# MULTI-PROJECT SCHEDULING WITH 2-STAGE DECOMPOSITION 

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# MULTI-PROJECT SCHEDULING WITH 2-STAGE DECOMPOSITION 

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to my beloved ones

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# MULTI-PROJECT SCHEDULING 

WITH 2-STAGE DECOMPOSITION

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#### Abstract

A non-preemptive, zero time lag multi-project scheduling problem with multiple modes and limited renewable and nonrenewable resources is considered. A 2-stage decomposition approach is adopted to formulate the problem as a hierarchy of 01 mathematical programming models. At stage one, each project is reduced to a macro-activity with macro-modes, which are systematically generated by utilizing artificial budgets. The resulting single project network problem is a Multi-Mode Resource Constrained Project Scheduling Problem (MRCPSP) with positive cash flows. MRCPSP with positive cash flows is solved to maximize NPV and to determine the starting times and resource allocations for the projects. Using the starting times and resource profiles obtained in stage one each project is solved at stage two for minimum makespan. Three different time horizon setting methods, namely, relaxed greedy approach, artificial budget and Lagrangian relaxation are developed for setting the time horizon for MRCPSP with positive cash flows. A genetic algorithm approach is adopted to generate good solutions, which is also employed as a starting solution for the exact solution procedure. The result of the second stage is subjected to a post-processing procedure to distribute the resource capacities that have not been utilized earlier in the procedure. Since currently there are no data instances with the required structure, four new test problem sets are generated with $81,84,27$ and 4 problems each. Three different configurations of solution procedures are tested employing the first three problem sets. A new heuristic decision rule designated here as Resource Return factor is presented and tested employing the fourth problem set.


# İKí-AŞAMALI AYRIŞIMLI ÇOKLU PROJE ÇIZELGELEME 

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## Özet

Faaliyetlerin kesintisiz gerçekleştirildiği ve aralarındaki öncül ilişkilerinin bitişbaşlangıç tipinde olduğu, öncül ve ardıl faaliyetler arasındaki minimum zaman boşluğu kısıtının sıfır olduğu bir ortamda; çoklu kaynak reçeteli, yenilenebilir ve yenilenemez kaynak kısıtlı, çoklu proje çizelgeleme sorunu incelenmiştir. İki-aşamalı ayrışım yaklaşımı uygulanarak, sorun bir 0-1 matematiksel programlama modelleri hiyerarşisi şeklinde düzenlenmektedir. Ilk aşamada, her proje, farklı yapay bütçe değerlerinin sistematik bir biçimde kullanılmasıyla oluşturulan farklı süre ve kaynak reçetelerine sahip tek bir makro-faaliyete indirgenir. Bu sürecin sonunda oluşan proje serimi Net Bugünkü Değeri (NPV) ençoklamak hedefiyle çizelgelenerek, projelerin kaynak kullanımları ve başlangıç zamanları belirlenir. Ikinci aşamada ise her proje, ilk aşamada elde edilen başlangıç zamanları ve kaynak kısıtı çizgelerine göre proje süresini enazlamak hedefiyle çizelgelenir. Her iki aşamada da veri miktarını azaltmak amacıyla bazı önişleme yöntemleri gerçekleştirilmiştir. Uygun bir zaman ufku belirlemenin pozitif nakit akışlı çoklu kaynak reçeteli, kaynak kısıtlı proje çizelgeleme üzerindeki etkisi incelenmiş ve üç farklı zaman ufku belirleme yöntemi değerlendirilmiştir. Kesin çözüm yöntemi için başlangıç çözümü olarak da kullanabilecek iyi çözümler üreten bir genetik algoritma yaklaşımı da getirilmiştir. Bunun yanı sıra, 2-aşamalı ayrışım sonrası elde kalan kaynak kapasitelerini sonucu iyileştirmek amacıyla projelere dağıtan bir ardıl işleme yöntemi de geliştirilmiştr. İncelenen problem yapısına sahip test problemleri mevcut olmadığından önerilen çözüm yöntemini sınayabilmek için $81,84,27$ ve 4 problemden oluşan dört yeni problem kümesi oluşturulmuştur. Üç farklı çözüm yöntemi konfigürasyonu kullanılarak ilk üç kümedeki problemler çözülmüş ve bu tez çerçevesinde geliştirilmiş Resource Return olarak isimlendirilmiş yeni bir sezgisel karar kuralı dördüncü problem kümesi kullanılarak sınanmış ve sonuçlar paylaşılmıştır.

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## CHAPTER 1

## INTRODUCTION AND MOTIVATION

Executing a project is a type of undertaking that has a long history having its roots in ancient times. Earlier project management examples, which were sometimes witnessed in history as difficult conquest campaigns or merely construction of glorious temples, clearly lacked the scientific elements of modern project management approaches but they all involved some immense organizational skills as well as some astonishing planning regulations and also fit well into the basic description of executing a project, temporary endeavor undertaken to create a unique product or service.

From the scientific point of view, project scheduling is basically a problem of scheduling project tasks with some precedence relations between each other in order to achieve a certain objective. Project scheduling problem without resource constraints can be handled efficiently using the critical path method (CPM) developed by Kelley [2] yet even including only one type of resource makes the problem NPHard as shown by Blazewicz et al. [3]. An extension of resource constrained project scheduling problem (RCPSP) is resource constrained multi-project scheduling problem (RCMPSP), which consists of a collection of projects which are to be scheduled sharing limited resources.

RCMPSP, which has been studied for several decades now, is one of the more realistic problems in project management considering particularly that it increasingly becomes very common for firms to carry out multiple projects simultaneously. It has been suggested by Payne [4] that up to $90 \%$, by value, of all projects occur in a multiproject context. Large construction companies [5] and R\&D organizations
in particular [6] execute multi-project scheduling procedures regularly. As markets become more competitive, firms' obligation to simultaneously carry out multiple projects by managing scarce resources becomes even more critical and they need to form structures, which can satisfy this necessity.

The complexity of managing and planning multiple projects simultaneously persuades managers into forming management systems accordingly so that failures are avoided. Obviously, the main conflict arises from the sharing of resources scarce resources at the same time thus requiring a series of important long-term decisions on resource allocations and project execution times as well as short-term decisions related to managerial matters within individual projects. Naturally, these different types of decisions take their positions on different managerial levels considering their frequencies, time horizons and details thus making it suitable for a hierarchical managerial scheme as the one presented in Figure 1.1 by Hans et al. [1].


Figure 1.1: Hierarchical management framework by Hans et al. [1]

In today's global world, one of the arrangements frequently used for managing projects particularly those separated by both distance and time is the dual level management structure [7] which consists of a higher level manager and a number
of project managers. While the project managers work at an operational level and are responsible for scheduling the activities of individual projects, the higher level manager works on a more tactical level and is responsible for all projects and project managers. At the higher level, projects are scheduled as individual entities so as to generate start times and due dates for each project. Then based on these start times and due dates, each project is scheduled individually employing time-dependent renewable resource capacities together with non-renewable resource capacities imposed by the higher level. Dual level managerial mechanism also grants a more beneficial position to blend decision approaches with different performance criteria and so this also motivated researchers to exploit a similar approach in order to introduce dual level decomposition methodologies to multi-project planning and scheduling as in Speranza and Vercellis [8].

This study focuses on a 2-stage decomposition approach where the objective at higher level is NPV maximization and the objective at lower level is makespan minimization. A deterministic multi-project problem environment is considered and a 2-stage decomposition approach is adopted to formulate the problem as a hierarchy of 0-1 mathematical programming models as in Speranza and Vercellis [8]. At stage one, each project is reduced to a macro-activity with various mode alternatives and the resulting single project network is solved so as to maximize NPV. Using the starting times and resource profiles obtained in stage one, each project is solved in stage two for minimum makespan.

The focus in this study is mostly on the application aspect of the existing procedure in Speranza and Vercellis [8] and the intention is to decrease the required computational effort by adapting the mathematical programming models and applying some preprocessing methods to reduce the data size, determining an effective time horizon and suggesting alternative approaches for specific subprocedures.

Although this study deals with the resource constrained multi-project scheduling problem, some specific versions of the single project multi-mode RCPSP (MRCPSP) are directly dealt with as well due to the nature of decomposition based approach that is applied. A regular MRCPSP with makespan minimization objective and
fixed renewable resource capacities are encountered as well as an MRCPSP with discounted cash flows and NPV maximization objective (MRCPSPDCF) with timedependent renewable resource requirements and an MRCPSP with time-dependent renewable resource capacities. In order to develop a good multi-project scheduling procedure based on decomposition, some efficient solution approaches for the problems obtained by the decomposition must be employed.

### 1.1 Contributions

The primary purpose of the present study is to develop an effective 2-stage decomposition approach to the resource constrained multi-project problem with multiple activity modes. The following list shows the contributions of this study:

- Preprocessing methods which reduce the data size are applied to increase the solution speed.
- Macro-mode generation subprocedure in the first stage of the decomposition is enhanced by introducing a new search systematic.
- The effect of setting a proper time horizon for MRCPSPDCF with positive cash flows is examined and three different time horizon setting methods, namely, (i) relaxed greedy approach, (ii) artificial budget and (iii) Lagrangian relaxation are analyzed.
- A genetic algorithm approach is adopted to generate good starting solutions for MRCPSPDCF with time dependent renewable resource requirements.
- An efficient post-processing procedure to distribute the resource capacities that are left over after 2-stage decomposition to the projects to search for any improvements is also introduced.


### 1.2 Outline

The thesis is organized as follows. Chapter 2 provides a brief description of the problem environment and a survey on the related work in the literature. The math-
ematical models and the solution methodology are presented in Chapter 3. In Chapter 4, a genetic approach to MRCPSPDCF with time dependent renewable resource requirements is introduced. Chapter 5 provides the computational study and the results. Chapter 6 concludes with comments about the outcome and the future work.

## CHAPTER 2

## PROBLEM DESCRIPTION AND RELATED WORK

### 2.1 Multi-Project Scheduling

A multi-project scheduling problem consists of a collection of projects which are to be scheduled sharing limited resources. Besides determining the project start times and allocating resource among the projects, each project has to be scheduled individually by deciding on the activity start times. First, a 0-1 linear programming formulation of this problem was introduced by Pritsker [9] and three possible objective functions including minimizing total throughput time for all projects, minimizing the time by which all projects are completed and minimizing total lateness or lateness penalty for all projects were discussed. Then researchers with deterministic approaches introduced some heuristic sequencing rules, which have been categorized by Kurtulus and Davis [10]. A dual level approach, which suggests a decomposition of the problem into a hierarchy of integer programming models, is introduced in Speranza and Vercellis [8]. Bock and Patterson [11] studied setting due dates by a rule-based heuristic approach and the preemption of resources from one project to another in a multi-job assembly shop environment. Vanhoucke [12] also worked with due date setting in a project scheduling environment and emphasized the practical importance of optimal assignment of due dates to the project managers. Lova et al. [13] came up with a multi-criteria heuristic algorithm consisting of several algorithms based on the improvement of multi-project feasible schedules. In Lova and Tormos [14], the effect of the schedule generation schemes, and some priority rules with multi-project and single-project approaches are analyzed. Yang
and Sum [15] examined the performance of due date, resource allocation, project release, and activity scheduling rules in a multi-project environment. Kumanan et al. [16] established a heuristic and a genetic algorithm for scheduling a multi-project environment with an objective to minimize the makespan of the projects. Adapting a stochastic view, Cohen et al. [17] worked on the problem of resource allocation of a stochastic and dynamic multi-project system and introduced a cross entropy approach to determine near-optimal resource allocations to the entities that execute the projects. Hans et al. [1] proposed a positioning framework to distinguish between different types of project-driven organizations to aid project management in the choice between the various existing planning approaches.

### 2.2 Resource Constrained Project Scheduling Problem

RCPSP is proven to be an NP-hard problem by Blazewicz et al. [3] and has been studied intensely in the recent decades. RCPSP basically requires the scheduling of a given set of activities trying to fulfill an objective function, which is generally minimizing the project makespan, also considering the resource capacities and precedence relations between the activities. More information can be obtained from Klein [18], Özdamar and Ulusoy [19] and Kolisch and Padman [20]. Multi-mode RCPSP (MRCPSP) is an extension of RCPSP to the case with alternative activity modes which correspond to different combinations of time durations and resource usage as described, for example, in Brucker et al. [21]. Makespan minimization and net present value maximization are two performance measures employed most frequently. A multi-objective case employing both of these objectives has also been investigated in the literature.

### 2.2.1 Makespan Minimization

Makespan minimization is a regular performance measure and it is probably the most commonly researched objective type for this particular problem class. For RCPSP and MRCPSP with the makespan objective, various exact approaches haven been presented as in Sprecher et al. [22], Brucker et al. [23], Hartmann and Drexl [24],

Mingozzi et al. [25], Dorndorf et al. [26], Demeulemeester and Herroelen [27] and Zhu et al. [28]. Besides the exact procedures, several priority rule based heuristics have been presented as in Özdamar and Ulusoy [19] as well as several meta-heuristic approaches including simulated annealing (Bouleimen and Lecocq [29] and Jozefowska et al. [30]), genetic algorithm (Hartmann [31]) and tabu search (Baar et al. [32]).

### 2.2.2 Net Present Value Maximization

Initially, most of the attention was devoted to the development of solution procedures aiming at the minimization of the project makespan but later some approaches dealing with the maximization of the net present value (NPV) were also initiated. An initial version of this problem with no resource constraints was introduced by Russel [33] and Grinold [34] extended it by adding a project deadline. Later, Doersch and Patterson [35] proposed a binary integer programming model including a constraint on capital for expenditure on activities. Smith-Daniels and SmithDaniels [36] extended the problem by including material constraints and costs. A new dynamic programming approach was introduced by Tavares [37] and was successfully applied to a large railway project in Portugal. Yang et al. [38] proposed an integer programming approach utilizing a Branch and Bound (B\&B) strategy and extended some fathoming rules originally developed for the makespan minimization problem. İçmeli and Erengüç [39] came up with a B\&B method using minimal delay alternatives to solve RCPSPDCF with both positive and negative cash flows. Baroum and Patterson [40] presented a B\&B procedure directly designed to solve the project scheduling problem with positive cash flows. RCPSPDCF employing positive and/or negative cash flows associated with activities and generalized precedence relations were studied by De Reyck and Herroelen [41]. RCPSPDCF was extended to arbitrary minimal and maximal time lags between the starting and completion times of activities. There were also some metaheuristic approaches that were applied to solve RCPSPDCF such as the genetic algorithm by Ulusoy et al. [42]; simulated annealing method by Dayanand and Padman [43], Mika et al. [44] and He et al. [45]; and also tabu search by İçmeli and Erengüç [46], Zhu and Padman [47] and

Mika et al. [44]. In addition, Kimms [48] applied Lagrangian relaxation approach to calculate tight upper bounds on the objective function by relaxing the resource constraints and used those as a basis for a heuristic approach. More information can be found in the surveys by Özdamar and Ulusoy [19], Herroelen et al. [49] and Kolisch and Padman [20].

### 2.2.3 Multi-objective Resource Constrained Project Scheduling Problem

Even though works related with RCPSP involving multiple decision criteria in the literature is less common compared to ones related with single objective RCPSP, there have been some studies regarding the relation between project completion time, financial matters and robustness. Deckro and Hebert [50] have developed multiple objective approaches for resource unconstrained project scheduling problems allowing potentially conflicting objectives to be considered. Stewart [51] developed a multi-criteria Decision Support System (DSS) to handle project portfolio selection in R\&D environments. Davis et al. [52] claimed that the for years traditional approach was to include only project makespan in the objective, however including other relevant factors such as physical, financial, and human resources in the objective function enhances the scheduling in terms of flexibility by allowing evaluation of trade-offs between project makespan and resource requirements. Based on this approach, a decision support framework employing an interactive procedure based on vector maximization is introduced.

Speranza and Vercellis [8] proposed a model-based approach to nonpreemptive multi-project management problems, based on a hierarchical two-stage decomposition of the planning and scheduling process involving two performance measures NPV maximization, which includes investment costs, operating costs, revenues, penalties for late completion; and the service level, expressed as the agreement between the completion times of the different projects and the customer needs.

MIPS, a DSS for multi-objective interactive project scheduling, was provided by Rys et al. [53] and it utilized economic type of criteria like total income, total
project cost and NPV; as well as more traditional measures such as project makespan and earliness/tardiness costs. Slowinski et al [54] considered multi-objective project scheduling under multiple-category resource constraints and proposed a DSS based on three kinds of heuristics: parallel priority rules, simulated annealing and branch-and-bound. Ulusoy and Özdamar [55] presented a heuristic iterative scheduling algorithm consisting of forward/backward scheduling passes for RCPSP with makespan minimization and NPV maximization performance measures. Hapke et al. [56] reported an interactive search over a non-dominated solution space of a multiplecriteria project scheduling problem and developed an approach, where a set of approximately non-dominated schedules is formed using the Pareto Simulated Annealing first, and then an interactive search over this set is applied using discrete version of the Light Beam Search method.

Viana and de Sousa [57] applied multi-objective versions of simulated annealing and tabu search, in order to minimize the makespan, the weighted lateness of activities, and the violation of resource constraints. Recently, some evolutionary algorithms for multi-objective RCPSP have been developed such as the one by Hanne and Nickel [58] considering the problem of planning inspections and other operations within a software development project with respect to the objectives quality, project makespan and costs. Robustness maximization and makespan minimization measures have been considered together recently by Al-Fawzan and Haouari [59] and Abbasi et al. [60]. Kılıç et al. [61] formulated risk mitigation in project scheduling as a bi-objective optimization problem, where both the expected makespan and the expected total cost are to be minimized, and a fast and effective genetic algorithm approach is provided to solve it.

### 2.3 Problem Environment

The problem environment examined here contains multiple projects consisting of activities which can be carried out in one of multiple mode alternatives corresponding to distinct ways of performing the activity requiring different combinations of resource usages. Also, it is assumed that activities cannot be preempted.

### 2.3.1 Resources

Here, we consider two types of resource constraints: renewable and non-renewable. Renewable resources are constrained on a periodic basis only and the nonrenewable resources are limited over the entire planning horizon with no restrictions within each period. An example for a renewable resource would be construction cranes, while an example for a nonrenewable resource could be the capital budget for a project. Resource profile examples are given in Figure 2.1.

(a) Renewable resource usage profile

(b) Non-renewable resource usage profile

Figure 2.1: Resource usage profile examples

Although not studied in this particular problem environment, another type of resources classified in the literature (Talbot [62]) is doubly constrained resources. In a way, they are the combination of both renewable and non-renewable resources because they are limited on period basis as well as on a planning horizon basis. A capital budget could be an example in the case where it is limited for the entire project and its consumption is limited over each time period. Doubly constrained resource profile example is given in Figure 2.2.


Figure 2.2: Doubly constrained resource usage profile example

### 2.3.2 Network Structure

Mostly due to technological causes and nature of processes, some activities have to precede others. As referred by Elmaghraby and Kamburoski [63], there are four types of generalized precedence relations: start-start (S-S), start-finish (S-F), finishstart (F-S) and finish-finish (F-F). In S-S relations, a minimal time lag between the start times of activities are assumed. F-S relations imply that once an activity is finished, its successor(s) can be started immediately with a minimal time lag. In an environment with F-F relations, it is assumed that there is a minimal time lag between the finish time of activities in relation. S-F relations, which is relatively more rare, assume that there is a minimal time lag between start time of one activity and finish time of another activity.

In this particular problem environment, the project network is of activity-onnode (AoN) type with F-S zero time lag type precedence relations. The composite multi-project network is generated by combining single project networks with one dummy start node and one dummy finish node. A simple multi-project network example with three projects can be seen in Figure 2.3 showing the dummy start node A, which represents the event for starting to execute the given set of projects, is connected to the starting nodes $(\mathrm{B}, \mathrm{J}, \mathrm{P})$ of each project and similarly the finished nodes ( $\mathrm{I}, \mathrm{O}, \mathrm{Y}$ ) of each project is connected to the dummy finish node Z , which represents the event that all of projects are finished.


Figure 2.3: Multi-project network example

### 2.3.3 Cash Flows

There are three types of cash flows that are included in the NPV maximization objective function.

- Revenues: A lump sum payment is made at the end of each project.
- Fixed Costs: Setup costs which are resource independent and are incurred initially for each project.
- Variable Costs: Usage costs for renewable and non-renewable resources that are incurred periodically throughout each project. It is assumed that an activity's consumption of non-renewable resources as well as the variable cost distribution associated with is consumption are uniform over the execution period of that activity.


### 2.4 Problem Formulation

To represent this RCMPSP with a decision environment considering a primary and a secondary objective, a mathematical programming formulation is adopted from

Speranza and Vercellis [8] including both makespan minimization criterion type for each project and NPV maximization criterion type for the general problem.

### 2.4.1 Sets and indices

$S=$ set of all projects including dummy projects
$S^{a}=$ set of all actual projects
$s=$ project indices; $s \in S=\{1,2, \ldots,|S|\}$
$V=$ set of all activities including dummy activities
$V_{s}=$ set of activities in project $s$ including dummy activities
$i, k=$ activity indices; $i, k \in V_{s}$
$a_{s}=$ starting activity of project $s ; a_{s} \in V_{s}$
$z_{s}=$ finishing activity of project $s ; z_{s} \in V_{s}$
$P=$ set of precedence relations between all activities $i \in V$
$P_{s}=$ set of precedence relations between all activities $i \in V_{s}$ in project $s$
$M_{i}=$ set of modes of activity $i$
$j=$ activity execution mode indices; $j \in M_{i}=\left\{1,2, \ldots,\left|M_{i}\right|\right\}$
$\mathcal{R}=$ set of renewable resources
$r=$ renewable resource indices; $r \in \mathcal{R}=\{1,2, \ldots,|\mathcal{R}|\}$
$\mathcal{N}=$ set of non-renewable resources
$n=$ non-renewable resource indices; $n \in \mathcal{N}=\{1,2, \ldots,|\mathcal{N}|\}$
$\mathcal{T}=$ set of time periods
$t, \theta=$ time indices; $t \in \mathcal{T}=\{1, \ldots,|\mathcal{T}|\}$

### 2.4.2 Parameters

$d_{i j}=$ processing time for activity $i$ performed in mode $j$
$e_{i}=$ earliest starting time period for activity $i$
$l_{i}=$ latest starting time period for activity $i$
$W_{r}=$ amount of renewable resource $r$ available
$W_{r t}=$ amount of renewable resource $r$ available at period $t$
$Q_{n}=$ amount of non-renewable resource $n$ available
$w_{i j r}=$ amount of renewable resource $r$ utilized by activity $i$ performed in mode $j$
$w_{i j r t}=$ amount of renewable resource $r$ utilized by activity $i$ performed in mode $j$ at time period $t$
$q_{i j n}=$ amount of non-renewable resource $n$ consumed by activity $i$ performed in mode $j$
$T=$ total length of the time horizon
$C_{s}^{R}=$ lump sum payment made at the completion time of project $s$
$C_{s}^{I}=$ fixed cost to be incurred in order to start project $s$
$c_{r}^{u}=$ variable cost of utilizing one unit of renewable resource $r$ for one time period $c_{n}^{u}=$ variable cost of consuming one unit of non-renewable resource $n$

All parameters except $e_{i}, l_{i}$ and $T$ must be initially given to solve the problem. However, $e_{i}, l_{i}$ and $T$ parameters can be calculated using the precedence data and the $d_{i j}$ values. For instance, $T$ can be set by just summing up the durations of the longest modes of each activity. Then $e_{i}$ values can be determined by a forward pass and $l_{i}$ values can be determined by a backward pass starting at $T$ both passes being expected with resources being ignored. In addition, it is also possible that some or all of these time related parameters can also be just given. For example, some of the activities may have given earliest and/or latest start times because of practical reasons such as legal legislations or there might be a general due date forcing all projects to be finished before that date.

### 2.4.3 Decision Variables

A binary variable $x_{i j t}$ based on starting time period and mode selection of activities is introduced along with two other integer variables based on it. It was also possible to represent the precedence relation constraints without defining $T_{i}$ and $D_{i}$ but they are included for practical purposes.
$x_{i j t}=1$ if activity $i$ starts at time period $t$ in mode $j ;=0$ otherwise.
$T_{i}=$ Actual starting time period of activity $i ; e_{i} \leq T_{i} \leq l_{i}$
$D_{i}=$ Actual duration of activity $i ; \min _{j \in M_{i}}\left\{d_{i j}\right\} \leq D_{i} \leq \max _{j \in M_{i}}\left\{d_{i j}\right\}$

### 2.4.4 Mathematical Model

The mathematical model for the composite network project is a dual level model based on two types of performance criteria: (i) NPV maximization of all cash flows over the project duration and (ii) makespan minimization of projects, which is related to the service level regarding customer requirements. Level one, which is based on NPV maximization, considers $C_{t}^{R}, C_{t}^{I}$ and $C_{t}^{U}$ expressing cash flows related to, lump sum payments, investment costs and resource usage costs, respectively. Level two is based on project makespan minimization with given a starting time for each project $s \in S^{a}$.

Constraint set (2.3) represents the start times and constraint set (2.4) the durations for the projects. Constraint set (2.5) ensures the precedence relationships between the activities. Constraint set (2.6) is the capacity constraint for the renewable resources and constraint set (2.7) is the capacity constraint for the non-renewable resources. Constraint set (2.8) ensures that for each project a macro-mode alternative is selected and it is started at some point. Constraint sets (2.9), (2.10) and (2.11) regulate the cash flows incurred at time $t$. That the variables $x_{i j t}$ are zero-one variables are expressed in constraint set (2.12).

Model MPS:

Level 1:

$$
\begin{equation*}
\max N P V=\sum_{t \in \mathcal{T}} \frac{C_{t}^{R}-C_{t}^{I}-C_{t}^{U}}{(1+\alpha)^{t-1}} \tag{2.1}
\end{equation*}
$$

Level 2:

$$
\begin{align*}
& \min T_{z_{s}} \quad \forall s \in S^{a}  \tag{2.2}\\
& \text { s.t. } \\
& T_{i}=\sum_{j \in M_{i}} \sum_{t=e_{i}}^{l_{i}} t x_{i j t} \quad i \in V,  \tag{2.3}\\
& D_{i}=\sum_{j \in M_{i}} d_{i j} \sum_{t=e_{i}}^{l_{i}} x_{i j t} \quad i \in V,  \tag{2.4}\\
& T_{k}-T_{i} \geq D_{i} \quad(i, k) \in P,  \tag{2.5}\\
& \sum_{i \in V_{s}} \sum_{j \in M_{i}} \sum_{\theta=\max }^{\min \left(l_{i}+d_{i j}, t-d_{i j}+1\right)} w_{i j r} x_{i j \theta} \leq W_{r} \quad r \in \mathcal{R}, t \in \mathcal{T} \text {, }  \tag{2.6}\\
& \sum_{i \in V_{s}} \sum_{j \in M_{i}} q_{i j n} \sum_{t=e_{i}}^{l_{i}} x_{i j t} \leq Q_{n} \quad n \in \mathcal{N},  \tag{2.7}\\
& \sum_{j \in M_{i}} \sum_{t=e_{i}}^{l_{i}} x_{i j t}=1 \quad i \in V,  \tag{2.8}\\
& C_{t}^{R}=\sum_{s \in S} C_{s}^{R} x_{z_{s} 1 t} \quad t \in \mathcal{T},  \tag{2.9}\\
& C_{t}^{I}=\sum_{s \in S} C_{s}^{I} x_{a_{s} 1 t} \quad t \in \mathcal{T},  \tag{2.10}\\
& C_{t}^{U}=\left(\sum_{r \in \mathcal{R}} \sum_{i \in V} \sum_{j \in M_{i}} \sum_{\theta=\max }^{\min \left(l_{i}, t-d_{i j}-1, t\right)} w_{i j r} c_{r}^{U} x_{i j \theta}\right) \\
& +\left(\sum_{n \in \mathcal{N}} \sum_{i \in V} \sum_{j \in M_{i}} \sum_{\theta=\max }^{\min \left(l_{i}+d_{i j}-t-d_{i j}+1\right)} \frac{q_{i j n}}{d_{i j}} c_{n}^{U} x_{i j \theta}\right) \quad t \in \mathcal{T},  \tag{2.11}\\
& x_{i j t} \in\{0,1\}, i \in V, \quad j \in M_{i}, t \in \mathcal{T} \tag{2.12}
\end{align*}
$$

## CHAPTER 3

## SOLUTION APPROACH

In this chapter, a 2-stage decomposition solution approach to the problem described in the previous chapter is discussed. First, a general look at this approach is presented and then the subprocedures are explained in detail.

As in Speranza and Vercellis [8], 2-stage decomposition method employs NPV and service level represented by the makespan of each project as two different performance criteria. The higher level, where the tactical planning decisions are taken into account, is formulated as a single objective optimization model to avoid complexity of dealing with the whole multi-project network. Each project is reduced to a macro-activity and nodes representing these macro-activities form the macroproject network, which is a single project network and can be seen in Figure 3.1, signifying the multi-project planning problem. This macro-project scheduling problem is modeled with NPV maximization objective and used to determine start times and resource allocations for all projects. Then using the starting time obtained in the lower level, each project is scheduled to minimize its makespan to meet the customer requirements.

### 3.1 2-Stage Decomposition

At the very beginning of the whole procedure, preprocessing methods discussed in Sprecher et al. [22] are applied to reduce the data size. After eliminating all modes that are non-executable due to insufficient resource capacities and removing the non-renewable resources that are redundant, the actual decomposition procedure is started. In the first stage, each project is taken as a macro-activity and different
macro-modes are formed by evaluating various combinations of resource allocation through solving single project MRCPSPs with single artificial budgets constraining resource usage as in Speranza and Vercellis [8]. This macro-mode generation is referred as the shrinking process.


Figure 3.1: Macro-activities and macro-project

After the macro-modes are determined, a proper time horizon is determined to build a macro-project model with NPV maximization objective. While determining time horizon value, an initial feasible solution, which is a lower bound for the actual problem, is also obtained. Then the macro activities representing individual projects are scheduled subject to the general resource capacities with the objective of maximizing NPV. After this scheduling process, the due dates for projects and the allocation of resources among the projects are determined by the selection of macro-modes and completion times of macro-activities. Later at the second stage, each project's activities are scheduled within the project concerning the resource capacities allocated by the solution of the macro-project model in the first stage. Resource availabilities may differ from period to period for these single project scheduling problems. Also notice that these are tight constraints making the problems computationally easier to solve.

A brief summary is given in Algorithm 1:

```
Algorithm 1 2-Stage Decomposition
    Stage 0 - Data Reduction:
    Remove all non-executable modes
    Delete the redundant nonrenewable resources
    Stage 1a - Macro-mode Generation:
    for \(s=1\) to \(|S|\) do
            Generate macro-modes for project \({ }_{s}\)
    end for
    Stage 1b - Macro-Project Scheduling:
    Set time horizon and obtain an initial feasible solution
    Solve Macro Project Model for NPV maximization
    Allocate resources to projects
    Stage 2 - Detailed Single Project Scheduling:
    for \(s=1\) to \(|S|\) do
            Solve project \({ }_{s}\) for makespan minimization
    end for
```


### 3.2 Subprocedures

There are essentially four main subprocedures in the proposed 2-Stage Decomposition method: Data reduction, macro-mode generation, macro-project scheduling and project scheduling with time-dependent resources.

### 3.2.1 Data Reduction

At the very beginning of the whole procedure, two of the preprocessing methods discussed in Sprecher et al. [22] are applied to each project $s \in S^{a}$ in order to reduce the data size. First, all non-executable modes are eliminated and then all redundant non-renewable resources are removed.

### 3.2.1.1 Eliminating Non-executable Modes

Comparing execution modes may show that some modes are dominated by the others in the sense that a dominated mode of an activity will perform worse than or at the best as good as the other modes of that activity regarding processing time and resource usage efficiencies and these dominated modes or as also referred to non-executable modes, can never be selected in an optimal schedule.

A mode $m_{i}$ of an activity $i$ can be non-executable with respect to either a renewable and/or a non-renewable resource. Mode $m_{i}$ is a non-executable mode with respect to a renewable resource $r \in R$ if $w_{i m_{i} r}>W_{r}$. Further, denoting minimal request of activity $i$ for non-renewable resource $n$ as $q_{\text {in }}^{\min }:=\min \left\{q_{i j n} \mid j=\right.$ $\left.1, \ldots,\left|M_{i}\right|\right\}$, we call $m_{i}$ non-executable with respect to non-renewable resource $n$ if $\sum_{b=1 ; b \neq i}^{\left|V_{s}\right|} q_{b n}^{m i n}+q_{i m_{i} n}>Q_{n}$.

### 3.2.1.2 Eliminating redundant non-renewable resources

A non-renewable resource is redundant if there is enough capacity to meet even the maximal demand possible.

Let maximal request of activity $i$ for non-renewable resource $n$ be denoted as $q_{i n}^{\max }:=\max \left\{q_{i j n}\left|j=1, \ldots,\left|M_{i}\right|\right\}\right.$. Non-renewable resource $n$ is redundant, if $\sum_{i=1}^{\left|V_{s}\right|} q_{i n}^{\max } \leq Q_{n}$.

### 3.2.2 Macro-Mode Generation: A Shrinking Method

This subprocedure aims at transforming each project into a single macro-activity by identifying the efficient macro-modes of it. It is extremely significant to balance the trade-off between the diversity of macro-modes and the size of the macro-project model. Obviously, increasing the number of macro-modes increases number of possible outcomes thus may be leading to a better solution yet it increases also the required computational effort. Hence, a shrinking method is introduced to apply on each project $s \in S^{a}$, obviously excluding the dummy projects, to generate the efficient macro-modes. Two shrinking Models $M_{s}^{1}$ and $M_{s}^{2}$, which utilize artificial mode costs and an alterable budget based on resource usages, are adopted from the shrinking model introduced by Speranza and Vercellis [8] and used in a search systematic for efficient macro-modes.

### 3.2.2.1 Shrinking Models

Model $M_{s}^{1}$ :

$$
\begin{align*}
& x_{i j t}= \begin{cases}1 & \text { if activity } i \text { starts at time } t \text { in mode } j \\
0 & \text { otherwise }\end{cases}  \tag{3.1}\\
& \text { s.t. } \quad T_{i}=\sum_{j \in M_{i}} \sum_{t=e_{i}}^{\min _{i}} T_{z_{s}}, x_{i j t} \quad i \in V_{s},  \tag{3.2}\\
& D_{i}=\sum_{j \in M_{i}} d_{i j} \sum_{t=e_{i}}^{l_{i}} x_{i j t} \quad i \in V_{s},  \tag{3.4}\\
& T_{k}-T_{i} \geq D_{i} \quad(i, k) \in P_{s},  \tag{3.5}\\
& \sum_{i \in V_{s}} \sum_{j \in M_{i}} \sum_{\theta=\max }^{\min \left(l_{i}+d_{i j}-t-d_{i j}+1\right)} w_{i j r} x_{i j \theta} \leq W_{r} \quad r \in \mathcal{R}, t \in \mathcal{T}_{s},  \tag{3.6}\\
& \sum_{i \in V_{s}} \sum_{j \in M_{i}} q_{i j n} \sum_{t=e_{i}}^{l_{i}} x_{i j t} \leq Q_{n} \quad n \in \mathcal{N},  \tag{3.7}\\
& \sum_{j \in M_{i}} \sum_{t=e_{i}}^{l_{i}} x_{i j t}=1 \quad i \in V_{s},  \tag{3.8}\\
& g_{i j}=\sum_{r \in \mathcal{R}} d_{i j} w_{i j r} c_{r}^{U}+\sum_{n \in \mathcal{N}} q_{i j n} c_{n}^{U} \quad j \in M_{i}, i \in V_{s},  \tag{3.9}\\
& \sum_{i \in V_{s}} \sum_{j \in M_{i}} \sum_{t=e_{i}}^{l_{i}} g_{i j} x_{i j t} \leq k_{s}  \tag{3.10}\\
& x_{i j t} \in\{0,1\}, \quad i \in V_{s}, j \in M_{i}, t \in \mathcal{T}_{s}
\end{align*}
$$

As in a typical MRCPSP, constraints regarding start times (3.3), durations (3.4), precedence relations (3.5), assignments (3.8), resource capacities (3.6) and (3.7) and integrality (3.11) are included in Model $M_{s}^{1}$. For project $s$, there is also an artificial budget, $k_{s}$ constraining the resource usages. Considering renewable and non-renewable resources, variable usage costs, $g_{i j}$, are calculated as given in (3.9) and are constrained by a budget, $k_{s}$ as given in (3.10).

Model $M_{s}^{2}$ :

$$
\begin{array}{r}
\min k_{s} \\
\text { s.t. } \quad \sum_{i \in V_{s}} \sum_{j \in M_{i}} \sum_{t=e_{i}}^{l_{i}} g_{i j} x_{i j t}=k_{s} \\
T_{z_{s}} \leq T_{s}^{h}  \tag{3.14}\\
(3.3),(3.4),(3.5),(3.6),(3.7), \\
(3.8) \text { and }(3.11) \text { from Model } M_{s}^{1}
\end{array}
$$

In Model $M_{s}^{2}$, the budget is not included as a constraint (3.13) but it is taken as the objective (3.12). Here is an additional constraint (3.14) which sets an upperbound, $T_{s}^{h}$, on the makespan of the project. It should be remembered that there is a negative relation between project makespan and budget.

### 3.2.2.2 Method

```
Algorithm 2 Macro-Mode Generation
    for \(s=2\) to \(|S|-1\) do
            for all activity \(i \in V_{s}\) do
                        for all mode \(j \in M_{i}\) do
                        Calculate \(g_{i j}\)
                            end for
            end for
            Shift \(g_{i j} \quad i \in V_{s}, j \in M_{i}\) to 0
            Remove all inefficient modes \(i \in V_{s}, j \in M_{i}\)
            Calculate \(k_{s}^{\max }\)
            Solve Model \(M_{s}^{1}\) with \(k_{s}=k_{s}^{\max }\) and find \(D_{s}^{\min }\)
            Solve Model \(M_{s}^{1}\) with \(k_{s}=0\) and find \(D_{s}^{\max }\)
            for \(d=D_{s}^{\min }\) to \(D_{s}^{\max }\) do
            Solve Model \(M_{s}^{2}\) with \(T_{s}^{h}=d\)
                    if \(k_{s}\) decrease and generate the new macro-mode
            end for
    end for
```

Macro-mode generation procedure summarized in Algorithm 2 is initialized by calculating the artificial mode costs as expressed in (3.9). Then artificial mode costs
are shifted to zero by, calculating minimal artificial mode costs, $g_{i}^{\text {min }}$ for each activity $i \in V_{s}$ (3.15) and subtracting it from each artificial mode cost for each mode $j \in M_{i}$ (3.16).

$$
\begin{align*}
g_{i}^{\min } & =\min \left\{g_{i j} \mid j=1, \ldots, M_{i}\right\} \quad i \in V_{s}  \tag{3.15}\\
g_{i j} & =g_{i j}-g_{i}^{\min } \quad j \in M_{i}, i \in V_{s} \tag{3.16}
\end{align*}
$$

Later, inefficient modes are identified examining their durations and artificial costs. A mode $j$ of activity $i$ is considered as inefficient if there exists a mode $h$ of activity $i$ such that $d_{i j} \geq d_{i h}$ and $g_{i j} \leq g_{i h}$. After removing all the inefficient modes, maximum budget required, $k_{s}^{\max }$ is computed by calculating maximal artificial mode costs, $g_{i}^{\max }$ for each activity $i \in V_{s}$ (3.17) and adding them up (3.18).

$$
\begin{align*}
g_{i}^{\max } & =\max \left\{g_{i j} \mid j=1, \ldots, M_{i}\right\} \quad i \in V_{s}  \tag{3.17}\\
k_{s}^{\max } & =\sum_{i \in V_{s}} g_{i}^{\max } \quad j \in M_{i}, i \in V_{s} \tag{3.18}
\end{align*}
$$

Duration range $\left[D_{s}^{\min }, D_{s}^{\max }\right]$ for $T_{s}^{h}$, the upper on the makespan is computed by solving Model $M_{s}^{1}$ once setting $k_{s}$ equal to 0 and once setting it equal to $k_{s}^{\max }$. Duration range for $T_{s}^{h}$ signifies the durations for possible macro-modes to be generated. Solving Model $M_{s}^{2}$ gives a schedule with a makespan equal to $T_{s}^{h}$ and most efficient mode selections regarding the resource usage cost budget. Starting from $D_{s}^{\min }, T_{s}^{h}$ is increased by one at each step until $D_{s}^{\max }$ is reached. At each step, Model $M_{s}^{2}$ is solved and if $k_{s}$ value which is lower than the previous solution, a new macro-mode $v$ is generated using the duration and the renewable resource profile and the non-renewable resource consumption obtained in the solution of the model as shown in (3.20) and (3.19).

$$
\begin{align*}
q_{s v t} & =\sum_{i \in V_{s}} \sum_{j \in M_{i}} q_{i j n} \sum_{t=e_{i}}^{l_{i}} x_{i j t}^{*}  \tag{3.19}\\
w_{s v r t} & =\sum_{i \in V_{s}} \sum_{j \in M_{i}} \sum_{\theta=\max \left(e_{i}, t-d_{i j}+1\right)}^{\min \left(l_{i}+d_{i j}-1, t\right)} w_{i j r(t-\theta+1)} x_{i j \theta}^{*} \tag{3.20}
\end{align*}
$$

This condition that $k_{s}$ decreases is considered in order to ignore schedules representing identical mode selections but having different durations and, of course, it is not checked the first solution of Model $M_{s}^{1}$ where $T_{s}^{h}=D_{s}^{\min }$ and an initial $k_{s}$ value to be compared with has not been determined yet.

### 3.2.2.3 Macro-Mode Generation Example



Figure 3.2: Macro-mode generation example network

Here is an example on the application of macro-mode generation subprocedure. A project network with six activities is presented in Figure (3.2). Activities 0 and 5 are dummy activities. There is one renewable resource $r^{\prime}$ with 10 capacity and one non-renewable resource $n^{\prime}$ with 50 capacity employed with capacity. Usage costs are given as: $c_{r^{\prime}}^{u}=1$ and $c_{n^{\prime}}^{u}=2$. Duration and resource requirements data about execution modes of activities are shared in Table 3.1 along with mode cost calculations and shifted mode cost values. Note that dummy activities have 0 mode costs.

By using (3.17) and (3.18), $k_{s}^{\max }$ is calculated to be 23. Solving Model $M_{s}^{1}$ once setting $k_{s}$ equal to 0 and once setting it equal to 23 provides a duration range of [7, 10]. Then four macro-modes presented in Figure (3.3) are generated by solving

| $i$ | $j$ | $d_{i j}$ | $w_{i j r^{\prime}}$ | $q_{i j n^{\prime}}$ | $\left(d_{i j}\right)\left(w_{i j r^{\prime}}\right)\left(c_{r^{\prime}}^{u}\right)+\left(q_{i j n^{\prime}}\right)\left(c_{n^{\prime}}^{u}\right)=g_{i j}$ | $g_{i j}^{\prime}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | 3 | 3 | 2 | $(3)(3)(1)+(2)(2)=13$ | 3 |
|  | 2 | 4 | 2 | 1 | $(4)(2)(1)+(1)(2)=10$ | 0 |
| 2 | 1 | 5 | 4 | 3 | $(5)(4)(1)+(3)(2)=26$ | 8 |
|  | 2 | 7 | 2 | 2 | $(7)(2)(1)+(2)(2)=18$ | 0 |
| 3 | 1 | 4 | 3 | 4 | $(4)(3)(1)+(4)(2)=20$ | 8 |
|  | 2 | 6 | 2 | 0 | $(6)(2)(1)+(0)(2)=12$ | 0 |
| 4 | 1 | 1 | 2 | 0 | $(1)(2)(1)+(0)(2)=2$ | 0 |
|  | 2 | 2 | 0 | 3 | $(2)(0)(1)+(3)(2)=6$ | 4 |

Table 3.1: Macro-mode generation example data

Model $M_{s}^{2}$ with the upperbound values in the duration range set. At all steps following the first one, a decrease in the objective function value is observed thus making all the macro-modes generated acceptable as defined in the procedure.


Figure 3.3: Schedules and resource profiles for generated macro-modes

### 3.2.3 Macro-Project Scheduling

Macro-project scheduling problem here is a special kind of MRCPSPDCF. The amount of renewable resource $r$ utilized by an activity performed in one of its modes is time dependent. Although this problem looks similar to the scheduling of projects with variable-intensity activities as studied in, for example, Kis [64] in the sense that resource usage of each activity may vary over time, it is a quite different problem. In variable-intensity activities case, resource usage of each activity may vary over time proportionally to its varying intensity and determining these intensity levels is part of the problem yet in macro-project scheduling studied here intensity levels are not to be decided. Instead, there are macro-activities each with several macro-modes having time-dependent renewable resources requirements which are determined based on the schedules evaluated in the previous step, macro-mode generation.

Constraint set (3.23) represents the start times and constraint set (3.24) represents the durations for the projects. Constraint set (3.25) ensures the precedence relationships between the projects. Constraint set (3.26) is the capacity constraint for the renewable resources and constraint set (3.27) is the capacity constraint for the non-renewable resources. Constraint set (3.28) ensures that for each project a macro-mode alternative is selected and is started at some point in the interval $\left[e_{s}, l_{s}\right]$.

## Model MP:

$$
\tilde{x}_{s v t}= \begin{cases}1 & \text { if project } s \text { starts at time } t \text { in macro-mode } v  \tag{3.21}\\ 0 & \text { otherwise }\end{cases}
$$

$$
\begin{align*}
& \max N P V=\sum_{s \in S} \sum_{v \in M_{s}} \sum_{t=e_{s}}^{l_{s}}(1+\alpha)^{-t+1} C_{s v} \tilde{x}_{s v t}  \tag{3.22}\\
& \qquad T_{s}=\sum_{v \in M_{s}} \sum_{t=e_{s}}^{l_{s}} t \tilde{x}_{s v t}  \tag{3.23}\\
& \text { s.t. }  \tag{3.24}\\
& \qquad \begin{array}{rl}
D_{s}=\sum_{v \in M_{s}} d_{s v} \sum_{t=e_{s}}^{l_{s}} \tilde{x}_{s v t} & s \in S, \\
T_{k}-T_{s} \geq D_{s} & (s, k) \in P_{s}, \\
\sum_{s \in S} \sum_{v \in M_{s}} \sum_{\theta=\max }^{\min \left(l_{s}+d_{s v}-1, t\right)} w_{s v r(t-\theta+1)} \tilde{x}_{s v \theta} \leq W_{r} & r \in \mathcal{R}, t \in \mathcal{T}, \\
\sum_{s \in S} \sum_{v \in M_{s}} q_{s v n} \sum_{t=e_{s}}^{l_{s}} \tilde{x}_{s v t} \leq Q_{n} & n \in \mathcal{N}, \\
\sum_{v \in M_{s}} \sum_{t=e_{s}}^{l_{s}} \tilde{x}_{s v t}=1 & s \in S, \\
\tilde{x}_{s v t} \in\{0,1\}, s \in S, & v \in M_{s}, t \in \mathcal{T}
\end{array} \tag{3.25}
\end{align*}
$$

where

$$
\begin{align*}
C_{s v}= & C_{s}^{R}(1+\alpha)^{-d_{s v}}-C_{s}^{I} \\
& -\left(\sum_{\theta=0}^{d_{s v}-1}(1+\alpha)^{-\theta}\left(\sum_{r \in \mathcal{R}} c_{r}^{U} w_{s v r(\theta)}+\sum_{n \in \mathcal{N}} c_{n}^{U} q_{s v n} / d_{s v}\right)\right) \tag{3.30}
\end{align*}
$$

### 3.2.4 Scheduling Individual Projects with the Objective of Minimizing the Makespan

After setting the resource capacities and the start times of the projects, each schedule is individually solved for minimizing the project makespan. Mathematical Model $S_{s}$ is given below:

Model $S_{s}$ :

$$
\begin{gather*}
\min T_{z_{s}}  \tag{3.31}\\
\sum_{i \in V_{s}} \sum_{j \in M_{i}} \sum_{\theta=\max }^{\min \left(l_{i}+d_{i j}-1, t\right)} w_{i j r} x_{i j \theta} \leq \tilde{W}_{r t}^{s} \quad r \in \mathcal{R}, t \in \mathcal{T}_{s}, ~ \\
\sum_{i \in V_{s}} \sum_{j \in M_{i}} q_{i j n} \sum_{t=e_{i}}^{l_{i}} x_{s v t} \leq \tilde{Q}_{n}^{s} \quad n \in \mathcal{N} \tag{3.32}
\end{gather*}
$$

(3.3), (3.4), (3.5), (3.8) and (3.11) from Model $M_{s}^{1}$

The same constraints for activity duration (3.3), start time (3.4), precedence (3.5), assignment (3.8) and integrality (3.11) constraints as in Model $M_{s}^{1}$ are included. Note that the right hand side of resource capacity constraints in (3.32) and (3.33) in Model $S_{s}$ are different from the ones in Model $M_{s}^{1}$. The renewable resource capacity constraint in (3.32) has also a time index. Unlike in the multi-project model, where resource usages of macro-modes were time-dependent, resource capacities are time-dependent in this final stage because they are actually determined by the selection of macro-modes in the previous level. Normally, it is expected for time-dependency of resource capacity levels to cause a significant escalation in the computation time but it is not experienced in this particular problem because resource capacities are quite tight. Remember that they are determined by the selection of macro-modes which were generated through solving a very similar model repeatedly.

### 3.3 Proper Time Horizon Setting

Setting the time horizon vitally affects the number of total variables which has a direct effect on the computational time. A simple approach would be just summing up the durations of the longest macro-modes of each project. However, this method still suggests a time horizon that is too large, so it is necessary to employ a different method to obtain an estimate for the time horizon in order to reduce the computation time to a more reasonable level. For that purpose, three alternatives are examined:

1. Relaxed Greedy Heuristic (RGH).
2. Greedy Heuristic with Artificial Resource Budget (GHARB).
3. Lagrangian Relaxation Heuristic (LRH).

Makespan of the feasible solutions obtained through one of these methods is set as the time horizon for the actual problem. Also a genetic algorithm approach is introduced which

### 3.3.1 Relaxed Greedy Heuristic

In RGH, there is a very simple model with non-renewable resource capacity (3.36) and macro-mode assignments constraints (3.37). $C_{s v}$, cash flows of each mode $v$ of each project $s$ are calculated as described in (3.30) in Model MP. A new binary variable is defined in (3.34) to represent macro-mode selection of projects. Basically, this model is solved to obtain the non-renewable resource feasible list of macro mode selections with greatest sum of cash returns. These macro-modes are listed following the non-decreasing order of cash flows and they are scheduled according to this ordered list yet this time taking renewable resource capacities into consideration.

Model $G^{1}$ :

$$
\begin{align*}
& \tilde{x}_{s v}= \begin{cases}1 & \text { if project } s \text { is executed with macro-mode } v \\
0 & \text { otherwise }\end{cases}  \tag{3.34}\\
& \max \sum_{s \in S} \sum_{v \in M_{s}} C_{s v} \tilde{x}_{s v}  \tag{3.35}\\
& \text { s.t. } \\
& \sum_{s \in S} \sum_{v \in M_{s}} q_{s v r} \tilde{x}_{s v} \leq Q_{r} \quad r \in \mathcal{N},  \tag{3.36}\\
& \sum_{v \in M_{s}} \tilde{x}_{s v}=1  \tag{3.37}\\
& (3.30)  \tag{3.38}\\
& \tilde{x}_{s v} \in\{0,1\}, s \in S, \quad \text { from Model MP } \quad v \in M_{s},
\end{align*}
$$

### 3.3.2 Greedy Heuristic with Artificial Resource Budget

In GHARB, Model $G^{1}$ is extended by adding an artificial resource budget (3.39) to end up with Model $G^{2}$. Basic idea in GHARB is to try different budget values to generate various priority sequences and mode selections that lead to different feasible solutions. The best one among them is selected.

Model $G^{2}$ :

$$
\begin{equation*}
\max \sum_{s \in S} \sum_{v \in M s} C_{s v} \tilde{x}_{s v} \tag{3.35}
\end{equation*}
$$

s.t.

$$
\begin{align*}
& \sum_{s \in S} \sum_{v \in M_{s}} \breve{r}_{s v} \tilde{x}_{s v} \leq \quad B  \tag{3.39}\\
& (3.36),(3.37) \text { and (3.38) } \\
& \text { from Model } G^{1}
\end{align*}
$$

1. Initialization:
(a) Artificial costs, $\breve{r}_{s v}$, for each project and macro-mode are calculated:

$$
\breve{r}_{s v}=\sum_{r \in \mathcal{R}} \sum_{\theta=0}^{d_{s v}} w_{s v r(\theta)}, \quad s \in S, v \in M_{s}
$$

(b) Then artificial costs are shifted to 0 :
$\breve{r} \min _{s}:=\min \left\{\breve{r}_{s v} \mid v=1, \ldots, M_{s}\right\}, \quad s \in S$,
$\breve{r}_{s v}=\breve{r}_{s v}-\breve{r} \min _{s}, \quad v \in M_{s}, s \in S$,
(c) Then maximum budget needed, $B_{\max }$ is calculated:
$\breve{r} \max _{s}:=\max \left\{\breve{r}_{s v} \mid v=1, \ldots, M_{s}\right\}, \quad s \in S$,
$B_{\text {max }}=\sum_{s \in S} \breve{r} \max _{s}, \quad v \in M_{s}, s \in S$,
(d) $B=0$ and $B_{\text {step }}=\left(B_{\text {max }} /\right.$ no. of iterations $)$
2. Model $G^{2}$ is solved
(a) Obtain a list of macro-modes feasible for non-renewable resources
(b) Schedule the projects with the selected macro-modes one by one following the non-decreasing order of cash flows
(c) If obtained schedule is better than the the current best: Update the the current best
(d) $B=B+B_{\text {step }}$. If $B>B_{\max }$ : stop; otherwise, goto step 2a.

### 3.3.3 Lagrangian Relaxation Heuristic

### 3.3.3.1 Lagrangian Relaxation Approach

Lagrangian relaxation approaches was first proposed by Held and Karp [65] and followed by various successful adaptations as discussed, for example, in Fisher [66] and Kimms [48]. This approach is based upon the observation that many integer programming problems that are quite difficult can be modeled as a relatively easy problem complicated by a group of constraints and therefore, a Lagrangian problem is created replacing the complicating constraints with a penalty expression in the objective function involving the amount of violation of the constraints ( [66]). Solving this easier problem provides a lower bound (for a minimization problem) on the optimal value of the original problem which can be used in a heuristic or a branch and bound algorithm.

Consider the integer programming model $(I P)$ for a minimization problem and assume that removing the constraint set (3.41) makes the problem relatively easier to solve.

Model IP :

$$
\begin{align*}
& \min Z \quad c x  \tag{3.40}\\
& \text { s.t. } \quad A^{1} x=b^{1}  \tag{3.41}\\
& A^{2} x=b^{2}  \tag{3.42}\\
& x \geq 0 \quad \text { and integral } \tag{3.43}
\end{align*}
$$

Complicating constraint set, (3.41) is dropped from Model IP and multiplied with a vector of non-negative multipliers, $\lambda$ included as a penalty term in the objective function (3.44) to generate a Lagrangian relaxed Model $L R$.

Model $L R$ :

$$
\begin{equation*}
\min Z \quad c x+\lambda\left(b^{1}-A^{1} x\right) \tag{3.44}
\end{equation*}
$$

s.t. (3.42) and (3.43) from Model IP

Obviously, solving Model $L R$ where $\lambda$ vector is fixed provides a lower bound on $Z$ since merely a nonnegative term is added to the objective function.

In order to design a Lagrangian relaxation based mechanism, three major issues should be carefully thought: which constraints to relax, how to compute good $\lambda$ and how to find a good feasible solution to the original problem using the solution obtained for the relaxed problem.

### 3.3.3.2 Lagrangian Relaxation of Macro-Project Scheduling Problem

Being the most complicating constraints in Model MP, renewable resource capacity constraints (3.26) are relaxed and over-usages of renewable resources are included as penalties in the objective function (3.46) of Model LRMP.

Model LRMP :

$$
\begin{align*}
\max N P V=\sum_{s \in S} & \sum_{v \in M_{s}} \sum_{t=e_{s}}^{l_{s}}(1+\alpha)^{-t+1} C_{s v} \tilde{x}_{s v t} \\
& +\sum_{r \in \mathcal{R}} \sum_{t=0}^{T} \lambda_{r t}\left(W_{r}-\sum_{s \in S} \sum_{v \in M_{s}} \sum_{\theta=\max }^{\min \left(l_{s}+d_{s}, t-d_{s v}-1, t\right)} w_{s v r(t-\theta+1)} \tilde{x}_{s v \theta}\right) \tag{3.46}
\end{align*}
$$

s.t.

$$
(3.23),(3.24),(3.25),(3.27),(3.28) \text { and }(3.29) \quad \text { from Model } M P
$$

Lagrange multipliers:

$$
\begin{equation*}
\lambda_{r t}=\max \left\{0, \lambda_{r t}+\delta \frac{\left(U B^{*}-L B^{*}\right) \Delta_{r t}}{\sum_{r \in \mathcal{R}} \sum_{\tau=1}^{T} \Delta_{r \tau}^{2}}\right\} \quad r \in \mathcal{R}, t \in \mathcal{T} \tag{3.47}
\end{equation*}
$$

where

$$
\begin{equation*}
\Delta_{r t}=\sum_{s \in S} \sum_{v \in M_{s}} \sum_{\theta=\max }^{\min \left(l_{s}+d_{s v}, t-d_{s v}+1\right)} w_{s v r(t-\theta+1)} \tilde{x}_{s v \theta}-W_{r} \quad r \in \mathcal{R}, t \in \mathcal{T} \tag{3.48}
\end{equation*}
$$

Among various methods existing in the literature, one of the most common approaches, subgradient search is selected to update Lagrange multipliers. At each step, first, an upper bound $(U B)$ is obtained by simply solving Model LRMP and a lower bound $(L B)$ is determined by obtaining a renewable resource feasible schedule based on the model solution as in Kimms [48]. Then Lagrange multipliers are updated using expression (3.47); where $U B^{*}$ and $L B^{*}$ are respectively the best $U B$ and $L B$ at hand, $\Delta_{r t}$ represents the amount of over-usage for renewable resource $r$ at time $t$ as in (3.48) and $\delta$ is the step size.

Deducing a feasible solution for MP from optimal solution obtained for LRMP, is achieved by a serial scheduling scheme employing a list of macro-mode selections and priority ordering of macro-activities like in RGH and GHARB. Macro-mode selections are directly acquired from the solution of $L R M P$ and priory ordering is determined by relying on starting times of macro-activities meaning that earlier start times grant more priority to the macro-activities. If two macro-activities have
the same start time, the tie is broken by prioritizing the macro-activity with greater cash flow.
$\delta$ is set to 2 initially and it is reduced to its half whenever $U B^{*}$ has not been improved for $c_{\max }$ times. $c_{\max }$ is chosen to be 5 .

A summary of LRH is provided in Algorithm 3. LRH is started by setting lagrange multipliers to 0 , determining the initial values for $U B^{*}$ and $L B^{*}$ by respectively, solving $L R M P$ and obtaining a feasible solution to the original problem. After determining $\Delta_{r t}$, the procedure is carried on for $y_{\max }$ iterations.

```
Algorithm 3 Lagrangian Relaxation Heuristic
    Initialization:
    Set \(\lambda_{r t}=0 \quad r \in \mathcal{R}, t \in \mathcal{T}\) and \(c=0\)
    Solve Model \(L R M P\) and set \(U B^{*}\)
    Calculate \(\Delta_{r t} \quad r \in \mathcal{R}, t \in\)
    Obtain a feasible schedule and set \(L B^{*}\)
    Iterations:
    for \(y=1\) to \(y_{\max }\) do
            Update \(\lambda_{r t} \quad r \in \mathcal{R}, t \in \mathcal{T}\)
            Solve Model \(L R M P\) to obtain \(U B\)
            Update \(\Delta_{r t} \quad r \in \mathcal{R}, t \in \mathcal{T}\)
            if \(U B^{*}<U B\) then
                    Set \(U B^{*}=U B\)
            else
            Set \(c=c+1\)
                    if \(\left(c=c_{\max }\right)\) then
                    Set \(\delta=\delta / 2\) and \(c=0\)
                    end if
            end if
            Obtain a feasible schedule and \(L B\)
            if \(L B^{*}>L B\) then
                    \(\operatorname{Set} L B^{*}=L B\)
            end if
    end for
```


### 3.4 Post-Processing for Macro-Project Scheduling

In this section, a post-processing procedure to redistribute to the projects the renewable and non-renewable resource capacities that are left over after macro-project scheduling is introduced.

$$
\begin{array}{rlrl}
W_{r t}^{\prime} & =W_{r}-\sum_{s \in S} \sum_{v \in M_{s}} \sum_{\theta=\max \left(e_{s}, t-d_{s v}+1\right)}^{\min \left(l_{s}+d_{s v}-1, t\right)} w_{s v r(t-\theta+1)} \tilde{x}_{s v \theta}^{*} & r \in \mathcal{R}, t \in \mathcal{T} \\
Q_{n}^{\prime} & =Q_{n}-\sum_{s \in S} \sum_{v \in M_{s}} q_{s v n} \sum_{t=e_{s}}^{l_{s}} \tilde{x}_{s v t}^{*} & & n \in \mathcal{N} \tag{3.50}
\end{array}
$$

The main idea is to effectively distribute the left-over capacities for renewable resources expressed by $W_{r t}^{\prime}$ in (3.49) and for non-renewable resources as expressed by $Q_{n}^{\prime}$ in (3.50) from macro-mode assignments $v^{*}$ acquired from the solution $x_{s v t}^{*}$ of Model MP keeping the start times for each project the same as before. In order to benefit from the left-over capacities, for each project $s \in S^{a}$, a new macro-mode $v^{+}$ is generated by solving Model $M_{s}^{3}$. The new macro-mode $v^{+}$is generated so as to maximize the project NPV assuming all of extra resource capacities along with the currently assigned resource capacities made available for project $s$ as expressed in (3.52) and (3.53). NPV maximization objective (3.51) is defined in (3.54) by including initial investment cost, the lump sum payment at the end and the resource usage costs, which are incurred on a periodic basis, are calculated as in (3.55). Shifting a project's currently selected macro-mode $v^{*}$ to the newly created alternative $v^{+}$ always causes an improvement in the NPV of macro-project schedule but it may not be possible to shift macro-modes for all projects at the same time because of conflicting needs for common left-over capacities. On the other hand, it can easily be seen that making a shift for project $s$ may assign some left-over capacities to project $s$ but it may also release some of the resources that are no longer required once the shift is realized. This means that these possible macro-mode shifts are linked with each other. Hence, decisions on macro-mode shifts should be made considering the projects simultaneously.

Model $M_{s}^{3}$ :

$$
\begin{gather*}
\sum_{i \in V_{s}} \sum_{j \in M_{i}} q_{i j n} \sum_{t=e_{i}}^{l_{i}} x_{i j t} \leq Q_{n}^{\prime}+q_{s v^{*} n} \quad n \in \mathcal{N},  \tag{3.51}\\
\text { s.t. } \sum_{i \in V_{s}} \sum_{j \in M_{i}} \sum_{\theta=\max }^{\min \left(l_{i}+d_{i j}-1, t\right)} w_{i j} x_{i j \theta} \leq W_{r\left(T_{s}^{*}+t-1\right)}^{\prime}+w_{s v^{*} r t} \quad r \in \mathcal{R},  \tag{3.52}\\
N P V_{s}=\sum_{\theta=e_{z_{s}}}^{d_{s v^{*}}}(1+\alpha)^{\theta-1} C_{s}^{R}-C_{s}^{I}-\sum_{i \in V_{s}} \sum_{j \in M_{i}} \sum_{t=e_{i}}^{l_{i}} f_{i j} x_{i j t}  \tag{3.53}\\
t \in\left\{1, \ldots, d_{s v^{*}}\right\},  \tag{3.54}\\
f_{i j}=\sum_{t=1}^{d_{i j}}(1+\alpha)^{t-1}\left(c_{r}^{U} w_{i j r}+\sum_{n \in \mathcal{N}} c_{n}^{U} q_{i j n} / d_{i j}\right) \quad i \in V_{s}, j \in M_{i}  \tag{3.55}\\
x_{i j} \in\{0,1\}, i \in V_{s}, j \in M_{i}, \quad t \in\left\{1, \ldots, d_{s v^{*}}\right\} \tag{3.56}
\end{gather*}
$$

(3.1), (3.3), (3.4), (3.5) and (3.8) from Model $M_{s}^{1}$

Once the new macro-mode $v^{+}$is formed for each project $s \in S^{a}$, trade-offs on NPV and resource capacities due to macro-mode shifts are calculated. In (3.57), $C_{s}^{\prime \prime}$, benefit gained on NPV due to macro-shift of project $s$ is calculated considering $T_{s}^{*}$, the start time of project $s$ obtained in the solution of model $M P . Q_{s n}^{\prime \prime}$, trade-off on non-renewable resource capacities in (3.58) and $W_{s r t}^{\prime \prime}$, trade-off on renewable resource capacities are set in (3.59).

$$
\begin{array}{ll}
C_{s}^{\prime \prime}=\left(C_{s v^{+}}-C_{s v^{*}}\right)(1+\alpha)^{\left(T_{s}^{*}-1\right)} & s \in S^{a}, \\
Q_{s n}^{\prime \prime}=Q_{s v^{+} n}-Q_{s v^{*} n} & s \in S^{a}, n \in \mathcal{N} \\
W_{s r t}^{\prime \prime}=W_{s v^{+} r t}-W_{s v^{*} r t} & s \in S^{a}, r \in \mathcal{R}, t \in\left\{1, \ldots, d_{s v^{*}}\right\} \tag{3.59}
\end{array}
$$

Then macro-mode shifting decisions are determined by solving Model MMS. In this model, it is aimed to maximize the total NPV gain by selecting which projects to apply macro-mode shift. Variable $y_{s}$ is defined in (3.60) to represent if macromode shift is applied to a project. Constraint sets (3.62) and (3.63) ensure that total resource availability constraints are not violated.

Model MMS:

$$
\begin{align*}
& y_{s}= \begin{cases}1 & \text { if macro-mode selection of project } s \text { is shifted } \\
0 & \text { otherwise }\end{cases}  \tag{3.60}\\
& \quad \max \sum_{s \in S^{a}} C_{s}^{\prime \prime} y_{s}  \tag{3.61}\\
& \text { s.t. } \quad \sum_{s \in S^{a}} Q_{s n}^{\prime \prime} y_{s} \leq Q_{n}^{\prime} \quad n \in \mathcal{N}  \tag{3.62}\\
& \sum_{s \in S^{a}} \sum_{\theta=T_{s}^{*}}^{T_{s}^{*}+d_{s v^{*}}-1} W_{s r \theta}^{\prime \prime} y_{s} \leq W_{r t}^{\prime} \quad r \in \mathcal{R}, t \in \mathcal{T}  \tag{3.63}\\
& x_{s} \in\{0,1\}, \quad s \in S^{a} \tag{3.64}
\end{align*}
$$

After applying the macro-mode shifts to the selected projects, project scheduling with time-dependent renewable resource constraints is realized.

## CHAPTER 4

## A GENETIC APPROACH FOR MRCPSPDCF WITH TIME-DEPENDENT RENEWABLE RESOURCE REQUIREMENTS

In this chapter, a genetic algorithm (GA) approach for the macro-project scheduling problem in the 2-stage decomposition procedure is introduced. This approach allows us to quickly obtain an efficient solution for the macro-project scheduling problem. The GA solution can also be employed as an initial solution which can be fed into the MIP solver to decrease the computation time of the exact solution procedure. Macro-project scheduling problem is basically a single project scheduling problem with multiple execution modes and discounted cash flows considering each project as an activity and each macro-mode as an activity execution mode. Due to the nature of the macro-project scheduling problem, it is assumed that there are no precedence relations between the activities. The objective is NPV maximization of positive cash flows under renewable and non-renewable resource constraints. Various GA approaches for single-mode and multi-mode RCPSPDCF with both makespan minimization and NPV maximization objectives have been proposed in the literature. Here, MRCPSPDCF is extended by employing time dependent renewable resource requirements.

### 4.1 Representation

Since the problem is a kind of multi-component combinatorial optimization problem with sequencing and selection components (MCCOP_SS), a common chromosome structure including two serial lists is used to represent a solution for the problem as in Şerifoğlu [67]. First list is basically a permutation of actual activities representing
the priority order of activities to schedule and second one is a list of mode selections for activities. The critical point here is that mode selections should be feasible with respect to the non-renewable resources as well.

| 5 | 4 | 1 | 2 | 7 | 6 | 3 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | 1 | 3 | 2 | 1 | 2 | 1 |

Figure 4.1: An example chromosome

An example for a schedule representation with 7 activities and with renewal modes each is given in Figure 4.1. Top row of the chromosome represents the priority sequence for the activities meaning that activity 5 has to be scheduled first and then activities $4,1,2,7,6$, and 3 have to follow in that order. Bottom row of the chromosome represents the list of mode selections for the activities. For example, activity 2 is executed in its second mode and activity 7 is executed in its first mode.

### 4.2 Evaluation of Chromosomes

Fitness of the chromosomes are determined by calculating NPV values considering the positive cash flows incurred at the start of the each activity. Start times are determined by obtaining the specific schedule represented by the lists stored in the chromosome. Since all cash flows are positive, starting activities as early as possible is more desirable to achieve higher NPVs.

A serial scheduling scheme is used to to schedule the activities based on the priority sequence and mode selections held in chromosomes. Procedure starts with an empty schedule and at each step the current partial schedule is extended by scheduling the next activity in the priority sequence to start at the earliest time point for which its execution does not violate any resource constraints. Once the starting times for each activity are determined, NPV can be calculated using the cash flows incurred at the start of each activity, thus resulting in the fitness of the chromosome.

### 4.3 Operators

### 4.3.1 Crossover Operator

Selecting an appropriate crossover operator is an important decision for GA applications. In the current formulation of the problem, it is assumed that there are no precedence relations between the activities thus making the decision easier. Considering that there is no precedence feasibility issue, 2-point crossover method is selected.


Figure 4.2: Crossover example

In 2-point crossover procedure, two random genes from the first parent are picked and then genes before the first randomly selected gene and after the second randomly selected gene are directly passed on to the child. Then the genes associated with the activities missing in child's priority order list are acquired from the second parent following the order in its priority order list together with the associated modes. An example of the crossover procedure is given in Figure 4.2.

### 4.3.2 Mutation Operators

There are two mutation operators used to randomly modify the newborn and reproduced chromosomes: the swap mutation operator and the bit mutation operator.

Swap mutation: It is executed on the priority order list to obtain different sequences, which may or may not lead to a different schedule, by swapping the places of two activities randomly selected. For example, in Figure 4.3, activities 1 and 4 are swapped.

Bit mutation: An activity is selected randomly and the mode selection associated with this activity is replaced with another randomly chosen mode value as shown in


Figure 4.3: Swap mutation example

Figure 4.4. Bit mutation may lead to a non-renewable resource infeasible solution. Therefore, if such a selection is made, the change is discarded.

| 5 | 4 | 2 | 7 | 1 | 6 | 3 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | 1 | 2 | 1 | 1 | 2 | 1 |$\longrightarrow$| 5 | 4 | 2 | 7 | 1 | 6 | 3 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 1 | 1 | 2 | 3 | 1 | 2 | 1 |

Figure 4.4: Bit mutation example

If a chromosome is chosen to be mutated, either only one of the mutation operators is applied or both of them are applied at the same time. Therefore, there are three possibilities, which have equal probabilities to be realized: (i) only swap mutation, (ii) only bit mutation, and (iii) both operators.

### 4.3.3 Population Management

Initial population is formed by generating as many chromosomes as the population size ( $n_{\text {pop }}$ ) using the following simple random chromosome generation scheme: first, mode selection list is generated by selecting a random mode for each activity and if the mode selections are not feasible considering the general non-renewable resource capacities, it is formed again from scrap. Then a random sequence of activities is created and combined with the non-renewable resource feasible mode selection list. If there are any existent solutions at hand, they can be also included in the initial solution.

At each iteration, a new population is created as the following: A number of new members, which corresponds to a ratio $r_{\text {new }}$ of population size, are created by using the 2-point crossover with members randomly selected from the current population and are added to the new population along with the elite individuals (i.e. best two individuals). Then the rest is reproduced using the roulette wheel
selection method on the current population with elite individuals deleted, which grants a higher chance to survive for the fitter individuals. Finally, each individual except the elite ones are considered for a swap mutation possibility with probability $p_{\text {swap }}$ and a bit mutation possibility with probability $p_{\text {bit }}$.

$$
n_{\text {pop }}=n_{\text {elite }}+\left\lceil r_{\text {new }} * n_{\text {pop }}\right\rceil+\text { reproduced individuals }
$$



Figure 4.5: New population generation scheme

### 4.3.4 Injection

GAs derive their strength from their ability to randomly search within a vast solution space very quickly. Survival of the fittest principle grants a higher chance for the stronger members to exist and to reproduce for a longer time period. After a number of population generations one might observe convergence in the population. In order to avoid this possibility and to refresh the population with a random touch, the ratio of identical individuals in the population is checked periodically after a certain number of generations. If the there are too many identical copies of a chromosome, it shows that a larger portion of the population represents the particular solution. Hence, injection is applied to increase the variety in the population. Through injection, all the members in the population except the elites are replaced by randomly generated new members and injections are accomplished periodically once every time $n_{i n j}$ number of generations are generated.

### 4.3.5 Termination

The procedure is carried out for a predetermined number of iterations and once this maximum iteration limit is reached, the procedure is terminated.

### 4.4 Parameter Finetunining

A series of experiments are performed to finetune the parameters for the proposed GA algorithm. Various values as shown in Table 4.1 are tested for the following parameters, which were previously explained in section 4.3: Population size, number of generations, ratio of new members to be created, swap and bit mutation probabilities, number of generations per injection possibility. As the number of parameters and levels of values increase, the number of possible combinations to be tested also increase dramatically thus making it extremely difficult to test and analyze the interactive relations between the parameters. Hence, the number of elites, which is relatively a less significant parameter, is set to be 2 and for each remaining parameter, representative values are tried to be selected for testing.

| Parameter | Identifier | Values |
| :---: | :---: | :---: |
| Number of elites | $n_{\text {elite }}$ | $\{2\}$ |
| Population size | $n_{\text {pop }}$ | $\{50,75,100\}$ |
| Number of generations | $n_{\text {gen }}$ | $\{200,300,400,500\}$ |
| Ratio of newborn | $r_{\text {new }}$ | $\{0.4,0.6,0.8\}$ |
| Probability of swap mutation | $p_{\text {swap }}$ | $\{0.2,0.5,0.8\}$ |
| Probability of bit mutation | $p_{\text {bit }}$ | $\{0.2,0.5,0.8\}$ |
| Number of generations per injection check | $n_{\text {inj }}$ | $\{0,50,100\}$ |

Table 4.1: Parameters and their range of values for fine-tuning

A test data set consisting of 17 data instances is sampled from the main data set, which is described in Chapter 5 with detail, and tested for various parameter combinations. For each test data set and parameter combination, five replications are executed and the average best solutions and the average computation times are calculated. Considering that the primary intention is to obtain solutions that are as good as possible and the computational time required for GA application is relatively not small, the combination performances are evaluated mainly based on
the closeness of the best solution obtained to the optimal. The computational time is the secondary performance measure. It is used as sort of a tie-breaker eliminating combinations that cannot perform efficiently.

Parameter combinations are tested in two phases. In the first phase, 324 combinations regarding parameters $n_{\text {pop }}, n_{\text {gen }}, r_{\text {new }}, p_{\text {swap }}$ and $p_{\text {bit }}$ are analyzed and set. Then using the parameter values fixed previously, 3 combinations regarding number of generations per injection check are tested in the second level.

Comparing the performances of the parameter combinations obtained excluding injection possibility, it has been observed that $n_{p o p}=100$ and $n_{g e n}=500$ perform better just as expected since larger values allow for more computation, which cannot have a negative effect on the objective value function. However, it was realized that there was not any significantly dominant value for parameters $r_{\text {new }}, p_{\text {swap }}$ and $p_{\text {bit }}$ and various combinations worked quite well with small differences between each other. Therefore, a small best performing segment of parameter combinations for each data instance is taken and the frequency of combinations are considered. It was seen that combinations with $r_{\text {new }}=0.6, p_{\text {swap }}=0.5, p_{\text {bit }}=0.2$ performed better. Fixing the parameter values determined so far, number of generations per injection check is tested and it turned out that $n_{i n j}=100$ performed better for the majority of data instances.

Finally, the following parameters are selected: $n_{\text {pop }}=100, n_{\text {gen }}=500, r_{\text {new }}=$ $0.6, p_{\text {swap }}=0.5, p_{\text {bit }}=0.2$ and $n_{i n j}=100$. Figure 4.6 shows how GA convergences employing the selected parameters together with the envelope expressed by the minimum and maximum results taken at every 25 iterations. The improvement rate seems to decrease as the number iterations increase just as it is expected. At each injection point we check whether the ratio of replicated individuals in the population exceeds $50 \%$ of the new born ratio. If so, we perform injection. Otherwise, we wait for the next injection point.


Figure 4.6: Convergence of GA with the selected parameters

## CHAPTER 5

## COMPUTATIONAL STUDY

Multi-project scheduling in practice is executed in different environments in which various factors seem to differ, thus affecting the behavior of the solution procedure significantly. Some of these factors may be listed as follows: number of projects, number of activities in projects, resource requirements, resource availabilities, variety of projects in the environment and financial parameters such as cash returns, investment costs and resource usage costs. In order to analyze the performance of proposed 2-stage decomposition method for the multi-project scheduling problem, a series of computational experiments are carried out. These experiments are meant to observe and examine the effects of various factors, which shape the problem environment, on the results obtained and the required computational effort.

### 5.1 Data

Since currently there are no benchmark problem sets with the required structure available, new problem sets are generated using the single project instances taken from PSBLIB developed by Kolisch and Sprecher [68]. Various instances with different number of jobs from PSPLIB were combined into multi-project problems by assigning cash flow values, general resource capacities, and resource utilization costs.

### 5.1.1 Resource Conditions

Resource Factor $\left(R F_{\tau}\right)$ and Resource Strength $\left(R S_{\tau}\right)$, which were defined to represent the resource based conditions of resource categories $\tau \in\{\mathcal{R}, \mathcal{N}\}$ and shown to exercise (Kolisch et al. [69]) a strong effect on the behavior of RCPSP solution pro-
cedures, are adapted here for multi-project scheduling environment. $R F_{\tau}$ measures the usages and consumptions of resource type $\tau$ and $R S_{\tau}$ measures the strength of resource availabilities of resource type $\tau$.

### 5.1.1.1 Resource Factor

$R F_{\mathcal{R}}$ is given by (5.1) and (5.3); and $R F_{\mathcal{N}}$ is given by (5.2) and (5.4).

$$
\begin{align*}
y_{i j r} & =1 \text { if } w_{i j r}>0 ; \quad 0 \text { otherwise }  \tag{5.1}\\
z_{i j n} & =1 \text { if } q_{i j n}>0 ; \quad 0 \text { otherwise }  \tag{5.2}\\
R F_{\mathcal{R}} & =\frac{1}{|\mathcal{R}|} \frac{1}{|S|-2} \sum_{s=2}^{|S|-1} \frac{1}{\left|V_{s}\right|-2} \sum_{i=2}^{\left|V_{s}\right|-1} \frac{1}{\left|M_{i}\right|} \sum_{j \in M_{i}} \sum_{r \in \mathcal{R}} y_{i j r}  \tag{5.3}\\
R F_{\mathcal{N}} & =\frac{1}{|\mathcal{N}|} \frac{1}{|S|-2} \sum_{s=2}^{|S|-1} \frac{1}{\left|V_{s}\right|-2} \sum_{i=2}^{\left|V_{s}\right|-1} \frac{1}{\left|M_{i}\right|} \sum_{j \in M_{i}} \sum_{n \in \mathcal{N}} z_{i j n} \tag{5.4}
\end{align*}
$$

### 5.1.1.2 Resource Strength

As described by Kolisch and Sprecher [68], $R S_{\tau}$ is a scaling parameter expressing the resource availability as a convex combination of a minimum and maximum level. Minimum and maximum levels for each non-renewable resource $n \in \mathcal{N}$ are expressed by $K_{n}^{\min }$ as in (5.5) and $K_{n}^{\max }$ as in (5.6), respectively.

$$
\begin{align*}
K_{n}^{\min } & =\sum_{i \in V} \min _{j \in M_{i}}\left\{q_{i j n}\right\}  \tag{5.5}\\
K_{n}^{\max } & =\sum_{i \in V} \max _{j \in M_{i}}\left\{q_{i j n}\right\} \tag{5.6}
\end{align*}
$$

Minimum and maximum levels for each renewable resource $r \in \mathcal{R}$ are expressed by $K_{r}^{\min }$ as in (5.7) and $K_{r}^{\max }$ is determined by the peak per period usage of renewable resource $r$ required in the earliest start schedule obtained selecting activity modes with the greatest requirements for renewable resource $r$.

$$
\begin{equation*}
K_{r}^{\min }=\max _{i \in V}\left\{\min _{j \in M_{i}}\left\{w_{i j r}\right\}\right\} \tag{5.7}
\end{equation*}
$$

Employing the maximum and minimum levels, resource availabilities for renewable and non-renewable resources are determined as in (5.8) and (5.9), respectively.

$$
\begin{align*}
K_{n}^{\tau} & =K_{n}^{\min }+\operatorname{round}\left(R S_{\tau}\left(K_{n}^{\max }-K_{n}^{\min }\right)\right)  \tag{5.8}\\
K_{r}^{\tau} & =K_{r}^{\min }+\operatorname{round}\left(R S_{\tau}\left(K_{r}^{\max }-K_{r}^{\min }\right)\right) \tag{5.9}
\end{align*}
$$

### 5.1.2 Financial Conditions

Discount rate $(\alpha)$ is selected to be 0.05 for all instances. Calculations based on time value of money are accomplished employing this discount rate throughout the time horizon. $c_{r}^{u}$, the variable cost of utilizing one unit of renewable resource $r$ for one time period for each $r \in \mathcal{R}$; and $c_{n}^{u}$, the variable cost of consuming one unit of nonrenewable resource $n$ for each $n \in \mathcal{N}$ are both assumed to be 3. Due to the nature of the problem and the solution procedure, cash flows for macro-modes cannot be initially known but they can only be calculated considering lump sum payments at the completion time of projects, $c_{s}^{R}$; fixed cost to be invested in order to start the project, $c_{s}^{I}$; and resource based variable costs, $c_{r}^{u}$ and $c_{n}^{u}$ as macro-modes are created one by one. This condition arises from a necessity for seeking a sensible approach to set $c_{s}^{R}$ and $c_{s}^{I}$ for each project $s . c_{s}^{R}$ and $c_{s}^{I}$ for each project $s \in S$ are simply determined by using (5.11) and (5.12) where $C R_{s}$, a base cost related with resource usages as expressed in (5.10), is multiplied by a factor $f^{R}$ for lumpsum payments and $f^{I}$ for investment costs, slightly affected by a random uniform distribution of parameters 0 and 1. $f^{R}=18$ and $f^{I}=0.2$ were used here for all problem instances so that positive cash flows were ensured at the macro-mode generation process.

$$
\begin{align*}
C R_{s} & =\sum_{i \in V_{s}} \frac{1}{\left|M_{i}\right|} \sum_{j \in M_{i}}\left(\sum_{r \in \mathcal{R}} d_{i j} c_{r}^{u} w_{i j r}+\sum_{n \in \mathcal{N}} c_{n}^{u} q_{i j n}\right)  \tag{5.10}\\
c_{s}^{R} & =C R_{s} f^{R}(1+(U \sim(0,1)))  \tag{5.11}\\
c_{s}^{I} & =C R_{s} f^{N}(1+(U \sim(0,1))) \tag{5.12}
\end{align*}
$$

### 5.1.3 Problem Sets

Three major problem sets (A,B,C) and one relatively small problem set (D) are created to represent a variety of different environmental factors. See Appendix A to get more information about the network and resource conditions of problem sets A, B and C .

- Problem set A is formed to analyze the effect of resource based factors by fixing other factors. It includes multi-project instances all having the same number of projects consisting of the same number of activities but different resource requirements and resource availability levels, categorized by $R S$ and $R F$ values for renewable and non-renewable resources. Each instance includes 14 projects consisting of 10 activities each as shown in the first two columns of Table 5.1. Three levels are selected for each factor including $R F_{R}, R F_{N}$, $R S_{R}$ and $R S_{N}$ as given in the last four columns of Table 5.1. To avoid any infeasibilities due to insufficient non-renewable resources, a minimum value for resource strength factor of non-renewable resources, $R S_{N}^{\min }$ is determined by simple testing and a medium level is also calculated by $R S_{N}^{\text {mid }}=R S_{N}^{m i n}+(1-$ $\left.R S_{N}^{\min }\right) / 2$. Combinations of these four variable factors with three levels each results in problem set A with 81 instances in total.

| noProj | noAct | $R F_{R}$ | $R F_{N}$ | $R S_{R}$ | $R S_{N}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 14 | 10 | $\{0.5,0.75,1\}$ | $\{0.5,0.75,1\}$ | $\{0.3,0.6,0.9\}$ | $\left\{R S_{N}^{m i n}, R S_{N}^{\text {mid }}, 1\right\}$ |

Table 5.1: Problem set A

- Problem set B focuses on the effects of different number of projects and activities. In these multi-project instances, three levels are set for number of projects and seven levels are set for number of activities as provided in the first two columns of Table 5.2. RF values for renewable and non-renewable resources are fixed to be 0.5 as shown in the third and fourth columns of Table 5.2. Two levels are determined for $R S_{R}$ and $R S_{N}$ values as shown in the last two columns of Table 5.2. Levels for $R S_{N}$ values are set using $R S_{N}^{m i d 1}=R S_{N}^{m i n}+\left(1-R S_{N}^{m i n}\right) / 3$ and $R S_{N}^{m i d 2}=R S_{N}^{m i n}+2 *\left(1-R S_{N}^{m i n}\right) / 3$.

Combinations of these four variable factors with different levels results in problem set B with 84 instances in total.

| noProj | noAct | $R F_{R}$ | $R F_{N}$ | $R S_{R}$ | $R S_{N}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\{10,15,20\}$ | $\{10,12,14,16,18,20,30\}$ | 0.5 | 0.5 | $\{0.4,0.7\}$ | $\left\{R S_{N}^{\text {mid1 }}, R S_{N}^{\text {mid2 }}\right\}$ |

Table 5.2: Problem set B

- In problem set C, a multi-project environment that is heterogeneous in terms of project sizes is emphasized by grouping projects consisting of different number of activities. Basically, three multi-project groups are formed and different levels of resource strengths are assigned. In the first group, equal number of projects having relatively small, medium and large sizes are brought together. In group two, a few larger projects are handled together with a collection of smaller sized projects. In the third group, a few smaller projects are thrown into a bunch of relatively larger sized projects. $R F$ values for renewable and non-renewable resources are fixed to be 0.5 as shown second and third column of Table 5.3. Three levels are determined for $R S_{R}$ and $R S_{N}$ values as shown in the last two columns of Table 5.3. Levels for $R S_{N}$ values are set following the same approach as it is done for problem set A.

| noProj \& noAct | $R F_{R}$ | $R F_{N}$ | $R S_{R}$ | $R S_{N}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\{(5 * J 10,5 * J 20,5 * J 30) ;$ <br> $(8 * J 10,8 * J 12,2 * J 30) ;$ <br> $(3 * J 10,7 * J 18,7 * J 20)\}$ | 0.5 | 0.5 | $\{0.3,0.6,0.9\}$ | $\left\{R S_{N}^{\text {min }}, R S_{N}^{\text {mid }}, 1\right\}$ |

Table 5.3: Problem set C

- Problem set $D$ is created to the analyze the effects of Resource Return factor $(R R)$, which is a new comparative measure introduced here for examining the relative financial return efficiency considering the resource requirements of all actual projects to be scheduled. $R R_{s}$ for each project $s \in S^{a}$ is calculated in four steps. First, $N P V_{\max }^{s}$, maximum net present value that can potentially be achieved from project $s \in S^{a}$, is determined by scheduling project $s$ for NPV maximization objective with all resource capacities made available. Then $A R_{s}$,
average resource requirement for each project $s \in S^{a}$, is calculated by using both renewable and non-renewable resources as expressed in (5.13). Then in the third step, $N P V_{\text {max }}^{s}$ is divided by $A R_{s}$ to obtain $R R_{s}^{\prime}$ for $s \in S^{a}$. Finally as a normalizing step, $R R_{s}^{\prime}$ for project $s \in S^{a}$ is divided by $R R_{\text {min }}^{\prime}=$ $\min _{s \in S^{a}}\left\{R R_{s}^{\prime}\right\}$ to end up with $R R_{s}$ which is a number greater than or equal to 1 .

$$
\begin{equation*}
A R_{s}=\sum_{i=2}^{\left|V_{s}\right|-1} \frac{1}{\left|M_{i}\right|} \sum_{j \in M_{i}}\left(\frac{1}{|\mathcal{R}|} \sum_{r \in \mathcal{R}} w_{i j r}+\frac{1}{|\mathcal{N}|} \sum_{n \in \mathcal{N}} q_{i j n}\right) \tag{5.13}
\end{equation*}
$$

### 5.2 Software \& Hardware Information

All codes were written in GNU C\# and the MIP solver in CPLEX 12.1, which is an optimization software package originally developed by Robert E. Bixby and currently owned by IBM, was called through ILOG Concert Technology 2.9 to perform B\&C. All experiments were performed on a HP Compaq dx 7400 Microtower with a 2.33 GHz Intel Core 2 Quad CPU Q8200 processor and 3.46 GB of RAM.

### 5.3 Experimental Studies

Basically three different experimental studies including comparison of time horizon setting methods, performance analysis of the proposed 2-stage decomposition procedure and analysis of resource return factor $R R_{s}$ are discussed here. The study about the time horizon setting methods is carried out to determine the most suitable time horizon setting method to apply within the experimental study to analyze the performance of the proposed 2-stage decomposition procedure and the analysis of resource return factor.

### 5.3.1 Time Horizon Setting Analysis

In order to determine the most proper procedure to set a proper time horizon ( $T H$ ) for the macro-project scheduling problem, three methods introduced in Section 3.3 (RGH, GHARB and LRH) are applied on 18 data instances randomly selected from
problem sets A, B and C. The results are presented in Table 5.4.

| Method | Average <br> $C P U_{\text {Total }}$ | Average <br> $C P U_{\text {Method }}$ | \# of Best in <br> $C P U_{\text {Total }}$ |
| :---: | :---: | :---: | :---: |
| RGH | 130.723 | 2.64 | 11 |
| GHARB | 138.388 | 3.094 | 4 |
| LRH | 134.942 | 3.336 | 3 |

Table 5.4: Time horizon setting test results

It is found out that RGH was more successful at reducing the total CPU required for the whole application of 2-stage decomposition approach on most of the multiproject instances selected for time horizon setting experimentation. Hence, RGH is used to obtain an initial feasible solution and to set the time horizon in the computational studies regarding 2-stage decomposition method performance analysis and resource return factor analysis.

### 5.3.2 2-Stage Decomposition Method Performance Analysis

The flow of the proposed 2-stage decomposition procedure is summarized in Figure 5.1.


Figure 5.1: 2-Stage decomposition procedure flow

All of the mathematical programming models presented as part of the proposed 2-stage decomposition procedure are solved using an MIP solver. However, there is also the GA approach presented in Chapter 4, which can be used as a stand-alone routine as well as an initial solution for the MIP solver. If GA is employed as a standalone routine, then post-processing is applied on the GA solution. Considering these possibilities, three configurations, which are expressed in Table 5.5, are selected to be tested.

Two hours time limit is set for the MIP solver to run. For all instance in problem set A, MIP solver succeded to obtain optimal solutions for the macro-project schedul-

| no |  <br> TH Setting | Solution <br> Method |
| :---: | :---: | :---: |
| 1 | RGH | GA |
| 2 | RGH | MIP solver |
| 3 | RGH+GA | MIP solver |

Table 5.5: Configuration options for macro-project scheduling
ing subproblem, however, some instances in problem sets B and C required more than two hours. Therefore, best solution obtained for the macro-project scheduling subproblem is not necessarily optimal.

### 5.3.2.1 Results

In this section, the general results obtained for problem sets $\mathrm{A}, \mathrm{B}$ and C by running the algorithm with all three configuration options are shared. The results are reported in terms of so-called total values which simply are the sum of the corresponding values over all the problems within a problem set. Table 5.6 presents the total objective function values and the total computational time required for solving each three problem sets with all three configurations both before post-processing. Table 5.7 contains the normalized values for the averages presented in Table 5.6 to make it easier to compare the performances.

| Config. | $N P V_{\text {Total }}$ |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Problem Set A |  | Problem Set B |  | Problem Set C |  |  |  |  |  |  |  |
|  | Average | Std. Dev. | Average | Std. Dev. | Average | Std. Dev. |  |  |  |  |  |  |
| 1 | 97444.48 | 42093.99 | 101915.89 | 44671 | 127550.39 | 22865.45 |  |  |  |  |  |  |
| 2 | 97548.96 | 41994.09 | 102701.87 | 44996.72 | 128384.67 | 22248.29 |  |  |  |  |  |  |
| 3 | 97552.53 | 41995.63 | 102700.17 | 44995.81 | 128351.97 | 22302.46 |  |  |  |  |  |  |
|  | $C P U_{\text {Total }}(\mathrm{sec})$ |  |  |  |  |  |  |  |  |  |  |  |
| Config. | Problem Set A |  |  |  |  |  |  |  | Problem Set B |  | Problem Set C |  |
|  | Average | Std. Dev. | Average | Std. Dev. | Average | Std. Dev. |  |  |  |  |  |  |
| 1 | 20.08 | 18.11 | 29.48 | 17.44 | 28.83 | 3.99 |  |  |  |  |  |  |
| 2 | 210.93 | 419.02 | 1951.59 | 2799.9 | 1516.14 | 2447.48 |  |  |  |  |  |  |
| 3 | 231.33 | 629 | 1814.41 | 2649.3 | 1469.63 | 2465.64 |  |  |  |  |  |  |

Table 5.6: General results for problem sets A, B and C

As previously stated, for some of the instances in problem sets B and C , the computation time limit of two hours set for MIP solver is reached so the best solutions obtained are not necessarily optimal. In order to eliminate the disrupting effect of

| Config. | Problem Set A |  | Problem Set B |  | Problem Set C |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $N P V_{\text {Total }}$ | $C P U_{\text {Total }}(\mathrm{sec})$ | $N P V_{\text {Total }}$ | $C P U_{\text {Total }}(\mathrm{sec})$ | $N P V_{\text {Total }}$ | $C P U_{\text {Total }}(\mathrm{sec})$ |
| 1 | 0.99889 | 0.0868 | 0.99236 | 0.01625 | 0.99375 | 0.01962 |
| 2 | 0.99996 | 0.91181 | 1.00002 | 1.07561 | 1.00025 | 1.03165 |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 |

Table 5.7: Normalized general results for the averages of $N P V_{\text {Total }}$ and $C P U_{\text {Total }}$
the instances with suboptimal macro-project scheduling subproblem solutions, the final results presented in Tables 5.6 and 5.7 are revised so that those instances are not included. Revised results are presented in Tables 5.8 and 5.9.

| Config. | $N P V_{\text {Total }}$ |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Problem Set A |  | Problem Set B |  | Problem Set C |  |
|  | Average | Std. Dev. | Average | Std. Dev. | Average | Std. Dev. |
| 1 | 97444.48 | 42093.99 | 97827.78 | 46957.83 | 131821.23 | 20483.18 |
| 2 | 97548.96 | 41994.09 | 98396.32 | 47188.27 | 132564.98 | 19885.3 |
| 3 | 97552.53 | 41995.63 | 98407.19 | 47190.32 | 132564.98 | 19885.3 |
| Config. | $C P U_{\text {Total }}$ (sec) |  |  |  |  |  |
|  | Problem Set A |  | Problem Set B |  | Problem Set C |  |
|  | Average | Std.Dev. | Average | Std.Dev. | Average | Std.Dev. |
| 1 | 20.08 | 18.11 | 29.14 | 18.72 | 28.96 | 4.22 |
| 2 | 210.93 | 419.02 | 904.26 | 1656.98 | 800.45 | 1400.46 |
| 3 | 231.33 | 629 | 796.85 | 1366.12 | 746.5 | 1400.55 |

Table 5.8: Revised results for problem sets A, B and C

| Config. | pProblem Set A |  | Problem Set B |  | Problem Set C |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $N P V_{\text {Total }}$ | $C P U_{\text {Total }}(\mathrm{sec})$ | $N P V_{\text {Total }}$ | $C P U_{\text {Total }}(\mathrm{sec})$ | $N P V_{\text {Total }}$ | $C P U_{\text {Total }}(\mathrm{sec})$ |
| 1 | 0.99889 | 0.0868 | 0.99411 | 0.03657 | 0.99439 | 0.03879 |
| 2 | 0.99996 | 0.91181 | 0.99989 | 1.13479 | 1 | 1.07227 |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 |

Table 5.9: Normalized revised results for the averages of $N P V_{\text {Total }}$ and $C P U_{\text {Total }}$

Examining Table 5.9, it can be concluded that employing GA as a stand-alone routine for the macro-project scheduling subproblem performs quite well considering the good objective function values obtained with small computational effort spent. Table 5.9 also shows that Configuration 3 performs slightly better than Configuration 2 for problem sets B and C in terms of computational effort required.

Post-processing procedure improves the objective function value considerably with quite little computational effort as it can be seen in Table 5.10 where the average improvement achieved through post-processing and the required CPU times for post-processing are shared for problem sets A, B and C.

| Config. | Average PostProcessing NPV Improvement (\%) |  |  |
| :---: | :---: | :---: | :---: |
|  | Problem Set A | Problem Set B | Problem Set C |
| 1 | 4.225 | 0.904 | 1.36 |
| 2 | 4.201 | 0.656 | 1.157 |
| 3 | 4.193 | 0.598 | 1.165 |
| Config. | $C P U_{\text {Post }}(\mathrm{sec})$ |  |  |
|  | Problem Set A | Problem Set B | Problem Set C |
| 1 | 0.601 | 0.426 | 0.923 |
| 2 | 0.524 | 0.404 | 0.648 |
| 3 | 0.513 | 0.41 | 0.646 |

Table 5.10: Performance of post-processing

### 5.3.2.2 General Observations

In this section, some general observations made on the results obtained with Configuration 3 (employing both GA and MIP solver) are reported.

| $R S_{\mathcal{R}}$ | $R S_{\mathcal{N}}$ | Average $C P U_{\text {Total }}(\mathrm{sec})$ |
| :---: | :---: | :---: |
| 0.3 | $R S_{N}^{\text {min }}$ | 237.24 |
| 0.3 | $R S_{N}^{\text {mid }}$ | 181.44 |
| 0.3 | 1 | 187.57 |
| 0.6 | $R S_{N}^{\text {min }}$ | 488.12 |
| 0.6 | $R S_{N}^{\text {mid }}$ | 413.11 |
| 0.6 | 1 | 406.54 |
| 0.9 | $R S_{N}^{\text {min }}$ | 49.09 |
| 0.9 | $R S_{N}^{\text {mid }}$ | 61.72 |
| 0.9 | 1 | 61.73 |

Table 5.11: Effects of $R S$ factor on computational effort required - Problem set A

Computational results obtained by testing on problem set A, point out to some interesting outcomes related to resource strength factor and Table 5.11 shows that resource strength has a significant effect on the computational effort required for macro-project scheduling step. The computational effort required increases up to a maximum level as $R S_{R}$, which indicates the level of renewable resource availabilities, increases up to a certain medium level and afterwards computational effort required seems to decrease dramatically as the renewable resource availabilities climb to a higher level.

Examining the results Table 5.12 presents the average $C P U_{\text {Total }}$ required to solve the instances from problem set B and having different number of projects. Column

| noProj | Average $C P U_{\text {Total }}(\mathrm{sec})$ | \# of instances solved to optimality |
| :---: | :---: | :---: |
| 10 | 104.72 | 28 out of 28 |
| 15 | 1124.59 | 26 out of 28 |
| 20 | 1608.88 | 16 out of 28 |

Table 5.12: Effect of number of projects - Problem set B
two includes the average values including only the instances for which macro-project scheduling problem is solved to optimality within the time limit. The fact that the values in column two increase as the number of projects increases, coincides with the expectation that the number of projects in the problem environment has a significant impact on the problem difficulty.

| noAct | Average $C P U_{\text {Total }}(\mathrm{sec})$ | \# of instances solved to optimality |
| :---: | :---: | :---: |
| 10 | 1681.53 | 12 out of 12 |
| 12 | 687.24 | 10 out of 12 |
| 14 | 822.7 | 10 out of 12 |
| 16 | 174.61 | 10 out of 12 |
| 18 | 1547.52 | 10 out of 12 |
| 20 | 619.38 | 10 out of 12 |
| 30 | 688.15 | 12 out of 12 |

Table 5.13: Effect of number of activities - Problem set B

Table 5.13 presents the average $C P U_{\text {Total }}$ required to solve the instances from problem set B and having different number of activities. Column two includes the average values including only the instances for which macro-project scheduling problem is solved to optimality within the time limit. Although it would be expected that the problem complexity increases as the number of activities increases,such a conclusion cannot be reached taking the values in column two. The reason for this outcome is possibly the effect of resource availabilities. Remember that in problem set B there are actually two levels of $R S_{\mathcal{R}}$ and $R S_{\mathcal{N}}$ values resulting in four resource availability combinations for each combination of project number and activity number.

### 5.3.3 Resource Return Factor Analysis

From the initial data, $R R$ provides an insight about the nature of each project resulting in a priority order for starting the projects and it has the potential to be used as a decision rule for a possible solution procedure. $R R$ can also be used as a control tool in data generation and provide, for example, the possibility of some projects dominate others. For example, setting an upper bound on the resource return factor $\left(R R_{\max }\right)$ close to 1 for a group of similar sized projects may make it harder to evaluate the trade-off between the projects. Four examples representing different environments in terms of $R R$ values are discussed to show the effect of $R R$ values. For all four examples, resource capacities are arranged in such a way that there is not sufficient resource available to simultaneously start all projects in the first period.

### 5.3.3.1 Example 1A: Similar sized projects with distinctive $R R$ values

| Project $s$ | noAct | $R R_{s}$ | Order $_{R R}$ | StartTime | FinishTime | Order $_{\text {StartTime }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 |  | 1.58 | 6 | 23 | 47 | 7 |
| 2 |  | 1.2 | 9 | 31 | 55 | 8 |
| 3 | 14 | 1 | 10 | 32 | 51 | 9 |
| 4 |  | 1.45 | 7 | 48 | 86 | 10 |
| 5 |  | 1.34 | 8 | 22 | 49 | 6 |
| 6 |  | 8.84 | 5 | 17 | 47 | 5 |
| 7 | 14 | 8.6 | 4 | 8 | 34 | 4 |
| 8 |  | 9.31 | 2 | 1 | 15 | 3 |
| 9 |  | 9 | 3 | 0 | 21 | 1 |
| 10 | 14 | 27.26 | 1 | 0 | 17 | 1 |

Table 5.14: Example 1A for $R R$ factor analysis

In Example 1A, there are 10 projects each consisting of 14 activities having similar resource structures. They are assigned such lump sum payment and investment cost values that they have the $R R$ values as expressed in the third column of Table 5.14 and considering these values, projects can be grouped in to three subsets. First subset contains the first five projects with relatively smaller $R R$ values $(1,1.58)$ and the second subset includes the four projects with relatively greater $R R$ values
$(8.34,9.31)$ leaving the tenth project with $R R$ value $=27.26$ alone in the third subset. The fourth column of Table 5.14 gives project ranks according to non-increasing order of $R R$ values. The start times and finish times obtained by scheduling with 2-stage decomposition are provided in the fifth and sixth columns of Table 5.14, respectively. The seventh column of Table 5.14 gives project ranks according to non-increasing order of start times. Comparing the fourth and the seventh columns, it is observed that even though the orders according to $R R$ values and start times do not exactly match on a project basis, $R R$ based ranks and the solution suggested by 2-stage decomposition (Figure 5.2) seem to support each other just as expected since tenth project, which is in subset three, is immediately started being followed by the projects in subset two and the projects in subset one precede projects in subset two.


Figure 5.2: Schedule 1A

### 5.3.3.2 Example 1B: Similar sized projects with distinctive $R R$ values

Example 1B, is very similar to Example 1A. Again, there are 10 projects each consisting of 14 activities having similar resource structures. Considering the $R R$ values expressed in the third column of Table 5.15, projects can be grouped in three subsets. First subset contains the first four projects with relatively greater

| Project $s$ | noAct | $R R_{s}$ | Order $_{R R}$ | StartTime | FinishTime | Order $_{\text {StartTime }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 |  | 29.34 | 1 | 1 | 23 | 3 |
| 2 | 4 | 28.87 | 2 | 0 | 21 | 1 |
| 3 |  | 27.96 | 3 | 0 | 19 | 1 |
| 4 |  | 24.34 | 4 | 11 | 49 | 4 |
| 5 |  | 11.02 | 5 | 13 | 41 | 5 |
| 6 | 14 | 10.64 | 6 | 21 | 51 | 7 |
| 7 |  | 7 | 34 | 61 | 8 |  |
| 8 |  | 9.28 | 8 | 20 | 34 | 6 |
| 9 | 14 | 1.25 | 9 | 40 | 63 | 9 |
| 10 |  | 1 | 10 | 44 | 55 | 10 |

Table 5.15: Example 1B for $R R$ factor analysis
$R R$ values $(24.34,29.34)$, the second subset includes the next four projects with relatively smaller $R R$ values $(9.28,11.02)$ and the third subset consists of the last two projects with even smaller $R R$ values $(1,1.25)$. The start times and finish times obtained by scheduling with 2-stage decomposition, are provided in the fifth and sixth columns of Table 5.15, respectively. Once again it is observed that the subsets consisting of projects with greater $R R$ values are executed earlier in the schedule obtained by 2-stage decomposition as shown in Figure 5.3.


Figure 5.3: Schedule 1B

### 5.3.3.3 Example 2: Large projects with high $R R$ values and a small project with lower $R R$ value

| Project $s$ | noAct | $R R$ | Order $_{R R}$ | Start Time | Finish Time | Order $_{\text {StartTime }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 5 | 1 | 10 | 1 | 8 | 3 |
| 2 | 20 | 2.62 | 9 | 62 | 86 | 9 |
| 3 | 20 | 2.92 | 8 | 54 | 79 | 8 |
| 4 | 20 | 3.05 | 7 | 76 | 99 | 10 |
| 5 | 20 | 3.46 | 6 | 32 | 51 | 6 |
| 6 | 20 | 3.7 | 5 | 20 | 47 | 5 |
| 7 | 20 | 4.74 | 4 | 47 | 66 | 7 |
| 8 | 20 | 5.23 | 3 | 0 | 21 | 1 |
| 9 | 20 | 6.09 | 2 | 8 | 44 | 4 |
| 10 | 20 | 10.38 | 1 | 0 | 20 | 1 |

Table 5.16: Example 2 for $R R$ factor analysis

In Example 2, there are 9 projects each consisting of 20 activities and 1 project consisting of 5 activities as shown in Table 5.16. Project 1 is the smallest sized project and also it has the smallest $R R$ value. Scheduling this set of projects using the 2-stage decomposition, the start and finish times, respectively presented in in the fifth and sixth columns of Table 5.14 are obtained. Considering the resultant schedule and $R R$ related expectations, it is interesting to see that project 1 is executed quite earlier. This example shows that in an environment where projects have different number of activities and distinctive resource requirements, optimal solution obtained may negate $R R$ based priority order of projects by fitting the smaller sized projects earlier in the schedule (Figure 5.4) although they have relatively smaller $R R$ values.

### 5.3.3.4 Example 3: Small and large projects with distinctive $R R$ value

In Example 3, there are 6 projects each consisting of 10 activities and 4 project consisting of 30 activities as shown in Table 5.17. Considering number of activities and the $R R$ values expressed in Table 5.15 , projects can be grouped in three subsets. First subset contains the first three projects having 10 activities and relatively smaller $R R$ values $(1,1.15)$ and the second subset includes the next three projects


Figure 5.4: Schedule 2

| Project $s$ | noAct | $R R$ | Order $_{R R}$ | Start Time | Finish Time | Order $_{\text {StartTime }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 |  | 1 | 10 | 48 | 61 | 10 |
| 2 | 10 | 1.08 | 9 | 45 | 60 | 8 |
| 3 |  | 1.15 | 8 | 49 | 60 | 9 |
| 4 |  | 9.97 | 7 | 26 | 35 | 6 |
| 5 | 10 | 9.97 | 6 | 12 | 37 | 3 |
| 6 |  | 10 | 5 | 23 | 37 | 5 |
| 7 |  | 10 | 4 | 0 | 25 | 1 |
| 8 |  | 10.03 | 3 | 1 | 24 | 2 |
| 9 | 30 | 10.05 | 2 | 21 | 55 | 4 |
| 10 |  | 10.09 | 1 | 35 | 55 | 7 |

Table 5.17: Example 3 for $R R$ Factor Analysis
having 10 activities and but relatively larger $R R$ values $(9.97,10)$. The third subset consists of the last four projects having 30 activities but $R R$ values $(10,10.09)$ close to the members of the second subset. The start times and finish times obtained by scheduling with 2-stage decomposition are provided in the fifth and sixth columns of Table 5.17, respectively. An conclusion similar to the one that is stated for examples 1 A and 1 B can be made by observing that the subsets consisting of projects with greater $R R$ values are executed earlier in the schedule obtained by 2 -stage decomposition as shown in Figure 5.5. An additional point that should be emphasized is that projects of the second subset although relatively smaller are handled parallel
to the projects of the third subset benefiting from the remaining renewable resource capacities.


Figure 5.5: Schedule 3

## CHAPTER 6

## CONCLUSION AND FUTURE WORK

In this study, a 2-stage decomposition approach is adopted to formulate the resource constrained multi-project scheduling problem as a hierarchy of 0-1 mathematical programming models. At stage one, each project is reduced to a so called macro-activity and the resulting single project network is solved to maximize NPV. Using the starting times and resource profiles obtained in stage one each project is solved in stage two for minimum makespan. Some preprocessing methods are also utilized in both stages to reduce data size. The effect of setting a proper time horizon for MRCPSP with positive cash flows is analyzed by examining three different time horizon setting methods: relaxed greedy approach, artificial budget and Lagrangian relaxation. A GA approach is adopted to generate good solutions, which can also be employed as a starting solution for the exact solution procedure. An efficient post-processing procedure to distribute the resource capacities that are left over after 2-stage decomposition to the projects to realize further improvements is also introduced. A new comparative measure (Resource Return) examining the relative financial return efficiency considering the resource requirements of projects is presented as a decision rule which can be utilized in a potential heuristic solution procedure. In order to analyze the performance and behavior of the proposed 2-stage decomposition method, new data sets are formed using the single project instances taken from PSBLIB compiled by Kolisch and Sprecher [68] and a series of computational experiments are carried out.

There are several extension possibilities which can be studied in the future.

- Precedence relations between projects can also be included considering that in
practice some projects need to precede others because of technological reasons especially in R\&D environments.
- Instead of only considering a lump sum payment structure, different payment alternatives such as payments at prespecified time points or progress payments can also be adopted to regulate the cash flows.
- Project termination deadlines can be specified and penalty costs related to violating these deadlines can be included in the cost structure.
- Proposed genetic algorithm approach can be improved by introducing a guided bit mutation operator, which attempts to select the mode change alternative with the high NPV improvement. Adapting the population management so that a number of parallel populations could be simultaneously managed letting them interact with each other under certain predefined conditions.
- An alternative macro-mode generation procedure utilizing a different objective function can be formed.
- Post-processing procedure can be updated by transforming it into an iterative process.
- Resource Return factor can be used as decision rule to design an efficient heuristic solution procedure.

Considering these future research possibilities, some of which alter the current problem environment and some directly aim to improve the proposed solution procedure, it is concluded that resource constrained multi-project scheduling with hierarchical decomposition based approaches is a rich topic still requiring further investigation. The fact that it increasingly becomes very common for particularly project based firms to carry out multiple projects simultaneously should also encourage researchers to carry out experimental studies on real data from the field.

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## Appendix A

## DATA SET NETWORK AND RESOURCE CONDITIONS

Table A.1: Data Set A

| $\#$ | Instance | noProj | noAct | $R F_{\mathcal{R}}$ | $R F_{\mathcal{N}}$ | $R S_{\mathcal{R}}$ | $R S_{\mathcal{N}}$ | $R 1$ | $R 2$ | $N 1$ | $N 2$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | A11_11 | 10 | 14 | 0.5 | 0.5 | 0.3 | 0.35 | 27 | 27 | 403 | 393 |
| 2 | A11_12 | 10 | 14 | 0.5 | 0.5 | 0.3 | 0.68 | 27 | 27 | 579 | 584 |
| 3 | A11_13 | 10 | 14 | 0.5 | 0.5 | 0.3 | 1 | 27 | 27 | 764 | 764 |
| 4 | A11_21 | 10 | 14 | 0.5 | 0.5 | 0.6 | 0.35 | 47 | 44 | 403 | 393 |
| 5 | A11_22 | 10 | 14 | 0.5 | 0.5 | 0.6 | 0.68 | 47 | 44 | 579 | 584 |
| 6 | A11_23 | 10 | 14 | 0.5 | 0.5 | 0.6 | 1 | 47 | 44 | 764 | 764 |
| 7 | A11_31 | 10 | 14 | 0.5 | 0.5 | 0.9 | 0.35 | 66 | 62 | 403 | 393 |
| 8 | A11_32 | 10 | 14 | 0.5 | 0.5 | 0.9 | 0.68 | 66 | 62 | 579 | 584 |
| 9 | A11_33 | 10 | 14 | 0.5 | 0.5 | 0.9 | 1 | 66 | 62 | 764 | 764 |
| 10 | A12_11 | 10 | 14 | 0.5 | 0.75 | 0.3 | 0.68 | 113 | 110 | 638 | 613 |
| 11 | A12_12 | 10 | 14 | 0.5 | 0.75 | 0.3 | 0.84 | 113 | 110 | 740 | 708 |
| 12 | A12_13 | 10 | 14 | 0.5 | 0.75 | 0.3 | 1 | 113 | 110 | 837 | 797 |
| 13 | A12_21 | 10 | 14 | 0.5 | 0.75 | 0.6 | 0.68 | 216 | 210 | 638 | 613 |
| 14 | A12_22 | 10 | 14 | 0.5 | 0.75 | 0.6 | 0.84 | 216 | 210 | 740 | 708 |
| 15 | A12_23 | 10 | 14 | 0.5 | 0.75 | 0.6 | 1 | 216 | 210 | 837 | 797 |
| 16 | A12_31 | 10 | 14 | 0.5 | 0.75 | 0.9 | 0.68 | 319 | 311 | 638 | 613 |
| 17 | A12_32 | 10 | 14 | 0.5 | 0.75 | 0.9 | 0.84 | 319 | 311 | 740 | 708 |
| 18 | A12_33 | 10 | 14 | 0.5 | 0.75 | 0.9 | 1 | 319 | 311 | 837 | 797 |
| 19 | A13_11 | 10 | 14 | 0.5 | 1 | 0.3 | 0.89 | 193 | 200 | 873 | 840 |
| 20 | A13_12 | 10 | 14 | 0.5 | 1 | 0.3 | 0.95 | 193 | 200 | 917 | 881 |
| 21 | A13_13 | 10 | 14 | 0.5 | 1 | 0.3 | 1 | 193 | 200 | 954 | 915 |
| 22 | A13_21 | 10 | 14 | 0.5 | 1 | 0.6 | 0.89 | 377 | 390 | 873 | 840 |
| 23 | A13_22 | 10 | 14 | 0.5 | 1 | 0.6 | 0.95 | 377 | 390 | 917 | 881 |
| 24 | A13_23 | 10 | 14 | 0.5 | 1 | 0.6 | 1 | 377 | 390 | 954 | 915 |
| 25 | A13_31 | 10 | 14 | 0.5 | 1 | 0.9 | 0.89 | 560 | 581 | 873 | 840 |
| 26 | A13_32 | 10 | 14 | 0.5 | 1 | 0.9 | 0.95 | 560 | 581 | 917 | 881 |
| 27 | A13_33 | 10 | 14 | 0.5 | 1 | 0.9 | 1 | 560 | 581 | 954 | 915 |
|  |  |  |  |  |  |  |  |  |  |  |  |

Table A.2: Data Set A - cont.

| \# | Instance | noProj | noAct | $R F_{\mathcal{R}}$ | $R F_{\mathcal{N}}$ | $R S_{\mathcal{R}}$ | $R S_{\mathcal{N}}$ | R1 | $R 2$ | N1 | N2 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 28 | A21.11 | 10 | 14 | 0.75 | 0.5 | 0.3 | 0.38 | 24 | 24 | 429 | 411 |
| 29 | A21_12 | 10 | 14 | 0.75 | 0.5 | 0.3 | 0.69 | 24 | 24 | 615 | 594 |
| 30 | A21_13 | 10 | 14 | 0.75 | 0.5 | 0.3 | 1 | 24 | 24 | 802 | 777 |
| 31 | A21_21 | 10 | 14 | 0.75 | 0.5 | 0.6 | 0.38 | 37 | 40 | 429 | 411 |
| 32 | A21_22 | 10 | 14 | 0.75 | 0.5 | 0.6 | 0.69 | 37 | 40 | 615 | 594 |
| 33 | A21_23 | 10 | 14 | 0.75 | 0.5 | 0.6 | 1 | 37 | 40 | 802 | 777 |
| 34 | A21_31 | 10 | 14 | 0.75 | 0.5 | 0.9 | 0.38 | 50 | 55 | 429 | 411 |
| 35 | A21_32 | 10 | 14 | 0.75 | 0.5 | 0.9 | 0.69 | 50 | 55 | 609 | 588 |
| 36 | A21_33 | 10 | 14 | 0.75 | 0.5 | 0.9 | 1 | 50 | 55 | 802 | 777 |
| 37 | A22_11 | 10 | 14 | 0.75 | 0.75 | 0.3 | 0.66 | 104 | 110 | 652 | 670 |
| 38 | A22_12 | 10 | 14 | 0.75 | 0.75 | 0.3 | 0.83 | 104 | 110 | 767 | 791 |
| 39 | A22_13 | 10 | 14 | 0.75 | 0.75 | 0.3 | 1 | 104 | 110 | 882 | 912 |
| 40 | A22_21 | 10 | 14 | 0.75 | 0.75 | 0.6 | 0.66 | 198 | 211 | 652 | 670 |
| 41 | A22_22 | 10 | 14 | 0.75 | 0.75 | 0.6 | 0.83 | 198 | 211 | 767 | 791 |
| 42 | A22_23 | 10 | 14 | 0.75 | 0.75 | 0.6 | 1 | 198 | 211 | 882 | 912 |
| 43 | A22_31 | 10 | 14 | 0.75 | 0.75 | 0.9 | 0.66 | 292 | 312 | 652 | 670 |
| 44 | A22_32 | 10 | 14 | 0.75 | 0.75 | 0.9 | 0.83 | 292 | 312 | 767 | 791 |
| 45 | A22_33 | 10 | 14 | 0.75 | 0.75 | 0.9 | 1 | 292 | 312 | 882 | 912 |
| 46 | A23_11 | 10 | 14 | 0.75 | 1 | 0.3 | 0.9 | 193 | 198 | 878 | 842 |
| 47 | A23_12 | 10 | 14 | 0.75 | 1 | 0.3 | 0.95 | 193 | 198 | 915 | 877 |
| 48 | A23_13 | 10 | 14 | 0.75 | 1 | 0.3 | 1 | 193 | 198 | 951 | 911 |
| 49 | A23_21 | 10 | 14 | 0.75 | 1 | 0.6 | 0.9 | 376 | 387 | 878 | 842 |
| 50 | A23_22 | 10 | 14 | 0.75 | 1 | 0.6 | 0.95 | 376 | 387 | 915 | 877 |
| 51 | A23_23 | 10 | 14 | 0.75 | 1 | 0.6 | 1 | 376 | 387 | 951 | 911 |
| 52 | A23_31 | 10 | 14 | 0.75 | 1 | 0.9 | 0.9 | 559 | 575 | 878 | 842 |
| 53 | A23_32 | 10 | 14 | 0.75 | 1 | 0.9 | 0.95 | 559 | 575 | 915 | 877 |
| 54 | A23_33 | 10 | 14 | 0.75 | 1 | 0.9 | 1 | 559 | 575 | 951 | 911 |
| 55 | A31_11 | 10 | 14 | 1 | 0.5 | 0.3 | 0.46 | 32 | 16 | 500 | 444 |
| 56 | A31_12 | 10 | 14 | 1 | 0.5 | 0.3 | 0.73 | 32 | 16 | 665 | 578 |
| 57 | A31_13 | 10 | 14 | 1 | 0.5 | 0.3 | 1 | 32 | 16 | 829 | 713 |
| 58 | A31_21 | 10 | 14 | 1 | 0.5 | 0.6 | 0.46 | 54 | 24 | 500 | 444 |
| 59 | A31_22 | 10 | 14 | 1 | 0.5 | 0.6 | 0.73 | 54 | 24 | 665 | 578 |
| 60 | A31_23 | 10 | 14 | 1 | 0.5 | 0.6 | 1 | 54 | 24 | 829 | 713 |
| 61 | A31_31 | 10 | 14 | 1 | 0.5 | 0.9 | 0.46 | 77 | 32 | 500 | 444 |
| 62 | A31_32 | 10 | 14 | 1 | 0.5 | 0.9 | 0.73 | 77 | 32 | 665 | 578 |
| 63 | A31_33 | 10 | 14 | 1 | 0.5 | 0.9 | 1 | 77 | 32 | 829 | 713 |

Table A.3: Data Set A - cont.

| $\#$ | Instance | noProj | noAct | $R F_{\mathcal{R}}$ | $R F_{\mathcal{N}}$ | $R S_{\mathcal{R}}$ | $R S_{\mathcal{N}}$ | $R 1$ | $R 2$ | $N 1$ | $N 2$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 64 | A32_11 | 10 | 14 | 1 | 0.75 | 0.3 | 0.65 | 108 | 106 | 651 | 592 |
| 65 | A32_12 | 10 | 14 | 1 | 0.75 | 0.3 | 0.83 | 108 | 106 | 775 | 702 |
| 66 | A32_13 | 10 | 14 | 1 | 0.75 | 0.3 | 1 | 108 | 106 | 891 | 806 |
| 67 | A32_21 | 10 | 14 | 1 | 0.75 | 0.6 | 0.65 | 205 | 202 | 651 | 592 |
| 68 | A32_22 | 10 | 14 | 1 | 0.75 | 0.6 | 0.83 | 205 | 202 | 775 | 702 |
| 69 | A32_23 | 10 | 14 | 1 | 0.75 | 0.6 | 1 | 205 | 202 | 891 | 806 |
| 70 | A32_31 | 10 | 14 | 1 | 0.75 | 0.9 | 0.65 | 302 | 298 | 651 | 592 |
| 71 | A32_32 | 10 | 14 | 1 | 0.75 | 0.9 | 0.83 | 302 | 298 | 775 | 702 |
| 72 | A32_33 | 10 | 14 | 1 | 0.75 | 0.9 | 1 | 302 | 298 | 891 | 806 |
| 73 | A33_11 | 10 | 14 | 1 | 1 | 0.3 | 0.9 | 188 | 192 | 895 | 867 |
| 74 | A33_12 | 10 | 14 | 1 | 1 | 0.3 | 0.95 | 188 | 192 | 933 | 904 |
| 75 | A33_13 | 10 | 14 | 1 | 1 | 0.3 | 1 | 188 | 192 | 971 | 941 |
| 76 | A33_21 | 10 | 14 | 1 | 1 | 0.6 | 0.9 | 366 | 374 | 895 | 867 |
| 77 | A32_22 | 10 | 14 | 1 | 1 | 0.6 | 0.95 | 366 | 374 | 933 | 904 |
| 78 | A33_23 | 10 | 14 | 1 | 1 | 0.6 | 1 | 366 | 374 | 971 | 941 |
| 79 | A33_31 | 10 | 14 | 1 | 1 | 0.9 | 0.9 | 544 | 555 | 895 | 867 |
| 80 | A33_32 | 10 | 14 | 1 | 1 | 0.9 | 0.95 | 544 | 555 | 933 | 904 |
| 81 | A33_33 | 10 | 14 | 1 | 1 | 0.9 | 1 | 544 | 555 | 971 | 941 |

Table A.4: Data Set B

| $\#$ | Instance | noProj | noAct | $R F_{\mathcal{R}}$ | $R F_{\mathcal{N}}$ | $R S_{\mathcal{R}}$ | $R S_{\mathcal{N}}$ | $R 1$ | $R 2$ | $N 1$ | $N 2$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | B1010_11 | 10 | $10 J$ | 0.5 | 0.5 | 0.4 | 0.47 | 21 | 25 | 402 | 355 |
| 2 | B1010_12 | 10 | $10 J$ | 0.5 | 0.5 | 0.4 | 0.73 | 21 | 25 | 507 | 450 |
| 3 | B1010_21 | 10 | $10 J$ | 0.5 | 0.5 | 0.7 | 0.47 | 31 | 37 | 402 | 355 |
| 4 | B1010_22 | 10 | $10 J$ | 0.5 | 0.5 | 0.7 | 0.73 | 31 | 37 | 507 | 450 |
| 5 | B1012_11 | 10 | $12 J$ | 0.5 | 0.5 | 0.4 | 0.63 | 33 | 26 | 498 | 452 |
| 6 | B1012_12 | 10 | $12 J$ | 0.5 | 0.5 | 0.4 | 0.82 | 33 | 26 | 572 | 535 |
| 7 | B1012_21 | 10 | $12 J$ | 0.5 | 0.5 | 0.7 | 0.63 | 52 | 39 | 498 | 452 |
| 8 | B1012_22 | 10 | $12 J$ | 0.5 | 0.5 | 0.7 | 0.82 | 52 | 39 | 572 | 535 |
| 9 | B1014_11 | 10 | $14 J$ | 0.5 | 0.5 | 0.4 | 0.53 | 33 | 24 | 533 | 504 |
| 10 | B1014_12 | 10 | $14 J$ | 0.5 | 0.5 | 0.4 | 0.77 | 33 | 24 | 654 | 633 |
| 11 | B1014_21 | 10 | $14 J$ | 0.5 | 0.5 | 0.7 | 0.53 | 51 | 37 | 533 | 504 |
| 12 | B1014_22 | 10 | $14 J$ | 0.5 | 0.5 | 0.7 | 0.77 | 51 | 37 | 654 | 633 |
| 13 | B1016_11 | 10 | $16 J$ | 0.5 | 0.5 | 0.4 | 0.56 | 39 | 46 | 584 | 558 |
| 14 | B1016_12 | 10 | $16 J$ | 0.5 | 0.5 | 0.4 | 0.78 | 39 | 46 | 715 | 686 |
| 15 | B1016_21 | 10 | $16 J$ | 0.5 | 0.5 | 0.7 | 0.56 | 62 | 73 | 584 | 558 |
| 16 | B1016_22 | 10 | $16 J$ | 0.5 | 0.5 | 0.7 | 0.78 | 62 | 73 | 715 | 686 |
| 17 | B1018_11 | 10 | $18 J$ | 0.5 | 0.5 | 0.4 | 0.6 | 44 | 41 | 685 | 677 |
| 18 | B1018_12 | 10 | $18 J$ | 0.5 | 0.5 | 0.4 | 0.8 | 44 | 41 | 830 | 822 |
| 19 | B1018_21 | 10 | $18 J$ | 0.5 | 0.5 | 0.7 | 0.6 | 70 | 64 | 685 | 677 |
| 20 | B1018_22 | 10 | $18 J$ | 0.5 | 0.5 | 0.7 | 0.8 | 70 | 64 | 830 | 822 |
| 21 | B1020_11 | 10 | $20 J$ | 0.5 | 0.5 | 0.4 | 0.62 | 51 | 47 | 818 | 784 |
| 22 | B1020_12 | 10 | $20 J$ | 0.5 | 0.5 | 0.4 | 0.81 | 51 | 47 | 979 | 947 |
| 23 | B1020_21 | 10 | $20 J$ | 0.5 | 0.5 | 0.7 | 0.62 | 83 | 76 | 818 | 784 |
| 24 | B1020_22 | 10 | $20 J$ | 0.5 | 0.5 | 0.7 | 0.81 | 83 | 76 | 979 | 947 |
| 25 | B1030_11 | 10 | $30 J$ | 0.5 | 0.5 | 0.4 | 0.6 | 65 | 61 | 1093 | 1103 |
| 26 | B1030_12 | 10 | $30 J$ | 0.5 | 0.5 | 0.4 | 0.8 | 65 | 61 | 1336 | 1359 |
| 27 | B1030_21 | 10 | $30 J$ | 0.5 | 0.5 | 0.7 | 0.6 | 107 | 100 | 1093 | 1103 |
| 28 | B1030_22 | 10 | $30 J$ | 0.5 | 0.5 | 0.7 | 0.8 | 107 | 100 | 1336 | 1359 |

Table A.5: Data Set B - cont.

| $\#$ | Instance | noProj | noAct | $R F_{\mathcal{R}}$ | $R F_{\mathcal{N}}$ | $R S_{\mathcal{R}}$ | $R S_{\mathcal{N}}$ | $R 1$ | $R 2$ | $N 1$ | $N 2$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 29 | B1510_11 | 15 | $10 J$ | 0.5 | 0.5 | 0.4 | 0.48 | 25 | 26 | 595 | 557 |
| 30 | B1510_12 | 15 | $10 J$ | 0.5 | 0.5 | 0.4 | 0.74 | 25 | 26 | 736 | 685 |
| 31 | B1510_21 | 15 | $10 J$ | 0.5 | 0.5 | 0.7 | 0.48 | 48 | 49 | 595 | 557 |
| 32 | B1510_22 | 15 | $10 J$ | 0.5 | 0.5 | 0.7 | 0.74 | 48 | 49 | 736 | 685 |
| 33 | B1512_11 | 15 | $12 J$ | 0.5 | 0.5 | 0.4 | 0.63 | 51 | 34 | 734 | 667 |
| 34 | B1512_12 | 15 | $12 J$ | 0.5 | 0.5 | 0.4 | 0.82 | 51 | 34 | 850 | 792 |
| 35 | B1512_21 | 15 | $12 J$ | 0.5 | 0.5 | 0.7 | 0.63 | 82 | 54 | 734 | 667 |
| 36 | B1512_22 | 15 | $12 J$ | 0.5 | 0.5 | 0.7 | 0.82 | 82 | 54 | 850 | 792 |
| 37 | B1514_11 | 15 | $14 J$ | 0.5 | 0.5 | 0.4 | 0.55 | 53 | 33 | 820 | 750 |
| 38 | B1514_12 | 15 | $14 J$ | 0.5 | 0.5 | 0.4 | 0.77 | 53 | 33 | 991 | 928 |
| 39 | B1514_21 | 15 | $14 J$ | 0.5 | 0.5 | 0.7 | 0.55 | 86 | 52 | 820 | 750 |
| 40 | B1514_22 | 15 | $14 J$ | 0.5 | 0.5 | 0.7 | 0.77 | 86 | 52 | 991 | 928 |
| 41 | B1516_11 | 15 | $16 J$ | 0.5 | 0.5 | 0.4 | 0.55 | 59 | 59 | 851 | 867 |
| 42 | B1516_12 | 15 | $16 J$ | 0.5 | 0.5 | 0.4 | 0.77 | 59 | 59 | 1045 | 1064 |
| 43 | B1516_21 | 15 | $16 J$ | 0.5 | 0.5 | 0.7 | 0.55 | 97 | 96 | 851 | 867 |
| 44 | B1516_22 | 15 | $16 J$ | 0.5 | 0.5 | 0.7 | 0.77 | 97 | 96 | 1045 | 1064 |
| 45 | B1518_11 | 15 | $18 J$ | 0.5 | 0.5 | 0.4 | 0.61 | 54 | 64 | 1010 | 1037 |
| 46 | B1518_12 | 15 | $18 J$ | 0.5 | 0.5 | 0.4 | 0.8 | 54 | 64 | 1217 | 1248 |
| 47 | B1518_21 | 15 | $18 J$ | 0.5 | 0.5 | 0.7 | 0.61 | 89 | 105 | 1010 | 1037 |
| 48 | B1518_22 | 15 | $18 J$ | 0.5 | 0.5 | 0.7 | 0.8 | 89 | 105 | 1217 | 1248 |
| 49 | B1520_11 | 15 | $20 J$ | 0.5 | 0.5 | 0.4 | 0.67 | 75 | 65 | 1265 | 1258 |
| 50 | B1520_12 | 15 | $20 J$ | 0.5 | 0.5 | 0.4 | 0.84 | 75 | 65 | 1477 | 1469 |
| 51 | B1520_21 | 15 | $20 J$ | 0.5 | 0.5 | 0.7 | 0.67 | 124 | 108 | 1265 | 1258 |
| 52 | B1520_22 | 15 | $20 J$ | 0.5 | 0.5 | 0.7 | 0.84 | 124 | 108 | 1477 | 1469 |
| 53 | B1530_11 | 15 | $30 J$ | 0.5 | 0.5 | 0.4 | 0.6 | 95 | 107 | 1619 | 1654 |
| 54 | B1530_12 | 15 | $30 J$ | 0.5 | 0.5 | 0.4 | 0.8 | 95 | 107 | 1983 | 2037 |
| 55 | B1530_21 | 15 | $30 J$ | 0.5 | 0.5 | 0.7 | 0.6 | 159 | 180 | 1619 | 1654 |
| 56 | B1530_22 | 15 | $30 J$ | 0.5 | 0.5 | 0.7 | 0.8 | 159 | 180 | 1983 | 2037 |

Table A.6: Data Set B - cont.

| $\#$ | Instance | noProj | noAct | $R F_{\mathcal{R}}$ | $R F_{\mathcal{N}}$ | $R S_{\mathcal{R}}$ | $R S_{\mathcal{N}}$ | $R 1$ | $R 2$ | $N 1$ | $N 2$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 57 | B2010_11 | 20 | $10 J$ | 0.5 | 0.5 | 0.4 | 0.53 | 64 | 54 | 788 | 745 |
| 58 | B201__12 | 20 | $10 J$ | 0.5 | 0.5 | 0.4 | 0.77 | 64 | 54 | 957 | 905 |
| 59 | B2010_21 | 20 | $10 J$ | 0.5 | 0.5 | 0.7 | 0.53 | 105 | 88 | 788 | 745 |
| 60 | B2010_22 | 20 | $10 J$ | 0.5 | 0.5 | 0.7 | 0.77 | 105 | 88 | 957 | 905 |
| 61 | B2012_11 | 20 | $12 J$ | 0.5 | 0.5 | 0.4 | 0.6 | 63 | 51 | 937 | 856 |
| 62 | B2012_12 | 20 | $12 J$ | 0.5 | 0.5 | 0.4 | 0.8 | 63 | 51 | 1102 | 1026 |
| 63 | B2012_21 | 20 | $12 J$ | 0.5 | 0.5 | 0.7 | 0.6 | 103 | 84 | 937 | 856 |
| 64 | B2012_22 | 20 | $12 J$ | 0.5 | 0.5 | 0.7 | 0.8 | 103 | 84 | 1102 | 1026 |
| 65 | B2014_11 | 20 | $14 J$ | 0.5 | 0.5 | 0.4 | 0.56 | 61 | 59 | 1060 | 1030 |
| 66 | B2014_12 | 20 | $14 J$ | 0.5 | 0.5 | 0.4 | 0.78 | 61 | 59 | 1286 | 1270 |
| 67 | B2014_21 | 20 | $14 J$ | 0.5 | 0.5 | 0.7 | 0.56 | 99 | 97 | 1060 | 1030 |
| 68 | B2014_22 | 20 | $14 J$ | 0.5 | 0.5 | 0.7 | 0.78 | 99 | 97 | 1286 | 1270 |
| 69 | B2016_11 | 20 | $16 J$ | 0.5 | 0.5 | 0.4 | 0.59 | 87 | 83 | 1156 | 1199 |
| 70 | B2016_12 | 20 | $16 J$ | 0.5 | 0.5 | 0.4 | 0.79 | 87 | 83 | 1396 | 1440 |
| 71 | B2016_21 | 20 | $16 J$ | 0.5 | 0.5 | 0.7 | 0.59 | 146 | 137 | 1156 | 1199 |
| 72 | B2016_22 | 20 | $16 J$ | 0.5 | 0.5 | 0.7 | 0.79 | 146 | 137 | 1396 | 1440 |
| 73 | B2018_11 | 20 | $18 J$ | 0.5 | 0.5 | 0.4 | 0.61 | 75 | 78 | 1332 | 1361 |
| 74 | B2018_12 | 20 | $18 J$ | 0.5 | 0.5 | 0.4 | 0.81 | 75 | 78 | 1623 | 1641 |
| 75 | B2018_21 | 20 | $18 J$ | 0.5 | 0.5 | 0.7 | 0.61 | 126 | 129 | 1332 | 1361 |
| 76 | B2018_22 | 20 | $18 J$ | 0.5 | 0.5 | 0.7 | 0.81 | 126 | 129 | 1623 | 1641 |
| 77 | B2020_11 | 20 | $20 J$ | 0.5 | 0.5 | 0.4 | 0.61 | 107 | 89 | 1540 | 1537 |
| 78 | B2020_12 | 20 | $20 J$ | 0.5 | 0.5 | 0.4 | 0.8 | 107 | 89 | 1850 | 1846 |
| 79 | B2020_21 | 20 | $20 J$ | 0.5 | 0.5 | 0.7 | 0.61 | 181 | 149 | 1540 | 1537 |
| 80 | B2020_22 | 20 | $20 J$ | 0.5 | 0.5 | 0.7 | 0.8 | 181 | 149 | 1850 | 1846 |
| 81 | B2030_11 | 20 | $30 J$ | 0.5 | 0.5 | 0.4 | 0.6 | 127 | 144 | 2178 | 2214 |
| 82 | B2030_12 | 20 | $30 J$ | 0.5 | 0.5 | 0.4 | 0.8 | 127 | 144 | 2670 | 2725 |
| 83 | B2030_21 | 20 | $30 J$ | 0.5 | 0.5 | 0.7 | 0.6 | 215 | 244 | 2178 | 2214 |
| 84 | B2030_22 | 20 | $30 J$ | 0.5 | 0.5 | 0.7 | 0.8 | 215 | 244 | 2670 | 2725 |

Table A.7: Data Set C

| $\#$ | Instance | noProj | noAct | $R F_{\mathcal{R}}$ | $R F_{\mathcal{N}}$ | $R S_{\mathcal{R}}$ | $R S_{\mathcal{N}}$ | $R 1$ | $R 2$ | $N 1$ | $N 2$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | C1_11 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.3 | 0.4 | 53 | 60 | 851 | 890 |
| 2 | C1_12 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.3 | 0.7 | 53 | 60 | 1209 | 1258 |
| 3 | C1_13 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.3 | 1 | 53 | 60 | 1568 | 1626 |
| 4 | C1_21 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.6 | 0.4 | 98 | 110 | 851 | 890 |
| 5 | C1_22 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.6 | 0.7 | 98 | 110 | 1209 | 1258 |
| 6 | C1_23 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.6 | 1 | 98 | 110 | 1568 | 1626 |
| 7 | C1_31 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.9 | 0.4 | 142 | 160 | 851 | 890 |
| 8 | C1_32 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.9 | 0.7 | 142 | 160 | 1209 | 1258 |
| 9 | C1_33 | 15 | $5 x 10,5 x 20,5 x 30$ | 0.5 | 0.5 | 0.9 | 1 | 142 | 160 | 1568 | 1626 |
| 10 | C2_11 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.3 | 0.35 | 41 | 53 | 701 | 670 |
| 11 | C2_12 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.3 | 0.675 | 41 | 53 | 990 | 958 |
| 12 | C2_13 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.3 | 1 | 41 | 53 | 1270 | 1237 |
| 13 | C2_21 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.6 | 0.35 | 74 | 97 | 701 | 670 |
| 14 | C2_22 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.6 | 0.675 | 74 | 97 | 990 | 958 |
| 15 | C2_23 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.6 | 1 | 74 | 97 | 1270 | 1237 |
| 16 | C2_31 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.9 | 0.35 | 106 | 140 | 701 | 670 |
| 17 | C2_32 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.9 | 0.675 | 106 | 140 | 990 | 958 |
| 18 | C2_33 | 18 | $8 x 10,8 x 12,2 x 30$ | 0.5 | 0.5 | 0.9 | 1 | 106 | 140 | 1270 | 1237 |
| 19 | C3_11 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.3 | 0.42 | 55 | 55 | 892 | 895 |
| 20 | C3_12 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.3 | 0.71 | 55 | 55 | 1231 | 1232 |
| 21 | C3_13 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.3 | 1 | 55 | 55 | 1569 | 1569 |
| 22 | C3_21 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.6 | 0.42 | 102 | 100 | 892 | 895 |
| 23 | C3_22 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.6 | 0.71 | 102 | 100 | 1231 | 1232 |
| 24 | C3_23 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.6 | 1 | 102 | 100 | 1569 | 1569 |
| 25 | C3_31 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.9 | 0.42 | 149 | 146 | 892 | 895 |
| 26 | C3_32 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.9 | 0.71 | 149 | 146 | 1231 | 1232 |
| 27 | C3_33 | 17 | $3 x 10,7 x 18,7 x 20$ | 0.5 | 0.5 | 0.9 | 1 | 149 | 146 | 1569 | 1569 |

## Appendix B

## LEGEND

In this appendix, results obtained solving problem sets A, B and C (See Appendix A) by employing the three solution configurations introduced in Section 5.3.2 are shared. First two columns show problems' numbers and names. Rest of the columns are organized in four different groups: Time Horizon, NPV, NPV(\%) and CPU (sec).

- Columns below Time Horizon:
- TH represents the time horizon set by employing an initial solution procedure (i.e. RGH, GA)
- $M$ represents the makespan obtained by the solution procedure (Cplex or GA) employed before post-processing.
- Prepresents the makespan obtained by the solution procedure (Cplex or GA) employed before post-processing.
- Columns below $N P V$ :
- RGH represents the initial objective function value obtained by RGH.
- GA represents the objective function value obtained by GA.
- Cplex represents the objective function value obtained by Cplex.
- Post represents the objective function value obtained by post-processing.
- Columns below NPV(\%):
- RGH represents the ratio of the initial solution to the best solution obtained (before applying post-processing). For Configuration 1, the best solution is obtained by GA and for Configurations 2 and 3 the best solution is obtained by Cplex.
- GA represents the ratio of the solution obtained by GA to the solution obtained by Cplex. Obviously, this column does not exist in the result tables related to Configuration 2 .
- Post represents the ratio of the solution obtained by post-processing to the best solution obtained (before applying post-processing). For Configuration 1, the best solution is obtained by GA and for Configurations 2 and 3 the best solution is obtained by Cplex.
- Columns below CPU (sec):
- Total represents CPU required to complete the whole 2-stage decomposition procedure. It includes macro-mode generation, macro-project scheduling, post-processing and individual single project scheduling so Total $=M M+M P+P+S$.
- MM represents CPU required for macro-mode generation.
- MP represents CPU required for macro-project scheduling step. It includes time horizon setting, GA and Cplex application so $M P=T H+G A+C p l e x$.
- $P$ represents CPU required for post-processing.
- $S$ represents CPU required for individual scheduling each project after macro-project scheduling.
- TH represents CPU required for RGH.
- GA represents CPU required for GA.
- Cplex represents CPU required Cplex application.

For Configurations 2 and 3 , star $\left({ }^{*}\right)$ before problem name indicates that optimal solution is not reached in the time limit of two hours set for Cplex.
Table B.1: Configuration 1 Set A












Table B.8: Configuration 2 Set B



Table B.12: Configuration 3 Set A-cont

Table B.13: Configuration 3 Set B




