	1	1	1	0	1	1	0	1	1	0	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	
34	0	0	0	0	1	1	0	1	1	0	0	0	1	0	1	1	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
36	0	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	
37	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0		
38	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0		
39	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	
40	1	1	1	0	0	0	1	1	1	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	
41	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
42	1	1	0	0	0	1	0	1	1	0	1	1	0	1	1	0	0	0	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	
43	0	0	0	0	1	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
44	0	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX 5.13: Demand for Resources for P4 Project Tasks 6 through 10

[illegible]

APPENDIX 5.14: Demand for Resources for P4 Project Tasks 26 through 44

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
26	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	2	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	2	0	0	0	0	0	0	0	3	3	3	0	0	0
29	3	3	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	2	2	2	2	2	0	0	0	3	0	0	3	2	2	0	2	1	1	2	2	2	2	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2	2	2	2	0	2	2	2	2	0	0	0	0	0	0	0	0	4	4	0	0	2	2	0	0	0	0	0	0	0	
33	5	0	0	5	2	2	0	2	2	2	2	0	2	0	0	2	2	0	2	0	2	2	0	2	2	0	4	4	0	2	2	0	1	1	4	5	4	4	0	0	0	0	0	0	0	
34	0	0	0	0	2	2	0	2	2	0	0	0	5	0	5	5	0	2	2	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
36	0	0	0	0	4	4	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	4	4	4	0	0	0
37	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	
38	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	4	4	4	0	0	0	0	2	0	0	0	0	0	0	0	0	0	
39	0	0	0	0	2	2	2	2	0	0	0	0	4	4	4	0	0	2	2	0	2	2	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
40	2	2	2	0	0	0	2	2	2	0	2	2	1	1	1	0	0	0	2	2	1	1	2	2	2	2	0	2	1	1	1	1	1	1	1	2	2	1	1	0	0	0	0	0	0	0
41	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
42	2	2	0	0	0	4	0	4	0	0	1	1	0	2	2	0	0	0	3	3	2	2	0	2	2	2	2	2	2	2	0	2	0	4	4	4	4	5	5	0	0	0	0	0	0	0
43	0	0	0	0	4	0	0	0	4	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
44	0	0	0	0	1	1	0	1	1	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX 5.15: Resource Capability Values for P4 Project Tasks 6 through 25

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
6	1	0	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
7	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
8	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	1	1	1	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	1	0	1	1	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	1	0	1	1	0	0	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	1	1	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0
13	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	1	0	0	1	1	0	0	0	1	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1
17	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	
21	0	0	1	1	0	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0
22	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1

APPENDIX 5.16: Resource Capability Values for P4 Project Tasks 26 through 44

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
26	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
28	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	1	1	1	0	0	0
29	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	
31	0	0	0	0	1	1	1	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0	0	
33	1	0	0	1	1	1	0	1	1	1	1	0	1	0	0	1	1	0	1	0	1	1	0	1	1	1	0	1	1	0	1	1	0	1	1	1	1	1	1	1	0	0	0	0	0	
34	0	0	0	0	1	1	0	1	1	0	0	0	1	0	1	1	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
36	0	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0
37	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	
38	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	
39	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	0	0	1	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
40	1	1	1	0	0	0	1	1	1	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
41	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
42	1	1	0	0	0	1	0	1	1	0	1	1	0	1	1	0	0	0	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0
43	0	0	0	0	1	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX 5.17: Demand for Resources for P5 Project Tasks 6 through 25

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44				
6	1	1	1	1	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
7	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	2	2	2	2	2	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
8	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	2	2	2	2	2	4	4	0	0	0	0	0	0	0	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
10	0	0	0	0	2	2	2	2	0	0	0	0	2	2	0	0	0	2	2	0	2	2	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
11	0	0	0	0	1	1	1	1	0	0	0	0	1	1	0	0	0	2	2	2	1	1	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
12	3	3	3	3	1	1	1	1	1	2	2	0	2	2	0	0	0	2	2	2	2	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	2	2	0	0	0	0	0	0	0	0	
13	0	0	0	0	0	2	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
14	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	0	1	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
15	0	0	0	0	3	0	0	3	3	0	0	0	1	0	0	1	2	0	2	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	3	3	3	
17	0	0	0	0	0	0	3	3	3	0	0	0	0	0	3	3	2	2	0	0	1	1	3	3	3	0	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0		
21	0	0	2	2	0	0	1	0	1	3	0	3	3	0	0	3	0	2	2	2	4	4	2	2	2	0	4	4	0	2	0	2	2	2	2	1	1	1	1	0	0	0	0	0	0	0	0	
22	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	2	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	

APPENDIX 5.18: Demand for Resources for P5 Project Tasks 26 through 44

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
26	4	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	5	5	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	2	0	0	0	0	0	0	0	0	3	3	3	0	0	0
29	3	3	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	2	2	2	2	2	0	0	0	2	2	2	3	2	2	0	2	1	1	2	2	2	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	0	2	2	2	2	0	0	0	0	0	0	0	0	0	4	4	0	0	2	2	0	0	0	0	0	0	0	
33	1	0	0	1	2	2	0	2	2	2	2	0	2	2	2	2	2	0	2	0	2	2	0	2	2	0	4	4	0	2	2	0	1	1	4	5	4	4	0	0	0	0	0	0	0	
34	0	0	0	0	2	2	0	2	2	0	0	0	1	1	1	1	0	2	2	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
36	0	0	0	0	4	4	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
37	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	
38	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	4	4	4	0	0	0	0	2	0	0	0	0	0	0	0	0	
39	0	0	0	0	2	2	2	2	0	0	0	0	4	4	4	0	0	2	2	2	2	2	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
40	2	2	2	0	0	0	2	2	2	0	2	2	1	1	1	0	0	0	2	2	1	1	2	2	2	2	0	2	1	1	1	1	1	1	2	2	1	1	0	0	0	0	0	0	0	0
41	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
42	2	2	0	0	0	4	0	4	0	0	1	1	0	2	2	0	0	0	3	3	2	2	0	2	2	2	2	2	2	2	0	2	0	4	4	4	4	5	5	0	0	0	0	0	0	0
43	0	0	0	0	4	0	4	0	4	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
44	0	0	0	0	1	1	0	1	1	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX 5.19: Resource Capability Values for P5 Project Tasks 6 through 25

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44			
6	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
7	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
8	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	1	1	1	1	0	0	0	0	1	1	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	1	1	1	1	0	0	0	0	1	1	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	
13	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
14	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	1	0	0	1	1	0	0	0	1	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1
17	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0		
21	0	0	1	1	0	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	
22	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
24	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	

APPENDIX 5.20: Resource Capability Values for P5 Project Tasks 26 through 44

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
26	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
28	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1	1	1	0	0	0	
29	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0	0	
33	1	0	0	1	1	1	0	1	1	1	1	0	1	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	0	1	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	
34	0	0	0	0	1	1	0	1	1	0	0	0	1	1	1	1	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
36	0	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	1	1	0	0	0	
37	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0		
38	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	
39	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
40	1	1	1	0	0	0	1	1	1	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	
41	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
42	1	1	0	0	0	1	0	1	1	0	1	1	0	1	1	0	0	0	1	1	1	1	0	1	1	1	1	1	1	0	1	0	1	0	1	1	1	1	1	1	0	0	0	0	0	0
43	0	0	0	0	1	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
44	0	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

APPENDIX 5.21: Demand for Resources for P6 Project Tasks 6 through 25

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44				
6	0	3	3	3	2	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
7	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	2	2	2	2	2	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
8	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	2	2	2	2	2	4	4	0	0	0	0	0	0	0	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	2	2	2	2	0	0	0	0	2	2	2	2	2	2	2	0	2	2	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	0	2	2	2	2	1	1	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	3	3	3	1	1	1	1	1	2	2	0	2	2	0	0	0	2	2	2	2	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	2	2	0	0	0	0	0	0	0	0	
13	0	0	0	0	0	2	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
14	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	0	3	3	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	3	0	0	3	3	0	0	0	1	0	0	1	2	0	2	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	3	3	3	3
17	0	0	0	0	0	0	3	3	3	0	0	0	0	0	3	3	2	2	0	0	1	1	3	3	3	0	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0		
21	0	0	2	2	0	0	1	0	1	3	0	3	3	0	0	3	0	2	2	2	4	4	2	2	2	0	4	4	0	2	0	2	2	2	1	1	1	1	0	0	0	0	0	0	0	0	0	
22	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	2	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
26	2	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
28	0	0	0	0	2	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	2	0	0	0	0	0	0	0	0	3	3	3	0	0	0
29	3	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
30	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	
31	0	0	0	0	2	2	2	2	2	0	0	0	3	0	0	3	2	2	0	2	1	1	2	2	2	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	0	2	2	2	2	0	0	0	0	0	0	0	0	4	4	0	0	2	2	0	0	0	0	0	0	0	
33	5	0	0	5	2	2	0	2	2	2	2	0	2	2	0	2	2	0	2	0	1	1	0	2	2	0	4	4	0	2	2	0	1	1	4	5	4	4	0	0	0	0	0	0	0	
34	0	0	0	0	2	2	0	2	2	0	0	0	5	0	5	2	0	2	2	0	5	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
36	0	0	0	0	4	4	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	2	2	2	0	0	0	
37	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	
38	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	4	4	4	0	0	0	0	2	0	0	0	0	0	0	0	0	
39	0	0	0	0	2	2	2	2	0	0	0	0	4	4	4	0	0	2	0	2	2	0</																								

APPENDIX 5.23: Resource Capability Values for P6 Project Tasks 6 through 25

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44					
6	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
7	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
8	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
10	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
11	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
12	0	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0		
13	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
14	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	1	0	0	1	1	0	0	0	1	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	
17	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0		
21	0	0	1	1	0	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	1	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	
22	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX 5.24: Resource Capability Values for P6 Project Tasks 26 through 44

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
26	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
28	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0
29	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
30	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	1	1	1	1	1	0	0	0	1	0	0	1	1	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0	0	
33	1	0	0	1	1	1	0	1	1	1	1	0	1	1	0	1	1	0	1	0	1	1	0	1	1	1	0	1	1	0	1	1	0	1	1	1	1	1	1	0	0	0	0	0	0	
34	0	0	0	0	1	1	0	1	1	0	0	0	1	0	1	1	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
36	0	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	
37	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	
38	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	
39	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	0	0	1	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
40	1	1	1	0	0	0	1	1	1	0	1	1	1	1	1	0	0	0	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	
41	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
42	1	1	0	0	0	1	0	1	1	0	1	1	0	1	1	0	0	0	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	0	0	0	0	0	
43	0	0	0	0	1	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
44	0	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44						
13	0	0	0	0	0	2	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0					
14	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	0	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
17	0	0	0	0	0	0	3	3	3	0	0	0	0	0	3	3	2	2	0	0	1	1	3	3	3	0	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0		
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
21	0	0	2	2	0	0	1	0	1	3	0	3	3	0	0	3	0	2	2	2	4	4	2	2	2	2	0	4	4	0	2	0	2	2	2	1	1	1	1	0	0	0	0	0	0	0	0	0		
22	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
24	0	0	0	0	2	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0		
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
28	0	0	0	0	2	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	2	0	0	0	0	0	0	0	0	3	3	3	0	0	0	0			
31	0	0	0	0	2	2	2	2	2	0	0	0	3	0	0	3	2	2	0	2	1	1	2	2	2	0	0	0	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0		
32	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	0	2	2	2	2	2	0	0	0	0	0	0	0	0	0	4	4	0	0	2	2	0	0	0	0	0	0	0	0			
33	5	0	0	5	2	2	0	2	2	2	2	0	2	2	0	2	2	0	2	0	2	2	0	2	2	0	4	4	0	2	2	0	1	1	4	5	4	4	0	0	0	0	0	0	0	0	0	0		
34	0	0	0	0	2	2	0	2	2	0	0	0	2	0	2	2	0	2	2	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
36	0	0	0	0	4	4	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0		
37	0	0	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0		
38	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	4	4	4	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	
39	0	0	0	0	2	2	2	2	0	0	0	0	4	4	4	0	0	2	2	2	2	2	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
40	2	2	2	0	0	0	2	2	2	0	2	2	1	1	1	0	0	0	2	2	1	1	2	2	2	2	0	2	1	1	1	1	1	1	2	2	1	1	0	0	0	0	0	0	0	0	0	0	0	
44	0	0	0	0	1	1	0	1	1	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

PENDIX 5.26: Resource Capability Values for P7 Project Tasks 13

1	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44				
13	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
14	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
17	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
21	0	0	1	1	0	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	
22	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
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33	3	0	0	3	2	2	0	2	2	2	2	0	2	2	2	2	2	0	2	0	2	2	0	2	2	0	4	4	0	2	2	0	1	1	4	5	4	4	0	0	0	0	0	0	0	
34	0	0	0	0	2	2	0	2	2	0	0	0	1	1	1	1</																														

■	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
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17	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
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22	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
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27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
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34	0	0	0	0	1	1	1	1	1	0	0	0	1	0																																

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44		
13	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
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22	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
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24	0	0	0	0	2	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	0	0	0	0	0	0	0	2	2	2	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
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34	0	0	0	0	2	2	0	2	2	0	0	0	2	0	2	2	0</																													

181

I	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40	R41	R42	R43	R44	
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17	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
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