HYBRID META-HEURISTIC ALGORITHMS FOR THE RESOURCE CONSTRAINED MULTI-PROJECT SCHEDULING PROBLEM

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ABSTRACT

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The general resource constrained multi-project scheduling problem (RCMPSP) consists of simultaneous scheduling of two or more projects with common resource constraints, while minimizing duration of the projects. Critical Path Method and other scheduling methods do not consider resource conflicts and practically used commercial project management software packages and heuristic methods provide very limited solutions for the solution of the RCMPSP. Considering the practical importance of multi-project scheduling and the fact that resource constraints impact the schedules and costs significantly, achieving an adequate solution to the problem is crucial for the construction sector.

In this research, we present a new hybrid algorithm which is based on genetic algorithm, simulated annealing, backward forward improvement heuristics. The performance of the algorithms is compared with the performances of the known heuristic procedures and commonly used software packages using test instances particularly developed for multi-project environment. Effectiveness of the developed algorithm is further improved with the application of parallel computing strategies with a Graphical Processing Unit (GPU). Results revealed that effective resource management is a vital process but it is ignored by practitioners, heuristic methods and current software packages. Proposed algorithm showed significant improvements on the state of the art algorithms. It is also shown that parallel computing strategies with a GPU has high potential for meta-heuristic applications

specifically for construction management research area in which there is a significant gap in the GPU research.

Key Words: Scheduling, Project Portfolio Management, Meta-heuristic algorithms, GPU

ÖZ

KAYNAK KISITLI BİRDEN FAZLA PROJENİN ÇİZELGELENMESİ PROBLEMİ İÇİN ÜST-SEZGİSEL YÖNTEMLER

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Doktora, İnşaat Mühendisliği Bölümü

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Kaynak kısıtlı birden fazla projenin çizelgelenmesi problemi, iki ya da daha fazla projenin ortak kaynak havuzu kullanılarak çizelgelenmesi ve toplam proje süresinin kısaltılmasını amaçlamaktadır. Kritik yol yöntemi ve diğer çizelgeleme yöntemleri kaynak kısıtlarını dikkate almamakta, pratikte kullanılan yazılımlar ve yazılımların sezgisel yöntemleri ise probleme sınırlı çözümler sunabilmektedir. Birden fazla projenin çizelgelenmesi probleminin inşaat sektöründe pratik önemi ve kaynak kısıtlarının proje süresini ve maliyetini etkilediği düşünüldüğünde, probleme daha iyi çözümler bulmanın gerekliliği ortaya çıkmaktadır.

Bu çalışmada, genetik algoritma, tavlama benzetimli algoritma ve ileri geri iyileştirme sezgiseli kullanılarak yeni bir melez üst-sezgisel algoritma geliştirilmiştir. Geliştirilen algoritma bu çalışma kapsamında oluşturulan ve birden fazla projenin yer aldığı test projelerinde, pratikte kullanılan yazılımların sezgisel yöntemleriyle ve bilinen diğer üst-sezgisel yöntemlerin sonuçlarıyla kıyaslanmıştır. Algoritmanın etkinliğini artırmak için paralel hesaplama stratejisi geliştirilmiş ve bir grafik işlem biriminde uygulaması yapılmıştır. Sonuçlar literatürdeki algoritmalara kıyasla belirgin ilerlemeler kaydetmiş ve paralel hesaplama

stratejilerinin grafik işlem birimiyle uygulamasının yapım yönetimi alanındaki yüksek potansiyeli gösterilmiştir.

Anahtar Kelimeler: Çizelgeleme, Proje Portföy Yönetimi, Üst Sezgisel Algoritmalar, Grafik İşlem Birimi

To my wife and expected twins...

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"*Sometimes life hits you in the head with a brick. Don't lose faith. I'm convinced that the only thing that kept me going was that I loved what I did. You've got to find what you love. And that is as true for your work as it is for your lovers. Your work is going to fill a large part of your life, and the only way to be truly satisfied is to do what you believe is great work. And the only way to do great work is to love what you do. If you haven't found it yet, keep looking. Don't settle. As with all matters of the heart, you'll know when you find it. And, like any great relationship, it just gets better and better as the years roll on. So keep looking until you find it. Don't settle" (A part from speech of Steve Jobs at Stanford University commencement, 2005).*

The question "Am I doing what I loved to do?" is a challenging question that I ask myself many times. I worked at procurement and design departments of different companies. I have been in public sector as a senior expert for many years. I also enrolled in Ph.D. program at year 2007. I always kept looking. Sometimes I demoralized, sometimes I was hopeful, sometimes both! Now, it has been 10 years since my graduation! I finally realized that making research is what I want to do. Endless thanks to those who help me to find "*what I loved to do*".

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
CPM	Critical Path Method
FCFS	First Come First Served
GAs	Genetic Algorithms
GPU	Graphical Processing Unit
PERT	Program Evaluation and Review Technique
PSO	Particle Swarm Optimization
PSP	Project Scheduling Problem
RCMPSP	Resource Constrained Multi-Project Scheduling Problem
RCPSP	Resource Constrained Project Scheduling Problem
SA	Simulated Annealing
SGS	Schedule Generation Schema

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CHAPTER 1

INTRODUCTION

Whether a project is as big as Marmaray Project which consists of 76 km long railway, various type of tunnels, three underground stations, 37 surface stations, 165 bridges, 63 culverts, many yards, workshops, maintenance facilities, and procurement of 440 modern rolling stocks (Lykke and Belkaya, 2005) or as small as a single floor construction of a building, planning and scheduling is indispensable in order to control total project execution time and its overall cost. Even on a single floor construction of a building, the sequence of the activities, dependencies between activities and resource allocation can be complicated. Without planning and scheduling, project will end with a chaos; jobs execute in a randomly manner and it would not be possible finish the project within planned time and cost. This results in a significant loss for a company.

This issue has been the focus of extensive research in project management since 1900s. Researchers tried to define ways to plan and schedule projects by dividing them into manageable parts, drawing charts and developing algorithms. Since then, Gantt charts and the well-known critical path method (CPM) has been extensively used and taken for granted as good scheduling tools for small to large scale projects especially in the construction industry.

The first attempt to divide a project into manageable parts was proposed with Gantt charts at 1900s during World War I (Meredith and Mantel, p.354, 1995). In this method, activities are shown according to their start and finish times on a horizontal table called bar charts. Taken for granted as an easy way of representing project plan, Gantt chart is used commonly in the construction sector. Main weakness of Gantt chart is its complexity in making large scale projects due to lack of precedence relations among activities harder to manage.

After 1950s, CPM has been one of the most commonly used method to model and control a project within its own assumptions and boundaries. In this method, critical paths are defined as those work orders in which if an activity is delayed whole project is delayed at the same time. Project is divided into manageable parts; work packages and activities. Activity relations are shown with arcs. Due to its visual aspect, a project can be portrayed as a network and it is possible to see predecessor and successor relations between activities. A logical framework is schematized through the activities and minimum time algorithm can be applied to the problem.

PERT technique which followed CPM, was incorporated to deal with stochastic nature of projects. Since real life complexity brings uncertainty to activity duration estimates, PERT brought the ability to incorporate with this uncertainties. Using PERT, one can find either the probability of completing a project to a given date or find time duration corresponding to a probability value (Cottrell, 1999).

However, with Gantt charts, CPM and PERT decision makers are focused on time aspects of a project without considering the resource limitations. This '*time only*" analysis, brings a main drawback since resource limitations are not considered. Therefore, its practicability decreases significantly. In practice, resource conflicts arise when two or more activities are demanding same scarce resources. Due to the scarcity of resources, a trade-off exits between available resources and activity durations. From a company level perspective, situation is magnified if there is more than one project. Neither Gantt chart nor CPM or PERT methods are capable of dealing with resource management. Therefore, a complete tool of scheduling should not only consider "time only" analysis of projects but also should reflect resource limitations. Since the late 1980s there has been a growing interest on scheduling algorithms that considers resource limitations.

In scheduling where real life complexity drives us to use some models (Gantt Charts, CPM and PERT) and models bring drawbacks (resource management), resource constrained project scheduling problem (RCPSP) arises. The objective of the problem is to determine a start date for each activity in such a way that precedence and resource constraints are satisfied, and at the same time project

duration is minimized. If this problem is in a corporate level where more than one project is managed, it is called as resource constrained multi-project problem (RCMPSP).

During the last decades RCPSP has become a well-known standard problem in project scheduling (Hartmann and Briskorn, 2010), and has attracted numerous researchers from multiple areas including operation research, and construction management.

While majority of projects are scheduled on a multi-project environment, most research on RCPSP have focused on single projects (Kurtulus and Davis, 1982; Krüger and Scholl, 2009; Browning and Yassine, 2010). Despite the importance of RCMPSP in practice, there are few studies on this problem. Therefore, there is a significant potential for improving the state–of–the–art algorithms. Hence, the main objective of this study is to develop a new efficient optimization algorithm for the RCMPSP to fill the gap within the literature.

1.1 Practical Importance of the Problem:

In construction management practice since the size of projects are comparably bigger than any other sector, possible delays, crew size and equipment selection, and resource allocation process could lead to significant problems like cost overruns or longer project durations. Project delays and delay costs affect negatively on the profit and repetition of the company. Due to the characteristics of construction work such as unforeseen events, risks involved, multi-dimensional partners, cultural differences, resource demands and resources assigned to a project is rarely met. In addition, shorter project life cycles due to time pressure, little tolerance to cost overruns due to the market competition and high resource costs makes sector more vulnerable to bad scheduling practices. This makes scheduling process of construction projects more complex than any other sector. Therefore, both the effect of costs, prestige and sustainability of company, finding effective, efficient and good enough solutions to project scheduling problem (PSP) is very important.

It is generally known that today's business environment is challenging and companies manage multiple projects which share enterprise resources (Payne, 1995; Lova and Tormos, 2001; Liberatore and Pollack-Johnson, 2003). Sharing the resources requires corporate level optimization of available resources. Frequently the availability of the enterprise resources is limited, and is not sufficient to concurrently schedule the activities. In these circumstances, optimal allocation of limited enterprise resources is crucial for minimizing the project durations and costs to achieve project portfolio success.

Improving the solution algorithms' performances would improve the state of the art algorithms and current software packages. Eventually, an efficient algorithm that will solve the real life problems within a reasonable time period would results in better organized schedules, better resource allocation and cost reductions for corporate level. Therefore, the need for better algorithms is a practical need and serves a great opportunity to develop commercial software packages.

1.2 Prospects from the Thesis

Since RCPSP is an NP-hard[1] problem (Blazewicz et al., 1983), RCMPSP is also NP-hard. The complexity[2] of the problem sets a boundary to the solution methods of the problem. Therefore, it can be solved by exact methods only for small projects. Within the RCMPSP, researches are oriented to priority based heuristics and meta-heuristics which do not guarantee the optimal solution. Performances of the algorithms are arguable and as the network complexity[3] increases performance of the algorithm reduces significantly (Kolish, 1999). Moreover, extensively used popular software packages' performances on resource allocation are arguably low and need to be improved.

[1] *NP-Hard: A problem is called non-deterministic (NP) polynomial if its solution cannot be evaluated in polynomial time and solution is not guaranteed. No known exact algorithms can be able to solve the problem for large instances and only approximate solutions or heuristics are available (Yang, p.9, 2008).*

2 Complexity: A measure of the efficiency of the algorithm. For details see (Yang, p.24, 2008)

3 Network Complexity (NC) is average number of precedence relations per activity (Kolish, 1999).

The main objective of this research is to develop an efficient algorithm for obtaining optimum or near-optimum solutions to the RCMPSP. Meta-heuristics are used to improve the current state of the art algorithms.

As an output, a sole genetic algorithm (GA), a sole simulated annealing (SA) algorithm, a backward-forward implemented GA and finally, a hybrid backward-forward GA-SA algorithm is developed. Developed algorithms are tested with known test instances. Optimum solutions are also used for comparisons. Previous results from the literature are also used in order to compare algorithm performances. An educational software RESCON (Deblaere et al., 2011), and its tabu search algorithm is used for base line solutions.

Computer programs are written with Microsoft Visual Studio 2010 and coded with C and C++ programing languages. In order to test the parallel programing effects on meta-heuristics, final algorithm is implemented with a parallel evolutionary strategy and computed on a Graphical Processing Unit (GPU).

1.3 Scope and Limitations of the Thesis

RCPSP is stemmed from job-shop scheduling problem in operational research. Job-shop scheduling problem has various cases so does RCPSP and RCMPSP. Basic problem definition is used throughout the study and mathematical model of the problem will be given in the following sections. In the scope of this research, activity pre-emption is not allowed[4]. Every activity is assumed to have non-negative durations and resource usage. All parameters are assumed to be deterministic and portfolio has a static structure. Activity durations are assumed to be discrete. Finish to Start (FS) activity relation is used for majority of the test cases but model can handle other relations, too. As network complexities of each test instance increases, computational time increase significantly. Therefore, most of the tests were solved with time limits.

4 It is stated that duration of an activity cannot be split up.

1.4 Organization of the Thesis

Following chapters are organized as follows: In the second chapter project scheduling problems are summarized and literature survey of RCPSP and RCMPSP are given. In the third chapter, a mathematical model of the problem is illustrated. Problem is solved also heuristics and meta-heuristics. It includes novel meta-heuristic solution that is developed in the scope of this thesis. Details of the algorithms and their test results are given. Fourth chapter is for experiment design of algorithm parameters. Finally, a conclusion section is given as the last chapter.

CHAPTER 2

PROJECT SCHEDULING PROBLEMS AND LITERATURE REVIEW

2.1.Definition of the Problem

Project scheduling problems (PSP) are one of the important practical optimization problems which are extensively studied in operations research, management science and construction management research area. Due to the practical importance, some methods already been incorporated and many software packages has been developed. PSP in general consists of three different problems. These are time-cost tradeoff analysis, resource leveling problem and resource allocation problem. In time-cost tradeoff analysis the tradeoff between duration of an activity and cost of that activity is examined. It is known that in order to meet deadline requirements of a schedule if more resource is added to the project, direct cost of an activity increases. Adding more resource decreases the activity duration. This tradeoff should be carefully examined in order to determine the extra cost of adding new resources. Thus, in this type of problems, normal cost and crash cost of the project is analyzed and decision is made based on time-cost tradeoff analysis. Time-cost tradeoff analysis may include single objectives such as minimization of the cost or minimization of duration (Ke and Liu, 2005) or multi objective cases such as the work of Zheng et al., (2004). Different from time cost tradeoff problem, in resource leveling problem aim is to obtain smooth resource curve so as to minimize resource fluctuations under fixed project duration. It is assumed to have enough resources for the project and fluctuations in resource demand is minimized. These fluctuations mean idle resources and extra cost to the project. Leveling is done with shifting non critical activities within their available floats (Easa, 1989). As for resource allocation problems, resources are assigned to activities so as to optimize certain objectives. In this type of problems, mostly single objectives such as cost minimization is used and in recent studies multi objective resource allocation problem can also be found in the literature (Osman et al., 2005; Chaharsooghi and

Kermani, 2008). Being a special case of resource allocation problems, RCPSP can be extensively found in the literature. RCPSP can be defined as finding an optimal solution for the sequence of activities based on a predefined objective function where resources are limited. RCPSP and its multi-project case are the objectives of this research and will be examined in the following chapters in detail. Although PSP problems are complicated problems, a minimum time algorithm is extensively used in the literature for solution purposes. This method is called CPM.

Practically used and taken for granted as a good scheduling method, CPM can be considered as a basic solution methodology for the scheduling problem, but explicitly it is assumed that there is no resource constraints. Most project scheduling software packages are capable of serving as good CPM scheduler and get visual help to practitioners. CPM and software combinations are extensively used in the practice. Nevertheless, the unlimited resource assumption makes this method more vulnerable to bad scheduling practices.

In practice, there are usually limitations for a number of resources. Thus, under the consideration of resource limitation basic PSP becomes a mathematical problem which is more complicated than the simple model and cannot be solved with CPM model.

2.2. An Example Problem: How Can Activity Sequences Affect the Duration of a Project?

A scheduler has to decide activity sequences of a project under given resource limitations. Deciding the right activity sequence is a key choice since some activity sequences may result longer durations, some results shorter durations under same resource limitations. Consider the example given by Toklu (2002) at Figure 2.1.

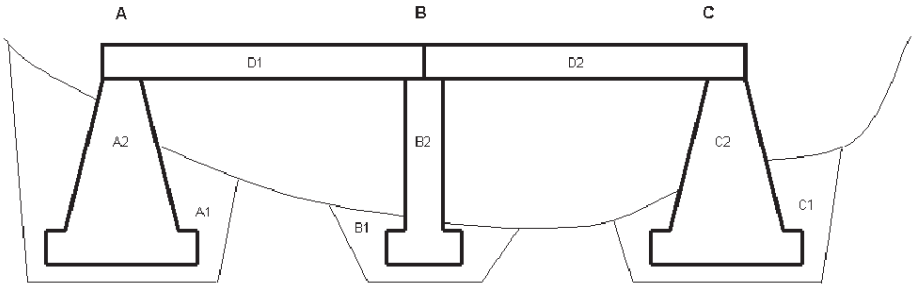


Figure 2.1: Two span bridge example (Toklu, 2002)

A two span bridge construction is given as an example of the importance of activity sequences. Suppose there exists only one excavation team, one pier construction team and one span construction team. Considering the method of construction one can say that construction may be started with any of the pier excavation: A1, B1, and C1. Construction either follows the same locations in order to start pier works as soon as possible or follows other locations independent from excavation works. For example, if excavation is selected as A1, B1 and C1, pier construction would follow A2, B2, C2 sequences in order to start pier construction as soon as possible. A different strategy can also be selected such as starting pier construction after all of the excavation work is finished. That way would obviously results longer duration than expected. Assuming the strategy that pier construction work follows excavation work in advance, possible construction sequences are as follows.

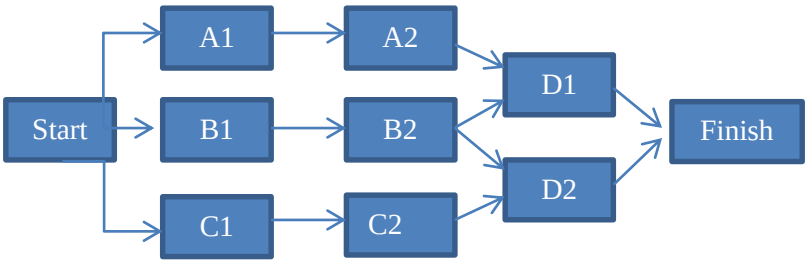


Figure 2.2: Activity on node diagram of two span bridge example

Considering the Figure 2.2 excavation can start from anywhere at sections A, B or C. Thus, 6 different alternatives are possible, such as A1>B1>C1, A1>C1>B1, B1>A1>C1, B1>C1>A1, C1>A1>B1, and C1>B1>A1. Since we have one team for

pier construction and we have a strategy that pier construction follows excavation work in advance, possible pier construction alternatives are A2>B2>C2, A2>C2>B2, B2>A2>C2, B2>C2>A2, C2>A2>B2, and C2>B2>A2. And also 2 different deck constructions are possible, such as D1>D2 or D2>D1. It makes totally 6x2 different construction sequences. If we consider the pier construction team is not dependent on excavation team, we would have 6 x 6 x 2 different combinations.

One way of choosing minimum project duration is calculation of all alternative sequences and selecting the best one. In our example case total of 12 or 72 construction sequence can be analyzed and minimum duration can be selected. Bettemir and Sönmez (2014) analyzed the same example under same resource constraints mentioned before. Microsoft Project 2010 and Primavera P6 Enterprise Version 7.0 are used to solve the case examples. The results of Standard priority-based heuristic of MSP 2010, and six priority-based heuristics of P6 V.7 showed that neither software packages could be able to achieve an adequate solution to this simple network. These findings showed that even with small networks, with changing the activity sequences project duration can be shortened and famous software packages are not capable of finding good enough solutions.

Similar results is reported with Kolisch (1997) resulting that commercial software packages generate schedules with an average deviation of 4.3–9.8% of the optimal solution even for small projects which has a scale of up to 30 activities. In the same manner, Trautmann and Baumann (2009) analyzed seven different project software packages and their heuristics. It was advised that using these popular software packages one must be aware that possible solutions are longer than optimum solutions. The gap between optimum solution and heuristic solutions also increases as activity number increases and resource scarcity is tightened. As an example given at same research: for J120 sets and RS[5] 0.1, average deviation of seven heuristics

[5] Resource Strength is a measure of resource scarcity. RS has a minimum value of 0 and maximum value of 1 indicating the tightest and loosest schedule respectively.

were about %24 where the minimum value is %17. 93 and maximum value is %39. 53.

Although it is possible to find minimum duration under all possible activity sequences, it can only be possible for such small networks. As the network size and resource combinations increase, it becomes impossible to analyze every sequence combination of a schedule. As network size and resource number increases, the combination of resource/activity increases exponentially. This phenomena is known as the "*combinatorial explosion"* which imply that since the problem itself is NP-Hard (Blazewicz et al., 1983), no polynomial time algorithm is capable of solving the problem. Therefore, this huge amount of data cannot be calculated by hand.

Although some exact methods do exist which guarantee the optimum solution, their capabilities are limited (Chen et al., 2010). Due to its limited applicability to large problem instances, some heuristics and meta-heuristics are extensively used.

2.3.Classification of RCPSP

RCPSP has been a standard problem in operations research and since 1960s abundant amount of research has been reported. This section is devoted to its classification efforts.

With the efforts given to the problem itself and the variations of the problem in the literature, classification need was emerged. In 1997 a workshop was conducted at the University of California, Riverside and a classification schema was established (Demeulemeester and Herroelen, p: 72, 2002). Brucker et al., (1999) classified the RCPSP along with a notation procedure. This notation is stemmed from machine scheduling and follows $\alpha|\beta|\gamma$ schema which represents resource characteristics, activities and objective functions. Further attempts accepted the works of Brucker et al., (1999) and Herroelen et al., (1999) which are basically built upon machine scheduling literature. Example of Herroelen et al., (1999) can be seen at Table 2.1.

Table 2.1: Examples of α|β|γ schema

α|β|γ schema (Herroelen et al., 1999)	Definition
m,1/cpm/C_{max}	Resource Constrained Scheduling Problem with Single Mode
m,1/gpr/C_{max}	Resource Constrained Scheduling Problem with General Precedence Relations

Kolisch and Padman (2001) defined the elements of RCPSP as activities, precedence relation, resources and objective functions. Objective functions are summarized as makespan minimization, minimization of flow time of activities, minimization of delays, net present value maximization, quality maximization, cost minimization. Implicitly it is assumed that all data is available, deterministic and integer valued. Network representation issues are also mentioned and summarized as networks which are on activity on node or activity on arrow diagrams.

Yang et al., (2001) categorized RCPSP as 6 different classes. It is assumed that commonly known objective function is makespan minimization and difference is stemmed from the problem mode- being a single mode problem or multi-mode problem. The six different problems are basic single-mode RCPSP, basic multi-mode RCPSP, RCPSP problems with non-regular objective functions, stochastic RCPSP, bin-packing-related RCPSP problems and multi-resource constrained project scheduling problems (MRCPSP).

Hartman and Briskorn (2010) used basically machine scheduling schema and gave about further developments of the RCPSP. Preemptive scheduling, resource demands with varying time, set up times, multi-modes are mentioned and defined for further models.

It is stated in this work that, although RCPSP can be categorized and represented with α|β|γ schema well, a practical categorization must include constraints, and

project environment in addition to the schema. More specifically, model based constraints can be added and the problem becomes more specific for important practical cases. Problems can be modeled in a static environment where all jobs are available before the scheduling starts or problems may be in a dynamic environment where any job may enter to the scheduling process while scheduling is going on. Within all literature so far it can be stated that, at least 5 main factors affect the problem itself. These are; activities, resources, objective functions, constraints and project environment. In order to define each factor and be more specific each factor is defined in the following section.

2.3.1. Elements of a RCPSP

2.3.1.1.Activities

Activities are those jobs that can be measured in time, consume resources and have specified start and finish dates. Problem type changes according to activity characteristics such as;

- Activities can have two different modes: single mode and multi-mode. In single mode an activity performs only a defined mode, which does not change with resource excess. Nevertheless, multi-mode of an activity states that adding more resource would decrease the duration of that activity to some extent.
- Activity preemption is another option for activity type. In some problems it is possible to cut an activity from a point and define it with more than one activity.
- The duration of an activity can be deterministic and stochastic.

2.3.1.2.Resources

Resources are necessary inputs for activities. Manpower, machines and money are some examples of resources in a construction project. In literature, resources are categorized by its type and value (Blazewich et al., 1986). Basic distinction

according to its type is about the *availability* concept. If a resource is continuously available through the project with the same amount every step of needed it is called renewable, if it is consumed through the project horizon it is called nonrenewable. Example of a renewable resource is manpower and machines, for nonrenewable resources is capital. If the value of the resource is exact and does not change by activity mode, it is called deterministic, otherwise it is called stochastic. Thus, problem type can change according to resources such as;

- Type of the resources can change the problem. Resources can be renewable, nonrenewable or both.
- Resources can be deterministic and stochastic.

2.3.1.3.Objective Function

The objective of a schedule is important to define a mathematical model for the problem. Minimization of total project duration is very commonly used objective function in the literature. However, in the practice one objective may not cover all other strategic issues, and may not be valid for every project. Thus, different objective functions are possible and sometimes one objective may conflict with each other. Earliness/tardiness minimization, present value maximization, cost minimization and time/cost minimization problems are examples of objectives used in literature. The type of the problem can change according to its objective function.

2.3.1.4.Constraints

Constraints define the boundaries of the problem. Constraints can be due to the project itself, such as deadline constraints, budget constraints and can also be due to inside the project itself such as technological constraints or activity sequences. Others can be mathematical constraints such as activity resource consumption, or activity duration should be integer valued. Moreover, model specific constraints can be added to general mathematical models so as to specifically define a case.

2.3.1.5.Project Environment

Project environment can change the characteristics of the problem. For single case, all resources are assumed to be dedicated to a project and only one project manager

is assumed to be in charge of resource allocation. Nevertheless, in a multi project environment, resources are considered as corporate resources. Therefore, resource allocation in a top level managers' perspective makes this problem more complex than the single case.

Also, multi project environment characteristics may be different. Being a static environment, all jobs are known and during scheduling no new job is added. In this form of problems once a mathematical model is determined, it would not change until the schedule has been completed. On the other hand, dynamic environment can change mathematical model significantly. Therefore, project environment should be considered in classifications. The importance of the project environment becomes significant when some heuristics are applied to the problem. For example, if slacks are determined considering dynamic environment, it should be updated within a routine while in a static case slacks will not change until scheduling is over.

Table 2.2: A classification of RCPSP

DIMENSIONS	**PROPERTIES**				
Activity	Single Mode	Multi-mode	Activity Preemption	Deterministic	Stochastic
Resource	Resource Type	Deterministic	Stochastic		
Objective Functions	Minimization of Makespan	Cost Minimization	Earliness/tardiness Minimization	Present value Maximization	Model-specific
Constraints	Mathematical	Resource	Time	Cost	Model-specific
Project Environment	Single Project	Multi-project	Dynamic	Static	

All mentioned properties are summarized at Table 2.2. It can be seen that for each factor and its different type problem type changes significantly. Therefore in the scope of this research basic cases will be used. In order to stick into the literature

and to be on the side of known problem types, basic RCPSP problems is given in the following paragraphs.

Case Example #1 "*Basic Deterministic Case*": In this case, all parameters are assumed to be deterministic and resources are assumed to be unlimited. This very broad definition of PSP is generally used by practitioners and a minimum time algorithm is used to solve the problem. This minimum time algorithm is called CPM. In this method, aim is to find a schedule which is consisting of critical paths orders. The time frame of a schedule is captured and effect of an activity delay can be determined from the network. Resources are assumed to be unlimited but as a final schedule resource leveling strategy is used in order to minimize resource fluctuations.

Case example #2 "*Deterministic Case with Resource Constraints*": In addition to basic deterministic case, the resource limitation constraint is added and the problem and it is called RCPSP. If more than one project is under consideration problem becomes RCMPSP. Both analytical and heuristic solution attempts are available in the literature and the model will be studied in the next sections.

Case example #3 "*Multi-mode with Resource Constraints*": In this case, either activity durations or resource limitation can vary. For multi-mode PSP, a set of different modes is available for execution. For example, in a mode 1 worker can work 6 days and finish the job, while if 2 workers work in the same amount of work they can finish the job in 3 days. This type of variable crew assignment is possible. Different from the mode of the activity, activity duration can be a random variable which obeys a probability distribution.

From this point further, case example #2 will be analyzed in detail:

2.4.Resource Constrained Single Project Scheduling Problem (RCPSP)

2.4.1. Problem Definition

With the basic assumptions of CPM, a time order of activities can be modeled and schedule of a project can be drawn as nodes and arrows. The unlimited resource

assumption is valid in this method and this assumption is not suited in majority of the real life problems. More importantly, if resources are not meeting with the demands of the activities, activities should be shifted to a time where resources are adequate. Therefore, real durations under the resource limitations would be beyond the CPM duration. Then, a question arises *"how can this duration shift be minimized?"* and the problem of RCPSP arises.

RCPSP modeled in this research is aiming to find an optimal scheduling of a set of activities within a network while precedence and resource constraints are not violated. The precedence constraints force an activity to be started within an imposed time frame after all of its predecessors are completed. It is a reality that activity execution requires an amount of resource usage and some of the resources are limited. Thus, resource constraints force an activity to consume a limited amount of resources. Within the constraints of activities and resource limitations, more than one schedules can be generated which would have different project durations-some are longer while some are shorter. Therefore, the aim in RCPSP is to find the minimum duration of a project without violating the assumptions of the problem.

The basic RCPSP is modeled in a project network *G (N, A)* with a set of *N* nodes and *A* arcs, each node representing the project activities using the activity on node representation. Each activity *j* has a duration of d_j, finish time F_j and resource usage r_i. The activities in the network are subject to precedence constraints which force to start an activity only after completing its predecessor(s). It is assumed that there are *m* renewable resource types, with a per period availability R_m.

The problem is mathematically modeled in this way;

- The objective is to:

Minimize Total Project Duration

$\sum_i^n F$ ..... (2.1)

Where some constraints exist such that:

$$F_i < F_j - d_j \quad \text{.....(2.2)}$$

$$r_j < R_m \quad \text{..... (2.3)}$$

$$F_j, r_j, d_j \geq 0 \quad \text{..... (2.4)}$$

Other than two constraints above, there is also a sign convention, which forces the model to be solved in non-negative and integer values.

2.4.2. RCPSP Literature

The objective of RCPSP is to determine a start date for each activity in such a way that precedence and resource constraints are satisfied, and the project duration is minimized. As RCPSP is NP-hard in the strong case (Blazewicz et al. 1983) it can be solved by exact methods only for small projects. Hence, many researchers have proposed heuristic and meta-heuristic methods for RCPSP. There are basically three solution methods to the problem (Figure 2.3) Exact methods used for finding the optimal schedule but not appropriate to complex problem sets. Heuristics are fast and often provide adequate solutions, but they do not usually provide high quality solutions. Meta-heuristics are capable of finding high quality but sometimes they are time consuming.

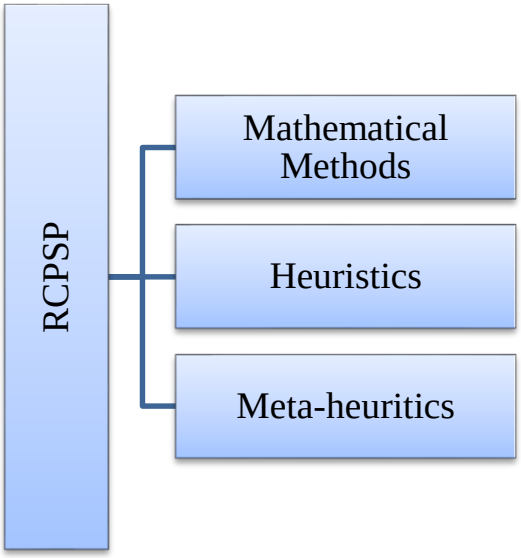


Figure 2.3: RCPSP and solution methods

2.4.2.1.Exact Methods

Exact solutions include linear integer programing methods: zero-one programing and dynamic programing, enumeration; especially branch and bound methods. Very limited works have been done in term of exact solutions. It is proven that neither method is computationally feasible for large-sized networks (Kim and Ellis, 2008; Alcaraz and Maroto, 2001). Kolish et al., (1995) worked on 480 test sets with 30 activities which are soon becoming a standard test set and concluded that 428 of them can be solved optimally with exact methods, remaining are cannot be solved even with 1 hour of computation time. Afterwards the researchers concentrated on 52 "hard test sets". Mingozzi et al., (1995) and their algorithm BBLB3 showed significant improvements on the optimal solutions, but it was very slow in terms of computational efficiency.

Pioneering work about zero-one programing approaches are focused on a linear programming formulation of job-shop scheduling (Pritsker et al., 1969; Patterson and Roth, 1976). Due dates, job splitting, resource, substitutability, and concurrency and non-concurrency of job performance requirements are added to the model and three different objective functions, namely; minimizing the total time for all projects, minimizing the time by which all projects are completed and minimizing total lateness or lateness penalty for all projects are researched.

Patterson and Huber (1974) used bounding techniques in conjunction with zero one programming techniques. Rather than solving one schedule with zero-one technique, it is intended to examine feasibility of a series of schedules. Its advantages over simple zero-one programming techniques are compared.

An example of dynamic programming techniques is given at Carruthers and Battersby (1966). Elmaghraby (1993) investigated the dynamic programming technique with the assumption that there is a relationship between the amount of the resources allocated to an activity and its duration. A dynamic programming optimization procedure and an approximation are given for upper bound solutions.

In all of exact solution methods above mentioned branch and bound algorithms (Christofides et al., 1987; Demeuelemeester and Herroelen, 1992) are very common in the literature. Branching can be defined as dividing disjoint solution subsets into subsets (Demeulemeester and Herroelen, p: 220, 2002). Basically, it is a divide and conquer algorithm in which large problem set cannot be solved directly, instead it is *divided* into smaller sub problems that can be *conquered*. Two actions are required for the algorithm. The first action is dividing the problem into sub problems-which is called *branching*; second action is giving a bound for best solution in the subset-which is called *bounding.* Thus, it is a search algorithm to find the best solution among other solutions available.

Table 2.3: Example heuristics

Heuristic	Working Mechanism
Min. Slack (MinSlack)	Give priority to activities those have smaller slack
Min. Late Finish Time (LFT)	Give priority to activities those have smaller late finish time
First Come First Served (FCFS)	Give priority to activities those first come to a priority list
Most Total Successor (MTS)	Give Priority to activities those have more total successors
Greatest Resource Demand (GRD)	Give Priority to activities those have greatest resource demand
Worst Case Slack (WCS)	Give Priority to activities those have worst case slack

Christofides et al. (1987) proposed a branch and bound algorithm which is based on the idea of disjunctive arcs for resolving conflicts when resource constraints are not enough. Four lower bound solutions are examined. The first is a simple lower bound based on longest path computations. The second and third bounds are derived from a relaxed integer programming formulation of the problem. The fourth bound

is based on the disjunctive arcs used to model the problem as a graph. The report is done based on the performances of randomly generated sets which involve up to 25 activities and 3 resources.

Demeuelemeester and Herroelen (1992) used a branch-and-bound procedure which is described for scheduling the activities of a project of the PERT/CPM variety subjects to precedence and resource constraints where the objective is to minimize project duration. The procedure is based on a depth-first solution strategy in which nodes in the solution tree represent the resource and precedence feasible partial schedules. The procedure is programmed in the C and validated using a standard set of test problems with between 7 and 50 activities requiring up to three resources.

2.4.2.2.Heuristics

Heuristics are experienced based techniques which have a subroutine applied to problem solving strategy and generally have adequate solutions in a very short time. Most heuristics are rules that are tailored to fit for specific types of problems. They may be deterministic and stochastic whether the same results can be found at each iteration or not. Some examples can be seen from Table 2.3.

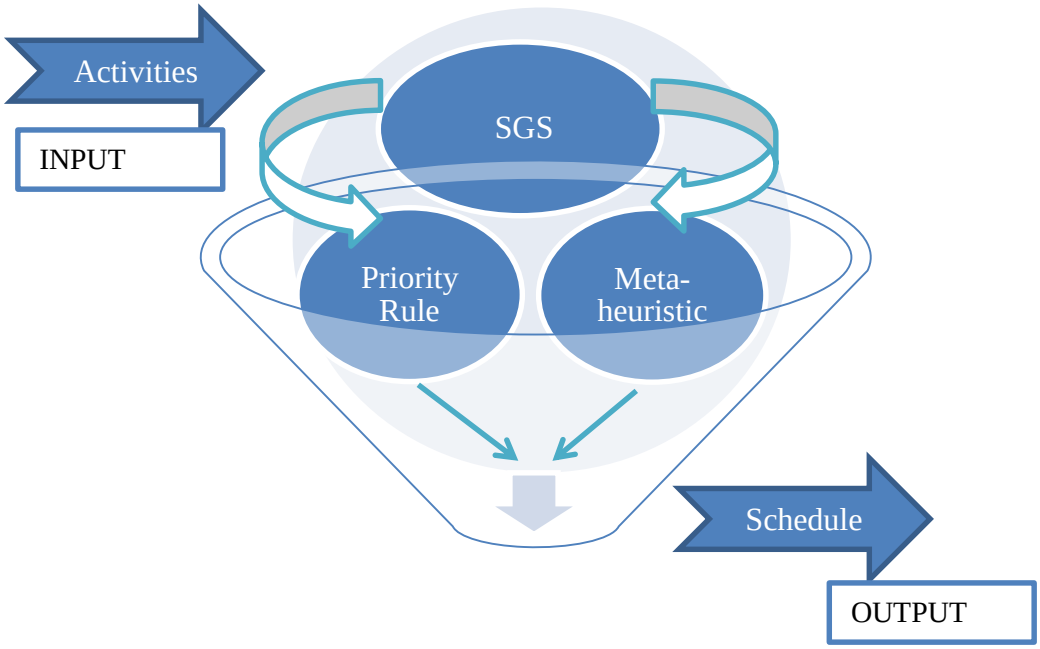


Figure 2.4: Working mechanism of heuristics and meta-heuristics

Minimum Slack Rule (MinSlack) is generally accepted as an adequate solution for RCPSP and can be applied with First Come First Served (FCFS) rule as a tie breaker. Heuristics are important since they offer some upper bounds for those cannot be solved optimally.

The heuristic studies for the RCPSP date back to Kelley (1963) with a schedule generation schema (SGS). SGS is at the hearth of heuristics and meta-heuristics as well as it is a heuristic itself. It starts from zero to build a schedule by stepwise improvements. There are two different SGS available in the literature. One is based on activity increment- *serial SGS* and the other is based on time increment - *parallel SGS.* In serial SGS, based on activity selection principle, activities are scheduled at the earliest possible time under the resource constraints. Nevertheless, at parallel SGS, for every time increment activities are scheduled under the resource constraints (Kolish and Hartmann, 1999). In order to build a schedule either SGS is used together with a priority rule or meta-heuristics. The mechanism is shown at Figure 2.4. An ordered list is obtained with a priority or a meta-heuristic, the schedule is configured with SGS

Davis and Patterson (1975) tested various heuristic sequencing rules on RCPSP with the total project minimization objective function. Effectiveness of heuristics shown by comparison to optimum solutions available. Minimum Slack Rule performed best from eight heuristic test with eighty tree problems. It is reported that, the performance of heuristics was relatively small as resource constraints get tightened.

Backward forward improvement method (Li and Willis, 1992) is a special improvement method that is based on scheduling with same SGS and heuristics, in reverse time direction. In backward scheduling the exact duration of feasible schedule is not known, an arbitrary completion time is selected and all precedence relations are reversed. Finally, all activities are scheduled as late as possible according to activity selection principle. In the same manner resulting schedule can be scheduled in forward direction according to starting dates as early as possible

and final schedule generally be denser and shorter than starting schedule, at least it has the same duration

Priority-rule-based heuristics (PR-H) use a SGS in order to build a schedule. Priority rule is used for selecting the nominee activities from the activity set. PR-H can be classified according to criteria it employs, i.e. network, time and resource based rules. If PR-H generates a single solution it is called single pass method, if it generates more than one schedules, it is called multi pass methods (Kolish and Hartman, 1999). PR-H can be applied to get one solution at a time. As an example of shown heuristics see Hartman et al. (2000), where Late Finish Time (LFT) and Worst Case Slack (WCS) rule is used in experiments on test of algorithms performances.

Some heuristics produce more than one solution and best of them can be selected. Sampling methods (Cooper, 1976) are examples of this kind of heuristics. The selection probability of activities from decision set is determined according to a selection principle and the schedule is constructed upon selection probabilities. Another method is selecting more than one heuristics in a random manner which can be found at Storer et al., (1992).

Hartman et al., (2000) conducted an experiment on the performances of heuristic algorithms by applying an experimental design with control parameters on test sets. A full experiment design is applied in order to test different heuristics' performances on standard J sets (Kolish et al., 1999). Influence of increasing project size, network complexity, resource factor and resource straight is tested. Worst Case Slack (WCS) and Late Finish Time (LTF) combined with parallel SGS outperformed other priority rule based heuristics. Meta-heuristics performed better as schedule number was increased from 1000 to 5000. It was concluded that since meta-heuristics use knowledge exploited from different schedules, they have superiority on priority rule based heuristics. It is stated that the selection of SGS may be influenced by project size since serial SGS performed better in J30 sets while parallel SGS performed better in J120 sets.

Kanit et al., (2009) investigated MinSlack, LFT and Maximum Remaining Path Length (MRPL) heuristics on the scheduling of housing projects. Tests were conducted using ten real projects. MRPL rule performed better at six projects, LFT performed better at three projects and MinSlack rule performed better at one project. It is suggested that MRPL rule can be used for housing projects with resource constrained where activity numbers are high.

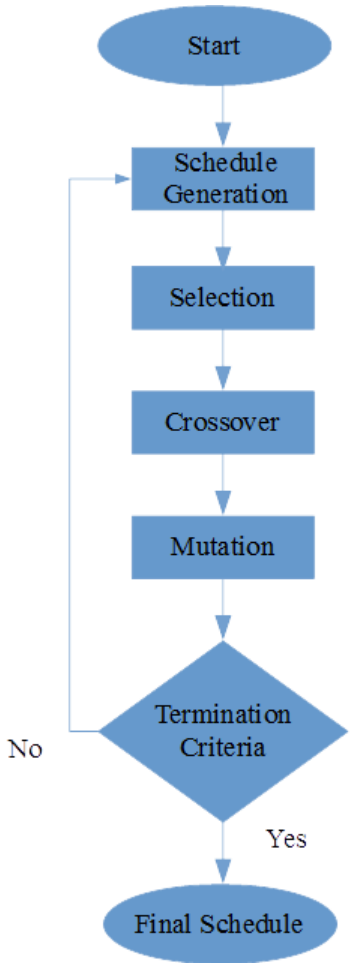


Figure 2.5: A simple GA

2.4.2.1.Meta-heuristics

Meta-heuristics are higher level heuristic methods which can be applied for different type of problems without being specific for one specific type of problem. The meta-heuristics are included variety of methods such as genetic algorithms (GAs), simulated annealing (SA), tabu search, particle swarm optimization (PSO)

and ant colony optimization (ACO) which mimic a natural phenomenon in order to find a global optimum in a large search space.

Among all meta-heuristics, GAs have a large variety of application areas. It is a population-based and stochastic search algorithm based on evolutionary computation principles inspired by the Darwinian principles of natural selection (Holland, 1975). GAs finds for best solution from a pool of solutions according to some selection and diversification mechanisms as shown at Figure 2.5. A solution is called *individuals* where an individual is represented by a *chromosome*. Number of solutions constitute a set which is called as a *generation*.

New solutions are produced depending on previous generations' chromosomes according to *crossover* and *mutation* operators. The best solutions are given to higher change to survive and some of them are moved to new generations with *elitism*. A fitness function is used in order to evaluate a chromosome's performance. What makes GAs strong compared with other algorithms is that it has the ability of exploiting the best solution while exploring the search space effectively (Michalewich, p. 15, 1992).

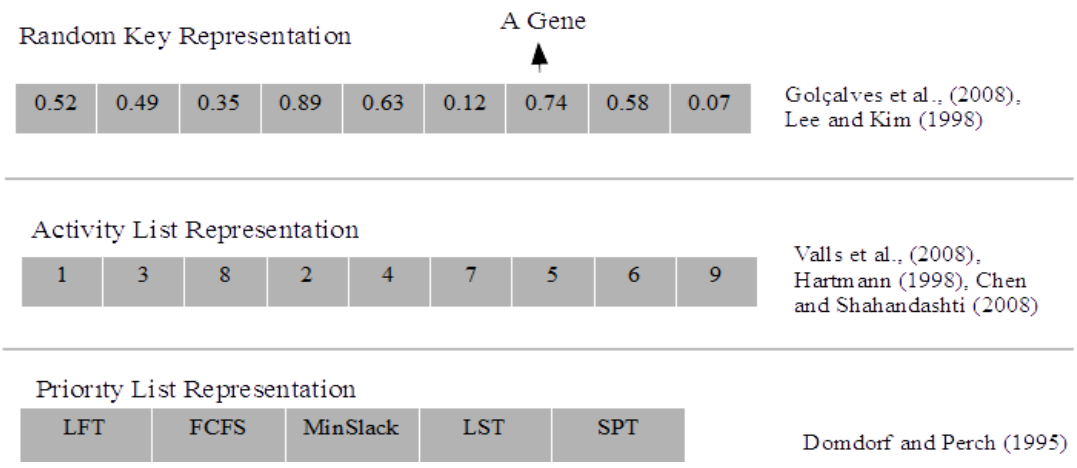


Figure 2.6: Different type of chromosome representations

In GAs different schedule representations are possible, such as random key value activity list or priority list. In random key representation each gene represented by a priority number, i.e. highest random key value represents highest priority to the

activity. Whereas in an activity list representation, a schedule is represented with list of activities; order of an activity means it is scheduled prior to others. A priority list representation is also available where a heuristic is used to choose activities and chromosome representations show priority of that heuristics. At Figure 2.6 some examples of different chromosome representations are shown.

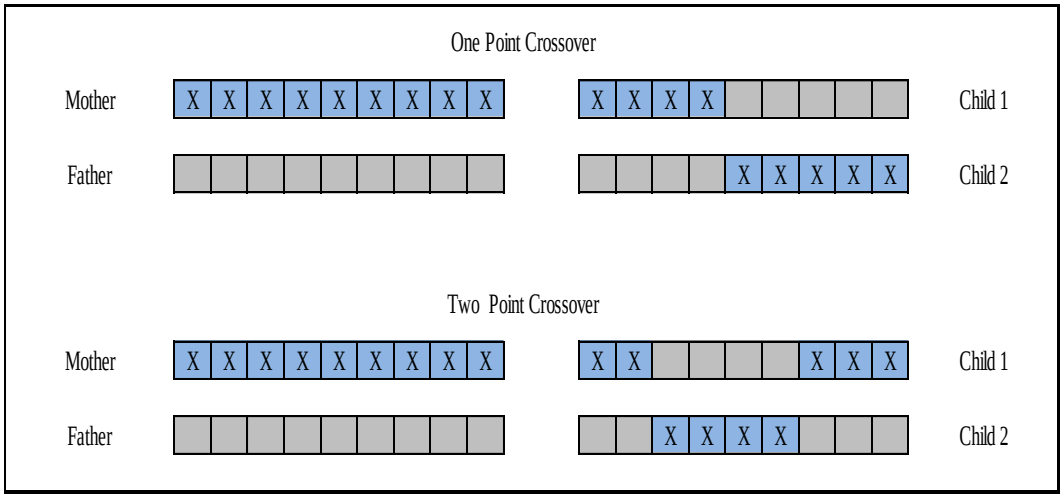


Figure 2.7: Crossover examples

Crossover and *mutations* are two main methods in order to produce new solution from existing solutions. In a crossover, from two different chromosomes, namely mother and father, two different children are obtained. The simplest crossover method is one point crossover where a random gene is selected as a point and the remaining parts are exchanged by mother and father's chromosomes. Another crossover method is two point crossovers. In this method two random points are selected and chromosomes are divided into three sections. Middle sections are exchanged between mother and father's chromosomes (Figure 2.7).

Apart from these two basic crossover methods, several complex methods are also available. Parameterized uniform crossover (Dejong and Spears, 1991), decomposition based crossover (Debels and Vanhoucke, 2007) are examples of more improved crossover methods. The parameterized uniform crossover method is applied on a random key vector. A random number is generated between 0 and 1 and those genes having higher than that number is exchanged between

corresponding mother locations. Decomposition based crossover is started with determining the weakest resource used regions in a father chromosome and best resource used regions in a mother's chromosome. Finally, worse parts are replaced with the better part of father chromosome.

Mutations are applied as a random change of a gene or a number of genes on a chromosome. Along iterations chromosomes may trap into local minimums. Thus, the solution may lead a premature convergence, which does not allow reaching of optimum results. Mutations may lead to skip from local minimums. Generally mutation ratio is too small since too many mutant genes may also avoid to converge (Yang, p: 25, 2008).

Hartmann (1998) studied RCPSP with makespan minimization objective. A new GA is proposed and it has been compared with two other GAs. Starting with the empty job sequence list, preceding activities are selected randomly from an unselected activity set. In addition, a known sampling method and a priority rule are used to derive activity selection probabilities. Results were compared with two known GAs and some heuristics.

Leu and Hwang (2001) studied RCPSP in a repetitive construction project- precast production. It is stated that line of balance method (LOB) is not sufficiently enough to solve scheduling problems under resource constraint. In the paper random key representation is used along with GA. Influencing factors of the repetitive precast production scheduling model and their impacts were examined. Results revealed that GAs are very efficient in precast production scheduling.

Leu and Yang (1999) proposed a GA based scheduling system called GARCS. A new crossover and mutation is shown and its effectiveness was tested on problem instances.

Chen and Weng (2009) proposed a two-phase GA in which both the effects of time-cost trade-off and resource scheduling are combined in order to get the best result for RCPSP. A GA based time-cost trade-off analysis is used to select the execution

mode of each activity and it is followed by other GA-based resource scheduling method.

Chen et al. (2010) proposed a hybrid algorithm called as ACOSS which combines a local search strategy, ant colony optimization, and a scatter search in an iterative process.

In recent years, other than RCPSP there has been an increasing interest in the adaptation of GAs to optimization problems in construction engineering and management. Multi-mode RCPSP (Mori and Tseng, 1997), resource leveling (Hegazy 1999, El-Rayes and Jun 2009), planning of construction resource utilization (Kandil and El-Rayes 2006; Kandil et al. 2010), planning of post disaster temporary housing projects (Kandil et al. 2010), time-cost tradeoff problem (Feng et al. 1997; Kandil and El-Rayes 2005), and time-cost-quality trade-off (Kandil and El-Rayes 2005) are among the construction management problems in which GAs are proposed.

Simulated annealing (SA) has fine tuning capabilities, and is usually capable of escaping of local optima for locating a good approximation to the global optimum (Hwang and He, 2006). But a sole SA has a low search efficiency as it maintains one solution at a time. It was applied in the optimization problem by Kirkpatrick et al., (1983). It mimics the annealing process of materials. The basic idea behind the algorithm is to use a randomized search technique with accepting worse solutions to some extent. In the early stages of the algorithm the probability of accepting worse solutions is high. This acceptance probability is reduced in a cooling schema where probability is:

$$p = e^{-\frac{\Delta E}{kT}} \quad \text{(2.5)}$$

where ΔE is the rate of change in the objective function, T is temperature and k is Boltzmann's constant. A flow chart of the basic SA algorithm is given at Figure 2.8.

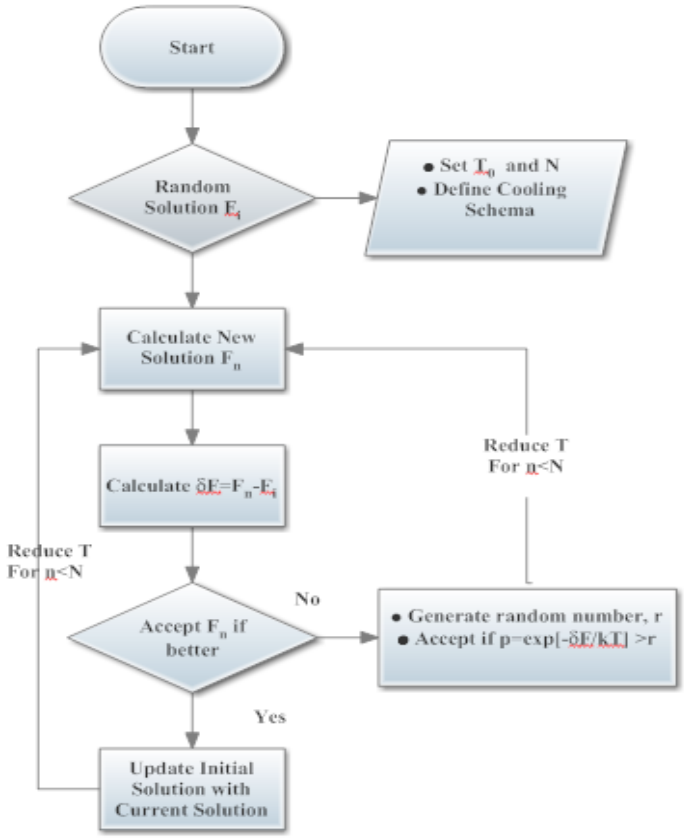


Figure 2.8: Flow of SA algorithm

Boctor (1996) applied SA technique to RCPSP and tested its efficiency via statistical methods. Results revealed that SA is capable of finding near-optimum results. Another SA algorithm was proposed by Cho and Kim (1997) in which a solution is represented with a priority list, and algorithm is used with a priority scheduling method using total project duration minimization objective. Further works generally used SA along with other meta-heuristics since SA gives one solution at a time and it is not efficient when compared to population based approaches. Chen and Shahandashti (2009) used SA along with GA and results were revealed that hybrid GA-SA algorithm performed better than sole SA.

Tabu search (Glover, 1990) algorithm uses a past memory of actions and it builds solutions based on a best neighboring solution which is obtained using a search method and an appropriate objective function evaluation. To avoid selecting same neighborhood and previous solutions, some selected moves are recorded as tabu

list. The iteration continues until a stopping criteria is met (Thomas and Salhi, 1998). Due to use of memory and record of past actions, algorithm could save computing time and can increase the efficiency significantly (Yang, p. 92, 2008). The mechanism of the algorithm in RCPSP works such as; an initial feasible solution is obtained and this solution is disturbed with a move function and finally a new solution is obtained.

Lee and Kim (1996) used random solution for initial solutions and neighborhood generation method for new solutions. They selected activities from previous four and next four activities randomly in neighborhood search mode. Tabu list is obtained by defining tabu moves such as interchanging priorities of activities *i* and *j*, if activities are interchanged recently.

Icmeli and Erenguç (1994) used tabu search algorıthm on RCPSP with discounted cash flows. The method was tested on 50 problems derived from Patterson's data set. Solutions were compared with upper bound results and MinSlack rule used solutions.

Particle Swarm Optimization (PSO) is another evolutionary technique that mimics the behaviors of birds flocking. It starts with an initial solution and looks for solution in the search space by iterations. Unlike GAs, PSO does not use evolutionary operators. The particles follow its paths one by one with its good experiences. For n particles there would be n current best solutions. The aim is to find globally best solution compared with current solutions.

Jia and Seo (2013) proposed an improved PSO method which treats the solutions of RCPSP as particle swarms and employs a double justification skill. It uses operator for the particles, in association with rank-priority-based representation, greedy random search, and serial scheduling scheme.

Ant Colony Optimization (ACO) is another meta-heuristic method that mimics the behaviors of ants looking for best foraging paths. Ants that find foods mark it with a chemical (pheromone) in order to be trailed by other ants. Those ants following same route improves the chemical concentration. As more ants follow the same

route, the route becomes a favorable one. It gives a feedback for those ants which start to find food sources.

Merkle et al., (2002) proposed an ACO method for RCPSP. Proposed method uses combinations of two pheromone evaluation methods to find new solutions, these are: a change of the influence of the heuristic on the decisions of the ants during the run of the algorithm, and the option that an elitist ant forgets the best-found solution.

Tseng and Chen (2006) proposed a hybrid approach called ANGEL, which combines (ACO), (GA) and a local search strategy together. In this method first, ACO searches the solution space and generates the initial population for GA. Next, GA is executed and the pheromone set in ACO is updated when GA obtains a better solution. When GA terminates, ACO searches again by using a new pheromone set. ACO and GA search alternately and cooperatively in the solution space. Finally a local search strategy fine tunes the results of ACO and GA.

2.5.Resource Constrained Multi-Project Scheduling Problem (RCMPSP)

2.5.1. Problem Definition

The resource constrained multi-project scheduling problem (RCMPSP) is an extension of the RCPSP and consists of simultaneous scheduling of two or more projects with common resource constraints, while minimizing some performance measure. It is quite often that managers deal with more than one projects in practical cases (Browning and Yassine, 2010). Payne (1995) states that %90 of the projects are carried out in a multi-project context. Lova et al., (2000) made a survey in construction, textile, IT and public administration sectors about the project environment. %84 of correspondents answered that they work in a multi-project environment. Same survey concluded that project scheduling software programs are not practical to manage multi-projects and they should be adapted to this need. These survey results reveal that multi-project environment is a more practical and common case compared with a single project for scheduling purposes.

The basic RCMPSP can be stated as follows: A project portfolio consisting of projects i= 1,…, M has to be scheduled with limited portfolio resources. Each project is composed of j= 1,…, J_i activities. The activities can start after all of its predecessors are completed. Each activity requires r_{ijk} units of resource type k, during every instant of its non-preemtable duration d_{ij}. The availability for each resource k, in each time period is R_k units. At any time instant *t*, if the set of precedence feasible activities requires more than R_k units for any k, then some activities will have to be scheduled at a later time to satisfy the resource constraints. With these definitions, the problem of finding a precedence and resource feasible portfolio schedule with the minimum overall project portfolio completion time (*C*) can be formulated as follows (Christofides et al. 1987):

Minimize (*C*)……..……(2.6)

Subject to:

$$\sum_{t} S_{i,j,t} = 1, \quad \mathrm{i} = 1, \dots, M, \quad \mathrm{j} = 1, \dots, J_i \tag{2.7}$$

$$\sum_{t} t(S_{i,m,t} - S_{i,j,t}) \geq d_{i,j}, \quad (j,m) \in H_i, \quad \mathrm{i} = 1, \dots, M \tag{2.8}$$

$$\sum_{i=1}^{M} \sum_{j=1}^{J_i} \sum_{q=t-d_{i,j}+1}^{t} r_{i,j,k} S_{i,j,q} \leq R_k, \quad \mathrm{k} = 1, \dots, K, \quad \mathrm{t} = 1, \dots, T \tag{2.9}$$

$$S_{i,j,t} \in (0,1) \tag{2.10}$$

Eq. 2.6 minimizes the overall project portfolio completion time (*C*). Eq. 2.7 indicates that every activity must start once. Eq. 2.8 presents the precedence constraints, where H_i is the set of activity pairs with precedence relations in project *i*, and J_i+1 is the dummy activity used to determine completion time of project *i*. The constraints given in Eq. 2.9 satisfies the resource requirement of activities at each time instant *t* does not exceed the availability R_k, for each resource k, where *T*

is an upper bound on the portfolio completion time. Finally, the constraints of Eq. 2.10 define the decision variables as binary.

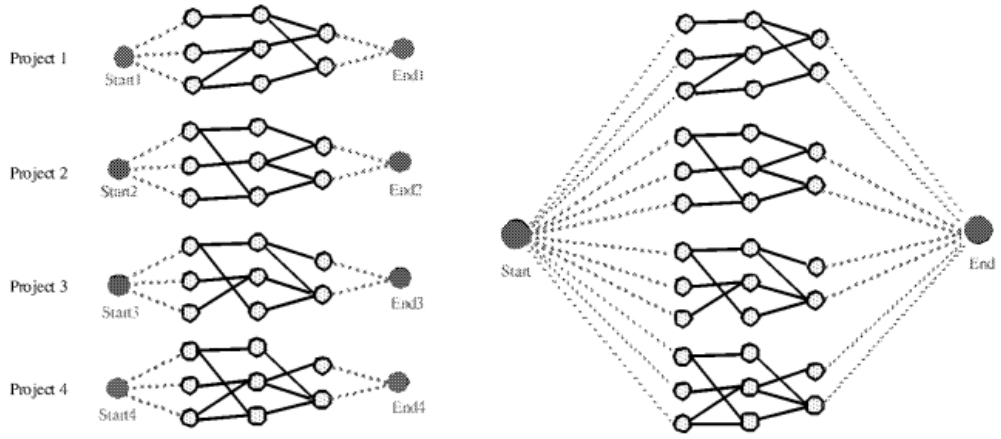


Figure 2.9: Multiple single projects vs. single project approach (Lova and Tormos, 2001)

2.5.2. RCMPSP Literature

The basic RCMPSP can be solved by combining all project networks in one super-network by adding a super-dummy start and a super-dummy end node considering it as a single project network (Figure 2.9). Under this assumption, RCPSP solutions would be valid and solution methods can be used. Nevertheless, the combinatorial explosion problem would be more significant as small networks are compared. Furthermore, that problem which can be taken as multiple single project networks, each considered as alone would be more practical since in real life practices each project has its own project manager, budget and accounting system, only resources may be used from the common enterprise pool. Therefore, throughout this study problem is taken as multiple single projects.

RCMPSP can be expanded in several ways. Activities could have multiple duration/resource alternatives, rather than a single duration and resource consumption option-which gives a stochastic nature to the problem (Tseng 2004). Since resources are used from a common pool resource transfer times could be non-zero (Kruger and Scholl 2009). Project environment may be static where all project details are clear and set before scheduling starts or dynamic where project details

are changed trough execution. Although the basic RCMPSP has certain practical limitations such as the assumption of a single duration/resource mode for activities, or the assumption that resources can be transferred between projects without any expense in time and cost, the majority of the research on resource constrained multi-project scheduling have studied the basic problem. In this research, we have focused on the basic RCMPSP since the majority of the multi-project problem instances available in the literature include basic RCMPSPs, and commonly used project management software such as Microsoft Project 2010 can only solve the basic problem. It can be seen from the literature that while the majority of projects is scheduled on a multi-project environment, most research on resource-constrained project scheduling have focused on single projects (Kurtulus and Davis 1982; Krüger and Scholl 2009; Browning and Yassine 2010). Therefore, in multi project environment there exists less number of researches. Following section summarizes the works done in the multi project environment.

2.5.2.1.Exact Methods

Since RCMPSP is a generalization of the RCPSP, it is also NP-hard (Golçalves et al., 2008). Although exact methods were proposed in the literature, previous studies have mainly attempted to develop efficient heuristics and meta-heuristics for the solution of RCMPSP.

Some exact solution methods such as zero-one programming approach (Pritsker et al., 1969) are proposed in the literature which is unable to solve large instances. Another example of exact methods is Drexl (1991), in his work a branch and bound algorithm together with dynamic programming model is proposed. The models and assumptions under exact models of RCPSP are valid for RCMPSP. Since the project sizes are larger, exact methods is not practical to use. Further attempt to solve the problem by exact solution methods are limited with the NP-Hard characteristics of the problem. Therefore, due to the combinatorial explosion problem many studies focused on heuristics and meta-heuristics.

Table 2.4: Priority rules tested by Kurtulus and Davis (1982)

Priority Rule	Explanation	References
SOF	Shortest Operation First	Conway (1965), Patterson (1973)
MinSlack	Minimum Slack Rule	Wiest (1963), Fendley (1968)
SASP	Shortest Activity From Shortest Project	Kurtulus (1978)
LALP	Longest Activity From Longest Project	Kurtulus (1978)
MOF	Maximum Operation First	Kurtulus (1978)
MaxSlack	Maximum Slack First	Kurtulus (1978)
MinTWK	Minimum Total Work Content	Kurtulus (1978)
MaxTWK	Maximum Total Work Content	Kurtulus (1978)
FCFS	First Come First Served	Mize (1964)

2.1.1.1.Heuristics

Priority based heuristics, meta-heuristics, non-standard meta-heuristics and miscellaneous heuristics are four main groups which is extensively mentioned by Kolish and Hartman, (1999) and Browning and Yassine, (2010). The aim is to find a near-optimum solution within a reasonable time period.

Kurtulus and Davis (1982) proposed two new categorization processes within time-only analysis in order to measure the effects of the priority rule based heuristics which are summarized at Table 2.4. Average Resource Load Factor (ARLF) is defined as a measure of the peak resource requirement is in the first half of the project or second half. Average Utilization Factor (AUF) measures tightness of the schedule which is calculated as the ratio of the total amount required resource on available resources. An experiment design was made where ARLF changes -3 to 3 and AUF changes 0.6 to 1.6. Totally 77 project sets were tested where sets have activity numbers ranging 34 to 63 activities. Nine heuristic rules were tested.

Table 2.5: Priority rules according to ARLF and AUF ranges (Kurtulus and Davis, 1982)

	AUF Range	
ARLF Range	0.6 to 0.8	0.9 to 1.6
-3.5 to -2.5	MINSLACK	SASP
-2.5 to -1.5	MAXTWK	SASP
-1.5 to -0.5	SASP	MAXTWK
-0.5 to 0.5	MINSLACK	SASP, SOF, MAXTWK
0.5 to 1.5	SASP	SASP
1.5 to 2.5	MINSLACK	MOF, SASP
2.5 to 3.5	MINSLACK	SASP

SASP and MaxTWK rules were outperformed other seven rules with different objective functions. An important result was concluded from the research that artificial super-network approach which is extensively used by software packages is an inferior approach for multiple single project approach. As summarized at Table 2.5 a directive approach was given to researchers. From given Table researchers and practitioner can choose the best heuristic based on ARLF and AUF measures of test cases.

Kurtulus (1985) studied these ten priority rules along with five penalty functions, namely: 1) assigning the highest penalty to the project requiring the greatest amount of resources; 2) assigning the highest priority to the longest project; 3) assigning the highest priority to the project requiring the least amount of resources; 4) assigning the highest priority to the shortest project; and 5) random assignment. Priority rule performances were tabulated along with penalty functions and it is concluded that project measures ARLF and AUF along with penalty functions gives different results on different priority rules.

Lova et al. (2000) proposed a multi-criteria heuristic method for multi project scheduling problems. It is stated that while managing more than one project, more flexibility is required to use scheduling tools. Heuristic method was developed in

order to account for two criteria, one is project splitting and other is mean project delay. Heuristic work is given in two phases: in the first phase iterative forward-backward process is used with mean project delay objective function. In the second phase, results is improved with no time criteria. MaxTWK and MinLFT priority rules were the bet rules that dominate others under different criteria.

Lova and Tormos (2001) studied the effect of the SGS – serial or parallel – and priority rules – MinLFT, MinSLK, MaxTWK, SASP or FCFS – with two approaches – multi-project and single-project under mean project delay objective. A two stage iterative process is proposed where in the first stage priority is given to a project, in the second stage activities are selected with heuristics. It is stated that P-SGS found better results performing under mean project delay objective functions.

Lova and Tormos (2002) further examined the two stage project selection principle with other possibilities of selecting SGS and other multi-pass heuristics. A new hybrid heuristic method combining random sampling and forward backward iteration is given.

Krüger and Scholl (2009) studied the problem under resource transfer times. In this model resources transferred to another project is modelled. Sequence and resource dependent transfer time constraints are added to the model which represent setup times for activities when a resource is removed from one project and reassigned to another. It is concluded that commonly accepted static environment assumption and static nature of portfolio cannot represent real life problems. Resource transfer times should be included in the models despite the models may include more comprehensive work.

Browning and Yassine (2010) studied RCMPSP with its two lateness objectives-project lateness and portfolio lateness. Five measures of RCMPSP characteristics are used along with a full factorial experiment on 12,320 randomly generated problem instances. A directive tool is given for a manager to choose which priority rule is best under selected project network.

2.1.1.2.Meta-heuristics

Focusing on the main objective of this thesis it can be seen that meta-heuristic studies are primarily aiming to solve RCPSP. Particle swarm optimization (Jarboui et al. 2008; Wang and Qi 2009; Chen 2011; Jia and Seo, 2013), ant colony optimization (Merkle et al. 2002; Tseng and Chen, 2006), simulated annealing (Cho and Kim, 1997; Hwang and He, 2006), honey-bee mating optimization (Bozorg Haddad et al. 2010; Akbari et al. 2011), hybrid GA and SA (Bettemir and Sönmez, 2014) and tabu search algorithm (İçmeli and Erenguç, 1994; Lee and Kim, 1996) are the main studies aiming to solve RCPSP. There is also particular interest for GAs such as (Lee and Kim 1996; Hartmann 1998; Leu and Yang 1999; Leu and Hwang 2001; Toklu 2002; Kim and Ellis 2008; Cheng and Weng 2009; Lin et al. 2013).

Majority of the studies with extensive literature is focusing on RCPSP. Being a more practical case, RCMPSP has not drown the attention of researches yet. Very limited research was proposed in the literature. One of them is a sole genetic algorithm along with a priority rule which is proposed by Kumanan et al. (2006). A GA is used to select the sequence of projects where priority rule is used for scheduling within projects. The proposed method outperformed other heuristics such as FCFS and SPT.

A multi-agent systems (Confessore et al., 2007) is proposed within a decentralized multi project problem. In the model agents are used to communicate with project managers and portfolio manager.

Gonçalves et al., (2008) proposed a GA with random key representation. In order to capture real practices, model were capable of integrating due dates, work in process, and inventory. Constraints enforcing the release date concept are also introduced.

A hybrid meta-heuristic was proposed by Chen and Shahandashti (2009) where GA and SA approaches combined together to give better results. SA approach was

integrated to model in order to improve GA's search capacity with accepting worse solutions.

Within above aforementioned limited works, it can be said that there is a significant research potential for RCMPSP. Meta-heuristics have high potential to solve the RCMPSP.

2.6. Parallel Computing Literature on Meta-heuristics

2.6.1. Introduction

Different from parallel computing, serial computing is the usual computing, which engineers have been using for 50 years. In this type of computing instructions given to the computer is running one after another and speed of the computation relies on the central processing unit (CPU) clock speed. Traditional computers' CPUs follow Moore's Law, which describes a long-term trend in the history of computing hardware. According to this law, the number of transistors that can be placed on an integrated circuit has doubled approximately every two years. The trend has continued for more than half a century and is not expected to stop (Arenas et al., 2011). Nevertheless, physically CPUs has reached its limits. This resulted in a new era of computing, which called parallel is computing. In parallel computing, instructions can be run on different cores at the same time. It makes possible to increase applications' effectiveness.

Although as end users, we are not aware of the parallel computing era, it has already been started and incorporated with many devices. Electronic devices, multi-core PCs, cell phones have all had parallel computing capabilities. Due to the limits of current processor clock speed, it is expected that parallel computing will be the new era of computers. Therefore, possible parallel computing applications would bring new opportunities to the engineers and end users such that faster applications, robust calculations and low cost of computing.

Although GAs are effective in solving many optimızation problems in science, engineering, and business applications, longer execution time to compute each fitness value of the problem limits its performance. Due to the subroutine of the

algorithm, for each cycle time one fitness calculation is possible. Considering the huge amount of data computation together with several iterations, GAs built solutions in a considerable time. An approach to use several distributed computers together for calculation makes it possible to speed up this computation process. One of the main examples of this process can be seen from Kandil and El-Rayes (2006). The main objective of Kandil and El-Rayes (2006) work is to develop a parallel multi-objective genetic algorithm framework that is capable of distributing the computations over a network of computers. Five research questions are examined. These are;

- Can parallel GAs enable an efficient optimization of large-scale projects?
- What are the time savings achieved?
- How many processors are needed?
- What is the effect of parallel GA design on efficiency and effectiveness?
- Which parallel GA paradigm is more suitable for optimization large-scale projects?

Two parallelism approach was applied namely the global parallel GA and coarse-grained GA. In the first approach a main processors is selected in charge of all others and other processors are used for fitness evaluation. In the second approach, the global population is divided into sub-populations called demes that are evolved independently. A migration process is applied where best solutions are exchanged within clusters. Results of first approach revealed a time saving of 7.14 times for 720 activities network. In the second approach three different sized large-scale construction project is selected that contains 180, 360 and 720 activities as test cases. Elapsed time for 180 activities network in one processors was 4 hours and it significantly reduced to 0.5 hours with 5 processors (8 times). Nevertheless, computation time of 5 processors and 50 processors was almost same and it was not possible to speed up the computations. In the similar manner, for 360 activities network almost 8 times speed up was possible up to 5 processors and increasing the processors beyond 5 did not decrease the computation time. One of the best results of this study was it is shown that computational time savings are possible. Adding

more processors although do not increase computational time beyond 5 to 10 processors, it can increase the quality of the solutions with applied coarse-grained model. Global parallel GA approach was found as more efficient but less effective way of parallelism compared to coarse-grained model.

Nevertheless, these networked computers are not easy to manage, requires more resource and they are expensive. Some researchers use different platforms in order to search solution space more effectively. A low cost computing device which is called a Graphical Processing Unit (GPU) is also used by researchers in order to increase effectiveness of algorithms together with meta-heuristics.

A GPU is a device which has multiple cores on it and used for parallel computing purposes. It can be programmed with less programing knowledge, it has low initial and maintenance cost and ease of use together with personal computers make them suitable for general purpose computing.

2.6.2. Literature Review of GPU Applications

Although GAs are very effective in searching solutions within a domain, crossover, mutation and selection process requires considerable time. For every population that has to be evaluated, fitness value should be calculated. Traditional computing technique is the evaluation of each fitness value at each cycle time of the computer. Fortunately, GAs are suitable for distributing the computational load to different cores (Paz and Goldberg, 2000). At this point parallel computing technology brings new opportunities. There are three different parallelism approaches available in the literature. These are: master-slave model, fine-grained model and island model (coarse-grained). With these models it is possible to design different types of GAs. The master - slave model includes one population but fitness evaluations are distributed among different cores (Figure 2.10). This model has many advantages: they explore the search space as a serial GA, it is easy to implement, and it has several significant improvements in performance (Pospichal et al., 2010). In fine-grained model it is assumed that any individual can only mate with individuals located on the neighboring processing nodes. Whereas island model includes more

than one population, each evolves independently, may have different sizes and they may communicate within each other or not.

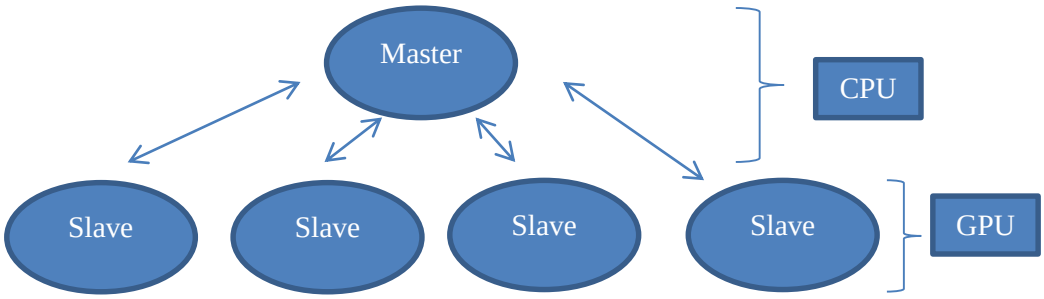


Figure 2.10: Master-slave model of GPU application

Application of GPUs in scheduling is very limited, although meta-heuristic applications have large application area. Melab et al., (2012) used GPU on a branch and bound algorithm. The focus of the application is on the bounding mechanism of branch and bound algorithm, which is the most time consuming part of their exploration process. An NVIDIA Tesla C2050 GPU is used for testing and significant improvements have been achieved.

Zajicek and Sucha (2011) used GPUs for the flow shop scheduling problem. They used a homogeneous computing strategy where all computations are done on the GPU.

Nesmachnow and Canab´e (2011) used GPUs in order to improve the efficiency of two scheduling heuristics. It is implemented in a heterogeneous computing system where more than one computer is available. Experimental results demonstrated that the parallel implementations of these two heuristics on GPU provide significant improvements compared to the sequential implementations at large scale instances.

Other GPU applications include a parallel traveling salesman problem of Fujimoto and Tsutsui (2011). In this implementation GA is run at m thread blocks where m is the number of individuals, each individual is processed by n threads where n is

the number of cities and each thread block performs special crossover and mutation operators at the same time.

A parallel ant colony optimization is proposed by Delevacq et al., (2013). Max–Min Ant System (MMAS) algorithm augmented with 3-opt local search is used as a framework for the implementation of the parallel ants and significant improvements have been achieved in term of the efficiency of algorithms.

CHAPTER 3

SOLUTION METHODS

This chapter includes the proposed algorithms for the RCMPSP. First of all, a mathematical formulation is given. After that, the problem is solved with four heuristics, a sole GA, a sole SA, a hybrid GA-SA algorithm and a backward forward hybrid GA-SA. In the last section, algorithm is tested on a Graphical Processing Unit (GPU) through which it is intended to increase the efficiency of the algorithm. Test instances, algorithm details and performance of each algorithm is given in corresponding sections. Throughout the study, a new hybrid algorithm is developed. GPU implementation of GA is also one of the first research efforts in scheduling practices.

Mathematical model, heuristics and each meta-heuristic are tested with generated test instances. In addition, RESCON (Deblaere et al., 2011) and MS Project heuristics are used for comparison purposes. For small test instance RESCON can obtain optimum results and its meta-heuristic algorithm is accepted as a successful method in the literature. Since MS Project's two heuristics namely standard order and ID order heuristics are commonly used in practice, it is an important test to see the capacity of tools available in practice and compare them with developed algorithm.

3.1.Test Instances

Standard Kolish (Kolisch and Sprecher, 1997) test instances which are J30, J60 and J120 sets are used for testing purposes. These test instances are extensively used in literature and commonly accepted for comparison purposes. Percent deviation from optimum results are given if an optimum result is available. Otherwise lower bound (CPM based) solutions are used for comparison.

Proposed mathematical model is tested with only J30 and J60 problems since large test instances cannot be solved with exact methods. Existing results are also given and model is compared with literature findings.

Table 3.1: PSLIB project instances

Project No	PSLIB Instance
1	J30_2_2
2	J30_45_8
3	J60_1_7
4	J60_48_6
5	J120_32_4

A new multi-project test instance set is developed for multi-project testing .Twenty six test portfolios were generated using five single Kolish benchmark instances. In order to generate multi-project test instance five projects consisted of two projects with 30 activities, two projects with 60 activities, and one project with 120 activities which were randomly selected from well-known instance sets J30, J60, and J120 as shown in Table 3.1. The projects of each portfolio and enterprise resource constraints are presented in Table 3.2.

Table 3.2: Multi-project test case details

Portfolio	Projects	Total Activity	Resource Availability			
Set 1	*1_2*	60	13	11	13	16
Set 2	*1_3*	90	13	10	12	16
Set 3	*1_4*	90	34	28	27	33
Set 4	*1_5*	150	19	14	16	22
Set 5	*2_3*	90	13	13	14	13
Set 6	*2_4*	90	34	32	29	30
Set 7	*2_5*	150	19	17	18	19
Set 8	*3_4*	120	34	30	29	30

Table 3.2: (Continued)

Portfolio	Projects	Total Activity	Resource Availability			
Set 9	*3_5*	180	19	15	18	19
Set 10	*4_5*	180	40	34	33	36
Set 11	*1_2_3*	120	13	11	13	15
Set 12	*1_2_4*	120	27	24	23	26
Set 13	*1_2_5*	180	17	14	16	19
Set 14	*1_3_4*	150	27	22	23	26
Set 15	*1_3_5*	210	17	13	15	19
Set 16	*1_4_5*	210	31	25	25	30
Set 17	*2_3_4*	150	27	25	24	24
Set 18	*2_3_5*	210	17	15	17	17
Set 19	*2_4_5*	210	31	28	27	28
Set 20	*3_4_5*	240	31	26	26	28
Set 21	*1_2_3_4*	180	23	20	21	23
Set 22	*1_2_3_5*	240	16	13	15	17
Set 23	*1_2_4_5*	240	26	23	23	26
Set 24	*1_3_4_5*	270	26	22	22	26
Set 25	*2_3_4_5*	270	26	23	23	24
Set 26	*1_2_3_4_5*	300	24	20	21	23

For multi-project test cases Chen and Shahandashti (2009) presented two multi-project case examples consisted of three test projects including 74 activities and two resources, and the second portfolio (real portfolio) consisted of three real projects including 130 activities and 11 resources. These test instances is used for comparison of algorithms.

3.2. A Mathematical Formulation of RCPSP

Since mathematical model gives insight behavior of the problem itself, a mathematical model is given in this section. Considering the previous works mathematical model of the problem is regenerated for this problem is as follows;

A finite set which includes activities $N = \{1,2,\cdots,n\}$ and activity relations $A = \{(i, j) : i, j \in N\}$ is given. If $(i, j) \in A$ that means activity j cannot start before i is finished. In addition, resources $k \in K$ is given, the availability of resource k is shown as R_k and resource usage of activity j is defined as $r_{j,k}$ ($0 \le r_{j,k} \le R_k$)

3.2.1. Parameters

$G = (N, A)$ Graph with arcs and activities

$N = \{1,2,\cdots,n\}$ Activities

$A = \{(i, j)\, i, j \in N\}$ Precedence set

K: Type of resource $k = 1,2,\cdots,K$

R_k : Resource limits of k

$r_{j,k}$: Resource usage of activity j from resource k

p_i : Processing time of activity i

M : A large number

3.2.2. Variables

s_i : i start time of task i

c_i : Finish time of task i

$C_{\max}$: Finish time of last dummy activity,

$x_{i,j}$: If start time of task i is smaller than finish time of task j than $x_{i,j} = 1$, otherwise $x_{i,j} = 0$. That is;

$$x_{i,j} = \begin{cases} 1 & , s_i < c_j \\ 0 & , o.w. \end{cases}$$

$h_{i,j}$:If start time of task i is larger or equal than start time of task j $h_{i,j} = 1$, otherwise $h_{i,j} = 0$. That is:

$$h_{i,j} = \begin{cases} s_j \le s_i \Rightarrow 1 \\ o.w. \Rightarrow 0 \end{cases}$$

$z_{i,j}$: If start time of task i is between the start time and finish time of task j $z_{i,j} = 1$, otherwise $z_{i,j} = 0$. That is:

$$z_{i,j} = \begin{cases} s_j \le s_i < c_j \Rightarrow 1 \\ o.w. \Rightarrow 0 \end{cases}$$

Where binary variables $y_{i,j}$, $t_{i,j} \in \{0,1\}$

3.2.3. Constraints

$$s_j \ge p_i + s_i \qquad \forall (i,j) \in A \qquad (3.1)$$

$$c_i = p_i + s_i \qquad \forall i \in N \qquad (3.2)$$

$$C_{\max} \ge c_i \qquad \forall i \in N \qquad (3.3)$$

$$s_i \ge c_j - M * y_{i,j} \qquad \forall (i,j) \notin A \text{ and } i \ne j \qquad (3.4)$$

$$x_{i,j} \ge 1 - M * (1 - y_{i,j}) \qquad \forall (i,j) \notin A \text{and } i \ne j \qquad (3.5)$$

$$s_i \le s_j - 1 + M * t_{i,j} \qquad \forall (i,j) \notin A \text{and} i \ne j \qquad (3.6)$$

$$h_{i,j} \ge 1 - M * (1 - t_{i,j}) \qquad \forall (i,j) \notin A \text{and } i \ne j \qquad (3.7)$$

$$z_{i,j} \leq (x_{i,j} + h_{i,j})/2 \qquad \forall(i,j) \tag{3.8}$$

$$z_{i,j} \geq x_{i,j} + h_{i,j} - 1 \qquad \forall(i,j) \tag{3.9}$$

$$\sum_{j} r_{j,k} * z_{j,i} \leq R_k - r_{i,k} \qquad \forall(i,k) \tag{3.10}$$

3.2.4. Objective Function

$$Min\, C_{\max} \tag{3.11}$$

Constraint 3.1 states that processing time of activity j should be greater than processing time of activity i plus its duration. Finish time of any activity is determined with (3.2) and (3.3) is used for determining the last task finish time, (3.4)-(3.9) is used for determining the task ongoing in same time periods, (3.10) is an upper limit of resources in order to restrict the total resource usage.

3.2.5. Performance of Mathematical Model

The mathematical model is used in Gurobi 5.0 solver and Python 2.7 interface. Model is tested with J30 and J60 test instances. Total time is limited to 300 seconds for J30 sets and 1000 seconds for j60 sets.

Table 3.3: Number of optimum solutions and mean CPU times

Problem Set	Number of Problems Optimally Solved	Mean CPU Time (Seconds)*
30	454	14.3
60	351	19.9

*CPU time is measured with Intel I5 processor computer

All of the J30 sets is solved with this model and %94.5 of the sets are optimal results. In case of J60 sets, only %73 is optimally solved. Mean CPU time for Intel Core I5 computer is 14.3 and 19.9 seconds for J30 and J60 sets respectively. Results are tabulated at Table 3.3.

Table 3.4: Results Comparison between the model and Kone (2011)

	Problem Set	Results (This Study)	Optimum (Upper Bounds)	Deviation (%)
1	J309_2	92	92	0
2	J3013_1	61	58	5.17
3	J3013_2	68	62	9.68
4	J3013_3	80	76	5.26
5	J3013_4	73	72	1.39
6	J3013_5	73	67	8.96
7	J3013_6	68	64	6.25
8	J3013_7	83	77	7.79
9	J3013_8	108	106	1.89
10	J3013_9	71	71	0
11	J3013_10	64	64	0
12	J3014_2	54	53	1.89
13	J3014_7	50	50	0
14	J3025_5	72	72	0
15	J3029_1	86	85	1.18
16	J3029_2	90	90	0
17	J3029_3	79	78	1.28
18	J3029_4	105	103	1.94
19	J3029_6	98	92	6.52
20	J3029_7	74	73	1.37
21	J3029_8	86	80	7.5
22	J3030_10	53	53	0
23	J3041_10	99	99	0
24	J3045_2	125	125	0
25	J3045_6	129	129	0
26	J3046_7	60	59	1.69

Test sets that cannot be solved optimally are compared with the model results of Kone (2011) which is based on mix integer programming. Kone (2011) used 500 seconds as time limit. Totally %97 of the J30 sets is solved optimally in the model. Furthermore, upper bound solutions are given where optimum results are not reached.

In order to compare our models' performance with those sets that cannot be solved optimally, optimum results and upper bounds are used whichever is available (Table 3.4.). On the average, our model results depicts from optimum and upper-bounds only %2.68. Results revealed the acceptance of the mathematical model.

3.3.Heuristic Solutions

In the literature best heuristics in multi-project test cases are found as Minimum Slack (MinSlack), Shortest Activity from Shortest Project (SASP) and Maximum Total Work Content (MaxTWK). In order to use heuristic results as comparison, multi-project test cases are solved with these three heuristics. Therefore, a heuristic solver is developed in order to solve test cases with known heuristics. Basic algorithms used in these heuristics are summarized in this section.

The developed algorithm gives opportunity to choose priority rule at the beginning of execution. Results are summarized as ordered activity list. It is written with C++ computer language and compiled with Microsoft Visual Studio 2010.

The algorithm applied in each heuristic rule is explained in the following sections. Test results are also tabulated and compared between each heuristics.

3.3.1. MinSlack Rule

First heuristics implemented in the solver is MinSlack rule which is defined as "*Give higher priority to activity which has minimum slack"* by (Kurtulus and Davis, 1982);

Where

$$Slack = LFT\ (i,j) - EFL(i,j) \tag{3.11}$$

LFT denotes late finish time; *EFL* denotes early finish time of activity.

The algorithm applied in heuristic solver is as follows;

1. *Apply CPM forward pass*
2. *Apply CPM backward pass*
3. *Calculate slack of each activity with equation 3.11*
4. *Select activities with zero predecessor and move to decision set D.C*
5. *Select activity from D.C. which have lowest slack value*
6. *Check resource availability;*
   - *6.1. if available: move activity to started activity set S.A.S, reduce resource availability with consumed quantity*
   - *6.2.if not: select other activity from D.C. which have lowest slack value*
7. *Go to step 4*
8. *Continue until all activities are scheduled.*

3.3.2. SASP Rule

SASP rule defined as "*Give priority to shortest activity from shortest project"* by *(*Kurtulus and Davis, 1982);

$$Min\ F(i,j)\ where\ \ F(i,j) = CPM(i) - D(i,j) \tag{3.12}$$

F(i,j) denotes finish time, D(i,j) denoted duration of activity j from project i and CPM(i) denoted CPM duration of project i

Algorithm applied in heuristic solver is as follows;

1. *Apply CPM forward pass*
2. *Apply CPM backward pass*
3. *Calculate CPM(i) of each project*
4. *Calculate F(i,j) of each activity*
5. *Select activities with zero predecessor and move to decision set D.C*

6. *Select activity from D.C. which have* $Min\ F(i,j)$
7. *Check resource availability;*
   7.1. *If available: move activity to started activity set S.A.S, reduce resource availability with consumed quantity*
   7.2. *If not: select other activity from D.C. which have* $Min\ F(i,j)$
8. *Go to step 5*
9. *Continue until all activities are scheduled.*

3.3.3. MaxTWK Rule

Maximum Total Work content (MaxTWK) rule defined as "*Give priority to activities that have maximum total work content value"* by (Kurtulus and Davis, 1982);

Where

$$Max\ \ G(i,j) = TWKi + D(i,j) * \sum_k^K R(i,j,k) \quad (3.13)$$

$$TWKi = \sum_k^K \sum_{j \in S.A.S} D(i,j) * R(i,j,k) \quad (3.14)$$

Algorithm applied in heuristic solver is as follows;

1. *Apply CPM forward pass*
2. *Apply CPM backward pass*
3. *Calculate G(i,j) of each activity*
4. *Select activities with zero predecessor and move to decision set D.C*
5. *Select activity from D.C. which have* $Max\ G(i,j)$
6. *Check resource availability;*
   6.1. *if available: move activity to started activity set S.A.S, reduce resource availability with consumed quantity*
   6.2. *if not: select other activity from D.C. which have* $Max\ G(i,j)$
7. *Go to step 4*
8. *Continue until all activities are scheduled.*

3.3.4. Backward Forward Heuristic

Backward planning is constructing a schedule from backward direction where dummy finish activity is selected as the beginning of a schedule. An arbitrary long duration is selected and schedule is constructed gradually until all activities are started. The resulting start times can be adjusted by setting dummy start activities' start time as 0. Forward planning considers a given priority list and constructs schedule from forward direction where dummy start activity is selected as beginning of a schedule.

These two directional scheduling heuristics can be combined together and used for compressing the schedule. Li and Willis (1992) used this method to improve schedule by an iterative process. It has been proposed the backward and forward pass will never make the schedule worse as time criterion is considered (Lova and Tormos, 2002: Li and Willis, 1992).

Algorithm applied in Backward Forward (BF) heuristic is as follows;

1. *Given a priority list*

   <u>Backward Pass</u>

2. Set an arbitrary duration, D_l

3. Start with dummy finish activity

4. Find activities those have 0 successor

4.1. From these activities find activity that have highest finish time

4.1.1. Check resource availability

4.1.1.1 If available schedule () activity with latest time possible

4.1.1.2. If not go to step 4.1.

5. Continue until all activities are scheduled.

6. Find start time of dummy start activity, D_s

7. Adjust all activities start times by subtracting D_s

Forward Pass

9. Given backward schedule

10. Find activities those have 0 predecessor

10.1. From these activities find activity that have smallest start time

10.1.1. Check resource availability

10.1.1.1 If available schedule () activity with latest time possible

10.1.1.2. If not go to step 10.1

11. Continue until stopping criteria met

3.3.5. Performance Tests of Heuristics

Performances of heuristics are tested with created multi-project test instances. We can categorize results in two dimensions. First one is the results of single pass methods: MinSlack, SASP and MaxTWK. Within these methods generally MaxTWK heuristics outperformed the others. Out of 26 test projects 16 of them scheduled with minimum time using MaxTWK. Worse performance was from SASP heuristic. Second dimension is a multi-pass method which is BF heuristic. It outperformed other three single pass methods and obtained best results. Results are tabulated at Table 3.5.

Table 3.5: Heuristics' results on multi-project test instances

	MinSlack	SASP	MaxTWK	BF	Best
Set 1	141	169	146	128	BF
Set 2	104	112	104	104	MinSlack, MaxTWK, BF
Set 3	112	102	102	92	BF
Set 4	257	287	253	234	BF
Set 5	175	170	183	154	BF
Set 6	119	126	122	112	BF

Table 3.5: (Continued)

	MinSlack	SASP	MaxTWK	BF	Best
Set 7	301	301	286	267	BF
Set 8	110	114	103	98	BF
Set 9	257	292	250	240	BF
Set 10	174	188	173	164	BF
Set 11	208	185	196	172	BF
Set 12	161	159	158	151	BF
Set 13	337	373	342	322	BF
Set 14	154	156	142	132	BF
Set 15	288	347	290	285	BF
Set 16	231	258	225	220	BF
Set 17	171	189	170	161	BF
Set 18	337	389	337	322	BF
Set 19	253	268	256	240	BF
Set 20	235	256	224	234	MaxTWK
Set 21	204	227	198	196	BF
Set 22	400	462	399	379	BF
Set 23	296	334	297	288	BF
Set 24	278	311	282	274	BF
Set 25	308	345	315	302	BF
Set 26	345	397	355	341	BF

3.4.Meta-heuristic Solutions

This section includes meta-heuristic solutions to the RCMPSP. A step by step new algorithm development process is explained. Final algorithm is based on GA, SA and BF improvement techniques along with improvements and new techniques on crossover and mutation operators. Therefore, in order to clarify the final algorithm each basic step is explained in this section detaily.

3.4.1. A Sole GA

Algorithm development process within the meta-heuristic solutions was started with a sole GA. To start with a GA, one has to decide the method of GA which consists of its chromosome coding and decoding, fitness evaluation procedure, crossover, mutation and selection. Before proceeding to details of the algorithm mechanism is explained as follows;

1. *Encode schedule into random key based chromosomes*
2. *Define fitness function*
3. *Define elitism, crossover and mutation ratio*
4. *Generate random initial population of chromosomes*
5. *Set current population*
   - 5.1. *Generate new solutions via crossover and mutation*
     - 5.1.1. *If better accept new solutions*
     - 5.1.2. *If not reject*
   - 5.2. *Select better chromosomes via selection mechanism and copy them to new population*
   - 5.3. *Protect %5 of chromosomes and copy them to new population*
   - 5.4. *Replace current population with new population*
6. *Continue until stopping criteria met and go to step 5*

3.4.1.1. Chromosome Coding and Decoding

Each chromosome consists $\sum_{i=1}^{M} N(i)$ number of genes where each gene represents the priority number of an activity. Starting from dummy start activity to dummy finish activity each gene has a value between 0 and 1. First N_1 genes represent activities from project 1, second N_2 genes represent activities from project 2 and it continues to number of project M. General representation can be seen from Figure 3.1.

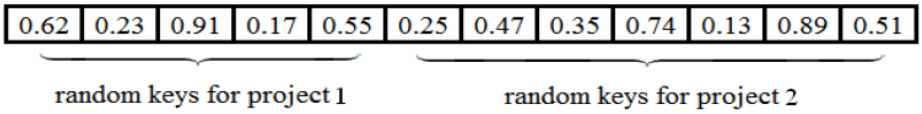


Figure 3.1: Chromosome representation

The order of chromosome is defined same as activity numbers, i.e. 5th gene represents activity 4 for project 1and so on. Random keys change through GA iterations but the order of activities does not change. Figure 3.1 shows a random key representation of two projects where 0.62 represents dummy activity of project 1, 0.23 represents activity 1 from project 1.

Coded chromosomes are decoded with an algorithm that is designed to build schedule with an S-SGS. Decoding algorithm is as follows;

1. Read Chromosome

2. Find the gene that has lowest random key value

3. Check precedence availability

3.1. If precedence value is equal to zero, check resource availability

3.1.1 If there is enough resource, start() activity

3.1.2. If there is not enough resource go to step 2

3.2. If precedence value is not equal to zero go to step 2

4. Continue until all activities are scheduled.

3.4.1.2.Fitness Evaluation

Fitness evaluation is particularly at the heart of a GA design and it is the most intellectual part of it since most of the selection mechanism is based on fitness evaluation. It is basically related with how a solution can be measured in terms of its quality. Sometimes it can be a measure of performance of a single solution

output. Therefore, fitness function used in this GA is selected as the total duration of project portfolio.

Fitness Function:

C_{max} (3.15)

Fitness calculation algorithm is as follows:

1. *Read activity ordered list*
2. *Start activity with earliest time possible*
3. *Read last activity's finish time*

3.4.1.3.Crossover

One point crossover is applied to chromosomes where crossover ratio is predefined before the algorithm is started.

Algorithm designed for crossover is as follows;

1. Read crossover ratio

2. Select father and mother chromosome randomly from population

3. Randomly generate a number r between 1 and N, where N is the total activity number

4. Change genes from 1 to r and r+1 to N between father and mother chromosomes

5. Continue until crossover ratio is reached.

3.4.1.4.Mutation

Mutation is necessary in any GA in order to prevent premature convergence of the algorithm. Therefore, a standard mutation technique is applied. In this technique, randomly selected genes are applied to change its random key value.

Algorithm designed for mutation is as follows;

1. Read mutation ratio

2. Randomly select chromosomes where mutation is applied.

2.1. Randomly select genes on this chromosome

2.1.1. Replace its value by a new random key number

3. Continue until mutation ratio is reached.

3.4.1.5.Roulette Wheel Selection

The idea of evolutionary computing is to give higher change to better chromosomes. Therefore as population evolves better chromosomes should have higher chance to live. In order to apply this principle, some kind of selection methods should be used. In this simple GA roulette wheel selection method is used through iterations. In this method, those schedules which are shorter have high probability of selection.

Probability of a chromosome selected calculated as:

$$\frac{1}{P(i)} \qquad where \qquad P(i) = {Fitness\ (i)}\Big/{\sum_{J=1}^{N} Fitness(j)} \tag{3.16}$$

As the equation implies if a solution have good fitness values, its probability value would be higher so that probability of selected would be higher.

Algorithm designed for roulette wheel selection is as follows;

1. Find all fitness values of a population,

2. Calculate P(i) of each chromosome,

3. Sort all chromosomes in ascending form according to P(i) values where $0 \leq P(i) \leq 1$

4. Create a random number where $0 \leq r \leq 1$

5. Select chromosome that corresponds random number r

3.4.1.6.Elitism

Elitism is passing knowledge from population to population by protecting best chromosomes. The amount of elitism is an important parameter. It is generally applied up to %10 of a population. Therefore in order to keep best solutions in the generation and in order to be inherited to the generations elitism is applied.

Algorithm designed for roulette wheel selection is as follows;

1. *Find all fitness values of a population,*
2. *Sort all chromosomes in ascending form according to fitness value*
3. *Protect best %X chromosomes from crossover and mutation*

3.4.1.7.Parameter Setting

For test instances 1000, 10000 and 50000 number of schedule generated and it is used together with a crossover ratio if %80, mutation ratio of 0.003 and elitism ratio of %5. Population size is selected as 100.

3.4.1.8.Performance of the Algorithm

Table 3.6: GA versus heuristics performances

Test #	GA	MinSlack	SASP	MaxTWK	BF	% Deviation From Best
Set 1	*119*	141	169	146	128	7.03%
Set 2	*88*	104	112	104	104	15.38%
Set 3	*83*	112	102	102	92	9.78%
Set 4	*217*	257	287	253	234	7.26%
Set 5	*140*	175	170	183	154	9.09%
Set 6	*104*	119	126	122	112	7.14%
Set 7	*247*	301	301	286	267	7.49%
Set 8	*92*	110	114	103	98	6.12%
Set 9	*218*	257	292	250	240	9.17%
Set 10	*152*	174	188	173	164	7.32%
Set 11	*155*	208	185	196	172	9.88%
Set 12	*140*	161	159	158	151	7.28%

Table 3.6: (Continued)

Test #	GA	MinSlack	SASP	MaxTWK	BF	% Deviation From Best
Set 13	*296*	337	373	342	322	8.07%
Set 14	*123*	154	156	142	132	6.82%
Set 15	*268*	288	347	290	285	5.96%
Set 16	*206*	231	258	225	220	6.36%
Set 17	*152*	171	189	170	161	5.59%
Set 18	*303*	337	389	337	322	5.90%
Set 19	*228*	253	268	256	240	5.00%
Set 20	*217*	235	256	224	234	3.13%
Set 21	*186*	204	227	198	196	5.10%
Set 22	*350*	400	462	399	379	7.65%
Set 23	*272*	296	334	297	288	5.56%
Set 24	*256*	278	311	282	274	6.57%
Set 25	*288*	308	345	315	302	4.64%
Set 26	*328*	345	397	355	341	3.81%
Average						**7.04%**

It can be seen from table 3.6 that % difference from best heuristics, which is calculated as a percentage of difference between GA and best heuristic, has an average value of %7.04. That is a sole GA can find as an average %7.04 better solutions for test cases. Moreover, this value increases for some test cases up to %15.38. Therefore, GA outperformed all other heuristics.

Table 3.7: GA versus MS Project heuristics comparison

	GA	MS Project		Comparison	
		ID Order	Standard Order	GA-ID Order	GA-Standard Order
Set 1	119	143	139	16.78%	14.39%
Set 2	88	97	96	9.28%	8.33%
Set 3	83	99	94	16.16%	11.70%
Set 4	217	280	258	22.50%	15.89%
Set 5	140	169	156	17.16%	10.26%
Set 6	104	119	111	12.61%	6.31%
Set 7	247	300	294	17.67%	15.99%
Set 8	92	104	103	11.54%	10.68%
Set 9	218	274	271	20.44%	19.56%
Set 10	152	193	164	21.24%	7.32%
Set 11	155	195	200	20.51%	22.50%
Set 12	140	173	161	19.08%	13.04%
Set 13	296	352	375	15.91%	21.07%
Set 14	123	147	138	16.33%	10.87%
Set 15	268	348	364	22.99%	26.37%
Set 16	206	254	234	18.90%	11.97%
Set 17	152	173	174	12.14%	12.64%
Set 18	303	368	377	17.66%	19.63%
Set 19	228	272	251	16.18%	9.16%
Set 20	217	261	246	16.86%	11.79%
Set 21	186	210	208	11.43%	10.58%
Set 22	350	431	458	18.79%	23.58%
Set 23	272	323	313	15.79%	13.10%
Set 24	256	307	302	16.61%	15.23%
Set 25	288	340	343	15.29%	16.03%
Set 26	328	390	382	15.90%	14.14%
Average				**16.76%**	**14.31%**

When the results are investigated, it can be seen that GA results are far better from MS Projects' heuristics. This difference is %26.37 at test instance 15 and % 6.31 at test instance 6. On the average, GA is %16.76 better than ID-Order heuristic results and %14.31 better than standard order heuristics. Therefore, sole GA outperformed the known software packages' heuristics.

Table 3.8 is constructed in order to compare Chen and Shahandashti (2009) real test case with our results. It can be seen that random key based sole GA performed better compared with their results. Test is run 10 times and average and best results are tabulated.

Table 3.8: Comparison of GA results of this study with Chen and Shahandashti (2009)

Method	Best	Average
Genetic algorithm	547	544.1
Genetic Algorithm (this study)	537	542.7

3.4.2. A Sole SA

Simulated Annealing (SA) is a stochastic meta-heuristic algorithm inspired by the physical process of annealing (Kirkpatrick et al., 1983; Cerny, 1985). SA has fine tuning capabilities, and is usually capable of escaping of local optima for locating a good approximation to the global optimum (Hwang and He, 2006).

Basic idea behind a SA algorithm is to accept worse solutions according to metropolis criterion (Metropolis et al., 1953). Probability of accepting worse solutions are high at the beginning and it is decreased with a chosen cooling schema. A linear cooling schema is as follows:

$$T_{i+1} = \alpha \; x \; T_i \qquad (3.17)$$

where T is temperature, i is iteration number and $0<\alpha<1$

New solution is formed with previous solutions by changing activity orders. After forming new solution cost function is calculated as:

$$\delta F = F_{i+1} - F_i \tag{3.18}$$

With cost function at hand, probability of new solution accepted is calculated as:

$$P = e^{-\delta F/T} \tag{3.19}$$

A schedule is represented with a vector consisting of random key values of activities which are starting from dummy start activity 0 to dummy finish activity N. New solution is generated via randomly changing vector values based on a predefined changing ratio.

With decreasing temperature probability value also decreases and probability of accepting worse solution decreases. For early stages of iterations probability of accepting worse solution is higher than late stages of iteration.

Algorithm designed for SA is as follows:

1. Initiate initial temperature T_0, final temperature T_f, max. number of iterations N and initial schedule

2. Calculate new solution by changing random key values of a schedule

2.1. Calculate δF

2.1.1. Accept new solution if $\delta F < 0$ (better solution)

2.1.2. If not

2.1.2.1. Generate a random number, r

2.1.2.2. Accept new solution if $P = e^{-\delta F/T} > r$

2.1.2.2.1. If not reject solution

2.2. Update F_i, Reduce T

2.3. Continue until $T<T_f$ and $n<N$

3.4.2.1.Parameter Setting

Choice of parameters is crucially important in a SA algorithm. If T is selected too high p value converge to 1 which means almost all worse solutions will be accepted. Nevertheless, if T is selected too small p value converge to 0 which means almost all solutions would be rejected. Iteration number is also important since too many iterations would lead time loss, too few iterations would lead system not to converge near optimum values. Therefore proper setting of T is important. Mostly try and error method would help to optimize T and N parameters.

For test instances a linear cooling schema with α=0.99, T_i=4000 and T_f=0 is selected. Total of 5000 iterations used for stopping criterion.

3.4.2.2.Performance of Algorithm

Performance of SA algorithm is tested against the results obtained with GA algorithm. It can be seen from Table 3.9 that GA performed better in all cases except in set 1. GA on the average performed %5.89 better. GA outperformed with %11.97 on the problem instance 16.

Table 3.9: GA-SA comparison

Set	GA	SA	GA-SA Performance Comparison
Set 1	*119*	119	0.00%
Set 2	*88*	89	1.12%
Set 3	*83*	92	9.78%
Set 4	*217*	234	7.26%
Set 5	*140*	150	6.67%
Set 6	*104*	112	7.14%
Set 7	*247*	258	4.26%
Set 8	*92*	99	7.07%
Set 9	*218*	234	6.84%
Set 10	*152*	167	8.98%
Set 11	*155*	163	4.91%
Set 12	*140*	149	6.04%

Table 3.9: (Continued)

Set	GA	SA	GA-SA Performance Comparison
Set 13	*296*	310	4.52%
Set 14	*123*	139	11.51%
Set 15	*268*	279	3.94%
Set 16	*206*	234	11.97%
Set 17	*152*	159	4.40%
Set 18	*303*	330	8.18%
Set 19	*228*	238	4.20%
Set 20	*217*	234	7.26%
Set 21	*186*	195	4.62%
Set 22	*350*	369	5.15%
Set 23	*272*	290	6.21%
Set 24	*256*	273	6.23%
Set 25	*288*	293	1.71%
Set 26	*328*	339	3.24%
Average			**5.89%**

SA algorithm is also tested with Chen and Shahandashti (2009) real portfolio test set and results are tabulated at Table 3.10.

Table 3.10: Comparison of SA results of this study with Chen and Shahandashti (2009)

Method	Best	Average
Simulated annealing	544	547.9
Modified simulated annealing-1	540	544.3
Modified simulated annealing-2	542	555.9
Simulated annealing (this study)	546	551.3

3.4.3. A hybrid GA-SA Algorithm

A sole SA has low search efficiency as it maintains only one solution at each iteration. GA on the other hand, can contain knowledge of previous good solutions, and is suitable for implementing search in parallel architecture. However, a sole GA can be restrictive since it has limited fine tuning capabilities, and may suffer from rapid population convergence to local optima (Rudolph, 1994; Leung et al., 1997).

In recent years, several skilled combinations of GA and SA were proposed to achieve an efficient search algorithm by integrating the complementary strengths of both methods. The results of the hybridizing mechanism GA and SA have been promising as the hybrid algorithm is capable of escaping local optima (deficiency of a sole GA), has fine-tuning capability (deficiency of a sole GA), can implement search in parallel architecture (deficiency of a sole SA) and can use knowledge of previous solutions (deficiency of a sole SA) (Wang and Zeng 2001; Chen et al. 2005; Hwang and He 2006; Han and Sun 2006; Chen and Shahandashti, 2009; Sonmez and Bettemir, 2012).

The idea behind GA-SA hybrid algorithm is increasing GA's fine tuning capability via accepting worse solutions with SA principles.

1. Random key based chromosome representation is used as coding mechanism. Fitness evaluation is the finish time of last activity, crossover, mutation and roulette wheel selection mechanism is all same as defined in previous chapters. %5 elitism is used in order to pass best knowledge from population to population. Algorithm designed for GA-SA hybrid algorithm is as follows; *Initiate initial temperature T_0 ,final temperature T_f, max. number of iterations N and initial schedule*
2. *Encode schedule into random key based chromosomes*
3. *Define fitness function*
4. *Define elitism, crossover and mutation ratio*
5. *Generate random initial population of chromosomes*
6. *Set current population*
   6.1. Generate new solutions via crossover and mutation

6.1.1. If better accept new solutions

6.1.2. If not

6.1.2.1. Generate a random number, r

6.1.2.2. Accept new solution if $P = e^{-\delta F/T} > r$

6.2. Select better chromosomes via selection mechanism and copy them to new population

6.3. Protect %5 of chromosomes and copy them to new population

6.4. Replace current population with new population

7. Reduce T, continue until stopping criteria met and go to step 5

3.4.3.1.Performance of the Algorithm

Performance of GA-SA algorithm is tested against the results obtained with sole GA and sole SA algorithm. It can be seen from Table 3.11 that GA-SA performed better in all cases. GA-SA on the average performed %3.26 better. It can be concluded that GA and SA hybrid algorithm performs better and this performance improvement is significant when we compared with set 5 results which is %6.06.

Table 3.11: GA-SA comparison with sole GA and sole SA

Set	GA	SA	GA-SA	GA-SA Performance Comparison
Set 1	*119*	119	115	3.48%
Set 2	*88*	89	88	0.00%
Set 3	*83*	92	83	0.00%
Set 4	*217*	234	211	2.84%
Set 5	*140*	150	132	6.06%
Set 6	*104*	112	101	2.97%
Set 7	*247*	258	241	2.49%
Set 8	*92*	99	89	3.37%
Set 9	*218*	234	214	1.87%
Set 10	*152*	167	148	2.70%
Set 11	*155*	163	150	3.33%

Table 3.11: (Continued)

Set	GA	SA	GA-SA	GA-SA Performance Comparison
Set 12	*140*	149	137	2.19%
Set 13	*296*	310	281	5.34%
Set 14	*123*	139	120	2.50%
Set 15	*268*	279	255	5.10%
Set 16	*206*	234	202	1.98%
Set 17	*152*	159	146	4.11%
Set 18	*303*	330	289	4.84%
Set 19	*228*	238	222	2.70%
Set 20	*217*	234	207	4.83%
Set 21	*186*	195	177	5.08%
Set 22	*350*	369	332	5.42%
Set 23	*272*	290	265	2.64%
Set 24	*256*	273	249	2.81%
Set 25	*288*	293	281	2.49%
Set 26	*328*	339	317	3.47%
Average				**3.26%**

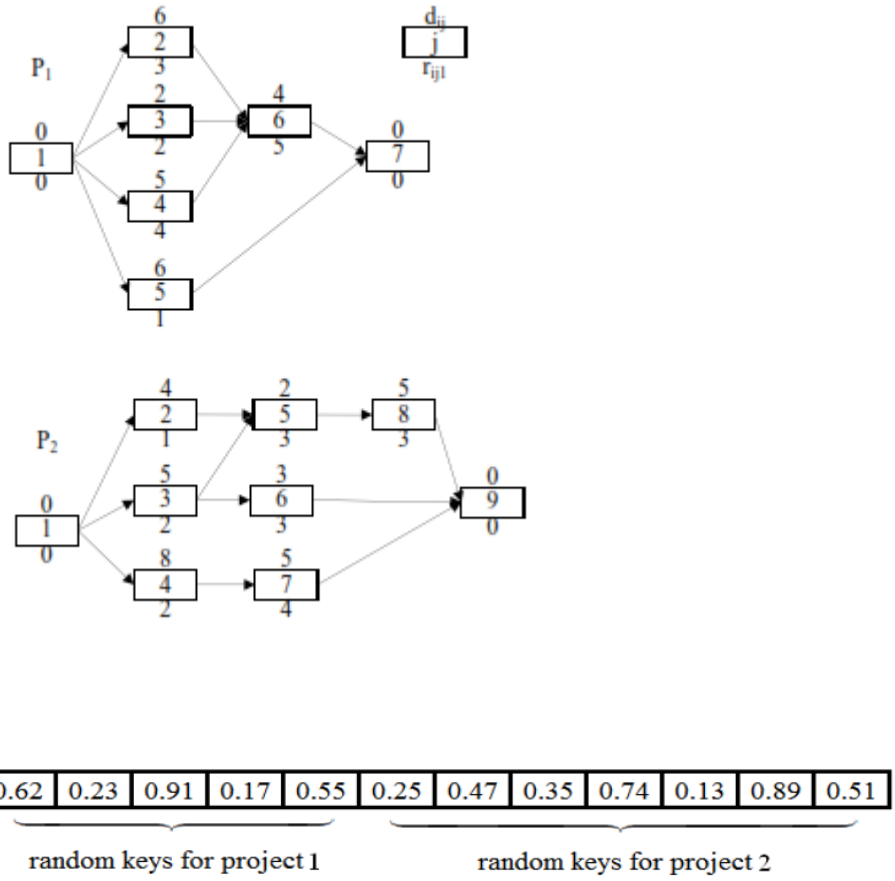
Table 3.12 summarized the result comparison of this study with the work of Chen and Shahandashti (2009). Although the best result cannot be obtained within this study, on the average with 10 consecutive runs there has been significant improvement.

Table 3.12: Comparison of GA-SA results with Chen and Shahandashti (2009)

Method	Best	Average
Genetic algorithm/simulated annealing	525	544.0
GA-SA (this study)	527	535.4

3.4.4. A Backward-forward Hybrid GA-SA Algorithm

When we examine the previous algorithms it can clearly be observed that BF heuristic outperformed in all tests sets when compared with other heuristics. In the same manner, although GA and SA performed solely better against heuristics, if a hybrid combination which brings strengths of each algorithm together has been made results behave better than GA and SA alone. BF heuristic is fast, robust and has fine tuning capabilities compared to other heuristics. In addition, it can be adapted to GA solutions easily. Therefore, in order to use complementary strength of heuristics and meta-heuristics a new optimization strategy is developed. In this method, together with GA and SA hybrid algorithm, backward- forward scheduling iteration method is hybridize for solution of RCMPSP. The proposed backward-forward hybrid genetic algorithm (BFHGA) is described in the following sections.



0.62	0.23	0.91	0.17	0.55	0.25	0.47	0.35	0.74	0.13	0.89	0.51

Figure 3.2: Example problem and chromosome representation

The first step in algorithm is backward scheduling. Backward scheduling is constructing a schedule from backward direction where dummy finish activity is selected as beginning of a schedule and schedule is constructed with backward direction, from finish to start direction. An arbitrary long duration is selected as a time buffer and schedule is constructed gradually until all activities are scheduled to start. All precedence relations are reversed and activities are scheduled as late as possible in the reverse time direction according to the priority list. The resulting schedule can be adjusted easily such that the start time of the dummy start activity equals 0 (Demeulemeester and Herroelen, p.275, 2002). The resulting start times can be adjusted by setting dummy start activities start time as 0.

The method will be explained with an example and differences from sole GA and sole SA will be highlighted. To start with the BFHGA, below example can be considered.

Fig. 3.2. shows the example resource-constrained multi-project scheduling problem and its chromosome representation consisting of two projects. The first project is composed of five non-dummy activities, and the second project is composed of seven non-dummy activities. There is only one common resource and the availability of R1 in each time period is seven units. In the chromosome representation, the first gene represents the priority of the first non-dummy activity of project 1 (activity 1–2), the second gene represents the priority of the second non-dummy activity of project 1 (1–3), the sixth (N1 =1) gene represents the priority of the first non-dummy activity of project 2 (2–2), and finally the twelfth (N1 =N2) gene represents the last non-dummy activity of project 2 (2–8)

The proposed backward-forward hybrid genetic algorithm (BFHGA) transforms random key chromosome representation into a feasible schedule by using the backward-forward (BF) scheduling method through the following steps:

1. Set the portfolio duration to an arbitrary large duration to start backward scheduling.

2. Let ns_{ij} be the number of backward-unscheduled successors for activity j of project i. Among the activities with $ns_{ij} = 0$ in the backward unscheduled activities list, select the activity with the largest random key value.

2.1. Backward schedule the selected activity in its latest precedence and resource feasible start time in the reverse time direction.

2.2. Decrease the ns_{ij} values of its predecessors by one, and remove the activity from the backward unscheduled activities list.

3. Repeat step 2 until all the activities in the backward unscheduled activities are backward scheduled. Complete backward scheduling by adjusting the schedule so that the start time of the super-dummy start node is equal to zero.

4. Among the activities in the forward unscheduled activities list, select the activity with the earliest start time (according to the backward schedule). In case of a tie, select the activity with smaller activity number. If both activities have the same activity number, select the activity with the smallest project number. Forward schedule the selected activity in its earliest precedence and resource feasible start time, and remove the activity from the forward unscheduled activities list.

5. Repeat step 4 until all the activities in the forward unscheduled activities list are forward scheduled

The projects that do not start at the same time can be solved by imposing start times to the dummy start nodes of projects. The portfolio completion time is set as 30 days arbitrarily, to start backward scheduling. In the initial backward unscheduled activities list, all of the non-dummy activities are included. In the backward list, activities 1–5, 1–6, 2–6, 2–7, and 2–8 have a number of backward-unscheduled successors (ns_{ij}) values of zero. Among these activities, 2–7 has the highest random key value and is backward scheduled first to start at day 26 as shown in Figure 3.3.

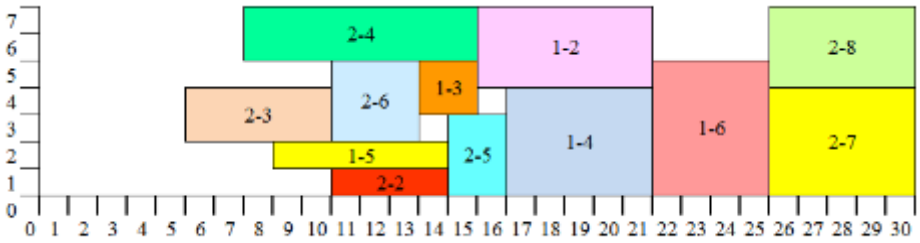


Figure 3.3: Backward scheduling part 1

Once 2–7 is scheduled, the ns_{24} value is decreased by one to zero, and 2–7 is removed from the backward list. Among activities 1–5, 1–6, 2–4, and 2–6, activity 1–6 has the highest random key value and is backward scheduled next to start at day 22, which is the latest time that this activity can start without violating the resource constraint of 7. After 1–6 is scheduled, the ns_{ij} values of 1–2, 1–3, and 1–4 are decreased by one to zero, and 1–6 is removed from the backward list. The remaining activities are backward scheduled to their possible latest start times similarly (Figure 3.4).

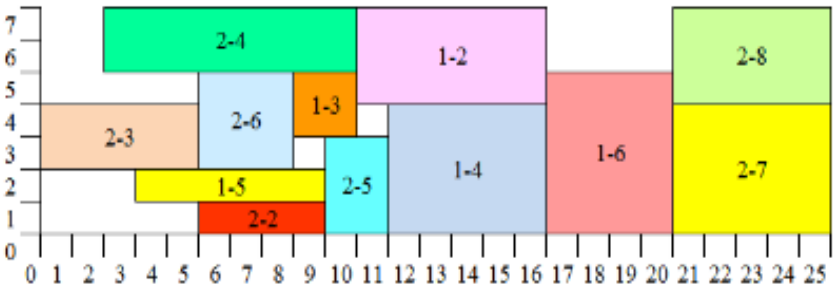


Figure 3.4: Backward scheduling part 2

Finally, the schedule is adjusted so that the start time of the super-dummy start node is equal to zero. The portfolio duration is obtained as 25 days as shown in figure. 3.3. The start times of activities that are obtained in backward scheduling are used to determine the activity priorities in forward scheduling improvement. In the initial forward unscheduled activities list, all of the non-dummy activities are included. Activity 2–3, which has the earliest start time in backward scheduling, is scheduled

first to start at day 0. Once activity 2–3 is scheduled, it is re moved from the forward unscheduled activities list. Activity 2–4 is forward scheduled second, and activity 1–5 is scheduled third. The activities 2–2 and 2–6 both have a start date of 6. Because the activity number of 2–2 is smaller, this activity is scheduled to start at date 0. Next, activity 2–6 is scheduled to start at date 6, which is the earliest time that this activity can start without violating the resource constraint. The remaining activities are scheduled to their possible earliest start times as shown in Figure 3.5, and the portfolio duration is decreased to 24 days at the end of the forward improvement.

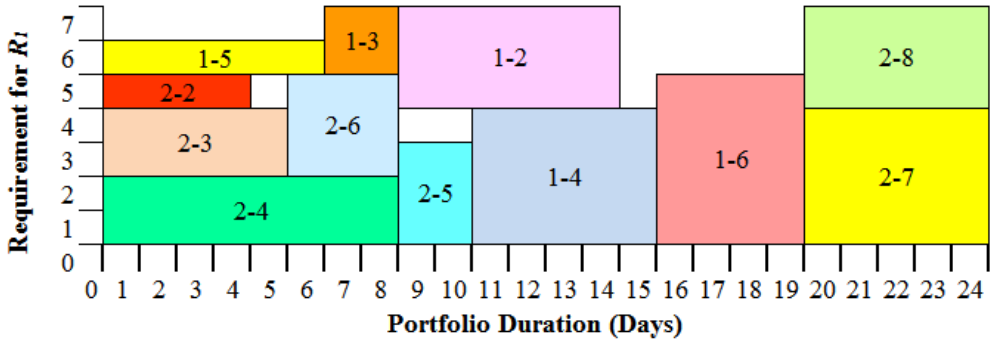


Figure 3.5: Final schedule

3.4.4.1.Crossover, Mutation and Selection

The backward-forward hybrid genetic algorithm creates the initial population by generating PS chromosomes randomly, where PS is the population size. The random key representation of each chromosome is transformed into a feasible schedule by the backward-forward scheduling method. The portfolio durations of each chromosome are used for fitness evaluation. The chromosomes that will survive in the next generation are determined by elitist selection method. The top 10% of the chromosomes are copied from the current generation into the next.

The remaining chromosomes that will survive in the next generation are determined by the roulette wheel selection. New chromosomes are created by crossover or mutation operators. Hartmann (1998) has shown that a two-point crossover operator performs better than the one-point and uniform crossover operators for the RCPSP.

Hence, in BFHGA, two chromosomes are combined by using a two-point crossover operator. Mutation is performed by changing a number of random keys of selected chromosomes with new random keys.

3.4.4.2.Integration of Simulated Annealing

The SA is integrated into GA during mutation in the proposed hybrid algorithm. In BFHGA, two types of mutations are performed. The first type of mutation is performed after a crossover operation when there is not sufficient diversification between a child and one of its parents. The elitist selection method adopted in BFHGA can lead to a homogeneous population that may result in rapid population convergence to a local optimum. Hence, the first type of mutation is performed on a child after the crossover operation, when the mean absolute difference of random key values of a child and one of its parents (father or mother) is smaller than a predefined diversification value τ (Equation 3.19). The value of τ is reduced based on a cooling scheme defined by temperature t.

Do *Mutation*

While $\sum_{i=0}^{N} |RK_{child} - RK_{parents}| \Big/ N \leq \tau$ (3.19)

The second type of mutation is the regular mutation that is performed randomly based on a predefined mutation rate. The main objective of both types of mutations is to achieve diversification for escaping premature convergence to achieve the global optimum or near-global optimum results.

In BFHGA, every mutation that leads to a chromosome with a better (or equal) fitness evaluation function value is accepted. However, a mutation that leads to a chromosome with a worse fitness evaluation function value may be accepted or

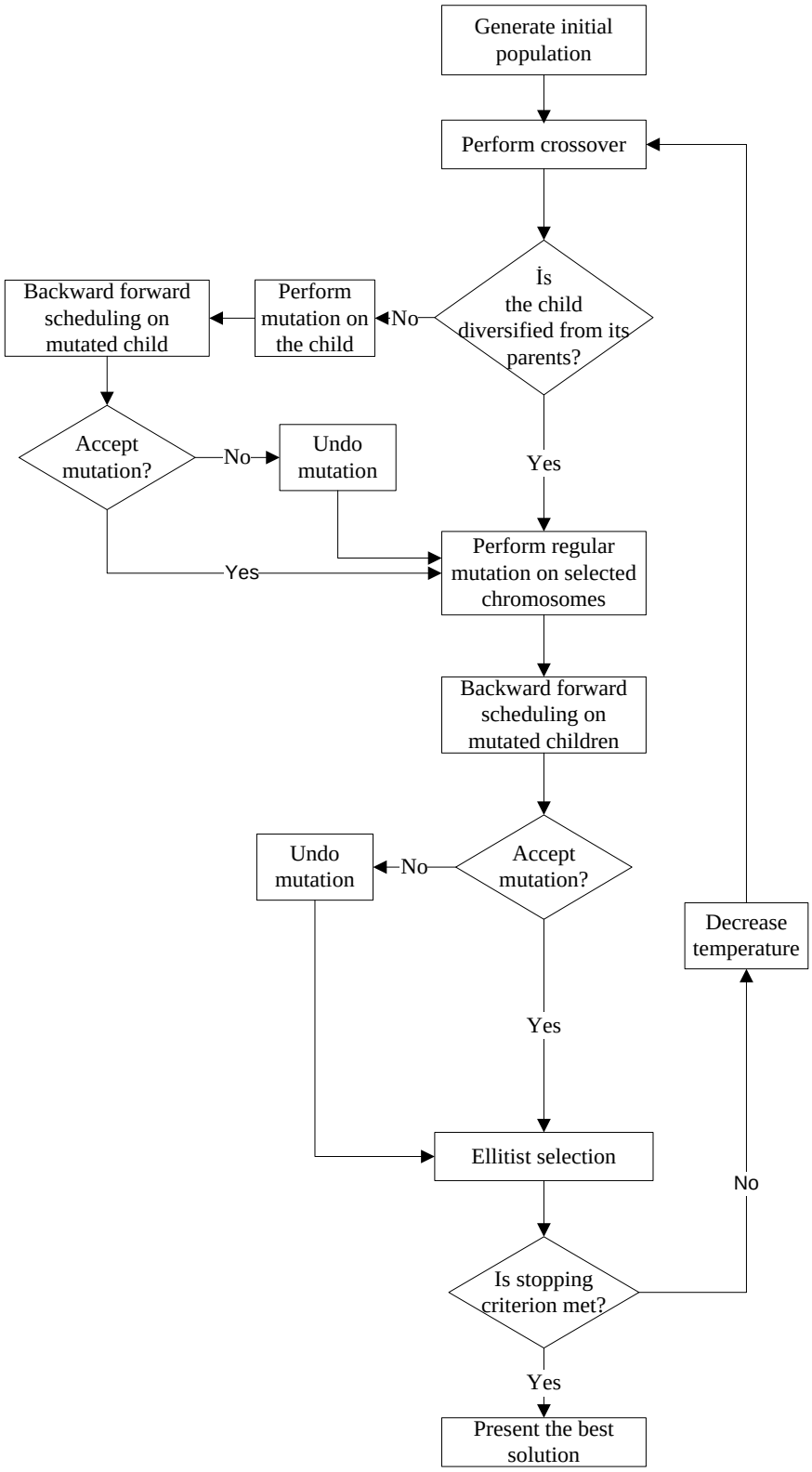


Figure 3.6: Flow of BFHGA

rejected (not executed) based on a decision function (DF1). The general flow of BFHGA can be seen at Figure 3.6 and the decision function DF1 is defined in Equation (3.20) as follows:

$$DF1 \begin{cases} accept \ \ if \ \ r_u \le e^{\frac{\left(fs - fs''\right)}{f_S} x \frac{B}{t}} \\ \\ reject \ \ if \ \ r_u > e^{\frac{\left(fs - fs'\right)}{f_S} x \frac{B}{t}} \end{cases} \tag{3.20}$$

3.4.4.3.Performance of Algorithm

The initial comparisons include four single project RCPSP case examples. The sources of the examples were Anagnostopoulos and Koulinas (2012), Christodoulou (2010), Hegazy (1999), and Leu and Yang (1999) respectively. The single project examples included between 17 and 25 activities, and one and six resources. The optimal solutions for the first three case examples were obtained by using RESCON (Deblaere et. al. 2011). RESCON can obtain the optimal solutions for relatively small resource constrained project networks including finish to start precedence relations. The fourth single project case example was not solved by RESCON, since this example included start-to-start type of precedence relations.

As can be summarized at Table 3.13, the BFHGA algorithm was able to obtain the optimal solutions of 54, 133, and 43 days for single-project case examples one, two, and three, respectively. The algorithm also successfully determined the best available solution (upper bound) 35 days for case example four. BFHGA was able to obtain successful solutions within less than 0.5 CPU seconds for the single case examples.

Among the previous methods, the greedy randomized adaptive search procedure (GRASP) inspired hyper heuristic also obtained the optimal results for the first three examples, and GA2 (Leu and Yang 1999), and GA3 (Abido and Elazouni 2010)

achieved a solution of 35 days for the fourth case example The ant colony optimization (ACO) (Christodoulou 2010) was able to determine a solution of 141 days for the second case example, and GA1 (Hegazy 1999) was able to achieve a solution of 44 days for the third case example.

Table 3.13: Performance comparison of BFHGA

Case	Source	Optimal	BFHGA (This Study)	Time
1	Anagnostopoulos and Koulinas (2012)	54	54	0.345
2	Christodoulou (2010)	133	133	0.028
3	Hegazy (1999)	43	43	0.432
4	Leu and Yang (1999)	NA	35	0.346

Chen and Shahandashti (2009) presented two multiproject case examples to compare performances of five meta-heuristic methods, namely, a sole genetic algorithm, a sole simulated annealing algorithm, a hybrid genetic algorithm with simulated annealing, an arithmetically improved modified simulated annealing algorithm (modified simulated annealing), and a logarithmically improved modified simulated annealing algorithm (modified simulated annealing-2).

Table 3.14: Comparison of BFHGA results with Chen and Shahandashti (2009) Test Case

Method	Best	Average
Genetic algorithm	133	135.5
Simulated annealing	134	135.4
Genetic algorithm/simulated annealing	132	134.5
Modified simulated annealing-1	133	134.2
Modified simulated annealing-2	130	133.0
BFHGA (This Study)*	124	125.1

*Solution can be found at Appendix.

Results of BFHGA are presented along with the results of the five previous meta-heuristics for test portfolio and real portfolio in Tables 3.14 and 3.15 respectively. The stopping criterion for BFHGA was set as 500,000 schedules for multi-project case examples. Results indicate that BFHGA significantly out performs state-of-the-art meta-heuristics for project portfolio duration minimization. Among the five previous meta-heuristics the modified simulated annealing-2 method had the best performance for test portfolio and was able to find the best solution of 130 days, and an average duration of 133.0 days. BFHGA obtained a best solution of 124 days as shown in Table 3.14, and an average duration of 125.1 days with a standard deviation of 0.6 for the test portfolio.

The best performing previous method for the real portfolio was the genetic algorithm/simulated annealing method. The genetic algorithm/simulated annealing method was able to find a best solution of 525 days, and an average duration of 544.0 days within 606 seconds. BFHGA achieved a best solution of 517 and an average duration of 523.3 days with a standard deviation of 3.1. Because 3.06 GHz is used in experiments the CPU time was adjusted for 1.83-GHz clock speed. The average adjusted CPU time of BFHGA in 10 experiments for the real portfolio was 139 seconds. The comparisons validate the effectiveness of the proposed algorithm for the RCMPSP.

Table 3.15: Comparison of BFHGA results with Chen and Shahandashti Real Case (2009)

Method	Best	Average	Time (Secs)
Genetic algorithm	547	544.1	491
Simulated annealing	544	547.9	592
Genetic algorithm/simulated annealing	525	544.0	606
Modified simulated annealing-1	540	544.3	NA
Modified simulated annealing-2	542	555.9	NA
BFHGA (This Study)**	517	523.3	139*

*Adjusted CPU time

**Solution can be found at Appendix.

Table 3.16: Performance comparison based on BFHGA as upper bound

%Deviation from BFHGA (1,000 Schedule)					
Set	MINSLK	SASP	MAXTWK	MSP-STD	BF
Set 1	20.5	44.4	24.8	18.8	9.4
Set 2	18.2	27.3	18.2	9.1	18.2
Set 3	33.3	21.4	21.4	11.9	9.5
Set 4	17.4	31.1	15.5	17.8	6.8
Set 5	25.9	22.3	31.7	12.2	10.8
Set 6	15.5	22.3	18.4	7.8	8.7
Set 7	21.9	21.9	15.8	19.0	8.1
Set 8	22.2	26.7	14.4	14.4	8.9
Set 9	17.4	33.3	14.2	23.7	9.6
Set 10	15.2	24.5	14.6	8.6	8.6
Set 11	31.6	17.1	24.1	26.6	8.9
Set 12	15.0	13.6	12.9	15.0	7.9
Set 13	15.4	27.7	17.1	28.4	10.3
Set 14	26.2	27.9	16.4	13.1	8.2
Set 15	9.1	31.4	9.8	37.9	8.0
Set 16	11.6	24.6	8.7	13.0	6.3
Set 17	14.0	26.0	13.3	16.0	7.3
Set 18	12.7	30.1	12.7	26.1	7.7
Set 19	12.9	19.6	14.3	12.1	7.1
Set 20	11.9	21.9	6.7	17.1	11.4
Set 21	12.7	25.4	9.4	14.9	8.3
Set 22	17.3	35.5	17.0	34.3	11.1
Set 23	9.6	23.7	10.0	15.9	6.7
Set 24	9.0	22.0	10.6	18.4	7.5
Set 25	8.5	21.5	10.9	20.8	6.3
Set 26	7.5	23.7	10.6	19.0	6.2
Average P.D.(%):	16.6	25.7	15.1	18.2	8.8
Average CPU (S.):	0.1	0.1	0.1	13.4	0.7

The results of the computational experiments for project portfolio duration minimization are presented in Table 3.16. BFHGA obtained the best solution for all of the 26 test portfolios. Hence, the percentage of deviation of the heuristics from the solution obtained by BFHGA (upper bound) is used as a performance measure in comparisons. The computational test results reveal the performance gap between the state-of-art heuristics and the proposed BFHGA. The CPU time for BFHGA varied between 0.2 and 1.5 s for 1,000 schedules, and the average CPU time was 0.7 s with a standard deviation (SD) of 0.3. The maximum amount of memory (RAM) usage of BFHGA for the benchmark instances was 0.05 GB. Since BFHGA stores only 100 solutions at a time, it requires low memory usage. The computational comparisons confirm the effectiveness of the BFHGA

Table 3.17: Performance comparison of BFHGA with other methods

Set	GA	SA	GA-SA	BFHGA	BFHGA Performance Comparison
Set 1	*119*	119	115	113	1.74%
Set 2	*88*	89	88	86	2.27%
Set 3	*83*	92	83	82	1.20%
Set 4	*217*	234	211	208	1.42%
Set 5	*140*	150	132	131	0.76%
Set 6	*104*	112	101	101	0.00%
Set 7	*247*	258	241	238	1.24%
Set 8	*92*	99	89	88	1.12%
Set 9	*218*	234	214	210	1.87%
Set 10	*152*	167	148	148	0.00%
Set 11	*155*	163	150	149	0.67%
Set 12	*140*	149	137	136	0.73%
Set 13	*296*	310	281	279	0.71%
Set 14	*123*	139	120	119	0.83%

Table 3.17 : (Continued)

Set	GA	SA	GA-SA	BFHGA	BFHGA Performance Comparison
Set 15	*268*	279	255	253	0.78%
Set 16	*206*	234	202	200	0.99%
Set 17	*152*	159	146	146	0.00%
Set 18	*303*	330	289	288	0.35%
Set 19	*228*	238	222	218	1.80%
Set 20	*217*	234	207	205	0.97%
Set 21	*186*	195	177	177	0.00%
Set 22	*350*	369	332	329	0.90%
Set 23	*272*	290	265	262	1.13%
Set 24	*256*	273	249	248	0.40%
Set 25	*288*	293	281	278	1.07%
Set 26	*328*	339	317	314	0.95%
Average					**0.92%**

Table 3.17. shows the results of GA, SA, GA-SA and BFHGA together. As can be seen that, although sole GA and SA results are challenging compared with ordinary heuristics, hybrid algorithm outperforms others. Hybrid algorithm with BF improvement and GA-SA hybrid and ımproved crossover methods further improved the algorithm's performances. Final algorithm has on average %0.92 better results compared with GA-SA hybrid one.

Table 3.18: Performance comparison of RESCON with BFHGA

Test Set	BFHGA	RESCON Results		%Deviation from best solution	
	Time	**Result**	**Tabu Search**	**Best**	**BFHGA**	**TABU**
Set 1	1,4	113	115	113	0.00%	1.77%
Set 2	2,2	86	88	86	0.00%	2.33%
Set 3	2,2	82	84	82	0.00%	2.44%
Set 4	4,6	208	213	208	0.00%	2.40%
Set 5	2,3	131	133	131	0.00%	1.53%
Set 6	2,3	101	102	101	0.00%	0.99%
Set 7	4,8	238	242	238	0.00%	1.68%
Set 8	3,2	88	90	88	0.00%	2.27%
Set 9	5,9	210	217	210	0.00%	3.33%
Set 10	5,8	148	146	146	1.37%	0.00%
Set 11	3,4	149	152	149	0.00%	2.01%
Set 12	3,5	136	138	136	0.00%	1.47%
Set 13	6,2	279	284	279	0.00%	1.79%
Set 14	4,5	119	122	119	0.00%	2.52%
Set 15	7,5	253	259	253	0.00%	2.37%
Set 16	7,4	200	201	200	0.00%	0.50%
Set 17	4,6	146	148	146	0.00%	1.37%
Set 18	7,8	288	300	288	0.00%	4.17%
Set 19	7,6	218	219	218	0.00%	0.46%
Set 20	9,0	205	208	205	0.00%	1.46%
Set 21	6,0	177	180	177	0.00%	1.69%
Set 22	9,4	329	332	329	0.00%	0.91%
Set 23	9,4	262	267	262	0.00%	1.91%
Set 24	10,9	248	251	248	0.00%	1.21%
Set 25	11,0	278	281	278	0.00%	1.08%
Set 26	13,2	314	319	314	0.00%	1.59%
Avr.						**1.74%**

Another result comparison is made with RESCON results and BFHGA (Table 3.18). The results are compared with the RESCON's tabu search algorithm by running them exactly same time on the same computer. Out of 26 test cases BFHGA found 25 test case better than tabu search algorithm. On the average BFHGA is found %1.74 better than tabu search algorithm. This result revealed again the improved performance of final algorithm.

Algorithm performance is also tested with optimum results of J30 test sets. 462 of all 480 J30 sets are solved optimally within 13 seconds. 18 of them could not be solved optimally but as an average of 480 sets, BFHGA depicts from optimum results only %0.06.

3.4.5. GPU Implementation of BFHGA

3.4.5.1.Application of BFHGA on GPU

As far as the literature is concerned, GPU application with RCMPSP will be the first work. A master-slave model with homogeneous computing strategy is selected as its implementation is easy and have higher effectiveness compared to coarse-grained models (Kandil and El-Rayes, 2006).

The model works with N population sizes where N is also the block number. CUDA (Computer Unified Device Architecture) is selected as framework, the C language is selected as programing language and a GPU of Tesla C 2050 is used together with I7 Core CPU.

3.4.5.2.Theory

In this part of the research the master-slave model implemented in this research is given. In master-slave computation model, a CPU is in the heading position and GPU cores work as slaves. Due to the high computational effort, fitness evaluation is directed to slaves and master CPU is responsible for crossover, selection and mutation operators as well as controlling the whole iteration process. In this model as N increases, thread number increases and parallelism increases. The efficiency of the algorithm is expected to increase as thread number increases. Consider the Figure 3.7 where a parallel GA is schematized. In traditional computing, after

random population is produced each individual's performance is evaluated by the fitness function. After that, known fitness values are used for selection. Crossover and mutations are done in regular ways. Nevertheless, in parallel computing strategy a population of size *N* is randomly generated and each individual's fitness value is evaluated by one block. This makes possible to compute N fitness value at each cycle time of CPU. Due to hardware limitations N has a limit and after that limit device cannot be able to evaluate all of the fitness values. Therefore, the model implemented in this work is based on the application of fitness evaluations on GPU's blocks.

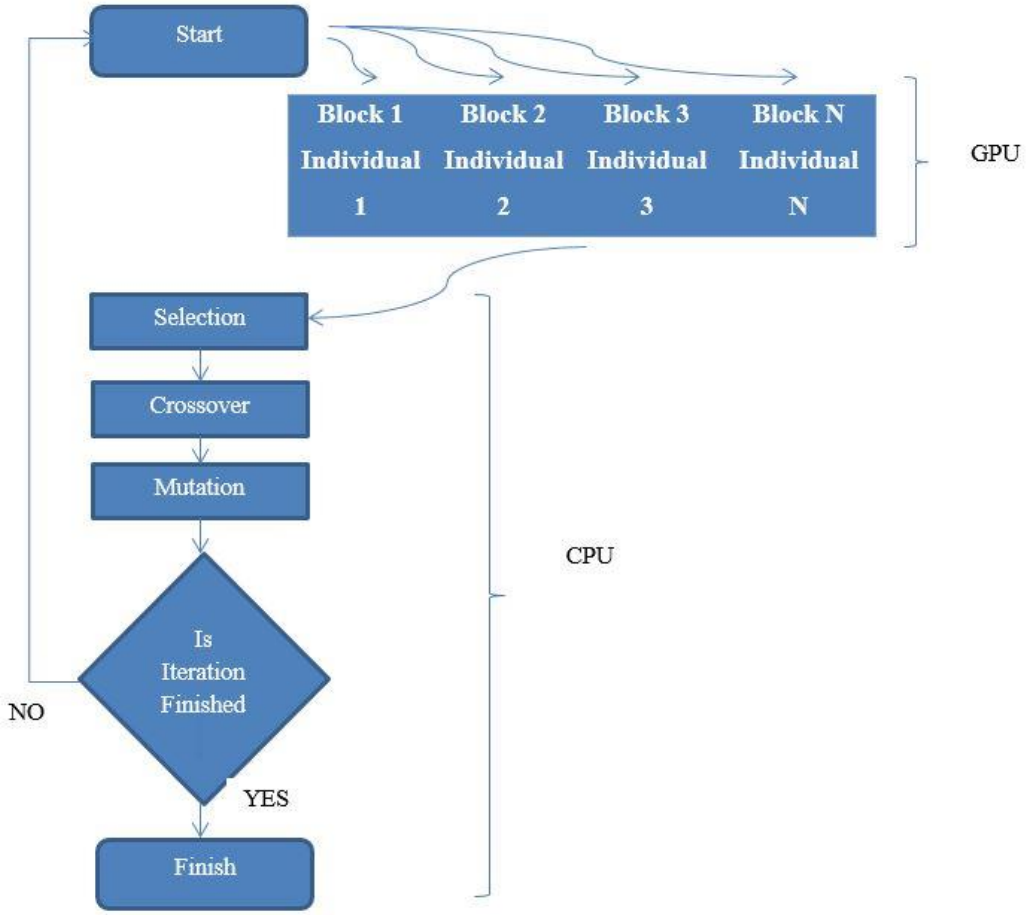


Figure 3.7: Flow of GPU and CPU based algorithm

3.4.5.3.Test of the Model

Model is tested on the 26 projects test case. Total computation time of each case is measured on a CPU and same test problem is solved with a time limitation of same as CPU computation time. Results are tabulated at Table 3.19. Out of 26 test cases 9 of them are further improved with GPU application. Test case 7 has an improvement of %1.68. As an average, %0.68 improvement was possible considering total 26 cases.

Table 3.19: BFHGA performance with GPU

Set	BFHGA	GPU	Performance Comparison
Set 1	113	113	0.00%
Set 2	86	86	0.00%
Set 3	82	82	0.00%
Set 4	208	208	0.00%
Set 5	131	131	0.00%
Set 6	101	101	0.00%
Set 7	238	234	1.68%
Set 8	88	87	1.14%
Set 9	210	210	0.00%
Set 10	148	148	0.00%
Set 11	149	149	0.00%
Set 12	136	135	0.74%
Set 13	279	279	0.00%
Set 14	119	119	0.00%
Set 15	253	253	0.00%
Set 16	200	198	1.00%
Set 17	146	144	1.37%
Set 18	288	288	0.00%
Set 19	218	217	0.46%
Set 20	205	205	0.00%
Set 21	177	176	0.56%
Set 22	329	329	0.00%
Set 23	262	261	0.38%
Set 24	248	248	0.00%
Set 25	278	278	0.00%
Set 26	314	312	0.64%
Average			**0.31%**

The performance of GPU implemented BFHGA is also tested on multi-project test instances of Vanquez et al., (2013). There are 26 test portfolios, which are originated from known single project test instances. First fourteen instances are created by single projects taken from the Kolish instances and their resource constraints remain unchanged. Seven instances 20 × 3 are generated by Browning and Yassine's (2010) random generator. Five instances were generated by Vanquez et al., (2013) each have 10 projects with 10 activities. Table 3.20 is constructed with their work, BFHGA and GPU implemented BFHGA. All comparisons are made on 100.000 schedule generation. The GPU is run exactly the same clock speed of the BFHGA run on the CPU. Therefore, the comparison is made based on percent deviations from best solution. Test case 3 is ignored since the data of this test case is corrupted on the internet site. Therefore, 25 test cases are solved.

Table 3.20: Comparison of BFHGA on CPU and GPU

Vanquez et. al (2013)		BFHGA With CPU		BFHGA With GPU	CPU	GPU
Test Case	Result	Result	Time	Result	%Dev from Best	
1	113	111	8.8	110	0.88%	0.00%
2	228	229	17.8	228	0.44%	0.00%
3	314	314	63.4	314	0.00%	0.00%
4	117	114	15.4	112	1.71%	0.00%
5	276	268	30.4	266	0.72%	0.00%
6	356	348	47.7	346	0.56%	0.00%
7	149	148	51.1	146	1.34%	0.00%
8	90	88	22.4	88	0.00%	0.00%
9	390	388	53.2	386	0.51%	0.00%
10	698	690	86.7	689	0.14%	0.00%
11	114	114	87.1	114	0.00%	0.00%
12	181	178	37.1	176	1.10%	0.00%
13	511	506	85.6	505	0.20%	0.00%
14	1332	1332	100.2	1332	0.00%	0.00%
15	1326	1326	100.1	1326	0.00%	0.00%
16	1226	1226	100.1	1226	0.00%	0.00%
17	1220	1220	100.1	1220	0.00%	0.00%
18	1186	1186	100.1	1186	0.00%	0.00%
19	29	29	7.7	29	0.00%	0.00%

Table 3.20: (Continued)

Vanquez et. al (2013)		BFHGA With CPU		BFHGA With GPU	CPU	GPU
Test Case	Result	Result	Time	Result	%Dev from Best	
20	30	30	7.9	29	3.33%	0.00%
21	29	29	7.8	29	0.00%	0.00%
22	29	29	8.1	29	0.00%	0.00%
23	31	31	8.1	31	0.00%	0.00%
24	29	29	7.9	29	0.00%	0.00%
25	50	50	8.1	50	0.00%	0.00%
Avr.					**0.44%**	**0.00%**

BGHGA implemented on GPU showed a significant improvement in Vanquez et al., (2013) results. If we look closely to the Table 3.20. It can clearly be seen that at an average %0.65 improvement has been succeeded with CPU. If we compare CPU based BFHGA with GPU, it can be seen that for some test cases GPU results are better such as %3.3, totally on average GPU results are better than CPU results as %0.4. As a conclusion it can be said that larger problem instances can be solved with GPU and efficiency of the algorithm increases compared to CPU based algorithm.

Table 3.21: CPU and GPU comparison of Chen and Shahandashti (2010) real case

Method (500.000 Schedule)	Best	Average
BFHGA (This study)	517	523.3
BFHGA Implemented on GPU (This Study)	515	522.4

BGHGA implemented on the GPU is also run with Chen and Shahandashti (2010) real portfolio case and the best result ever is obtained. Results are tabulated at Table 3.21.

Table 3.22: GPU and CPU Comparison for Large Projects

	Test Case	# of Activities	CPU	GPU	Computational Time (seconds)
1000 Schedule	Test 1	500	1866	1859	3.4
	Test 2	1000	2057	2048	1.1
	Test 3	1500	1820	1815	6.9
10000 Schedule	Test 1	500	1851	1840	36.6
	Test 2	1000	2039	2027	11.5
	Test 3	1500	1809	1805	60.1

One of the key questions of GPUs performance is how they contribute to the efficiency of the algorithm as far as the large projects are considered. For this reason a test that contains large projects is conducted. For this reason a test set is created with 500, 1000 and 1500 activities and that contains 1, 2 and 3 projects respectively. Test sets are solved with 1000 and 10000 schedule generation limits and their results are compared with GPU results with same computational time limits. Results are tabulated at Table 3.22. For every test set GPU found better solutions compared to CPU results. This revealed the effectiveness of the GPU application.

CHAPTER 4

ANALYSIS OF ALGORITHM PARAMETERS

Meta-heuristics' power comes from the iteration process and the capability to search the domain effectively. Although stochastic nature of the meta-heuristics gives an extra power to explore the domain extensively, validity of the algorithm is also important. In order to analyze the behavior of the algorithm with various parameters, it is important to analyze their effects. Analyzing the effects of parameters and design them in order to optimize meta-heuristics' parameters is not only an ad hoc process but also requires some statistics. Some conventions are used extensively such as high population size and low mutation rate etc. Thus, there is not an exact solution to optimize the parameters and fine tune them.

In this chapter it is intended to make an experiment design in order to obtain as much information as possible on the parameters and its effects on algorithm performance. Since boundary of the parameters can be set as minimum and maximum, two level factorial design procedures is selected. Main advantage of factorial design is the ability to understand parameter effects solely and simultaneously with the minimum and maximum parameter settings.

4.1.Two Level Factorial Design

4.1.1. Theory:

Aim of a factorial design is to measure systematically the output and to test the validity of the experiment. Parameters are changed in a systematical way and the response of the algorithm is measured. The lower level of an input parameter is usually indicated with a `-' sign; the higher level with a `+' sign.

Basic case of a factorial design is to measure the effect of one variable. If one variable and its effect is considered the model becomes a linear model as follows;

Assuming the output of a model with Y and parameter with X;

$$Y = \beta_0 + \beta_1 X \tag{4.1}$$

Effect of a parameter is defined as the difference in the average response between the high and low levels of a factor.

The main effect of *X* is modelled in this way;

$$E\ (X) = \overline{Y}_{X^+} - \overline{Y}_{X^-} \tag{4.2}$$

Variance of *N* observations can be modelled such as;

$$Var\ (X) = \frac{4}{N}\sigma^2 \tag{4.3}$$

As more parameters are considered the model becomes more complex. If more than one parameter is considered both the effects of each variable and their interactions should be taken into account and experiment number increases exponentially such that if there is 2 level and k dependent variable there should be 2^k number of experiments in order to make a factorial design.

2^k factorial design is used extensively in the early stages of an experiment where the effects of dependent variables are investigated. Since two level of factor is considered, response is assumed to be linear over the range (Montgomery D.C., p.233, 2012).

For two level and two variables, interaction is defined as one-half of the difference between the effect of parameter X_1 at the high level of X_2 and the effect of X_1 at the low level of X_2.

The effect of two dependent variables is modelled in this way;

$$E(X_1, X_2) = \frac{1}{2}\left[\left(\overline{Y}_{x_{1+}} - \overline{Y}_{x_{1-}}\right)_{X_{2+}} - \left(\overline{Y}_{x_{1+}} - \overline{Y}_{x_{1-}}\right)_{X_{2-}}\right] \tag{4.4}$$

where inside double brackets is called *contrast* of treatment (Montgomery D.C., p.244, 2012).

If we consider more than two variables, it is necessary to use design matrix which makes easier to measure the variable effects. To measure the effect of any factor, matrix can be used according to signs designated at the each cell $M_{[i]\,[j]}$.

For example:

Effect of variable A and AB is calculated easily considering design matrix such as:

$$A = \frac{1}{8}[a - T - b + ab - c + ac - bc + abc - d + ad - bd + abd - cd + acd - bcd + abcd]$$

$$AB = \frac{1}{8}[T - a - b + ab + c - ac - bc + abc + d - ad - bd + abd + cd - acd - bcd + abcd]$$

Sum of square of any factor is calculated as:

$$SS_{ij} = \frac{1}{2^k}\left(Contrast_{ij}\right)^2 \tag{4.5}$$

Mean square error is calculated as:

$$MSE_{ij} = \frac{SS_{ij}}{Dof_{ij}} \tag{4.6}$$

Finally F value is calculated as:

$$F = \frac{MSE_{ij}}{MSE_{error}} \tag{4.7}$$

A half normal graph is obtained using the experiment results. Cumulative distribution of observed effects can be used for interpretation of each variable. If a half normal plot paper is used only probability for each test and their effects are drawn. Otherwise if plot paper is not available effects are converted to z values. Main factors can easily be determined since they exist as outliers. All effects lie along trend line are negligible whereas outliers have significant effects.

4.1.2. Application

As a methodology, developed BFHGA ıs tested with four selected. These are population size, mutation rate, crossover and temperature. Pareto of interactions and normal probability graph is also obtained in order to see the effect of parameters. At last, an F test is conducted.

During this computations J sets (Kolish, 1999) is used. Library contains different problem sets for different types of resource constrained project scheduling problem as well as optimal and heuristic solutions. Instances are generated with a software named as ProGen (Kolish et al., 1995). J sets consists of totally 480 test cases for 30 and 60 activity sets, 600 test cases for 120 activity sets. In experiments along each ten case of J sets first network example is selected which in turn gives 48 test sets for J30 and J60, 600 test sets for J120. Each experiment is done separately and repeated two times.

Table 4.1: Independent variables

		Low Level -1	High Level +1
A	POPULATION_SIZE	50	200
B	MUTATION_RATE	0	0.01
C	CROSS_OVER__NUM	30%	90%
D	TEMPERATURE	0	4000

For J30 and J60 test case optimum results are used as references. Nevertheless, lower bound solutions are used for J120 since there is no optimum result. Independent variables are selected as population size, mutation rate, crossover number and temperature (Table 4.1.)

Dependent variable is calculated as;

$$Y = \frac{\left(\sum_i^j \frac{[F_i - F_o]}{F_o}\right)}{j} x100 \quad (4.8)$$

where;

F_o is the optimum solution if it is available or lower-bound solution,

i= {0, 1, 2, 3….j},

J≤48 for J30 and J60,

J≤60 for J120.

4.1.2.1.Test of J30 Sets

J30 sets are run up to 50000 schedule and mean computation time for repeated to experiment is 2.8 sec. When the results of experiment are examined it can easily be seen that two factor namely C and A have relatively higher effects than others (Figure 4.1). Mean value of effects is 5.6. C has a value of 23.87 which is far away from double mean. When the Pareto Graph is examined, other factors such as B and D have less effects than main factors. In addition, interaction effects are getting smaller as factors are added.

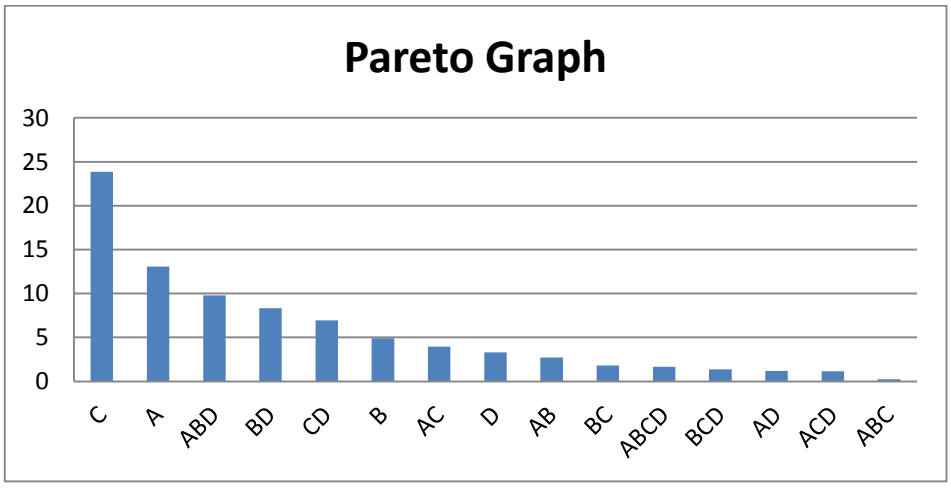


Figure 4.1: Pareto graph of J30 test results

When we examine the results of half normal plot (Figure 4.2), it can easily be seen that factor C is a possible outlier. Therefore, the effect of factor C is significantly high. Other factors accumulate on a trend line. Whether the effect of C is significant statistically F test results must be analyzed.

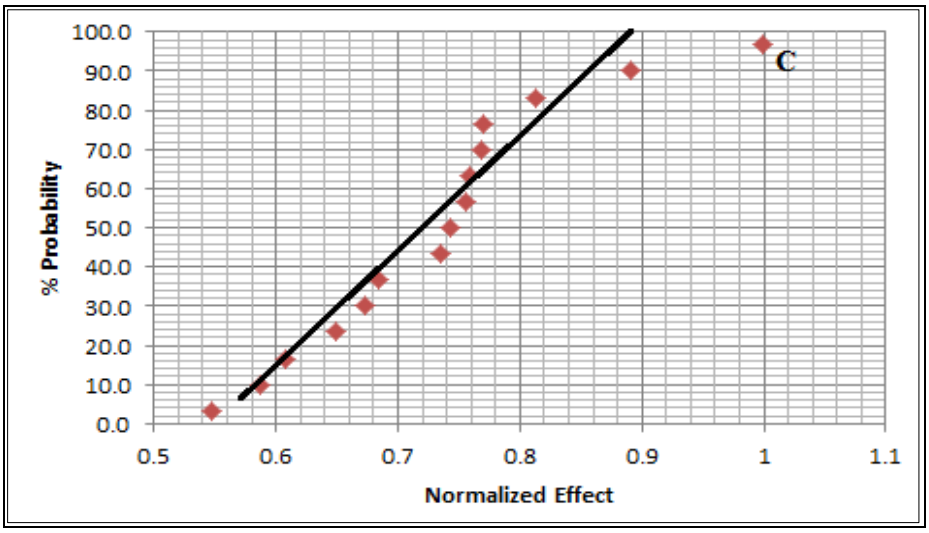


Figure 4.2: Normal plot for J30 test results

Table 4.2: Results of F test

Variable	DoF	Sum of Squares	Mean Square Error	F Value	Test Result
A	1,0	682,2	682,2	2,67	accept
B	1,0	96,6	96,6	0,38	accept
C	1,0	2279,2	2279,2	8,91	reject
D	1,0	43,5	43,5	0,17	accept
AB	1,0	29,7	29,7	0,12	accept
AC	1,0	62,9	62,9	0,25	accept
AD	1,0	5,7	5,7	0,02	accept
BC	1,0	13,1	13,1	0,05	accept
BD	1,0	277,6	277,6	1,09	accept
CD	1,0	193,8	193,8	0,76	accept
ABC	1,0	0,2	0,2	0,00	accept
ABD	1,0	384,7	384,7	1,50	accept
ACD	1,0	5,2	5,2	0,02	accept
BCD	1,0	7,4	7,4	0,03	accept
ABCD	1,0	11,2	11,2	0,04	accept
Error	16,0	4093,2	255,8		
Model	31,0	8186,4	264,1		

Final results can be obtained from F test results. From Table 4.2 it can be seen that 15 factors have degree of freedom 1. Calculating sum of squares and mean square errors from Equation 4.7, F values can be computed. (1/16) degree of freedom table can be used since error term has 16 degrees of freedom. With these values it can be said that only factor C is rejected, which means effect of factor C is significant.

4.1.2.2. Test of J60 Sets

J60 sets are run up to 50000 schedule and mean computation time for repeated to experiment is 8.3 sec. When the results of experiment are examined it can easily be seen that two factors A and C have relatively higher effects than others. Mean value of effects is 3.6. A has a value of 16.76 which is far away from double mean. When the Pareto Graph is examined (Figure 4.3), other factors such as B and D have less effects than main factors. In addition, interaction effects are getting smaller as factors are added. ABC interaction is significant than other interaction effects.

When we examine the results of half normal plot (Figure 4.4), it can easily be seen that factors A and C are outliers. Therefore, the effect of factor A and C is significantly high. Other factors accumulate on a trend line. Whether the effect of A and C are significant statistically F test results must be analyzed.

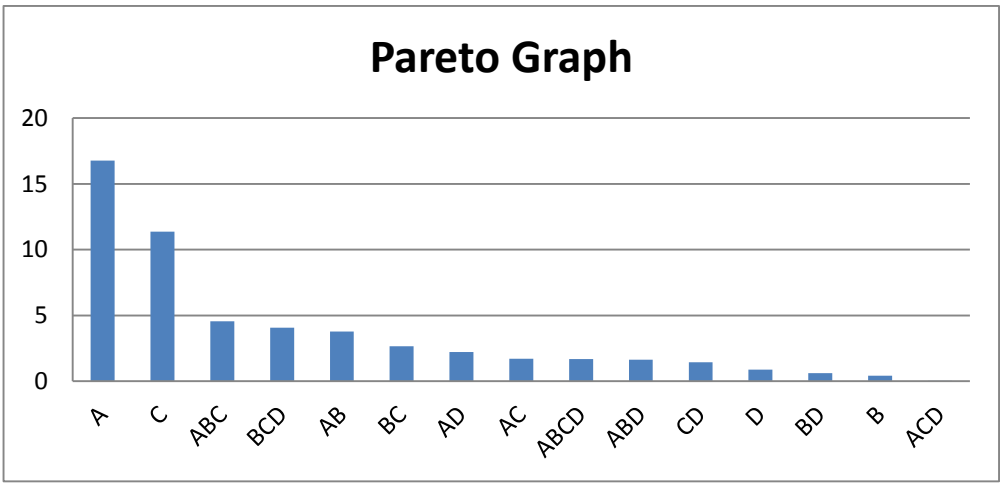


Figure 4.3: Pareto graph of J60 test results

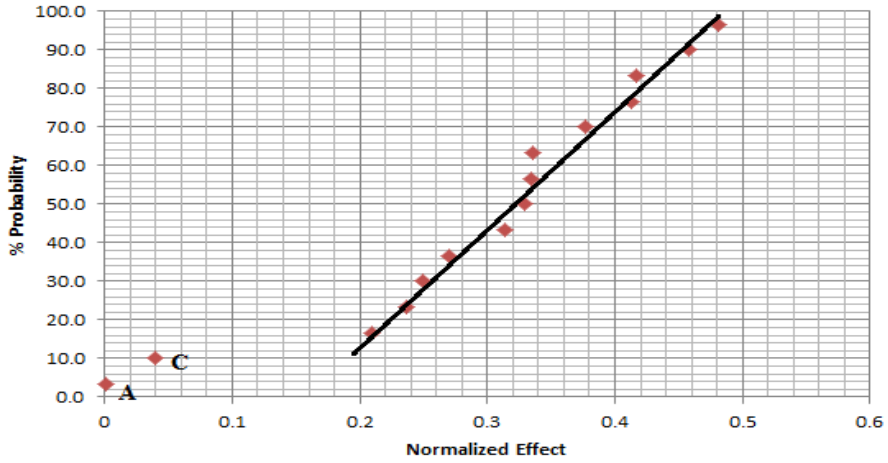


Figure 4.4: Normal plot for J60 test results

Table 4.3: Design matrix and results for J60 Sets

	DoF	Sum of Squares	Mean Square Error	F Value	Test Result
A	1.0	1124.3	1124.3	4.63	reject
B	1.0	0.7	0.7	0.00	accept
C	1.0	516.3	516.3	2.13	accept
D	1.0	3.2	3.2	0.01	accept
AB	1.0	57.0	57.0	0.23	accept
AC	1.0	11.8	11.8	0.05	accept
AD	1.0	19.5	19.5	0.08	accept
BC	1.0	28.4	28.4	0.12	accept
BD	1.0	1.5	1.5	0.01	accept
CD	1.0	8.3	8.3	0.03	accept
ABC	1.0	83.1	83.1	0.34	accept
ABD	1.0	10.8	10.8	0.04	accept
ACD	1.0	0.0	0.0	0.00	accept
BCD	1.0	65.9	65.9	0.27	accept
ABCD	1.0	11.4	11.4	0.05	accept
Error	16.0	3884.0	242.8		
Model	31.0	7768.0	250.6		

Final results can be obtained from F test results. From Table 4.3 it can be seen that 15 factors have degree of freedom 1. Calculating sum of squares and mean square errors from Equation 4.7, F values can be computed. (1/16) degree of freedom table can be used since error term has 16 degrees of freedom.

4.1.2.3.Test of J120 Results

J120 sets are run up to 50000 schedule and mean computation time for repeated to experiment is 18.8 sec. When the results of experiment are examined it can easily be seen that two factors A and C have relatively higher effects than others (Figure 4.5). Mean value of effects is 8.3. A has a value of 41.2 which is far away from double mean. When the Pareto Graph is examined, other factors such as B and D have less effects than main factors. In addition, interaction effects are getting smaller as factors are added. BCD interaction is significant than other interaction effects.

When we examine the results of half normal plot (Figure 4.6), it can easily be seen that factors A, C, AD and B are outliers. Therefore, the effect of these factors may be significantly high and other factors accumulate on a trend line. Whether the effect of these factors is significant statistically F test results must be analyzed.

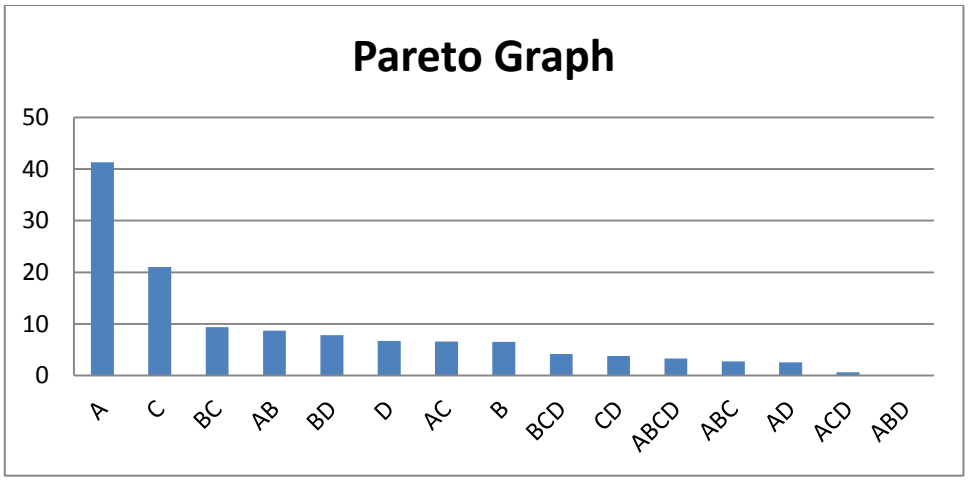


Figure 4.5: Pareto graph of J120 test results

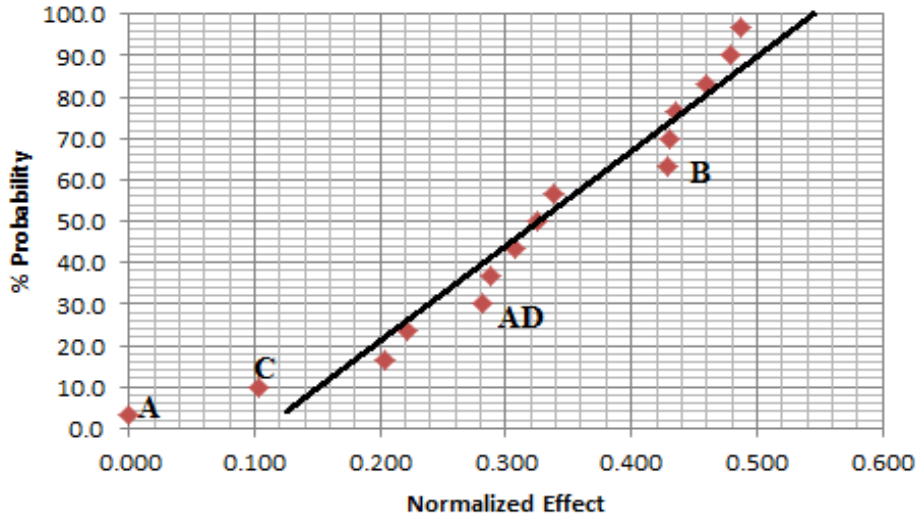


Figure 4.6: Normal plot for J120 test results

Table 4.4: Design matrix and results for J120 sets

	DoF	Sum of Squares	Mean Square Error	F Value	Test Result
A	1.0	6816.3	6816.3	5.33	reject
B	1.0	170.7	170.7	0.13	accept
C	1.0	1772.1	1772.1	1.39	accept
D	1.0	178.9	178.9	0.14	accept
AB	1.0	301.3	301.3	0.24	accept
AC	1.0	172.3	172.3	0.13	accept
AD	1.0	25.6	25.6	0.02	accept
BC	1.0	349.2	349.2	0.27	accept
BD	1.0	244.7	244.7	0.19	accept
CD	1.0	57.4	57.4	0.04	accept
ABC	1.0	30.2	30.2	0.02	accept
ABD	1.0	0.0	0.0	0.00	accept
ACD	1.0	1.5	1.5	0.00	accept
BCD	1.0	68.8	68.8	0.05	accept
ABCD	1.0	43.0	43.0	0.03	accept
Error	16.0	20464.0	1279.0		
Model	31.0	30696.0	990.2		

Final results can be obtained from F test results. From Table 4.4 it can be seen that 15 factors have degree of freedom 1. Calculating sum of squares and mean square errors from Equation 4.7, F values can be computed. (1/16) degree of freedom table can be used since error term has 16 degrees of freedom. With these values it can be said that only factor A is rejected which means effect of factor A is significant. Therefore other factors` effects are not statistically significant.

Figure 4.7: Main effect plots of each test sets

4.1.1. Interpretation from Main Effect Plots

A rough estimation of effects can also be seen from main effect plots. Main effect of a factor is calculated when it is minimum while the others are maximum and maximum while others are minimum. When the Figure 4.7 is considered effect of A and C are looks similar. Increasing A and C would increase the effects significantly. Whereas factors B and D behave different for each test case. For test case J30, if B increases result would be incresing on the other hand for test case J60 and J120 result would be decreasing with incresing value of B. As for factor D, if it increases for J30 tests effects would be increasing, for J60 tests effects would not change significantly and for J120 sets effects would be decreasing. It can be concluded that for every test sets different parameter combinations should be used in order to gain maximum benefit from the algorithm. It is also worth saying that high population size, low mutation number, low crossover ratio would contribute higher effects. Temperature parameter is not that significant but, rather it has fine tuning capability.

CHAPTER 5

CONCLUSION

5.1. Summary and Discussion of Results

Effective resource management is vital in project management since idle resources or excess resources increase the cost of the projects. Due to the challenging market conditions and competition between companies, resource management process becomes more important since cost overruns would result profit loss of the company. This situation is well known in the construction sector but, practically used techniques such as CPM does not cover resource management related issues. Moreover, practically used software packages are neither capable of dealing with multiple projects and its resources, nor have sufficient performances.

Resource allocation process which is extensively worked in operations research and project management literature gives some directions to the practitioners through heuristic methods, available software packages and developed algorithms. However, majority of the existing research has focused on single projects. The performances of these methods and software packages can be argued. Fast and robust algorithms should be developed and this gap gives opportunities to the researchers. Therefore, in this research it is aimed to obtain optimum or near optimum solutions to the RCMPSP via meta-heuristics. For this purpose, a new meta-heuristic algorithm was developed and its performance is tested with known test instances. Developed algorithm is based on GA, SA and backward forward heuristics through with improvements on mutations, crossover and selection methods. Moreover, in order to increase the effectiveness of the algorithm parallel computing strategy is applied to the algorithm and it is used with a GPU. The results revealed the effectiveness of the algorithm.

Research has four main phases. In the first phase, a linear-integer model is developed and it is tested with the previous test results. Also, it is shown that for networks larger than 60 activities, linear-integer models are not capable of solving the problem. It has been shown that software packages used extensively in the

practice have very low resource management capabilities. The second phase is the algorithm development processes. It includes GA, SA, hybridization process and new novel contributions to the algorithm. In order to clarify the development process each part of the algorithm is summarized in corresponding sections. Third phase is the performance measurement of the algorithms. Heuristics and known test results are used for comparison purposes. Last phase is the parallel computing application of final algorithm.

As a summary, the developed mathematical model is tested with optimum results or upper bound solutions available in the literature. Standard Kolish (Kolisch and Sprecher, 1997) test instance are used. Total time is limited to 300 seconds for J30 sets and 1000 seconds for j60 sets. J30 sets are completely solved with this model and %94.5 of the results are optimum. %73 of J60 sets are solved optimally within time and mean CPU time for Intel Core I5 computer is 14.3 and 19.9 seconds for J30 and J60 sets respectively. J120 test sets cannot be solved within reasonable time limits. Those sets cannot be solved optimally compared with upper bound solutions and on the average, our model results depict from optimum and upper-bounds only %2. 68. Most important conclusion of the model is the limitation of the mathematical models for larger sets which is compatible with literature findings.

In order to test algorithms' performances a heuristic solver was developed. In this solver Minimum Slack (MinSlack), Shortest Activity from Shortest Project (SASP) and Maximum Total Work Content (MaxTWK) heuristics are used. Also BF heuristic is applied for each problem and results are compared within heuristics and with meta-heuristics in further sections. BF heuristics outperformed other heuristics.

A sole GA is developed with random key based chromosome representation. This representation has been seldom used in the literature. Nevertheless, it has various opportunities such as the fast crossover capability and compatibility with coding techniques. It has been shown that even a sole GA is better %3.6 from best heuristics with an average value of %7.04. In some test cases this value increases up to %15.38. Developed GA is tested with MS Project's heuristics. Test results

showed that in some test cases sole GA is better %26.37 with an average of %16.76. Therefore, sole GA outperformed the known software packages' heuristics.

A sole SA with the idea of worse solutions can also be accepted to some extend is applied. The probability of accepting worse solutions is high at the beginning and it is decreased according to a linear cooling schema. Results are compared with GA results. It has been revealed that GA solutions performed better in all cases. GA on the average performed %5.6 better. Since GA explores a large space compared to SA, the results verified the effectiveness of GA.

A sole SA has a low search efficiency as it maintains only one solution at each iteration. GA on the other hand, can contain knowledge of previous good solutions and have high search capacity. An intelligent hybrid algorithm which has better sides of each algorithm would perform better results. Therefore, a GA and SA hybrid algorithm is developed and tested with sole GA and sole SA results. Results revealed that the hybrid algorithm performance is better than sole algorithms and it has an average performance improvement of % %3.26.

Based on the findings of previous algorithms and the results revealed by hybrid algorithm, it can be said that if complementary strengths of algorithms can be put together and work coherently results would improve. Within these findings a novel approach was developed to problem solving strategy. A new method together with GA and SA hybrid algorithm, backward- forward scheduling iteration method is hybridized for solution of RCMPSP. Initial comparisons with Anagnostopoulos and Koulinas (2012), Christodoulou (2010), Hegazy (1999), and Leu and Yang (1999) revealed best results available in the literature. Furthermore, results of Chen and Shahandashti (2009) used as performance comparison and the method applied in the work was able to find 525 days, and an average duration of 544.0 days within 606 s. BFHGA achieved a best solution of 517 and an average duration of 523.3 days. The results of the algorithm showed significant performance improvements on literature findings. Another significant improvement has been achieved for comparisons of RESCON results with final algorithm. Out of 26 test cases BFHGA found 25 test cases better than tabu search. On the average BFHGA is found %1.74 better than tabu search algorithm.

It is known in the literature that although GAs are effective in solving many optimization problems, longer execution time to compute each fitness value of the problem limits its performance. Due to the subroutine of the algorithm, for each cycle time one fitness calculation is possible. In order to increase the effectiveness of the algorithm developed novel BFHGA is rearranged to work with parallel computing strategy. In order to apply the algorithm with a parallel computing strategy, firstly the fitness calculation process which is the most time consuming part is recoded to work compatibly with a GPU. Parallel computing strategies are effective for large problem instances due to the fact that the time to communicate between CPU and GPU is high for small test instances. Therefore, a multi-project test instance of Vanquez et al. (2013) is used for comparison purposes. Results revealed that both BFHGA and GPU based BFHGA performs better %0.4 and %1.1 respectively. Algorithm performance was further tested with generated 26 portfolio projects. Out of 26 test cases 9 of them are further improved with GPU application. As an average, %0.68 improvement was possible. The performance of a GPU for large scale projects was tested with 500, 1000 and 1500 activities networks. Results revealed the effectiveness of GPU application. This research is the first research in the literature on the application of meta-heuristics with a GPU in the scheduling practices. The most important conclusion of GPU based BFHGA is the high potential of parallel computing strategies on meta-heuristic algorithms and improved effectiveness on solution quality.

In compliance with the literature, it is shown that the most important factors in BFHGA are the population size and crossover ratio. Other tested factors also affect the behavior of the algorithm, but rather have fine tuning capabilities.

5.2.Conclusion

Throughout the study basic resource allocation problem with its multi-project case definition is used. Basic definition includes deterministic durations and resource usage. Due to the necessity compliance with standard Kolish instances, only finish to start activity relations are considered in the majority of the instances.

In the problem, it is assumed that each resource is renewable and there are no resource transfer times between projects. All comparisons are made to the literature are compared with same CPU time units.

Project portfolio duration minimization is used as the objective function of this study. In this objective function each project assumed to have the same importance to the company and have an equal chance to use each resource. This may bring some limitations in practice since companies may have projects with different priorities and different concerns.

Although the developed algorithm has shown significant improvements it cannot be used easily by the practitioner with the current interface. Therefore, algorithm can either be integrated into a known project management software or can be developed in order to work as an individual scheduling tool. This situation needs further improvements.

Project portfolio duration minimization is commonly used in the literature for optimal scheduling of multiple construction projects with common limited resources. However, this objective function has limitations in practice, as it is based on the assumption that resources can be transferred between projects without any expense in time and cost. In addition, stochastic durations can be added to the model and model can be regenerated. Hence, models, instance sets, and approaches, including resource transfer times and costs, models including stochastic durations are appear to be promising areas for future research.

Parallel computing technologies bring many new opportunities to the researchers. Being the low cost parallel computing opportunity, GPUs have a vast amount of application areas in construction management practice of meta-heuristics to 4D modelling. Therefore, new algorithms with different parallel computing strategies may increase the effectiveness of the current algorithms.

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APPENDICES

A. Test Case Results

Results of Multi Project Test Case of Chen and Shahandashti (2010)

Test Project 1				Test Project 2				Test Project 3		
Activity	Start	Finish		Activity	Start	Finish		Activity	Start	Finish
1-2	22	32		1-2	0	7		1-2	8	10
1-3	32	34		1-3	0	10		1-3	0	3
2-3	34	39		2-5	7	8		2-5	25	29
2-4	34	35		2-6	7	10		3-4	14	23
3-5	39	45		2-8	14	20		3-7	3	7
4-5	45	46		3-4	10	14		4-6	46	55
4-7	79	84		3-5	10	14		4-7	25	34
5-6	53	59		4-7	21	22		5-11	35	39
5-9	91	97		4-9	14	23		6-8	55	63
6-8	59	69		5-9	14	21		7-9	53	59
7-9	101	102		6-9	10	14		7-10	59	60
7-10	84	88		7-10	32	35		7-11	41	47
8-11	80	83		8-11	20	25		8-13	69	79
8-12	84	91		9-10	23	31		9-13	83	90
9-12	102	109		9-12	43	47		9-12	69	79
10-13	90	91		10-12	35	43		10-12	61	69
11-14	91	98		11-12	31	41		11-12	49	59
12-14	109	113		12-13	47	49		11-16	60	61
13-15	113	121		12-14	47	53		12-14	79	83
14-15	116	121		13-15	71	80		12-15	98	101
15-16	121	124		14-15	63	71		13-14	97	105
				15-16	103	105		14-18	110	116
				15-17	99	103		15-17	102	104
				16-18	105	110		16-17	91	99
				17-19	106	109		17-18	105	106
				18-19	110	120		18-19	121	124
				19-20	120	**124**				

Result of Multi Project Real Test Case of Chen and Shahandashti (2010)

Real Project 1				Real Project 2				Real Project 3		
Activity	Start	Finish		Activity	Start	Finish		Activity	Start	Finish
1	0	1		1	0	1		1	0	0
2	23	29		2	22	23		2	0	25
3	45	62		3	27	29		3	0	11
4	45	54		4	23	24		4	25	46
5	79	93		5	25	27		5	1	22
6	62	76		6	11	16		6	16	31
7	62	66		7	23	23		7	46	55
8	124	142		8	54	58		8	31	45
9	94	108		9	87	108		9	31	41
10	142	147		10	108	115		10	55	67
11	148	158		11	142	148		11	45	55
12	148	159		12	159	180		12	67	79
13	148	160		13	199	213		13	67	77
14	160	166		14	213	313		14	77	87
15	180	181		15	254	282		15	94	108
16	181	193		16	213	343		16	77	84
17	193	199		17	336	350		17	108	115
18	215	226		18	282	326		18	108	115
19	226	232		19	223	343		19	108	120
20	232	244		20	350	364		20	108	108
21	244	254		21	335	365		21	159	169
22	254	262		22	384	510		22	120	134
23	313	335		23	364	368		23	87	94
24	326	336		24	370	384		24	134	148
25	336	342		25	370	400		25	169	179
26	326	336		26	368	368		26	115	124
27	365	370		27	368	388		27	134	141
28	388	398		28	414	442		28	148	162
29	444	464		29	368	408		29	199	215
30	464	479		30	370	410		30	179	189
31	449	464		31	412	472		31	141	147
32	456	463		32	414	444		32	254	257
33	464	474		33	398	412		33	167	179
34	479	492		34	442	472		34	262	267
35	443	464		35	442	456		35	189	199
36	456	456		36	410	410		36	267	274
37	463	471		37	472	479		37	274	281
38	492	509		38	472	510		38	400	414
39	471	481		39	456	466		39	413	414
40	494	504		40	479	479				
41	481	505		41	479	482				
42	504	515		42	510	510				
43	505	505		43	456	471				
44	491	515		44	482	489				
45	515	**517**		45	482	486				
				46	488	489				

B. Code Details

```
#define WINDOWS 1
#define CUDA 0
#include <stdio.h>
#include <stdlib.h>
#include <string.h>
#if WINDOWS
#include <conio.h>
#endif

#if WINDOWS
#include <limits.h>
#endif
#include <math.h>
#include <time.h>
#define DEBUG 0
#define TRUE 1
#define FALSE 0

int numOfActivities;
int numOfResources;
int *maxAvailableResources;
#define MAX_DURATION 1000
#define ELITISM_NUM 4
#define POPULATION_SIZE 100
#define MUTATION_RATE 0.003
#define CROSS_OVER__NUM 80
#define TEMPERATURE 1000
#define XOVERDIFF 0.05
#define DIVERSIFICATION_IMPROVEMENT_RATE 0.20
#define LOWER_BOUNDARY_XOVER_IMPROMENT_RATE (0.05 * numOfActivities)
int rouletteWheelSelectionNum = (int) (POPULATION_SIZE
              - (CROSS_OVER__NUM + ELITISM_NUM));

typedef struct Activity {
       int nofPre; //number of predecessors
       int noOfPreConst; //constant number of predecessor
       int noOfSucConst;
       int nofSuc;
       int *precedessor; //precedence array
       int *successor; //successor array
       int duration;
       int *maxResourceUse; //resource usage if an activity
       int starttime; //start time of an activity
       int finishtime; //finish time of an activity
       int id; //global id of an activity
       double priority;
} Activity, PActivity;


#define MAX_RESOURCE_NUM 4
#define MAX_ACTIVITY_NUM 100
#define BLOCK_SIZE 128
int *d_maxAvailableResources_org;
int *d_maxAvailableResources;
int * d_nofSuc_org;
int * d_nofSuc;
```

```
void quickSortRK(Activity **list, int left, int right);
#define cuCheck(stmt) do {                                      \
              cudaError_t err = stmt;                           \
              if (err != cudaSuccess) {                         \
                    printf("cuda error: %d :%s \n",(int)
stmt,cudaGetErrorString(stmt));     \
                    exit(EXIT_FAILURE)  ;
\
              }                                                 \
} while(0);

typedef struct  {
       int nofPre; //number of predecessors
       int noOfPreConst; //constant number of predecessor
       int noOfSucConst;
       int nofSuc;
       int *precedessor; //precedence array
       int *successor; //successor array
       int duration;
       int *maxResourceUse; //resource usage if an activity
       int starttime; //start time of an activity
       int finishtime; //finish time of an activity
       int id; //global id of an activity
       double priority;
       void Activity_CUDA(Activity const & activity){
              this->nofPre = activity.nofPre;
              this->noOfPreConst = activity.noOfPreConst;
              this->noOfSucConst = activity.noOfSucConst;
              this->nofSuc = activity.nofSuc;
              this->duration = activity.duration;
              this->starttime = activity.starttime;
              this->finishtime = activity.finishtime;
              this->id = activity.id;
              this->priority = activity.priority;

              if (precedessor != NULL){
                    cuCheck(cudaFree(precedessor));
              }
              if (successor != NULL){
                    cuCheck(cudaFree(successor));
              }
              if (maxResourceUse != NULL){
                    cuCheck(cudaFree(maxResourceUse));
              }


              if (noOfPreConst > 0 && activity.precedessor != NULL){
                    cuCheck(cudaMalloc((void**) & precedessor, noOfPreConst
* sizeof(int)));
                    cuCheck(cudaMemcpy(precedessor, activity.precedessor,
noOfPreConst * sizeof(int), cudaMemcpyHostToDevice));
              }

              if (noOfSucConst > 0 && activity.successor != NULL){
                    cuCheck(cudaMalloc((void**) & successor, noOfSucConst *
sizeof(int)));
                    cuCheck(cudaMemcpy(successor, activity.successor,
noOfSucConst * sizeof(int), cudaMemcpyHostToDevice));
              }
```

```
		if (numOfResources > 0 && activity.maxResourceUse != NULL){
			cuCheck(cudaMalloc((void**) & maxResourceUse,
numOfResources * sizeof(int)));
			cuCheck(cudaMemcpy(maxResourceUse,
activity.maxResourceUse, numOfResources * sizeof(int),
cudaMemcpyHostToDevice));
		}
	}
	void Activity_CUDA(void) {
		nofPre = 0;
		noOfPreConst = 0;
		noOfSucConst = 0;
		nofSuc = 0;
		precedessor = NULL;
		successor = NULL;
		duration = 0;
		maxResourceUse = NULL;
		starttime = 0;
		finishtime = 0;
		id = 0;
		priority = 0;
	}
	void free() {
		if (precedessor != NULL){
			cuCheck(cudaFree(precedessor));
		}
		if (successor != NULL){
			cuCheck(cudaFree(successor));
		}
		if (maxResourceUse != NULL){
			cuCheck(cudaFree(maxResourceUse));
		}
	}
	void set(Activity const & activity){
		this->nofPre = activity.nofPre;
		this->noOfPreConst = activity.noOfPreConst;
		this->noOfSucConst = activity.noOfSucConst;
		this->nofSuc = activity.nofSuc;
		this->duration = activity.duration;
		this->starttime = activity.starttime;
		this->finishtime = activity.finishtime;
		this->id = activity.id;
		this->priority = activity.priority;

		if (precedessor != NULL){
			cuCheck(cudaFree(precedessor));
		}
		if (successor != NULL){
			cuCheck(cudaFree(successor));
		}
		if (maxResourceUse != NULL){
			cuCheck(cudaFree(maxResourceUse));
		}
		if (noOfPreConst > 0 && activity.precedessor != NULL){
			cuCheck(cudaMalloc((void**) & precedessor, noOfPreConst
* sizeof(int)));
			cuCheck(cudaMemcpy(precedessor, activity.precedessor,
noOfPreConst * sizeof(int), cudaMemcpyHostToDevice));
		}
```

```
            if (noOfSucConst > 0 && activity.successor != NULL){
                  cuCheck(cudaMalloc((void**) & successor, noOfSucConst *
sizeof(int)));
                  cuCheck(cudaMemcpy(successor, activity.successor,
noOfSucConst * sizeof(int), cudaMemcpyHostToDevice));
            }

            if (numOfResources > 0 && activity.maxResourceUse != NULL){
                  cuCheck(cudaMalloc((void**) & maxResourceUse,
numOfResources * sizeof(int)));
                  cuCheck(cudaMemcpy(maxResourceUse,
activity.maxResourceUse, numOfResources * sizeof(int),
cudaMemcpyHostToDevice));
            }

      }
} Activity_CUDA;

typedef struct {
// Declare pointer that point to device memory
      int * id;
      double * priority;
      int * starttime;
      int * finishtime;
      int * duration;

      int * id_buff;
      double * priority_buff;
      int * starttime_buff;
      int * finishtime_buff;
      int * duration_buff;
// Declare host pointer
      int * h_id;
      double * h_priority;
      int * h_starttime;
      int * h_finishtime;
      int * h_duration;

      int numOfActivity;
      void ActivityManager(){
            id  = starttime = finishtime = duration = NULL;
            priority = NULL;
            h_id  = h_starttime = h_finishtime = h_duration = NULL;
            h_priority = NULL;
      }
      void ActivityManager(int numOfAct) {
            int size =  POPULATION_SIZE * numOfAct;

            numOfActivity = numOfAct;
            cuCheck(cudaHostAlloc((void**)&h_id, sizeof(int) * size,0));
            cuCheck(cudaHostAlloc((void**)&h_priority, sizeof(double) *
size,0));
            cuCheck(cudaHostAlloc((void**)&h_starttime, sizeof(int) *
size,0));
            cuCheck(cudaHostAlloc((void**)&h_finishtime, sizeof(int) *
size,0));
      }
      void initializeDeviceMemory(){
            int size = numOfActivity * (POPULATION_SIZE);
```

```
		cuCheck(cudaMalloc((void**) & id, size * sizeof(int)));
		cuCheck(cudaMalloc((void**) & starttime, size * sizeof(int)));
		cuCheck(cudaMalloc((void**) & finishtime, size *
sizeof(int)));

		cuCheck(cudaMalloc((void**) & priority, size *
sizeof(double)));

		cuCheck(cudaMalloc((void**) & id_buff, size * sizeof(int)));
		cuCheck(cudaMalloc((void**) & starttime_buff, size *
sizeof(int)));
		cuCheck(cudaMalloc((void**) & finishtime_buff, size *
sizeof(int)));

		cuCheck(cudaMalloc((void**) & priority_buff, size *
sizeof(double)));
	}

	void transferDataFromHostToDevice(){
		int size = numOfActivity * (POPULATION_SIZE );

		cuCheck(cudaMemcpy(id, h_id, size * sizeof(int),
cudaMemcpyHostToDevice));
		cuCheck(cudaMemcpy(starttime, h_starttime, size * sizeof(int),
cudaMemcpyHostToDevice));
		cuCheck(cudaMemcpy(finishtime, h_finishtime, size *
sizeof(int), cudaMemcpyHostToDevice));

		cuCheck(cudaMemcpy(priority, h_priority, size *
sizeof(double), cudaMemcpyHostToDevice));


	}
	void transferDataFromDeviceToHost(){
		int size = numOfActivity * (POPULATION_SIZE );

			cuCheck(cudaMemcpy( h_id, id,size * sizeof(int),
cudaMemcpyDeviceToHost));
			cuCheck(cudaMemcpy( h_starttime,starttime, size *
sizeof(int), cudaMemcpyDeviceToHost));
			cuCheck(cudaMemcpy( h_finishtime,finishtime, size *
sizeof(int), cudaMemcpyDeviceToHost));

			cuCheck(cudaMemcpy( h_priority,priority ,size *
sizeof(double), cudaMemcpyDeviceToHost));

	}
	void set(Activity *** list){

		for (int i = ELITISM_NUM ; i < POPULATION_SIZE ; i ++) {
			quickSortRK(list[i], 0, numOfActivities - 1);
		}
		for (int i = 0; i < numOfActivity; i++) {
			for (int j = 0 ; j < POPULATION_SIZE; j++){
				int index = i * POPULATION_SIZE + j;
				h_id[index] = list[j][i]->id;
				h_priority[index] = list[j][i]->priority;
				h_starttime[index] = list[j][i]->starttime;
				h_finishtime[index] = list[j][i]->finishtime;
```

```
                }
        }

    }
    void set_back(Activity *** list){

        for (int i = 0; i < numOfActivity; i++) {
            for (int j = 0 ; j < POPULATION_SIZE; j++){
                int index = i * POPULATION_SIZE + j;

                list[j][i]->id = h_id[index] ;
                list[j][i]->priority = h_priority[index] ;
                list[j][i]->starttime = h_starttime[index] ;
                list[j][i]->finishtime = h_finishtime[index];

            }
        }

    }
    void set_temp(Activity ** list,int i){

        for (int j = 0 ; j < numOfActivity ; j++){
            int index = j * POPULATION_SIZE + i;
            h_id[index] = list[j]->id;
            h_priority[index] = list[j]->priority;
            h_starttime[index] = list[j]->starttime;
            h_finishtime[index] = list[j]->finishtime;

        }



    }
}ActivityManager;

__global__ void solveSchedule_kernel1(int numOfResources, Activity_CUDA *
temp, ActivityManager am, int *d_maxAvailableResources, int * nofSuc){

    int idx = blockIdx.x * blockDim.x + threadIdx.x;

    if (idx < POPULATION_SIZE - ELITISM_NUM){
        idx = idx + ELITISM_NUM;

        for (int i = am.numOfActivity - 1; i >= 0;) {
            for (int j = am.numOfActivity - 1; j >= 0; j--) {
                int jpos = j * POPULATION_SIZE + idx;
                if (nofSuc[am.id[jpos] * POPULATION_SIZE + idx]
== 0) {

                    am.id_buff[i * POPULATION_SIZE + idx] =
am.id[jpos];
                    am.priority_buff[i * POPULATION_SIZE +
idx] = am.priority[jpos];
                    i-- ;
                    nofSuc[am.id[jpos] * POPULATION_SIZE +
idx]--;


                    for (int k = 0; k <
temp[am.id[jpos]].noOfPreConst; k++) {
```

```
                                        int preId =
temp[am.id[jpos]].precedessor[k];
                                        nofSuc[preId * POPULATION_SIZE +
idx]--;
                                }
                        }
                }
        }

        int successerStartTime = MAX_DURATION;

        int dpos = (am.numOfActivity - 1) * POPULATION_SIZE + idx;
        am.finishtime_buff[dpos] = MAX_DURATION;
        am.starttime_buff[dpos]= MAX_DURATION;

        for (int i = am.numOfActivity - 1; i >= 0; i--) {
               successerStartTime = MAX_DURATION;
               int index = am.id_buff[i * POPULATION_SIZE +idx];

               for (int k = 0; k < temp[index].noOfSucConst; k++) {
                      int successorId = temp[index].successor[k];
                      int spos = temp[successorId].id *
POPULATION_SIZE + idx;
                      if (successerStartTime > am.starttime[spos])
                             successerStartTime =  am.starttime[spos];
               }
               int pos = index * POPULATION_SIZE + idx;
               am.finishtime[pos] = successerStartTime;

               for (int n = 0; n < numOfResources; n++) {
                      for (int j = am.finishtime[pos]; j >
am.finishtime[pos] - temp[index].duration;
                                        j--) {
                             if (d_maxAvailableResources[n *
(MAX_DURATION +1) * POPULATION_SIZE + j * POPULATION_SIZE + idx] <
temp[index].maxResourceUse[n]) {
                                        am.finishtime[pos] = j - 1;
                                        n = -1;
                                        break;
                             }
                      }
               }

               am.starttime[pos] = am.finishtime[pos] -
temp[index].duration;


               am.starttime_buff[i * POPULATION_SIZE + idx] =
am.starttime[pos];
               am.finishtime_buff[i * POPULATION_SIZE + idx] =
am.finishtime[pos];

               for (int e = 0; e < numOfResources; e++) {
                      for (int k = 0; k < temp[index].duration; k++) {
                             d_maxAvailableResources[e * (MAX_DURATION
+1) * POPULATION_SIZE + (am.finishtime[index * POPULATION_SIZE + idx] - k)
* POPULATION_SIZE + idx]
                                        -=
temp[index].maxResourceUse[e];
                      }
```

```
			}
		}


		for (int i = 0; i < am.numOfActivity; i++) {

			int starttime = INT_MAX;
			int s_id;
			for (int j = 0; j < am.numOfActivity; j++) {
				if (starttime > am.starttime_buff[j *
POPULATION_SIZE + idx]) {
					s_id = j;
					starttime = am.starttime_buff[j *
POPULATION_SIZE +idx];
				}

			}
			int dpos = i * POPULATION_SIZE + idx;
			int spos = s_id * POPULATION_SIZE + idx;
			am.id[dpos] = am.id_buff[spos];
			am.starttime[dpos] = starttime;
			am.finishtime[dpos] = am.finishtime_buff[spos];
			am.priority[dpos] = am.priority_buff[spos];
			am.starttime_buff[spos] = INT_MAX;
		}


	}// end if idx <

}

__global__ void solveSchedule_kernel2(int numOfResources, Activity_CUDA *
temp, ActivityManager am, int *d_maxAvailableResources, int * nofSuc){

	int idx = blockIdx.x * blockDim.x + threadIdx.x;

	if (idx < POPULATION_SIZE - ELITISM_NUM){
		idx = idx + ELITISM_NUM;

		for (int i = 0; i < am.numOfActivity; i++) {
			am.starttime_buff[i * POPULATION_SIZE + idx] = 0;
			am.finishtime_buff[i * POPULATION_SIZE + idx] = 0;
		}

		for (int i = 0; i < am.numOfActivity; i++) {

			int index = am.id[i * POPULATION_SIZE + idx];
			int pos = index * POPULATION_SIZE + idx;
			for (int k = 0; k < temp[index].noOfPreConst; k++) {
				int curPreId = temp[index].precedessor[k];

				if (am.starttime_buff[pos] <
am.finishtime_buff[curPreId * POPULATION_SIZE +idx]) {
					am.starttime_buff[pos] =
am.finishtime_buff[curPreId * POPULATION_SIZE +idx];
				}
			}

			for (int n = 0; n < numOfResources; n++) {
```

```
                        for (int j = am.starttime_buff[pos]; j <
am.starttime_buff[pos] + temp[index].duration; j++) {
                                if (d_maxAvailableResources[n *
(MAX_DURATION +1) * POPULATION_SIZE + j * POPULATION_SIZE + idx] <
temp[index].maxResourceUse[n]) {
                                        am.starttime_buff[pos] = j + 1;
                                        n = -1;
                                        break;
                                }
                        }
                }

                am.finishtime_buff[pos] = am.starttime_buff[pos] +
temp[index].duration;

                am.starttime[i * POPULATION_SIZE + idx] =
am.starttime_buff[pos];
                am.finishtime[i * POPULATION_SIZE + idx] =
am.finishtime_buff[pos];

                for (int e = 0; e < numOfResources; e++) {
                        for (int k = 0; k < temp[index].duration; k++) {
                                d_maxAvailableResources[e * (MAX_DURATION
+1) * POPULATION_SIZE + (am.starttime_buff[pos] + k) * POPULATION_SIZE +
idx]
                                                                        -=
temp[index].maxResourceUse[e];
                        }
                }

        }

        }// end if idx <

}
Activity ***geneticAlgoritm_CUDA(Activity ***list, double *preTemp,
                double *premotherXoverRate, double *coolingRateXover,
                double *coolingRate);

ActivityManager * activityManager;
Activity ***solutionListBeforeGeneticAlgoritm_CUDA;

Activity_CUDA * dev_temp;


Activity** temp;

int** availabilityMatrix;
int numSchedules = 500000;

Activity **earlyStartLeftScheduling(Activity **solution);

double getRandomNumber() {
        return (rand() % 10000) / (double) 10000;
}

Activity *createActivityPriority() {
        Activity *act = (Activity *) malloc(sizeof(Activity));
        act->priority = getRandomNumber();
        return act;
```

```
}

void freeMemoryOfActivity(Activity *other) {
	free(other->maxResourceUse);
	free(other->precedessor);
	free(other->successor);

}

void createAvailabilityMatrix() {
	int k;
	availabilityMatrix = (int**) malloc(sizeof(int *) * numOfResources);
	for (k = 0; k < numOfResources; k++) {
		availabilityMatrix[k] = (int *) malloc(sizeof(int) *
MAX_DURATION);
	}
}

void initializeAvailabilityMatrix() {
	int i, k;
	for (k = 0; k < numOfResources; k++) {
		for (i = 0; i < MAX_DURATION; i++) {
			availabilityMatrix[k][i] = maxAvailableResources[k];
		}
	}

}

Activity *createActivity(Activity *other) {
	Activity *act = (Activity *) malloc(sizeof(Activity));
	act->duration = other->duration;
	act->starttime = other->starttime;
	act->finishtime = other->finishtime;
	act->id = other->id;
	act->priority = other->priority;
	return act;
}

void calculateScheduleFromLeft(Activity **solution, int
**availabilityMatrix) {
	int i, k, n, e, j, curPreId;
	Activity *cur, *pre;
	int startTime;

	for (i = 0; i < numOfActivities; i++) {
		temp[i]->starttime = 0;
		temp[i]->finishtime = 0;
	}

	for (i = 0; i < numOfActivities; i++) {

		cur = temp[solution[i]->id];


		for (k = 0; k < cur->noOfPreConst; k++) {
			curPreId = cur->precedessor[k];
			pre = temp[curPreId];

			if (cur->starttime < pre->finishtime) {
				cur->starttime = pre->finishtime;
```

```
                        }
                }

                for (n = 0; n < numOfResources; n++) {
                        for (j = cur->starttime; j < cur->starttime + cur-
>duration; j++) {
                                if (availabilityMatrix[n][j] < cur-
>maxResourceUse[n]) {
                                        cur->starttime = j + 1;
                                        n = -1;
                                        break;
                                }
                        }
                }


                cur->finishtime = cur->starttime + cur->duration;
                startTime = cur->starttime;

                solution[i]->starttime = cur->starttime;
                solution[i]->finishtime = cur->finishtime;

                for (e = 0; e < numOfResources; e++) {
                        for (k = 0; k < cur->duration; k++) {
                                availabilityMatrix[e][startTime + k] -= cur-
>maxResourceUse[e];
                        }
                }

        }

        if (DEBUG) {
                for (i = 0; i < numOfResources; i++) {
                        for (j = 0; j < numOfActivities; j++) {
                                if (availabilityMatrix[i][j] < 0) {
                                        printf("as");
                                }
                        }
                }
        }
}

Activity **scheduleFromLeft(Activity **list) {
        int k, i, j;
        Activity **scheduledChromose = (Activity**) malloc(
                        sizeof(Activity *) * numOfActivities);
        for (j = 0; j < numOfActivities; j++) {
                temp[j]->nofPre = temp[j]->noOfPreConst;
        }

        if (DEBUG) {
                for (j = 0; j < numOfActivities; j++)
                        printf("%d %d, ", temp[j]->id, temp[j]->noOfPreConst);
                printf("\n");
        }

        for (i = 0; i < numOfActivities;) {
                for (j = numOfActivities - 1; j >= 0; j--) {
                        if (temp[list[j]->id]->nofPre == 0) {
```

```
                        scheduledChromose[i++] =
createActivity(list[j]);

                        temp[list[j]->id]->nofPre--;
                        for (k = 0; k < temp[list[j]->id]->noOfSucConst;
k++) {
                                int succesorId = temp[list[j]->id]-
>successor[k];
                                temp[succesorId]->nofPre--;
                        }
                }
        }

        return scheduledChromose;

}

void quickSortRK(Activity **list, int left, int right) {
        int x = left, y = right;
        Activity *tmp;
        double pivot = list[(left + right) / 2]->priority;

        while (x <= y) {
                while (list[x]->priority < pivot)
                        x++;
                while (list[y]->priority > pivot)
                        y--;
                if (x <= y) {
                        tmp = list[x];
                        list[x] = list[y];
                        list[y] = tmp;
                        x++;
                        y--;
                }
        }

        if (left < y)
                quickSortRK(list, left, y);
        if (x < right)
                quickSortRK(list, x, right);

}

Activity **findRightSolution(Activity **list) {
        int j, i, k, preId;
        Activity **scheduledChromose = (Activity**) malloc(
                        sizeof(Activity *) * numOfActivities);
        for (j = 0; j < numOfActivities; j++) {
                temp[j]->nofSuc = temp[j]->noOfSucConst;
        }

        for (i = numOfActivities - 1; i >= 0;) {
                for (j = numOfActivities - 1; j >= 0; j--) {
                        if (temp[list[j]->id]->nofSuc == 0) {

                                if (DEBUG) {
                                        printf("%d ", list[j]->id);
                                }
```

```
                        scheduledChromose[i--] =
createActivity(list[j]);
                        temp[list[j]->id]->nofSuc--;

                        for (k = 0; k < temp[list[j]->id]->noOfPreConst;
k++) {
                                preId = temp[list[j]->id]->precedessor[k];
                                temp[preId]->nofSuc--;
                        }
                }
        }
        return scheduledChromose;
}

void calculateRightSchedule(Activity **solution, int **availabilityMatrix)
{

        int successerStartTime = MAX_DURATION;
        Activity *cur;
        int i, k, e, n, j, finishtime;
        int successorId;
        Activity *suc;

        solution[numOfActivities - 1]->finishtime = MAX_DURATION;
        solution[numOfActivities - 1]->starttime = MAX_DURATION;

        for (i = numOfActivities - 1; i >= 0; i--) {
                successerStartTime = MAX_DURATION;
                cur = temp[solution[i]->id];

                for (k = 0; k < cur->noOfSucConst; k++) {
                        successorId = cur->successor[k];
                        suc = temp[successorId];
                        if (successerStartTime > suc->starttime)
                                successerStartTime = suc->starttime;
                }

                cur->finishtime = successerStartTime;

                for (n = 0; n < numOfResources; n++) {
                        for (j = cur->finishtime; j > cur->finishtime - cur-
>duration;
                                        j--) {
                                if (availabilityMatrix[n][j] < cur-
>maxResourceUse[n]) {
                                        cur->finishtime = j - 1;
                                        n = -1;
                                        break;
                                }
                        }
                }

                cur->starttime = cur->finishtime - cur->duration;
                finishtime = cur->finishtime;

                solution[i]->starttime = cur->starttime;
                solution[i]->finishtime = cur->finishtime;

                for (e = 0; e < numOfResources; e++) {
```

```
                    for (k = 0; k < cur->duration; k++) {
                        availabilityMatrix[e][finishtime - k] -= cur-
>maxResourceUse[e];
                    }
                }
        }
}

Activity **earlyStartLeftScheduling(Activity **solution) {

        Activity **earlyLeftStartInputChromosome = (Activity**) malloc(
                    sizeof(Activity *) * numOfActivities);
        Activity *activityWithSmallestStartTime = (Activity *) malloc(
                    sizeof(Activity));
        int i, j;
        for (i = 0; i < numOfActivities; i++) {

                activityWithSmallestStartTime->starttime = INT_MAX;

                for (j = 0; j < numOfActivities; j++) {
                    if (activityWithSmallestStartTime->starttime
                                > solution[j]->starttime) {
                        activityWithSmallestStartTime = solution[j];
                    }

                }

                earlyLeftStartInputChromosome[i] = createActivity(
                            activityWithSmallestStartTime);
                //activityWithSmallestStartTime->starttime = INT_MAX;
        }

        //free(activityWithSmallestStartTime);
        return earlyLeftStartInputChromosome;

}

void quickSortWithStartTimes(Activity **list, int left, int right) {
        int x = left, y = right;
        Activity *tmp;
        double pivot = list[(left + right) / 2]->starttime;

        while (x <= y) {
                while (list[x]->starttime < pivot)
                        x++;
                while (list[y]->starttime > pivot)
                        y--;
                if (x <= y) {
                        tmp = list[x];
                        list[x] = list[y];
                        list[y] = tmp;
                        x++;
                        y--;
                }
        }

        if (left < y)
                quickSortWithStartTimes(list, left, y);
        if (x < right)
                quickSortWithStartTimes(list, x, right);
```

```
}

void swapPriority(Activity *mother, Activity *father) { //swap function. it
is used for xover
	double temp = mother->priority;
	mother->priority = father->priority;
	father->priority = temp;
}

Activity **solveSchedule(Activity **list) {
	int i;
	Activity **scheduled;
	Activity **earlyStartLeftScheduled;

	quickSortRK(list, 0, numOfActivities - 1);
	initializeAvailabilityMatrix();
	scheduled = findRightSolution(list);
	calculateRightSchedule(scheduled, availabilityMatrix);

	earlyStartLeftScheduled = earlyStartLeftScheduling(scheduled);
	initializeAvailabilityMatrix();
	calculateScheduleFromLeft(earlyStartLeftScheduled,
availabilityMatrix);

	for (i = 0; i < numOfActivities; i++) {
		free(scheduled[i]);
	}

	free(scheduled);
	numSchedules--;
	return earlyStartLeftScheduled;
}

Activity **readFile(char *fileName) {
	int i = 0, j, k;
	Activity **activityList;
	int *numOfPres;
	FILE *fd = fopen(fileName, "r");
	if (fd == NULL) {
		printf("unable to open file %s\n", fileName);
		exit(1);
	}

	fscanf(fd, "%d%d", &numOfActivities, &numOfResources);

	if (DEBUG)
		printf("%d %d\n", numOfActivities, numOfResources);


	maxAvailableResources = (int*) malloc(sizeof(int) * numOfResources);
	for (i = 0; i < numOfResources; i++) {
		fscanf(fd, "%d", &maxAvailableResources[i]);

		if (DEBUG) {
			printf("%d ", maxAvailableResources[i]);
		}
	}

	//printf("\n");
```

```
	activityList = (Activity **) malloc(sizeof(Activity *) *
(numOfActivities));
	numOfPres = (int *) malloc(sizeof(int) * numOfActivities);
	for (k = 0; k < numOfActivities; k++) {
		numOfPres[k] = 0;
	}

	for (k = 0; k < numOfActivities; k++) {

		Activity *activity = createActivityPriority();

		activity->id = k;
		activity->maxResourceUse = (int*) malloc(sizeof(int) *
numOfResources);


		fscanf(fd, "%d", &(activity->duration));

		if (DEBUG) {
			printf("%d ", activity->duration);
		}


		for (j = 0; j < numOfResources; j++) {
			fscanf(fd, "%d", &(activity->maxResourceUse[j]));
			if (DEBUG)
				printf("%d ", activity->maxResourceUse[j]);
		}

		fscanf(fd, "%d", &(activity->noOfSucConst));
		activity->nofSuc = activity->noOfSucConst;
		if (DEBUG)
			printf("%d ", activity->noOfSucConst);


		activity->successor = (int *) malloc(
				sizeof(int) * activity->noOfSucConst);

		for (i = 0; i < activity->noOfSucConst; i++) {
			fscanf(fd, "%d", &(activity->successor[i]));


			activity->successor[i]--;

			numOfPres[activity->successor[i]]++;
			if (DEBUG) {
				printf("%d ", activity->successor[i]);
			}
		}

		//printf("---%d\n", 12);

		if (DEBUG)
			printf("\n");

		activityList[k] = activity;
	}

	fclose(fd);
```

```
	for (k = 0; k < numOfActivities; k++) {

		Activity *runner = activityList[k];
		runner->noOfPreConst = numOfPres[k];
		runner->precedessor = (int*) malloc(sizeof(int) * runner-
>noOfPreConst);
		runner->nofPre = 0;
		for (i = 0; i < numOfActivities; i++) {
			Activity * cur = activityList[i];
			for (j = 0; j < cur->noOfSucConst; j++) {
				if (cur->successor[j] == runner->id) {
					runner->precedessor[runner->nofPre] = cur-
>id;
					runner->nofPre++;
				}
			}
		}

		runner->noOfPreConst = runner->nofPre;
		if (DEBUG) {
			printf("\n%d %d %d \n", runner->id, runner->nofPre,
					runner->noOfPreConst);
			for (i = 0; i < runner->nofPre; i++)
				printf("%d ", runner->precedessor[i]);
			printf("\n");
		}
	}

	return activityList;
}

void crossOver(Activity ***solutionListBeforeGeneticAlgoritm, int motherId,
		int fatherId, int *curIndex,
		Activity ***solutionListAfterGeneticAlgoritm, double
motherXoverRate) {
	int firstLocation = (rand() % (numOfActivities));
	int secondLocation = (rand() % (numOfActivities));
	int i;
	double diffSum;
	Activity **motherRow = (Activity **) malloc(
			sizeof(Activity*) * numOfActivities); //new chromosome
	Activity **fatherRow = (Activity **) malloc(
			sizeof(Activity*) * numOfActivities); //new chromosome
	Activity **mother = solutionListBeforeGeneticAlgoritm[motherId];
	Activity **father = solutionListBeforeGeneticAlgoritm[fatherId];
	int *choosenLocations = (int*) malloc(sizeof(int) * numOfActivities);
	double averageDiffSum;
	for (i = 0; i < numOfActivities; i++) {
		motherRow[i] = createActivity(mother[i]);
		fatherRow[i] = createActivity(father[i]);
	}

	diffSum = 0;
	for (i = 0; i < numOfActivities; i++) {
		diffSum += abs((motherRow[i]->priority - fatherRow[i]-
>priority));
	}

	//cout<< "diffsum " << diffSum << "\t" << "motherXoverRate "<<
motherXoverRate << endl;
```

```
	for (i = 0; i < numOfActivities; i++)
		choosenLocations[i] = 0;

	averageDiffSum = diffSum / numOfActivities;
	if (averageDiffSum <= XOVERDIFF) {
		for (i = 0; i < (int) (motherXoverRate);) {
			int location = (rand() % numOfActivities);
			if (choosenLocations[location] == 0) {
				motherRow[location]->priority =
getRandomNumber();
				choosenLocations[location] = 1;
				i++;
			}
		}
	}

	if (firstLocation > secondLocation) {
		int temp = firstLocation;
		firstLocation = secondLocation;
		secondLocation = temp;

	} else if (firstLocation == secondLocation) {

		for (i = firstLocation; i < numOfActivities; i++)
			swapPriority(fatherRow[i], motherRow[i]);

	} else {

		for (i = firstLocation; i <= secondLocation; i++) {
			swapPriority(fatherRow[i], motherRow[i]);
		}
	}

	solutionListAfterGeneticAlgoritm[(*curIndex)++] = motherRow;
	solutionListAfterGeneticAlgoritm[(*curIndex)++] = fatherRow;

	free(choosenLocations);

}

Activity **copyChromosome(Activity **other) {
	Activity **chromosome = (Activity **) malloc(
			sizeof(Activity *) * numOfActivities);
	int i;
	for (i = 0; i < numOfActivities; i++)
		chromosome[i] = createActivity(other[i]);
	return chromosome;

}

void mutation(Activity ***solutionListAfterGeneticAlgoritm,
		double currentTemp) {
	int mutationIndex;
	int mutationGeneNum, i, finishTimeBeforeMutation,
finishTimeAfterMutation;
	Activity **chromozomeBeforeMutation;
	Activity **mutationRow;
	Activity **chromozomeAfterMutation;
```

```
	do {
		mutationIndex = (rand() % POPULATION_SIZE);
	} while (mutationIndex < ELITISM_NUM);

	chromozomeBeforeMutation = solveSchedule(
			solutionListAfterGeneticAlgoritm[mutationIndex]);
	finishTimeBeforeMutation =
			chromozomeBeforeMutation[numOfActivities - 1]-
>finishtime;

	mutationRow = solutionListAfterGeneticAlgoritm[mutationIndex];

	mutationGeneNum = (int) ceil(
			POPULATION_SIZE * (numOfActivities) * MUTATION_RATE);
	for (i = 0; i < mutationGeneNum; i++) {
		int geneLocation = (rand() % (numOfActivities));
		double priority = getRandomNumber();
		mutationRow[geneLocation]->priority = priority;
	}

	chromozomeAfterMutation = solveSchedule(mutationRow); //chromozome
has been resolved.
	finishTimeAfterMutation =
			chromozomeAfterMutation[numOfActivities - 1]-
>finishtime;


	if (finishTimeAfterMutation >= finishTimeBeforeMutation) {
		int delta = finishTimeAfterMutation -
finishTimeBeforeMutation;
		double power = -(delta / (currentTemp));
		double acceptancePro = exp(power);
		double pro = getRandomNumber();
		if (acceptancePro > pro) {
			//rejected

			for (i = 0; i < numOfActivities; i++) {
				free(mutationRow[i]);
			}
			free(mutationRow);

			solutionListAfterGeneticAlgoritm[mutationIndex] =
					chromozomeBeforeMutation;

		} else {
			//accepted

			for (i = 0; i < numOfActivities; i++) {
				free(chromozomeBeforeMutation[i]);
			}
			free(chromozomeBeforeMutation);

		}
	}

	for (i = 0; i < numOfActivities; i++) {
		free(chromozomeAfterMutation[i]);
	}

	free(chromozomeAfterMutation);
```

```
}

void crossOverWrapper(Activity ***solutionListBeforeGeneticAlgorithm,
		Activity ***solutionListAfterGeneticAlgorithm, double
motherXoverRate,
		int *elitIndex) {
	int i;
	for (i = 0; i < CROSS_OVER__NUM / 2; i++) {
		int motherIndex = (rand() % POPULATION_SIZE);
		int fatherIndex = (rand() % POPULATION_SIZE);
		if (motherIndex == fatherIndex) {
			i--;
			continue;
		}
		crossOver(solutionListBeforeGeneticAlgorithm, motherIndex,
fatherIndex,
				elitIndex, solutionListAfterGeneticAlgorithm,
motherXoverRate);
	}
}

void elitism(int *elitIndex, Activity ***solutionListAfterGeneticAlgoritm,
		Activity ***solutionListBeforeGeneticAlgoritm) {
	//	cout << solutionListBeforeGeneticAlgoritm[0]-
>solution[TOTAL_ACTIVITY - 1]->finishtime << "\n";
	for (; *elitIndex < ELITISM_NUM; (*elitIndex)++) {
		solutionListAfterGeneticAlgoritm[(*elitIndex)] =
copyChromosome(

	solutionListBeforeGeneticAlgoritm[(*elitIndex)]);
	}

}

void quickSortsolutionList1(Activity ***list, int left, int right) {
	int x = left, y = right;
	Activity **tmp;
	double pivot = list[(left + right) / 2][numOfActivities - 1]-
>finishtime;

	while (x <= y) {
		while (list[x][numOfActivities - 1]->finishtime < pivot)
			x++;
		while (list[y][numOfActivities - 1]->finishtime > pivot)
			y--;
		if (x <= y) {
			tmp = list[x];
			list[x] = list[y];
			list[y] = tmp;
			x++;
			y--;
		}
	}

	if (left < y)
		quickSortsolutionList1(list, left, y);
	if (x < right)
		quickSortsolutionList1(list, x, right);
}
```

```
void rouletteWheelSelection(int *elitIndex,
		Activity ***solutionListAfterGeneticAlgoritm,
		Activity ***solutionListBeforeGeneticAlgoritm) {

	double selectionProbability[POPULATION_SIZE];
	double sum = 0;
	int i, k, j;
	double probabilitySum = 0;
	for (i = 0; i < POPULATION_SIZE; i++) {
		sum +=

	solutionListBeforeGeneticAlgoritm[i][numOfActivities - 1]-
>finishtime;
	}

	for (i = 0; i < POPULATION_SIZE; i++)
		selectionProbability[i] =
				sum
					/
solutionListBeforeGeneticAlgoritm[i][numOfActivities
						- 1]->finishtime;

	for (i = 0; i < POPULATION_SIZE; i++)
		probabilitySum += selectionProbability[i];

	selectionProbability[0] /= probabilitySum;
	for (i = 1; i < POPULATION_SIZE; i++)
		selectionProbability[i] = selectionProbability[i] /
probabilitySum
				+ selectionProbability[i - 1];

	for (k = 0; k < rouletteWheelSelectionNum; k++) {
		double randNum = getRandomNumber();

		for (j = 0; j < POPULATION_SIZE; j++) {
			if (randNum < selectionProbability[j]) {
				solutionListAfterGeneticAlgoritm[(*elitIndex)] =
copyChromosome(

	solutionListBeforeGeneticAlgoritm[j]);
				(*elitIndex)++;
				break;
			}
		}
	}
}

Activity ***geneticAlgoritm(Activity ***list, double *preTemp,
		double *premotherXoverRate, double *coolingRateXover,
		double *coolingRate) {
	int elitIndex = 0, i, j;
	Activity ***solutionListBeforeGeneticAlgoritm = (Activity***) malloc(
			sizeof(Activity**) * POPULATION_SIZE); //Solution list
is stored before GA starts
	Activity ***solutionListAfterGeneticAlgoritm = (Activity***) malloc(
			sizeof(Activity**) * POPULATION_SIZE); //Solution list
is stored after GA

	*preTemp = *preTemp * *coolingRate;
```

```
	if (LOWER_BOUNDARY_XOVER_IMPROMENT_RATE < *premotherXoverRate)
		*premotherXoverRate = *premotherXoverRate * *coolingRateXover;

	for (i = 0; i < ELITISM_NUM; i++) {
		solutionListBeforeGeneticAlgoritm[i] =
copyChromosome(list[i]);
	}

	for (i = ELITISM_NUM; i < POPULATION_SIZE; i++) {
		solutionListBeforeGeneticAlgoritm[i] = solveSchedule(list[i]);
	}

	quickSortsolutionList1(solutionListBeforeGeneticAlgoritm, 0,
			POPULATION_SIZE - 1);

	elitism(&elitIndex, solutionListAfterGeneticAlgoritm,
			solutionListBeforeGeneticAlgoritm); //elitism
	crossOverWrapper(solutionListBeforeGeneticAlgoritm,
			solutionListAfterGeneticAlgoritm, *premotherXoverRate,
&elitIndex); //crossover
	rouletteWheelSelection(&elitIndex, solutionListAfterGeneticAlgoritm,
			solutionListBeforeGeneticAlgoritm); //rouletwheel
selection

	mutation(solutionListAfterGeneticAlgoritm, *preTemp); //mutation

	for (i = 0; i < POPULATION_SIZE; i++) {
		for (j = 0; j < numOfActivities; j++) {
			free(solutionListBeforeGeneticAlgoritm[i][j]);
			free(list[i][j]);
		}
		free(solutionListBeforeGeneticAlgoritm[i]);
		free(list[i]);

	}

	free(solutionListBeforeGeneticAlgoritm);
	free(list);

	return solutionListAfterGeneticAlgoritm;

}

Activity ***firstIteration(char *fileName, double *preTemp, double
*coolingRate,
		double *coolingRateXover, double *premotherXoverRate) {
	int elitIndex = 0, i, j;
	Activity ***solutionListBeforeGeneticAlgoritm = (Activity***) malloc(
			sizeof(Activity**) * POPULATION_SIZE); //Solution list
is stored before GA starts
	Activity ***solutionListAfterGeneticAlgoritm = (Activity***) malloc(
			sizeof(Activity**) * POPULATION_SIZE); //Solution list
is stored after GA

	*preTemp = *preTemp * (*coolingRate);
	*premotherXoverRate = numOfActivities * (*coolingRateXover)
			* DIVERSIFICATION_IMPROVEMENT_RATE;

	for (i = 0; i < POPULATION_SIZE; i++) {
		Activity** list = readFile(fileName);
```

```
			solutionListBeforeGeneticAlgoritm[i] = solveSchedule(list);

			for (j = 0; j < numOfActivities; j++) {
				free(list[j]);
			}
			free(list);
		}

		quickSortsolutionList1(solutionListBeforeGeneticAlgoritm, 0,
				POPULATION_SIZE - 1);

		elitism(&elitIndex, solutionListAfterGeneticAlgoritm,
				solutionListBeforeGeneticAlgoritm); //elitism
		crossOverWrapper(solutionListBeforeGeneticAlgoritm,
				solutionListAfterGeneticAlgoritm, *premotherXoverRate,
&elitIndex); //crossover
		rouletteWheelSelection(&elitIndex, solutionListAfterGeneticAlgoritm,
				solutionListBeforeGeneticAlgoritm); //rouletwheel
selection

		mutation(solutionListAfterGeneticAlgoritm, *preTemp); //mutation

		return solutionListAfterGeneticAlgoritm;
}

void solveProblemSet(char *fileName) {
		int i, j;
		double preTemp = TEMPERATURE;
		double coolingRate = 0.97;
		double coolingRateXover = 0.97;
		double premotherXoverRate;
		Activity ***firstGeneration;
		clock_t startTime;
		FILE *fd = fopen("out.txt", "w");
		temp = readFile(fileName);

		srand(time(NULL));
		//srand(0);
		createAvailabilityMatrix();

		firstGeneration = firstIteration(fileName, &preTemp, &coolingRate,
				&coolingRateXover, &premotherXoverRate);

		startTime = clock();
#if CUDA
		Activity_CUDA * h_temp = new Activity_CUDA[numOfActivities];
		for (int i = 0 ; i < numOfActivities ; i++){
			h_temp[i].Activity_CUDA();
			h_temp[i].set(*temp[i]);
		}
		cuCheck(cudaMalloc((void**)& dev_temp, numOfActivities *
sizeof(Activity_CUDA)));
		cuCheck(cudaMemcpy(dev_temp, h_temp, numOfActivities *
sizeof(Activity_CUDA),
				cudaMemcpyHostToDevice));

		activityManager = (ActivityManager*) malloc(sizeof(ActivityManager));
		activityManager->ActivityManager(numOfActivities);
		activityManager->initializeDeviceMemory();
```

```
	int * h_maxAvailableResources;
	int size =  numOfResources * (MAX_DURATION +1) * POPULATION_SIZE;
	h_maxAvailableResources = (int *) malloc(sizeof(int) * size );

	for (int k = 0; k < numOfResources; k++) {
		for (i = 0; i <= MAX_DURATION; i++) {
			for (int p = 0 ; p < POPULATION_SIZE ; p++)
				h_maxAvailableResources[k * (MAX_DURATION + 1)
* POPULATION_SIZE + i* POPULATION_SIZE + p] =
					maxAvailableResources[k];
		}
	}
	cuCheck(cudaMalloc((void**) & d_maxAvailableResources_org, size *
sizeof(int)));
	cuCheck(cudaMalloc((void**) & d_maxAvailableResources, size *
sizeof(int)));
	cuCheck(cudaMemcpy( d_maxAvailableResources_org,
h_maxAvailableResources,size * sizeof(int), cudaMemcpyHostToDevice));

	int * h_nofSuc;
	h_nofSuc = (int *) malloc(sizeof(int) * numOfActivities *
POPULATION_SIZE);
	for (int i = 0 ; i < numOfActivities ; i++)
		for (int p = 0 ; p < POPULATION_SIZE ; p++){
			h_nofSuc[i * POPULATION_SIZE + p] = temp[i]-
>noOfSucConst;
		}

	cuCheck(cudaMalloc((void**) & d_nofSuc, numOfActivities *
POPULATION_SIZE * sizeof(int)));
	cuCheck(cudaMalloc((void**) & d_nofSuc_org, numOfActivities *
POPULATION_SIZE * sizeof(int)));
	cuCheck(cudaMemcpy( d_nofSuc_org, h_nofSuc,numOfActivities *
POPULATION_SIZE * sizeof(int), cudaMemcpyHostToDevice));


#endif

	for (; numSchedules >= 0;) {
		//printf("%d\n", numSchedules);
#if CUDA
		firstGeneration = geneticAlgoritm_CUDA(firstGeneration,
&preTemp,&premotherXoverRate, &coolingRateXover, &coolingRate);
#else
		firstGeneration = geneticAlgoritm(firstGeneration, &preTemp,
			&premotherXoverRate, &coolingRateXover,
&coolingRate);
#endif
	}

#if CUDA

	for (int i = 0; i < numOfActivities; i++){
		h_temp[i].free();
	}
	free(h_temp);
	cuCheck(cudaFree(dev_temp));

	free(h_maxAvailableResources);
    free(h_nofSuc);
```

```
	cuCheck(cudaFree(d_maxAvailableResources));
	cuCheck(cudaFree(d_maxAvailableResources_org));
	cuCheck(cudaFree(d_nofSuc));
	cuCheck(cudaFree(d_nofSuc_org));



#endif

	printf("%s %d %f \n", fileName,
			firstGeneration[0][numOfActivities - 1]->finishtime,
			((double) (clock() - startTime)) / CLOCKS_PER_SEC);

	for (i = 0; i < POPULATION_SIZE; i++) {
		for (j = 0; j < numOfActivities; j++) {
			fprintf(fd, "%d %d %d\n", firstGeneration[i][j]->id +
1,firstGeneration[i][j]->starttime, firstGeneration[i][j]->finishtime);
		}
		fprintf(fd, "\n***%c***\n", ' ');
	}

}

int main(int argc, char **argv) {
	solveProblemSet("in.txt");

#if WINDOWS
	printf("Finished\n");
	_getch();
#endif
	return 0;
}

Activity ***geneticAlgoritm_CUDA(Activity ***list, double *preTemp,
		double *premotherXoverRate, double *coolingRateXover,
		double *coolingRate) {
	int elitIndex = 0, i, j;

	Activity ***solutionListAfterGeneticAlgoritm = (Activity***) malloc(
			sizeof(Activity**) * POPULATION_SIZE); //Solution list
is stored


	*preTemp = *preTemp * *coolingRate;
	if (LOWER_BOUNDARY_XOVER_IMPROMENT_RATE < *premotherXoverRate)
		*premotherXoverRate = *premotherXoverRate * *coolingRateXover;



	activityManager->set(list);

	activityManager->transferDataFromHostToDevice();
	//** Kernel Launch section
	cuCheck(cudaMemcpy(d_maxAvailableResources,
d_maxAvailableResources_org, numOfResources *
				(MAX_DURATION +1) * POPULATION_SIZE *
sizeof(int),cudaMemcpyDeviceToDevice));
	cuCheck(cudaMemcpy(d_nofSuc, d_nofSuc_org, numOfActivities *
					POPULATION_SIZE *
sizeof(int),cudaMemcpyDeviceToDevice));
```

```
	solveSchedule_kernel1<<< (POPULATION_SIZE - ELITISM_NUM -1)/
BLOCK_SIZE + 1, BLOCK_SIZE>>>( numOfResources,
			dev_temp, *activityManager,
d_maxAvailableResources,d_nofSuc);
	cuCheck(cudaMemcpy(d_maxAvailableResources,
d_maxAvailableResources_org, numOfResources *
				(MAX_DURATION +1) * POPULATION_SIZE *
sizeof(int),cudaMemcpyDeviceToDevice));

	solveSchedule_kernel2<<< (POPULATION_SIZE - ELITISM_NUM -1)/
BLOCK_SIZE + 1, BLOCK_SIZE>>>( numOfResources,
			dev_temp, *activityManager,
d_maxAvailableResources,d_nofSuc);

	//** End Kernel Launch section
	activityManager->transferDataFromDeviceToHost();
	activityManager->set_back(list);


	numSchedules -= POPULATION_SIZE - ELITISM_NUM;


	quickSortsolutionList1(list, 0,
			POPULATION_SIZE - 1);

	elitism(&elitIndex, solutionListAfterGeneticAlgoritm,
			list); //elitism
	crossOverWrapper(list,
			solutionListAfterGeneticAlgoritm, *premotherXoverRate,
&elitIndex); //crossover
	rouletteWheelSelection(&elitIndex, solutionListAfterGeneticAlgoritm,
			list); //rouletwheel selection

	mutation(solutionListAfterGeneticAlgoritm, *preTemp); //mutation

	for (i = 0; i < POPULATION_SIZE; i++) {
		for (j = 0; j < numOfActivities; j++) {
			free(list[i][j]);
		}
		free(list[i]);
	}
	free(list);

	return solutionListAfterGeneticAlgoritm;

}
```

C. Curriculum Vitae

Furkan UYSAL

Kalkınma Bakanlığı

Ar-Ge ve Girişimcilik Dairesi

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Ilgi Alanları

- C ve C++ programlama ve yazilim geliştirme,
- Proje yönetimi
- Bilim, teknoloji ve yenilik alanında politika oluşturma
- Hibe programlarının yönetimi
- Teknoloji yönetimi

Eğitim

2007-2014	Orta Doğu Teknik Üniversitesi İnşaat Mühendisliği Bölümü Doktora Derecesi
2004-2007	Orta Doğu Teknik Üniversitesi İnşaat Mühendisliği Bölümü Yüksek Lisans Derecesi
2000 -2004	Orta Doğu Teknik Üniversitesi İnşaat Mühendisliği Bölümü Lisans Derecesi

İş Deneyimi

2012-2014	Kalkınma Bakanlığı Ar-Ge ve Girişimcilik Dairesi Uzman Bilim, teknoloji ve yenilik politikaları çalışmaları, Kamu Ar-Ge yatırımlarının değerlendirilmesi, Araştırma altyapılarına yönelik mevzuat hazırlama çalışmaları

2006-2012	Türkiye Bilimsel ve Teknolojik Araştırma Kurumu
	Uzman
	Türkiye araştırma alanının oluşturulması (TARAL),Ulusal hibe programlarının tasarımı, mevzuatının oluşturulması, Araştırma projelerinin değerlendirme süreçlerinin yönetilmesi
2004-2006	Apeas İnş., Arı Proje, Temelsu Ltd. Şti.
	Teklif Mühendisi, Betonarme Tasarım Mühendisi

Başlıca Makale ve Projeler

Sonmez R & Uysal F., (2014), A Backward-Forward Hybrid Genetic Algorithm for Resource Constrained Multi-Project Scheduling Problem, ASCE Journal of Computing in Civil Engineering, Doi: 10.1061/(ASCE)CP.1943-5487.0000382

Sonmez R.& Uysal F., (2008),Geographic Information System-based Visualization System for Planning and Monitoring of Repetitive Construction Projects, Canadian Journal of Civil Engineering, Volume 35(11), 1342-1346

Sonmez R. & Uysal F., (2008), Planning of Linear Construction Projects Using Geographic Information Systems, Fifth International Conference on Construction in the 21st Century (CITC-V), İstanbul

Birden fazla projenin melez genetik algoritmalar ile çizelgelenmesi, Orta Doğu Teknik Üniversitesi BAP Projesi (2012-2014)

Boru hattı projeleri için Coğrafi Bilgi Sistemleri (CBS) temelli planlama ve izleme sistemi tasarımı, Orta Doğu Teknik Üniversitesi BAP Projesi (2006-2007)

Sertifikalar

Portland Eyalet Üniversitesi ve Portland Teknoloji Enstitüsü Teknoloji Yönetimi Sertifikası, 2008

Kore Bilim, Teknoloji ve Gelecek Planlama Bakanlığı, INNOPOLIS Vakfı Bilim Teknoloji Politikaları Eğitimi Sertifikası, Daejeon, Güney Kore, 2014