Multi-Objective Multi-Project Construction Scheduling Optimization

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ABSTRACT

Multi-Objective Multi-Project Construction Scheduling Optimization

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In construction industry, contractors usually manage and execute multiple projects simultaneously within their portfolio. This involves sharing of limited resources such as funds, equipment, manpower, and others among different projects, which increases the complexity of the scheduling process. The allocation of scarce resources then becomes a major objective of the problem and several compromises should be made to solve the problem to the desired level of optimality. In such cases, contractors are generally concerned with optimizing a number of different objectives, often conflicting among each other. Thus, the main objective of this research is to develop a multi-objective scheduling optimization model for multiple construction projects considering both financial and resource aspects under a single platform. The model aims to help contractors in devising schedules that obtain optimal/near optimal tradeoffs between different projects' objectives, namely: duration of multiple projects, total cost, financing cost, maximum required credit, profit, and resource fluctuations. Moreover, the model offers the flexibility in selecting the desired set of objectives to be optimized together. Three management models are built in order to achieve the main objective which involves the development of: (1) a scheduling model that establishes optimal/near optimal schedules for construction projects; (2) a resource model to calculate the resource fluctuations and maximum daily resource demand; and (3) a cash flow model to calculate projects' financial parameters. The three management models are linked with the designed optimization model, which consequently performs operations of the elitist non-dominated sorting genetic algorithm (NSGA-II) technique, in three main phases: (1) population initialization; (2) fitness evaluation; and (3) generation evolution. The optimization model is implemented and tested using different case studies of different project sizes obtained from literature. Finally, an automated tool using C# language is built with a friendly graphical user interface to facilitate solving multi-objective scheduling optimization problems for contractors and practitioners.

إهداء إلى

والدتي الغالية "صفاء العباسي" ووالدي الغالي "سعيد العباسي"

توأم روحي زوجتي الحبيبة الغالية "داليا نوح"

قرة عيني ابنتي الحبيبة الغالية "أميرة"

اخوتي واخواتي الأعزاء

Dedicated To

My beloved mother "Safaa El-Abbasy" and inspiring father "Saeed El-Abbasy"

My soulmate, beautiful, and supportive wife "Dalia Nouh"

My little lovely daughter and precious angel "Amira"

My dear brother and sisters and their kids

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May ALLAH bless you all.

Mohammed El-Abbasy
February, 2015, Montreal, Quebec, Canada

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LIST OF ACRONYMS

BFF	Backward Free Float
C#	C Sharp Programming Language
CL	Credit Limit
CP	Constrained Programming
CPM	Critical Path Method
DP	Dynamic Programming
FC	Financing Cost
FFF	Forward Free Float
GAs	Genetic Algorithms
GUI	Graphical User Interface
IP	Integer Programming
LP	Linear Programming
MOEAs	Multi-Objective Evolutionary Algorithms
MOP	Multi-objective Optimization
MOSCOPEA	Multi-Objective SCheduling OPtimization using Evolutionary Algorithm
MRD	Maximum Resource Demand
MPI	Message Passing Interface
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA-II	Elitist Non-dominated Sorting Genetic Algorithm
PR	Profit
RC	Required Credit
RFPD	Resource Fluctuation and Peak Demand
RID	Resource Idle Days
RL	Resource Limit
RRH	Release and Re-Hire
RWGA	Random Weighted Genetic Algorithm
SPEA	Strength Pareto Evolutionary Algorithm
SPEA-II	Improved Strength Pareto Evolutionary Algorithm

TC	Total Cost
TCT	Time Cost Tradeoff
TD	Total Duration
VEGA	Vector Evaluated Genetic Algorithm
WBGA	Weighted-Based Genetic Algorithm

CHAPTER 1: INTRODUCTION

The capability to timely obtain sufficient cash is considered one of the most common and critical challenges that contractors usually face during the execution of any construction project. As a result, cash must be thought of as a limited resource because its procurement has always been the first concern of contractors. During any project period, contractors never carry out any work that has no cash availability despite the commitment to stick to schedules. This clear principle of operation makes the establishment of a balance between financing needs and available cash, along the project's duration, a very vital concept to produce realistic schedules. Should sufficient cash not be available, delays in project completion times are anticipated which result in increased overheads and decreased profits. Therefore, a sound and well managed project finance-based scheduling model should be established in order to allow the contractor to identify his/her cash needs during each period of the constructed project(s).

Since the execution of construction projects demands huge investments, contractors rarely rely on their own savings to carry out projects (Elazouni and Metwally 2005). Usually, contractors procure an external source of financing to cover the cash deficit. Loans, line of credits, leases, trade financing, and credit cards are the most common financing instruments used in construction industry (Fathi and Afshar 2010). One of the prevalent methods of financing construction projects is line of credit which allows contractors to withdraw cash up to a specified credit limit. When a line of credit is available to the contractor; projects' schedules should be devised under cash constraint of the credit limit to maximize the predicted profit, maximize the utilization of cash flow at the company level, and satisfy each project's constraints.

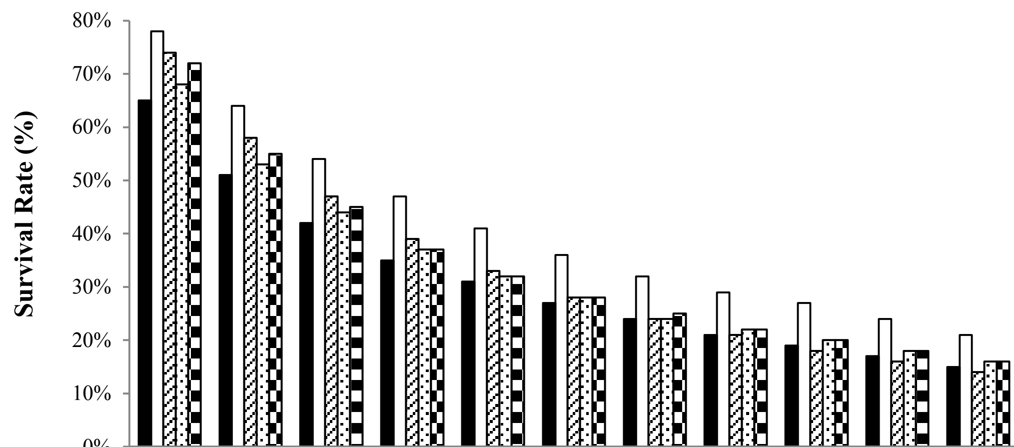
1.1 RESEARCH MOTIVATION AND PROBLEM STATEMENT

Construction industry is considered as one of the most risky sectors due to high level of uncertainties in their nature. Every year thousands of contractors face bankruptcy and business failure. According to a relatively recent study made by the marketing research firm "BizMiner", of the 918,483 U.S. general contractors and operative builders, heavy construction contractors, and special trade contractors operating in 2010, only 696,441 were still in business in 2012 resulting in a 24.2% failure rate (Surety Information Office 2012). This failure was not only from the year 2010 to 2012, but according to the reachable sources, this significant failure rate goes back from the year 2002 as shown in Table 1.1. Moreover, it was stated that only 47% of the U.S. startup businesses in construction are still operating after four years (Statistic Brain 2014).

Table 1.1: U.S. Contractors' Failure Rate (Surety Information Office 2012)

In Business		**Survivors**		**Failure Rate**
Year	**No. of Contractors**	**Year**	**No. of Contractors**	
2002	853,372	**2004**	610,357	28.5%
2004	850,029	**2006**	649,602	23.6%
2006	1,155,245	**2008**	919,848	20.4%
2009	897,602	**2011**	702,618	21.7%
2010	918,483	**2012**	696,441	24.2%

Similarly, the Canadian construction industry suffers from significant failure rates as it was reported that around 65 to 78% of startup construction businesses in Canada survived after one year of operation (Statistics Canada 2000). Such survival rate decreases with time as shown in Figure 1.1.



	1	2	3	4	5	6	7	8	9	10	11
Atlantic Provinces	65%	51%	42%	35%	31%	27%	24%	21%	19%	17%	15%
Quebec	78%	64%	54%	47%	41%	36%	32%	29%	27%	24%	21%
Ontario	74%	58%	47%	39%	33%	28%	24%	21%	18%	16%	14%
Prairie Provinces	68%	53%	44%	37%	32%	28%	24%	22%	20%	18%	16%
British Columbia	72%	55%	45%	37%	32%	28%	25%	22%	20%	18%	16%

Duration (Years)

Figure 1.1: Survival Rates in Canadian Construction Industries (Statistics Canada 2000)

Although there are many reasons for construction business failure, surveys of construction practitioners point to financial and budgetary factors as the leading causes of failures (Kangari 1988; Arditi et al. 2000; Kivrak and Arslan 2008). Such leading causes are mainly due to inefficient control and management of contractor's cash flow (Pate-Cornel et al. 1990; Kaka and Price 1993; Boussabaine and Kaka 1998; Zayed and Liu 2014). Thus, controlling and regulating the movement of the cash is necessary for the success of the construction projects.

Financial management has long been recognized as an important management tool and proper cash flow management is crucial to the survival of a construction company because cash is the most important corporate resource for its day-to-day activities (Peer 1982). However, contractors mainly deal with the project scheduling and financing as two independent functions of construction project management. The absence of the required linkage between those two functions resulted in devising non-executable schedules which lead to a high volume of project failure due to finance deficit. It has been reported that the lack of finance experience comprised 77 to 95% of the total contractors' failures during 30-year period (Russell 1991). Other consequences of the absence of the required linkage includes; fund has inefficiently been utilized because projects' schedules were devised separately without considering the overall liquidity situation of contractors' portfolios, the substantial finance cost has been omitted which has eaten up contractors' profit, and eventually the whole purpose behind scheduling has been defeated to a certain extent.

Several studies were carried to integrate project scheduling along with available finance in order to achieve project's objectives. This integration is known as "finance-based scheduling" which re-schedules the projects' activities without violating specified project's constraints to achieve company's objectives. These objectives focused on minimizing the total project duration, financing costs, and maximum required credit while maximizing the profit. However, there is a lack of research that considers integrating resource management techniques including resource leveling and resource allocation simultaneously with the finance-based scheduling concept. Considering those two aspects together have a significant impact on many areas of project management including time, cost, resource, and risk. Moreover, few researches solved the finance-based scheduling problem considering the contractor's entire portfolio rather than single project. Multiple concurrent projects involves sharing and competing for limited resources such as funds, equipment, manpower and other resources among different projects, which increases the complexity of the scheduling process. The allocation of scarce resources then becomes a major objective of the problem. In such cases, planners are generally concerned with a number of different decision criteria, often conflicting among each other, according to their importance and priorities.

1.2 RESEARCH OBJECTIVES

The main objective of this research is to develop a multi-objective scheduling optimization model for multiple projects considering resource leveling and allocation together with projects' financing. The model aims to solve for enterprises problems of prioritizing projects under resource-conflict conditions, allocating limited resources, and optimizing all the projects' multi-objectives under certain funding limits. This is done by producing optimal/near optimal tradeoffs between different selected projects' objectives including duration, total cost, financing cost, required credit, profit, and resource fluctuations. The model takes into account projects' activities to have one or more resource utilization mode with multi-resources. In order to achieve the stated main objective; the following sub-objectives are to be attained:

1. Develop scheduling, resource, and cash flow models for multiple construction projects.

2. Integrate the aforementioned management models to formulate and develop a multi-objective scheduling optimization model for multiple projects.
3. Implement, test, and automate the developed optimization model.

1.3 SUMMARY OF RESEARCH METHODOLOGY

As shown in Figure 1.2, the methodology of this research can be summarized as follows:

1. Literature review is performed which involves identifying previous research efforts made by different researchers to solve the finance-based scheduling, time/cost tradeoff, resource leveling, and resource allocation problems. In addition, a survey of different multi-objective techniques used to solve such problems is reviewed.
2. Three main management models are developed, namely: (1) scheduling model that establishes optimal/near optimal schedules for construction projects; (2) resource model to calculate the resource fluctuations and maximum daily resource demand; and (3) cash flow model to calculate projects' cash flow parameters.
3. Model formulation is established to convert the basic multi-objective and their constraints into a mathematical model. The objectives involves minimizing the duration of multiple projects, total cost, financing cost, maximum required credit, and resource fluctuations and maximizing the profit. On other hand, the constraints set to achieve those objectives are: (1) dependencies between projects' activities are to be fulfilled; (2) credit limit not to be exceeded; and (3) daily resource limit not to be exceeded.

4. Multi-objective scheduling optimization model is developed using NSGA-II to optimize the projects' objectives under specified constraints. The model performs genetic algorithms operations in three main phases: (1) population initialization; (2) fitness evaluation; and (3) generation evolution.
5. The developed model is tested and implemented using different case studies obtained from literature to prove its validity and ability to optimize such problems successfully and efficiently.
6. An automated tool using C# language is built with a friendly graphical user interface to facilitate solving multi-objective scheduling optimization problems for contractors and practitioners.
7. Finally, the conclusions and contributions achieved from this research is summarized as well as the suggested recommendations for future work.

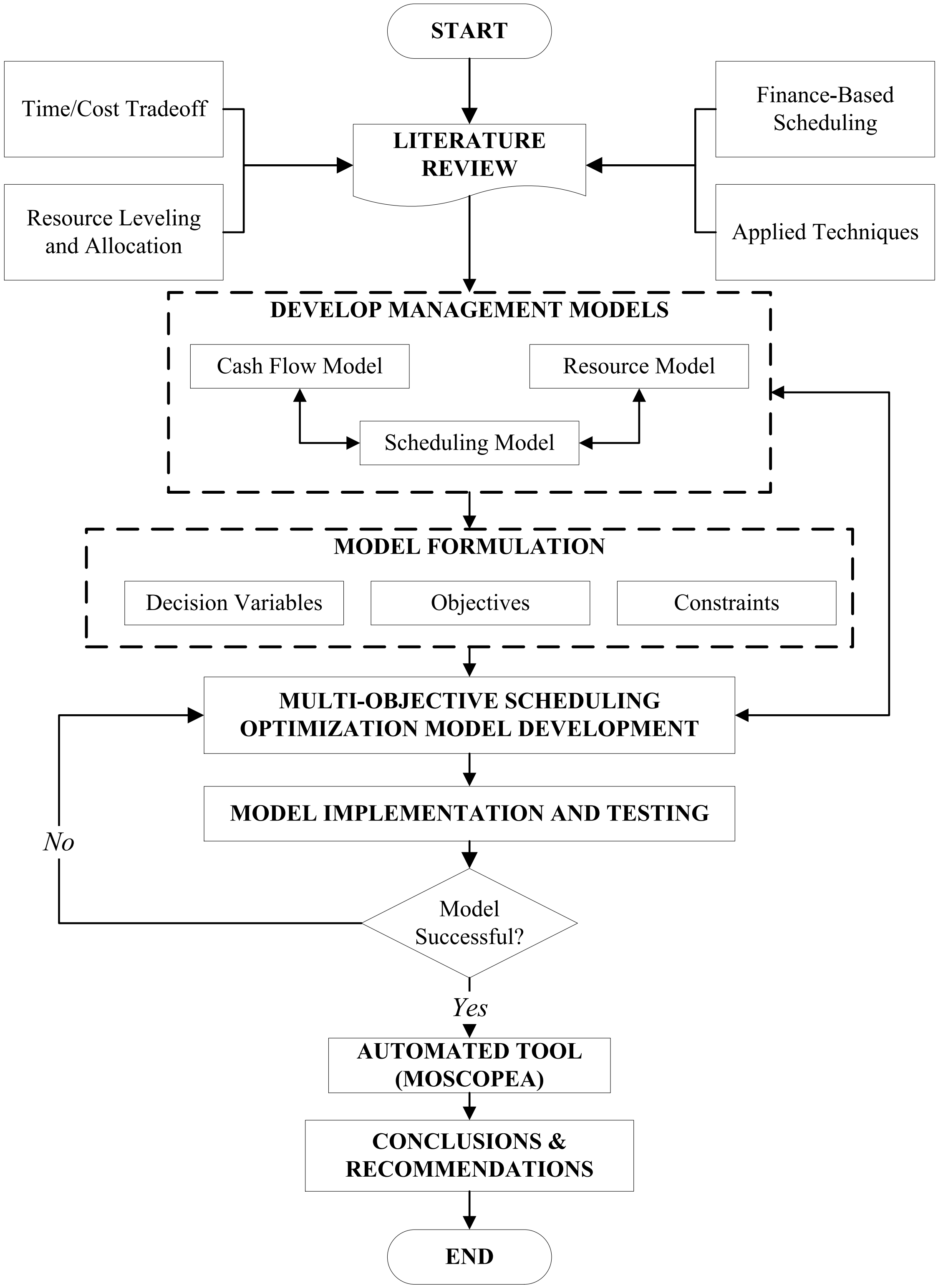


Figure 1.2: Summary of Research Methodology

1.4 THESIS ORGANIZATION

This thesis consists of seven chapters. Chapter 1 includes the research motivations and problem statement, research objectives, and summary of the research methodology. Chapter 2 involves a detailed literature review on the previous attempts carried by different researchers to solve the finance-based scheduling, time/cost tradeoff, resource leveling, and resource allocation problems. In addition it involves a brief review on the different used optimization techniques and a detailed review on the elitist non-dominated sorting genetic algorithm (NSGA-II) technique. Chapter 3 provides a detailed description of the research methodology. Chapter 4 explains in details the multi-objective scheduling optimization model development process. Chapter 5 shows the testing and implementation results and analysis of the developed optimization model. Chapter 6 presents the built automated tool for the developed model. Finally, Chapter 7 summarizes the research conclusions and contributions, and discusses its limitations and suggested recommendations for future work.

CHAPTER 2: LITERATURE REVIEW

Optimization problems in construction scheduling are traditionally classified, depending on their objective, into one of the following: (1) time/cost tradeoff; (2) resource allocation; or (3) resource leveling. Time/cost tradeoff is concerned with minimizing the direct cost while meeting a desired completion time (Hegazy 1999b). Resource allocation fulfills constraints on resource with the minimum increase in project duration (Hegazy 1999a). Resource leveling is concerned with minimizing peak resource requirements and period-to-period fluctuations in resource usage while maintaining the original project duration (Moselhi and Lorterapong 1993).

This chapter is divided into seven sections. The first two sections include brief reviews of time/cost tradeoff analysis and resource management techniques including the resource allocation and resource leveling. The third section describes in detail the concept and technique of finance-based scheduling. The fourth section reviews research work in the literature related to the utilization of single and multiple-objective optimization techniques to solve scheduling problems. In addition, the fourth section reviews the research efforts related to usage of optimization techniques to solve scheduling problems of multiple projects within a portfolio. The fifth section reviews a background on the multi-objective evolutionary algorithms focusing in the sixth section on the fast non-dominated sorting genetic algorithm (NSGA-II) as an optimization technique. Finally, the seventh section summarizes the findings and limitations of the literature.

2.1 TIME/COST TRADEOFF ANALYSIS

Time/Cost Tradeoff (TCT) is defined as a process to identify suitable construction activities for speeding up, and for deciding 'by how much' so as to attain the best possible savings in both time and cost (Eshtehardian et al. 2008). It is a technique used to overcome critical path method's (CPM) lack of ability to confine the schedule to a specified duration (Hegazy and Menesi 2012). The objective of the analysis is to reduce the original CPM duration of a project in order to meet a specific deadline with the minimum cost (Chassiakos and Sakellaropoulos 2005). TCT analysis is an important management tool because it can also be used to accelerate a project so that delays can be recovered and liquidated damages avoided. The project can be accelerated through the addition of resources, e.g., labor or equipment, or through the addition of work hours to crash critical activities. Reducing project duration therefore results in an increase in direct costs, e.g., the cost of materials, labor, and equipment. However, the increase in direct cost expenditures can be justified if the indirect costs, e.g., expenditures for management, supervision, and inspection, are reduced or if a bonus is earned (Gould 2005).

TCT analysis involves selecting some of the critical activities in order to reduce their duration through the use of a faster construction method, even at an additional cost. Different combinations of construction methods for the activities can then be formed, each resulting in a specific project duration and direct cost. To determine the optimum TCT decision for a project, the direct cost and indirect cost curves are plotted individually so that the total cost curve can be developed from the addition of these two components, as shown in Figure 2.1. The minimum point on the total cost curve represents the set of optimum combination of construction methods for the activities. However, for projects involving large number of activities with varying construction options, finding optimal TCT decisions becomes difficult and time consuming (Zheng et al. 2004).

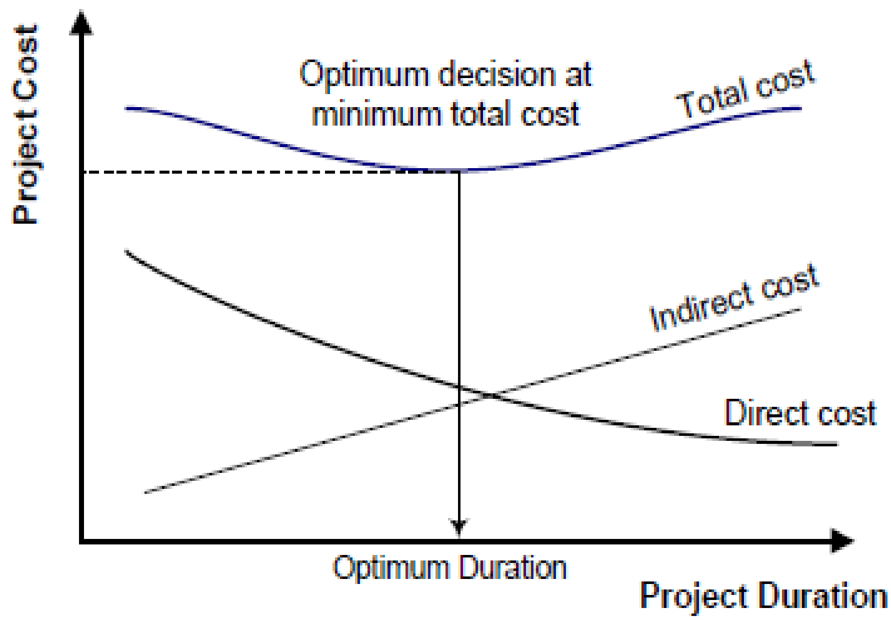


Figure 2.1: Illustration of Project Time/Cost Tradeoff (Hegazy 1999b)

2.2 RESOURCE MANAGEMENT

Traditionally, resource management problems in construction projects have been solved either as a resource leveling or as a resource allocation problem (Wiest and Levy 1969; Antill and Woodhead 1982; Moder et al. 1983). The objective in the resource leveling problem is to reduce peak resource requirements and smooth out period-to-period resource usage within the required project duration, with the premise of unlimited resource availability (Chan et al. 1996). The resource allocation arises when there are definite limits on the amount of resources available. The scheduling objective is to extend the project duration as minimum as possible beyond the original critical path duration in such a way that the resource constraints are met. In this process, both critical and noncritical activities are shifted (Senouci and Adeli 2001).

2.2.1 Resource Leveling

The resource leveling problem arises when there are sufficient resources available and it is necessary to reduce the fluctuations in the resource usage over the project duration. The objective of the leveling process is to “smooth” resource usage profile of the project without elongating the project duration as much as possible. This is accomplished by rescheduling of activities within their available slack to give the most acceptable profiles (Davis 1973). In resource leveling, the project duration of the original critical path remains unchanged.

Fluctuations of resources as shown in Figure 2.2a are undesirable for the contractor. It is expensive to hire and fire labor on a short term basis to satisfy fluctuating resource requirements. The short term hiring and firing presents labor, utilization, and financial difficulties because (1) the costs for employee processing are increased; (2) top-notch journeymen are discouraged to join a company with a reputation of doing this; and (3) new, less experienced employees require long periods of training (Senouci and Adeli 2001). As a result, the scheduling objective of the resource leveling problem is to make the resource requirements as uniform as possible (Figure 2.2b) or to make them match a particular non-uniform resource distribution in order to meet the needs of a given project (Figure 2.2c).

Therefore, efficient use of project resources will decrease construction costs to owners and consumers, and at the same time, will increase contractor's profits (Hegazy and Kassab 2003). In other words, alternative labor utilization strategies and better utilization of existing labor resources are needed to improve work productivity and reduce construction costs.

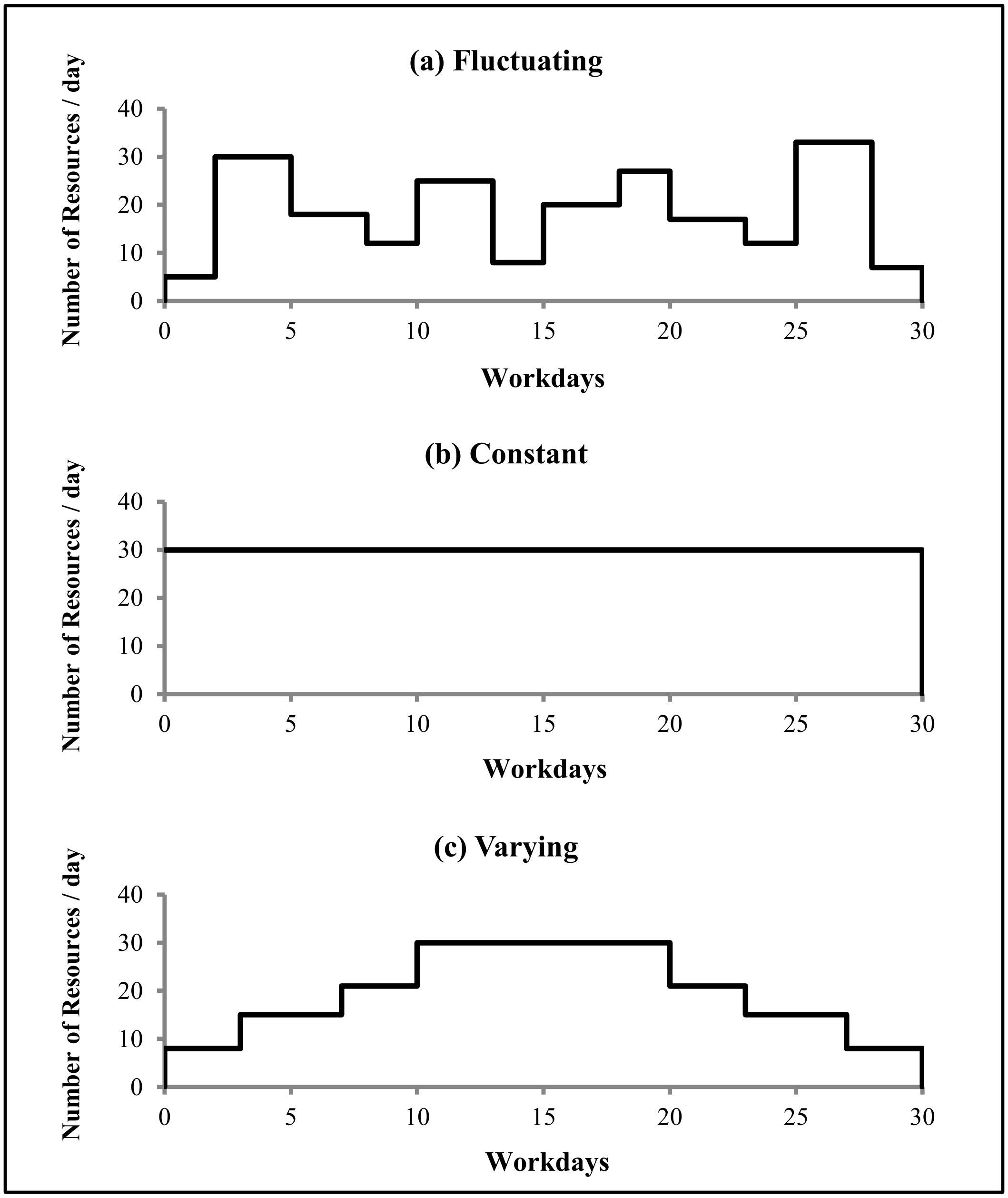


Figure 2.2: Resource Usage Patterns

2.2.2 Resource Allocation

Resource allocation attempts to reschedule a project's activities so that a limited number of resources can be efficiently utilized while keeping the unavoidable extension of the project to a minimum (Hegazy 1999a). A simple illustration for a project's initial resource profile in which resource limit was exceeded is shown in Figure 2.3a. On the other hand, Figure 2.3b shows the rescheduled project's resource profile where the resource limit is kept at or below the maximum limit, however, the initial duration was exceeded.

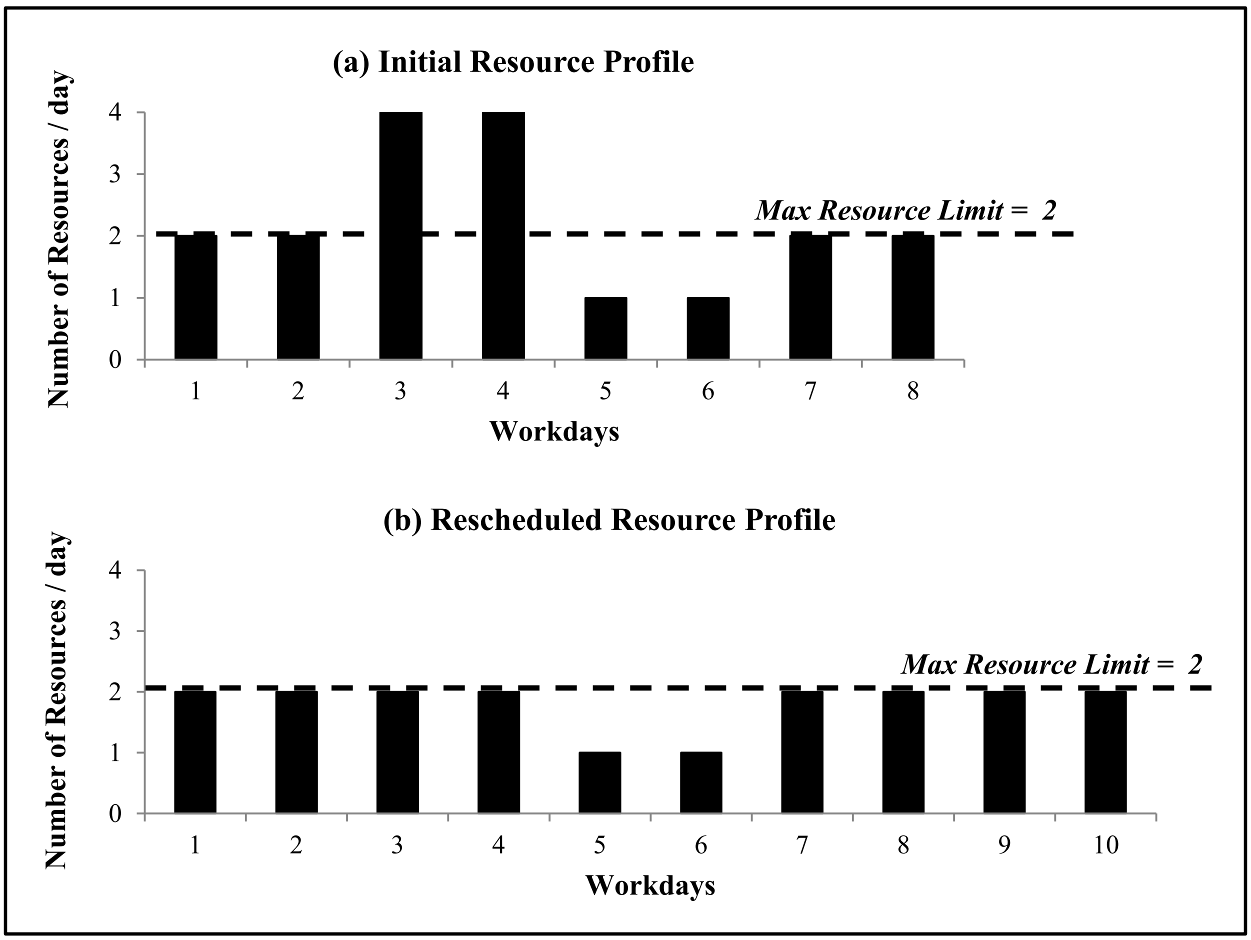


Figure 2.3: Illustration of Resource-Constrained Scheduling

The focus of scheduling in these situations is to prioritize and allocate resources in such a manner that there is minimal project delay. Beside the importance of ensuring that the resource limit is not exceeded; the logical relationships between the activities of a project network should simultaneously be preserved. Resource allocation problems can be classified into single-mode resource allocation and multi-mode resource allocation when there is more than one alternative for activity duration and resource requirement.

2.2.3 Resource Management Models

Two new metrics that were developed by El-Rayes and Jun (2009) to solve the resource leveling problem will be adopted in this research. These two new resource leveling metrics were developed to directly measure and quantify the impact of resource fluctuations on construction productivity and cost. These fluctuations can be classified based on their impact on the efficiency of resource utilization into two types: (1) acceptable fluctuations; and (2) undesirable fluctuations, as shown in Figure 2.4. Acceptable fluctuations represent gradual build-up and run-down of resources, and they can be depicted graphically by a mountain shape in the resource histogram, as shown in Figure 2.4a. In this type of fluctuation, a contractor needs to gradually increase the level of resource utilization to satisfy resource demands during different periods of the project and then gradually release them toward the end of the project (El-Rayes and Jun 2009). Gradual build-up and run-down of construction resources will minimize the number of times that a contractor has to hire, layoff, and then rehire the same resources (Mattila and Abraham 1998).

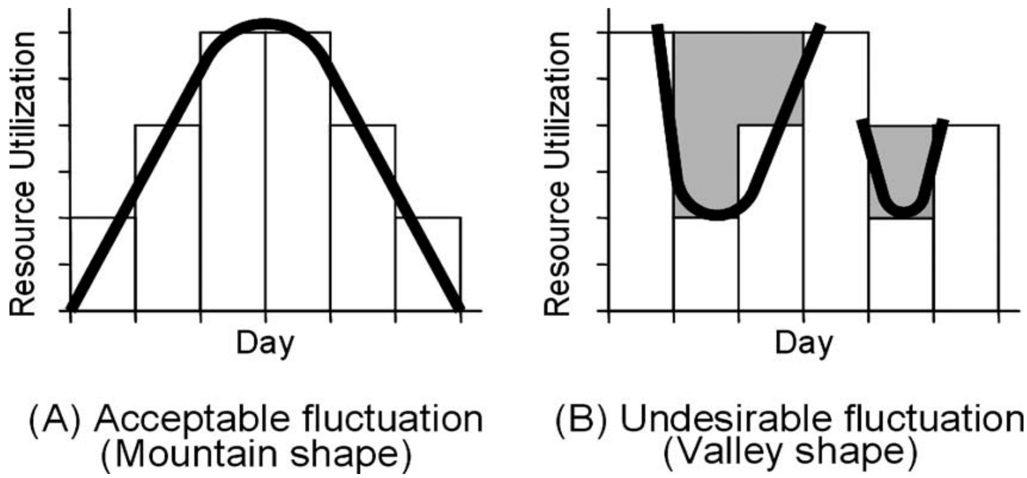


Figure 2.4: Types of Resource Fluctuations (El-Rayes and Jun 2009)

On the other hand, undesirable fluctuations represent temporary decreases in the demand for construction resources. This can be depicted graphically by a valley shape in the resource histogram as shown in Figure 2.4b. In this type of fluctuation, a contractor is forced to either: (1) release the additional construction resources and rehire them at a later stage when needed or (2) retain the idle construction resources on site until they are needed later in the project (El-Rayes and Jun 2009). In order to generate productive and cost effective construction schedule, this undesirable fluctuation should be directly measured and minimized. To accomplish this, two new resource leveling metrics were developed: (1) Release and Re-Hire (RRH); and (2) Resource Idle Days (RID) (El-Rayes and Jun 2009).

2.2.3.1 Release and Re-Hire (RRH)

This metric is designed to quantify the total amount of resources that need to be temporarily released during low demand periods and rehired at a later stage during high demand periods, as shown in Figure 2.5b. The present model utilizes Equation 2.1 to calculate the RRH metric in three sequential steps: (1) calculate the total daily resource fluctuations (*HR*) using Equation 2.2 which sums up all the increases and decreases in the daily resource demand, as shown in Figure 2.5b; (2) identify the total increases in the daily resource demand (*H*) which is half the total daily resource fluctuations (*HR*); (3) determine the number of released and rehired resources by subtracting the maximum resource demand (MRD) from the total increases in the daily resource demand (*H*), as shown in Equation 2.1.

$$RRH = H - MRD = ((1/2) \times HR) - MRD \quad (2.1)$$

$$HR = [r_1 + \sum_{t=1}^{T-1} |r_t - r_{t+1}| + r_T] \quad (2.2)$$

$$MRD = Max\ (r_1, r_2, \ldots, r_T) \quad (2.3)$$

Where; RRH = total amount of resources that need to be temporarily released and rehired during the entire project duration; H = total increases in the daily resource demand; HR = total daily resource fluctuations; T = total project duration; r_t = resource demand on day (t); r_{t+1} = resource demand on day (t + 1); and MRD = maximum resource demand during the entire project duration. It should be noted that the RRH metric can be practical and useful in projects that allow the release and rehire of construction workers. In other projects that restrict this type of resource release and rehire, contractors are often required to keep the additional resources idle on site during low demand periods, as shown in

Figure 2.5b. To quantify and minimize the impact of this decision on construction productivity and cost, the following section presents the development of the new metric named RID.

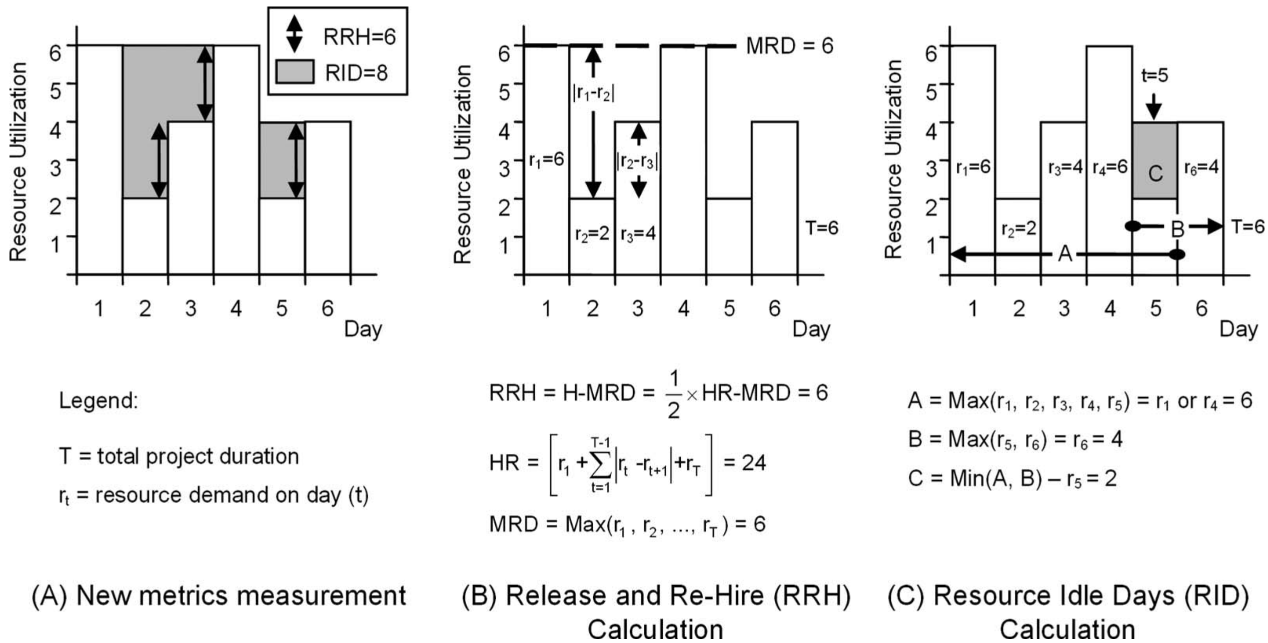


Figure 2.5: Calculations of the New Metrics (El-Rayes and Jun 2009)

2.2.3.2 Resource Idle Days (RID)

This metric is designed to quantify the total number of idle and nonproductive resource days caused by undesirable resource fluctuations and it can be calculated using Equation 2.4. As shown in Figure 2.5c, idle resources occur on day (*t*) when the resource demand on that day (*t*) dips to a lower level than the peak demand levels experienced prior to and after that day (*t*). When this dip in resource demand occurs, the idle resources on day (*t*) can be calculated by subtracting its resource level from the least of the peak demands that occur before or after that day as shown in Figure 2.5c. For example, the number of idle resources on the fifth day (t=5) in Figure 2.5c can be calculated by subtracting the resource level on that day (r_5=2) from the next peak level occurring on the sixth day (r_6=4). As stated earlier, this metrics can be more practical and useful than the earlier described RRH metric in projects that impose restriction on releasing and rehiring construction resources.

$$RID = \sum_{t=1}^{T} [Min\{Max(r_1, r_2, \ldots\ldots, r_t), Max(r_t, r_{t+1}, \ldots\ldots, r_T)\} - r_t] \quad \ldots\ldots\ldots(2.4)$$

Where; RID = total number of idle and nonproductive resource days during the entire project duration; T = total project duration; and r_t = resource demand on day (t).

The two newly developed metrics (RRH and RID) are designed to address different project needs. For projects that allow the release and rehire of construction workers, RRH can be effectively used to directly measure and minimize the release of resources during low demand periods and rehiring them when needed at a later stage. For other projects that restrict resource release and rehire, RID can be effectively used to directly measure and minimize total resource idle time on site during low demand periods (El-Rayes and Jun 2009). Each of the two newly developed metrics adopts a unique methodology to minimize undesirable resource fluctuations, and accordingly they can produce different schedules and resource profiles, as shown in the simple example in Figure 2.6.

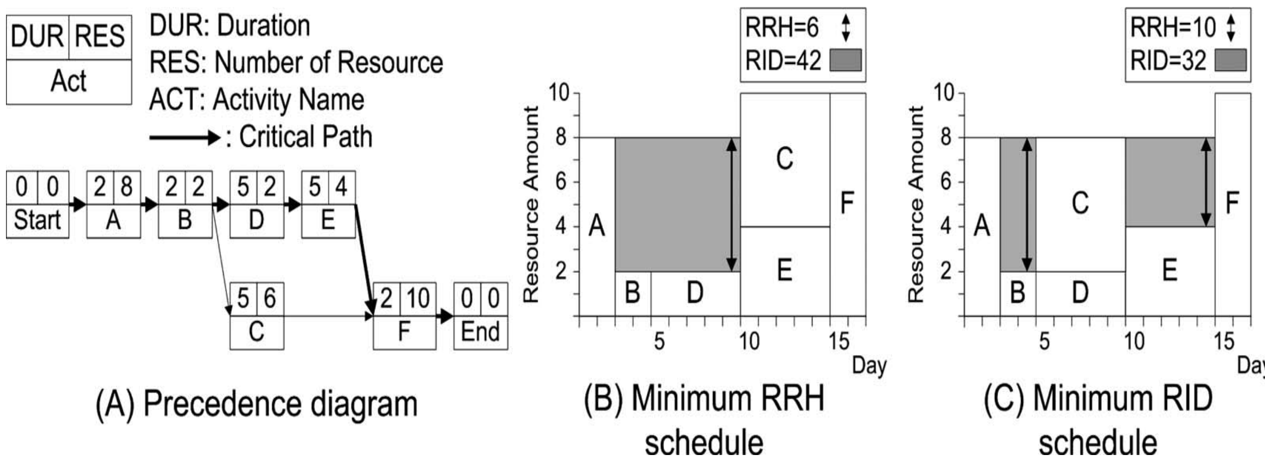


Figure 2.6: Difference Between RRH and RID Metrics (El-Rayes and Jun 2009)

While existing metrics attempt to transform fluctuating resource profile to a predetermined desirable shape (e.g., a rectangular or a parabolic), the new metrics focus on minimizing only undesirable fluctuation, and accordingly they are capable of generating more efficient resource utilizations than existing ones (El-Rayes and Jun 2009).

2.3 FINANCE-BASED SCHEDULING

Establishing bank overdrafts has been one of the prevalent methods of financing construction projects (Ahuja 1976). Finance-based scheduling enables producing schedules that correspond to overdrafts of desired credit limits. Control of the credit limit of an overdraft provides many benefits including negotiating lower interest rates with bankers, setting favorable terms of repayment, and reducing penalties incurred for any unused portions of overdraft cash (Elazouni and Gab-Allah 2004). In addition, the ability to adjust credit limits helps contractors avoid the phenomenon of progressive cash deficit.

This situation occurs when cash available in a given month does not allow the scheduling of much work. During the next month, when a reimbursement is expected, the generated income allows scheduling less work and so forth (Elazouni and Gab-Allah 2004).

Typically, an additional cost component for financing is associated with the cash procurement through the banks' credit lines. Contractors normally deposit owners' progress payments into the credit-line accounts to continually reduce the outstanding debit and consequently the financing costs (Abido and Elazouni 2010). As the cash flow shown in Figure 2.7 indicates; contractors charge the expenses caused by labor, equipment, materials, subcontractors, and other indirect costs (cash outflow E_t) against, and deposit progress payments (cash inflow P_t) into the credit-line accounts. In practice, it can be reasonably assumed that these transactions occur as of the cut-off times between periods (Abido and Elazouni 2010). Accordingly, the values of the outstanding debt (F_t) as of the cut-off times are determined. The financing costs as of the cutoff times are determined by applying the prescribed interest rate to the outstanding debt. The summations of the values of the outstanding debt and the accumulated financing costs (I'_t) constitute the negative cumulative balance (F'_t). The cumulative net balance value (N'_t) constitutes the negative cumulative balances after depositing the progress payments. The cumulative net balance of all E_t, P_t, and I'_t transactions constitutes the profit as of the end of the project (Abido and Elazouni 2010).

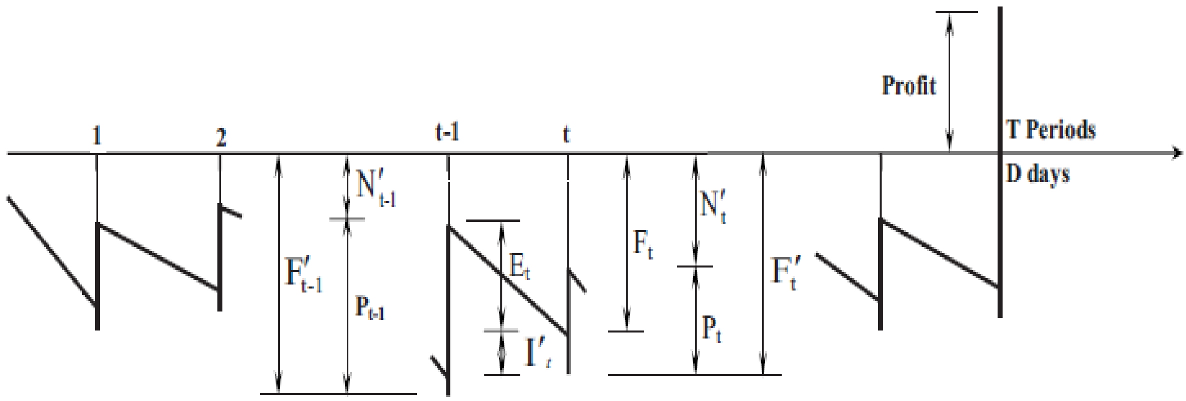


Figure 2.7: Cash Flow of a Typical Construction Project (Abido and Elazouni 2010)

Another concern of financing, though more important than the incorporation of financing costs, constitutes the credit-limit constraints imposed on the credit lines (Abido and Elazouni 2010). The credit limit specifies the maximum value the negative cumulative balance as of the cutoff times are allowed to reach. Thus, finance-based scheduling achieves the desired integration between scheduling and financing by incorporating financing costs into the project total cost as well as scheduling activities such that the values of the negative cumulative balance as of the cutoff times never exceeds the specified credit limit (Abido and Elazouni 2010). The techniques employed to devise finance-based schedules normally fulfill this financial constraint with the objectives of minimizing the financing costs and maximizing the contractor's profit.

Being an aspect of the whole corporate rather than the individual projects, contractors manage the financing aspect at the corporate level. In other words, contractors' concern is generally to timely procure cash for all ongoing projects (Abido and Elazouni 2011). Finance-based scheduling in this context ensures that the resulting values of the negative cumulative balances of all projects do not add up to exceed the credit limit, whereas the positive cumulative balances that occur in some projects are utilized to schedule activities of some other projects. This ensures that scheduling concurrent projects can be related to the overall liquidity situation of contractors. The sole objective of maximizing the profit of a single project is changed in this context to the objective of maximizing the profit value of all ongoing projects. Finance-based scheduling techniques schedule projects' activities such that the total profit of the projects is maximized while the financial constraint is fulfilled.

2.3.1 Cash Flow Model

The equations in this subsection are presented conforming to the financial terminology used by Au and Hendrickson (1986). Let direct cost disbursements of all activities performed on day i be denoted by y_i; this is referred to as project direct cost disbursement of day i. Thus y_i can be calculated as follows:

$$y_i = \sum_{p=1}^{n_i}(y_{pi}) \qquad i = 1, 2, ...D \qquad \text{(2.5)}$$

Where; n_i = number of activities ongoing with day i; y_{pi} = direct cost disbursement rate of activity p in day i; and D = total project duration.

The cash outflow during a typical period t - a week in this model - is represented by E_t and encompasses the costs of overheads and taxes in addition to the direct cost disbursements including the costs of materials, equipment, labor, and subcontractors. In case of multiple simultaneous projects, the cash outflow at the end of a given period includes the E_t components of the individual projects ongoing during the same week. E_t can be calculated as follows:

$$E_t = \sum_{i=1}^{m}(y_i) + O_t \text{ ....(2.6)}$$

Where; m = number of days comprising a week; and O_t = expenses of overheads, taxes, mobilization, and bond at period t.

On the other hand, the cash inflow, represented by P_t, includes the payments contractors receive, at the ends of periods, as an earned value of the accomplished works calculated based on the unit prices. In case of multiple simultaneous projects, the cash inflow at the end of a given period includes the P_t components collected of the projects at this time. P_t can be calculated as follows:

$$P_t = KE_t \text{ ....(2.7)}$$

Where; K = multiplier to determine the amount of payment for a given amount of disbursement E_t $(K > 1)$. In order to calculate the multiplier K; first a bid price factor BF must be calculated as follows:

$$BF = \frac{Total\ Price}{Total\ Direct\ Cost} =$$

$$= \frac{(Total\ Direct\ Cost + Total\ Overheads + Mobilization + Taxes + Markup + Bond\ Premium)}{Total\ Direct\ Cost} \text{ ....(2.8)}$$

Then the amount of retention R must be defined. Retention is a percentage of each bill which clients often withhold to ensure the contractor completes the construction project satisfactorily. The retained portion of the progress payments will often be released when the job is completed. In addition, in the case where the contractor receives from the client an advance payment AP at the beginning of the project; this amount of advance payment will be cut as a percentage from each bill. As a result the multiplier K can be calculated as follows:

$$K = (1 - (R\% + AP\%)) \times BF \quad \text{(2.9)}$$

It should be noted that the last payment P_T will be calculated as shown in Equation 2.7 with adding to the equation the total amount of retention to be as follows:

$$P_T = KE_t + R \quad \text{(2.10)}$$

Contractors normally deposit the payments into the credit-line accounts to continually reduce the outstanding debit (cumulative negative balance). The cumulative balance at the end of period t (disregarding interest charges) is defined by F_t:

$$F_t = N_{t-1} + E_t \quad \text{(2.11)}$$

The cumulative net balance at the end of period t after receiving payment P_t is defined as N_t. At the end of period $t-1$, F_{t-1} = cumulative balance; P_{t-1} = payment received; and N_{t-1} = cumulative net balance where

$N_{t-1} = F_{t-1} + P_{t-1}$ ……………………………………………………………..…….(2.12)

Typically, cash procurement through the banks' credit lines incurs financing costs. The financing cost charged by the bank at the end of period t is I_t which is calculated using Equations 2.13 – 2.15. For period t, if the cumulative net balance of the previous period N_{t-1} is positive, this implies that the contractor debit is null and the contractor can use the surplus cash to finance activities during the current period. If the surplus cash completely cover the amount of E_t, the contractor borrows no cash and Equation 2.15 applies, otherwise, the contractor will pay financing costs only for the amount of borrowed money in excess of the surplus cash as in Equation 2.14. In case N_{t-1} is negative, Equation 2.13 applies to calculate the financing cost,

$$I_t = rN_{t-1} + r\frac{E_t}{2} \qquad \text{if } N_{t-1} \leq 0 \ \ldots\ldots (2.13)$$

$$I_t = r\left(\frac{E_t - N_{t-1}}{2}\right) \qquad \text{if } N_{t-1} > 0 \text{ and } (N_{t-1} - E_t) < 0 \ \ldots\ldots (2.14)$$

$$I_t = 0 \qquad \text{if } (N_{t-1} - E_t) \geq 0 \ \ldots\ldots (2.15)$$

The first term in Equation 2.13 represents the financing costs per period on the cumulative net balance N_{t-1} at a fixed interest rate r per period and the second term approximates the financing costs on the cash outflow E_t during period t. The summation of the values of I_t over the periods comprising the duration of the group of projects constitutes the value of the financing costs objective.

When contractors decide to pay the financing costs at the end of the project, the periodical financing costs are compounded by applying Equation 2.16 as follows:

$$I'_t = \sum_{l=1}^{t} I_l (1+r)^{t-l} \quad \text{(2.16)}$$

Thus, the cumulative balance at the end of period t including accumulated financing costs is represented by F'_t which is calculated as shown in Equation 2.17 below:

$$F'_t = F_t + I'_t \quad \text{(2.17)}$$

The contractor debit amounts at the end of the periods are represented by the values of the negative cumulative balance F'_t. The maximum negative F'_t value signifies the required credit that must be procured to carry out the group of projects within the portfolio. The cumulative net balance including financing cost is represented by N'_t as shown in Equation 2.18:

$$N'_t = F'_t + P_t \quad \text{(2.18)}$$

The positive value of N'_T at the end of the last period T, which encompasses the total duration of D working days, represents the contractor profit as shown in Figure 2.7.

2.4 PREVIOUSLY DEVELOPED SCHEDULING OPTIMIZATION MODELS

Optimizing construction project scheduling has received a significant amount of attention over the past 20 years. As a result, numerous methods and algorithms have been developed to address specific scenarios or problems. The developed algorithms for solving the construction scheduling optimization problem can be classified into two methods: exact (mathematical) and approximate (heuristic and meta-heuristic).

2.4.1 Time/Cost Tradeoff Analysis Previous Studies

A number of models have been developed using a variety of methods to optimize construction time and cost. Heuristic methods are based on rule of thumb, which generally lack mathematical rigidity (Feng et al. 1997). Examples of heuristic approaches include Fondahl's method (Fondahl 1961), Prager's structural model (Prager 1963), Siemens's effective cost slope model (Siemens 1971), and Moselhi's structural stiffness method (Moselhi 1993). Although these heuristic methods provide good solutions, they do not guarantee optimality. Most heuristic methods, however, assume only linear time-cost relationships within activities. In addition, the solutions obtained by heuristic methods do not provide the range of possible solutions, making it difficult to experiment with different scenarios for what-if analysis (Feng et al. 1997).

Mathematical programming methods convert the TCT problem to mathematical models and utilize linear programming (LP), integer programming (IP), or dynamic programming (DP) to solve them. Kelly (1961) formulated TCT problem by assuming linear time-cost relationships within activities. Other approaches such as those by Hendrickson and Au

(1989) and Pagnoni (1990) also used LP as the tool to solve the TCT problem. LP approaches are suitable for problems with linear time-cost relationships, but fail to solve those with discrete time-cost relationships. Meyer and Shaffer (1965), Patterson and Huber (1974), and Moussourakis and Haksever (2004) solved TCT problem including both linear and discrete time-cost relationships by using mixed IP. However, IP requires a lot of computational effort once the number of options to complete an activity becomes too large or the network becomes too complex (Feng et al. 1997). Liu et al. (1995) and Burns et al. (1996) took a hybrid approach which used LP to find a lower bound of the tradeoff curve and IP to find the exact solution for any desired duration. Chassiakos and Sakellaropoulos (2005) introduced an exact and an approximate method to solve the TCT problem. The exact method utilizes an LP/IP model to provide the optimal project time-cost curve and the minimum cost schedule considering all activity time-cost alternatives together. The approximate method performs a progressive project length reduction providing a near-optimal project time-cost curve but it is faster than the exact method as it examines only certain activities at each stage. Robinson (1975), Elmaghraby (1993), and De et al. (1995) used DP to solve TCT problems for networks that can be decomposed to pure series or parallel sub-networks.

Since the heuristic methods and the mathematical programming got their drawbacks as previously discussed; researchers focused on using different meta-heuristic techniques of which GAs was the most common in order to overcome those drawbacks. GAs was used as an optimization technique for TCT problems to minimize both duration and cost (Feng et al. 1997; Li and Love 1997; Hegazy 1999b; Li et al. 1999; Zheng et al. 2002; Zheng et al. 2004; Zheng et al. 2005; Eshtehardian et al. 2008; Senouci and Al-Derham 2008). In addition, as an attempt to transform the traditional two-dimensional TCT analysis to an advanced three-dimensional time-cost-quality tradeoff analysis, El-Rayes and Kandil (2005) developed an optimization model that supports decision makers to search for an optimal resource utilization plan that minimizes construction cost and time while maximizing its quality. The model was developed as a multi-objective GA to provide the capability of quantifying and considering quality in construction optimization. Xu et al. (2012) developed a discrete time-cost-environment tradeoff model for large scale construction projects with multiple modes under fuzzy uncertainty. Esfahan (2011) presented a new method to circumvent the limitations of current schedule compression methods, which reduce schedule crashing to the traditional time-cost trade-off analysis, where only cost is considered. The schedule compression process is modeled as a multi-attributed decision making problem in which different factors contribute to priority setting for activity crashing.

2.4.2 Resource Management Previous Studies

Limited-resource allocation algorithms deal with a difficult problem that mathematicians refer to as a "large combinatorial problem" (Hegazy 1999a). There exist optimization methods as well as heuristic methods for solving the resource allocation problem that go back in time to the 1960s (e.g. Wiest 1964). Various approaches have been formulated to solve the problem optimally, including IP, branch-and-bound, and DP (Gavish and Pirkul 1991). None of these, however, is computationally tractable for any real-life problem size, rendering them impractical (Moselhi and Lorterapong 1993; Allam 1988).

Alternatively, heuristic approaches have been proposed for solving the resource allocation problem. These approaches apply selected heuristic that are based on activity characteristics, such as the ‘‘minimum total-slack’’ rule, to prioritize the activities that compete for the limited resource (Hegazy 1999a). Accordingly, the resource is given to the top-ranked activities and the others are delayed. When ties occur during the implementation of a rule (e.g. when two or more activities have the same total slack), another rule such as ‘‘shortest duration’’ can be used to break the tie (Hegazy 1999a). The scheduling process, as such, starts from the project’s start time, identifying eligible activities according to the network logic and resolving the over-requirements of resources using the selected set of heuristic rules. The process, as such, ensures that all project activities are scheduled without violating the logical relationships or the resource constraints. However, this comes on the expense of the total project duration, which often exceeds the duration determined by the original CPM analysis (Hegazy 1999a).

Heuristic rules have the advantage of being simple to understand, easy to apply, and very inexpensive to use in computer programs. They are able to rationalize the scheduling process and make it manageable for practical-size projects. Furthermore, research has identified rules such as the ‘‘least total-slack’’ and the ‘‘earliest late-start,’’ which generally provide good solutions (Davis and Patterson 1975). Almost all commercial software for planning and scheduling, therefore, utilizes heuristic rules to provide resource allocation capabilities. Despite these benefits, however, heuristic rules perform with varying effectiveness when used on different networks, and there are no hard guidelines that help in selecting the best heuristic rule to use for a given network. They, as such, cannot guarantee optimum solutions (Hegazy 1999a). Furthermore, their drawbacks have contributed to large inconsistencies among the resource-constrained capabilities of commercial project management software, as reported in past surveys (Hegazy and El-Zamzamy 1998; Johnson 1992).

On the other hand, optimal solutions for the resource leveling problem are based on mixed IP formulations (Shah et al. 1993; Easa 1989). Such formulations are NP-complete and optimal solutions are reached for small-sized construction projects only. Heuristic algorithms are therefore needed. Heuristic procedures developed for the resource leveling problem include those reported in Burgess and Killebrew (1962), Harris (1978), Shaffer et al. (1965), Woodworth and Willie (1975). The basic concept of these heuristics is to reschedule non-critical activities within the limits of available float according to some heuristic rule to achieve a better distribution of resource usage.

Despite the classical approaches used to solve resource leveling and resource allocation problems; many studies were made using different meta-heuristic techniques of which GA was the most common. Different studies were made to solve the resource allocation problem using GAs (Alcaraz and Maroto 2001; Hyari and El-Rayes 2006; Kandil and El-Rayes 2006; Valls et al. 2008; Torres et al. 2010). An optimal resource allocation simulation model was developed by Leu and Hung (2002) in which the effects of both uncertain activity duration and resource constraints were taken into account. Probability distribution was used to model the uncertainties of activity duration. An optimal schedule simulation model was then established in which a GA based search technique was adopted to search for the probabilistic optimal project duration under resource constraints. Hegazy and Kassab (2003) developed a new approach for resource optimization by combining a flow-chart based simulation tool with a powerful genetic optimization procedure. Also, the GAs technique was employed to solve limited resource allocation problem with multiple execution modes for each activity (Mori and Tseng 1997; Hartmann 2001; Dawood and Sriprasert 2006; Chen and Weng 2009; Long and Ohsato 2009) in where there is more than one alternative for activity duration and resource requirement. Fast non-dominated sorting genetic algorithms (NSGA-II) was also used to solve such problem by Wang et al. (2005). Studies were also made to solve the resource leveling problem using GAs (Leu et al. 2000; El-Rayes and Jun 2009) to overcome drawbacks of traditional construction resource leveling algorithms. Other studies concentrated in encompassing both resource leveling and limited resource allocation problems simultaneously using GAs (Chan et al. 1996; Hegazy 1999a; Toklu 2002; Senouci and Eldin 2004). Leu and Yang (1999) proposed a multi-criteria computational optimal scheduling model using GAs, which integrates the TCT model, resource-limited model, and resource leveling model. Furthermore, the non-dominated solutions were found by the multiple attribute decision-making method, technique for order preference by similarity to ideal solution.

Other artificial intelligence techniques such as neural networks or fuzzy set theory were also utilized. Lorterapong (1995) developed a method that integrates resource allocation model with a suitable technique for modeling uncertainties in construction scheduling. The resource allocation model incorporated a decomposition technique that generates partial schedule alternatives and examines the negative impact of each alternative on the overall project duration. Fuzzy set theory was employed for modeling the uncertainties associated with the durations of project activities and the resource availabilities. Savin (1995) developed a neural network model to solve the resource leveling problem. The model was derived by mapping a formulation of the resource leveling problem as a quadratic augmented Lagrangian multiplier (QALM) optimization onto and artificial neural network (ANN) architecture employing a Hopfield network.

However, due to the distinctive feature of cash, none of the previous studies mentioned whether for the TCT or the resource management problems can be used to devise cash-constrained schedules. The distinctive feature is that while cash is being used to carry out construction works like any other resources, the completed construction works generate the same resource of cash which is used to finance the remaining activities of the projects. As a result, some research efforts have integrated CPM schedules with cash flow models to devise what is called “finance-based scheduling”.

2.4.3 Finance-Based Scheduling Previous Studies

Finance-based scheduling was initiated by Elazouni and Gab-Allah (2004) followed by improvements and modifications in the techniques used to solve this problem. Also other researchers made attempts to solve the finance-based scheduling and related problems. Elazouni and Gab-Allah (2004) developed an IP finance-based scheduling method to produce financially feasible schedules that balance the financing requirements of activities at any period with the cash available during that same period. The proposed method offered twofold benefits of minimizing total project duration and fulfilling finance availability constraints. Later, GAs technique was utilized to devise finance-based schedules (Elazouni and Metwally 2005; Elazouni and Metwally 2007; Ali and Elazouni 2009; Abido and Elazouni 2010) through searching for an activities schedule that minimizes total project duration under a cash constraint while also minimizing financing cost. Liu and Wang (2008) established a resource-constrained project scheduling model based on constraint programming. The proposed model considers resource usage and cash flow in project scheduling to fulfill management requirements, such as resource and credit limits, and attempts to maximize project profit from the viewpoint of contractors. Also a Monte Carlo Simulation technique was employed by Ahmed et al. (2011) to assess the criticality of activities related to cash flow parameters by randomly specifying the activities' start times within the ranges between their respective early and late start times. The model offers project managers very useful criteria to identify the activities that should be completed on time to assure project completion within the time and cash constraints

All of these efforts focused on single-objective optimization approach without considering multiple objectives. As a result, some attempts were made to consider multi-objective in integrating the project's cash flow with its schedule using multi-objective GA optimization model (Senouci and El-Rayes 2009; Afshar and Fathi 2009; Fathi and Afshar 2010; Elazouni and Abido 2011). Recently, Elazouni and Abido (2014) proposed a multi-objective multimode scheduling optimization model using SPEA to establish optimal tradeoff between the objectives of finance requirement, resource leveling, and contractor's profit.

2.4.4 Multi-project Scheduling Optimization

Scheduling of a single construction project involves the allocation of given resources to a certain project to determine the start and completion times of the detailed activities. However, there may be multiple projects - often carried out simultaneously - that involves sharing and competing for limited resources such as funds, equipment, manpower and other resources among different projects, which increases the complexity of the scheduling process. The allocation of scarce resources then becomes a major objective of the problem and several compromises have to be made to solve the problem to the desired level of optimality. In such cases, planners are generally concerned with a number of different decision criteria, often contrasting among each other, according to their importance and priorities. Therefore, efficient multi-project scheduling is a key problem to solve for enterprises on how to prioritize the projects with resource conflicts, how to reasonably allocate the limited resources among multiple projects to meet the resource requirements of different projects, and to optimize all the projects' multi-objectives.

According to previous research, over 90% of all projects worldwide are executed in a multi-project environment (Payne 1995) and 84% of firms handle multiple projects in parallel (Lova and Tormos 2001). This high percentage led to the proposal of various approaches to fulfill the needs of contractors for practical scheduling of multiple projects.

Fendley (1968) first investigated modeling multi-project scheduling problems, examined various measurements in computational analysis for multi-project scheduling, and concluded the priority rule of minimum slack to achieve highest efficiency. Subsequently, a number of researches have paid close attention to the multi-project scheduling problems (Pritsker et al. 1969; Kurtulus and Davis 1982; Kurtulus and Narula 1985; Dumond and Mabert 1988; Mohanty and Siddiq 1989; Tsubakitani and Deckro 1990; Lawrence and Morton 1993; Vercellis 1994; Lova et al. 2000).

Lately, several techniques were used for solving the multi-project scheduling problems in terms of resource leveling and allocation. Simulation models were developed to solve the resource constrained scheduling problems in multi-project environment (Fatemi-Ghomi and Ashjari 2002; Kanagasabapathi and Ananthanarayanan 2005). Lova and Tormos (2002) presented a combined random sampling and backward-forward heuristics for solving resource constrained multi-project scheduling problems. Kruger and Scholl (2009) presented a heuristic solution framework and priority rules for resource constrained multi-project scheduling problems with transfer times. Tsai and Chiu (2010) developed two efficient heuristic priority rules for the resource-constrained multi-project scheduling problem.

Beside the heuristic methods used; meta-heuristics were also used to solve the multi-project scheduling problem. Chen and Shahandashti (2007) used the simulated annealing algorithm for optimizing multi-project linear scheduling with multiple resource constraints. Guo et al. (2009) used the particle swarm optimization method to solve multiple resource leveling for multi-project scheduling problem. Particle swarm optimization was also used and enhanced to solve the resource-constrained multi-project scheduling problem with multiple activity performance modes (Li et al. 2010). Tseng (2004) applied genetic algorithms for scheduling multiple projects with multiple modes subject to limited resource availabilities. Goncalves et al. (2008) also proposed a genetic algorithm for the resource constrained multi-project scheduling problem and used a heuristic to generate parameterized active schedules.

The previously mentioned studies did not take into consideration “cash”, which is typically regarded as a shareable resource, and have also neglected cash flow issues in multiple project environment. A project schedule which does not consider cash outflows and inflows may overlook costs associated with financial factors and payment conditions, leading to budget overruns and project failure (Liu and Wang 2010). Managing project finance becomes complex and tough for contractors in situations involving various periodical inflows and outflows of multiple projects. Few studies have paid close attention to cash flow issues involved in both financing and scheduling multiple projects for contractors. Chiu and Tsai (2002) developed a mixed-integer nonlinear programming model to solve resource constrained multi-project scheduling problem with discounted cash flows. However, the model cannot be used to devise cash-constrained schedules. As a result, Elazouni (2009) developed a heuristic rule for scheduling multiple concurrent projects subject to cash constraints. The heuristic determines cash availability during a given period, identifies all possible activities’ schedules, determines the cash requirements for each schedule, ranks schedules based on the contribution to minimizing the increase in the project duration, schedules all activities of the selected schedule and determines the impact of the scheduled activities on the project cash flow. Liu and Wang (2010) proposed a profit optimization model for multi-project scheduling problems using constraint programming considering cash flow and the financial requirements of contractors. Abido and Elazouni (2011) utilized the strength Pareto evolutionary algorithm to devise a set of optimum finance-based schedules of multiple projects being implemented simultaneously by a construction contractor. The problem involves the minimization of the conflicting objectives of financing costs, duration of the group of projects, and the required credit.

2.5 MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS (MOEAs)

In contrast to single-objective optimization, where objective function and fitness function are often the same, in multi-objective optimization (MOP), both fitness assignment and selection must support several objectives. Therefore, MOEAs varies from the simple GA only in the way fitness assignment and selection works (Zitzler et al. 2004). Different versions of MOEAs have been introduced with different fitness assignment and selection strategies. Based on their fitness assignment and selection strategies, MOEAs can be categorized as aggregation-based approaches, population-based approaches, and Pareto-based approaches (Coello 2000). These approaches are described briefly as follows:

2.5.1 Aggregation-Based Approaches

Since the simple GA relies on a scalar fitness function to guide the search, the most intuitive approach for using a GA to solve a MOP is to combine all objectives of a problem into a single-objective problem using one of the traditional aggregating functions method at which then the GA is used to solve the problem (Coello 2000). Well known examples of this approach are the Weight-Based Genetic Algorithm (WBGA) (Hajela and Lin 1992) and the Random Weighted Genetic Algorithm (RWGA) (Murata and Ishibuchi 1995) which consists of adding the entire objective functions together using different weighting coefficients for each one.

Aggregation-based approaches do not require any changes to the basic mechanism of a simple GA. Therefore, they are efficient, simple, and easy to implement. They can be used to solve simple MOP problems with few objective functions and convex search spaces. However, they suffer from the following difficulties (Deb 2001):

- A Pareto-optimal solution is specific to the preference parameters used in converting a MOP into a single-objective optimization problem. In order to find a different Pareto-optimal solution, the preference parameters must be changed and the new single-objective optimization problem has to be solved again. Thus, in order to find n different Pareto-optimal solutions, at least n different single-objective optimization problems need to be formed and solved (Deb 2001).
- They are sensitive towards the preference vector of weighted objective values (Deb 2001).
- They require the user to have some knowledge about the problem being solved in order to generate the preference parameters (Deb 2001).

- Some aggregating-functions methods are sensitive to the shape of the Pareto-optimal front (e.g. the weighted sum method cannot find a good tradeoff solution to all problems when the Pareto front is concave) (Deb 2001).

2.5.2 Population-Based Approaches

This class of MOEAs switches between the objectives during the selection phase. Each time an individual is selected for reproduction, potentially a different objective will decide which member of the population will be copied into the mating pool (Coello 2000). The Vector Evaluated Genetic Algorithm (VEGA) (Schaffer 1985) is one of the examples of these approaches. It is a simple GA with a modified selection strategy. A loop is added around the traditional selection procedure so that the selection method is repeated for each objective to fill up a portion of the mating pool. With this proportional selection, at each generation a number of subpopulation is generated. The GA then applies the crossover and mutation operators on the new population in the usual way (Schaffer 1985).

Since only the selection mechanism of the GA needs to be modified, the VEGA is easy to implement and quite efficient. However, the solutions generated by the VEGA are often locally non-dominated because the non-dominance is limited to the current population at each generation. VEGA also tends to bias toward some particular objectives (Tran 2006). These problems occur because the algorithm selects solutions with high fitness in one objective, without looking at the others (Coello et al. 2005). As a result, the VEGA is able to find a Pareto-optimal set but fails to obtain a good spread of solutions.

2.5.3 Pareto-Based Approaches

The idea of assigning an individual's fitness based on Pareto dominance in order to overcome the problems associated with VEGA was initially proposed by David Goldberg in his non-dominated sorting procedure (Goldberg 1989). In the non-dominated sorting procedure, a ranking selection method based on the concept of Pareto optimality is used to assign non-dominated solutions in a population and a niche strategy with fitness sharing is used to maintain good spread of solutions among a non-dominated ranking class (Tran 2006).

Many researchers have developed different versions of MOEAs based on the concept of Pareto optimality such as Multi-Objective Genetic Algorithm (MOGA) (Fonseca and Fleming 1993), Strength Pareto Evolutionary Algorithm (SPEA) (Zitzler and Thiele 1999), Improved SPEA (SPEA-II) (Zitzler et al. 2001), Non-dominated Sorting Genetic Algorithm (NSGA) (Srinivas and Deb 1994), and Fast Non-dominated Sorting Genetic Algorithm (NSGA-II) (Deb et al. 2002). MOGA uses the dominance rank, i.e., the number of individuals by which an individual is dominated, to determine the fitness values. SPEA and SPEA-II calculate fitness values based on both dominance rank and dominance count, i.e. the number of individuals dominated by a certain individual. NSGA and NSGA-II use the dominance depth to assign the fitness values, i.e. the population is divided into several fronts and the depth reflects to which front an individual belongs to. Regardless of the fitness strategy used, a fitness value is related to the whole population in contrast to other approaches, which assign an individual's fitness value independently of other individuals (aggregation-based approaches) or calculate an individual's fitness value is limited to the current population at each generation (population-based approaches) (Tran 2006).

2.6 FAST NON-DOMINATED SORTING GENETIC ALGORITHM (NSGA-II)

The original NSGA that was developed by Srinivas and Deb (1994) was found to have three main weaknesses as follows (Deb et al. 2002):

- ***High Computational Complexity of Non-dominated Sorting:***

The currently-used non-dominated sorting algorithm has a computational complexity of $O(MN^3)$ (where M is the number of objectives and N is the population size). This makes NSGA computationally expensive for large population sizes. This large complexity arises because of the complexity involved in the non-dominated sorting procedure in every generation (Deb et al. 2002).

- ***Lack of Elitism:***

Recent studies' results show that elitism can speed up the performance of the GA significantly, which also can help preventing the loss of good solutions once they are found (Deb et al. 2002).

- ***Need for Specifying the Sharing Parameter σ_{share}:***

Traditional mechanisms of ensuring diversity in a population so as to get a wide variety of equivalent solutions have relied mostly on the concept of sharing. The main problem with sharing is that it requires the specification of a sharing parameter (σ_{share}). Though there has been some work on dynamic sizing of the sharing parameter, a parameter- less diversity-preservation mechanism is desirable (Deb et al. 2002).

As a result, Deb et al. (2002) developed an improved version of the NSGA called NSGA-II in order to overcome the above three weaknesses. This algorithm has been recognized to perform as well or better than other MOEAs with the same goal of finding a diverse Pareto-optimal solution set.

2.6.1 Major Features of NSGA-II

The major features of NSGA-II, which include low computational complexity, elitism, and parameter-less diversity preservation are reviewed in details as follows (Deb et al. 2002):

- ***Low Computational Complexity:***

The NSGA-II requires at most $O(MN^2)$ computational complexity, which is lower compared to $O(MN^3)$ of NSGA. The procedure for finding non-dominated front used in NSGA-II is similar to the non-dominated sorting procedure suggested by Goldberg (1989) except that a better bookkeeping strategy is used to make it more efficient. In this bookkeeping strategy, every solution from the population is compared with a partially filled population for domination instead of with every other solution in the population as in the NSGA (Deb et al. 2002). Initially, the first solution from the population is kept in a set P'. Thereafter, each solution p (the second solution onwards) is compared with all solutions in P' one by one. If the solution p dominates any solution q in P' then solution *q* is removed from *P'*. Otherwise, if solution *p* is dominated by any solution *q* in *P'*, the solution *p* is ignored. If solution *p* is not dominated by any solution in *P'* then it is saved in *P'*. Therefore the set *P'* grows with non-dominated solutions. When all solutions of the population is checked, the solutions in *P'* constitute the non-dominated set. To find the other fronts, the non-dominated solutions in *P'* will be discounted from *P* and the above procedure is repeated until all solutions in *P* are ranked. Therefore, the domination checks requires a maximum of $O(N^2)$ because the second solution is compared with only one solution of *P'*, the third solution with at most two solutions of *P'*, and so on. Since each domination check requires *m* function value comparisons, the maximum complexity of this approach to find the first Pareto-optimal front is $O(MN^2)$ (Deb et al. 2002).

- ***Elitism:***

Elitism in NSGA-II is ensured by comparing the current population with previously found best non-dominated solutions (i.e. kept in a set *P'* as described above) and by combining the parent and child populations to form a combined population with size 2*N* (Deb et al. 2002).The combined population is then sorted according to non-domination. Solutions belonging to the best non-dominated front (front 1) are of the best solutions in the combined population. If the size of front 1 is smaller than *N*, then all solutions in front 1 are selected for the new population. The remaining solutions of the new population are selected from subsequence non-dominated fronts in the order of their ranking front 2, front 3, and so on. This procedure is continued until *N* solutions are selected for the new population. To choose exactly *N* solutions, the solutions in the last front (front L) are sorted using the crowded comparison operator ($\prec_c$) in descending order (crowding distance sorting), and the best solutions needed to fill *N* populations are chosen (Deb et al. 2002).

- ***Parameter-less Diversity Preservation:***

To maintain diversity among solutions, the NSGA-II replaces the fitness sharing approach in the NSGA with a crowded comparison approach, which does not require any user-defined parameter (Deb et al. 2002). As a result, the sharing parameter σ_{share} used in the NSGA is eliminated. In the crowded comparison approach, every solution i in the population has two attributes: a non-domination rank (i_{rank}) and a crowding distance ($i_{distance}$). The value of i_{rank} is obtained through fast non-dominated sort as described before. The crowding distance $i_{distance}$ of a solution i is a measure of the perimeter of the largest cuboid enclosing the solutions i, without including any other solution in the population, formed by using the nearest neighbor solutions as the vertices (Deb et al. 2002). Figure 2.8 illustrates the crowding distance calculation for the solution i in its non-dominated front, which is the average side-length of the cuboid enclosing the solutions i (shown with a dash box). The process of assigning crowding distance $i_{distance}$ values to all solutions in the population requires the population sorted according to each objective function value in their ascending order of magnitude. Thereafter, for each objective function, the boundary solutions (solutions with smallest and largest function values) are assigned an infinite distance value. All other intermediate solutions are assigned a distance value equal to the absolute difference in the function values of two adjacent solutions. This calculation is repeated with other objective functions. The overall crowding distance value is calculated as the sum of individual distance values corresponding to each objective (Deb et al. 2002).

The crowded tournament selection operator, which is used to guide the search towards a spread-out Pareto-optimal front, is defined as follows (Deb 2001): A solution i wins a tournament with another solution j (denoted as $i \prec_c j$) if solution i has a better rank ($i_{rank} < j_{rank}$) or i and j has the same rank but solution i has a better crowding distance than solution j ($i_{rank} = j_{rank}$ and $i_{distance} > j_{distance}$). If i and j has the same rank and the same crowding distance then one of them is randomly chosen as a winner. Where; $\prec_c$ is the crowded comparison operator.

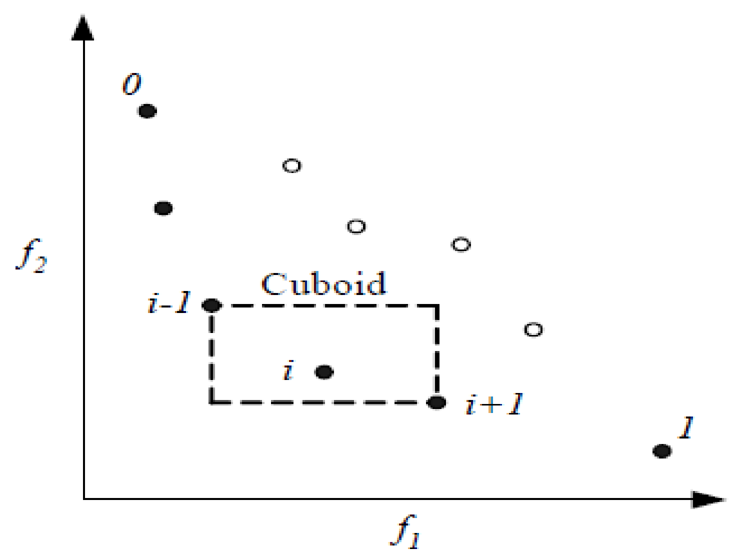


Figure 2.8: Illustration of the Crowding Distance Calculation (Deb et al. 2002)

2.6.2 Process Details of NSGA-II

The working of the NSGA-II is shown in Figure 2.9 and briefly described as follows where *g* represents the current generation and *g+1* represents the next generation:

2.6.2.1 Initial Population

Before a genetic algorithm begins its search, an initial population must be generated. The initial population (comprised of system solutions called chromosomes) is generated randomly to ensure diversity in the starting population. The population size *N* for a particular problem is pre-specified by the user and is held fixed throughout the optimization run. The initial random population for the NSGA-II is double the size, *2N*, of a normal population, which ensures additional diversity of the initial population (Deb et al 2002).

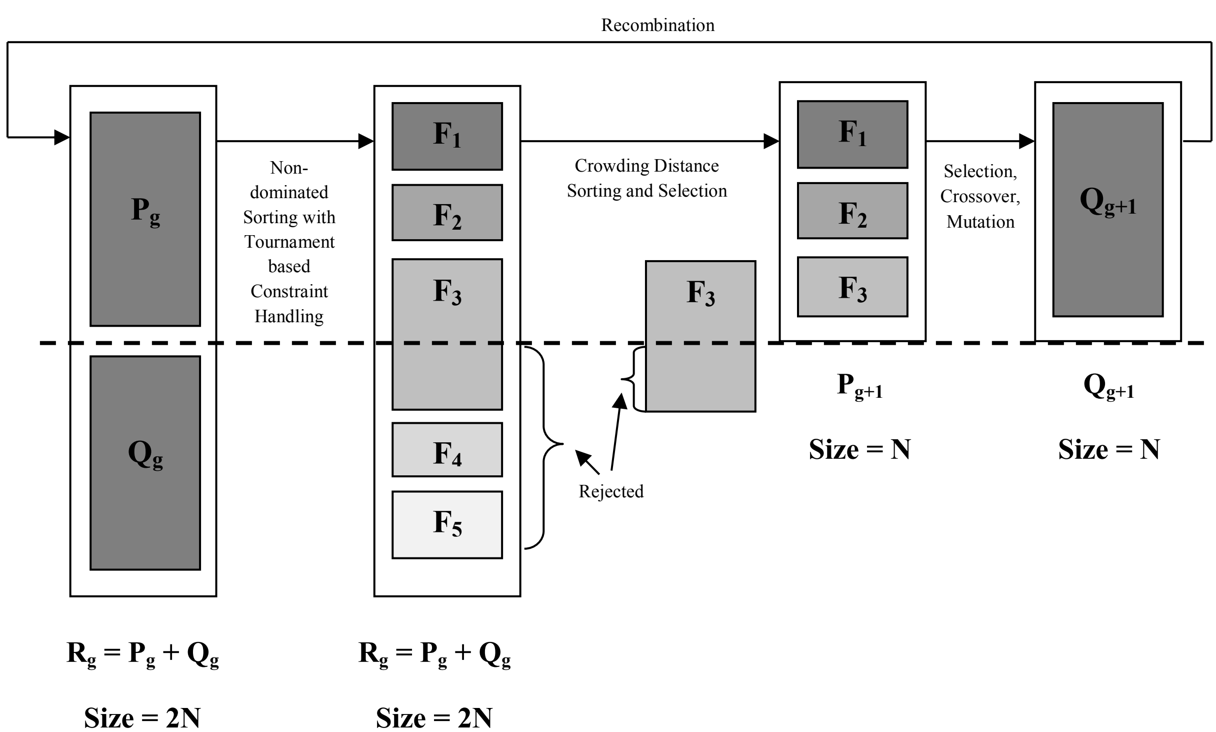


Figure 2.9: NSGA-II Process

2.6.2.2 Non-dominated Sorting of the Initial Population

The initial generation g is shown in Figure 2.9 and consists of a population P_g of size N and a second population Q_g of size N. This initial double population is sorted into fronts with the non-dominated sorting procedure of the NSGA-II. The basis of this procedure is to evaluate the objective functions of each solution in the initial population relative to other solutions in the initial population, organize the solutions according to their dominance over one another, and choose a population, P_{g+1}, of size N from the initial population, of $2N$.

Figure 2.10 presents an example of the non-dominated sorting of population of five solutions into three fronts. The procedure begins by evaluating each solution p in the initial population to determine the number of solutions n_p that dominate each solution p and a set of solutions S_p that are dominated by p. All solutions with $n_p = 0$ will be in the first non-dominated front (front 1) and each of these front 1 solutions will feature its own set S_p. For each member of front 1, the value of n_p for each solution in the set S_p is reduced by one. All solutions in S_p with $n_p = 0$ will be in the next non-dominated front (front 2). This de-incrementing procedure continues for each consecutive front until all solutions have been placed in a front (front 3, front 4,…etc.).

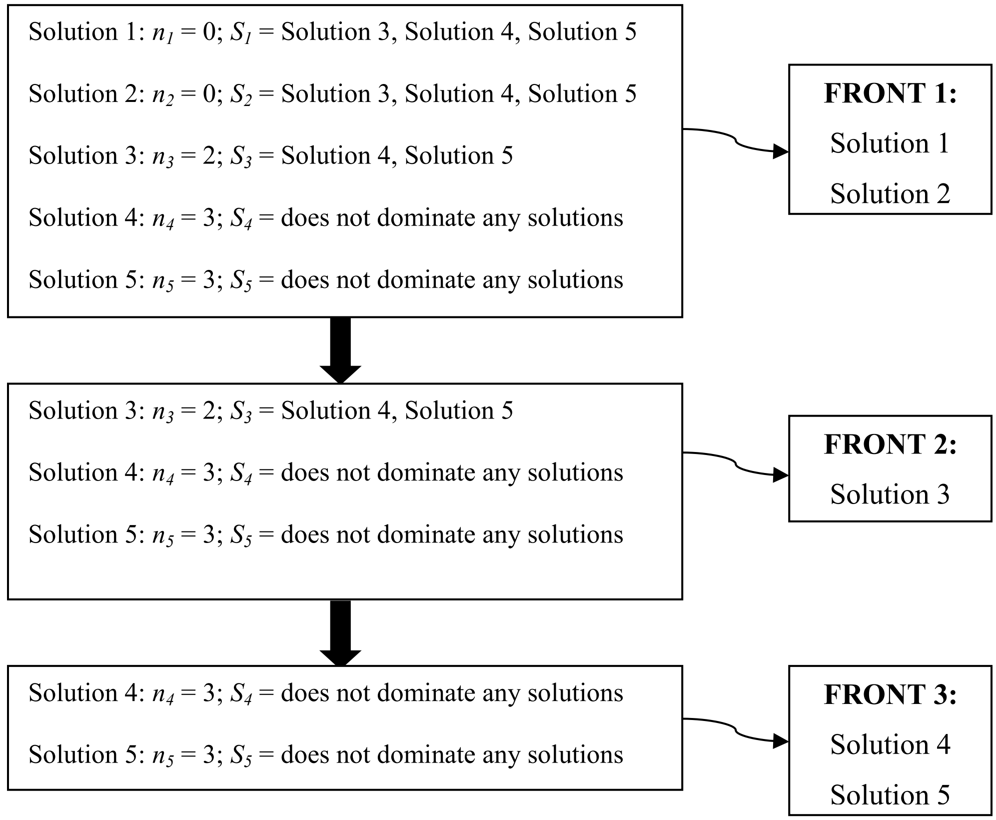


Figure 2.10: Example of Non-dominated Sorting Procedure

2.6.2.3 Post-Sorting Population

Figure 2.9 shows how a post-sorting population, P_{g+1}, is selected from the non-dominated sorted population of size 2*N*. This population P_{g+1} can only comprise *N* population members. Therefore, *N* solutions are chosen from the double initial population ($R_g = P_g + Q_g$) starting with the first front, front 1, and continuing to the next fronts until *N* solutions have been chosen for the new population, P_{g+1}. In some cases, including all front members of the last chosen front of the initial population results in more than *N* chosen solutions. Only *N* solutions can be chosen and all members of the last chosen front are equally as non-dominated, resulting in the need to implement a crowding distance comparison procedure to compare solutions from the same front (Herstein 2009).

The crowding distance is a measure of how similar a solution is to another solution in the same front when all objective functions are compared (Deb et al 2002). A longer crowding distance denotes a solution that is further away from other front solutions and these solutions are preferred as they preserve diversity in the newly chosen population. The crowding distance of each solution in the last chosen front is calculated and the front is organized in descending order of crowding distance. The solutions from the last chosen front with the largest crowding distance values are chosen for the population P_{g+1} and the other front solutions are discarded.

2.6.2.4 Selection, Crossover, and Mutation

At this point, the selection procedure has identified the "fittest" members of the initial population based on non-dominated sorting and the crowding-distance comparison method. To further improve the population, the resulting population P_{g+1} is subject to the genetic operations of selection, crossover, and mutation to create a new population, Q_{g+1}, as shown in Figure 2.9. There are a number of methods that can be used for each genetic operation of the NSGA-II procedure. One example for each operation is described below:

- ***Selection: Tournament Selection without Replacement:***

Tournament selection is the process by which a user-specified number of population members of the population P_{g+1} are selected randomly (Herstein 2009). The best (dominant) individual from this chosen sample continues on for further operations such as crossover and mutation and the process is repeated for the rest of the population members. Therefore, the purpose of the selection process is to identify the fittest members of the sorted population. Figure 2.11 shows the tournament selection without replacement featuring a tournament size of two for simplicity. Members are first shuffled and then compared two at time until all members have been compared once. The population is then shuffled a second time and each member is compared again to arrive at a selected population of size N. The result of the selection process is a new population with some of the best randomly chosen members of the population P_{g+1}.

- ***Crossover: One-Point Crossover:***

The new population resulting from the selection of population P_{g+1} is subject to the crossover process whereby two parent population members are "crossed" to create two child population members with each child containing part of each parent's solution. One-point crossover is shown in Figure 2.12. The one-point crossover process randomly chooses two members, or parents from the newly selected population, then randomly selects one cut-point at parent chromosomes (solutions) and exchanges the genes (decision variables) at the right parts of the two parent chromosomes to create two new children each containing part of both parental chromosomes (Herstein 2009).

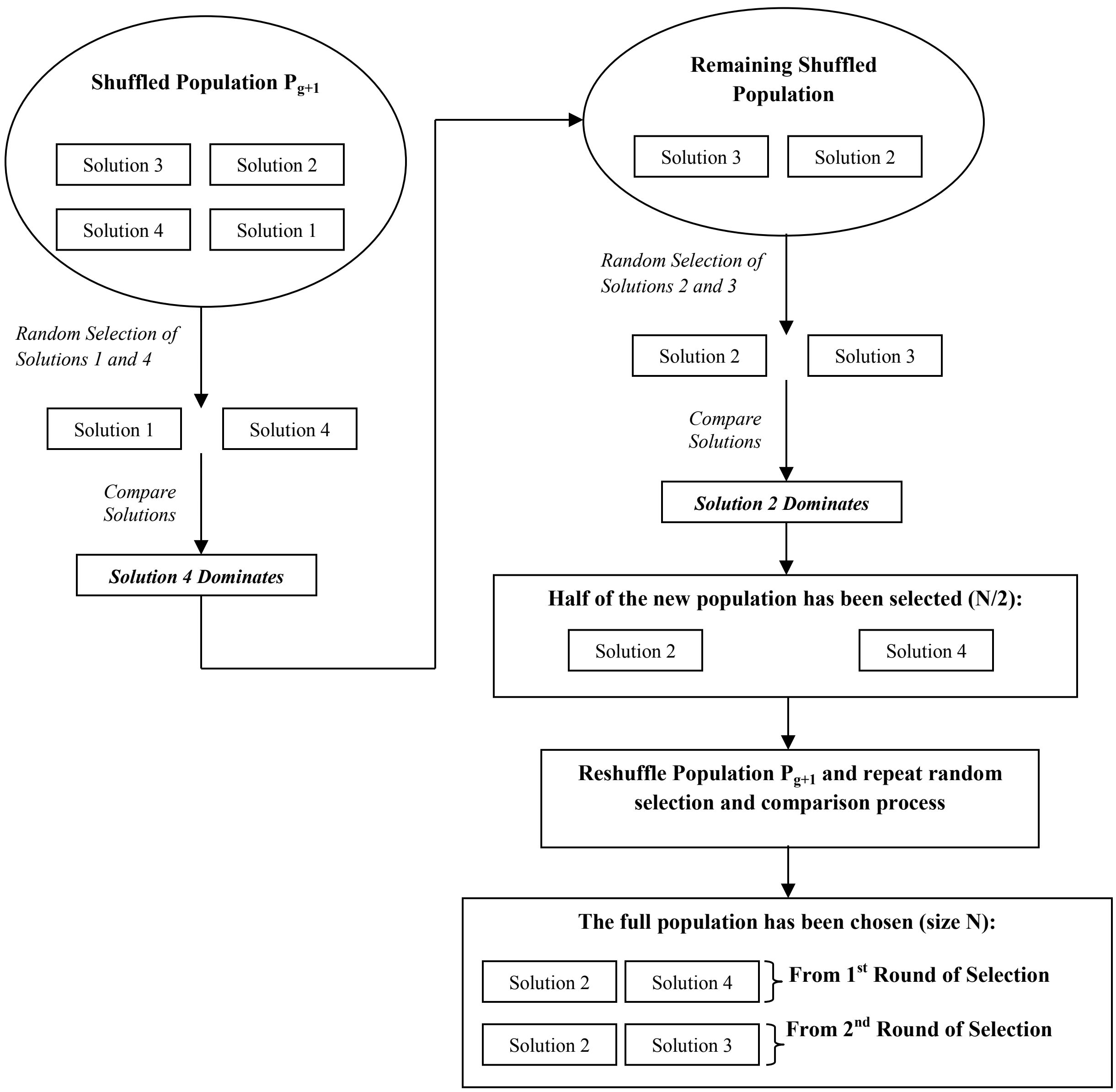


Figure 2.11: Example of Tournament Selection without Replacement

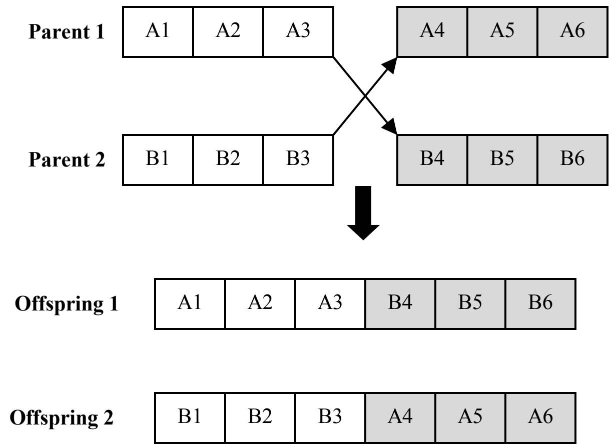


Figure 2.12: Example of One-Point Crossover

- ***Mutation: Selective Mutation:***

The child population resulting from the selection and crossover of the previous population is based on the initial randomly chosen population and thus bears characteristics of that initial population. Although the random initial population provides a good sample of the entire solution space, additional solution diversity is ensured by the random process of mutation (Deb et al 2002). A random mutation operator introduces solutions into the population that may not be created through the selection and crossover processes, but may be "fitter" than those solutions in the current population. The mutation operator also restores individual decision variable values that may have been lost in previous generations. Figure 2.13 shows the selective mutation process, which randomly selects a decision variable of a solution from a child member and replaces the decision variable with a random variable within a specified range. In the example shown in Fig. 2.13, decision variables can have a value of either 0 or 1. Mutation of each solution in the child population occurs with a pre-specified probability (Herstein 2009).

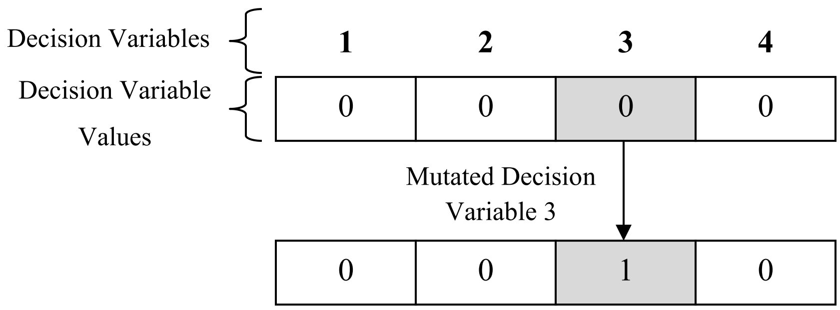


Figure 2.13: Example of Selective Mutation

2.6.2.5 Recombination and Reevaluation

Once selection, crossover, and mutation have occurred, a population, Q_{g+1}, of size N *is* resulted. This population is combined with the population P_{g+1} to create a population (P_{g+1} + Q_{g+1}) with a size of 2N. This combined population is subject to another non-dominated sorting and N solutions are chosen for the next population using a crowding comparison operator to compare solutions in the same front, if necessary. Therefore, the resulting population consists of the best solutions from the newly formed population as well as best solutions from the previous population that may have been lost through the selection, crossover, and mutation operations. The newly formed population undergoes selection, crossover, and mutation and then recombination and reevaluation in subsequent generations to eventually arrive at the Pareto-optimal front (Herstein 2009).

2.6.2.6 Constraint Handling

When constraints exist for a given problem, solutions that meet constraints are designated "feasible solutions" and those that do not meet constraints are designated "infeasible solutions" (Herstein 2009). An effective constraint-handling approach based on tournament selection was proposed in the NSGA-II by Deb et al. (2002). This tournament-based constraint handling technique is implemented within the non-dominated sorting procedure shown in Figure 2.10, wherein Solutions A and B are being compared for dominance and Solution A dominates Solution B under any one of the following conditions:

1. Solution A is feasible and Solution B is infeasible
2. Both solutions are infeasible and Solution A has a lower total constraint violation than Solution B
3. Both solutions are feasible and Solution A dominates Solution B

2.6.2.7 Finance and Resource-Infeasible Chromosomes Treatment

Finance and resource-infeasible chromosomes often arise when new individual chromosomes are generated for the initial population and/or when offspring chromosomes are reproduced within the population using the conventional crossover and mutation operators. A chromosome is said to be “finance-infeasible” when its maximum periodical required credit exceeds the preset credit limit. Similarly, a chromosome is said to be “resource-infeasible” when its maximum daily resource demand exceeds the preset daily resource limit. As a result, such infeasible chromosomes must be treated properly in the population before proceeding to the next generation of the NSGA-II implementation. There are three different treatment methods for the finance and resource-infeasible chromosomes, namely: (1) replacing; (2) penalizing, and (3) repairing method (Alghazi et al. 2013). The first method is to discard the infeasible chromosomes in the population, generate or reproduce an equal number of feasible chromosomes, and replace the infeasible chromosomes with the feasible ones. The second method is to keep the infeasible chromosomes in the population and assign a penalty to the evaluation (fitness) criterion of the infeasible chromosomes. The assigned penalty decreases the chances that these chromosomes are selected for reproduction in the subsequent generations and eventually exclude them from the population after some iterations. The third treatment method is to repair the infeasible chromosomes by rescheduling the start times of some activities such that the maximum periodical required credit and daily resource demand never exceeds the preset credit limit and resource limit, respectively. Alghazi et al. (2013) introduced a repair algorithm for the finance-infeasible chromosomes. The algorithm identifies the periods exhibiting finance needs that exceed the constrained cash, calculates the amounts of finance needs above the constraints, identifies the ongoing activities, selects randomly an activity for delaying its start time, determines the impact of the delay on the finance needs, and repeats the procedure until finance feasibility is attained.

2.6.3 Technique Selection

As mentioned earlier, the mostly common algorithms or optimization methods used for solving the construction scheduling optimization problem can be classified into two methods: exact (mathematical) and approximate (heuristic and meta-heuristic) as shown in Figure 2.14.

- ***Exact Methods:***

Exact or mathematical programming methods convert the scheduling optimization problem to constraints and objective functions. Various mathematical approaches have been used for solving TCT, resource management, and finance-based scheduling problems such as LP, IP, LP/IP, DP, or implicit enumeration with branch and bound. The advantages of mathematical approaches include efficiency, accuracy, and can guarantee optimal solutions on small-scale problems.

However, such optimization approaches remain computationally impractical once the number of options to complete an activity becomes too large or the network becomes too complex. In other words they require high computational effort for large projects encountered in real-life practice due to an enormous number of variables and constraints resulting in a phenomenon called "combinatorial explosion" (Allam 1988; Moselhi and Lorterapong 1993; Chan et al. 1996; Feng et al. 1997; Leu and Yang 1999; Leu et al. 2000; Que 2002; Zheng et al. 2002; Chen and Weng 2009; Joshi and Jain 2012). In addition, mathematical models suffer from being complex in formulating constraints and objective functions that is time consuming, prone to errors, and may be trapped in local optimum (Liu et al. 1995; Li and Love 1997; Hegazy 2002; Zheng et al. 2002).

Blazewich et al. (1983) showed that construction scheduling optimization problem is a generalization of the well-known job-shop-scheduling problem and is NP-Hard. As an NP-hard problem, the optimal solution can only be achieved by exact methods in small projects, usually with less than 60 activities, which are not highly resource-constrained (Alcaraz and Maroto 2001). While exact solution methods are able to solve smaller problems, heuristic and meta-heuristic approaches are needed for larger problem instances.

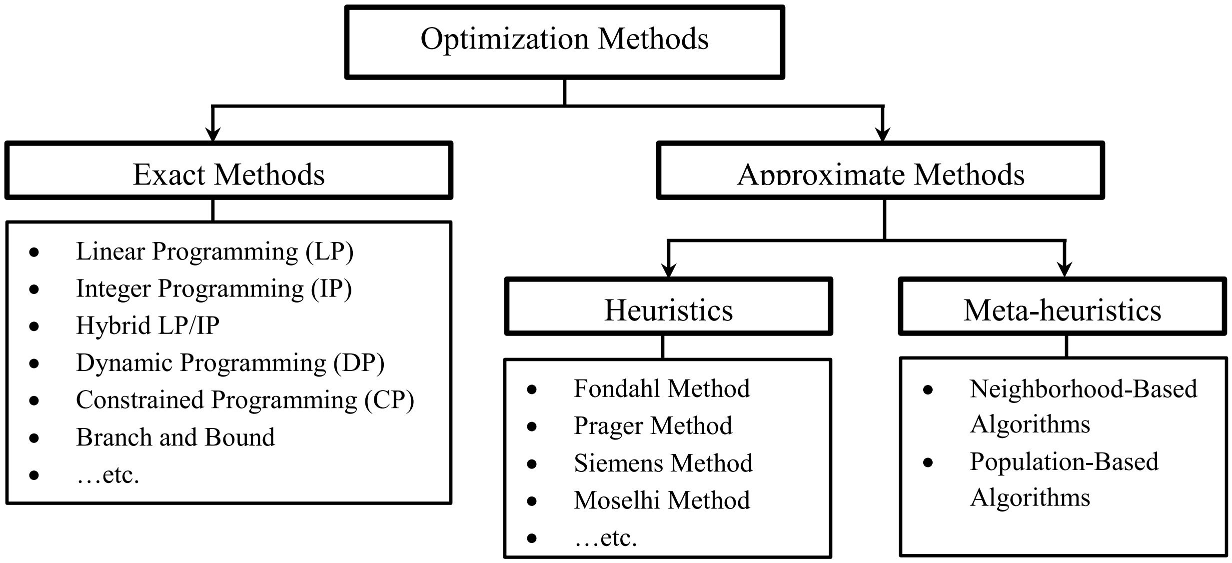


Figure 2.14: Classification of Common Optimization Methods

- ***Heuristic Methods:***

To avoid the problem of combinatorial explosion, heuristic methods were developed for solving construction scheduling optimization problems (Leu and Yang 1999). Heuristic methods are non-computer approaches that require less computational efforts and time as they use experience and rule-of-thumbs, rather than rigorous mathematical formulations (Zheng et al. 2002; Hegazy and Kassab 2003). These methods have the advantages of being simple to understand, easy to apply, and very inexpensive to use in computer programs. They are able to rationalize the scheduling process and make it manageable for practical-size projects (Talbot and Patterson 1979).

Despite these benefits, heuristic methods are problem-dependent so that their rules of thumb could not be equally applied to all construction cases. In other words, they perform with varying effectiveness when used on different networks, and there are no hard guidelines that help in selecting the best heuristic rule to use for a given network (Hegazy and Kassab 2003). In addition, once trapped in local optima, heuristic tends to converge earlier thus showing their inability to explore larger search space (Joshi and Jain 2012). They, as such, cannot guarantee global optimum solutions (Liu et al. 1995; Feng et al. 1997; Leu et al. 2000; Zheng et al. 2002; Que 2002; Chen and Weng 2009). Furthermore, their drawbacks have contributed to large inconsistencies among the resource-constrained capabilities of commercial project management software, as reported in recent surveys (Hegazy and El-Zamzamy 1998; Johnson 1992).

Based on the above discussion, both mathematical and heuristic approaches are inefficient and inflexible when solving practical construction scheduling optimization problems. The major deficiency with most of the mathematical and heuristic models is their algorithmic restriction to handle multi-objectives simultaneously (Zheng et al. 2005). These methods often employ a kind of hill climbing algorithm, which has only one randomly generated solution exposed to some kind of variation to create a better solution. In addition, these methods may not easily be adapted to discontinuous decision space and very large-scale problems (Eshtehardian et al. 2008). This led to development of better search algorithms belonging to the class of meta-heuristics.

- ***Meta-heuristic Methods:***

A meta-heuristic is formally defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions (Osman and Laporte 1996). It is designed to attack complex optimization problems where classical heuristics and optimization methods have failed to be effective and efficient (Osman and Laporte 1996). According to an investigation made by Kolisch and Hartmann (2006) for solving the resource-constrained scheduling problem, it was found that meta-heuristic methods outperform heuristic methods. As shown in Figure 2.15, meta-heuristic includes several algorithms that have been used for solving different construction scheduling optimization problems of which GAs was the most common. However, MOEAs have been shown to intelligently balance exploration and exploitation of the solution search space (Deb et al. 2002). Other major advantages of using MOEAs to solve multi-objective scheduling problems include:

1) They are robust, do not experience combinational explosion, and do not rely much on assumptions or on heuristic rules (Que 2002).
2) They are capable of exploring the search space more thoroughly within a smaller number of solution evaluations than other point-to-point local search procedures (April et al. 2003).
3) They are less dependent on the selection of the starting solutions, and they do not require definition of a neighborhood (April et al. 2003).

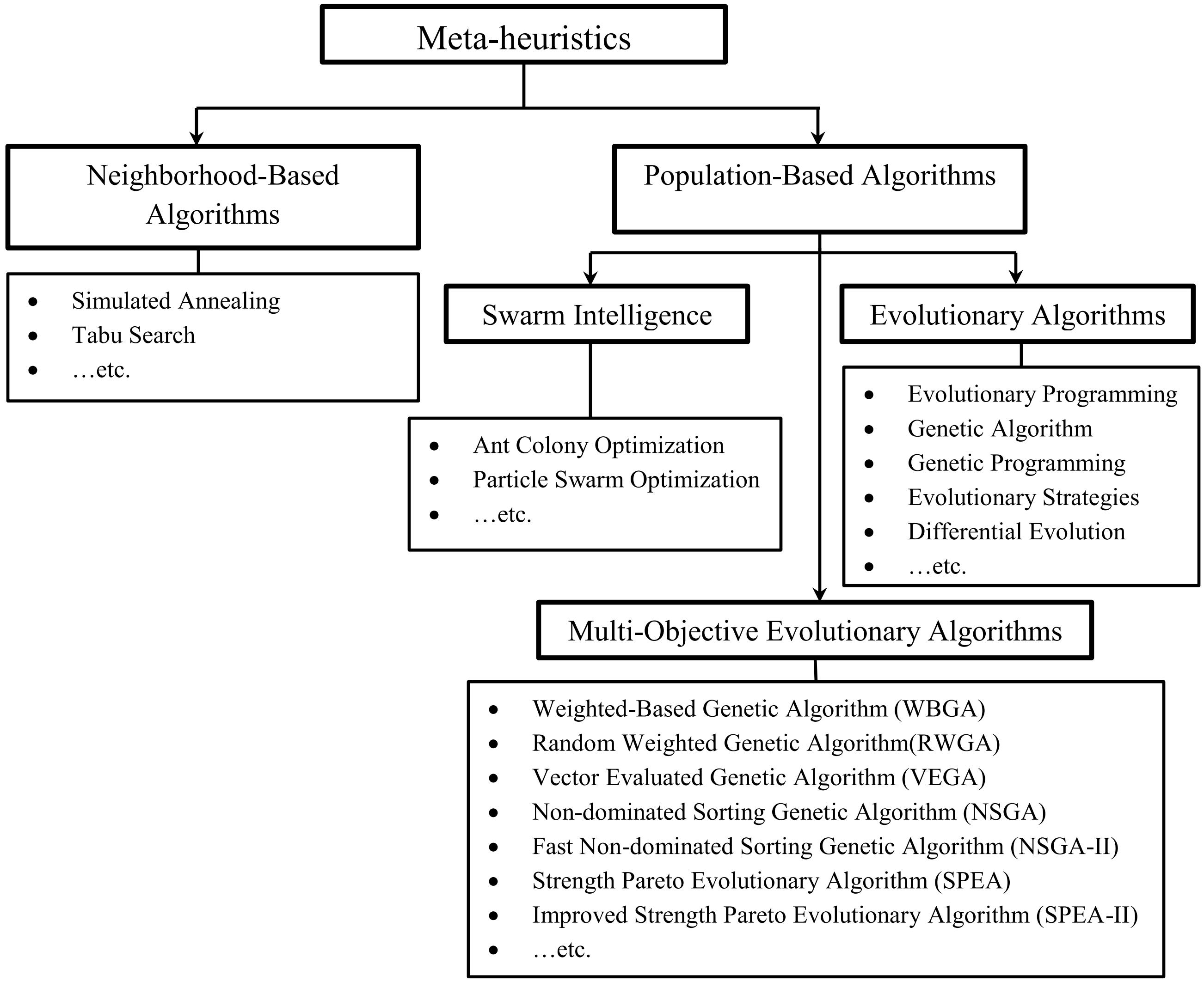


Figure 2.15: Classification of Common Meta-heuristics

In recent years, several variations of MOEAs have been developed to handle multi-objective optimization problems as discussed earlier in section 2.5. In fact, a multi-objective evolutionary algorithm to efficiently solve a specific problem, may not adequately solve other optimization problems. Similarly, a problem can be solved differently by various algorithms. To determine which algorithm is appropriate for a specific problem, it is necessary to compare the results obtained by each of the algorithms and choose according to these, the best. However, among the different MOEAs, NSGA-II stands out for its fast non-dominated sorting approach, elitism approach, and its overall capability to maintain a better solution spread (Martinez 2008). Further, it has been reported that NSGA-II outperforms most other MOEAs in terms of convergence to the true Pareto optimal front while maintaining solution diversity (Deb et al. 2002). As a result, it is motivated in this study to use the NSGA-II as an optimization technique for solving the multi-objective finance-based scheduling problem.

2.7 SUMMARY

This chapter has presented a comprehensive literature review covering the major tools that are essential for construction scheduling optimization. The review focused on studying the different optimization problems in construction management including time/cost tradeoff analysis, resource leveling and allocation, and finance-based scheduling along with the previous attempts made in those areas. In addition, brief review on the previously used different optimization techniques was carried focusing on the NSGA-II technique. According to the literature, several studies were carried to integrate project scheduling along with available finance in order to optimize different project's objectives. These objectives focused on minimizing the total project duration, financing costs, and maximum required credit while maximizing the profit. However, there was a lack of research that considers integrating resource management techniques including resource leveling and resource allocation simultaneously with the finance-based scheduling. Considering those two aspects together have a significant impact on many areas of project management including time, cost, resource, and risk. Moreover, few researches solved the finance-based scheduling problem considering the contractor's entire portfolio rather than single project. Multiple concurrent projects involves sharing and competing for limited resources such as funds, equipment, manpower and other resources among different projects, which increases the complexity of the scheduling process. The allocation of scarce resources then becomes a major objective of the problem. In such cases, planners are generally concerned with a number of different decision criteria, often conflicting among each other, according to their importance and priorities.

CHAPTER 3: RESEARCH METHODOLOGY

This chapter presents the description of the methodology followed in order to achieve the main research objectives. The methodology shown in Figure 3.1 starts with a comprehensive literature review to collect information on topics related to this research. Then, three management models are developed to adapt for multiple construction projects, namely: scheduling, cash flow, and resource model. The main aim of these models is to evaluate the projects' different multi-objectives values. After that, the relationships between those different objectives are identified. Consequently, a complete optimization model formulation is established to identify the model's decision variables, objectives, and constraints. Hence, a multi-objective scheduling optimization model is developed using the basic concepts of NSGA-II. The developed model is then tested and implemented using different case studies obtained from literature to prove its validity and ability to optimize such problems successfully and efficiently. Finally, an automated tool using C# language is built with a friendly graphical user interface to facilitate solving multi-objective scheduling optimization problems.

3.1 LITERATURE REVIEW

The literature review was conducted in Chapter 2. It comprehensively covered the major fields that are essential to the topic of this research. The review focused on studying the different optimization problems in construction management including time/cost tradeoff analysis, resource leveling and allocation, and finance-based scheduling along with the previous attempts made in those areas. In addition, brief review on the previously used different optimization techniques was carried focusing on the NSGA-II technique.

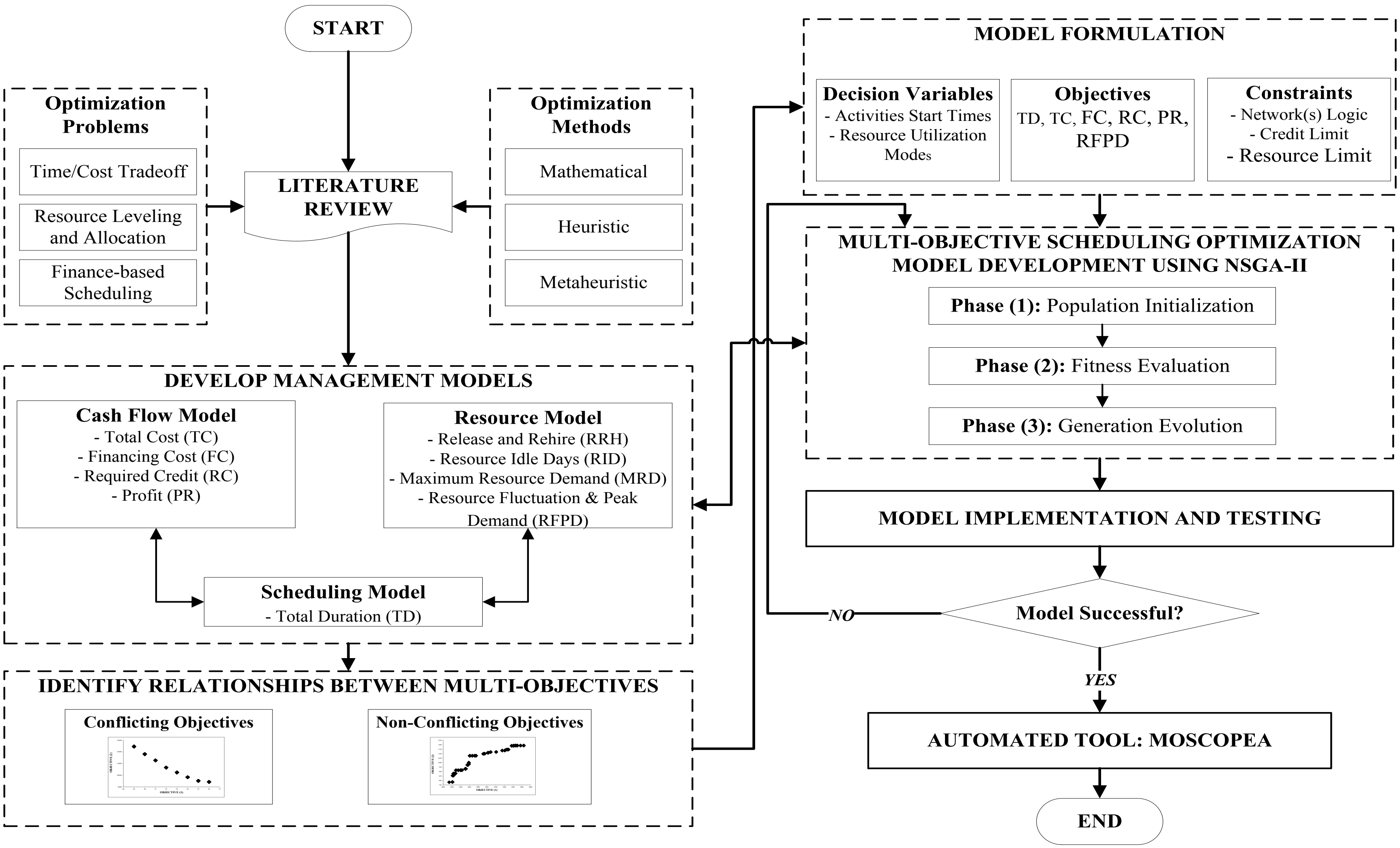


Figure 3.1: Research Methodology Flowchart

3.2 DEVELOP MANAGEMENT MODELS

As mentioned earlier, the main objective of this research is to develop a multi-objective scheduling optimization model for multiple construction projects. The multi-objectives to be optimized are the: total duration (TD), total cost (TC), financing cost (FC), required credit (RC), profit (PR), and resource fluctuation and peak demand (RFPD). Thus, three management models are developed to determine such objectives' values as follows:

1. *Scheduling Model:* to determine the TD
2. *Cash Flow Model:* to determine the TC, FC, RC, and PR
3. *Resource Model:* to determine the RFPD

Cash flow and resource models, which are presented in Chapter 2, only fit single project. As a result, since this study focuses on multiple projects; the cash flow and resource models described in the literature review are modified in order to suit and consider the existence of more than one project. Beside determining the TD, the scheduling model acts as the main core of the three management models as it is linked to both the cash flow and resource models to determine their respective objectives. In other words, both cash flow and resource models depend on the schedule obtained from the scheduling model.

3.2.1 Multiple Projects Cash Flow Model

Let direct cost disbursements of all activities performed on day i for project z be denoted as $(c_i)_z$, this is referred to as direct cost disbursement of day i for project z. Thus $(c_i)_z$ can be calculated as follows:

$$(c_i)_z = \sum_{v=1}^{n_i} (c_{vmi})_z \qquad i = 1, 2, \ldots D_z \quad \ldots\ldots(3.1)$$

Where; n_i = number of activities ongoing with day i; $(c_{vmi})_z$ = direct cost disbursement rate of activity v using resource utilization mode m in day i for project z; and D_z = total project duration of project z.

The cash outflow during a typical period t - a week in this model – for project z is represented by $(E_t)_z$ and encompasses the costs of overheads and taxes in addition to the direct cost disbursements including the costs of materials, equipment, labor, and subcontractors. $(E_t)_z$ can be calculated as follows:

$$(E_t)_z = \sum_{i=1}^{d} (c_i)_z + (O_t)_z \qquad (3.2)$$

Where; d = number of days comprising a week; and $(O_t)_z$ = expenses of overheads, taxes, mobilization, and bond at period t for project z.

As a result, in case of multiple simultaneous projects, the cash outflow at the end of a given period includes the E_t components of the individual projects ongoing during the same week. E_t can be calculated as follows:

$$E_t = \sum_{z=1}^{Z} (E_t)_z \qquad (3.3)$$

Where; Z = total number of projects.

On the other hand, the cash inflow for project z, represented by $(P_t)_z$, includes the payments contractors receive, at the ends of periods, as an earned value of the accomplished works calculated based on the unit prices. $(E_t)_z$ can be calculated as follows:

$$(P_t)_z = K_z(Et)_z \quad \text{……………………………………………………………(3.4)}$$

Where; K_z = multiplier for project z to determine the amount of payment for a given amount of disbursement $(E_t)_z$ $(K_z > 1)$. In order to calculate the multiplier K_z; first a bid price factor BF_z for project z must be calculated as follows:

$$BF_z = \frac{Total\ Price_z}{Total\ Direct\ Cost_z} \quad \text{……………………………………………………………(3.5)}$$

Then, the amount of retention R_z for project z must be defined. Retention is a percentage of each bill which clients often withhold to ensure the contractor completes the construction project satisfactorily. The retained portion of the progress payments will often be released when the job is completed. In addition, in the case where the contractor receives from the client an advance payment AP_z at the beginning of the project; this amount of advance payment will be cut as a percentage from each bill. As a result the multiplier K_z can be calculated as follows:

$$K_z = (1 - (R_z\% + AP_z\%)) \times BF_z \quad \text{……………………………………………………(3.6)}$$

It should be noted that the last payment $(P_T)_z$ will be calculated as shown in Equation 3.4 with adding to the equation the total amount of retention to be as follows:

$(P_T)_z = K_z(E_t)_z + R_z$ ……………………………………………………..………...…...(3.7)

In case of multiple simultaneous projects, the cash inflow at the end of a given period includes the P_t components collected of the projects at this time. P_t can be calculated as follows:

$$P_t = \sum_{z=1}^{Z} (P_t)_z \quad \text{……………………………………………………….……...…(3.8)}$$

To that point, the total value of the E_t and P_t for all the ongoing projects can be calculated. The rest of the financial parameters described in the literature review are to be calculated based on Equations 2.11 – 2.18 in Chapter 2.

3.2.2 Multiple Projects Resource Model

Let the total resource demand of all activities performed on day i for project z be denoted by $(r_i)_z$, this is referred to as total resource demand of day i for project z. Thus $(r_i)_z$ can be calculated as follows:

$$(r_i)_z = \sum_{v=1}^{n_i} (r_{vi})_z \qquad i = 1, 2, \ldots D_z \quad \text{…..…..…………………..……………….…(3.9)}$$

Where; n_i = number of activities ongoing with day i; $(r_{vi})_z$ = resource demand of activity v in day i for project z; and D_z = total project duration of project z.

As a result the total daily resource demand for all ongoing projects r_i can be calculated as follows:

$$r_i = \sum_{z=1}^{Z} (r_i)_z \quad (3.10)$$

Finally, the rest of the resource leveling model parameters described in the literature review are to be calculated based on Equations 2.1 – 2.4 in Chapter 2.

3.2.3 Multiple Projects Scheduling Model

The main purpose of this model is to develop optimal/near optimal schedules for construction projects. The model starts by calculating the start times and finish times of the project activities as shown in Equations 3.11 and 3.12, respectively. The start time is defined as the earliest start time of activity v when resource utilization mode m_v is used. Similarly, the finish time is defined as the earliest finish time of activity v using resource utilization mode m_v. Accordingly, the total project duration can be calculated as shown in Equation 3.13.

$$(st_v)_z \geq max:(ft_p, m_p)_z \quad (3.11)$$

$$(ft_v, m_v)_z = (st_v)_z + (d_v, m_v)_z \quad (3.12)$$

$$D_z = max:(ft_v, m_v)_z \quad (3.13)$$

Where; $(st_v)_z$ = start time of activity v in project z; $(ft_v\ ,\ m_v)_z$ = finish time of activity v using resource utilization mode m_v in project z; $(ft_p\ ,m_p)_z$ = finish time of activities preceding activity v using resource utilization mode m_p in project z; $(d_v\ ,\ m_v)_z$ = duration of activity v when resource utilization mode m_v is used in project z; and D_z = total duration of project z.

3.3 IDENTIFY RELATIONSHIPS BETWEEN MULTI-OBJECTIVES

Multi-objective scheduling optimization of contractors carrying out simultaneous projects incorporates minimizing duration of group of projects, total cost, financing cost, maximum required credit, and resource fluctuation and peak demand while maximizing the profit. In fact, it is impractical to optimize all those objectives simultaneously as some of them could be non-conflicting.

Identifying the non-conflicting objectives varies from project to another. For instance, in some projects, both financing cost and total cost can be considered as non-conflicting objectives where the former represents a percentage of the latter. In other projects, financing cost depends on the overdraft which depends on many additional factors such as available cash, subcontracting, and front end loading which can conflict with the total cost. Also, shortening the project duration to a certain point will reduce the additional overheads which in turn maximize the profit. However, any further reduction in the project duration will significantly increase the direct cost and accordingly reduce profit due to an increase in acceleration costs such as overtime and nighttime shifts.

Based on that, the objectives' set of "total cost and financing cost" and "total duration and profit" can sometimes in specific cases be non-conflicting objectives. Moreover, both financing cost and total cost can be added and combined as one objective for more practicality and simplicity in the optimization process. As a result, the efforts of contractors should be focused on optimizing the four objectives of combined total cost and financing cost, required credit, profit, and resource fluctuation and peak demand. According to a previous study in finance-based scheduling optimization carried by Abido and Elazouni 2011; the relations among different objectives were illustrated as follows: First, reducing the financing costs definitely increases the profit and usually takes place when the project duration is shortened due to the eliminated extra overheads and liquidated damages. Shortening the project duration requires the continuous utilization of the available resources during each period which in turn increases the maximum required credit. Second, minimizing the maximum required credit increases the possibility of the required credit to be approved by bankers and offers the contractors more leverage to negotiate better interest rates and terms of payment back but definitely results in an inevitable increase in the duration and financing costs which in turns decreases the profit. Third, shortening the duration increases the profit by reducing the overhead costs and the financing costs but requires high credit, in other words it increases the maximum required credit.

Since the previous studies did not take into consideration the objective of resource fluctuation; two experiments are carried to investigate the effect of minimizing the resource fluctuations and peak demand on the financing cost, required credit, and profit.

In these two experiments the two new metrics of resource leveling (RRH and RID) discussed before are used to measure the resource fluctuations.

- ***Experiment (1): Six-Activity Network:***

The first experiment is applied on an example of a six-activity project network that was presented in El-Rayes and Jun (2009) study as shown in Figure 2.6. In this example, the minimum reached RRH = 6 and the minimum reached RID = 32. It should be noted that reaching the minimum RID did not change the initial schedule which can be considered as an exception since the network is small. The experiment is carried first by reasonably assuming different direct costs to the project activities and other time, financial, and contractual data concerning the project as shown in Tables 3.1 and 3.2. Then the cash flow model that was explained earlier is applied twice; once on the initial schedule and the other on the minimum RRH schedule to determine for each schedule the financing cost, maximum required credit, and profit.

Table 3.1: Direct Costs (Experiment 1)

Activity	Duration	Direct Cost / day	Total Direct Cost
A	2	1800	3600
B	2	1400	2800
C	5	2600	13000
D	5	2000	10000
E	5	2500	12500
F	2	2400	4800

Table 3.2: Time, Financial, and Contractual Data (Experiment 1)

Data Type	Item	Value
TIME	No. of Days per Week	5
	Original Duration (days)	16
	Original Duration (weeks)	4
FINANCIAL	Interest Rate % per Week	0.30%
	Overheads per week ($)	2,000
	Mobilization Costs ($)	8,000
	Tax %	2%
	Mark-Up %	20%
	Bond Premium ($)	1,000
CONTRACT TERMS	Advance Payment % of Bid Price	6%
	Weeks to Retrieve Advance Payment	4
	Retained % of Pay Requests	5%
	Lag to Pay Retained Money After Last Payment (weeks)	0
	Weeks to Submit Pay Requests Regularly	1
	Lag to Pay Payment Requests (weeks)	1

- ***Experiment (2): Twenty-Activity Network:***

The second experiment is applied on an example of a twenty-activity project network that was also presented in the study of El-Rayes and Jun (2009). The network and the initial resource profile of this example are shown in Figures 3.2 and 3.3, respectively. In this example, the minimum reached RRH = 0 and the minimum reached RID = 0. In addition, the MRD was reduced from 21 to 17. The same procedure followed in the first experiment is repeated and the assumed data are shown in Tables 3.3 and 3.4. The modified schedule after minimizing the resource fluctuations and the peak demand is shown in Figure 3.4.

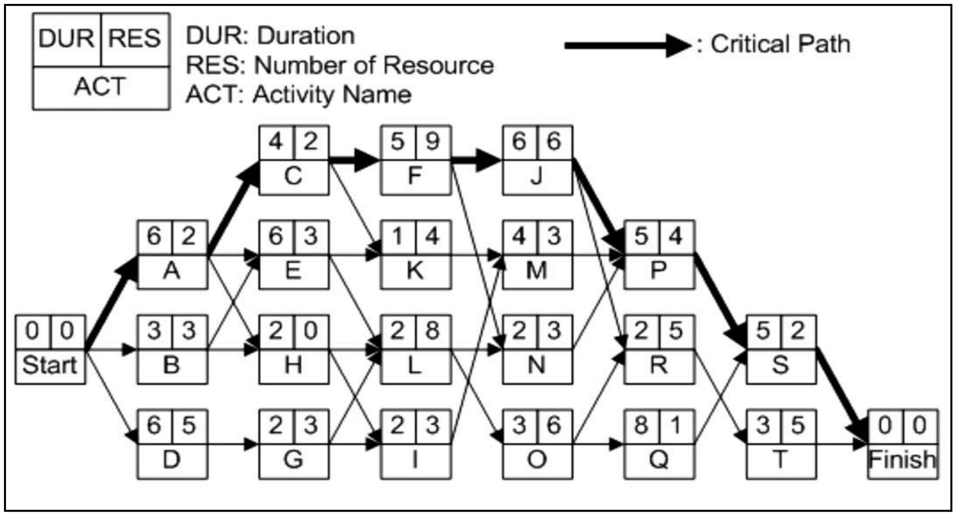


Figure 3.2: Twenty-Activity Project Network (El-Rayes and Jun 2009)

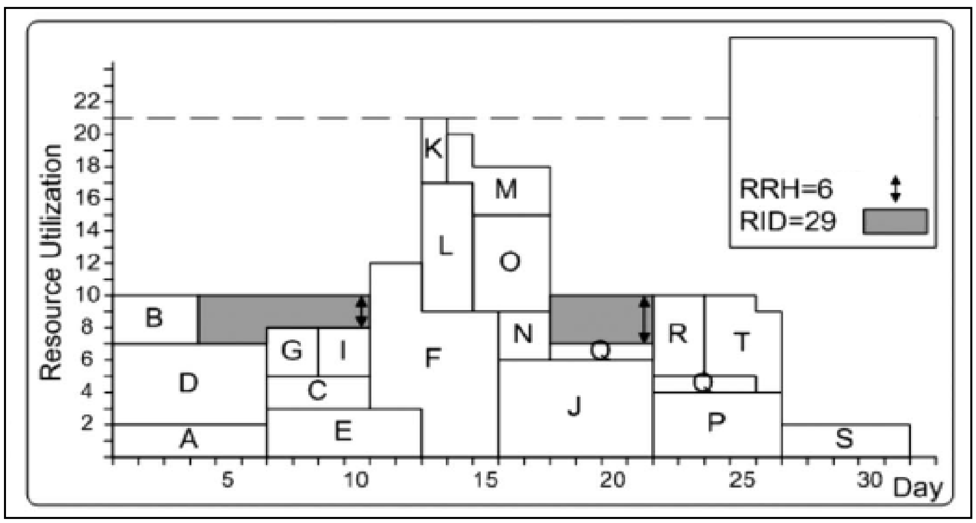


Figure 3.3: Twenty-Activity Project Initial Resource Profile (El-Rayes and Jun 2009)

Table 3.3: Direct Costs (Experiment 2)

Activity	Duration	Direct Cost / day	Total Direct Cost
A	6	1200	7200
B	3	1400	4200
C	4	1500	6000
D	6	1700	10200
E	6	1800	10800
F	5	2600	13000
G	2	1700	3400
H	2	1400	2800
I	2	1800	3600
J	6	2400	14400
K	1	2200	2200
L	2	2400	4800
M	4	2100	8400
N	2	2200	4400
O	3	2500	7500
P	5	1800	9000
Q	8	1800	14400
R	2	2000	4000
S	5	1400	7000
T	3	1900	5700

Table 3.4: Time, Financial, and Contractual Data (Experiment 2)

Data Type	Item	Value
TIME	**No. of Days per Week**	5
	Original Duration (days)	31
	Original Duration (weeks)	7
FINANCIAL	**Interest Rate % per Week**	0.30%
	Overheads per week ($)	3,500
	Mobilization Costs ($)	25,000
	Tax %	2%
	Mark-Up %	20%
	Bond Premium ($)	2,500
CONTRACT TERMS	**Advance Payment % of Bid Price**	6%
	Weeks to Retrieve Advance Payment	7
	Retained % of Pay Requests	5%
	Lag to Pay Retained Money After Last Payment (weeks)	0
	Weeks to Submit Pay Requests Regularly	1
	Lag to Pay Payment Requests (weeks)	1

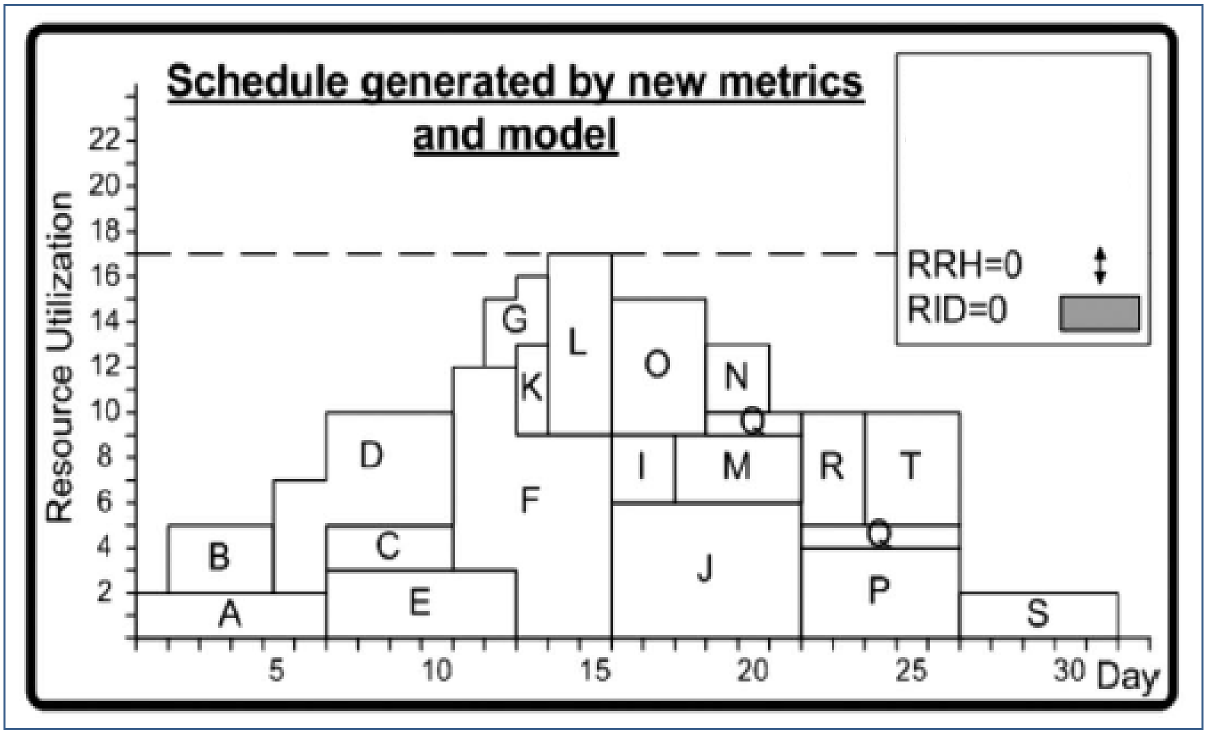


Figure 3.4: Twenty-Activity Project Minimum Resource Profile (El-Rayes and Jun 2009)

- ***Results:***

The results obtained from the two experiments - as shown in Table 3.5 - indicate that as the RRH or RID are minimized along with the MRD, the maximum required credit increases. This is for a reason that better and efficient utilization of resources reduces the resource idle days which in turn leads to continuous use of resources in each period resulting to an increase in the required credit. Simultaneously, minimizing resource fluctuations results in an increase in the financing cost which eventually decreases the profit. However, this case may be the opposite if the optimization model in hand will consider the resource idle days cost. In other words, minimizing resource fluctuations can increase the financing cost but at the same time reduces the resource idle days cost which can positively affect the profit. Therefore, the objectives of duration, financing costs, maximum required credit, profit, and resource fluctuations and peak demand will constitute a set of multiple contractor conflicting objectives.

Table 3.5: Effect of Minimizing Resource Fluctuations

OBJECTIVES / SCHEDULE	EXPERIMENT (1)			EXPERIMENT (2)		
	Financing Cost	**Required Credit**	**Profit**	**Financing Cost**	**Required Credit**	**Profit**
Initial Schedule	255	41,262	12,514	732	39,104	38,477
Minimum Resource Fluctuation Schedule	277	43,901	12,492	774	42,690	38,435

3.4 MULTI-OBJECTIVE OPTIMIZATION MODEL FORMULATION

The principles of multi-objective optimization are different from that of a single objective optimization. The main goal in a single objective optimization is to find the global optimal solution, resulting in the optimal value for the single objective function. In a multi-objective optimization problem, it is aimed to simultaneously optimize several objective functions. Generally, these functions are non-commensurable and often represent competing and conflicting objectives. Multi-objective optimization with such conflicting objectives gives rise to a set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that no one is better than any other one with respect to all objectives. These optimal solutions are referred to as Pareto-optimal solutions.

The primary purpose of this development stage is to create a robust optimization model formulation that supports the multi-objective scheduling problem. As shown in Figure

3.5, the present model is formulated in two major steps: (1) determining the major decision variables and (2) formulating the major six objectives of duration, total cost, financing cost, maximum required credit, profit, and resource fluctuations and peak demand in a robust optimization model. Although it was discussed in the previous section that not all of the listed objectives are conflicting, yet, all of them will be formulated. That is to add flexibility in the model to select the set of objectives to be optimized simultaneously. In other words, different tradeoffs between different set of selected objectives can be obtained from the model. The merit of this flexibility is to allow the contractor to examine the impact of one or more objectives over the other on the projects' schedule. The selection of such objectives is based on whether they are conflicting or not as well as the contractor's preference.

3.4.1 Decision Variables

For each construction activity in the project, the present model is designed to consider two decision variables that may have an impact on the selected conflicting objectives. The first decision variable comprises the start times (*st*) of each activity in a project. The second decision variable – since the study focuses on multimode activities - will include different daily crew formations which represent feasible sizes and configurations for construction crews. This variable will be called resource utilization mode (*m*) of which each has a different activity duration and cost. The major challenge confronting construction planners in this problem is to select an optimal start time and a resource utilization mode from the available set of feasible alternatives for each activity in the project. The possible combinations of these alternatives create a large search space, where each solution in this space represents a possible start time and resource utilization mode for delivering the project. As a result the optimization model to be built will help planners in the challenging task of searching this large solution space in order to identify optimal/near optimal start time of activities and their resource utilization mode that achieves multiple project objectives.

3.4.2 Optimization Objectives

The multi-objective optimization problem in hand will involve minimizing the duration of group of projects, total cost, financing cost, maximum required credit, and resource fluctuation and peak demand while maximizing the profit. The model is designed to quantify and measure the impact of various activities' start times and their corresponding resource utilization mode on the multiple project objectives. Those objectives can be expressed mathematically as follows:

- ***Objective (1): Minimize Total Project Duration:***

$O_1(TD) = D_z$ ……..………………………………………………………………….(3.14)

- ***Objective (2): Minimize Total Cost:***

$O_2(TC) = \sum_{t=1}^{T}(E_t)$……………………………………………………………….(3.15)

- ***Objective (3): Minimize Financing Cost:***

$$O_3(FC) = \sum_{t=1}^{T}(I_t) \quad (3.16)$$

- ***Objective (4): Minimize Maximum Required Credit:***

$$O_4(RC) = -F, \quad F = min\{F'_t : t = 1,2, \dots, T\} \quad (3.17)$$

- ***Objective (5): Minimize Resource Fluctuations and Peak Demand:***

$$O_5(RFPD) = (W_1 xRRH) + (W_2 xMRD) \quad (3.18a)$$

OR

$$O_5(RFPD) = (W_1 xRID) + (W_2 xMRD) \quad (3.18b)$$

- ***Objective (6): Maximize Profit:***

$$O_6(PR) = N'_T \quad (3.19)$$

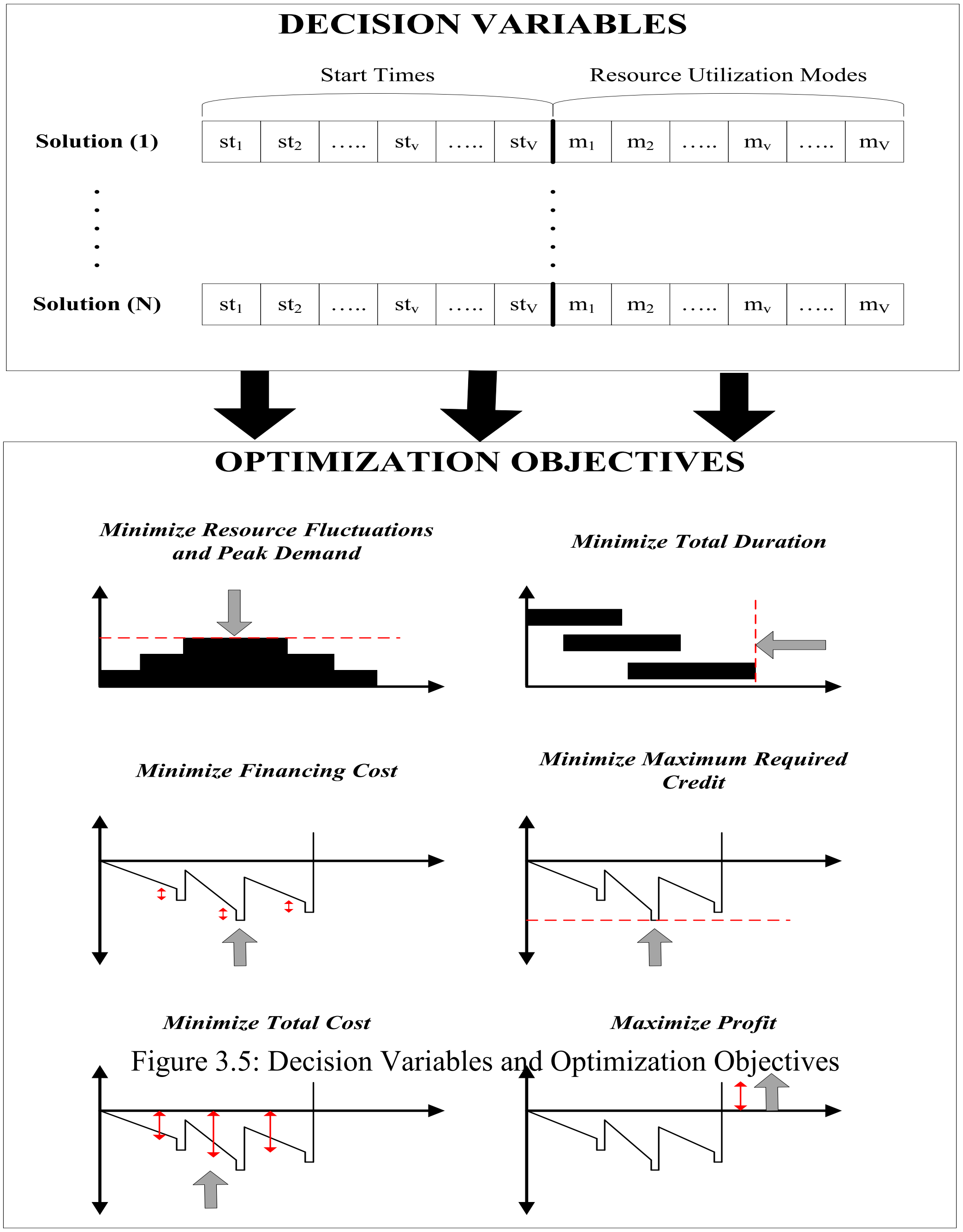


Figure 3.5: Decision Variables and Optimization Objectives

Where; W_1 = planner defined weight or relative importance for the RRH or RID; and W_2 = planner defined weight or relative importance for the MRD. Construction planners can specify these weights of W_1 and W_2 to reflect the relative importance of minimizing undesirable resource fluctuations and minimizing the MRD in their projects. The relative importance of these two important objectives depends on the specific project conditions and needs and may vary from one project to another. Accordingly, the present model is designed to provide construction planners with the flexibility to easily experiment with varying weights and analyze their impact on the generated optimal schedules.

Although the “profit” objective is dependent on the “total cost” and “financing cost” objectives, yet such objectives are formulated separately to give more flexibility in solving the desired scheduling optimization problem. In other words, the optimization model can be used to solve separately time/cost tradeoff, resource leveling, resource allocation, or finance-based scheduling problems. Alternatively, integration of such problems can be also solved. Time/cost tradeoff problem is applied when the contractor’s first concern is to identify the optimal/near optimal execution mode for each activity. In such case, the selected objectives to optimized simultaneously will be the total duration and total cost. Resource leveling is applied when the contractor’s first concern is to search for an optimal schedule that minimizes the project’s undesired resource fluctuation within the required duration. In this case the selected objective to be optimized will be the RRH or RID resource leveling metric. Resource allocation is applied when resources are limited and an optimal/near optimal schedule is required such that the resource limit is not exceeded with the minimum extension in duration (if required). In this case, the selected objectives to be optimized simultaneously will the total duration and MRD. Finance-based scheduling problem is applied when maximum required credit is needed to be generally minimized or minimized below a certain credit limit while maximizing the contractor’s profit. In this case, the selected objectives to be optimized simultaneously will be the maximum required credit and the maximum profit. Combinations of such problems can also be achieved depending on the project's main objective. For example, both resource leveling and allocation can be solved simultaneously by selecting the RFPD objective. Also, finance-based scheduling can be integrated with both resource leveling and allocation in order to achieve optimal/near optimal schedules that minimizes the undesirable resource fluctuations and peak demand while maximizing the profit and keeping the maximum required credit below a specified credit limit.

The optimization problem including the objective function and constraints can be formulated as shown in Equations 3.20 – 3.25:

Decision Variables

$x_z = \{(st,m)_1, (st,m)_2, \ldots, (st,m)_v, \ldots, (st,m)_{N_{ACT}}\},\ \ z = 1,2,\ldots,Z$ ……..……(3.20)

Where;

$X = \{x_1, x_2, \ldots, x_z, \ldots, x_Z\}$ ………………………………..……………………(3.21)

Minimize/Maximize

$O_i(X),\quad i = 1,2,\ldots,N_{OBJ}$ …………….…………………………….…...……...(3.22)

Subject to

$$st_k - st_v - d_{m_v} \geq 0, \qquad \forall\ k \varepsilon SC_v \ldots\ldots (3.23)$$

$$RC \leq CL \ldots\ldots (3.24)$$

$$MRD \leq RL \ldots\ldots (3.25)$$

Where; O_i = ith objective; Z = total number of projects; x_z = vector that represents a candidate activities' start times and their associated resource utilization mode for the zth project; X = matrix that represents candidates' project schedule and their activities' associated resource utilization mode for all projects; st_v = start time of activity v; d_{m_v} = duration of activity v based on its associated resource utilization mode; st_k = start times of successors of activity v; m_v = resource utilization mode of activity v; N_{ACT} = number of project's activities; N_{OBJ} = number of objectives; SC_v = set of successors of activity v, CL = credit limit, and RL = resource limit.

For a scheduling problem having multiple objectives, there exist two possibilities of any two solutions X_1 and X_2. The first is that one solution dominates the other when it is better with respect to all the objective values. The second possibility is that no one dominates the other when none is better than the other with respect to all the objective values. In the current minimization problem, a schedule X_1 dominates X_2 if the condition shown in Equation 3.26 is met as follows:

$$\forall\ i\ \varepsilon\{1,2,\ldots,N_{OBJ}\}: O_i(X_1) \leq O_i(X_2) \quad \ldots\ldots(3.26)$$

Dominance of X_1 can be alternately written as: X_2 is dominated by X_1. The violation of the condition stated in Equation 3.26 implies that X_1 does not dominate X_2 as shown in Equation 3.27.

$$\exists\ i\ \varepsilon\{1,2,\ldots,N_{OBJ}\}: O_i(X_1) \leq O_i(X_2) \quad \ldots\ldots(3.27)$$

Generally, the multi-objective optimization algorithm must guide the search toward the Pareto-optimal region, and maintain population diversity in the Pareto-optimal front. The first task is a common goal in all optimization algorithms. The second task is unique to multi-objective optimization. A summary of the full model formulation is shown in Figure 3.6.

Decision Variables:

- Activities' Start Time (st)
- Activities' Resource Utilization Mode (m)

Objective Functions:

- *Minimize* Total Duration (TD)
- *Minimize* Total Cost (TC)
- *Minimize* Financing Cost (FC)
- *Minimize* Required Credit (RC)
- *Minimize* Resource Fluctuation & Peak Demand (RFPD)
- *Maximize* Profit (PR)

Subject to:

- Precedence Relationships
- Credit Limit
- Resource Limit
- st , m > 0

Figure 3.6: Model Formulation Summary

3.5 MULTI-OBJECTIVE OPTIMIZATION MODEL DEVELOPMENT

As mentioned earlier in Chapter 2, both mathematical and heuristic approaches were found to be inefficient and inflexible when solving practical construction scheduling optimization problems. This led to focusing on using metaheuristic techniques in solving multi-objective construction scheduling optimization problems. Among the different metaheuristics, NSGA-II is selected in this research as it stands out for its fast non-dominated sorting approach, elitism approach, and its overall capability to maintain a better solution spread.

This step of research methodology involves the development of the multi-objective scheduling optimization model using NSGA-II to optimize the mentioned objectives without violating the set constraints. The designed model performs genetic algorithms operations in three main phases: (1) population initialization phase that generates an initial set of *N* possible solutions for the problem; (2) fitness evaluation phase that calculates the mentioned objectives of each generated solution; and (3) generation evolution phase that seeks to improve the fitness of solutions over successive generations using the NSGA-II technique. The model is intended to be used in the initial planning stage for the project(s) being considered for bidding as well as during the construction phase. Usually, during construction, the project(s) being executed may fall ahead or behind the planned schedule. Moreover, new project(s) may be considered with the existing ones. Thus it is very important for the model to accommodate such changes and additions by updating the planned schedules during the construction phase.

The model can be applied to solve the resource leveling, resource allocation, and finance-based scheduling problems for either single or multiple projects. On the other hand, the model solves the time/cost tradeoff problem for only single project where each individual project has its unique time/cost tradeoff. Detailed description of the model development will be explained later in Chapter 4.

3.6 MODEL IMPLEMENTATION AND TESTING

After developing the multi-objective optimization model, it is tested using different case studies from literature. The testing is done with respect to three optimization problems:

1. Time/cost tradeoff
2. Resource leveling and allocation
3. Finance-based scheduling

The model testing results are compared with the actual results obtained from literature to prove its credibility and validity in optimizing such problems. Moreover, the model is implemented on three other case studies to demonstrate its capabilities in optimizing the schedules of multiple projects with multi-modes and multi-resources activities. Such demonstration integrated the problems of finance-based scheduling together with resource leveling and allocation which is the main scope of this research. The results and analysis of the model implementation and testing are described in details in Chapter 5.

3.7 AUTOMATED TOOL: MOSCOPEA

Finally, an automated tool named MOSCOPEA, an acronym for **M**ulti-**O**bjective **SC**heduling **OP**timization using **E**volutionary **A**lgorithm, is designed and built to provide a platform for performing optimization of multiple projects scheduling. The tool is built with a friendly graphical user interface using the C# language. The C# offers the potential of being available across many platforms. It is a very powerful high-level language, an object-oriented programming language encompassing imperative, declarative, functional, generic, and component-oriented programming language. The automated tool detailed description is presented in Chapter 6.

CHAPTER 4: MULTI-OBJECTIVE SCHEDULING OPTIMIZATION MODEL DEVELOPMENT

This chapter is divided into two main sections. The first section describes the major features of the optimization model to be developed using the NSGA-II technique. The second section illustrates the detailed process of developing the multi-objective scheduling optimization model. Related to financing and resources, there are two model options: (1) non-constrained credit limit and resource limit; and (2) constrained credit limit and resource limit. The first option will take into account the constraint of preserving the precedence relationships between the projects' activities only. While the second option will also take into consideration the constraint of preserving precedence relationships between the projects' activities in addition to preventing the maximum required credit and the maximum resource demand from exceeding the specified credit limit and resource limit, respectively. It should be noted that this optimization takes into account multiple projects with multimode activities using multi-resources. Generally, the input of the model as shown in Figure 4.1 includes the initial schedules of the projects along with their time, financial, and contractual terms. On the other hand, the output will include different optimized schedules that achieve the desired objectives.

4.1 MODEL BASIC FEATURES

Prior developing the optimization model, there are five basic features to be described, namely: (1) extension scheme; (2) chromosome structure; (3) chromosome fitness evaluation; (4) infeasible chromosome treatment; and (5) reproduction.

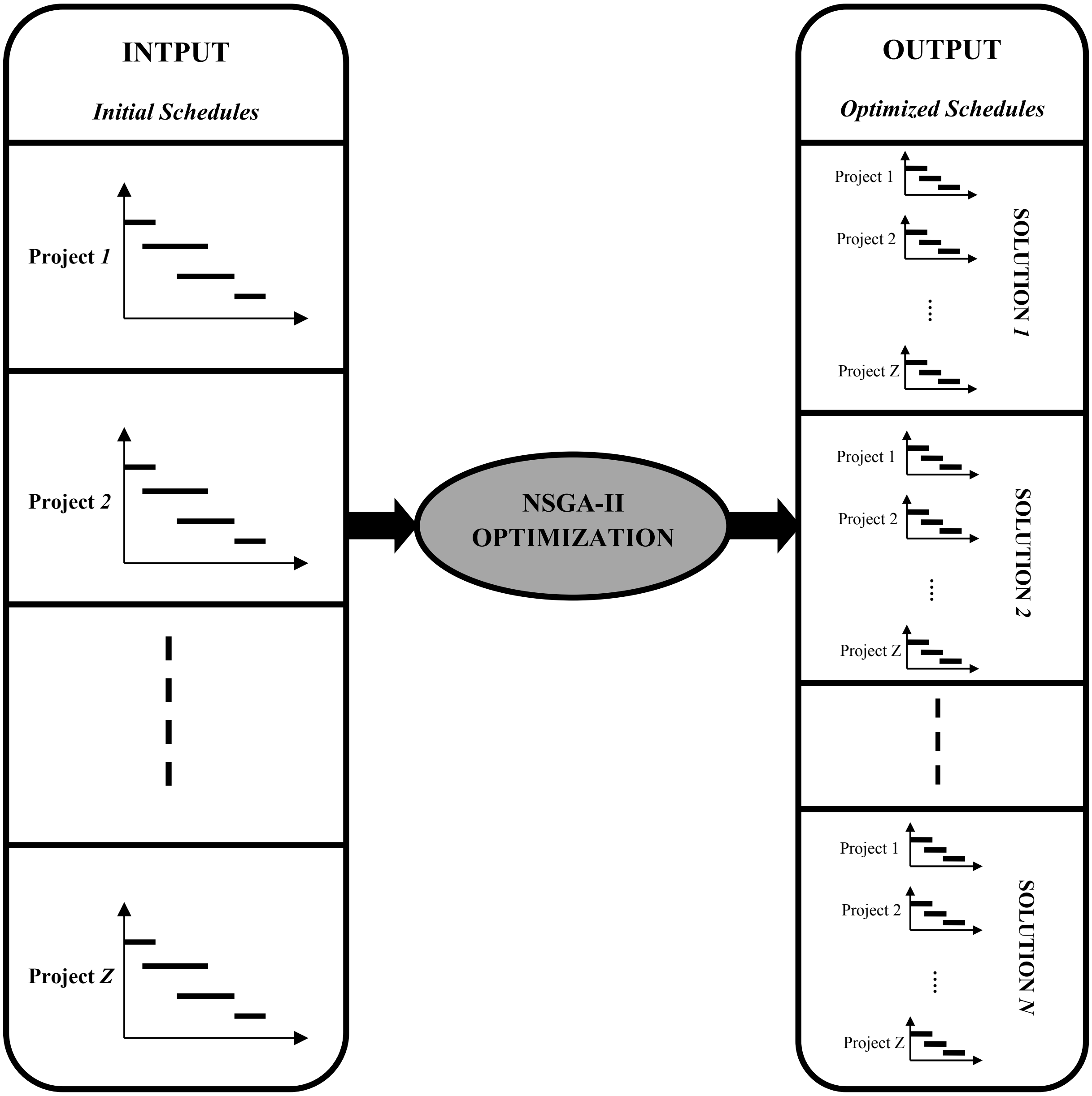


Figure 4.1: Model Overview

4.1.1 Extension Scheme

Minimizing the initial maximum required credit can be achieved by performing several trials of shifting the projects' activities within their floats while keeping the original project's duration unchanged. However, such minimization may still exceed the contractor's credit limit. Thus, the project may be required to be extended beyond its original duration to achieve the desired credit limit. Although such extension has the drawbacks of increasing the overheads costs and implying liquidated damages to the contractor, yet it is essential if the contractor's financing capability is limited. The basic concept here is to minimize such extension.

Based on the above, it is essential to devise a project initial scheme and extension scheme. For instance, the initial scheme for the 5 month schedule shown in Figure 4.2a is illustrated in Figure 4.2b which is basically a bar chart with total floats portrayed before activities. The extension scheme, as illustrated in Figure 4.3, is a modification of the initial scheme that allows a definite extension increment (5 months in Figure 4.3) to the initial project duration to determine an extended duration, and extends total floats of activities by the extension increment to produce adjusted total floats. The adjusted total float is the time space within which an activity can be shifted without affecting the extended project duration. For instance, Activity (A) can be shifted all the way to the end of its adjusted total float and still allows us to finish Activity (F), which depends on Activity (A), before the end of its adjusted total float. Thus, the shift of Activity (A) could be done without causing further extension beyond the extended project duration.

Practically, numerous extended schedules could be produced for a given schedule. Thus, a fundamental objective of the method is to minimize schedule extensions. Extension schemes allow formulating schedules such that negative cash values are always minimized, and minimize extensions in the initial critical path method schedules. Thus, extension schemes transform the process of seeking extended schedules that fulfill cash constraints from searching in boundless solution spaces to searching in well-defined and definite solution spaces (Elazouni and Metwally 2005).

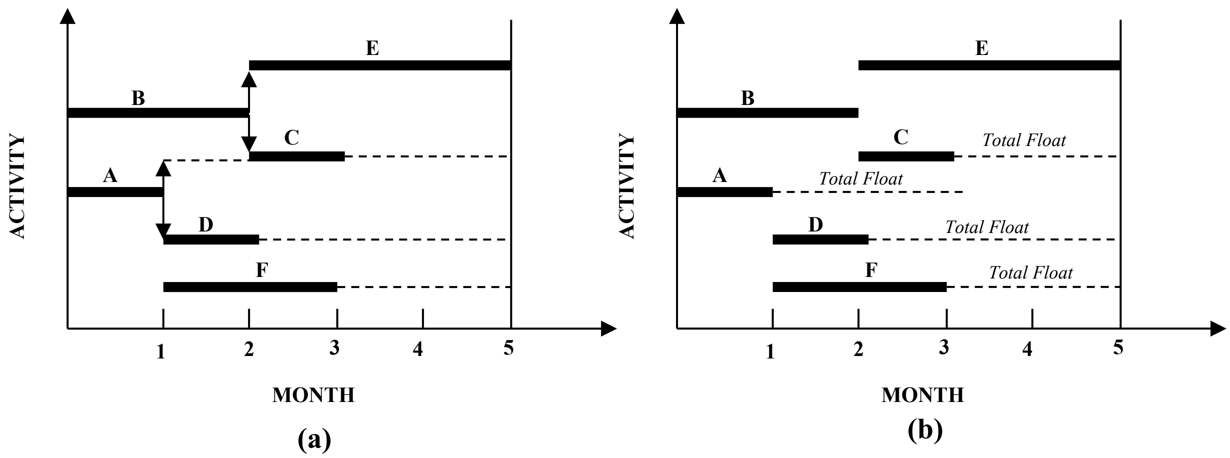


Figure 4.2: Initial Scheme

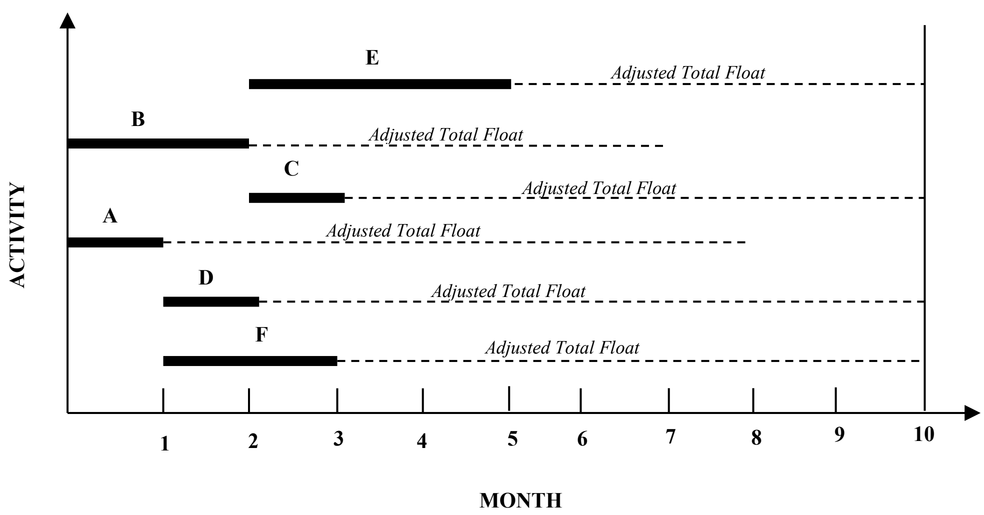


Figure 4.3: Extension Scheme

4.1.2 Chromosome Structure

The chromosome structure, as shown in Figure 4.4, is to be set as two strings of genes separated by a heavy line in the middle. The left hand string represents the start times of the activities. While, the right hand strings represents the resource utilization mode of activities' alternatives. As such, each chromosome represents one possible schedule.

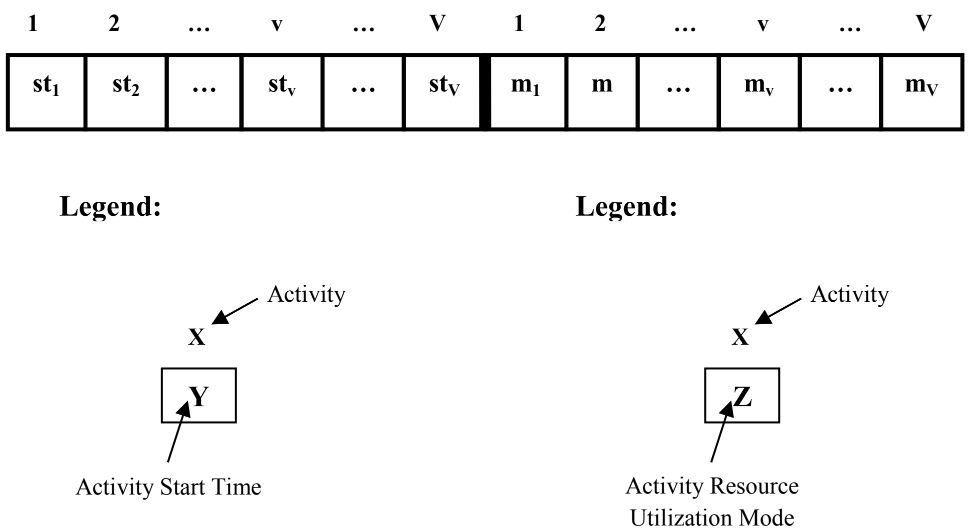


Figure 4.4: Chromosome Structure Representation

4.1.3 Chromosome Fitness Evaluation

When a chromosome is being evaluated, its start time values and resource utilization modes are assigned to the corresponding project activities to produce a new schedule. Such schedule produced by each chromosome is evaluated based on its resulted objectives' values by applying non-dominance ranking. All chromosomes are sorted based on non-domination into each front. The first front being completely non-dominant set in the current population and the second front being dominated by the chromosomes in the first front only and the front goes so on. Each chromosome in the each front are assigned a rank (fitness) value based on the front in which they belong to. Chromosomes in first front are given a fitness value of 1 and chromosomes in second are assigned fitness value of 2 and so on. In addition to the fitness value, the crowding distance is calculated for each chromosome as a secondary ranking. As mentioned before, the crowding distance is a measure of how close a chromosome is to its neighbors. Large average crowding distance will result in better diversity in the population.

4.1.4 Infeasible Chromosome Treatment

Infeasible solutions may arise when new individual chromosomes are generated for the initial population and/or when offspring chromosomes are reproduced within the population using the crossover and mutation operators. The infeasibility takes place by having a chromosome that either: (1) violates the precedence logical relationship between the projects' activities; (2) produces maximum required credit exceeding the set credit limit; or (3) produces maximum resource demand exceeding the set resource limit.

The first type of infeasibility is treated by improving the crossover and mutation operators as it will be explained in the next sub-section. As for the second and third type of infeasibility, the treatment is carried by assigning a lower rank for the infeasible chromosome throughout the non-domination ranking process. When sorting the entire population by comparing each two chromosomes at a time, two cases may arise with respect to infeasibility: (1) one chromosome is feasible while the other is infeasible; and (2) both chromosomes are infeasible. In the first case, the feasible chromosome is kept in front X and the infeasible chromosome is shifted to front X+1. Such shifting of the infeasible chromosome to the next fronts will continue until there is no any feasible chromosome left with it in the same front. The second case happens when all the infeasible chromosomes in the entire population are shifted to the last front Z. In other words, front Z will contain all the infeasible chromosomes. In this case, when two infeasible chromosomes are compared, the chromosome with the lower constraint violation will be kept in front Z while the other will be further shifted to front Z+1 and so on. This way of treatment decreases the chances that these infeasible chromosomes are selected for reproduction in the subsequent generations and eventually exclude them from the population after some iterations.

4.1.5 Reproduction

The reproduction process among the population members takes place by either crossover or mutation as explained before. However, the basic crossover or mutation operators may not maintain the precedence relationship between the activities. Operations facilitated by crossover and mutation alter the contents of the genes, thus causing the violation of the precedence constraint. In other words, most new strings generated from crossover and mutation becomes infeasible solutions. For example, for the bar chart shown in Figure 4.2, it is noticed after the basic crossover that offspring 2 in Figure 4.5 became an infeasible solution, as Activities (D), (E), and (F) are scheduled to start before the finish of the preceding activities, violating the constraint of precedence. Consequently, repair of infeasible chromosomes is required after each crossover or mutation operation which consumes processing time.

Initially, an improved crossover was used to repair infeasible genes causing prolonged processing time due to computational inefficiency. To overcome this problem Abido and

Elazouni (2010) developed an improved crossover and mutation operators that caused potential reduction in processing time without affecting results. These operators are explained as follows being applied on the 13-activity CPM network and its seven-day extension scheme shown in Figures 4.6 and 4.7, respectively.

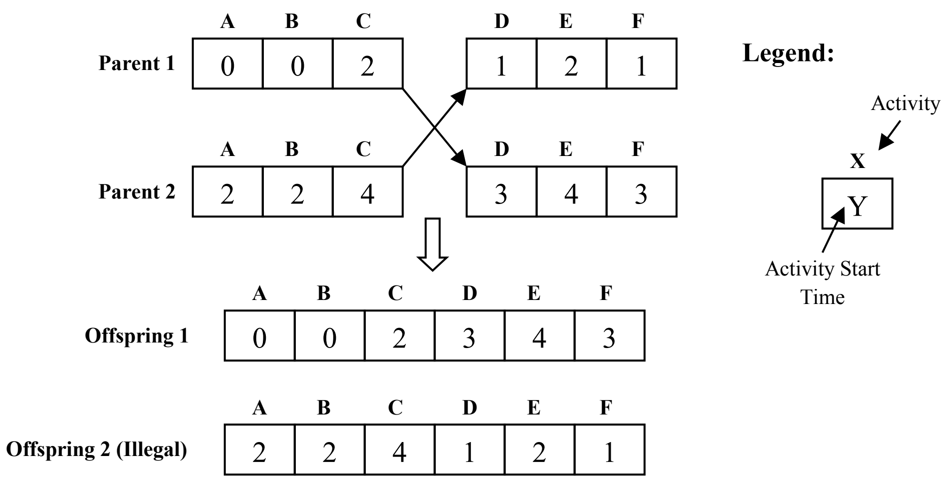


Figure 4.5: Example of Illegal Offspring from Crossover

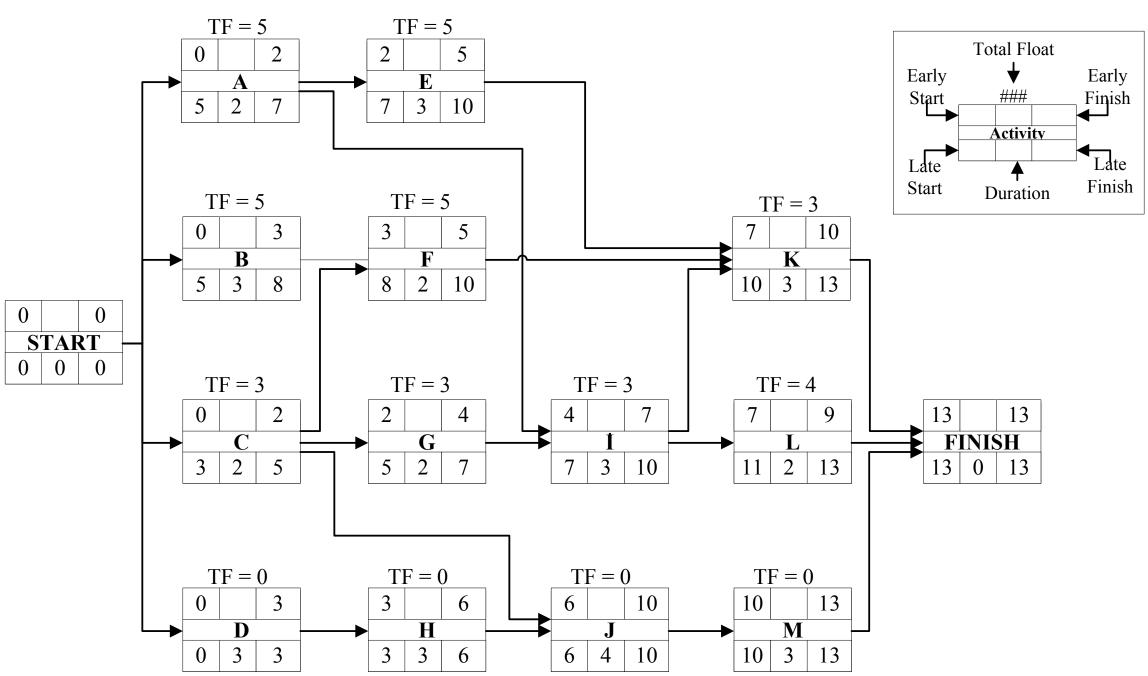


Figure 4.6: CPM Network of a 13-Activity Project

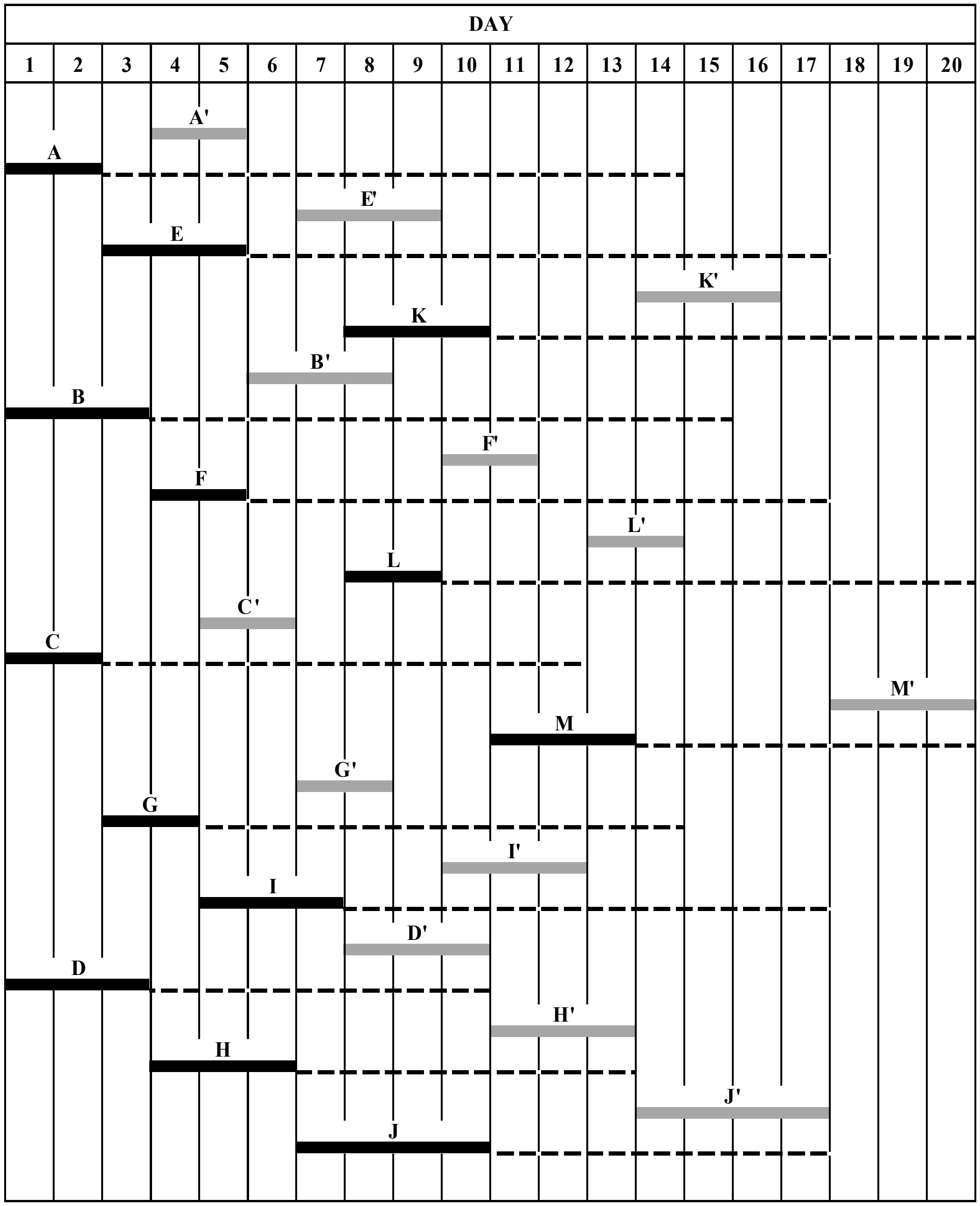


Figure 4.7: Seven-day Extension of the 13-Activity Project

4.1.5.1 Improved Crossover

The algorithm of the crossover operator comprises two paths: forward path and backward path. The latter utilizes the conventional forward free float (FFF) while the former utilizes the backward free float (BFF). The BFF is the number of days the start time of an activity can be advanced without violating the finish-to-start relationships between this activity and the preceding activities. The BFF arises with the device of the extension scheme when a certain activity is shifted forward leaving a gap between its start time and the finish times of the preceding activities. The algorithm used to generate the child chromosomes in Figures 4.8 and 4.9 is explained in the following steps:

1. Select randomly two parent chromosomes from the population. It is to be noted that the Parent (1) chromosome is the generated chromosome shown in Figure 4.7.
2. Calculate the BFF of the activities. The BFF values of the starting activities (A, B, C, and D) are considered null so as not to allow these activities to move backward.
3. Calculate the FFF of the activities. The FFF values of the terminating activities (K, L, and M) are considered null so as not to allow these activities to move forward.
4. Select randomly the cut-point activity; it is located after the first seven genes.
5. Form the chromosomes for two children by randomly selecting either the forward path or backward path to implement as follows:
    - *a.* *Forward Path:*
        - *i.* The first and second child chromosomes are formed by copying the start times of the activities to the left sides of the cut points of Parents 1 and 2, respectively, into the left-hand parts of the child chromosomes.
        - *ii.* The start times of activities of the right-hand parts of the first and second child chromosomes are determined by forwardly applying the BFF values of their counterparts in Parents 2 and 1, respectively, to the finish times of the preceding activities in the left-hand parts of the child chromosomes.

iii. The forward path may result in durations of the offspring chromosomes that exceed the duration of the extension scheme. This happened in Child 1 as Activity M ends at Day 22. These chromosomes are considered infeasible.

b. *Backward Path:*

i. The first and second child chromosomes are formed by copying the start times of the activities to the right sides of the cut points of Parents 1 and 2, respectively, into the right-hand parts of the child chromosomes.

ii. The finish times of the activities of the left-hand parts of the first and second child chromosomes are determined by backwardly applying the FFF values of their counterparts in Parents 2 and 1, respectively, to the start times of the following activities in the right-hand parts of the child chromosomes. The start times are determined based on the finish times.

iii. The backward path may result in the negative start time of certain activities in the beginning on the network. In this case, the start times of all the activities of the network are increased to make this activity start at Day 0.

4.1.5.2 Improved Mutation

The improved mutation operator also utilizes the FFF and BFF to change the start time of the mutated activity. The developed algorithm ensures the feasibility of the schedule after mutation. The steps of the improved mutation operator are outlined as follows and illustrated in Figure 4.10:

1. Select randomly one activity, say, Activity E.

2. Determine the FFF and BFF of the selected activity; for Activity E, the FFF is 4 days and the BFF is 1 day.
3. Shift randomly the activity forward or backward within the range determined by the FFF and the BFF; the start of Activity E is shifted by 2 days.

	A	B	C	D	E	F	G	H	I	J	K	L	M
Parent 1	3	5	4	7	6	9	6	10	9	13	13	12	17

Cut Point

	A	B	C	D	E	F	G	H	I	J	K	L	M
Parent 2	4	7	6	5	9	13	10	9	14	12	17	17	17

Cut Point

Backward Free Floats (BFF)													
Activity	A	B	C	D	E	F	G	H	I	J	K	L	M
Parent 1	0	0	0	0	1	1	0	0	1	0	1	0	0
Parent 2	0	0	0	0	3	3	2	1	2	0	0	0	1

	A	B	C	D	E	F	G	H	I	J	K	L	M
Child 1	3	5	4	7	6	9	6	11	10	14	13	13	19

	A	B	C	D	E	F	G	H	I	J	K	L	M
Child 2	4	7	6	5	9	13	10	8	13	11	17	16	15

Figure 4.8: Improved Crossover Operator – Forward Path

	A	B	C	D	E	F	G	H	I	J	K	L	M
Parent 1	3	5	4	7	6	9	6	10	9	13	13	12	17

Cut Point

	A	B	C	D	E	F	G	H	I	J	K	L	M
Parent 2	4	7	6	5	9	13	10	9	14	12	17	17	17

Cut Point

Forward Free Floats (FFF)													
Activity	A	B	C	D	E	F	G	H	I	J	K	L	M
Parent 1	1	1	0	0	4	2	1	0	0	0	0	0	0
Parent 2	3	3	2	1	5	2	2	0	0	1	0	0	0

	A	B	C	D	E	F	G	H	I	J	K	L	M
Child 1	0	3	1	6	5	9	5	10	9	13	13	12	17

	A	B	C	D	E	F	G	H	I	J	K	L	M
Child 2	7	9	9	6	10	13	11	9	14	12	17	17	17

Figure 4.9: Improved Crossover Operator – Backward Path

	A	B	C	D	E	F	G	H	I	J	K	L	M
Parent	3	5	4	7	6	9	6	10	9	13	13	12	17

Selected Gene

Free Floats													
Activity	A	B	C	D	E	F	G	H	I	J	K	L	M
Backward	0	0	0	0	1	1	0	0	1	0	1	0	0
Forward	1	1	0	0	4	2	1	0	0	0	0	0	0

	A	B	C	D	E	F	G	H	I	J	K	L	M
Child	3	5	4	7	8	9	6	10	9	13	13	12	17

Figure 4.10: Improved Mutation Operator

4.2 MODEL DEVELOPMENT

The optimization model at hand, as shown in Figure 4.11, will be developed in three major phases: (1) population initialization phase that generates an initial set of N possible solutions for the problem; (2) fitness evaluation phase that calculates the values of the desired set of objectives to be optimized simultaneously; and (3) generation evolution phase that seeks to improve the fitness of solutions over successive generations using the NSGA-II technique. The detailed computational procedure of these three phases is explained in the following sub-sections. Moreover, a small illustrative example is solved manually in Appendix A to show the details of the NSGA-II operations focusing on the "generation evolution" phase.

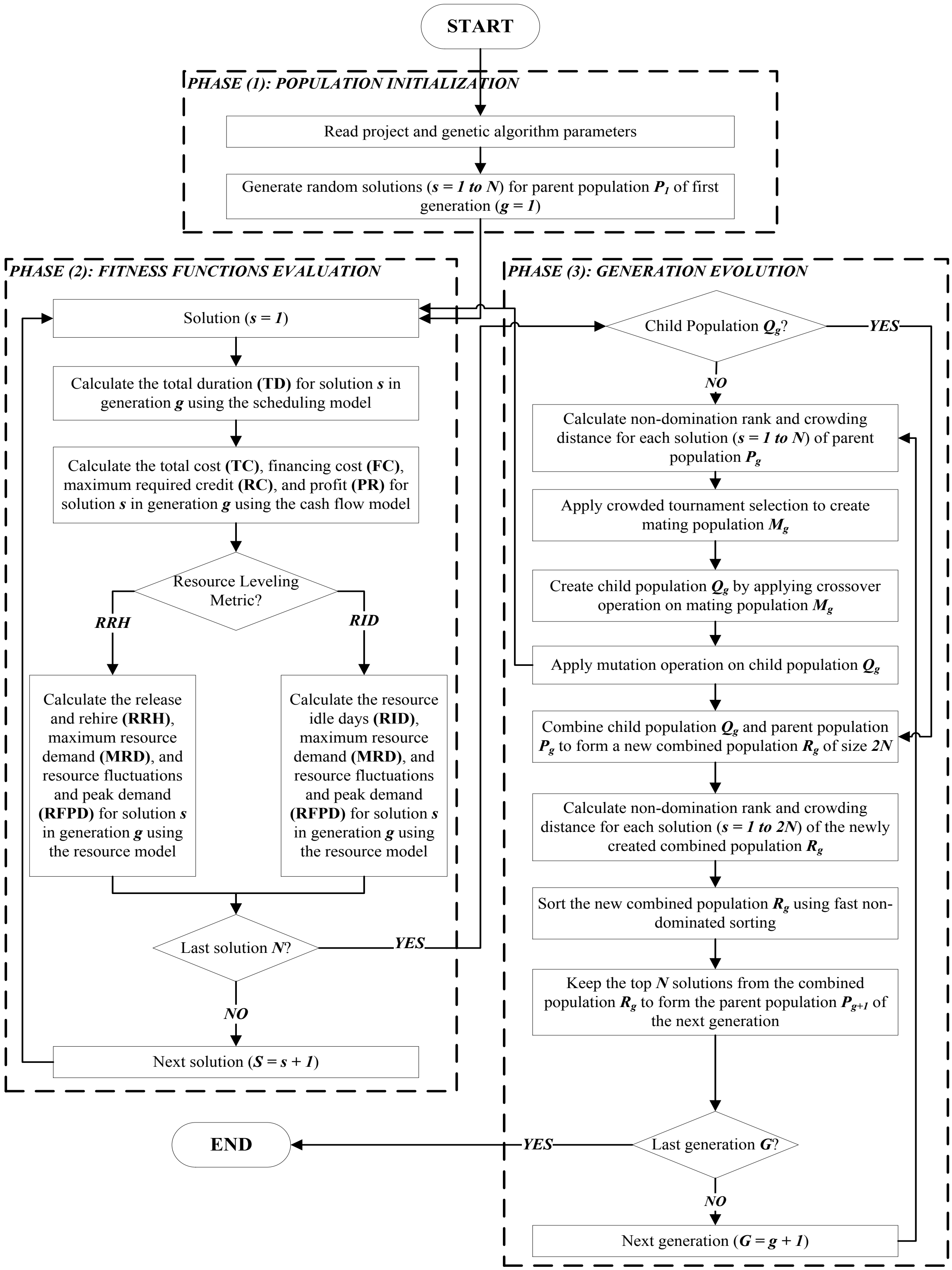


Figure 4.11: Model Development Framework

4.2.1 Phase (1): Population Initialization

The main purpose of this phase is to generate an initial set of N possible solutions that will evolve in subsequent generations to a set of optimal/near optimal solutions. The initialization phase in this model is performed in two main steps as follows:

1. Read project and genetic algorithm parameters needed to initialize the search process. The project parameters include the following:
    - Number of project activities
    - Number of resource utilization mode for each activity
    - Activity duration and direct cost for each resource utilization mode
    - Precedence relationship between activities
    - Interest rate %
    - Mark-up %
    - …etc.

    On the other hand, the genetic algorithm parameters will include the following:
    - Population size
    - Number of generations
    - Crossover probability
    - Mutation probability

    The string size is determined by the model, considering the total number of activities in the analyzed project(s) multiplied by two since there are two decision variables for each activity as explained before. The number of generations G and population size N are identified based on the selected string size to improve the quality of the solution. Similarly, the mutation and crossover rates are determined considering the population size and the method of selection employed by the algorithm.

2. Generate random solutions (s = 1 to N) for the initial population P_1 in the first generation (g = 1). These solutions represent an initial set of activity start times and their corresponding resource utilization mode. This set of possible solutions is then evolved in the following two phases in order to generate a set of activity optimal start times and resource utilization modes to establish an optimal tradeoff between project total duration, financing costs, maximum negative cumulative balance, and resource fluctuations and peak demand.

4.2.2 Phase (2): Fitness Evaluation

The main purpose of this phase is to evaluate the project's desired selected multi-objectives for each possible solution *s* in generation *g* to determine the fitness of the solution. This fitness determines the likelihood of survival and reproduction of each solution in following generations. As such, this phase will evaluate the fitness function for each solution by calculating one or more of the following multi-objectives:

1. The total duration T*D(s,g)* for solution *s* in generation *g* using the scheduling model.
2. The total cost TC*(s,g)* for solution *s* in generation *g* using the cash flow model.
3. The financing cost FC*(s,g)* for solution *s* in generation *g* using the cash flow model.
4. The maximum required credit RC*(s,g)* for solution *s* in generation *g* using the cash flow model.
5. The total profit PR*(s,g)* for solution *s* in generation *g* using the cash flow model.

6. The resource fluctuation and peak demand RFPD*(s,g)* by calculating the project's RID*(s,g)* or RRH*(s,g)* along with the MRD*(s,g)* for solution s in generation g using the resource model.

4.2.3 Phase (3): Generation Evolution

The purpose of this phase is to create three types of population in each of the considered generations: parent, child, and combined. For each generation g, a parent population P_g is used to generate a child population Q_g in a manner similar to that used in traditional genetic algorithms. The purpose of generating this child population is to introduce a new set of solutions by rearranging and randomly changing parts of the solutions of the parent population. This child population can then be combined with the parent population to create an expanded set of possible solutions that forms the combined population R_g for generation g. This combined population R_g is used to facilitate the comparison among the initial solutions in the parent population and those generated in the child population. The best solutions in this combined population regardless of their origin are retained and passed to the following generation as a parent population. The computational procedure in this phase is implemented in the following steps:

1. Calculate non-domination rank (i_{rank}) and crowding distance $(i_{distance})$ for each solution (s = 1 to N) in the parent population P_g as described before.
2. Apply crowded tournament selection to create a mating population M_g. In this selection procedure, two solutions (s_1, s_2) from the parent population P_g are selected at random for a tournament using the crowded comparison operator as described previously. The winner will be inserted in the mating pool for

reproduction. This selection process is repeated until the mating pool is filled with N solutions.

3. Create a new child population Q_g by applying crossover operation on the solutions obtained in the mating pool M_g. For each solution in the mating pool the following steps are performed. The crossover probability (p_c) is compared with a random number in [0, 1] to determine if the crossover operation should be carried out or not on each solution. If the random number is less than or equal to the crossover probability then crossover operation is applied on each variable of two parent solutions selected from the mating pool to produce two offspring solutions. These two offspring solutions are then stored in the new child population. If the random number is greater than the crossover probability then the crossover operation is not carried out and the solution in the mating pool is simply copied over to the new child population.
4. Apply mutation on the solutions in the new child population Q_g. For each variable in each solution of the new child population the following steps are performed. The mutation probability (p_m) is compared with a random number in [0, 1] to determine if the mutation operation should be carried out or not on the current variable. If the random number is less than or equal to the mutation probability then mutation operation is applied on the variable. The fitness of the generated child population is then analyzed using the earlier described steps of Phase 2 to obtain the values of the selected multi-objectives.
5. Combine child population Q_g and parent population P_g to form a new combined population R_g of size $2N$. This combined population acts as a vehicle for the

elitism, where good solutions of the initial parent population are passed on to the following generation to avoid the loss of good solutions of the initial parent population once they are found.

6. Calculate non-domination rank *(i_{rank})* and crowding distance *($i_{distance}$)* for each solution (s = 1 to 2N) of the newly created combined population R_g. This step will perform the same operations as Step 1 of this phase on the new combined population R_g.
7. Sort the new combined population R_g using the fast non-dominated sorting procedure. This sorting rule selects solutions with higher non-domination ranks and breaks ties between solutions with the same rank by favoring solutions with higher crowding distances.
8. Keep the top N solutions from the combined population R_g to form the parent population P_{g+1} of the next generation. This parent population is then returned to Step 1 of this phase for generating a new child population as shown in Figure 4.11. This iterative execution of the second and third phases of the model continues until the specified number of generations is completed.

Due to the unique characteristics of each construction project, the main contribution of the model developed in this research arises in integrating the issues of both resource leveling and allocation while considering the contractor's cash flow for multiple projects. Such integration enables construction companies in solving simultaneously the problems of how to prioritize the projects with resource conflicts, how to reasonably allocate the limited resources among multiple projects to meet the resource requirements of different projects, how to minimize the undesirable resource fluctuations while maximizing the profit under certain cash limits.

CHAPTER 5: IMPLEMENTATION, TESTING, RESULTS AND ANALYSIS

As previously mentioned, the developed model gives the flexibility of selecting the objectives required to be optimized simultaneously. Thus, the model can solve individually the time/cost tradeoff, resource leveling, resource allocation, or finance-based scheduling problems. Alternatively, integration of such problems can be also solved. This chapter is divided into two main sections. The first section shows the implementation of the developed model to test it on three examples retrieved from literature to solve a time/cost tradeoff problem, integrated time/cost tradeoff and resource allocation problem, and a finance-based scheduling problem. Consequently, the obtained results are compared with the previous studies to validate the model. The second section illustrates the use of the developed model and demonstrates its capabilities by applying it on three case studies to solve integrated resource leveling, resource allocation, and finance-based scheduling problems for single and multiple projects.

5.1 MODEL TESTING

Three tests are carried to validate and verify the efficiency of the developed model in obtaining optimal/near optimal solutions to solve a time/cost tradeoff problem, integrated time/cost tradeoff and resource allocation problem, and a finance-based scheduling problem.

5.1.1 Test (1): Time/Cost Tradeoff Problem

To test the performance of the developed model in solving time/cost tradeoff problems, the test example of Feng et al. (1997) is used. The example consists of 18 construction activities, where each has a number of possible resource utilization modes that can be used to construct the activity as shown in Table 5.1.

Table 5.1: Data for Test (1) (adapted from Feng et al. 1997)

Activity	Predecessor(s)	Mode 1		Mode 2		Mode 3		Mode 4		Mode 5	
		Duration (days)	Cost ($)	Duration (days)	Cost ($)	Duration (days)	Cost ($)	Duration (days)	Cost ($)	Duration (days)	Cost ($)
1	-	24	1200	21	1500	16	1900	15	2150	14	2400
2	-	25	1000	23	1500	20	1800	18	2400	15	3000
3	-	33	3200	22	4000	15	4500	-	-	-	-
4	-	20	30000	16	35000	12	45000	-	-	-	-
5	1	30	10000	28	15000	24	17500	22	20000	-	-
6	1	24	18000	18	32000	14	40000	-	-	-	-
7	5	18	22000	15	24000	9	30000	-	-	-	-
8	6	24	120	21	208	16	200	15	215	14	220
9	6	25	100	23	150	20	180	18	240	15	300
10	2,6	33	320	22	400	15	450	-	-	-	-
11	7,8	20	300	16	350	12	450	-	-	-	-
12	5,9,10	30	1000	28	1500	24	1750	22	2000	-	-
13	3	24	1800	18	3200	14	4000	-	-	-	-
14	4,10	18	2200	15	2400	9	3000	-	-	-	-
15	12	16	3500	12	4500	-	-	-	-	-	-
16	13,14	30	1000	28	1500	24	1750	22	2000	20	3000
17	11,14,15	24	1800	18	3200	14	4000	-	-	-	-
18	16,17	18	2200	15	2400	9	3000	-	-	-	-

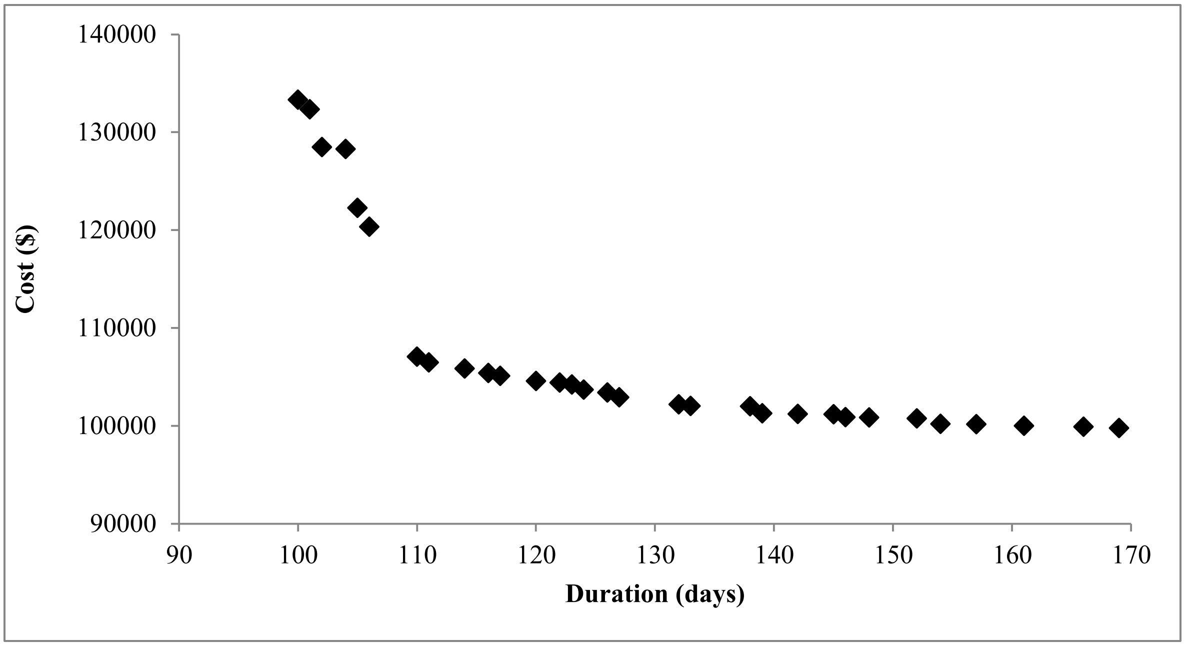
Since this example is a pure time/cost tradeoff problem, the considered decision variable will be only the resource utilization mode. The objectives selected to be optimized (minimized) will be the “total duration and total cost”. Multiplying the number of resource utilization modes in each of the 18 activities by each other will result in around 5.9 billion possible combinations for delivering the entire project. Each of these possible combinations leads to a unique impact on project performance, and the main challenge here is to search this large search space to find solutions that establish an optimal tradeoff between construction time and cost.

The developed multi-objective optimization model is used to search this large space of possible solutions. The model was able to significantly reduce this large space by precluding dominated solutions in the successive generations of the GA, using the Pareto optimality principles as explained before. This led to the selection of 31 Pareto optimal (i.e. non-dominated) solutions for this example as shown in Table 5.2. Each of these solutions identifies an optimal resource utilization mode for each of the 18 construction activities and, accordingly, it provides a unique and optimal tradeoff between project time and cost.

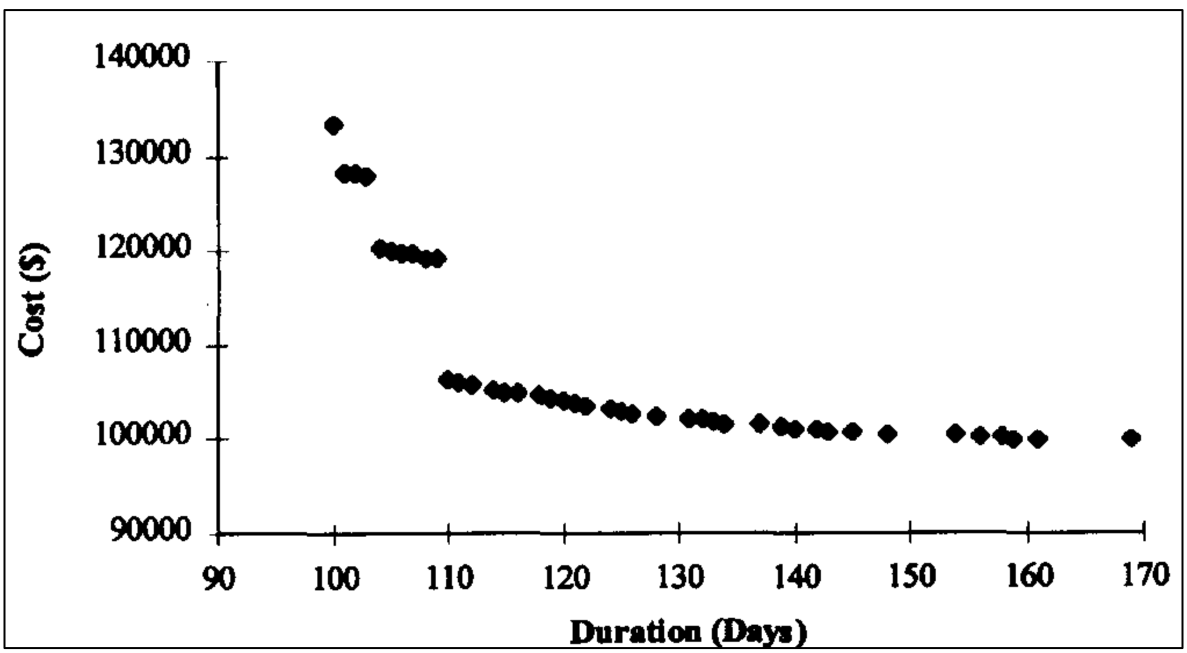
In order to validate the results provided by the current model, they are compared to those reported in the literature for the same application example (Feng et al. 1997). The comparison confirms that the current model is capable of generating almost the same set of optimal solutions as those reported by Feng et al. (1997) for the time/cost tradeoff problem as shown in Figure 5.1. The figure shows a slight difference between the obtained solutions of the two models due to the GA’s randomness nature in searching for optimal/near optimal solutions.

Table 5.2: Optimum Solutions for Test (1)

Solution #	**Duration (days)**	**Cost ($)**	**Selected Resource Utilization Mode for Activity #**																	
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
1	100	133318	5	1	1	1	2	3	1	1	5	3	2	4	1	1	2	1	3	3
2	161	99967	1	1	1	1	1	1	1	5	1	3	1	1	1	1	1	1	1	1
3	106	120318	4	1	1	1	1	2	1	5	5	3	1	4	1	2	2	1	3	3
4	169	99738	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	114	105848	5	2	1	1	1	1	1	3	5	3	1	4	1	1	1	1	3	3
6	101	132316	5	3	2	1	1	3	2	5	5	3	3	4	1	2	2	1	3	3
7	152	100748	1	1	1	1	1	1	1	3	1	3	1	1	1	1	1	1	1	3
8	111	106467	4	1	1	1	1	1	1	5	5	3	3	4	1	2	2	1	3	3
9	105	122262	4	1	1	1	1	2	2	4	5	3	3	4	1	1	2	1	3	3
10	110	107047	5	2	1	1	1	1	1	3	5	3	1	4	1	2	2	1	3	3
11	148	100828	1	1	1	1	1	1	1	3	3	3	1	1	1	1	1	1	1	3
12	145	101167	2	1	1	1	1	1	1	1	5	3	1	1	1	1	1	1	1	3
13	123	104198	2	1	1	1	1	1	1	3	5	3	1	3	1	1	1	1	3	3
14	142	101198	2	1	1	1	1	1	1	3	5	3	1	3	1	1	1	1	1	1
15	127	102898	5	1	1	1	1	1	1	3	5	3	1	3	1	1	1	1	1	3
16	122	104397	5	2	1	1	1	1	1	3	5	3	1	3	1	1	2	1	1	3
17	139	101247	2	1	1	1	1	1	1	3	5	3	1	1	1	1	1	1	1	3
18	138	101967	1	1	1	1	1	1	1	5	5	3	1	1	1	1	2	1	1	3
19	154	100167	1	1	1	1	1	1	1	5	5	3	1	1	1	1	1	1	1	1
20	124	103662	5	2	1	1	1	1	1	4	5	3	1	4	1	1	1	1	1	3
21	120	104567	5	2	1	1	1	1	1	1	5	3	1	4	1	1	2	1	1	3
22	117	105098	5	1	1	1	1	1	1	3	5	3	1	3	1	1	1	1	3	3
23	126	103398	5	2	1	1	1	1	1	3	5	3	1	3	1	1	1	1	1	3
24	132	102167	5	1	1	1	1	1	1	5	5	3	1	1	1	1	1	1	1	3
25	157	100148	1	1	1	1	1	1	1	3	5	3	1	1	1	1	1	1	1	1
26	133	101998	2	1	1	1	1	1	1	3	5	3	1	3	1	1	1	1	1	3
27	104	128261	4	1	1	1	1	3	1	4	5	3	3	4	1	1	2	1	3	3
28	146	100868	1	1	1	1	1	1	1	1	5	3	1	1	1	1	1	1	1	3
29	116	105362	5	1	1	1	1	1	1	4	5	3	1	4	1	1	1	1	3	3
30	102	128467	4	1	1	1	1	3	1	5	5	3	3	4	1	2	2	1	3	3
31	166	99898	1	1	1	1	1	1	1	1	3	2	1	1	1	1	1	1	1	1



(a) Current Model Results



(b) Feng et al. (1997) Results

Figure 5.1: Pareto-optimal Time/Cost Tradeoff Curve for Test (1)

5.1.2 Test (2): Integrated Time/Cost Tradeoff and Resource Allocation Problem

The second test is carried using a test example retrieved from Leu and Yang (1999) who developed a multi-objective GA-based optimization model to perform a time/cost tradeoff analysis under unconstrained and constrained-resource conditions. The example consists of nine activities and three resource types required by each activity as shown in Table 5.3. Each activity has from one to four possible number of resource utilization modes that can be used to construct the activity. For the resource-constrained condition, the maximum limit of each resource was assumed to be 10.

Table 5.3: Data for Test (2) (adapted from Leu and Yang 1999)

Activity		**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
Predecessor(s)		-	A	B,D	A	D,F	A	F	C,E	E,G,H
MODE 1	**Duration (days)**	6	9	13	15	14	19	14	8	9
	Cost ($)	300	450	600	420	1050	2000	1200	640	560
	Resource 1 (crew/day)	3	4	3	5	1	3	3	6	5
	Resource 2 (crew/day)	4	5	6	2	5	1	2	3	5
	Resource 3 (crew/day)	5	2	5	4	2	1	5	2	5
MODE 2	**Duration (days)**	5	-	12	-	13	18	13	7	-
	Cost ($)	480	-	850	-	1450	2600	1900	950	-
	Resource 1 (crew/day)	5	-	4	-	1	4	3	6	-
	Resource 2 (crew/day)	4	-	6	-	5	2	3	4	-
	Resource 3 (crew/day)	5	-	6	-	4	2	6	3	-
MODE 3	**Duration (days)**	-	-	-	-	12	17	-	-	-
	Cost ($)	-	-	-	-	1860	3220	-	-	-
	Resource 1 (crew/day)	-	-	-	-	1	5	-	-	-
	Resource 2 (crew/day)	-	-	-	-	5	3	-	-	-
	Resource 3 (crew/day)	-	-	-	-	6	3	-	-	-
MODE 4	**Duration (days)**	-	-	-	-	-	16	-	-	-
	Cost ($)	-	-	-	-	-	3860	-	-	-
	Resource 1 (crew/day)	-	-	-	-	-	6	-	-	-
	Resource 2 (crew/day)	-	-	-	-	-	4	-	-	-
	Resource 3 (crew/day)	-	-	-	-	-	4	-	-	-

The problem is solved twice using the developed optimization model. Once for the unconstrained-resource condition (i.e. pure time/cost tradeoff) and the other for the constrained-resource condition (i.e. integrated time/cost tradeoff and resource allocation). For the "unconstrained-resource" condition the considered decision variable will only be the resource utilization mode of each activity. On the other hand, the considered decision variables will be both the start time and resource utilization mode of each activity for the "constrained-resource" condition. The objectives selected to be optimized (minimized) will be the "total duration and total cost" and "total duration, total cost, and resource fluctuation and peak demand" for the unconstrained and constrained-resource conditions, respectively. The "resource fluctuation and peak demand" objective is calculated either by using Equation 3.18a or 3.18b. Since this example focuses on resource allocation only, therefore, the maximum resource demand weight factor (W_2) is assigned a value of 1 while W_1 is assigned a value of 0 for the constrained-resource condition. Moreover, the resource limit constraint was assigned to be equal to 10 for the constrained-resource condition.

The results obtained by the current model were identical to those of Leu and Yang (1999) as presented in Tables 5.4 and 5.5 for the unconstrained and constrained-resource conditions, respectively. Figure 5.2 shows the Pareto-optimal solutions obtained by Leu and Yang (1999) and the current model for the unconstrained and constrained-resource conditions. The Pareto-optimal front under unconstrained-resource condition comprised eight solutions of durations ranging between 56 and 49 days and costs ranging between \$7,220 and \$10,380, whereas the Pareto-optimal front under constrained-resource conditions comprised five solutions of durations ranging between 65 and 61 days and costs ranging between $7,220 and $8,960. The comparison of the current model results against those of Leu and Yang (1999) proves the validity of the current model in solving scheduling problems of multimode activities using multi-resources.

Table 5.4: Optimum Solutions for Test (2) – Unconstrained Resource

Solution	**Duration (days)**	**Cost ($) (Current Model)**	**Cost ($) (Leu and Yang 1999)**	**Resource 1**	**Resource 2**	**Resource 3**
1	49	10,380	10,380	15	13	16
2	50	9,740	9,740	14	13	16
3	51	9,120	9,120	13	13	16
4	52	8,520	8,520	12	13	16
5	53	8,110	8,110	12	13	14
6	54	7,710	7,710	12	13	12
7	55	7,400	7,400	12	13	12
8	56	7,220	7,220	12	13	12

Table 5.5: Optimum Solutions for Test (2) – Constrained Resource

Solution	**Duration (days)**	**Cost ($) (Current Model)**	**Cost ($) (Leu and Yang 1999)**	**Resource 1**	**Resource 2**	**Resource 3**
1	61	8,960	8,960	9	8	9
2	62	8,110	8,110	9	7	9
3	63	7,710	7,710	9	7	7
4	64	7,400	7,400	9	7	7
5	65	7,220	7,220	9	7	7

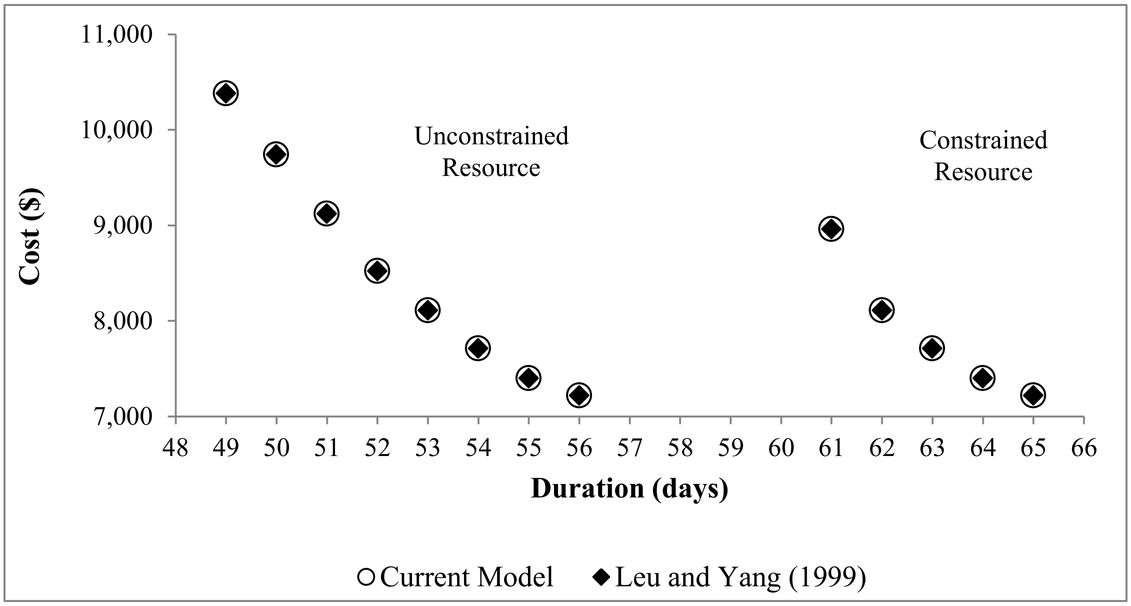


Figure 5.2: Pareto-optimal Time/Cost Tradeoff Curves for Test (2)

5.1.3 Test (3): Finance-Based Scheduling Problem

The final test carried for the current developed model is by applying it on five CPM networks of 12, 24, 36, 48 and 60 activities retrieved from Elazouni (2009) for solving finance-based scheduling problems. These five networks were solved by Elazouni (2009) using the IP technique to find the exact solutions or schedules that minimize the duration under credit limit constraints. For the purpose of validation, the results constitute the project durations obtained by the IP technique (Elazouni 2009) and the current model. Figure 5.3 shows the CPM network of a project consisting of 12 activities with four activities (A, B, C and D) being implemented over three sections (a, b and c). The 24, 36, 48 and 60-activity projects repeat the same four activities of the 12- activity project for 2, 3, 4 and 5 times, respectively. For instance, the 24-activity project repeats the same four activities A, B, C and D over three more identical sections (d, e and f). For example, activities Ba, Bb and Bc are duplicated to activities Bd, Be and Bf with the same respective durations such that Bd depends on Bc and Ad; Be depends on Bd and Ae; and Bf depends on Be and Af.

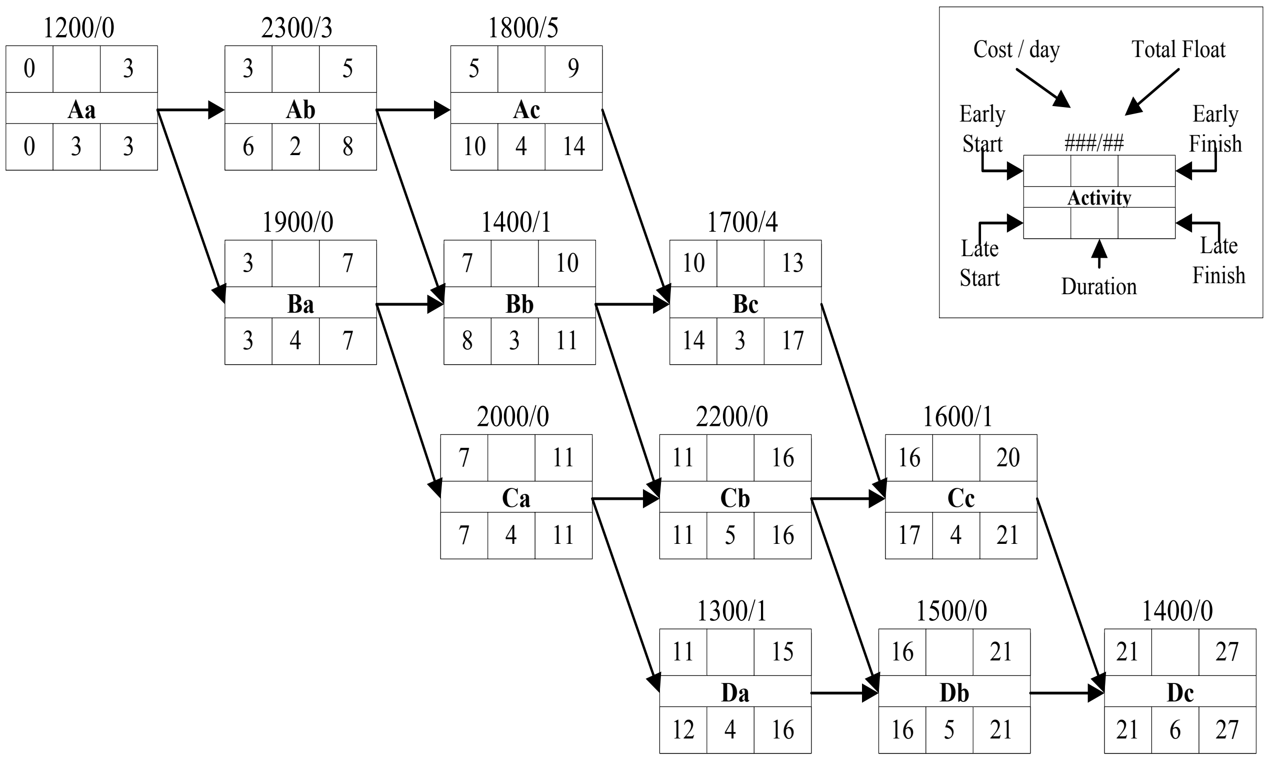


Figure 5.3: Twelve-Activity Project Network

The overhead costs of each project are considered as \$3500 per week. A mark-up of 20% is applied to the total weekly summation of cash outflows and the overheads. The owner's progress payments (cash inflows) are obtained one week after the submission of the weekly pay requests, with no advance payment considered. A financing rate of 1.5% per week was considered. The retention percentage of each cash inflow amounts to 16% and the retained money is to be paid eight weeks after the completion of the projects.

For each network, three credit limits are set and the main objective is to achieve an optimal/near optimal schedule that does not exceed such limits. As shown in Table 5.6, the original maximum required credit for each network is much higher than the set credit limits. Thus, extension of the project's original duration for each network may be sometimes essential in order to achieve the desired credit limits. The main challenge here is to minimize such extensions.

Table 5.6: Optimum Solutions for Test (3)

Network	Original Duration (days)	Original Max. Required Credit ($)	Credit Limits ($)	Total Duration (days)		Max. Required Credit ($) (Current Model)
				Elazouni (2009)	Current Model	
12 Activities	27	50,272.90	40,000	29	29	38,720.74
			37,000	32	32	36,602.34
			32,000	35	35	31,869.74
24 Activities	42	70,394.90	55,000	43	43	54,050.93
			50,000	46	46	49,377.65
			43,000	52	52	42,316.50
36 Activities	57	75,238.30	58,000	58	59	57,695.75
			54,000	62	62	53,339.99
			50,000	66	66	49,659.09
48 Activities	72	77,751.60	58,000	75	75	57,372.61
			56,000	77	77	55,813.01
			53,000	82	82	52,984.73
60 Activities	87	79,417.23	63,000	87	88	62,591.09
			58,000	93	93	57,885.75
			57,000	94	94	56,994.29

As a result, the objective selected to be optimized (minimized) using the current model will be the "total duration" under different credit limits constraints. The decision variable in this example will be the start time of the activities. Table 5.6 indicates clearly that the results of the current developed model are very comparable to the results of Elazouni (2009). The difference in the total duration amounted to only one day less in favor of the IP technique used by Elazouni (2009) in only two cases out of the 15 cases.

5.2 MODEL DEMONSTRATION

The developed optimization model is applied on three case studies to demonstrate its different optimization capabilities. The first case study is implemented to solve integrated resource leveling and finance-based scheduling for a small single project. Whereas, the second and third case studies are implemented to solve integrated resource leveling, resource allocation, and finance-based scheduling for multiple projects.

5.2.1 Case Study (1): 9-Activity Single Project

The same nine activity single project adopted from Leu and Yang (1999) for the second test (see section 5.1.2) is used herein as the first case study. The problem was originally solved as time/cost tradeoff analysis under unconstrained and constrained resource conditions. However, for demonstration purposes, the problem is to be solved this time considering financial aspects together with resource aspects. Table 5.7 shows the financial and contractual data assumed for the original example project to consider the financial aspects.

Table 5.7: Financial and Contractual Data (Case Study 1)

Data Type	Item	Value
FINANCIAL	**Interest Rate % per Week**	0.80%
	Overheads %	15%
	Mobilization Costs %	10%
	Tax %	2%
	Mark-Up %	10%
	Bond Premium %	1%
CONTRACT TERMS	**Advance Payment % of Bid Price**	5%
	Weeks to Retrieve Advance Payment	[a]
	Retained % of Pay Requests	5%
	Lag to Pay Retained Money After Last Payment (weeks)	0
	Weeks to Submit Pay Requests Regularly	1
	Lag to Pay Payment Requests (weeks)	1

[a] Number of weeks encompassing the total project duration

Unlike the traditional tradeoff problems in the literature, which exclusively consider the selection of the activities' execution or resource utilization modes, the current application considers the specification of the activities start times as well as the selection of activities' execution modes as the two main decision variables. Resource leveling is only considered in this case study by using the resource idle days (RID) leveling metric. Thus, the "resource fluctuation and peak demand" objective will be determined using Equation 3.18b. However, the RID weight factor (W_1) will be assigned a value of 1 while the MRD weight factor (W_2) will be assigned a value of 0. In other words, objective number 5 presented in the model formulation section in Chapter 3 (section 3.4.2) can be entitled as RID for this case study. Accordingly, the available objectives to be optimized for this case study will be as follows:

- Total Duration (TD)
- Total Cost (TC)
- Financing Cost (FC)

- Maximum Required Credit (RC)
- Profit (PR)
- Resource Idle Days for resource type 1 (RID1)
- Resource Idle Days for resource type 2 (RID2)
- Resource Idle Days for resource type 3 (RID3)

All of the above eight objectives are to be minimized except for the profit (PR) which is to be maximized. As a starting point, a number of runs of single-objective optimization is done to optimize these objectives individually. The achieved optimized objectives' value from the single-objective optimization runs is shown in Table 5.8.

Table 5.8: Single-Objective Optimization Results (Case Study 1)

Objective	Optimized Value
TD (days)	49
TC ($)	9,421.5
FC ($)	101.8
RC ($)	2,137.9
PR ($)	1,189.5
RID1	0
RID2	0
RID3	0

The second step is to carry different runs of two-objectives optimization to obtain different tradeoffs between two selected objectives at a time. The number of combinations (tradeoffs) between each two objectives is determined using Equation 5.1.

$$Combinations = \frac{n!}{(n-r)!\,(r!)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (5.1)$$

Where, n = total number of objectives; and r = number of selected objectives. Based on that, 28 different tradeoffs (combinations) can be obtained considering having a total number of eight objectives (n) and two objectives to be selected at a time (r).

The main benefit of this step is to identify the relationship between each two objectives set. Each relationship identifies if the two selected objectives are conflicting or not. It is actually impractical to consider all of the listed eight objectives to be optimized simultaneously. Such identification allows the selection of the required objectives to be optimized simultaneously. Another benefit can be for the contractor in which he/she can examine the effect of one objective over the other on the project performance. The current developed model has the flexibility to select and consider any number of objectives to be optimized simultaneously.

Table 5.9 shows the results of the carried 28 tradeoffs for two-objective optimization. The table summarizes the 28 optimized tradeoffs. The tradeoffs are divided into eight types of solutions that minimize the TD, TC, FC, RC, RID1, RID2, and RID3 and maximize the PR. For instance, the TD objective is optimized seven times, i.e. with the TC, FC, RC, PR, RID1, RID2, and RID3. Each time, the TD was globally minimized to 49 days and the corresponding optimized objective values were \$12,460.6, \$125.8, \$3,543.1, \$1,189.5, 12, 1, and 0 for the TC, FC, RC, PR, RID1, RID2, and RID3, respectively. As it can be seen in Table 5.9, the global optimized values for the TC, FC, RC, PR, RID1, RID2, and RID3 objectives were \$9,421.5, \$101.8, \$2,137.9, \$1,189.5, 0, 0, and 0, respectively. Thus, for this type of solution (minimum TD solution), the objectives TC, FC, RC, RID1, and RID2 were optimized but not globally optimized. On the other hand, the objectives PR and RID3 were globally optimized together with the minimum achieved TD. This indicates that TD is not conflicting with PR and RID3. It is worth to mention that achieving the minimum TD simultaneously with the minimum RID3 is a specific and not generic case based on the number of daily resource demand for resource type 3 of this problem. Moreover, it should be noted that the model developed in this research does not take into account the additional cost of the resource idle days. When considering the tradeoff between PR and RID1, it can be shown in Table 5.9 that a globally minimized RID1= 0 can be achieved at a PR = \$ 1188.6. On the other hand, a globally maximized PR = \$ 1189.5 can be achieved at a RID1 = 5. Thus, it would not be feasible for the contractor to keep his/her resource type 1 idle for five days to achieve just an extra \$ 0.9 profit. Accordingly, the cost of resource idle days should be considered in the financial calculation process to avoid such confusion in interpreting the tradeoff results.

Figure 5.4 shows the 28 tradeoff curves. The relationships comply with what was discussed earlier in Chapter 3 (section 3.3) except for the FC-PR or TC-PR relation. It was mentioned in Chapter 3 that the FC-PR relation is inversely proportional while in this case study the relation is directly proportional. In fact, both relations are correct, however, they are problem dependent. The first relation (inversely proportional) applies when the project is extended beyond its original duration. Such extension results in an increased overhead costs and liquidated damages that increases the financing cost (FC) and eventually decreases the profit (PR) since such additional costs were not originally included in the contractor's mark-up. As for this case study, no extension increment was applied beside that the problem consists of multi-mode activities. Assuming that all activities are assigned a utilization mode having the lowest duration will result in having the highest total cost and consequently the highest financing cost. This highest total cost is originally taken into consideration when calculating the contractor's mark-up since it falls within the original duration. Thus – considering a unit price contract - as the total cost increases the mark-up increases resulting in a higher profit and vice versa.

Table 5.9: Two-Objectives Optimization Results (Case Study 1)

SOLUTION TYPE	TRADEOFF BETWEEN	TD	TC	FC	RC	PR	RID1	RID2	RID3
min TD	**TD**		49 / 12460.6	49 / 125.8	49 / 3543.1	49 / 1189.5	49 / 12	49 / 1	49 / 0
min TC	**TC**	9421.5 / 56		9421.5 / 101.8	9421.5 / 2276.9	9421.5 / 821.2	9421.5 / 5	9421.5 / 10	9421.5 / 4
min FC	**FC**	101.8 / 56	101.8 / 9421.5		101.8 / 2407.8	101.8 / 821.2	101.8 / 14	101.8 / 50	101.8 / 40
min RC	**RC**	2137.9 / 56	2137.9 / 10175.2	2137.9 / 117.0		2137.9 / 779.9	2137.9 / 65	2137.9 / 27	2137.9 / 26
max PR	**PR**	1189.5 / 49	1189.5 / 13429.4	1189.5 / 134.2	1189.5 / 3844.8		1189.5 / 5	1189.5 / 40	1189.5 / 26
min RID1	**RID1**	0 / 50	0 / 10980.5	0 / 112.0	0 / 3010.4	0 / 1188.6		0 / 12	0 / 21
min RID2	**RID2**	0 / 51	0 / 11950.4	0 / 122.4	0 / 3569.6	0 / 1053.2	0 / 44		0 / 7
min RID3	**RID3**	0 / 49	0 / 9675.5	0 / 108.5	0 / 2354.0	0 / 1185.8	0 / 31	0 / 1	

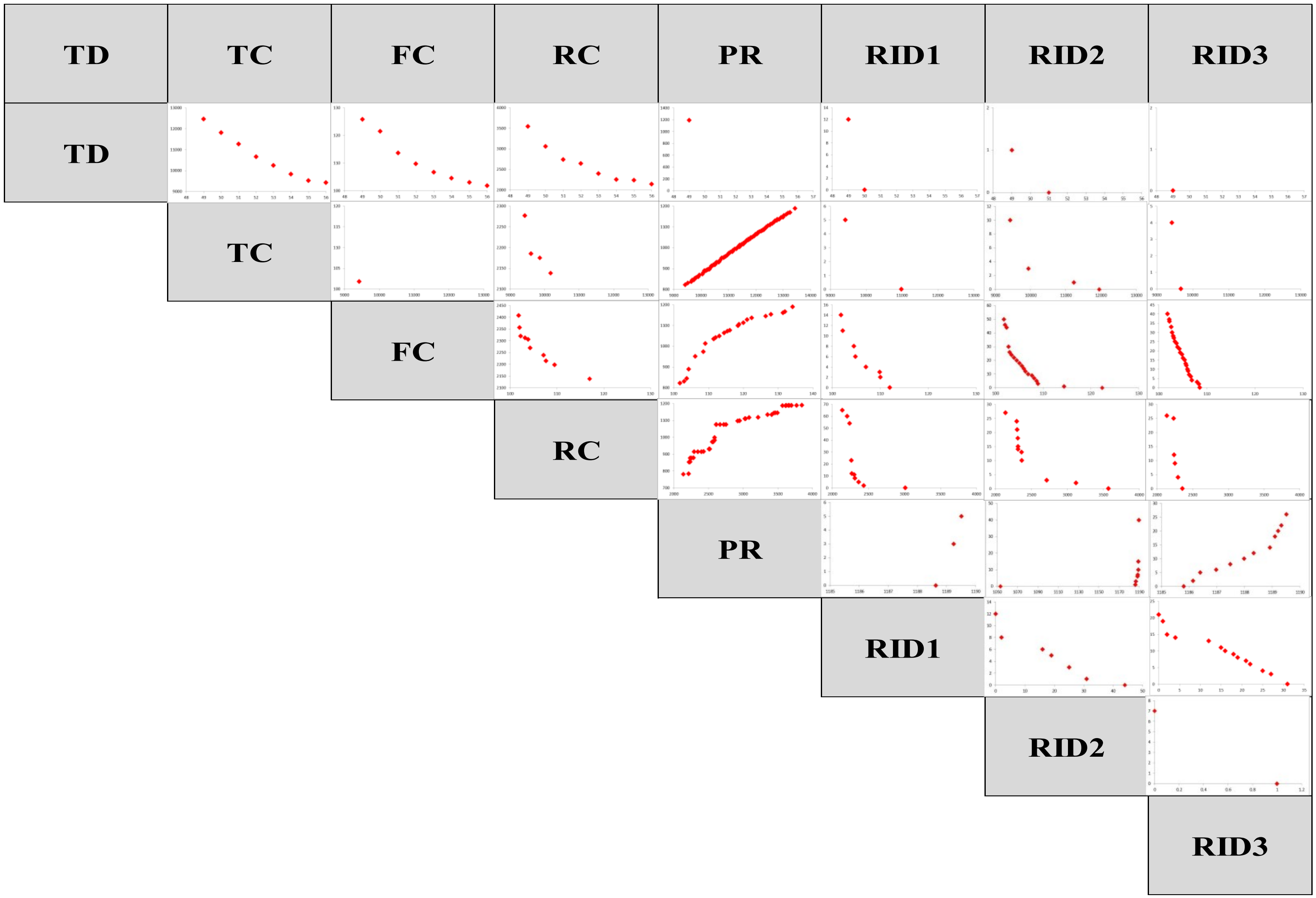


Figure 5.4: Two-Objectives Optimization Tradeoff Curves

Using Figure 5.4, the identified set of non-conflicting objectives are as shown in Table 5.10. Those sets help in determining the possible combinations of conflicting objectives to be optimized together in case more than two objectives are considered for simultaneous optimization. It should be noted that identified set of non-conflicting objectives shown in Table 5.10 are specific cases and may vary from project to another as discussed earlier in Chapter 3. For instance, assume optimizing the following set of objectives together:

{TD, FC, RC, PR, and RID3}

It will be meaningless to consider the TD with both PR and RID3 under the same set. Thus, there can be several options to consider. One of those options can be considering optimizing the TD, FC, and RC together and disregarding both PR and RID3. In other words, achieving the minimum TD will eventually achieve the minimum RID3 and maximum PR. Based on that, the main possible tradeoff combinations between all the objectives together can be summarized as shown in Table 5.11.

Table 5.10: Set of Non-Conflicting Objectives

Set #	Non-Conflicting Objectives
1	TD and PR
2	TD and RID3
3	TC and FC

Table 5.11: Main-Tradeoff Combination Sets

Main Tradeoff Set	Tradeoff Between	Disregarded Objectives
A	TD-TC-RC-RID1-RID2	PR, RID3 *due to non-confliction with* TD FC *due to non-confliction with* TC
B	TD-FC-RC-RID1-RID2	PR, RID3 *due to non-confliction with* TD TC *due to non-confliction with* FC
C	TC-RC-PR-RID1-RID2-RID3	TD *due to non-confliction with* PR, RID3 FC *due to non-confliction with* TC
D	FC-RC-PR-RID1-RID2-RID3	TD *due to non-confliction with* PR, RID3 TC *due to non-confliction with* FC

The tradeoffs shown in Table 5.11 focus on taking the possible maximum number of non-conflicting objectives to be optimized together. However, more other tradeoffs can be established by considering only three, four, or five objectives to be simultaneously optimized depending on the decision maker's concerns regarding specific objectives. For example, using the combinations and permutations concept, the main-tradeoff set (A) (which consists of five objectives) in Table 5.11 can create ten and five sub-tradeoff sets in which each consists of three and four different objectives, respectively. Thus, a total of 82 unique sub-tradeoff sets varying between three to five objectives are established as shown in Table 5.12. Having the 82 sub-tradeoff sets as well as the 28-two-objectives tradeoff sets (Figure 5.4) and the 4 main tradeoff sets (Table 5.11) will result in a total 114 unique tradeoff sets varying from two to six objectives. This gives the contractor a wide range of tradeoff options to examine based on his/her desired objectives to be optimized. Generally, the achievement of adequate profit is very essential for construction business sustainability. Moreover, fluctuations of resources are undesirable for the contractor as it is expensive to hire and fire labor on a short term basis to satisfy fluctuating resource requirements. Also, controlling the credit limit helps contractors to avoid progressive cash deficit which can result in difficulties to stick with the planned schedule. Therefore, balancing these three parameters (i.e. required credit, profit, and resource fluctuations) is crucial to ensure the achievement of project objectives. Accordingly, for this case study, the tradeoff set option "C-36" (i.e. RC, PR, RID1, RID2, and RID3) in Table 5.12 is considered to be optimized using the developed model.

Table 5.12: Main and Sub-Tradeoff Combination Sets

Main Tradeoff Set #	No. of Objectives	Tradeoff Between	Sub Tradeoff Set #	No. of Objectives	Tradeoff Between
A	5	TD-TC-RC-RID1-RID2	1	3	TD,TC,RC
			2	3	TD,TC,RID1
			3	3	TD,TC,RID2
			4	3	TD,RC,RID1
			5	3	TD,RC,RID2
			6	3	TD,RID1,RID2
			7	3	TC,RC,RID1
			8	3	TC,RC,RID2
			9	3	TC,RID1,RID2
			10	3	RC,RID1,RID2
			11	4	TD,TC,RC,RID1
			12	4	TD,TC,RC,RID2
			13	4	TD,TC,RID1,RID2
			14	4	TD,RC,RID1,RID2
			15	4	TC,RC,RID1,RID2
B	5	TD-FC-RC-RID1-RID2	1	3	TD,FC,RC
			2	3	TD,FC,RID1
			3	3	TD,FC,RID2
			4	3	FC,RC,RID1
			5	3	FC,RC,RID2
			6	3	FC,RID1,RID2
			7	4	TD,FC,RC,RID1
			8	4	TD,FC,RC,RID2
			9	4	TD,FC,RID1,RID2
			10	4	FC,RC,RID1,RID2
C	6	TC-RC-PR-RID1-RID2-RID3	1	3	TC,RC,PR
			2	3	TC,RC,RID3
			3	3	TC,PR,RID1
			4	3	TC,PR,RID2
			5	3	TC,PR,RID3
			6	3	TC,RID1,RID3
			7	3	TC,RID2,RID3

Table 5.12: Main and Sub-Tradeoff Combination Sets (Continued)

Main Tradeoff Set #	No. of Objectives	Tradeoff Between	Sub Tradeoff Set #	No. of Objectives	Tradeoff Between
C	6	TC-RC-PR-RID1-RID2-RID3	8	3	RC,PR,RID1
			9	3	RC,PR,RID2
			10	3	RC,PR,RID3
			11	3	RC,RID1,RID3
			12	3	RC,RID2,RID3
			13	3	PR,RID1,RID2
			14	3	PR,RID1,RID3
			15	3	PR,RID2,RID3
			16	3	RID1,RID2,RID3
			17	4	TC,RC,PR,RID1
			18	4	TC,RC,PR,RID2
			19	4	TC,RC,PR,RID3
			20	4	TC,RC,RID1,RID3
			21	4	TC,RC,RID2,RID3
			22	4	TC,PR,RID1,RID2
			23	4	TC,PR,RID1,RID3
			24	4	TC,PR,RID2,RID3
			25	4	TC,RID1,RID2,RID3
			26	4	RC,PR,RID1,RID2
			27	4	RC,PR,RID1,RID3
			28	4	RC,PR,RID2,RID3
			29	4	RC,RID1,RID2,RID3
			30	4	PR,RID1,RID2,RID3
			31	5	TC,RC,PR,RID1,RID2
			32	5	TC,RC,PR,RID1,RID3
			33	5	TC,RC,PR,RID2,RID3
			34	5	TC,RC,RID1,RID2,RID3
			35	5	TC,PR,RID1,RID2,RID3
			36	5	RC,PR,RID1,RID2,RID3
D	6	FC-RC-PR-RID1-RID2-RID3	1	3	FC,RC,PR
			2	3	FC,RC,RID3
			3	3	FC,PR,RID1
			4	3	FC,PR,RID2
			5	3	FC,PR,RID3
			6	3	FC,RID1,RID3
			7	3	FC,RID2,RID3
			8	4	FC,RC,PR,RID1
			9	4	FC,RC,PR,RID2
			10	4	FC,RC,PR,RID3
			11	4	FC,RC,RID1,RID3
			12	4	FC,RC,RID2,RID3
			13	4	FC,PR,RID1,RID2
			14	4	FC,PR,RID1,RID3
			15	4	FC,PR,RID2,RID3
			16	4	FC,RID1,RID2,RID3
			17	5	FC,RC,PR,RID1,RID2
			18	5	FC,RC,PR,RID1,RID3
			19	5	FC,RC,PR,RID2,RID3
			20	5	FC,RC,RID1,RID2,RID3
			21	5	FC,PR,RID1,RID2,RID3

The results of the 9-activity network indicated that the obtained Pareto-optimal front representing the tradeoff of the five objectives included 125 unique optimal/near optimal solutions. All of the obtained 125 solutions are non-dominated where no solution is better than the other with respect to all of the five objectives. In case the contractor do not have a preference towards a certain objective over the other, then a fuzzy approach can be utilized to help the decision maker in selecting the best compromise solution/schedule. Due to the imprecise nature of the decision maker's judgment, the *i*th objective function O_i is represented by a membership function μ_i defined by Dhillon et al. (1993) as shown in Equations 5.2-5.4.

$$\mu_i = 1 \quad O_i \leq O_i^{min} \quad \text{(5.2)}$$

$$\mu_i = \frac{O_i^{max} - O_i}{O_i^{max} - O_i^{min}} \quad O_i^{min} < O_i < O_i^{max} \quad \text{(5.3)}$$

$$\mu_i = 0 \quad O_i \geq O_i^{max} \quad \text{(5.4)}$$

Where O_i^{min} and O_i^{max}= minimum and maximum value of the *i*th objective function among all non-dominated solutions, respectively. The membership function value ranges from 0 to 1. For each non-dominated solution *s*, the normalized membership function μ^s is calculated as shown in Equation 5.5.

$$\mu^s = \frac{\sum_{i=1}^{N_{obj}} \mu_i^s}{\sum_{s=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^s} \quad \text{(5.5)}$$

Where M = number of non-dominated solutions. The best compromise solution is that having the maximum value of μ^s.

Table 5.13 presents six remarkable solutions that exhibit the minimum required credit, maximum profit, minimum RID1, minimum RID2, minimum RID3, and the best compromise solution. Such results are obtained by assigning the GAs parameters to 500, 400, 80%, and 10% for the population size, number of generations, crossover probability, and mutation probability, respectively.

Table 5.13: Five-Objectives Remarkable Solutions (Case Study 1)

Solution Type	**RC ($)**	**PR ($)**	**RID1**	**RID2**	**RID3**	**TD (days)**
Minimum Required Credit (RC)	2,157.3	780.4	66	25	25	56
Maximum Profit (PR)	3,844.8	1,189.5	5	40	26	49
Minimum Resource Idle Days 1 (RID1)	2,564.2	934.4	0	17	31	54
Minimum Resource Idle Days 2 (RID2)	3,571.5	1,048.9	38	0	1	52
Minimum Resource Idle Days 3 (RID3)	2,689.9	1,011.9	62	15	0	55
Best Compromise	3,188.1	1,116.2	44	7	5	52

If the decision maker's absolute priority is to maximize profit, the solution of the maximum profit shown in Table 5.13 should be selected wherein the optimization algorithm selects activities' start times and execution modes to achieve the global maximum profit value of $1,189.5, and minimizes, but not globally minimizes, the required credit and resource fluctuation of the three resources. The minimized required credit of $3,844.8 in the solution of maximum profit is definitely higher than its global minimum value of $2,157.3 associated with the solution of minimum required credit shown in Table 5.13. Similarly, the minimized RID1, RID2, and RID3 values of 5, 40, and 26, respectively in the solution of maximum profit are definitely higher than their global minimum values of 0, 0, and 0 associated with the solution of minimum RID1, minimum RID2, and minimum RID3, respectively shown in Table 5.13. In addition to the solution of maximum profit, the optimization model provides 124 additional solutions, which represent the complete tradeoff between the required credit, profit, and resource fluctuation of the three resources. In each one of these solutions, the profit value is maximized but not globally maximized, the required credit is minimized but not globally minimized (except for the solution of minimum required credit), and the RID1, RID2, and RID3 are minimized but not globally minimized (except for the solution of minimum RID1, minimum RID2, and minimum RID3). As mentioned before, when there is no reason to favor a particular objective over the other, the best compromise solution can be selected to achieve a balance between the five objectives.

Figure 5.5 shows the normalized values of the resulted RC, PR, RID1, RID2, and RID3 objectives on five separate vertical axes. The straight lines connecting the normalized values of the objectives represent the 125 solutions comprising the tradeoff. The non-dominance condition is fulfilled by violating Equation 3.26, which is graphically evidenced in Figure 5.5 by the fact that each solution, represented by a broken line composed of segments, crosses at least one segment of another solution. In addition, Figure 5.5 shows that the values of the five objectives are well-distributed along the vertical axis indicating good diversifications of the solutions.

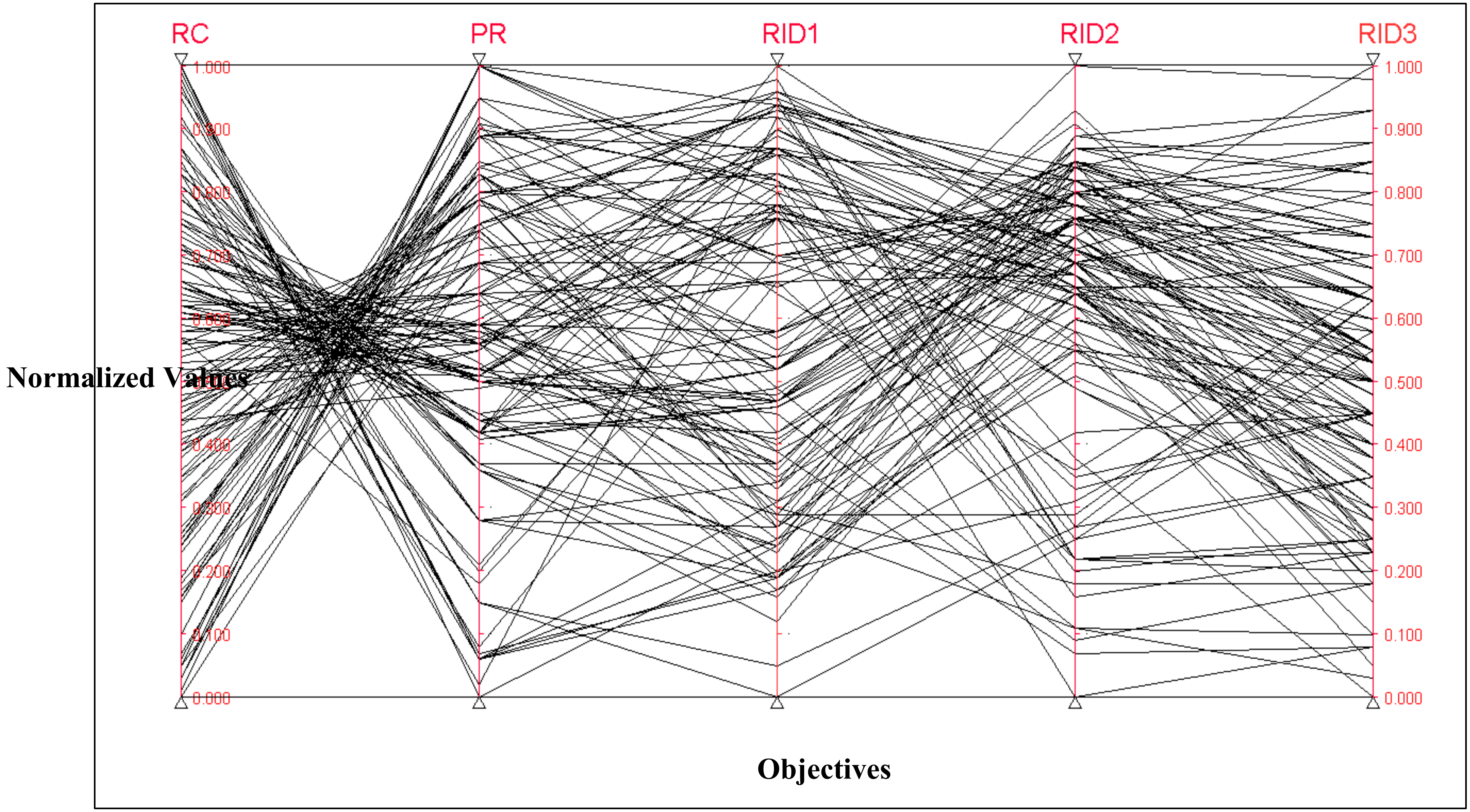


Figure 5.5: Five-Objectives Optimization Results (Case Study 1)

Figures 5.6, 5.7, and 5.8 show three-dimensional surface plot of the obtained 125 Pareto-optimal solutions for both RC and PR objectives versus the RID1, RID2, and RID3 objectives, respectively. Such three-dimensional representation of the identified solutions can be used to visualize the tradeoffs among the required credit, profit, and resource fluctuations in order to support decision makers in evaluating the impact of assigning various activities' start times and resource utilization modes on the project performance.

Finally, Table 5.14 summarizes the globally optimized values obtained for the RC, PR, RID1, RID2, and RID3 objectives by applying single-objective, two-objective, and five-objective optimizations. Comparison shows that the results of the five-objective optimization is identical to both single and two-objective optimizations with respect to PR, RID1, RID2, and RID3 objectives and very close with respect to RC.

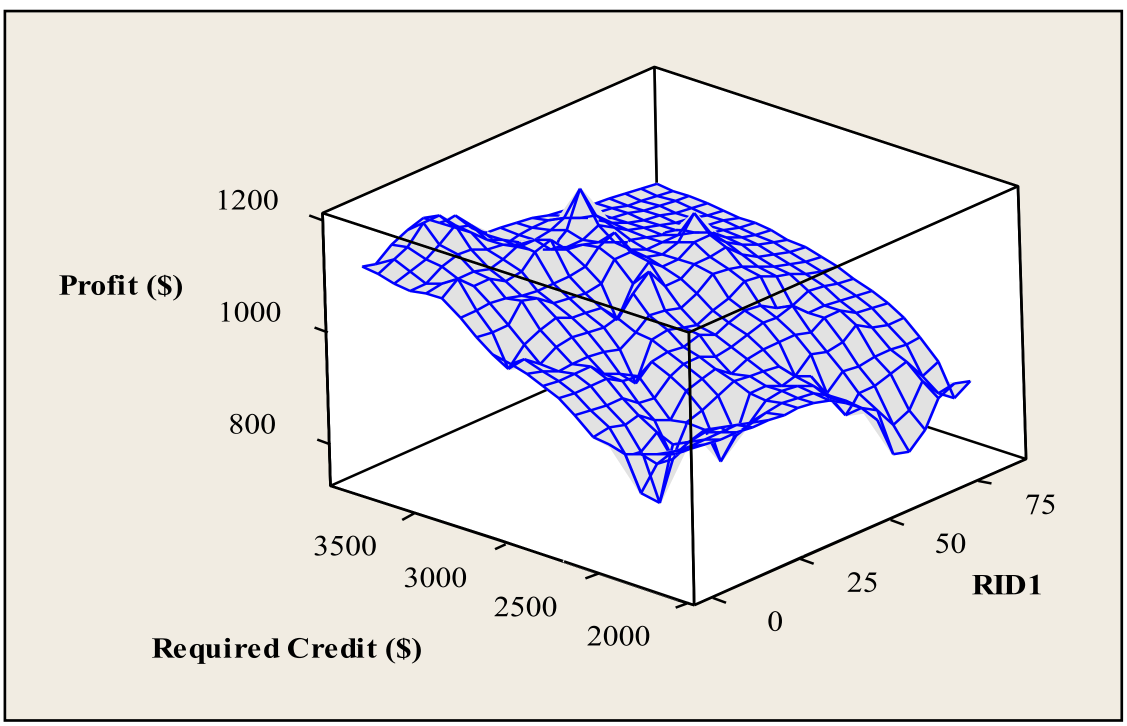


Figure 5.6: RC-PR-RID1 Tradeoff Surface Plot

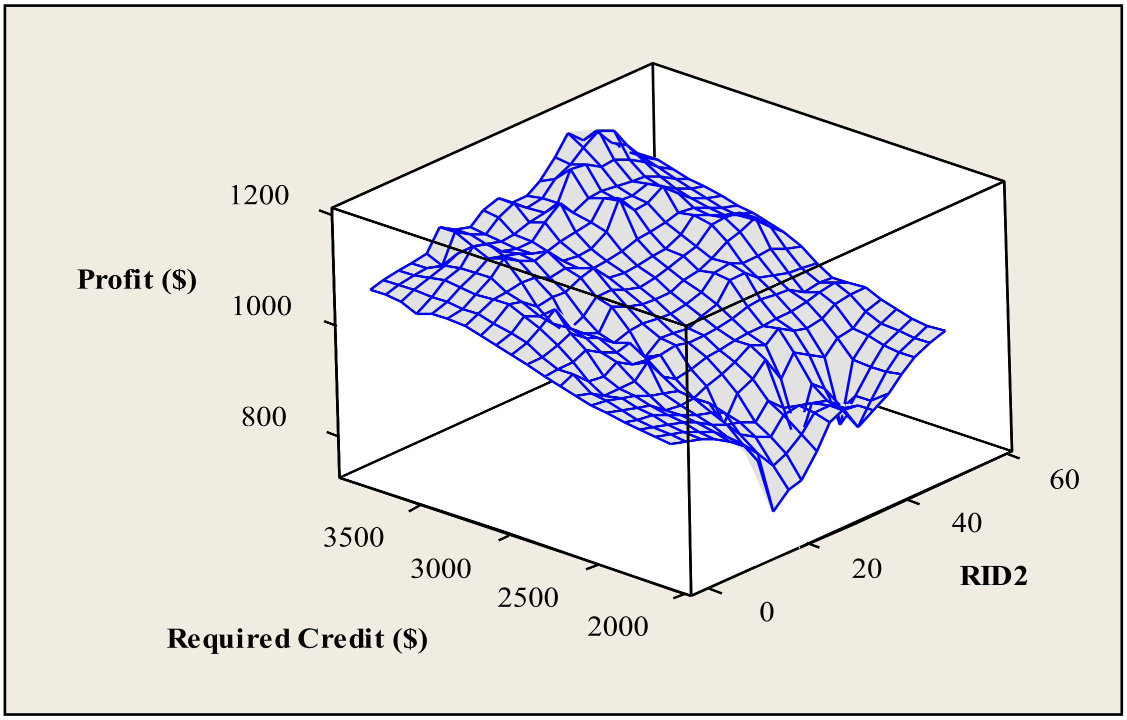


Figure 5.7: RC-PR-RID2 Tradeoff Surface Plot

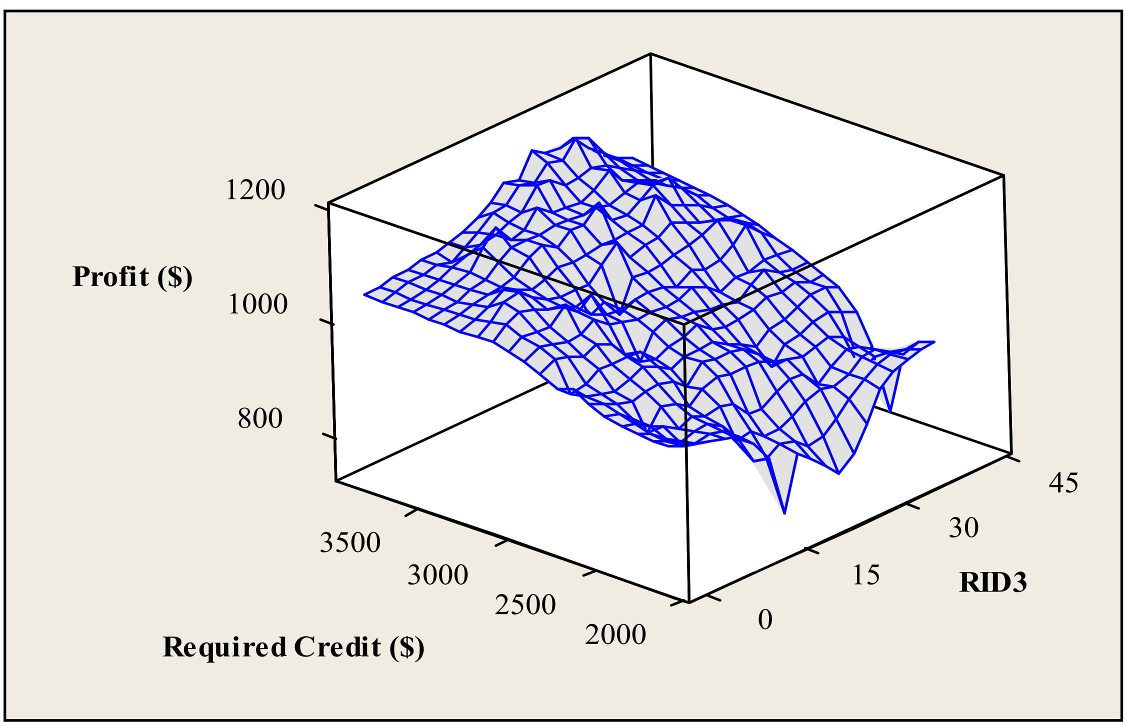


Figure 5.8: RC-PR-RID3 Tradeoff Surface Plot

Table 5.14: Summary of Optimization Results (Case Study 1)

Objectives	SINGLE Objective Optimization	TWO Objective Optimization	FIVE Objective Optimization
RC ($)	2,137.9	2,137.9	2,157.3
PR ($)	1,189.5	1,189.5	1,189.5
RID1	0	0	0
RID2	0	0	0
RID3	0	0	0

5.2.2 Case Study (2): 25 and 30-Activity Multiple Projects

The second case study uses an example of two concurrent projects of 25 and 30 activities adopted from Abido and Elazouni (2011). The problem was originally solved to optimize the tradeoff between the objectives of total duration, financing cost, and required credit under single resource utilization mode considering no resource levelling and allocation. The CPM networks of the 25 and 30 activity project are shown in Figures 5.9 and 5.10, respectively. Similar to the first case study, the problem is to be solved considering both financial and resource aspects. Thus, the objectives selected to be optimized simultaneously will consider maximizing the profit (PR) while minimizing the required credit (RC) and resource fluctuation and peak demand (RFPD). However, this time the RFPD objective will consider both resource allocation and levelling using the RRH metric under constrained resource limit. Hence, Equation 3.18a is used to determine the RFPD by assigning the RRH weight factor (W_1) and MRD weight factor (W_2) a value of 0.5 each. Moreover, two execution modes are assumed for most of the activities in both projects. The time period used for both projects is in weeks where each week is assumed to have five working days. The two projects were set up such that the start of the 30-activity project is shifted three weeks behind the start of the 25-activity project (i.e. day

15). The time, financial, and contractual terms data of the two projects are as shown in Table 5.15.

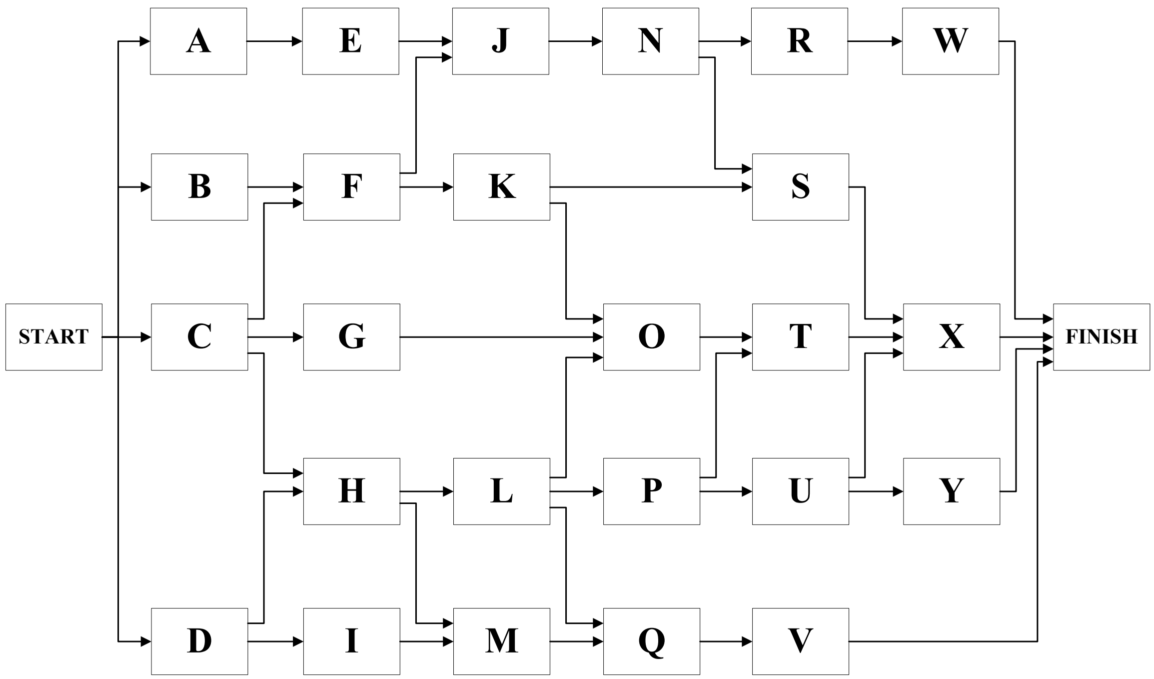


Figure 5.9: 25-Activity Project CPM Network

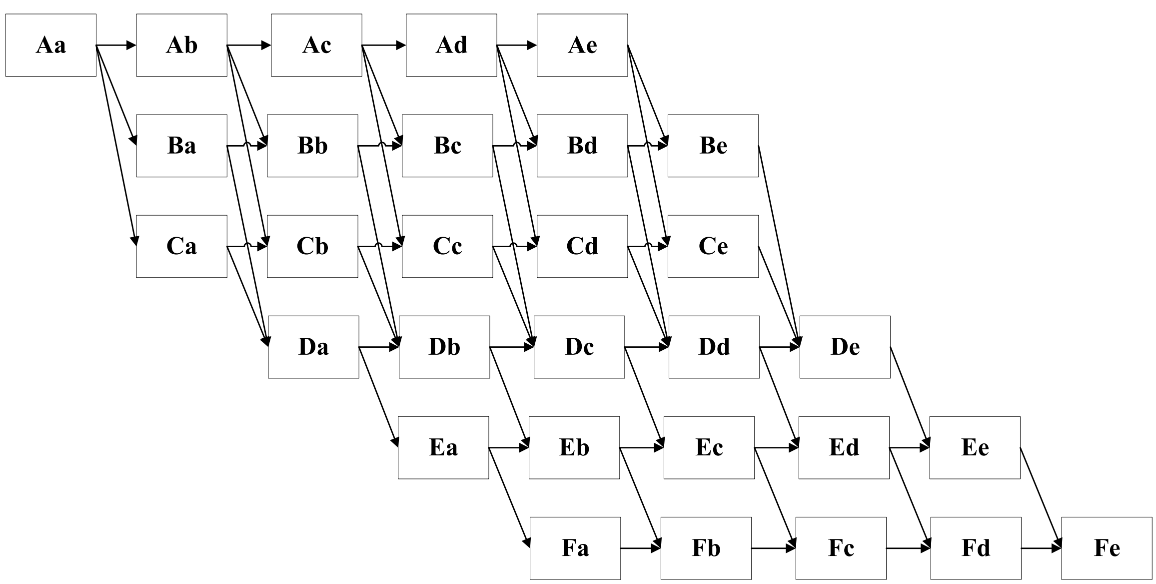


Figure 5.10: 30-Activity Project CPM Network

Table 5.15: Time, Financial, and Contractual Data (Case Study 2)

Data Type	Item	Project	
		25 Activity	30 Activity
TIME	Project Start Time (day #)	0	15
	No. of Days per Week	5	5
	Original Duration (days)	27[a]/20[b]	29[a]/21[b]
	Original Duration (weeks)	6[a]/4[b]	6[a]/5[b]
FINANCIAL	Interest Rate % per Week	0.80	0.80
	Overheads %	17	15
	Mobilization Costs %	8	5
	Tax %	2	2
	Mark-Up %	12	20
	Bond Premium %	4	1
CONTRACT TERMS	Advance Payment % of Bid Price	9	10
	Weeks to Retrieve Advance Payment	[c]	[c]
	Retained % of Pay Requests	6	5
	Lag to Pay Retained Money After Last Payment (weeks)	0	0
	Weeks to Submit Pay Requests Regularly	1	1
	Lag to Pay Payment Requests (weeks)	1	1
	Late Completion Penalty per Day ($ / day)	1,000	1,000

[a] If all activities are executed using Mode 1
[b] If all activities are executed using Mode 2
[c] Number of weeks encompassing the total project duration

Tables 5.16 and 5.17 present the activities' cost and resource data for the 25 and 30-activity projects, respectively. The indirect costs including the overhead costs, mobilization costs, taxes, and bond premium are calculated at the bottom of the tables assuming all activities are once executed using resource utilization mode 1 and another time using mode 2. Then, the markup and indirect costs are prorated to determine the activities' prices on daily basis. The initial values of the RC, PR, and RFPD objectives assuming all activities in both projects are once executed using resource utilization mode 1 and another time using mode 2 are shown in Table 5.18. Such values are obtained without considering any shifting of activities within their floats, i.e. no optimization took place yet.

Table 5.16: Cost and Resource Data (25-Activity Project)

Activity	MODE 1				MODE 2			
	Duration (days)	**Daily Direct Cost ($/day)**	**Daily Price ($/day)**	**Daily Resources**	**Duration (days)**	**Daily Direct Cost ($/day)**	**Daily Price ($/day)**	**Daily Resources**
A	2	1000	1501.28	3	1	1600	2402.04	4
B	3	1200	1801.53	2	2	1800	2702.30	3
C	2	1100	1651.41	1	1	2200	3302.81	2
D	3	900	1351.15	4	2	1300	1951.66	5
E	3	1250	1876.60	2	2	1950	2927.49	3
F	3	1150	1726.47	2	2	1850	2777.36	3
G	2	1050	1576.34	5	1	1350	2026.73	6
H	3	950	1426.21	2	1	2000	3002.56	4
I	2	650	975.83	5	1	950	1426.21	6
J	5	450	675.58	1	3	1250	1876.60	3
K	5	350	525.45	1	4	700	1050.89	2
L	5	500	750.64	2	4	850	1276.09	3
M	1	1450	2176.85	5	-	-	-	-
N	5	400	600.51	5	3	700	1050.89	7
O	5	550	825.70	5	4	850	1276.09	6
P	4	500	750.64	4	3	750	1125.96	5
Q	3	1350	2026.73	2	2	1900	2852.43	3
R	5	600	900.77	5	4	800	1201.02	6
S	5	850	1276.09	4	4	1200	1801.53	5
T	6	700	1050.89	3	4	1500	2251.92	5
U	4	1200	1801.53	2	3	1800	2702.30	3
V	3	1850	2777.36	1	2	3400	5104.35	2
W	5	650	975.83	4	4	900	1351.15	5
X	5	600	900.77	2	4	1050	1576.34	3
Y	2	1000	1501.28	1	1	1800	2702.30	2

Mode 1:

Total Cash Outflow = 72,750; Overheads = 12,367.5; Mobilization = 6,809.4; Cash Outflow + Overheads + Mobilization = 91,926.9; Taxes = 1,838.5; Taxes + Cash Outflow + Overheads + Mobilization = 93,765.4; Markup = 11,251.9; Markup + Taxes + Cash Outflow + Overheads + Mobilization = 105,017.3; Bond Premium = 4,200.7; Total Bid Price = 109,218; and Bid Price Factor (109,218 / 72,750) = 1.50128.

Mode 2:

Total Cash Outflow = 80,650; Overheads = 13,710.5; Mobilization = 7,548.8; Cash Outflow + Overheads + Mobilization = 101,909.3; Taxes = 2,038.2; Taxes + Cash Outflow + Overheads + Mobilization = 103,947.5; Markup = 12,473.7; Markup + Taxes + Cash Outflow + Overheads + Mobilization = 116,421.2; Bond Premium = 4,656.9; Total Bid Price = 1021,078; and Bid Price Factor (121,078 / 80,650) = 1.50128.

Table 5.17: Cost and Resource Data (30-Activity Project)

Activity	MODE 1				MODE 2			
	Duration (days)	Daily Direct Cost ($/day)	Daily Price ($/day)	Daily Resources	Duration (days)	Daily Direct Cost ($/day)	Daily Price ($/day)	Daily Resources
Aa:Ae	1	1700	2537.69	3	-	-	-	-
Ba:Be	2	1500	2239.14	2	1	3500	5224.66	4
Ca:Ce	3	1800	2686.97	4	2	2700	4030.45	5
Da:De	4	1900	2836.24	1	3	3800	5672.49	2
Ea:Ee	3	1600	2388.42	3	2	2500	3731.90	4
Fa:Fe	2	2000	2985.52	2	1	4200	6269.59	4

Mode 1:

Total Cash Outflow = 132,500; Overheads = 19,875; Mobilization = 7,618.8; Cash Outflow + Overheads + Mobilization = 159,993.8; Taxes = 3,199.9; Taxes + Cash Outflow + Overheads + Mobilization = 163,193.7; Markup = 32,638.7; Markup + Taxes + Cash Outflow + Overheads + Mobilization = 195,832.4; Bond Premium = 1,958.3; Total Bid Price = 197,790.7; and Bid Price Factor (197,790.7 / 132,500) = 1.49276.

Mode 2:

Total Cash Outflow = 156,000; Overheads = 23,400; Mobilization = 8,970; Cash Outflow + Overheads + Mobilization = 188,370; Taxes = 3,767.4; Taxes + Cash Outflow + Overheads + Mobilization = 192,137.4; Markup = 38,427.5; Markup + Taxes + Cash Outflow + Overheads + Mobilization = 230,564.9; Bond Premium = 2,305.7; Total Bid Price = 232,870.6; and Bid Price Factor (232,870.6 / 156,000) = 1.49276.

Table 5.18: Initial Objectives' Values (25-30 Activity Projects)

Resource Utilization Mode	Total Duration (days)	Main Objectives			MRD	RRH
		Required Credit ($)	Profit ($)	RFPD		
Mode 1	44	80,427.6	41,811.3	25.5	24	27
Mode 2	36	95,479.5	48,412.4	21	22	20

As an example of the detailed financial calculations, Figures 5.11 and 5.12 show the initial schedules of the 25 and 30-activity projects, respectively associated with assigning all the activities in both projects to be executed using resource utilization mode 1. The schedules in both figures show also the weekly calculated total direct cost and earned values. The earned value is the total worth of the work accomplished during a given week based on the contract prices.

Activity	Daily Direct Cost	Daily Price	Week 1					Week 2					Week 3					Week 4					Week 5					Week 6					Week 7					Week 8					Week 9				
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
A	1000	1501.3	■	■																																											
B	1200	1801.5	■	■	■																																										
C	1100	1651.4	■	■																																											
D	900	1351.2	■	■	■																																										
E	1250	1876.6			■	■	■																																								
F	1150	1726.5				■	■	■																																							
G	1050	1576.3			■	■																																									
H	950	1426.2				■	■	■																																							
I	650	975.8				■	■																																								
J	450	675.6							■	■	■	■	■																																		
K	350	525.4							■	■	■	■	■																																		
L	500	750.6							■	■	■	■	■																																		
M	1450	2176.9							■																																						
N	400	600.5												■	■	■	■	■																													
O	550	825.7												■	■	■	■	■																													
P	500	750.6												■	■	■	■																														
Q	1350	2026.7												■	■	■																															
R	600	900.8																	■	■	■	■	■																								
S	850	1276.1																	■	■	■	■	■																								
T	700	1050.9																	■	■	■	■	■	■																							
U	1200	1801.5																■	■	■	■																										
V	1850	2777.4															■	■	■																												
W	650	975.8																						■	■	■	■	■																			
X	600	900.8																							■	■	■	■	■																		
Y	1000	1501.3																			■	■																									
Direct Cost per Week ($)			21850					8750					13000					19050					8250					1850					-					-					-				
Earned Value per Week ($)			32802.9					13136.2					19516.6					28599.3					12385.5					2777.4					-					-					-				

Figure 5.11: 25-Activity Project Initial Schedule (Mode 1)

Activity	Daily Direct Cost	Daily Price	Week 1					Week 2					Week 3					Week 4					Week 5					Week 6					Week 7					Week 8					Week 9				
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
Aa	1700	2537.7																■																													
Ab	1700	2537.7																	■																												
Ac	1700	2537.7																		■																											
Ad	1700	2537.7																			■																										
Ae	1700	2537.7																				■																									
Ba	1500	2239.1																	■	■																											
Bb	1500	2239.1																			■	■																									
Bc	1500	2239.1																					■	■																							
Bd	1500	2239.1																							■	■																					
Be	1500	2239.1																									■	■																			
Ca	1800	2687.0																	■	■	■																										
Cb	1800	2687.0																				■	■	■																							
Cc	1800	2687.0																							■	■	■																				
Cd	1800	2687.0																										■	■	■																	
Ce	1800	2687.0																													■	■	■														
Da	1900	2836.2																				■	■	■	■																						
Db	1900	2836.2																								■	■	■	■																		
Dc	1900	2836.2																												■	■	■	■														
Dd	1900	2836.2																																■	■	■	■										
De	1900	2836.2																																				■	■	■	■						
Ea	1600	2388.4																								■	■	■																			
Eb	1600	2388.4																												■	■	■															
Ec	1600	2388.4																																■	■	■											
Ed	1600	2388.4																																				■	■	■							
Ee	1600	2388.4																																								■	■	■			
Fa	2000	2985.5																											■	■																	
Fb	2000	2985.5																														■	■														
Fc	2000	2985.5																																		■	■										
Fd	2000	2985.5																																						■	■						
Fe	2000	2985.5																																										■	■		
Direct Cost per Week ($)			-					-					-					23600					29200					30400					22100					20000					7200				
Earned Value per Week ($)			-					-					-					35229.1					43588.6					45379.9					32990.0					29855.2					10747.9				

Figure 5.12: 30-Activity Project Initial Schedule (Mode 1)

Table 5.19 presents the weekly cash outflow E_t and inflow P_t calculations of the individual projects and the two projects together. The calculations of E_t incorporates the mobilization and bond which occur at the beginning of the projects whereas the calculations of P_t incorporates the advance payment at the beginning of the projects, and the retained percentage applied to the payments. For clarification purposes, assume the 25-activity project schedule shown in Figure 5.11 is delayed 2 days. Accordingly, a late completion penalty is to be applied by assigning an extra amount of \$ 2,000 (i.e. 2 x 1,000) in the "deductions" cell at the end of week 7 in Table 5.19. Consequently, the E_t and P_t values of the two projects together are used to determine the other financial parameters as shown in Table 5.20. Moreover, Figure 5.13 shows the net cash flow diagram associated with the financial parameters obtained in Table 5.20.

Three runs of single-objective optimization are done to optimize the RC, PR, and RFPD objectives individually considering no resource limit constraint. The achieved optimized objectives' value from the single-objective optimization runs is shown in Table 5.21. Each of those individually optimized objectives' value represents a unique start times of the activities having a unique selected execution mode. The initial three objectives values ranged from \$80,427.6 to \$95,479.5, \$41,811.3 to \$48,412.4, and 21 to 25.5, for the RC, PR, and RFPD, respectively as shown in Table 5.18. The results in Table 5.21 show a significant improvement in both the RC and RFPD objectives being minimized to \$49,026.9 and 12.5, respectively. Such improvement is achieved by improving the initial population through several successive generations in which both the activities' start times and execution modes are optimally assigned using the NSGA-II technique in the developed model. However, the PR improvement is insignificant due to the fact of all activities being assigned to mode 2 (having higher costs thus higher mark-up) was already done in Table 5.18.

Consequently, another run is done to optimize the three objectives simultaneously assuming a daily maximum resource demand of 18. The results indicated that the obtained Pareto-optimal front representing the tradeoff of the three objectives included 67 unique optimal/near optimal non-dominated solutions. Table 5.22 presents four remarkable solutions that exhibit the minimum RC, maximum PR, minimum RFPD, and the best compromise solution. Such results are obtained by assigning the GAs parameters to 800, 600, 90%, and 15% for the population size, number of generations, crossover probability, and mutation probability, respectively. The average processing time to solve the problem was around 3 hours using a desktop of 3.2 GHz processor speed and 8 GB RAM. As seen in Table 5.22, the maximum resource demand in all types of solution did not exceed the set resource limit, i.e. 18.

Table 5.19: Initial Weekly Cash Outflow and Inflow Calculations (Mode 1)

End of Week	Cash Outflow (E_t)				Cash Inflow (P_t)			
	Item	**25-Act. Project**	**30-Act. Project**	**Sum of Two Projects**	**Item**	**25-Act. Project**	**30-Act. Project**	**Sum of Two Projects**
0	**Mobilization & Bond**	11230.3[e]	-	11230.3	**Advance Payment**	9829.6[f]	-	9829.6
1	**Direct Cost**	21850	-	-	**Earned Value**	-	-	-
	Overhead	2061.25[a]	-	-	**Deductions**	-	-	-
	Tax	478.23[b]	-	-	**Additions**	-	-	-
	Total	24389.5	-	24389.5	**Net**	-	-	-
2	**Direct Cost**	8750	-	-	**Earned Value**	32802.9	-	-
	Overhead	2061.25[a]	-	-	**Deductions**	4920.4[c]	-	-
	Tax	216.23[b]	-	-	**Additions**	-	-	-
	Total	11027.5	-	11027.5	**Net**	27882.5	-	27882.5
3	**Direct Cost**	13000	-	-	**Earned Value**	13136.2	-	-
	Overhead	2061.25[a]	-	-	**Deductions**	1970.4[c]	-	-
	Tax	301.23[b]	-	-	**Additions**	-	-	-
	Total	15362.5	9768.6[e]	25131.1	**Net**	11165.8	19779[f]	30944.8
4	**Direct Cost**	19050	23600	-	**Earned Value**	19516.6	-	-
	Overhead	2061.25[a]	3312.5[a]	-	**Deductions**	2927.5[c]	-	-
	Tax	422.23[b]	538.25[b]	-	**Additions**	-	-	-
	Total	21533.5	27450.8	48984.2	**Net**	16589.1	-	16589.1
5	**Direct Cost**	8250	29200	-	**Earned Value**	28599.3	35229.1	-
	Overhead	2061.25[a]	3312.5[a]	-	**Deductions**	4289.9[c]	5284.4[c]	-
	Tax	206.23[b]	650.25[b]	-	**Additions**	-	-	-
	Total	10517.5	33162.8	43680.2	**Net**	24309.4	29944.7	54254.1
6	**Direct Cost**	1850	30400	-	**Earned Value**	12385.5	43588.6	-
	Overhead	2061.25[a]	3312.5[a]	-	**Deductions**	1857.8[c]	6538.3[c]	-
	Tax	78.23[b]	674.25[b]	-	**Additions**	-	-	-
	Total	3989.5	34386.8	38376.2	**Net**	10527.7	37050.3	47578
7	**Direct Cost**	-	22100	-	**Earned Value**	2777.4	45379.9	-
	Overhead	-	3312.5[a]	-	**Deductions**	416.6[c]	6807[c]	-
	Tax	-	508.25[b]	-	**Additions**	6553.1[d]	-	-
	Total	-	34284.8	25920.8	**Net**	8913.9	38572.9	47486.8
8	**Direct Cost**	-	20000	-	**Earned Value**	-	32990.0	-
	Overhead	-	3312.5[a]	-	**Deductions**	-	4948.5[c]	-
	Tax	-	466.25[b]	-	**Additions**	-	-	-
	Total	-	23778.8	23778.8	**Net**	-	28041.5	28041.5
9	**Direct Cost**	-	7200	-	**Earned Value**	-	29855.2	-
	Overhead	-	3312.5[a]	-	**Deductions**	-	4478.3[c]	-
	Tax	-	210.25[b]	-	**Additions**	-	-	-
	Total	-	10722.8	10722.8	**Net**	-	25376.9	25376.9
10	**Direct Cost**	-	-	-	**Earned Value**	-	10747.9	-
	Overhead	-	-	-	**Deductions**	-	1612.2[c]	-
	Tax	-	-	-	**Additions**	-	9889.5[d]	-
	Total	-	-	-	**Net**	-	19025.2	19025.2

[a] Overhead per week = Total Overheads / Original duration in weeks
[b] Tax = (Tax %) x (Direct Cost + Overhead)
[c] Deductions = (Retained % + Advance Payment %) x Earned Value
[d] Additions = Total Retained Money
[e] (Mobilization + Bond) x (1 + Tax %)
[f] (Advance Payment %) x Total Bid Price

Table 5.20: Initial Financial Parameters Calculations (Mode 1)

Week #	0	1	2	3	4	5	6	7	8	9	10
Final E values (E)	-11230.3	-24389.5	-11027.5	-25131.1	-48984.2	-43680.2	-38376.2	-25920.8	-23778.8	-10722.8	0.0
Final P values (P)	9829.6	0.0	27882.5	30944.8	16589.1	54254.2	47578.0	47486.8	28041.5	25376.9	19025.2
Cumulative Balance (F)	-11230.3	-25790.1	-36817.6	-34066.2	-52105.6	-79196.7	-63318.8	-41661.5	-17953.5	-634.8	24742.2
Cumulative Net Balance (N)	-1400.7	-25790.1	-8935.1	-3121.4	-35516.5	-24942.5	-15740.8	5825.3	10088.0	24742.2	43767.4
Financing Cost (I)	-5.6	-108.8	-250.4	-172.0	-220.9	-458.9	-353.0	-229.6	-71.8	-2.5	0.0
Compounded Financing Cost (I')	-5.6	-114.4	-365.8	-540.7	-765.9	-1230.9	-1593.8	-1836.2	-1922.7	-1940.6	-1956.1
Cumulative Balance Including Financing Cost (F')	-11235.9	-25904.6	-37183.4	-34606.9	-52871.6	-80427.6	-64912.6	-43497.7	-19876.2	-2575.3	22786.1
Cumulative Net Balance Including Financing Cost (N')	-1406.3	-25904.6	-9300.9	-3662.1	-36282.4	-26173.4	-17334.5	3989.1	8165.3	22801.6	41811.3

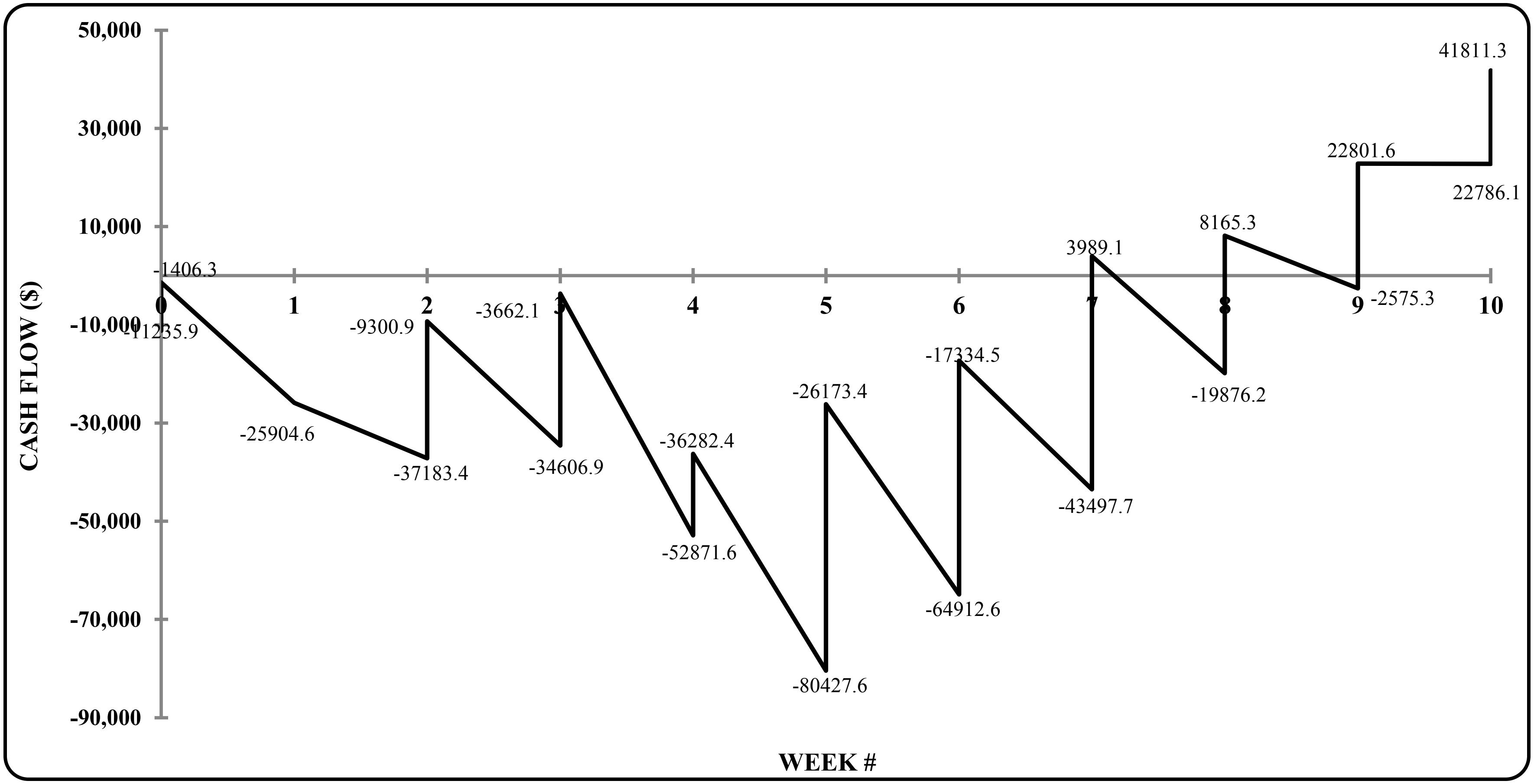


Figure 5.13: Initial Net Cash Flow (Mode 1)

Table 5.21: Single-Objective Optimization Results (Case Study 2)

Objective	Optimized Value	MRD	RRH
RC ($)	49,026.9	18	23
PR ($)	48,431.1	22	35
RFPD	12.5	18	7

Table 5.22: Three-Objectives Remarkable Solutions (Case Study 2)

Solution Type	Main Objectives			MRD	RRH	TD (days)
	RC ($)	PR ($)	RFPD			
Minimum Required Credit (RC)	50,281.2	46,354.4	24	18	30	44
Maximum Profit (PR)	68,706	47,313.8	29	18	40	40
Minimum RFPD	60,765.4	43,144.4	13	18	8	44
Best Compromise	52,452.4	46,549.1	15.5	17	14	42

As discussed in the first case study, if the decision maker's absolute priority is to maximize profit, the solution of the maximum profit shown in Table 5.22 should be selected wherein the optimization algorithm selects activities' start times and execution modes to achieve the global maximum profit value of $47,313.8, and minimizes, but not globally minimizes, the required credit and resource fluctuation and peak demand. The minimized required credit of $68,706 in the solution of maximum profit is definitely higher than its global minimum value of $50,281.2 associated with the solution of minimum required credit shown in Table 5.22. Similarly, the minimized RFPD value of 29 in the solution of maximum profit is definitely higher than its global minimum value of 13 associated with the solution of minimum RFPD shown in Table 5.22. In addition to the solution of maximum profit, the optimization model provides 66 additional solutions, which represent the complete tradeoff between the required credit, profit, and resource fluctuation and peak demand. In each one of these solutions, the profit value is maximized but not globally maximized, the required credit is minimized but not globally minimized (except for the solution of minimum required credit), and the RFPD is minimized but not globally minimized (except for the solution of minimum RFPD). Figure 5.14 shows the comparison of the net cash flow obtained from the “minimum RC” solution (see Table 5.22) to that obtained for the two cases presented in Table 5.18. The figure shows the significant improvement in minimizing the required credit when compared with the initial schedules’ results. Similarly, Figure 5.15 shows the comparison of the resource demand profile obtained from the “minimum RFPD” solution (see Table 5.22) to that obtained for the two cases presented in Table 5.18. Again, the figure shows the significant improvement in minimizing the resource fluctuations as well as minimizing the maximum daily resource demand by not exceeding the resource limit of 18 when compared with the initial schedules’ results. Figure 5.16 shows the three-dimensional surface plot of the obtained 67 Pareto-optimal solutions.

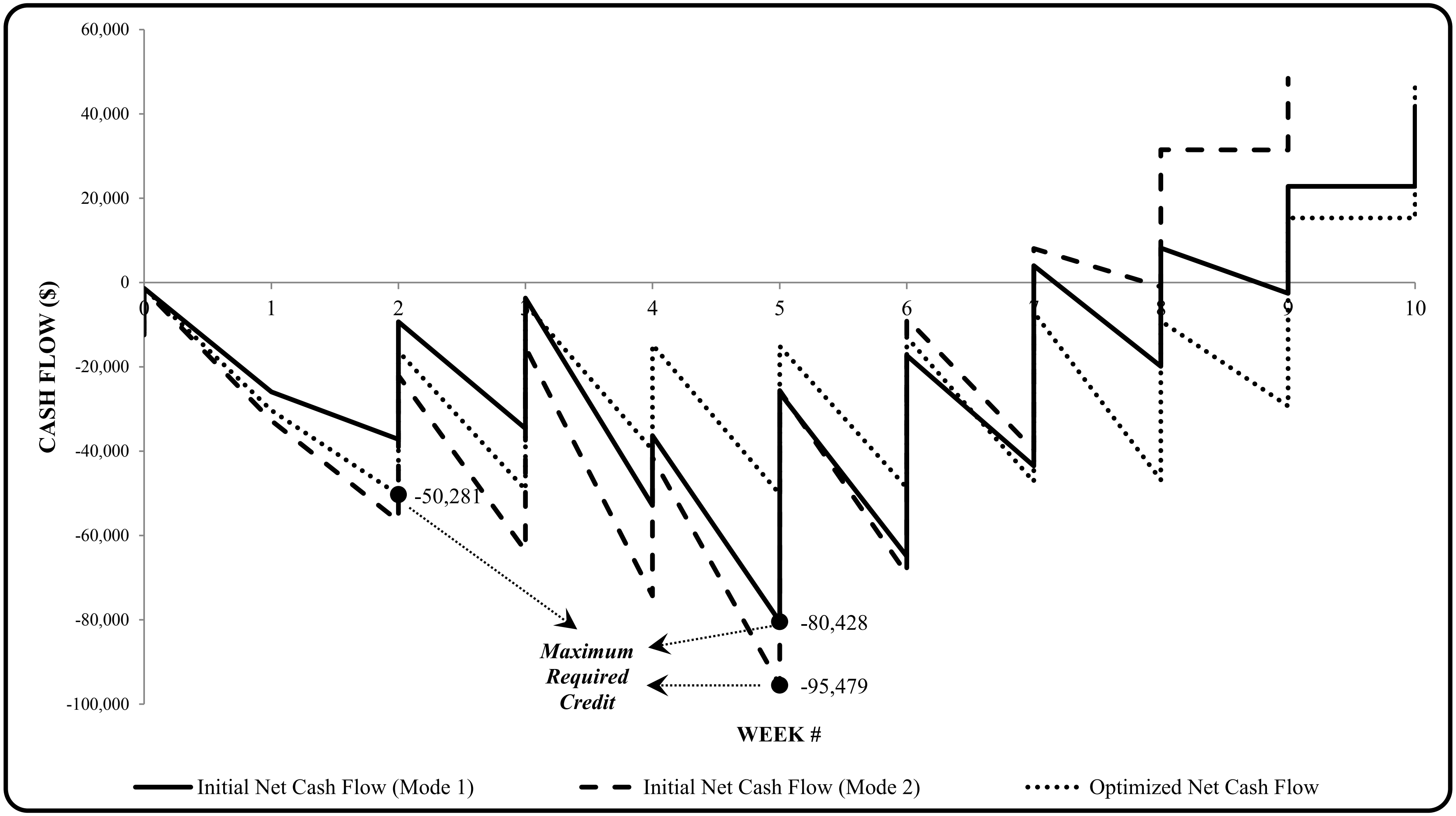


Figure 5.14: Net Cash Flows Comparison

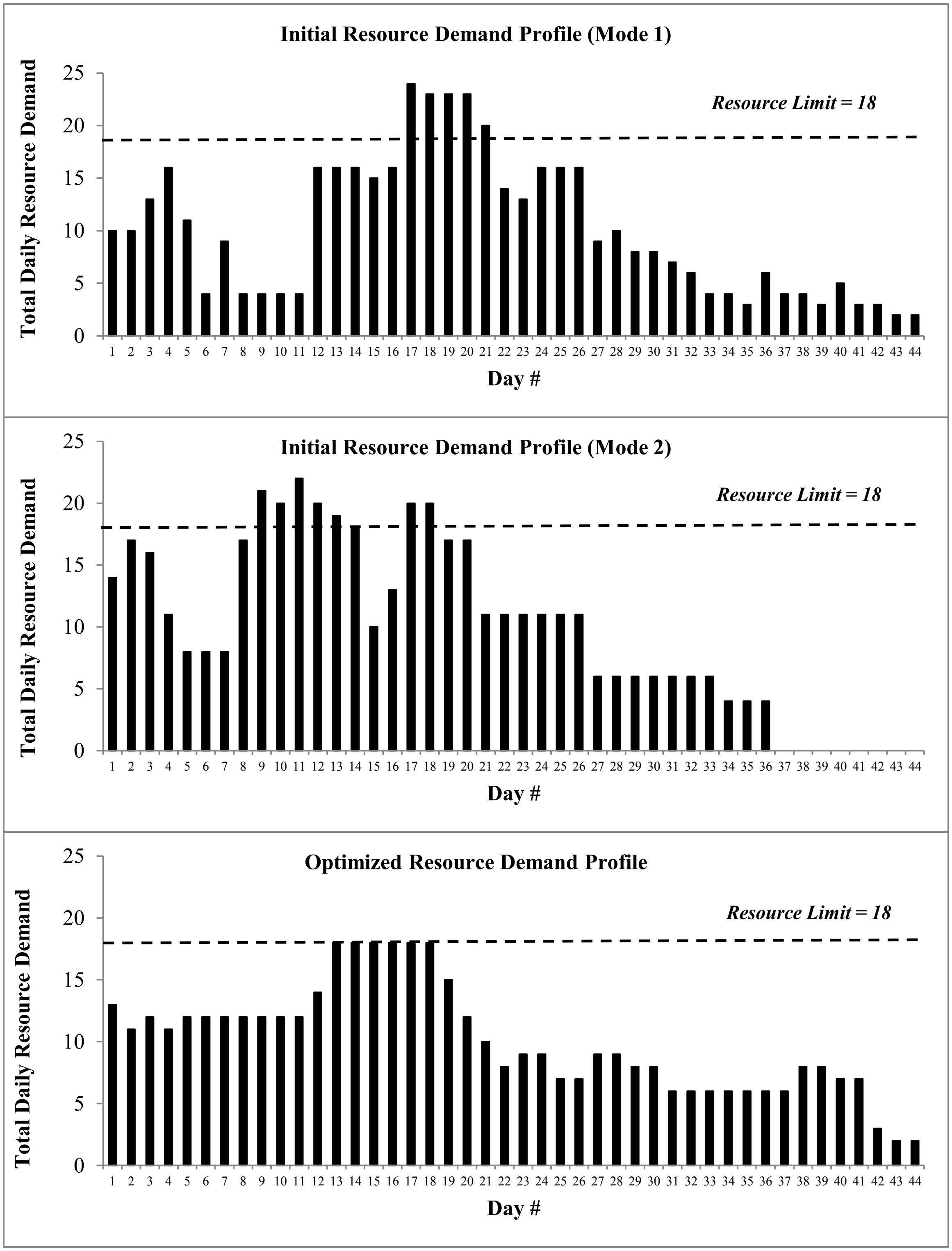


Figure 5.15: Resource Demand Profiles Comparison

A final run is done again to optimize the three objectives simultaneously assuming a daily maximum resource demand of 18. However, in this run, an extension increment of 15 days is assumed for both the 25 and 30 activity projects. Such extension intends to further minimize the required credit. The final results included 139 unique optimal/near optimal non-dominated solutions Table 5.23 presents the four remarkable solutions that exhibit the minimum RC, maximum PR, minimum RFPD, and the best compromise solution after applying the projects' extension scheme. Figure 5.17 shows the three-dimensional surface plot of the obtained 139 Pareto-optimal solutions after applying the projects' extension scheme.

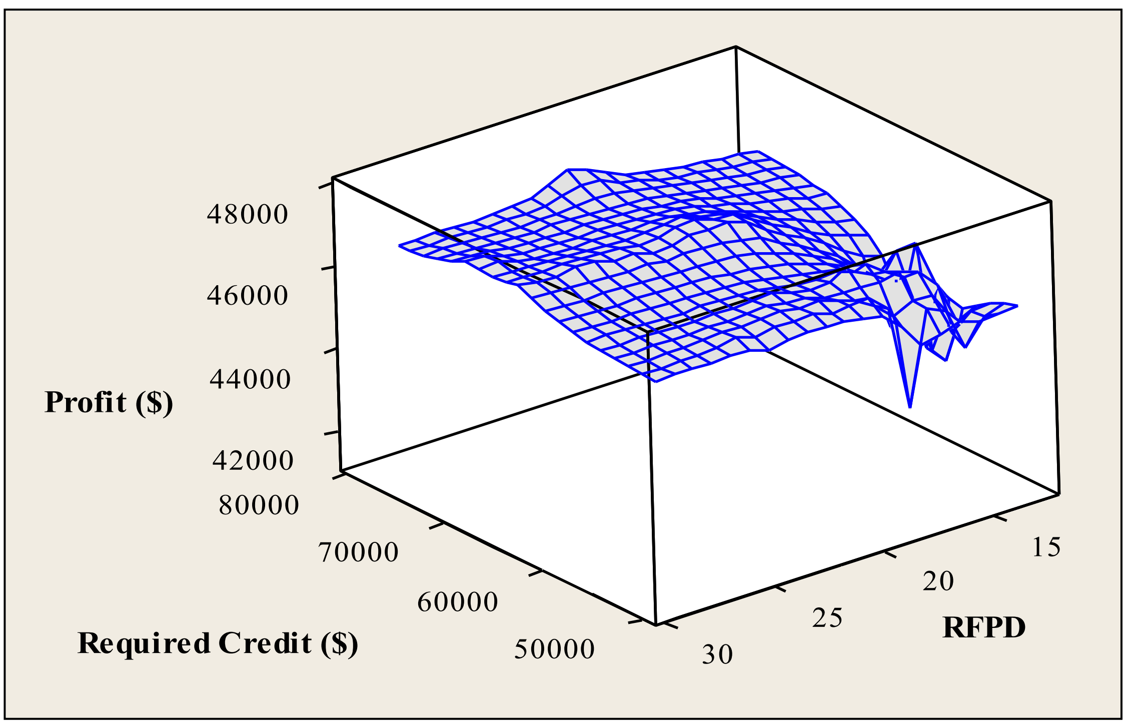


Figure 5.16: RC-PR-RFPD Tradeoff Surface Plot (Case Study 2)

Table 5.23: Three-Objectives Remarkable Solutions with Extension (Case Study 2)

Solution Type	Main Objectives			MRD	RRH	TD (days)
	RC ($)	PR ($)	RFPD			
Minimum Required Credit (RC)	39,450.6	15,932.2	36.5	16	57	58
Maximum Profit (PR)	64,370.5	47,299.8	27	18	36	40
Minimum RFPD	60,740.5	43,184.1	13.5	18	9	44
Best Compromise	53,482.4	46,430.5	15	18	12	44

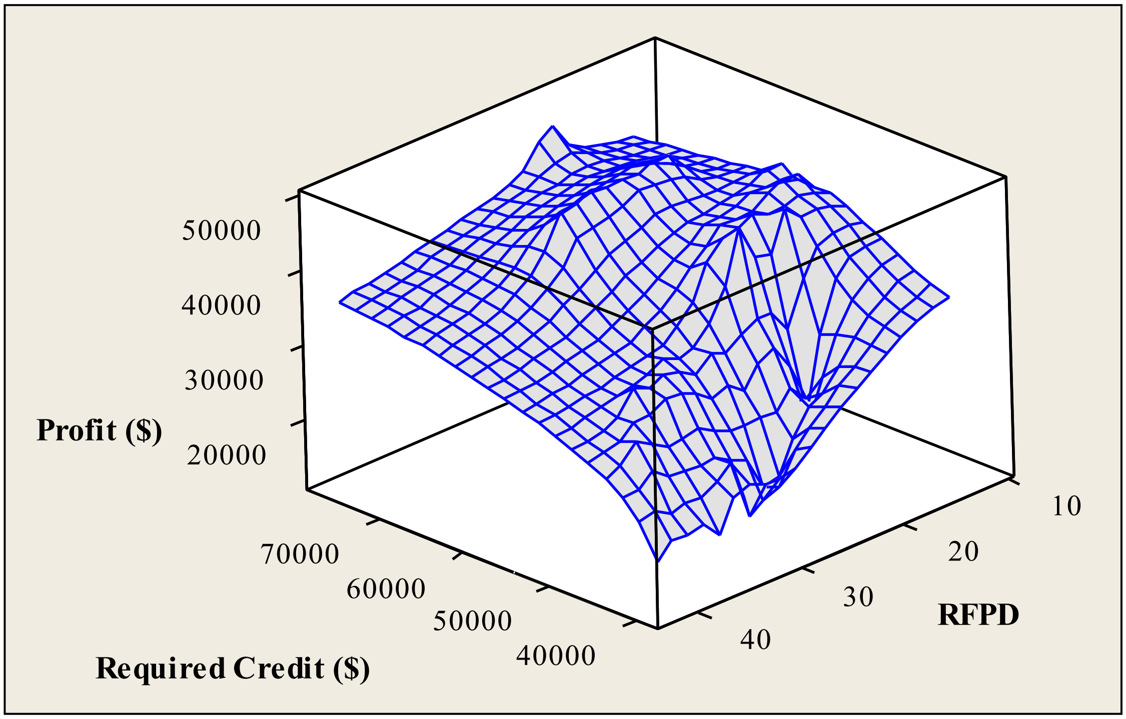


Figure 5.17: RC-PR-RFPD Tradeoff Surface Plot with Extension (Case Study 2)

Finally, Table 5.24 summarizes the globally optimized values obtained for the RC, PR, and RFPD objectives by applying single-objective, three-objective without extension, and three-objective with extension optimizations. Comparison shows that the results of the "three-objective without extension" and "single-objective" optimization are very close with respect to the three objectives RC, PR, and RFPD. The same applies when comparing the "three-objective with extension" with the "single-objective" optimization except for the RC. As shown in Table 5.24, the required credit is significantly improved being minimized to $39,450.6 after applying the extension scheme for the 25 and 30-activity projects. However, such improvement imposed a major reduction in the profit with a value of $15,932.2 as shown in Table 5.23. This reduction usually happens when projects are extended beyond their original duration due to the additional overheads and liquidated damages. Figure 5.18 illustrates the improvement achieved in minimizing the required credit before and after applying the extension increment and its effect on the total profit.

Table 5.24: Summary of Optimization Results (Case Study 2)

Optimization Type	Objective	Optimized Value	MRD	RRH
Single-Objective	RC ($)	49,026.9	18	23
	PR ($)	48,431.1	22	35
	RFPD	12.5	18	7
Three-Objective (Without Extension)	RC ($)	50,281.2	18	30
	PR ($)	47,313.8	18	40
	RFPD	13	18	8
Three-Objective (With Extension)	RC ($)	39,450.6	16	57
	PR ($)	47,299.8	18	36
	RFPD	13.5	18	9

5.2.3 Case Study (3): 100 and 120-Activity Multiple Projects

The final case study uses the same example of the two concurrent projects of 25 and 30 activities that were presented in the second case study. However, to investigate the scalability of the developed model, these two projects are enlarged to two bigger projects of 100 and 120 activities. The 25-activity project was copied into a 100-activity project by repeating the network in Figure 5.9 four times such that activities A, B, C, and D of any network depend on activities W, X, Y, and V of the previous network, respectively.

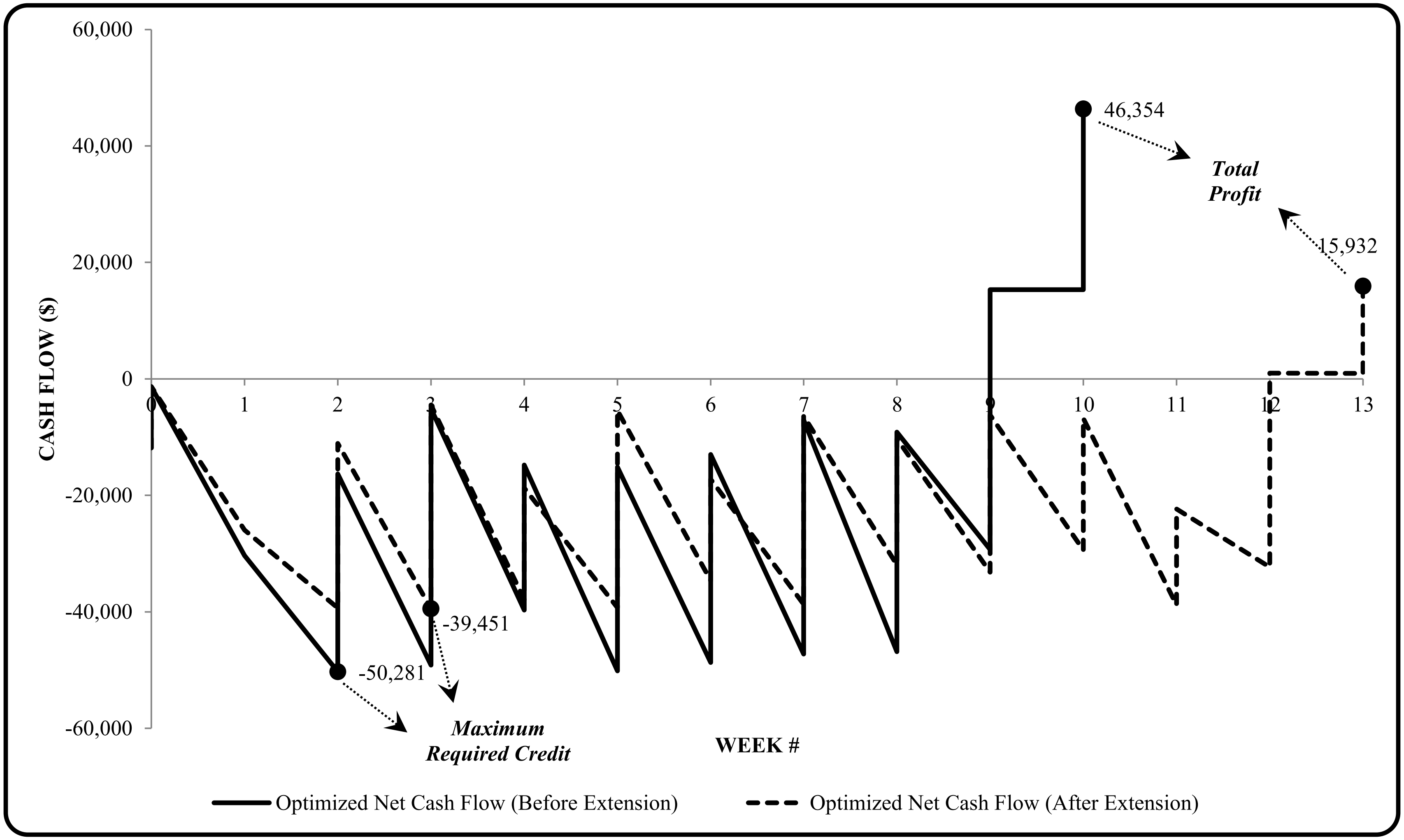


Figure 5.18: Effect of Applying Extension Increment on the Net Cash Flow

The 30-activity project was expanded into a 120-activity project by repeating the basic six activities A, B, C, D, E, and F (Figure 5.10) over 15 more sections. The two projects were set up such that the start of the 120-activity project is shifted eight weeks behind the start of the 100-activity project (i.e. day 40). The time, financial, and contractual terms data of the two projects are as shown in Table 5.25.

Table 5.25: Time, Financial, and Contractual Data (Case Study 3)

Data Type	Item	Project: 25 Activity	Project: 30 Activity
TIME	Project Start Time (day #)	0	40
	No. of Days per Week	5	5
	Original Duration (days)	108[a]/80[b]	89[a]/66[b]
	Original Duration (weeks)	22[a]/16[b]	18[a]/14[b]
FINANCIAL	Interest Rate % per Week	0.80	0.80
	Overheads %	15	15
	Mobilization Costs %	2	2
	Tax %	2	2
	Mark-Up %	15	15
	Bond Premium %	1	1
CONTRACT TERMS	Advance Payment % of Bid Price	6	8
	Weeks to Retrieve Advance Payment	[c]	[c]
	Retained % of Pay Requests	5	5
	Lag to Pay Retained Money After Last Payment (weeks)	0	0
	Weeks to Submit Pay Requests Regularly	1	1
	Lag to Pay Payment Requests (weeks)	1	1
	Late Completion Penalty per Day ($ / day)	1,000	1,000

[a] If all activities are executed using Mode 1
[b] If all activities are executed using Mode 2
[c] Number of weeks encompassing the total project duration

The initial values of the RC, PR, and RFPD objectives assuming all activities in both projects are once executed using resource utilization mode 1 and another time using mode 2 are shown in Table 5.26. Such values are obtained considering the early start times of the activities.

Table 5.26: Initial Objectives' Values (100-120 Activity Projects)

Resource Utilization Mode	Total Duration (days)	Main Objectives			MRD	RRH
		Required Credit ($)	Profit ($)	RFPD		
Mode 1	129	69,848.6	144,666.8	87	33	141
Mode 2	106	141,044.6	165,228.3	79	40	118

Similar to the second case study, three runs of single-objective optimization is done to optimize the RC, PR, and RFPD objectives individually considering no resource limit constraint. The achieved optimized objectives' value from the single-objective optimization runs is shown in Table 5.27. The initial three objectives values ranged from $69,848.6 to $141,044.6, $144,666.8 to $165,228.3, and 79 to 87, for the RC, PR, and RFPD, respectively as shown in Table 5.26. The results in Table 5.27 show a significant improvement in both the RC and RFPD objectives being minimized to $42,411.8 and 70.5, respectively. However, the PR improvement is insignificant due to the fact of all activities being assigned to mode 2 (having higher costs thus higher mark-up) was already done in Table 5.26.

Table 5.27: Single-Objective Optimization Results (Case Study 3)

Objective	Optimized Value	MRD	RRH
RC ($)	42,411.8	29	204
PR ($)	165,372.7	41	197
RFPD	70.5	29	112

Consequently, another run is done to optimize the three objectives simultaneously assuming a daily maximum resource demand of 29. The results indicated that the obtained Pareto-optimal front representing the tradeoff of the three objectives included 151 unique optimal/near optimal non-dominated solutions. Table 5.28 presents four remarkable solutions that exhibit the minimum RC, maximum PR, minimum RFPD, and the best compromise solution. Such results are obtained by assigning the GAs parameters to 1200, 1000, 90%, and 20% for the population size, number of generations, crossover probability, and mutation probability, respectively. The average processing time to solve the problem was around 33.4 hours using a desktop of 3.2 GHz processor speed and 8 GB RAM. As seen in Table 5.28, the maximum resource demand in all types of solution did not exceed the set resource limit, i.e. 29. Figure 5.19 shows the three-dimensional surface plot of the obtained 151 Pareto-optimal solutions.

Table 5.28: Three-Objectives Remarkable Solutions (Case Study 3)

Solution Type	Main Objectives			MRD	RRH	TD (days)
	RC ($)	PR ($)	RFPD			
Minimum Required Credit (RC)	42,430.7	141,487.7	113	29	127	129
Maximum Profit (PR)	76,285.9	158,137.6	104	29	179	120
Minimum RFPD	56,252.7	148,456.3	72	29	115	127
Best Compromise	45,474.5	151,068.0	84.5	29	140	129

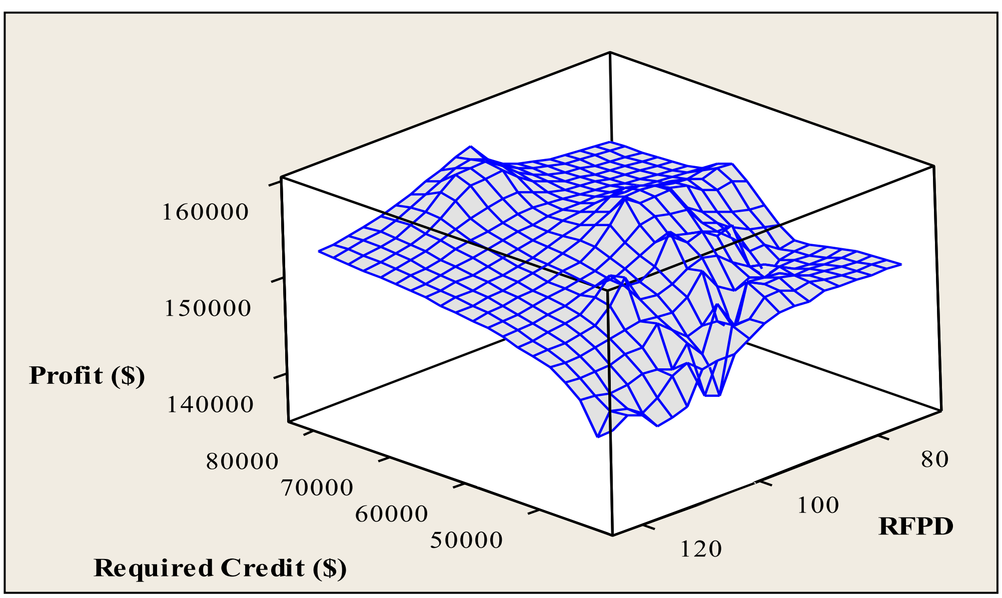


Figure 5.19: RC-PR-RFPD Tradeoff Surface Plot (Case Study 3)

A final run is done again to optimize the three objectives simultaneously assuming a daily maximum resource demand of 29. However, in this run, an extension increment of 40 days is assumed for both the 100 and 120 activity projects. The final results included 234 unique optimal/near optimal non-dominated solutions Table 5.29 presents the four remarkable solutions that exhibit the minimum RC, maximum PR, minimum RFPD, and the best compromise solution after applying the projects' extension scheme. Figure 5.20 shows the three-dimensional surface plot of the obtained 234 Pareto-optimal solutions after applying the projects' extension scheme.

Table 5.29: Three-Objectives Remarkable Solutions with Extension (Case Study 3)

Solution Type	**Main Objectives**			**MRD**	**RRH**	**TD (days)**
	RC ($)	**PR ($)**	**RFPD**			
Minimum Required Credit (RC)	35,732.6	41,062.1	113.5	23	204	160
Maximum Profit (PR)	77,799.3	158,005.2	100	29	171	120
Minimum RFPD	56,012.4	149,044.8	72.5	29	116	127
Best Compromise	51,441.5	148,663.4	75.5	29	122	127

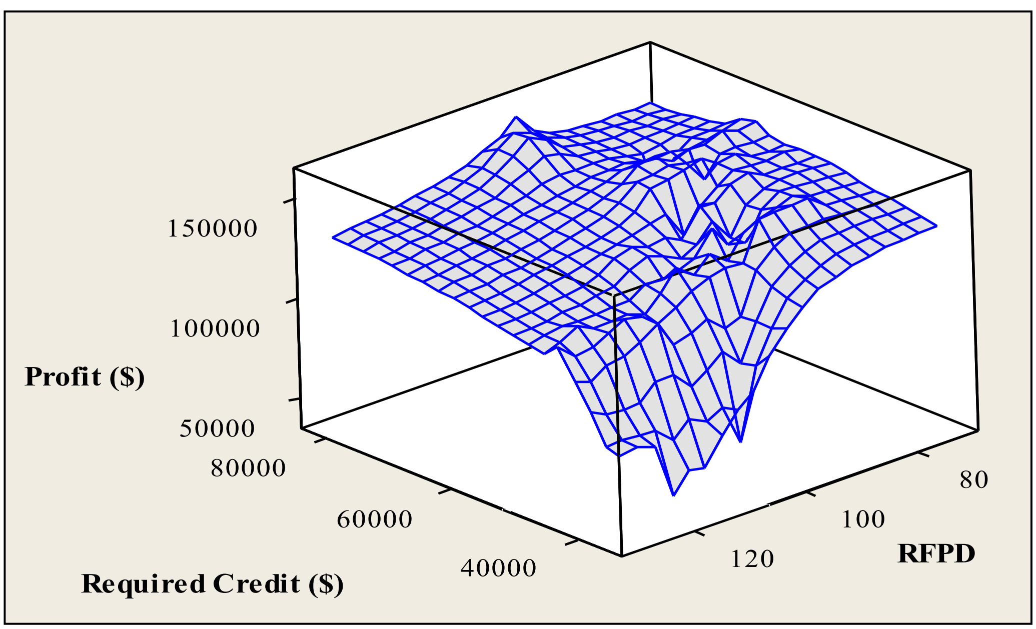


Figure 5.20: RC-PR-RFPD Tradeoff Surface Plot with Extension (Case Study 3)

Finally, Table 5.30 summarizes the globally optimized values obtained for the RC, PR, and RFPD objectives by applying single-objective, three-objective without extension, and three-objective with extension optimizations. Comparison shows that the results of the "three-objective without extension" and "single-objective" optimization are very close with respect to both RC and RFPD and somehow close with respect to PR due to the set resource limit. The same applies when comparing the "three-objective with extension" with the "single-objective" optimization except for the RC. As shown in Table 5.30, the required credit is significantly improved being minimized to $35,732.6 after applying the extension scheme for the 100 and 120-activity projects. However, such improvement imposed a major reduction in the profit with a value of $41,062.1 as shown in Table 5.29. As explained earlier, this reduction usually happens when projects are extended beyond their original duration due to the additional overheads and liquidated damages. The results show the capability of the developed model to solve relatively large projects.

Table 5.30: Summary of Optimization Results (Case Study 3)

Optimization Type	Objective	Optimized Value	MRD	RRH
Single-Objective	RC ($)	42,411.8	29	204
	PR ($)	165,372.7	41	197
	RFPD	70.5	29	112
Three-Objective (Without Extension)	RC ($)	42,430.7	29	127
	PR ($)	158,137.6	29	179
	RFPD	72	29	115
Three-Objective (With Extension)	RC ($)	35,732.6	23	204
	PR ($)	158,005.2	29	171
	RFPD	72.5	29	116

CHAPTER 6: AUTOMATED TOOL: MOSCOPEA

This chapter presents the development of a **M**ulti-**O**bjective **SC**heduling **OP**timization using **E**volutionary **A**lgorithm application named MOSCOPEA. The application system is built according to the optimization model development presented in Chapter 4. The main objective of the present application is to enable construction planners to optimize their desired multi-objectives in order to provide reliable and improved project(s) schedules. To achieve this, the MOSCOPEA application system is designed to provide a number of unique capabilities, including (1) providing effective interface to the newly developed model in this study to facilitate their ultimate use; (2) automating the development of tradeoff tables among the conflicting optimization objectives to facilitate the selection of optimal solutions that address the specific project needs; and (3) providing flexibility to select the desired objectives to be optimized. This chapter is divided into three sections. The first section briefly presents the technical features of the application. The second section discusses the application development units. Finally, the third section illustrates the procedure of implementing the application by the end user using a friendly graphical user interface.

6.1 MOSCOPEA TECHNICAL FEATURES

MOSCOPEA is a standalone Window Dot net application that uses “Microsoft Dot Net Framework” technology. The application uses the “Client Server Model” which is a distributed application structure that partitions tasks or workloads between the providers of a resource or service, called servers, and service requesters, called clients.

6.1.1 Application Architecture

Figure 6.1 shows the generic architecture of the application which is a multi-tier application consisting of three tiers as follows:

1. **Presentation Tier:** this is the topmost level of the application which represents the graphical user interface (GUI). The tier uses “Microsoft Dot Net Windows” desktop application with C# language.
2. **Business Logic Tier:** this tier coordinates the application, processes commands, makes logical decisions and evaluations, and performs calculations. Moreover, it moves and processes data between the two surrounding tiers, i.e. presentation and data. The tier uses “Microsoft Object Oriented Programming Model” combined with “Microsoft LINQ Technology” and all is implemented using C# language.
3. **Data Tier:** in this tier information is stored and retrieved from a database or file system. The information is then passed back to the business logic tier for processing, and then eventually back to the presentation tier. It includes two main layers:.
    a. ***Data Access Layer:*** this layer provides simple access to data stored in the database storage. It uses “Microsoft ADO.NET” as technology, Entity Framework” as data mapping, and “LINQ to SQL” for data manipulation.
    b. ***Database Storage Layer:*** this layer represents the actual physical data store of the application. It uses “Microsoft SQL Server” which is a relational database management system. It includes two sub-layers:

i. *Data Abstraction Layer:* this layer consists of a set of stored procedures, functions, and views that abstracts the physical schema of the database.

ii. *Physical Schema Layer:* this is the physical layer of the database that contains physical tables, indices, relations, and triggers.

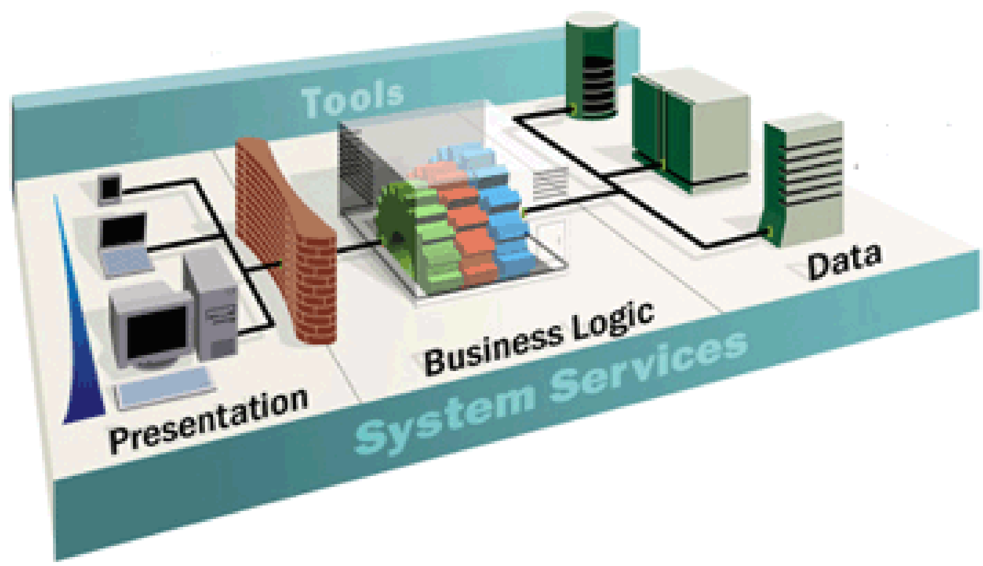


Figure 6.1: Application Architecture (Johnson Technology Systems 2014)

6.1.2 Parallel Computing

As the number of the projects' activities increases the computational processing time increases. Furthermore, existence of activities having more than single resource utilization mode will enlarge the search space which will eventually require assigning a larger population size leading to additional processing time. For instance, the two concurrent projects of 25 and 30 activities that were presented in section 5.2.2 in Chapter 5 were enlarged to two bigger projects of 200 and 240 activities, respectively. The population size and number of generations were assumed to be 1200 and 1000, respectively. The model was run using a desktop with a quad-core processor of 3.2 GHz speed. It took around 67 hours to complete the optimization process by reaching the preset number of generations. Moreover, the quality of optimized solutions was not satisfying due to the relatively small population size and number of generations defined. In fact, the search space becomes larger as the number of activities increases together with the number of utilization modes for each activity. Thus, a larger population size and number of generations will be required to improve the quality of solutions leading to additional processing time, i.e. more than 67 hours. The major portion of such high computational time is exerted in the fitness evaluation phase.

Accordingly, the application is designed and built to execute parallel computing. The parallelism takes place by performing parallel fitness evaluation of the multi-objectives over multi-processors with multi-cores to support the optimization of large-scale construction projects by reducing its processing time. As illustrated in Figure 6.2, the application is designed to distribute its computations using the following nine cyclic steps:

1. The message passing interface (MPI) functions are initialized to facilitate the communication between the manager and worker processors.
2. The manager processor generates a population of solutions that represents a number of feasible construction schedules.
3. The manager processor divides the population into sub-populations and sends each sub-population to a multi-core worker processor.

4. Each multi-core worker processor further divides the sub-population into sub-subpopulations and sends each sub-subpopulation to a core within the same worker processor.
5. Each core within each worker processor evaluates the fitness of the multi-objectives of each construction schedule in the sub-subpopulation.
6. Each core sends the objectives' values to their respective worker processor.
7. Each multi-core worker processor sends the objectives' values to the manager processor.
8. The manager processor collects the results and performs GA operations (i.e. selection, crossover, and mutation) to generate the next population.
9. Finally, steps 3 through 8 are repeated until total number of generations are met.

It was difficult to have an access for a supercomputing network facility to apply the parallel computing feature described above. Thus, this feature was applied on a small scale by running the 25-30 activity projects example using a dual-core and a quad-core processors to check its validity. The population size and number of generations were assumed to be 800 and 600, respectively. It took around 6 hours to solve the problem using the dual-core processor. On the other hand, the problem was solved in around 3 hours using the quad-core processor. As a result, increasing the number of cores from two to four resulted in a 50% reduction in the processing time. This reduction was due to the fact that the computational effort of the total population was distributed among four cores instead of two. Therefore, it can be expected to achieve more reduction in the processing time if more cores and/or processors are available.

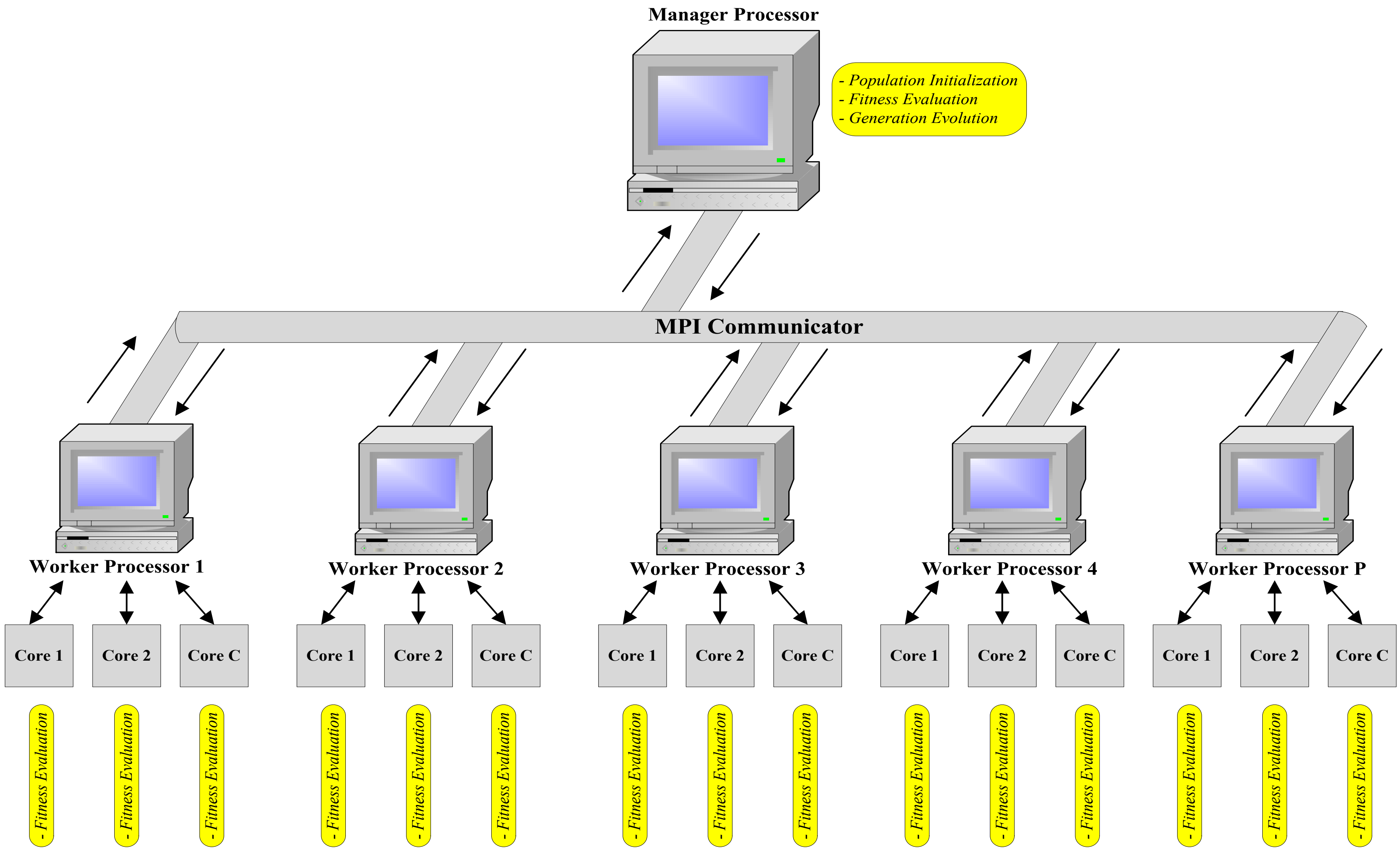


Figure 6.2: Parallel Computing Concept

6.1.3 Application Requirements

To setup and run the application, the following requirements should be available:

1. Microsoft Dot Net Framework 4
2. Microsoft SQL Server 2008 (either Express or Enterprise)
3. Windows 7 as an operating system or later

6.2 MOSCOPEA DEVELOPMENT

As shown in Figure 6.3, the development of MOSCOPEA application comprises three main units: (1) a relational database unit to facilitate the storage and retrieval of all the input and output data; (2) a processing unit that integrates both management and multi-objective optimization sub-units to perform all the required analysis; and (3) a GUI unit to facilitate the input of all the projects' data and visualize the outputs of the system. The GUI, processing, and relational database units are equivalent to the presentation, business logic, and data tiers, respectively as discussed earlier.

6.2.1 Relational Database Unit

The main purpose of this unit is to develop a relational database capable of storing the necessary input data (e.g. activities description and relations, available resource utilization modes for each activity, analysis parameters, etc.) and the produced output data (e.g. generated optimal tradeoff among different objectives). Thus, this unit is composed of eight main tables designed to store the following construction planning and analysis data: (1) projects set number; (2) projects' generic, time, financial, and contractual data; (3) projects' activities; (4) precedence relationships among activities; (5)

activities' cost, duration, and number of resources associated with each resource utilization mode; (6) analysis parameters; (7) optimal start time, finish time, and resource utilization mode for each activity; and (8) optimal multi-objective tradeoffs. Figure 6.4 shows a schematic representation of these database tables and the relationships among them using an entity relationship diagram.

The "project set" table is designed to store the number of concurrent projects set needed to be analyzed. This table is linked using a one-to-many relationship to (1) the "projects" table that stores each project's time, financial, and contractual data; and (2) the "analysis case" table which stores different analysis parameters including the GA parameters, credit and resource constraints, and desired objectives to be optimized simultaneously. The "projects" table is linked to the "activities" table which stores the descriptions and IDs of all projects' activities using a one-to-many relationship. The "activities" table is linked using a one-to-many relationship to (1) the "activities dependencies" table that stores the predecessors of each activity; and (2) the "activities resource utilization mode" table that stores the duration, cost, and number of resources of each activity associated with each resource utilization mode. The "activities" table is also linked using a many-to-many relationship to the "optimal activity schedules" table that is designed to store the identified optimal schedule for each activity, including its (1) optimal resource utilization mode; (2) optimal duration and cost; and (3) optimal start and finish times. Finally, the "optimal activity schedules" table is linked using a one-to-one relationship to the "optimal tradeoffs" table which stores the identified set of optimal tradeoffs among the projects' selected objectives to be optimized simultaneously. The main purpose of the relationships linking the tables in the relational database unit (one to one, one to many, or many to many) is to ensure the integrity of the data stored in the database during the input and output phases. For example, the relationship linking the "activities" table to the "activities resource utilization mode" table is specified to be a one-to-many relationship to ensure that each entered resource utilization mode is assigned to a single and unique activity in the project and that the deletion of that activity will automatically lead to the deletion of all its assigned resource utilization modes.

6.2.2 Processing Unit

The processing unit acts as the core unit of MOSCOPEA which coordinates all the data in order to perform all the required analysis. As shown in Figure 6.3, the processing unit is divided into two sub-units: (1) management sub-unit; and (2) multi-objective optimization sub-unit. The "management" sub-unit comprises the scheduling, cash flow, and resource models which are used to determine the multi-objectives (i.e. total duration, total cost, financing cost, required credit, profit, resource fluctuation and peak demand) values as explained earlier in Chapter 3. On the other hand, the "multi-objective optimization" sub-unit performs the three main phases of the NSGA-II technique (i.e. population initialization, fitness evaluation, and generation evolution) to obtain optimal tradeoffs between the multi-objectives as discussed earlier in Chapter 4. Both sub-units interacts together to perform all the required analysis using the data stored in the relational database unit.

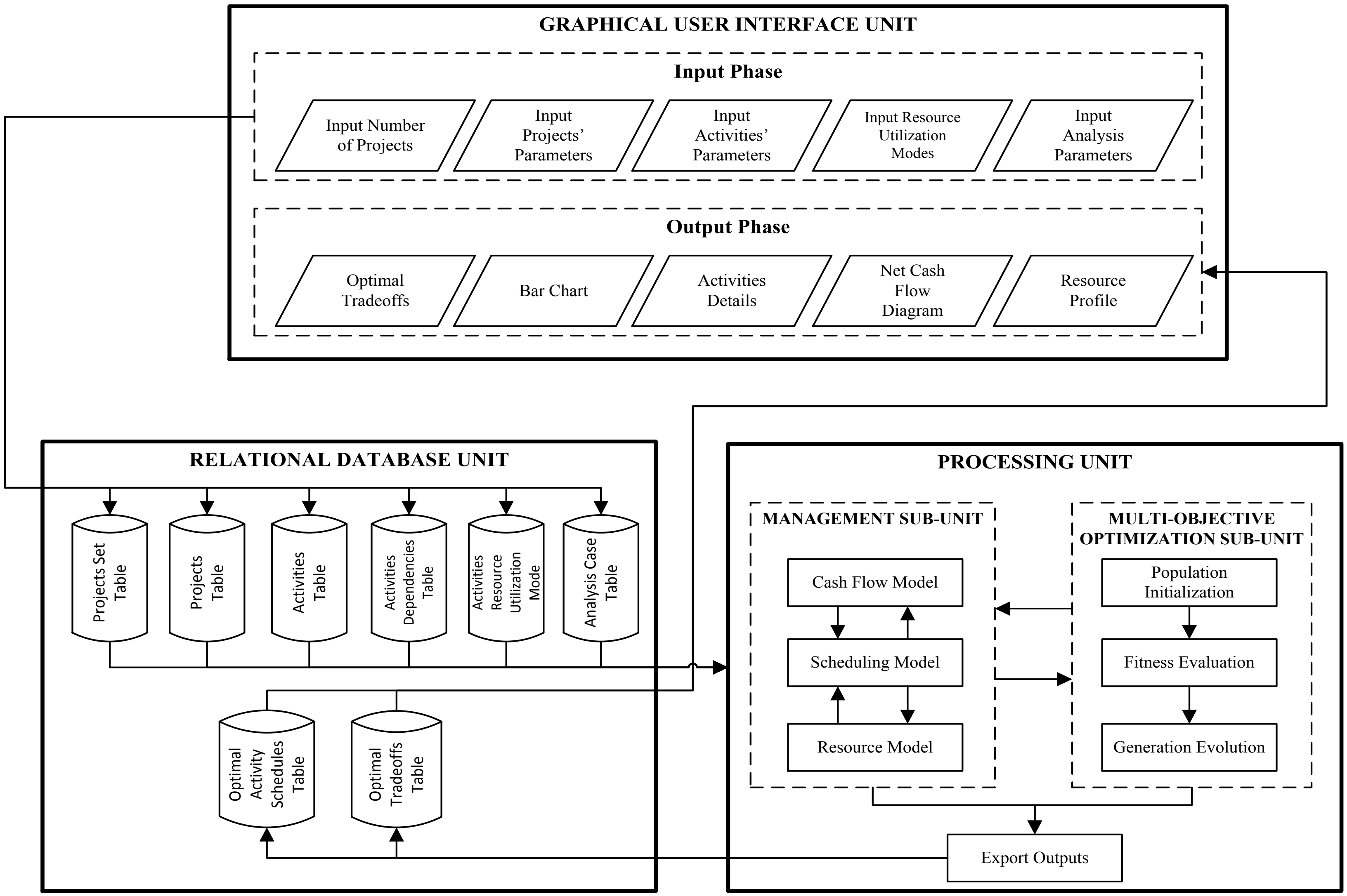


Figure 6.3: MOSCOPEA Development Framework

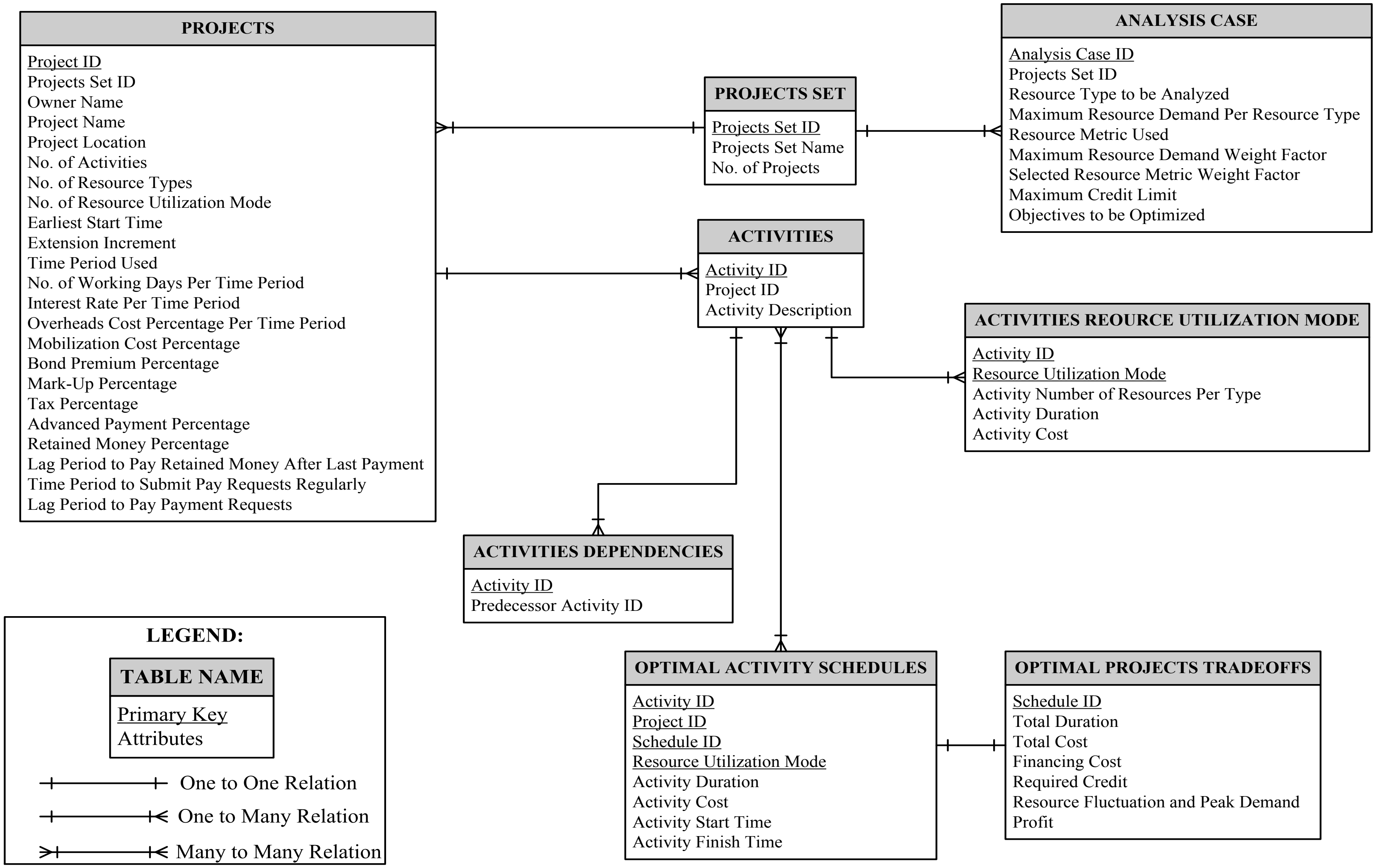


Figure 6.4: Relational Database Design

6.2.3 Graphical User Interface (GUI) Unit

The GUI unit is implemented in MOSCOPEA to facilitate the input of all the necessary construction scheduling data and the output of the generated optimal schedules. The unit is designed to implement the necessary interface functions in two main phases: (1) an input phase that facilitates the input of the projects' data, activities' data, resource utilization modes, and analysis parameters; and (2) an output phase that allows the end user to visualize the optimal activity schedules and the optimal tradeoffs among the desired multi-objectives obtained by MOSCOPEA. Figure 6.5 shows the welcome window of MOSCOPEA. The detailed procedure of implementing the GUI of MOSCOPEA is discussed in the next section.

Figure 6.5: MOSCOPEA Welcome Window

6.3 MOSCOPEA GUI IMPLEMENTATION PROCEDURE

The example of the nine-activity single project adopted from Leu and Yang (1999) is used herein to illustrate for the end user the procedure of implementing the GUI of MOSCOPEA.

6.3.1 Input Phase

The GUI input phase of MOSCOPEA comprises two main windows named A and B. Window (A) includes the activities' data, projects' data, and resource utilization modes. While, window (B) includes all the necessary analysis parameters. Window (A) is divided into eight panels (Figure 6.6) and window (B) is divided into two panels (Figure 6.7).

6.3.1.1 Window (A)

Step 1: Create New Solution

First the user is prompted using the "file" icon to either open an existing saved solution or to create a new solution as shown in Figure 6.8. Consequently, a pop-up window appear asking the user to input the solution name, number of projects, number of resource types, and number of resource utilization mode for each activity as shown in Figure 6.8. It is worth to mention that the number of resource utilization modes entered will be initially considered equal for all the activities. However, the user can delete or add later the number of modes for each activity based on the problem being solved.

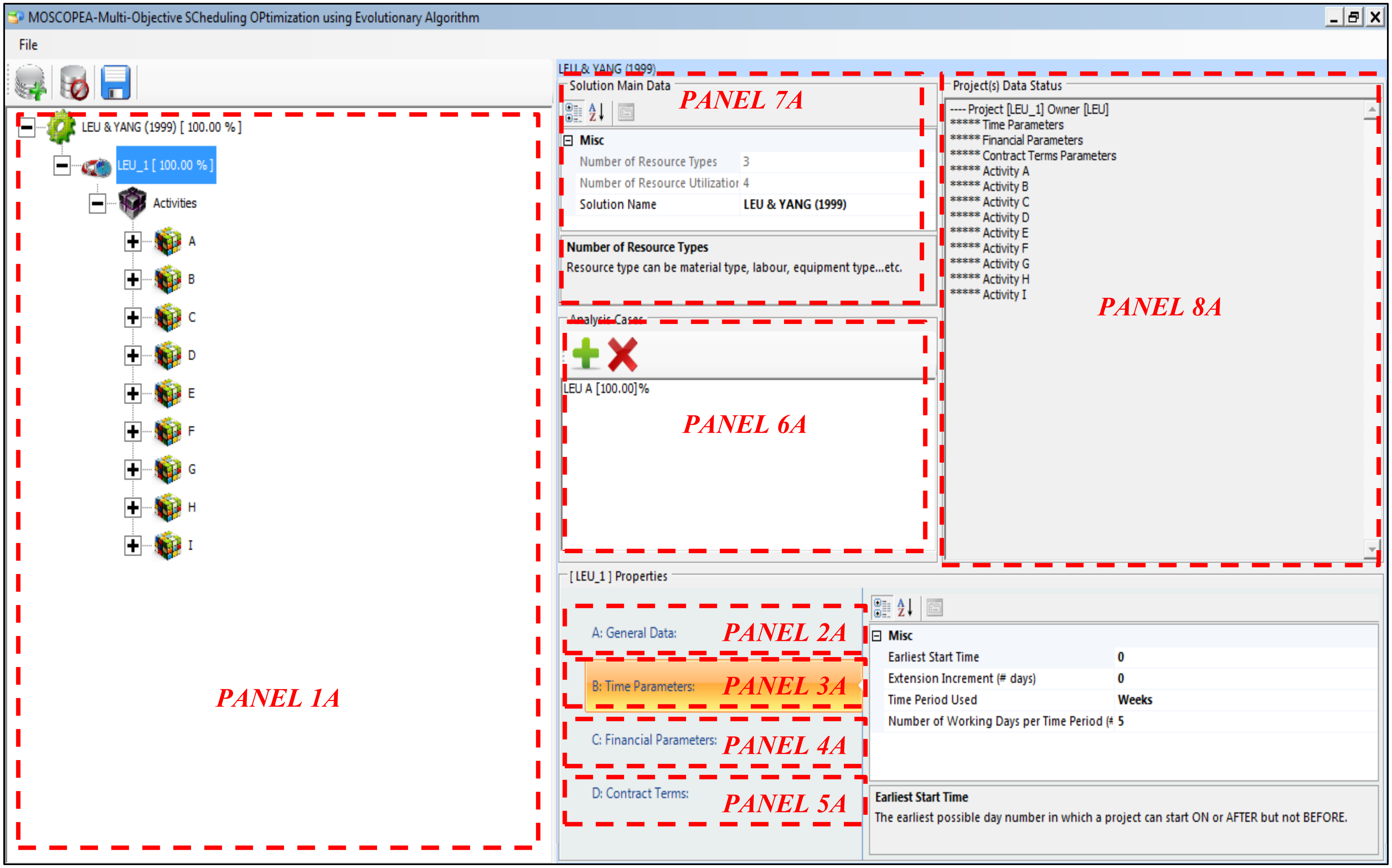


Figure 6.6: Window (A)

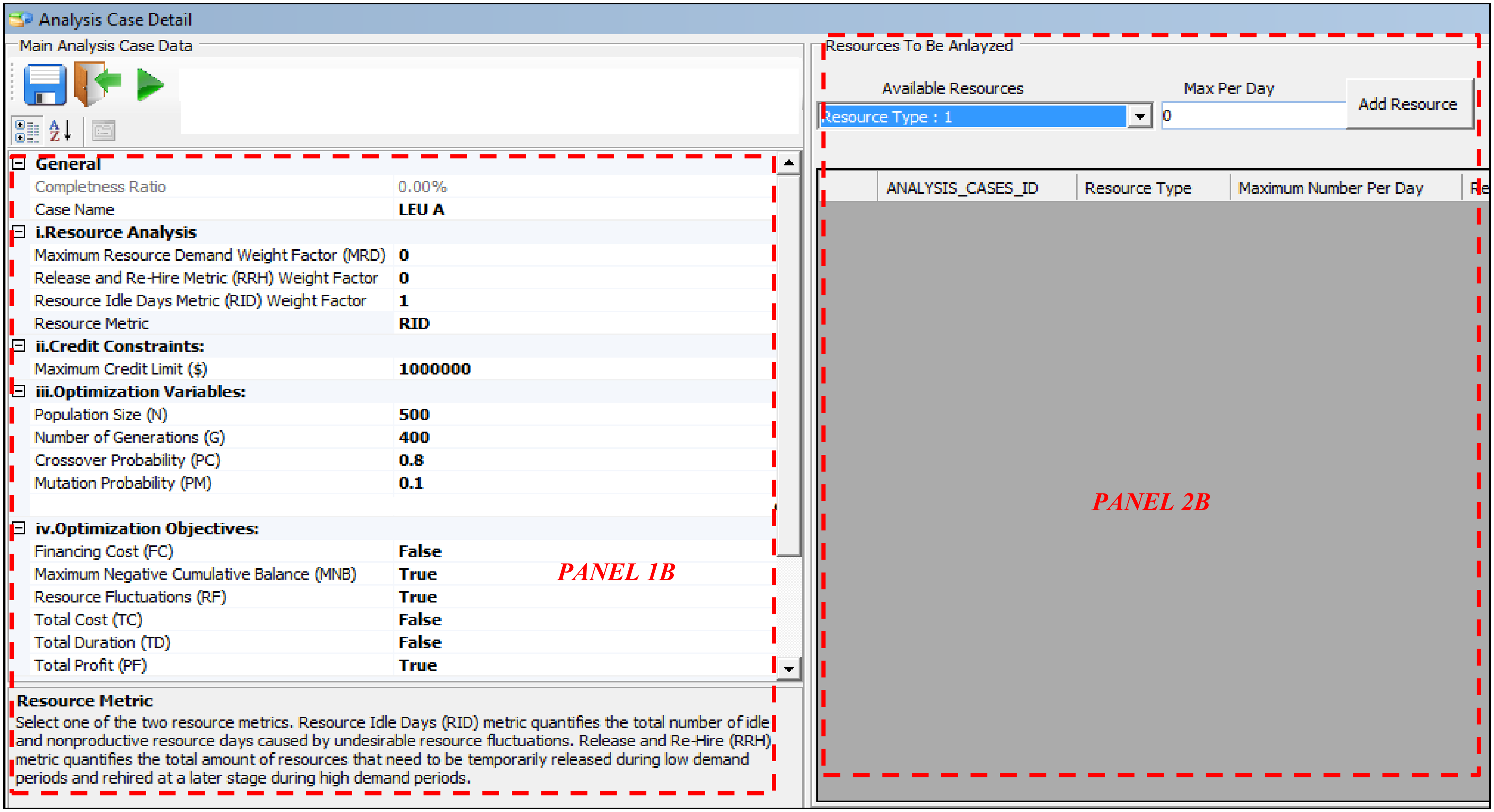


Figure 6.7: Window (B)

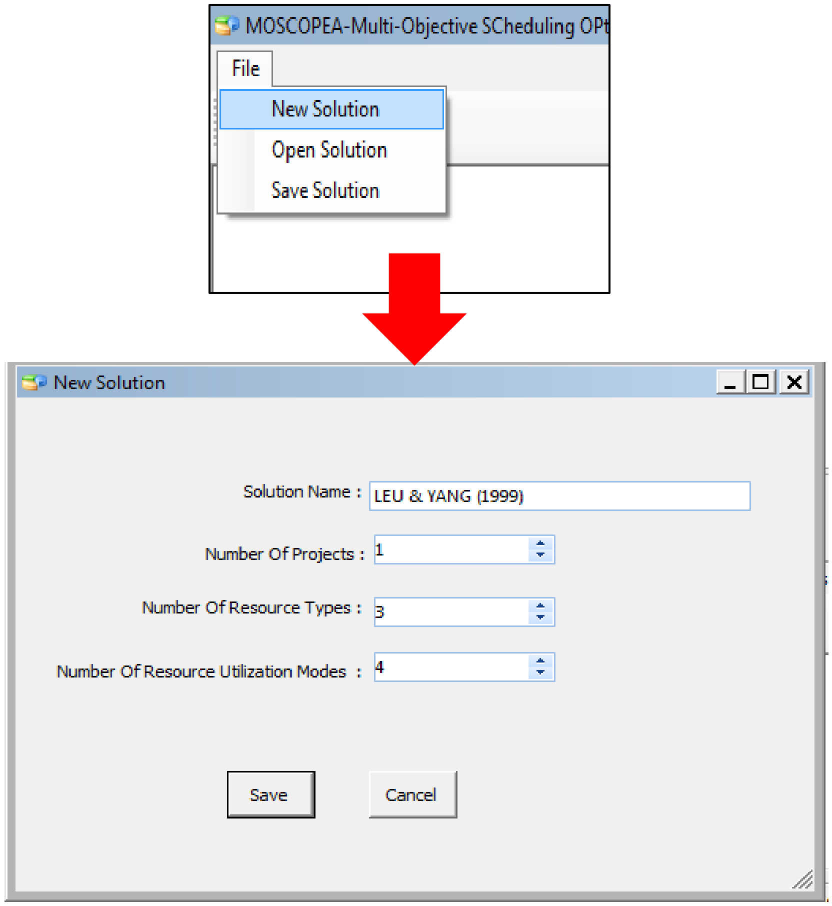


Figure 6.8: Create New Solution

Step 2: Identify Activities and Precedence Relationship

The user then has to identify all the activities and their precedence relationship in panel 1A as shown in Figure 6.9.

Step 3: Identify Resource Utilization Modes

Having all the activities identified, the user is then prompted to identify the duration, cost, and number of daily resources for each activity and its associated resource utilization mode in panel 1A as shown in Figure 6.10. Figure 6.11 shows a sample for one of the activities after all its necessary data are identified.

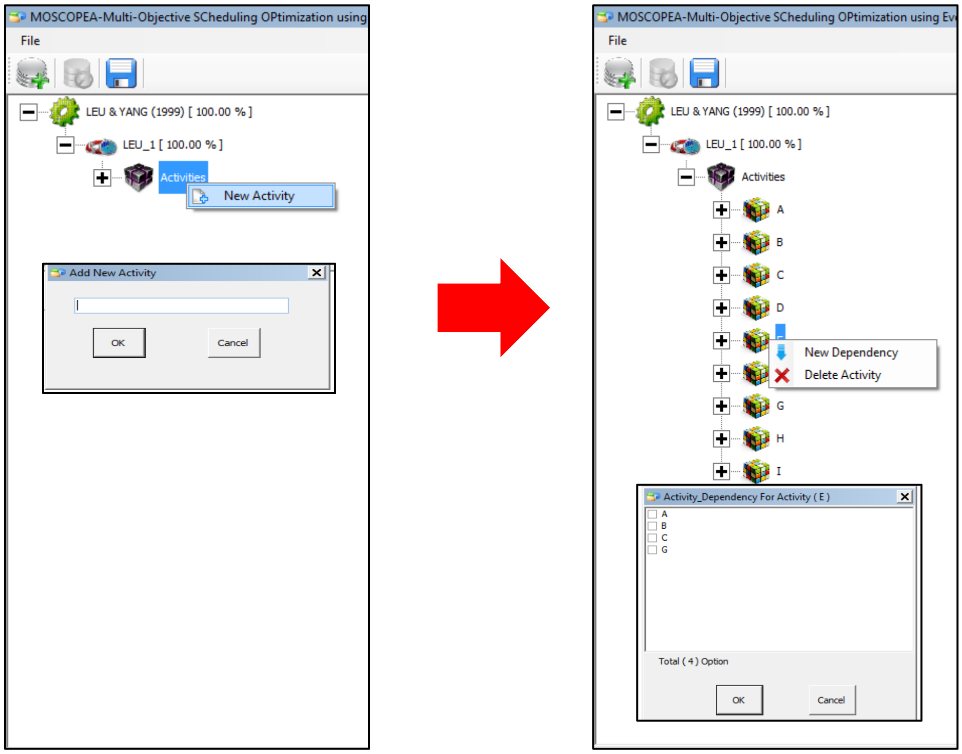


Figure 6.9: Identify Activities and Precedence Relationship

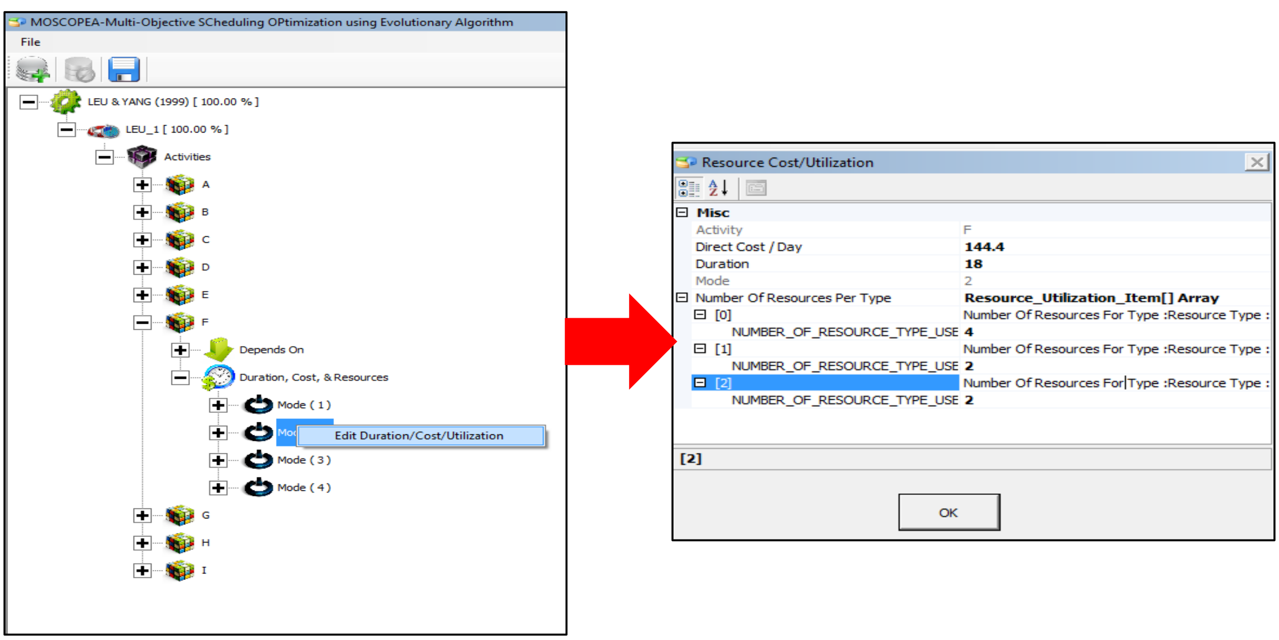


Figure 6.10: Identify Resource Utilization Modes

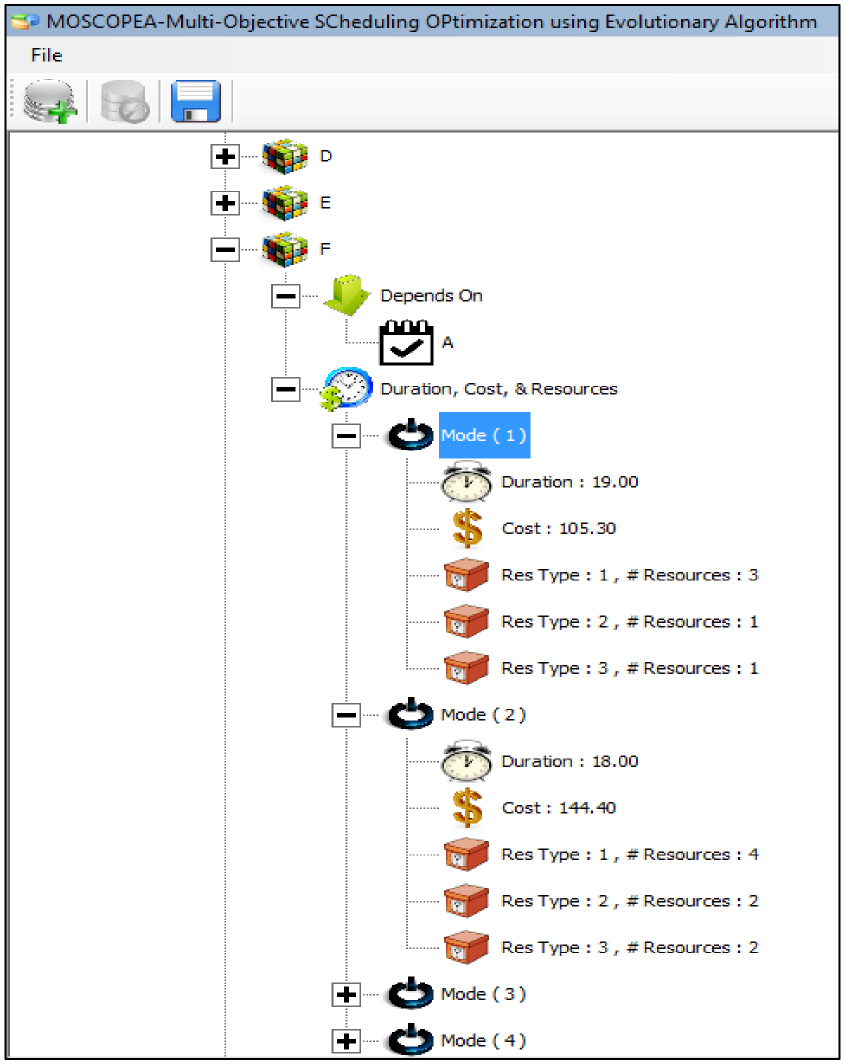


Figure 6.11: Full Identified Data for an Activity Sample

Step 4: Identify Project's Data

This step involves identifying the project's general data (panel 2A), time parameters (panel 3A), financial parameters (panel 4A), and contract terms (panel 5A) as shown in Figures 6.12 to 6.15. In case more than one project are considered, those four types of data are to be identified for each project individually.

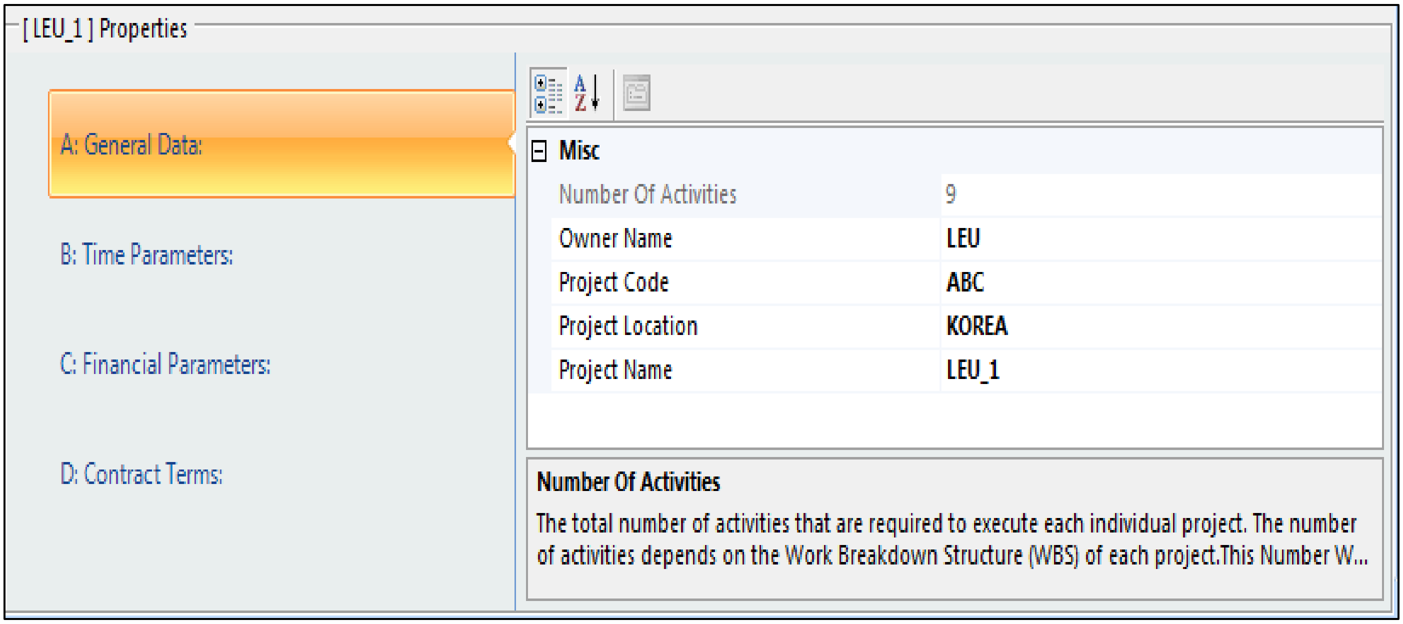


Figure 6.12: General Data (Panel 2A)

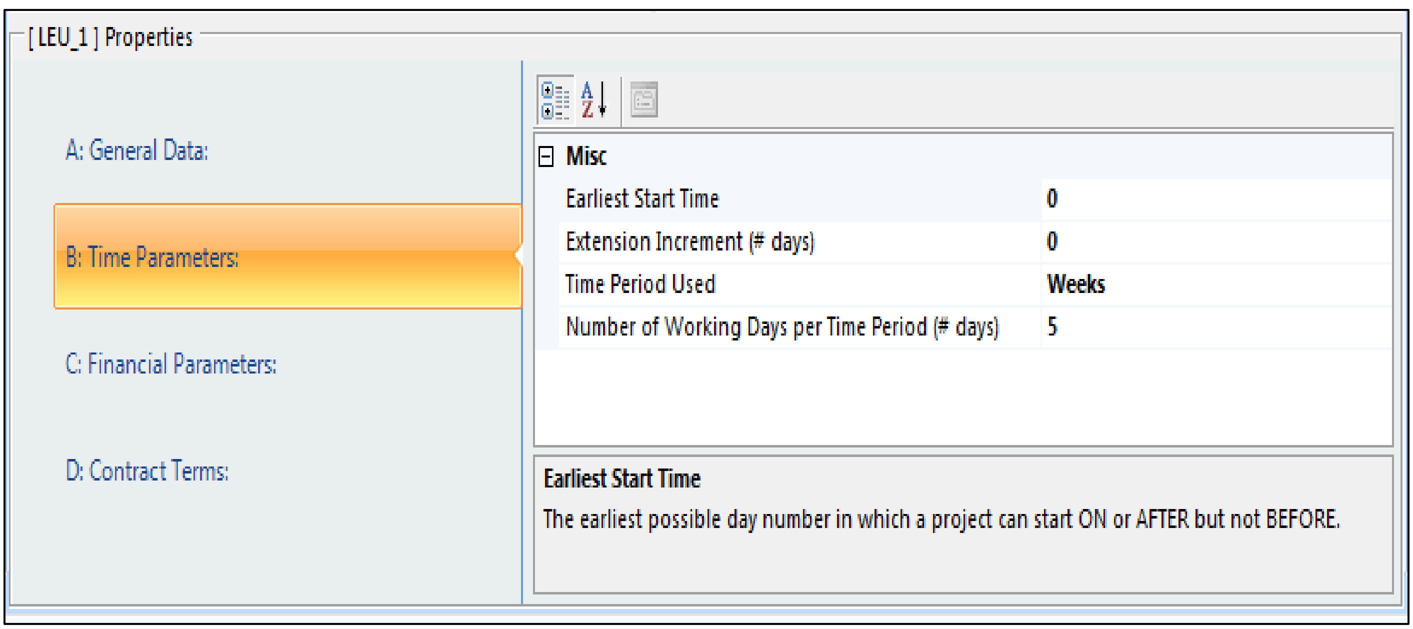


Figure 6.13: Time Parameters (Panel 3A)

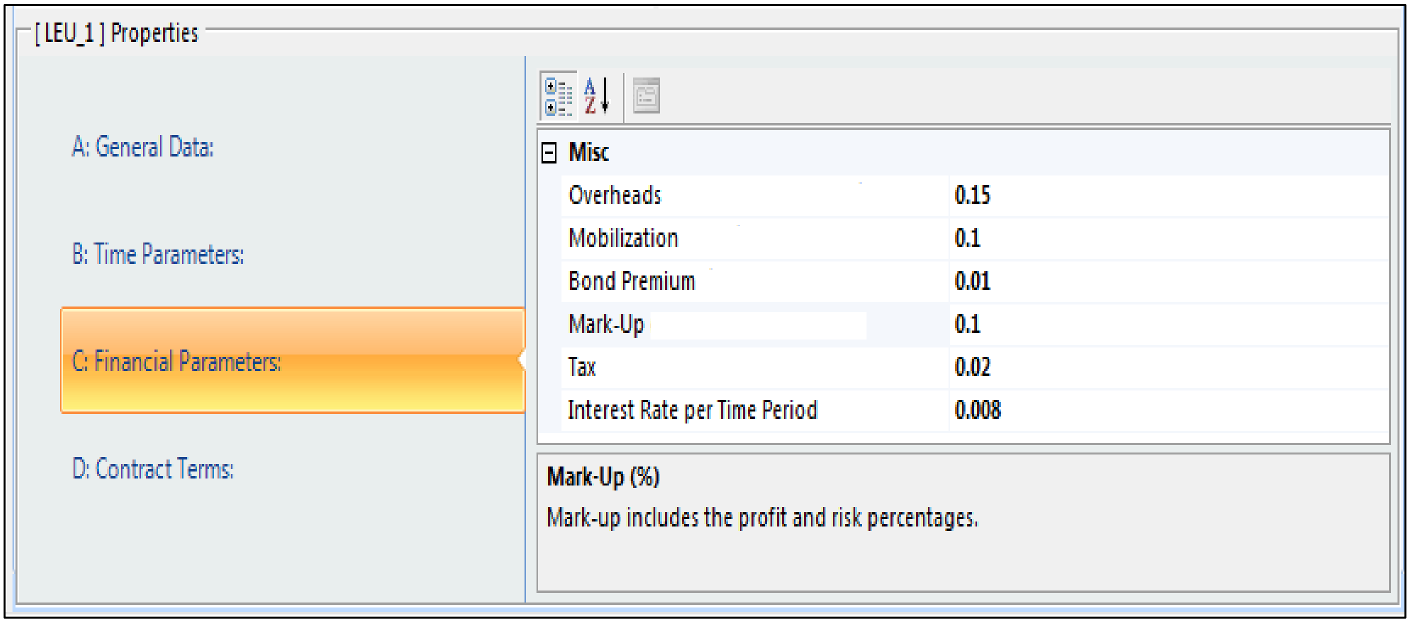


Figure 6.14: Financial Parameters (Panel 4A)

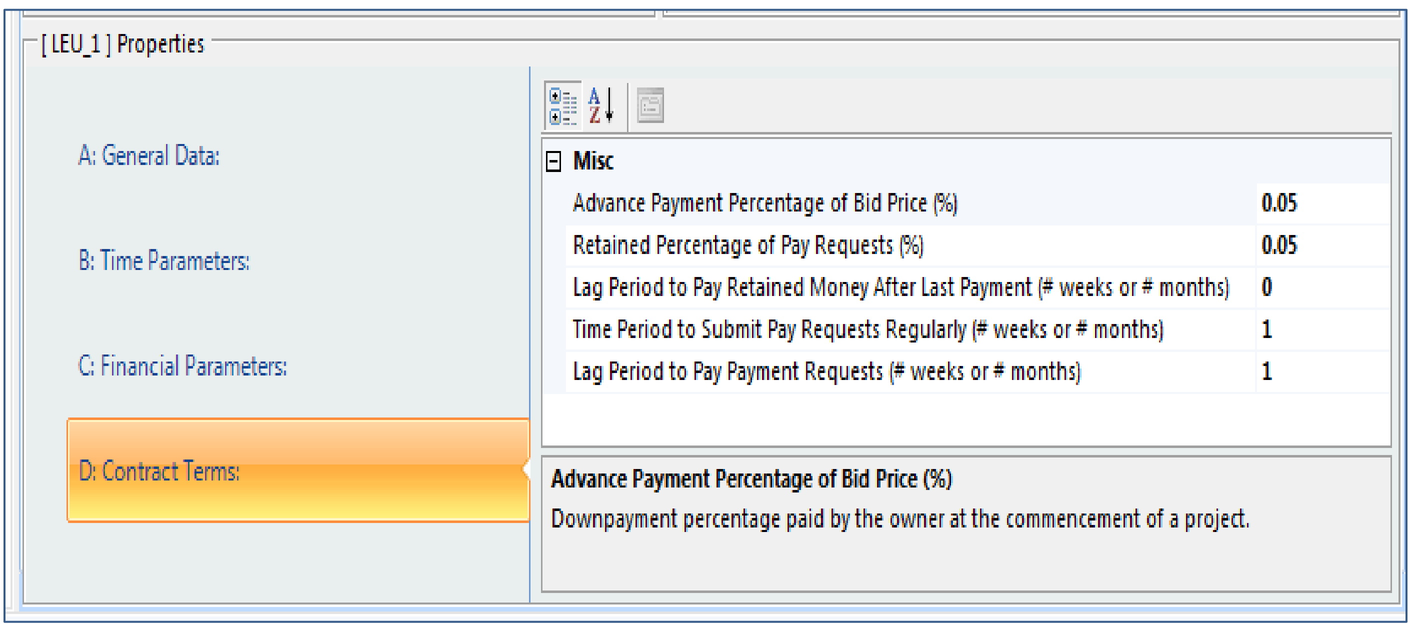


Figure 6.15: Contract Terms (Panel 5A)

Step 5: Create Analysis Case

This is the final step in windows (A) where the user is prompted to create and name an analysis case as shown in panel 6A in Figure 6.6 which will take him/her to windows (B) to identify the analysis parameters. This option allows users to create different analysis cases by altering the analysis parameters.

Panel 7A in Figure 6.6 just shows the solution name and number of resource types identified earlier in Figure 6.8. While panel 8A shows the status of the entered data to facilitate for the user identifying if any data is missing and to locate this missing data. For example, Figure 6.16 shows that the mark-up %, advance payment %, cost of activity F in one of the modes, and duration of activity F in one of the modes are missing.

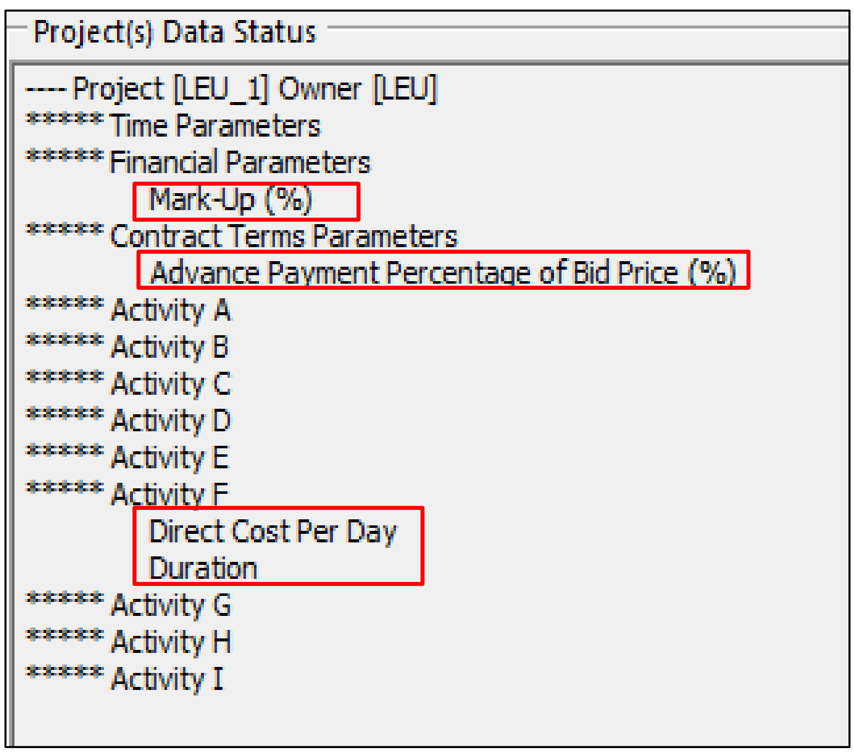


Figure 6.16: Projects Data Status (Panel 8A)

6.3.1.2 Window (B)

As shown in Figure 6.7, this window involves inputting all the different analysis parameters. In panel 1B, the user has the flexibility to select the resource metric to be used (i.e. RID or RRH) and to identify the MRD and selected resource metric weight factor. This is followed by identifying the maximum credit limit. In case no credit limit constraint is required, then the user can just input a very large value. After that, all the GA parameters are to be identified including the population size, number of generations, crossover probability, and mutation probability. Finally, the user has the flexibility to select one or more objective(s) to be optimized simultaneously by assigning for each objective a “true” or “false” value should the objective be selected or not, respectively. In panel 2B, the user has the flexibility to select one or more resource type to be analyzed – in case of multi-resources – and to identify the maximum daily resource limit for each resource type. Again, in case no resource limit constraint is required, then the user can just input a very large value. Finally, the user has to click on the optimize button and assign a folder on his/her desktop in which all the outputs will be exported as shown in Figure 6.17. Consequently, an analysis progress bar will appear as shown in Figure 6.18.

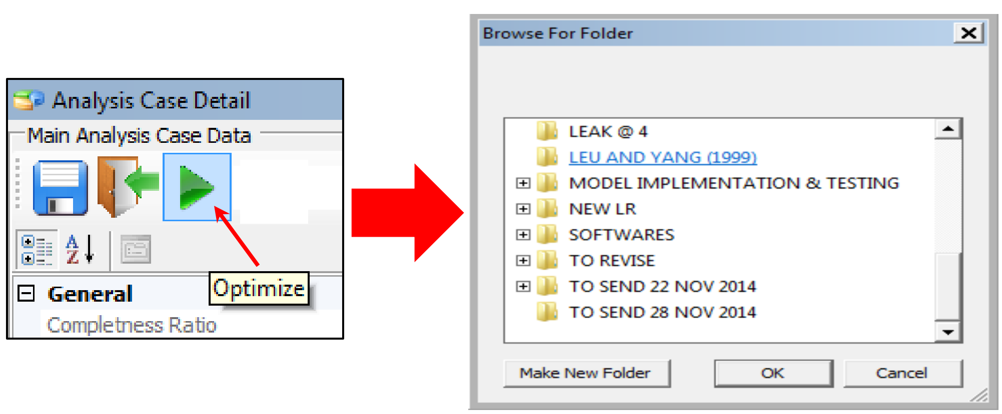


Figure 6.17: Optimize and Assign Output Folder

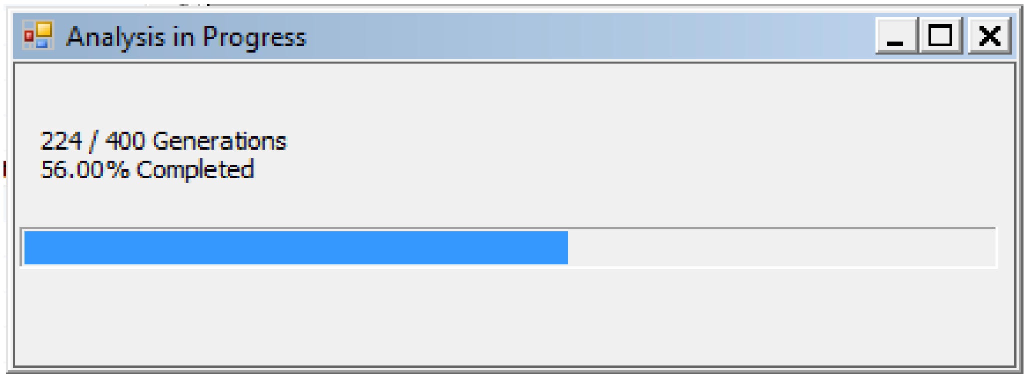
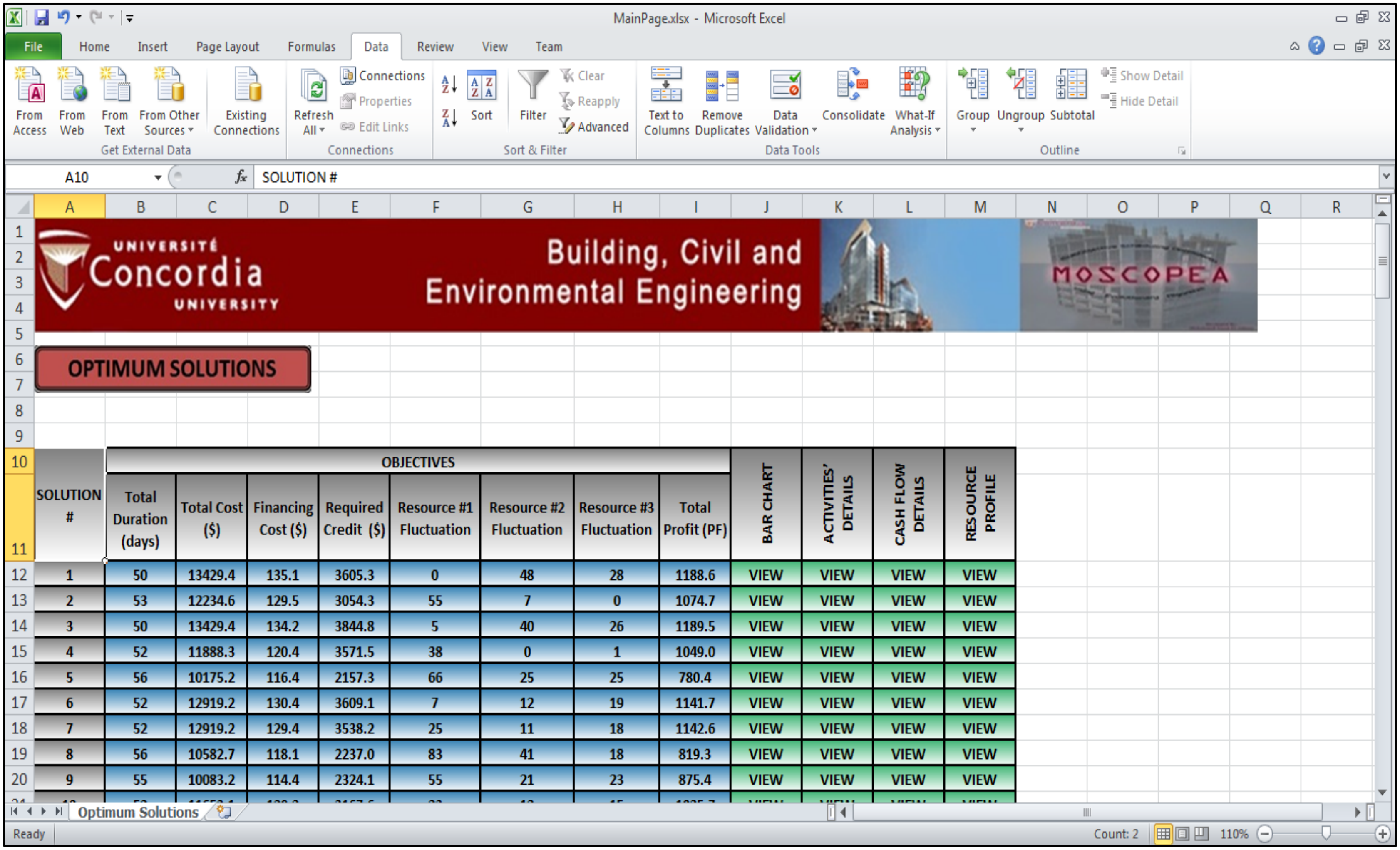


Figure 6.18: Analysis Progress Bar

6.3.2 Output Phase

The GUI output phase of MOSCOPEA is designed to export the output as a Microsoft Excel file. The main output shows the obtained non-dominated optimal solutions in a tabulated form. Such solutions or schedules represent the optimal tradeoffs between the selected multi-objectives as shown in Figure 6.19. For each solution, the total duration, total cost, financing cost, required credit, profit, and resource fluctuation and peak demand are presented. However, it should be noted that only the selected objectives are optimized. Using the tools of Microsoft Excel, several tradeoff curves between any two objectives can be plotted for better visualization. Also, the solutions can be ranked using the fuzzy approach explained earlier. Moreover, four types of output forms are associated within each solution: (1) schedule bar chart; (2) activities' details showing the optimum selected resource utilization mode, duration, start time, and finish time for each activity; (3) cash flow details showing the periodical financial parameters as well as the net cash flow diagram; and (4) resource profile to show the resource demand histogram. To retrieve such outputs, the user has to click on the corresponding "VIEW" link shown in Figure 6.19. Figures 6.20 to 6.23 show a sample for each output type.



SOLUTION #	Total Duration (days)	Total Cost ($)	Financing Cost ($)	Required Credit ($)	Resource #1 Fluctuation	Resource #2 Fluctuation	Resource #3 Fluctuation	Total Profit (PF)	BAR CHART	ACTIVITIES' DETAILS	CASH FLOW DETAILS	RESOURCE PROFILE
	OBJECTIVES											
1	50	13429.4	135.1	3605.3	0	48	28	1188.6	VIEW	VIEW	VIEW	VIEW
2	53	12234.6	129.5	3054.3	55	7	0	1074.7	VIEW	VIEW	VIEW	VIEW
3	50	13429.4	134.2	3844.8	5	40	26	1189.5	VIEW	VIEW	VIEW	VIEW
4	52	11888.3	120.4	3571.5	38	0	1	1049.0	VIEW	VIEW	VIEW	VIEW
5	56	10175.2	116.4	2157.3	66	25	25	780.4	VIEW	VIEW	VIEW	VIEW
6	52	12919.2	130.4	3609.1	7	12	19	1141.7	VIEW	VIEW	VIEW	VIEW
7	52	12919.2	129.4	3538.2	25	11	18	1142.6	VIEW	VIEW	VIEW	VIEW
8	56	10582.7	118.1	2237.0	83	41	18	819.3	VIEW	VIEW	VIEW	VIEW
9	55	10083.2	114.4	2324.1	55	21	23	875.4	VIEW	VIEW	VIEW	VIEW

Figure 6.19: Optimal Tradeoffs Output

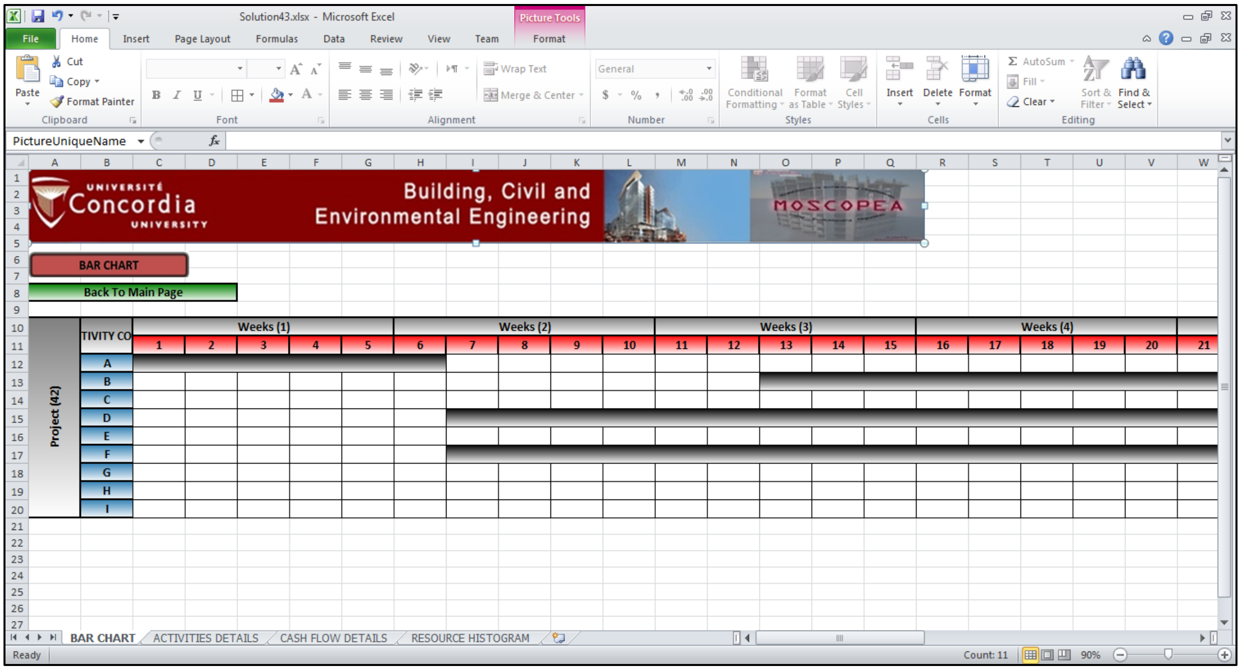


Figure 6.20: Bar Chart Output

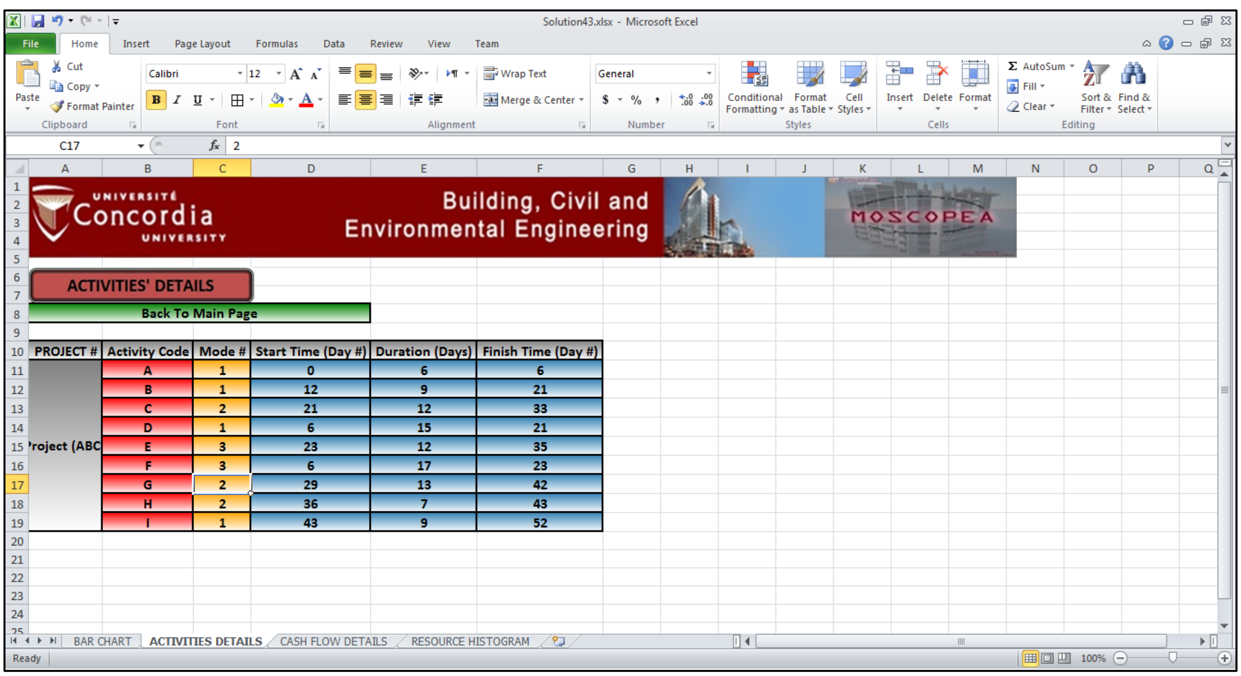


Figure 6.21: Activities' Details Output

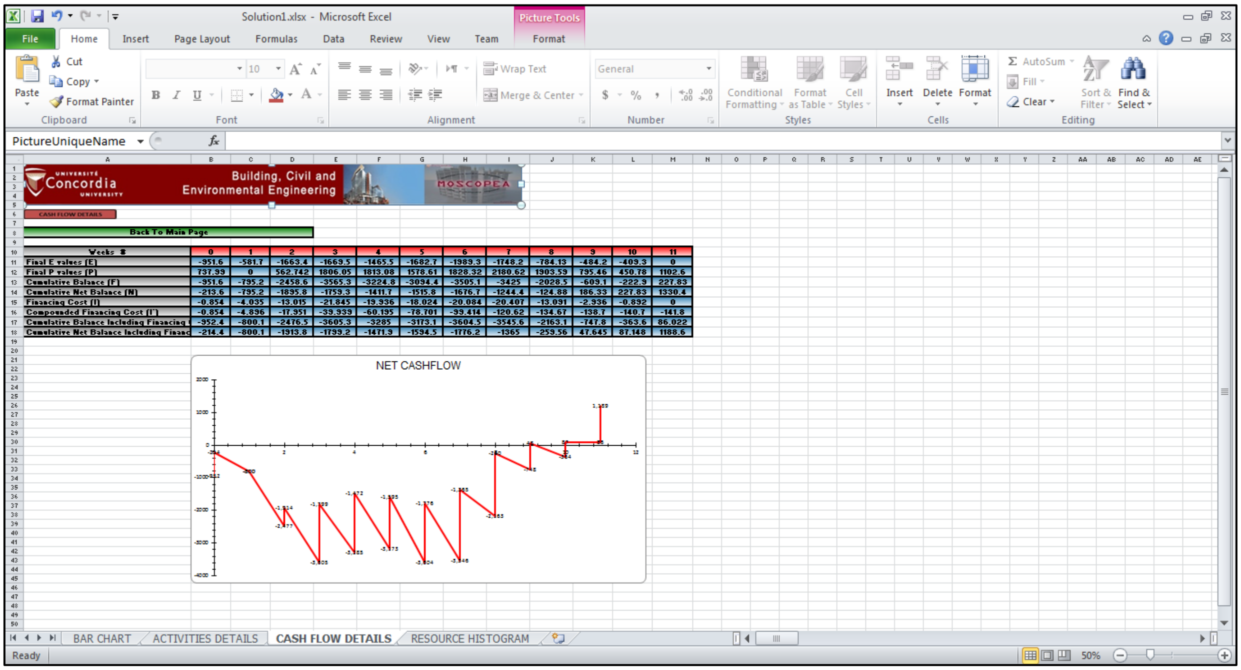


Figure 6.22: Cash Flow Details Output

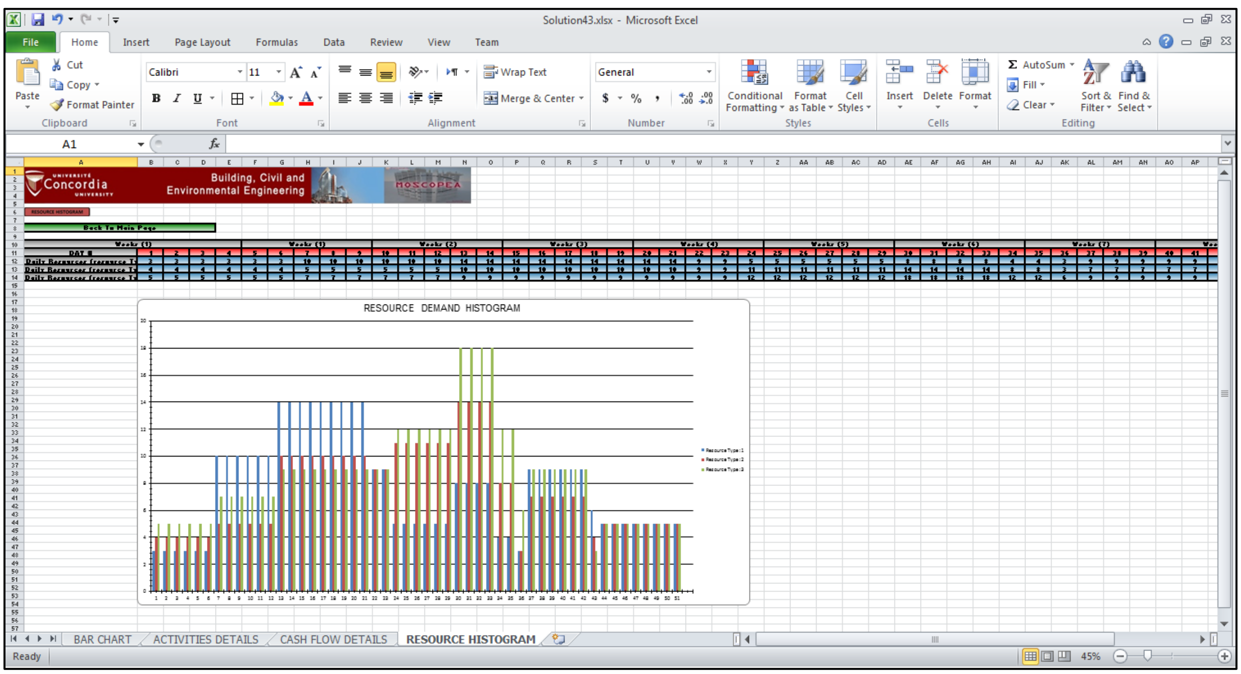


Figure 6.23: Resource Profile Output

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 SUMMARY AND CONCLUSIONS

Surveys of construction practitioners point to financial and budgetary factors as the leading causes of construction business failures. Such leading causes are mainly due to inefficient control and management of contractor's cash flow. This inefficiency is due to the fact that contractors mainly deal with the project scheduling and financing as two independent functions of construction project management. The absence of the required linkage between those two functions resulted in devising non-executable schedules which lead to a high volume of project failure due to finance deficit. Thus, controlling and regulating the movement of the cash is necessary for the success of the construction projects. According to the literature review carried in this research, there was a lack of research that considers integrating both resource leveling and allocation simultaneously with the finance-based scheduling concept. Considering those two aspects together have a significant impact on many areas of project management including time, cost, resource, and risk. Moreover, few researches solved the finance-based scheduling problem considering the contractor's entire portfolio rather than single project. Multiple concurrent projects involves sharing and competing for limited resources such as funds, equipment, manpower and other resources among different projects, which increases the complexity of the scheduling process.

As a result, it was motivated in this research to present the development of a novel multi-objective scheduling optimization model for multiple construction projects. The novelty arises throughout considering both financial and resource aspects under a single platform. Such aspects were considered by integrating the concept of finance-based scheduling together with resource leveling and allocation for concurrent multiple projects. The model enables construction companies in solving the problems of how to prioritize the projects with resource conflicts, how to reasonably allocate the limited resources among multiple projects to meet the resource requirements of different projects, and to optimize all the projects' multi-objectives under cash limits. The multi-objectives included in this optimization model were the total duration, total cost, financing cost, required credit, profit, resource fluctuations and peak demand.

Three main management models were developed to adapt for multiple construction projects, namely: scheduling, cash flow, and resource model. The main aim of these models is to evaluate the projects' different multi-objectives values. The scheduling model establishes optimal/near optimal schedules for multiple construction projects to determine the projects' total duration and identify the activities' start and finish times. The cash flow model determines the total cost, financing cost, required credit, and profit of multiple projects based on the schedules obtained from the scheduling model. Finally, the resource model determines the resource fluctuations and daily maximum resource demand for multiple projects based also on the schedules obtained from the scheduling model.

Consequently, a complete optimization model formulation was established to identify the model's decision variables, formulate the optimization objectives, and model the optimization constraints. The decision variables comprised both the start times and resource utilization modes of the projects' activities. On the other hand, the model was formulated under the constraints of preserving the logical relationship between activities while keeping the maximum required credit and resource demand below pre-defined limits.

Accordingly, a multi-objective scheduling optimization model was developed for multiple construction projects using multi-mode activities with multi-resources. The developed model was linked with the three management models (scheduling, cash flow, and resource) to search for schedules that optimize the projects' desired objectives using the NSGA-II technique. The model performed the genetic algorithm operations in three main phases: (1) population initialization; (2) fitness evaluation; and (3) generation evolution.

The model was tested to solve a time/cost tradeoff problem, integrated time/cost tradeoff and resource allocation problem, and a finance-based scheduling problem retrieved from literature. The testing results were compared with the previous ones and the model proved its robustness in solving such problems. Moreover, the model was applied on three case studies to demonstrate its capabilities to solve integrated resource leveling, resource allocation, and finance-based scheduling problems for single and multiple projects under unconstrained and constrained credit and resource limits.

Finally, an automated tool named MOSCOPEA (Multi-Objective SCheduing OPtimization using Evolutionary Algorithm) was built with a friendly graphical user interface to facilitate in selecting the optimum/near optimum start times and resource utilization modes of activities that optimizes the projects' desired objectives. The tool was designed and built to execute parallel computing by performing parallel fitness evaluation of the multi-objectives over multi-processors with multi-cores to support the optimization of large-scale construction projects by reducing its processing time.

7.2 RESEARCH CONTRIBUTIONS

The main contributions of this research can be summarized as follows:

1. Development of a strategy or methodology to integrate CPM schedules with their associated cash flows and resource profiles for multiple construction projects.
2. Development of a multi-objective scheduling optimization model for multiple construction projects considering both financial and resource aspects. Such model enables planners to devise optimal/near optimal schedules for multiple projects that simultaneously: (a) satisfies certain credit and resource limits; (b) minimize undesirable resource fluctuations, i.e. increase the efficiency of resource utilization; and (c) maximize contractors' profit.
3. Adding flexibility to the developed model in selecting the desired set of objectives to be optimized together. In other words, different tradeoffs between different set of selected objectives can be obtained from the model. The merit of this flexibility is in allowing contractors to examine the impact of one or more objectives over the other on the projects' schedule. Thus, the model can solve individually the

time/cost tradeoff, resource leveling, resource allocation, or finance-based scheduling problems. Alternatively, integration of such problems can be also solved.

4. Designing and building an automated tool (MOSCOPEA) with a friendly graphical user interface that incorporates the above points under a single platform to facilitate for practitioners the scheduling optimization process in the construction industry.

7.3 RESEARCH LIMITATIONS

The research has some limitations which can be summarized as follows:

1. The developed model considers only the finish-to-start precedence relationship between the projects' activities.
2. The scheduling model does not allow for activities' interruption or splitting caused by different parties.
3. The cash flow model applies only for unit-price type contracts. In addition, it does not consider for projects' activities that are executed by sub-contractors.
4. The cash flow model does not consider the cost of resource idle days as well as the early completion bonus.
5. The developed automated tool requires the user to manually enter the activities' time, cost, and resource data one by one which consumes more time than just simply importing such data in a tabulated form.
6. In the absence of multi-processors with multi-cores, the automated tool may not be suitable to solve large-scale projects due to high computational time.

7.4 RECOMMENDATIONS FOR FUTURE WORK

The current research study has been able to accomplish its main objectives. Yet, several points are recommended to enhance and extend the current research for future work.

7.4.1 Current Research Recommended Enhancements

- The model should cover all other types of precedence relationships (i.e. finish-to-finish, start-to-start, and start-to-finish) and should consider also the time lag between activities. Taking such relationships into consideration is essential to develop more practical schedules by overlapping the activities of a network to accelerate the execution of a project.
- The cash flow model can be modified to account for the charges of the unused credit limit. The interest rate of the unused credit fee is lower than the interest rate on actual negative balances because the bank can likely lend the unused funds to another borrower. Taking this into consideration can improve (minimize) the financing costs for the contractor.
- The optimization model can consider allocating a priority weight for each concurrent project to assign efficiently the available resources and cash among different projects.
- Using a certain metaheuristic technique to efficiently solve a specific problem, may not adequately solve other optimization problems. Similarly, a problem can be solved differently by various algorithms. As a result, other promising meta-heuristics techniques such as ant colony or particle swarm optimization can be experimented to solve the currently developed model. Such techniques can be

compared with the used NSGA-II technique to select the most suitable one based on the quality of the results as well as the processing time.

- In reality, many factors exist during construction that may affect the cash flow including time delays, cost overruns, unconfirmed earned values, change orders, and changes of cost plan elements. Thus, for more practical schedules, activities' interruption or splitting caused by different parties can be considered. Moreover, uncertainties in the activities' duration and cost can be considered while scheduling the projects.

7.4.2 Current Research Recommended Extensions

- The cash flow model of this research applies only for unit-price type contracts. Thus, the cash flow model structure can be adjusted to suit other different types of construction contracts. This can be done by studying and applying the different contracts' methods of payment as well as the timing of payment which can highly affect the project schedule.
- Sometimes contractors may face problems of being timely paid by the owner. A failure of the contractor getting regular and timely payment could result in project delay, reduced profitability, and in the extreme case, the company may go into liquidation. Therefore, the model should be further experimented to address owner's late payment. This can be done by altering the "lag to pay payment requests" parameter in the current model to create "what-if" scenarios. Thus, several late payment scenarios can be established, studied, and compared to account for delays in owner's payment.

- Heavy construction projects such as highways, tunnels, and bridges usually age and deteriorate at a fast rate requiring immediate rehabilitation efforts to enhance their quality. Therefore, other objectives such as the "construction method quality" can be added to be optimized together with the identified multi-objectives.

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APPENDIX A: ILLUSTRATIVE EXAMPLE FOR NSGA-II OPERATIONS

In this appendix, a small illustrative example which consists of two concurrent projects is solved manually to show the details of the NSGA-II operations step by step for one generation. The NSGA-II operations will pass through three main phases as discussed earlier in Chapter 4 focusing more on the third phase, i.e. generations evolution phase. The precedence relation, cost, and resource data for the activities in both projects are shown in Table A.1. In addition, the time, financial, and contractual data of both projects are shown in Table A.2. In this example, it is assumed to optimize the total financing cost (FC), maximum required credit (RC), and total profit (PR). A population size of eight is assumed with 80% and 5% crossover and mutation probability, respectively. Finally, the maximum credit limit during any period is set to be $100,000.

Table A.1: Precedence Relation, Cost, and Resource Data

		Project 1				**Project 2**				
Activity		**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
Predecessor(s)		-	A	A	B,C	-	E	E	F,G	H
Mode 1	**Duration (days)**	4	6	8	3	3	4	4	6	5
	Direct Cost ($ / day)	1000	2000	3000	2500	1500	3000	4000	5000	3000
	Resource (crew/day)	2	3	4	3	4	4	3	5	2
Mode 2	**Duration (days)**	3	4	6	2	2	3	2	4	3
	Direct Cost ($ / day)	1500	3500	4500	4000	2500	5000	9000	8000	5500
	Resource (crew/day)	3	4	6	4	5	6	6	7	3

Table A.2: Time, Financial, and Contractual Data

Data Type	Item	Project 1	Project 2
TIME	**Project Start Time (day #)**	0	10
	No. of Days per Week	5	5
	Extension Increment (days)	5	9
FINANCIAL	**Interest Rate % per Week**	0.30	0.30
	Overheads %	8	6
	Mobilization Costs %	10	10
	Tax %	2	2
	Mark-Up %	20	20
	Bond Premium %	1	1
CONTRACT TERMS	**Advance Payment % of Bid Price**	6	9
	Weeks to Retrieve Advance Payment	[a]	[a]
	Retained % of Pay Requests	5	5
	Lag to Pay Retained Money After Last Payment (weeks)	0	0
	Weeks to Submit Pay Requests Regularly	1	1
	Lag to Pay Payment Requests (weeks)	1	1
	Late Completion Penalty per Day ($ / day)	500	500

[a] Number of weeks encompassing the total project duration

A.1 PHASE (1): POPULATION INITIALIZATION

As a starting point, eight different solutions/schedules are randomly generated to represent the parent (P) population of the first generation (G_1). The random initialization takes place in two consecutive steps. First, a random "utilization mode" is allocated to each activity in each project. Second, a random "start time" is allocated to each activity in each project. Consequently, the finish time of each activity in each project is determined using the scheduling model described in Chapter 3. Table A.3 shows a sample for the generated schedule of parent 1 in the first generation (P_1-G_1).

Table A.3: Schedule Sample of P_1-G_1

	Project 1				Project 2				
Activity	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
Mode #	2	1	1	2	1	2	2	1	2
Start Time	0	4	5	13	10	14	13	18	24
Duration	3	6	8	2	3	3	2	6	3
Finish Time	3	10	13	15	13	17	15	24	27

A.2 PHASE (2): FITNESS EVALUATION

After generating the initial parent population in phase 1, the optimization objectives are to be determined. In other words, for each of the eight parent solutions generated, the FC, RC, and PR are calculated using the cash flow model described earlier in Chapter 3. Table A.4 shows the resulted objective values for each solution. It can be noticed that solutions P_6 and P_8 are considered as “infeasible” solutions since their RC objective values exceeded the set credit limit of $100,000.

Table A.4: Parent Population of First Generation (P-G_1)

Solution	OBJECTIVES			Feasibility
	FC	RC	PR	
P_1	682	96084	37848	Feasible
P_2	728	93221	37904	Feasible
P_3	678	75904	39115	Feasible
P_4	659	71616	38382	Feasible
P_5	785	84118	39479	Feasible
P_6	681	101606	39379	Infeasible
P_7	642	77767	38642	Feasible
P_8	790	132100	37802	Infeasible

A.3 PHASE (3): GENERATION EVOLUTION

In this final phase, three types of population are to be generated as follows:

1. Child population of the first generation (Q-G_1)
2. Combined population of the first generation (R-G_1)
3. Parent population of the second generation (P-G_2)

A.3.1 Child Population of the First Generation (Q-G_1)

To generate the child population of the first generation, the following three steps are to be applied:

- ***Step 1: Non-Domination Rank Determination:***

For each solution in the parent population of the first generation (P-G_1), the non-domination rank (i_{rank}) is to be determined. The ranking process takes place by comparing the three objectives' values (i.e. FC, RC, and PR) of each individual solution with those of the other solutions. Consequently, the solutions are distributed to different "fronts" that reflects their i_{rank}. When two solutions (X and Y) are compared at a time, two results are expected. Either both solutions are non-dominated or one solution dominate the other. A solution X dominates solution Y if:

1. Solution X is feasible and Solution Y is infeasible
2. Both solutions are infeasible and Solution X has a lower total constraint violation than Solution Y.
3. Both solutions are feasible and Solution X dominates Solution Y. In other words, Solution X have lower FC and RC values and higher PR value than those in Solution Y.

Based on the above discussion, all of the eight solutions in P-G_1 (see Table A.4) will be considered in Front 1 as a starting point. After that, the comparison process will take place as follows:

Front (1):

- P_1 is compared with all the other solutions in front 1 as shown below:

Solutions	Status	Decision
P_1 with P_2	Non-dominated	Keep both solutions in front 1
P_1 with P_3	P_3 dominates P_1	Keep P_3 in front 1 and move P_1 to front 2

- P_2 is compared with all the other solutions left in front 1 as shown below:

Solutions	Status	Decision
P_2 with P_3	P_3 dominates P_2	Keep P_3 in front 1 and move P_2 to front 2

- P_3 is compared with all the other solutions left in front 1 as shown below:

Solutions	Status	Decision
P_3 with P_4	Non-dominated	Keep both solutions in front 1
P_3 with P_5	Non-dominated	Keep both solutions in front 1
P_3 with P_6	P_3 dominates P_6	Keep P_3 in front 1 and move P_6 to front 2
P_3 with P_7	Non-dominated	Keep both solutions in front 1
P_3 with P_8	P_3 dominates P_8	Keep P_3 in front 1 and move P_8 to front 2

- P_4 is compared with all the other solutions left in front 1 as shown below:

Solutions	Status	Decision
P_4 with P_5	Non-dominated	Keep both solutions in front 1
P_4 with P_7	Non-dominated	Keep both solutions in front 1

- P_5 is compared with all the other solutions left in front 1 as shown below:

Solutions	Status	Decision
P_5 with P_7	Non-dominated	Keep both solutions in front 1

Thus, solutions P_3, P_4, P_5, and P_7 will remain in front 1.

Front (2):

- P_1 is compared with all the other solutions in front 2 as shown below:

Solutions	Status	Decision
P_1 with P_2	Non-dominated	Keep both solutions in front 2
P_1 with P_6	P_1 dominates P_6	Keep P_1 in front 2 and move P_6 to front 3
P_1 with P_8	P_1 dominates P_8	Keep P_1 in front 2 and move P_8 to front 3

Thus, solutions P_1 and P_2 will remain in front 2.

Front (3):

- P_6 is compared with all the other solutions in front 3 as shown below:

Solutions	Status	Decision
P_6 with P_8	P_6 dominates P_8	Keep P_6 in front 3 and move P_8 to front 4

P_6 dominated P_8 since it has lower constraint violation. Thus, solution P_6 will remain in front 3 and P_8 will be in front 4. Table A.5 summarizes the solutions distribution among the different fronts.

Table A.5: Non-Domination Ranking of P-G_1

Solution	FRONT #
P_3	Front 1 (i_{rank} = 1)
P_4	
P_5	
P_7	
P_1	Front 2 (i_{rank} = 2)
P_2	
P_6	Front 3 (i_{rank} = 3)
P_8	Front 4 (i_{rank} = 4)

❖ ***Step 2: Crowding Distance Calculation:***

The crowding distance ($i_{distance}$) is calculated for fronts having more the one solution (i.e. front 1 and 2) to determine the Euclidean distance between each individual in a front. The calculation procedure is explained in details in Chapter 2. The boundary solutions (solutions having the lowest or highest objective functions) in each front are assigned an infinite distance value to keep diversity. Thus, solutions P_4, P_5, and P_7 in front 1 and solutions P_1 and P_2 in front 2 will have an infinite distance value. This leaves for us only solution P_3 in front 1 to calculate its crowding distance as follows:

- Sort the solutions in front 1 based on their objectives' values from lowest to highest as shown below:

Sorted Solutions	FC	Sorted Solutions	RC	Sorted Solutions	PR
P_7	642	**P_4**	71616	**P_4**	38382
P_4	659	**P_3**	75904	**P_7**	38642
P_3	678	**P_7**	77767	**P_3**	39115
P_5	785	**P_5**	84118	**P_5**	39479

- Calculate the crowding distance of P_3 as shown below:

$$i_{distance}\,(P_3) = \frac{(785-659)}{(785-642)} + \frac{(77767-71616)}{(84118-71616)} + \frac{(39479-38642)}{(39479-38382)} = 2.13$$

In real case analysis, when population size is large, it is uncommon to find most of the solutions having infinite crowding distance.

❖ ***Step 3: Tournament Selection, Crossover, and Mutation:***

In order to generate the child population of the first generation, the parents should mate first through crossover and/or mutation. However, the question that arises here is which set of solutions in the parent population should be selected for the mating process. To answer this question the following should be done:

- Since we have eight solutions, four mating rounds are to be established. Randomly select any two solutions in the parent population twice for each round as shown below:

Round #	Sub-Round	Solutions
1	**1**	P_5 and P_3
	2	P_1 and P_8
2	**1**	P_6 and P_2
	2	P_5 and P_7
3	**1**	P_1 and P_2
	2	P_3 and P_4
4	**1**	P_5 and P_6
	2	P_7 and P_8

- For each sub-round, select the winner solution according to the following:
    - Solution X wins Solution Y if $i_{rank(X)} < i_{rank(Y)}$
    - If both solutions have equal i_{rank}, then Solution X wins Solution Y if $i_{distanceX} > i_{distanceY}$.
    - If both solutions have equal $i_{distance}$, then randomly select anyone of them as a winner.

As a result, the winner solutions from each sub-round is as shown below:

Round #	Sub-Round	Solutions	Winner
1	**1**	P_5 and P_3	P_5
	2	P_1 and P_8	P_1
2	**1**	P_6 and P_2	P_2
	2	P_5 and P_7	P_7
3	**1**	P_1 and P_2	P_2
	2	P_3 and P_4	P_4
4	**1**	P_5 and P_6	P_5
	2	P_7 and P_8	P_7

Table A.6 summarizes the mating pool in which the crossover and/or mutation processes will take place upon as discussed earlier in Chapter 4.

Table A.6: Mating Pool

Mating Pool #	Solutions
1	P_1 and P_5
2	P_2 and P_7
3	P_2 and P_4
4	P_5 and P_7

Applying crossover and mutation processes on the above set of solutions will result in generating eight new solutions that represent the child population of the first generation ($Q\text{-}G_1$). For each solution in $Q\text{-}G_1$, the FC, RC, and PR objectives' values are calculated as explained before in step 2. Table A.7 shows the resulted objective values for each solution.

Table A.7: Child Population of First Generation ($Q\text{-}G_1$)

Solution	OBJECTIVES			Feasibility
	FC	RC	PR	
Q_1	717	73334	38527	Feasible
Q_2	731	90305	40693	Feasible
Q_3	720	81240	38257	Feasible
Q_4	657	87159	38280	Feasible
Q_5	761	83864	38585	Feasible
Q_6	619	84676	37707	Feasible
Q_7	688	82264	40470	Feasible
Q_8	704	77804	38744	Feasible

A.3.2 Combined Population of the First Generation (R-G_1)

The parent and child population of the first generation are combined to generate the combined population (R-G_1) as shown in Table A.8.

Table A.8: Combined Population of First Generation (R-G_1)

Solution	OBJECTIVES			Feasibility
	FC	RC	PR	
P_1	682	96084	37848	Feasible
P_2	728	93221	37904	Feasible
P_3	678	75904	39115	Feasible
P_4	659	71616	38382	Feasible
P_5	785	84118	39479	Feasible
P_6	681	101606	39379	Infeasible
P_7	642	77767	38642	Feasible
P_8	790	132100	37802	Infeasible
Q_1	717	73334	38527	Feasible
Q_2	731	90305	40693	Feasible
Q_3	720	81240	38257	Feasible
Q_4	657	87159	38280	Feasible
Q_5	761	83864	38585	Feasible
Q_6	619	84676	37707	Feasible
Q_7	688	82264	40470	Feasible
Q_8	704	77804	38744	Feasible

A.3.3 Parent Population of the Second Generation (P-G_2)

To generate the parent population of the second generation (P-G_2), the non-domination ranking process discussed earlier will be first applied on the combined population of the first generation ($R\text{-}G_1$) shown in Table A.8. Table A.9 summarizes the solutions distribution among the different fronts.

Table A.9: Non-Domination Ranking of $R\text{-}G_1$

Solution	FRONT #
P_3	Front 1 (i_{rank} = 1)
P_4	
P_7	
Q_1	
Q_2	
Q_6	
Q_7	
P_5	Front 2 (i_{rank} = 2)
Q_4	
Q_8	
P_1	Front 3 (i_{rank} = 3)
Q_3	
Q_5	
P_2	Front 4 (i_{rank} = 4)
P_6	Front 5 (i_{rank} = 5)
P_8	Front 6 (i_{rank} = 6)

The solutions of the parent population of the second generation will be selected from the combined population giving the priority to those existing in front 1 then front 2 and so on until the population size of eight is fulfilled. As shown in Table A.9, there are seven solutions in front 1 which are to be taken for $P\text{-}G_2$. Still, there will be one left solution to be selected from front 2. The selection process will be according to the solution having the highest crowding distance in front 2. Since the $i_{distance}$ for all the solutions in front 2 is infinite, then one of them will be selected randomly to fulfill the eight required solutions (assume solution P_5). The same procedure is repeated according to the assigned number of generations.