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**META-HEURISTIC PROCEDURES FOR THE MULTI-RESOURCE
LEVELING PROBLEM WITH ACTIVITY SPLITTING**

A THESIS IN ENGINEERING SYSTEMS MANAGEMENT
Masters of Science in Engineering Systems Management, Engineering Management Option

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College of Engineering
in partial fulfillment of
the requirements for the degree

MASTER OF SCIENCE

by
HADEEL YACOUB ALSAYEGH
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| We approve the thesis of Hadeel Yacoub Alsayegh | Date of signature |
|---|-------------------|
| <p>Dr. Moncer Hariga Professor Engineering Systems Management Graduate Program Thesis Advisor</p> | |
| <p>Dr. Fouad Ben Abdelaziz Professor Engineering Systems Management Graduate Program Graduate Committee</p> | |
| <p>Dr. Hazim El-Baz Associate Professor Engineering Systems Management Graduate Program Graduate Committee</p> | |
| <p>Dr. Saleh Abu Dabous Assistant Professor Civil Engineering Graduate Committee (External)</p> | |
| <p>Dr. Moncer Hariga Director Engineering Systems Management Program Director</p> | |
| <p>Dr. Hany El-Kadi Associate Dean College of Engineering</p> | |
| <p>Dr. Yousef Al-Assaf Dean College of Engineering</p> | |
| <p>Dr. Gautam Sen Vice Provost, Research & Graduate Studies</p> | |

META-HEURISTIC PROCEDURES FOR THE MULTI-RESOURCE LEVELING PROBLEM WITH ACTIVITY SPLITTING

Hadeel Alsayegh, Candidate for the Master of Science Degree

American University of Sharjah, 2011

ABSTRACT

The proper utilization of resources is important to achieve project success. In project management, there are two types of resource scheduling problems. The first is resource allocation in which activities are scheduled depending on the availability of limited resources to ensure that resource limitations are not exceeded in any period. The second type is resource leveling which includes moving non-critical activities within their float to improve the resource profile while not extending the project's duration.

Based on the review of related literature, resource leveling techniques can be grouped into three categories: heuristics, optimization and meta-heuristics. Most resource leveling techniques assume that activities cannot be split, meaning that once an activity starts, the work continues until the activity is completed. Activity splitting may be needed to improve resource utilization. Even with the few previous methods that incorporated activity splitting, resource leveling was accomplished using optimization techniques, which are not efficient for large size projects. A more computationally efficient approach to solve larger projects is to use meta-heuristic procedures such as Particle Swarm Optimization (PSO) and Simulated Annealing (SA). The proposed resource leveling technique is developed using Particle Swarm Optimization combined with Simulated Annealing, which assumes a time constrained project, with unlimited resources and allows for the splitting of non-critical activities.

Since there are no benchmark problems available in the literature, a set of 180 test problems are created and used as a benchmark to test the proposed methods. An optimization model is then used to determine the exact solution for these benchmark problems. Next, six PSO heuristic procedures are developed and assessed using the 180 benchmark problems. The results of these procedures are then analyzed based on the percentage difference in cost and the computational time. From the analysis, it was observed that the heuristics are becoming trapped in local optimum and are unable to find optimal solutions. Hence, the six heuristic procedures are combined with Simulated Annealing, which searches for new solutions without being trapped in local optimum, and are assessed using the benchmark problems. PSO-SA Procedure 3, which is based on Quantum theory, generated the best results with an average of 4.23% cost difference between the generated and the optimal results. Moreover, 147 out of the 180 problems had a percentage cost deviation of less than or equal to 10%. As for the computation time, the heuristic procedures generated solutions with an average reduction of 7 times for the large size problems. Furthermore, the proposed heuristic is assessed for larger problems in which a near optimum solution is reached within 25 minutes, unlike the optimal procedure which takes longer than 24 hours.

This research is an important additional step in the ongoing research on resource leveling. The proposed heuristic procedure offers several improvements over the current resource leveling techniques. The proposed procedure allows for activity splitting, which is more realistic and results in better resource profile. The new procedure takes advantage of combining Particle Swarm Optimization with Simulated Annealing to reach the optimum or near optimum solution in a short time period. The proposed procedure allows planners to consider the tradeoff between the cost of activity splitting and the cost of resource fluctuations resulting in minimum overall project cost.

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DEDICATION

This thesis is dedicated to my husband, Sameh, my two children, Chantelle and Shadi, my parents, Yacoub and Rita, and my brother, Jeries, and sisters, Rola, and Rawan. Thank you for your continuous support, encouragement, and unconditional love.

Chapter 1: Introduction

1.1 Overview

A project is formally defined as a temporary endeavor undertaken to create a unique product or service, whereas project management is the application of knowledge, skills, tools, and techniques to manage project activities in order to complete the project on time, within budget, and meet or exceed stakeholders' needs and expectations from the project [1, 2]. In today's challenging and competitive environment, time is very critical in making products available in the market ahead of competitors. Therefore, the need to properly plan and schedule projects is vital for their successful completion.

Project planning involves identifying the activities needed to complete the project and the relationships among them. In other words, determining what needs to be done and how. Project Scheduling, on the other hand, is concerned with determining the duration of each activity along with its starting and completion time as well as the project duration. One of the most traditional project scheduling techniques used in project management is the Critical Path Method (CPM), which identifies the critical path(s) of the project, by calculating the Early Start (ES), Early Finish (EF), Late Start (LS) and Late Finish (LF) times and the slack (float) of each activity. The critical path consists of activities that may not be delayed without delaying the project, and are thus known as critical activities. However, activities that can be delayed without affecting the project duration are known as non-critical activities.

Projects rely on resources in completing their activities. Examples of resources include manpower, machines, money, and materials. While scheduling the project activities using CPM, resources are assumed to be unlimited, which is not the case in most practical situations. Ignoring the availability constraints on resources while scheduling projects, could result in unrealistic schedules that cannot be achieved.

There are two categories of project scheduling problems: resource-constrained and time-constrained. With resource-constrained projects, the objective is to schedule project activities so that a particular resource does not exceed a specific limit in any given

project time period, while holding the project duration to a minimum. This method is also known as resource allocation. Resource allocation usually results in extending project duration. This is especially true if the needed resources for critical activities are being utilized by non-critical activities. Some resource allocation techniques allow for the non-critical activities to be interrupted so that the needed resources are reallocated to the critical activities. However, even with allowed splitting, if the required resources are not available, extension of project duration may occur. Many optimization approaches exist for solving resource-constrained problems, some of which include Integer Programming, Dynamic Programming, and Heuristic Programming [3]. On the other hand, time-constrained projects assume that time is constrained while resources are available in unlimited quantities. Their main objective is to optimize the utilization and variation of the resources. Resource leveling is a technique used to minimize the change of the resource requirements from one period of time to the next; in other words, to minimize the peaks and valleys of resource usage. Resource leveling is accomplished by moving non-critical activities within their float. Figure 1 shows two histograms of resource utilization before and after resource leveling. After resource leveling, it can be noted that a smoother resource profile is achieved, with a gradual increase and gradual decrease in the resource usage. A more desirable distribution, but difficult to get, is the uniform distribution where the resource requirements are fixed throughout the project duration.

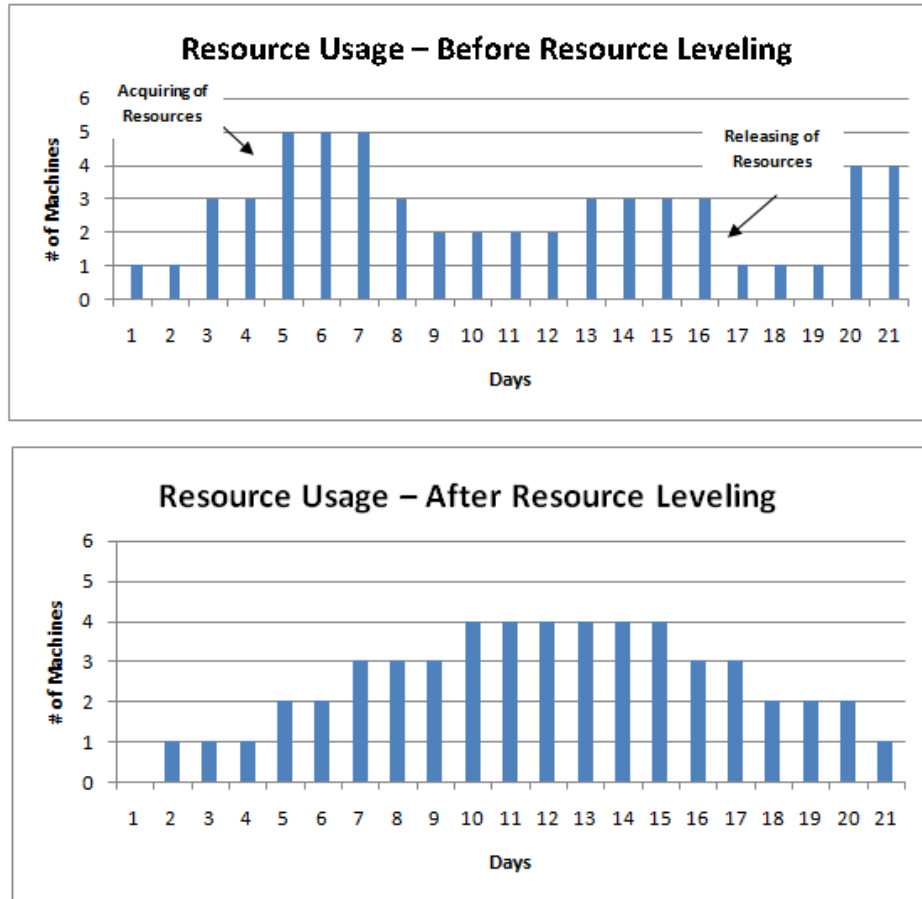


Figure 1: Resource Usage

Most resource leveling techniques assume that the activities may not be split, indicating that once an activity starts, it will continue until the work is finished. There are two main reasons behind this assumption. First, the non-splitting of activities make the mathematical computation easier and secondly, it is less costly. However, in reality, there are many projects in which the activities can be split. For example, a programmer may need to stop working on his/her current task to perform a more urgent task such as bug fixing, and then return to his/her current task once done. Another example, from the construction industry, is that during a construction of a house, the labor are working on the sidewalk are shifted to complete the fixing of the ceiling, as it is a critical activity. The workers can go back to the sidewalk once the critical activity is finished. These examples illustrate how non-critical activities are stopped to complete critical path activities.

Resource leveling with activity splitting is more mathematically complex as it introduces more decision variables and constraints [4]. Moreover, two types of costs are involved: resource dependent costs and activity dependent costs. Resource dependent costs are related to the resource itself and involve the costs of acquiring and releasing a resource from one period to the other. Activity dependent costs are costs related to the starting and stopping of the activity, such as the moving of equipment. In addition, upon splitting an activity, the learning process of the resources is affected, and it will take some time for the resources to re-achieve the learning level just prior to splitting the activity. Figure 2 shows an activity before and after splitting. The activity is split twice basically dividing the activity into three segments. For each of the two splits, there are associated stopping and starting cost.

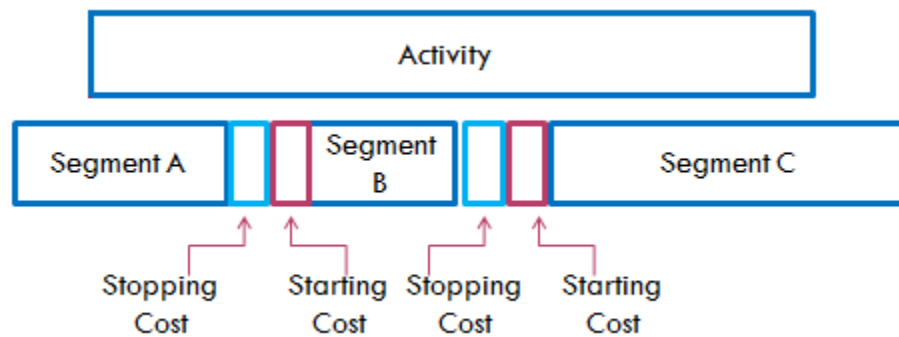


Figure 2: Activity Splitting

Although there is plenty of research done on resource leveling without splitting, very little research is done on resource leveling with activity splitting. Hariga and El-Sayegh [4] came up with a model based on a mixed integer linear programming formulation. Their model generates exact solutions to such problems; however, it is not efficient for large size projects. A more computationally efficient approach to solve larger projects is to use meta-heuristic procedures. Some examples of meta-heuristic approaches include Genetic Algorithms, Ant Colony, and Particle Swarm in solving such problems. Using meta-heuristic approaches, an optimum or “near optimum” solution is found rather than an exact solution as with exact optimization procedures. This thesis presents a new procedure for resource leveling that allows for activity splitting and uses Particle Swarm

Optimization and Simulated Annealing techniques to search for the optimum or near optimum solution.

1.2 Overview of Resource Management Categories

The techniques used to manage resources, either to allocate resources or to level the utilization of resources, are divided into three categories: heuristics, optimization, and meta-heuristics techniques. In the subsequent sub-sections, the first two categories are presented briefly, but the focus is more on the meta-heuristics since this thesis presents a resource leveling technique using two meta-heuristic approaches.

1.2.1 Heuristics

A heuristic method consists of a set of procedures that rely on common-sense ideas of how to search for fine solutions. These procedures are iterated several times until the best solution is found, hence heuristics are also known as “iterative algorithms”. Heuristic methods are procedures that are likely to discover very good feasible solutions, but not necessarily optimal solutions [5]. Each heuristic is designed for a particular type of problem. If the heuristic is well-designed, then a nearly optimal solution is obtained. Most heuristics are efficient enough to solve very large projects with numerous activities. Although heuristic methods can handle very large projects, the solutions they provide are not necessary optimum [6].

1.2.2 Optimization

Optimization techniques are techniques that rely on linear/nonlinear programming methods to determine the best outcome, where in resource management the outcome is the least cost (for resource leveling) and the shortest duration (resource allocation). An optimization technique usually consists of an objective function, which is used to minimize or maximize a variable (cost or duration) while satisfying one or more constraints. Unlike heuristics, optimization techniques provide optimum solutions; however they are limited by the project size. In other words, as the size of the problem increases, by adding more activities for example, the number of calculations also increase; and therefore, consuming a lot of time to reach the best outcome.

1.2.3 Meta-Heuristics

Complex combinatorial problems, such as the travelling salesman problem, the vehicle routing problem, the capacitated facility location-allocation problem, the resource constrained project problem, the problem addressed in this research work, and many other problems encountered in engineering economics, and industrial fields, are very hard to solve using exact optimization procedures. In fact, many of these problems are known as NP-hard, meaning that it is very unlikely to develop an algorithm capable of solving them in polynomial time.

The techniques used to solve complex combinatorial problems can be classified as either exact or approximate procedures. The former technique attempts to generate an optimal solution, which is proven to be indeed the global optimal. The branch and bound and dynamic programming are just two examples of exact procedures. However, for many problems, these procedures are computationally inefficient as the time required to obtain the optimal solution grows exponentially with the problem size. On the other hand, approximate procedures produce solutions in shorter computation time but are not guaranteed to be optimal. There are two main classes of approximate procedures: constructive and local search algorithms. The first class of algorithms, such as greedy constructive heuristics, constructs solutions from scratch by adding components to the solution one by one, whereas local search algorithms iteratively improve the current solution by moving to hopefully better neighboring solutions. The main drawback of the latter procedures is the likelihood of being stuck in local optimal solution.

Recent advances in optimization methods have shifted research attention to the development of general solution procedures, called meta-heuristics, to further improve the solution quality of local search heuristics. Because of their general structure, they can fit different kinds of optimization problems with relatively few modifications. They are based on concepts from different fields such as genetics, biology, artificial intelligence, social science, physics, and neurosciences, among others. The use of such concepts helps to create some degree of randomness in searching for optimal or near optimal solutions for well-known hard problems. Examples of common meta-heuristics include Tabu Search, Simulated Annealing, Genetic Algorithms, Ant Colony Optimization, and

Particle-Swarm Optimization. Each of these algorithms is discussed briefly in the following section; however the Particle-Swarm Optimization and Simulated Annealing are discussed more thoroughly in chapters 4 and 5, respectively.

1.2.3.1 Tabu Search

The Tabu Search (TS) is a meta-heuristic search procedure, which was initially proposed by Fred Glover in 1986. It has achieved many practical successes when applied to applications such as scheduling, routing and graph coloring [7]. The meta-heuristic maintains a tabu list with a maximum size L to keep track of the recently obtained candidate solutions. If the maximum size of the list is reached, then the oldest candidate is removed to make space for the recently improved solution. The search halts once a fixed number of iterations is reached or when no other improvement can be reached.

1.2.3.2 Simulated Annealing

Simulated Annealing (SA) is a probabilistic based search meta-heuristic to locate a good solution to a global optimization problem without being trapped in a local optimum. The concept of the simulated annealing is based on the analogy between the simulation of the annealing of the solids and the problem of solving large combinatorial optimization problems [8]. Annealing refers to the process in which the particles of a solid are randomly arranged once the solid turns to liquid at high temperatures. The procedure begins with an initial solution which is first considered as the best solution. Next, the procedure iterates until it finds a candidate solution. A solution is considered as a candidate if it is either a better solution than the one found so far or the probability of accepting it is high. This probability relies on a variable “ T ” which represents the temperature in an annealing process. The higher the value of T , the more chances a solution is accepted (i.e. more randomness).

1.2.3.3 Genetic Algorithms

The Genetic Algorithm (GA) technique was developed by John Holland in the 1970s. GAs are stochastic search techniques based on the natural phenomenon of “theory of evolution” formulated by Charles Darwin in the mid-19th century [5]. This phenomenon is also referred to as the “survival of the fittest”. In genetic terms, each parent is represented by a chromosome. A chromosome consists of a set of genes (traits).

When two chromosome parents merge, using a crossover operation, an offspring chromosome is reproduced. During merging, some chromosomes are modified by a mutation operation. Offspring usually inherit the more fit (better) genes from each parent. Fitter chromosomes are more likely to be inherited in the next generations. A population of chromosomes is produced overtime.

Genetic algorithms are popular in the areas of optimization, scheduling, and transportation, among others. Thus, genetic algorithms can be used for resource leveling and resource allocation. A chromosome is represented by a possible sequence of activities, taking into consideration the precedence relationships among activities (i.e. all preceding activities of an activity must appear prior to the activity itself in a chromosome representation). When two parent chromosomes are merged, by randomly choosing activities from each parent, taking into consideration the precedence relationship, an offspring chromosome is reproduced. If the main objective for using genetic algorithms is to reduce costs when leveling resources, for example, then a cost is linked to each activity. The sub-sequence of activities that denote a lesser cost are more fit, to be inherited by the children. Therefore, the final result is an optimum or near-optimum chromosome (sequence of activities).

1.2.3.4 Ant Colony Optimization

Ant Colony Optimization (ACO) is a random based parallel search procedure, which was proposed by Marco Dorigo in 1992 in his PhD thesis. ACO algorithms are designed to solve specific types of combinatorial optimization problems [9]. They inspired by the behavior of real-life ant colonies that search for food by finding optimal paths.

One main feature of ants is that they leave “pheromone trails” when searching for food. Pheromone is a chemical substance that ants deposit along their way from their nest (source) to the food source (destination). When other ants are looking for food, they often look for smell pheromone paths in hope to find some food. As more ants traverse the same path, the concentration of the pheromone tends to increase. The smell of the pheromone substance tends to fade with time, thus leaving only the most traversed paths that are more probable to be chosen.

1.2.3.5 Particle Swarm Optimization

Particle Swarm Optimization (PSO) algorithms, which were presented by Kennedy and Eberhart in 1995 [10], are based on the social behaviors of animals and insects, such as bird flocks and fish schools. Swarms, or groups, of these animals and insects, tend to self-organize themselves in optimal spatial patterns. Their behaviors, such as speed and direction, are determined based on a small number of neighboring individuals [9]. PSO algorithms conduct their search randomly by using a population (swarm) of individuals (particles) to find an optimum or near-optimum solution for hard optimization problems [11]. Each particle is a potential solution that consists of two parts representing its position in a N-dimensional space and its velocity.

The PSO was first developed to search for solutions in real space, in which the positions of the particles were represented as real numbers. However, in 1997, Kennedy and Eberhart [12] introduced a discrete binary version of the PSO where the positions of the particles held only binary values, 0 and 1. Also, the velocities of the particle represent the probability that the binary bit of the particle will change its value to one, and is restricted to [0, 1]. Therefore, a normalization function may be required to change the continuous values of the velocities to [0, 1].

1.3 Statement of the Problem

Most resource leveling techniques assume that activities are continuous and may not be split. Activity splitting may be desirable to smooth the profile of the resource utilization. In addition, most research done up until now, propose resource leveling approaches aiming at finding optimal solutions using exact optimization approaches. However, the more complex a project is and the more activities it has, the higher the computational time. Therefore, there is a clear need for a new resource leveling approach which is based on meta-heuristics, that is computationally efficient, to cater for activity splitting and handle large size projects.

Previous researches have shown that meta-heuristics algorithms are efficient in solving large size combinatorial problems in terms of computation time and quality of their solution. Therefore, the main objective of this research is to a design meta-heuristic approach based on the combination of Particle Swarm Optimization and Simulated

Annealing to generate a near optimal project schedule for the resource leveling problem with activity splitting.

1.4 Objectives

The objective of this research is to develop a meta-heuristic approach for resource leveling that is computationally efficient in finding near optimum solutions for large size projects. The proposed approach assumes a time constrained project, with unlimited resources and allow for the splitting of non-critical activities. Furthermore, the proposed approach is expected to achieve a reduction in the computational time for large size projects.

1.5 Significance

The main contributions of this research include the following:

1. Supplementing the project scheduling literature with a new resource leveling technique that can be implemented on large projects with large number of activities. This research work is the first to address heuristically the resource leveling problem with activity splitting with the objective of minimizing the cost by minimizing the fluctuations of the resources.
2. Developing heuristic procedure that reduces the computational time needed to perform resource leveling.
3. Allowing for activity splitting will ensure a better resource profile that is less costly overall.
4. Minimizing the overall project cost and reducing resource fluctuations over time.
5. Studying the possibility of linking the developed technique with other scheduling software will give better results and increase the chances of usage.

1.6 Methodology

The following steps are undertaken to achieve the research objectives:

Step 1: Review the literature related to meta-heuristic procedures with more focus on Particle Swarm Optimization.

Step 2: Develop benchmark problems to be used in the empirical computational analysis

As there are no benchmark problems available in the project scheduling literature, a set of test instances are developed to assess the solution quality of the proposed heuristics. The test problems are generated by varying the number of non-critical activities, nn , and number of resources, P . For each combination of $nn \in \{2, 4, 7, 8, 9, 10\}$ and $P \in \{2, 4, 6\}$, 10 instances with different problem parameters (resource utilization rates and costs) are created. The 180 problem instances are then solved using the exact procedure proposed by Hariga and El-Sayegh [4]. The obtained optimal solutions are later used as benchmarks to evaluate the cost performance of the heuristic procedures.

Step 3: Develop and code several heuristic procedures

Six different heuristic procedures are developed. The heuristic procedures are based on Particle Swarm Optimization (PSO) and Simulated Annealing (SA) to generate near optimal solution with less computation efforts. The PSO procedures are adapted to handle binary variables as PSO is designed for continuous optimization.

Step 4: Determine the proper parameter settings for PSO and SA

This step is concerned with the tuning of the PSO and SA parameters. In other words, different values for these parameters are attempted to decide on the best ones to be employed in the assessment of the performance of the proposed procedures. As a starting point, the values found to be good in the application of PSO to other types of applications are used as the initial solution. In addition, other parameter settings are tested using different empirical experiments to ensure that the appropriate value for each parameter is used.

Step 5: Conduct computational experiments to validate the proposed heuristic procedure

The generated benchmark problems are used to assess the quality of each proposed heuristic in terms of computational time and cost performance.

Step 6: Select the best heuristic procedure

1.7 Thesis Organization

Chapter one presents the introduction to the research problem and the objectives. Chapter 2 presents the summary of the related literature review. Chapter 3 presents the test problems and the optimum solution using Hariga and El-Sayegh [4] model. Chapter 4 presents the development of six Particle Swarm Optimization models. In chapter 5, each of the PSO models presented in chapter 4 are combined with Simulated Annealing in order to further improve the results. Finally, chapter 6 concludes the thesis with the conclusion and recommendations for application.

Chapter 2: Literature Review

2.1 Introduction

Managing resources is important to the successful execution of projects as the project schedule can only be implemented after assigning the required resources for each activity of the project. Gray and Larson [13] emphasized that “project network times are not a schedule until resources have been assigned”. In most projects, resources are limited and even if they are not limited, there is still a need for their proper utilization. Resource management mainly focuses on two areas: resource allocation and resource leveling. While the former deals with the allocation of limited resources, the latter is concerned with using the required resources efficiently given fixed project duration [14].

Resource allocation refers to scheduling project activities based on the availability of resources. If the needed resources are not available, this will result in delaying that activity. For critical activities, that means the project completion time will be extended. The objective of resource allocation is to determine the minimum project duration given the resource constraints. In this category, time is assumed to be flexible and the project duration may be extended. Hegazy [15] explained that scheduling with limited resources is mathematically difficult as it is considered a large combinatorial problem.

In reality, resources are not limited, but rather adding more resources is costly. Companies are usually constrained by the project’s duration and may not be in a position to extend the project’s duration [14]. Resource leveling is concerned with the efficient utilization of resources and assumes that resources are unlimited but the project duration is fixed. Resource leveling tends to reduce the peak demands for a given resource and minimize the fluctuations in resource usage over time. Fluctuations in resource demands require extensive hiring, training, firing, moving and starting-up which is costly. Furthermore, newly hired resources are also considered as less efficient.

In the following sections, previous resource management techniques are reviewed. Resource management techniques can be grouped in three categories: Heuristics, Optimization and Meta-Heuristics.

2.2 Heuristic Procedures

One of the famous techniques of resource leveling which is developed by Harris in 1978 is the “Minimum Moment” algorithm [16]. In this technique, activities are assumed to be uninterrupted; once an activity starts, it continues until it is completed. In addition, the technique assumes that the resource consumption is constant over the duration of the activity and only one activity can be leveled at a single time. Once the project is scheduled through CPM, for example, only the non-critical activities are leveled by shifting them using their free floats. The algorithm focuses on an improvement factor which is used for the basis of leveling decisions. The improvement factor is calculated for several activities, but the activity with the largest improvement factor is chosen to be leveled.

Hiyassat [17] proposes a modification to the “Minimum Moment” approach presented by Harris [16] which uses heuristics for resource leveling. The modified method, like the traditional approach, assumes that activity splitting is not allowed, project duration is limited (time-constrained) and the resource availability is unlimited. The main objective of the proposed method is to reduce the number of calculations without compromising the results. It is achieved by changing the criteria used to select the candidate activity to be shifted. Hiyassat’s selection is based on both the value of the activity’s free float and its resource rate; while Harris’s selection is based on selecting the activity having the maximum improvement factor. An activity having an improvement factor of 0 or above indicates that the resource profile will improve by shifting the activity. The proposed method drastically reduces the number of calculations while preserving the accuracy of the results. Hiyassat [17] further notes that the main drawback of both methods (traditional and modified) is that neither of them provide the “true” minimum moment.

Hiyassat [18] presents a heuristic procedure that applies the Modified Minimum Moment Method to both methods of multiple resources leveling: Series and Combined. Hiyassat demonstrated his procedure by using the same examples that were used by Harris [16] to present the traditional minimum moment method. A comparison is made between the two, which shows that the modified method, in most cases, obtained better

results than the traditional one. Furthermore, the research concludes that the Modified Minimum Moment Method is a valid heuristic method for multiple resources leveling.

Harris [19] presents another heuristic approach to level resources. This approach relies on the Critical Path Method (CPM) or Program Evaluation and Review Techniques (PERT) to determine the critical path, the duration of the project, and the critical activities. With resource leveling, it is always assumed that critical activities may not be leveled as they have zero float days and if shifted will lead to an increase to the project's duration. The resources of the critical activities are mapped onto a histogram, referred to as the base histogram. Next, the non-critical activities are queued in a priority order and added to the base histogram one-by-one. The activities are first ordered according to the decreasing resource rates, and then by the increasing total float and finally by the decreasing order of the sequence steps. Each activity is placed between its early start time and late finish time span. The activity is then assigned to the position with which the total sum of the resources is at minimum. The heuristic results in a histogram where the resources are leveled similarly as other heuristic and optimization techniques. As referred by Harris, the method is clear, logical and computationally efficient.

Zhang et al. [20] present a different heuristic approach for scheduling resource-constrained for repetitive projects that use multiple modes of resource demands. Unlike other research in which one activity is scheduled at a time, this approach considers scheduling alternative combinations of activities simultaneously. The combinations are determined through a permutation tree-based algorithm. The combination that results in the minimum project duration is selected. The researchers expect that the heuristic approach to be efficient and beneficial to others in their research and practice. Furthermore, using this heuristic, a feasible solution is always determined. This heuristic method does not take into consideration costs, and may be further extended to address resource leveling and other project uncertainties.

2.3 Optimization

One of the early models developed for scheduling multi-projects with limited resources is presented by Pritsker et al. [21]. The model is based on zero-one linear programming formulation. Some of the assumptions made in the model include limited

resources, activity splitting possibilities, and precedence relations between activities. The desired objectives of the model include minimizing the total throughput time, the time by which all projects are completed, and total lateness or lateness penalty for all projects. The model results in optimal solutions for projects with fewer numbers of activities.

Easa [6] presents an integer-linear optimization model to level resources. The model levels one resource at a time and assumes that activities are uninterrupted. Unlike the previously discussed heuristic models, this model guarantees optimal leveling. The model relies on CPM to determine the critical path and the critical activities. The main objective of the model is to minimize the deviations between the actual and desirable resource rates. The model can be generalized to level multiple resources at the same time and can be extended to take into consideration the trade-off of cost scheduling. As with most optimization models, the main drawback of this model is that it can only be applied to small and medium sized projects because of the large number of calculations.

Ramlogan and Goulter [22] formulate a mixed integer model to level resources for project scheduling. As with other models, this model relies on CPM as an input to the model and uses the free float of the non-critical activities to level its resource. However, this model uses binary integer programming to ensure that activities are allocated as a whole, in which activities may not be interrupted. However, one of its objectives is to minimize the total durations of the individual activities. The other objectives include the overall resource leveling of the project and the resource leveling of the individual activities, which is known as internal leveling. The main concept of internal leveling is to try to avoid activity interruption. The objectives are integrated in the formulation by using a weighted multi-objective framework. The model can be improved by scheduling multiple resources concurrently, efficiently, and by adding priorities to each type of resource.

Bandelloni et al. [23] develop a non-serial dynamic programming approach for resource leveling. The approach results with an optimum solution to minimize the variation between the desired levels of resources and the resource requirements. The model relies on CPM to identify the critical and non-critical activities along with the project duration. The main objective of the procedure is to schedule the activities within

their floats in order to achieve a rectangular-shaped histogram of the resource patterns. The model levels a single resource at a time, but may be further extended to allow for multiple resources leveling. The procedure assumes that activities are uninterrupted, with fixed durations, and constant resource rates. Like other resource leveling models, it is assumed that the project's completion date is fixed. The model looks for near-critical activities to reduce the number of interactions. Results have indicated that the procedure gives exact solutions for small and medium size projects.

Nudtasomboon and Randhawa [24] develop a zero-one integer programming model to schedule resource constrained projects. The model handles renewal and non-renewable resources, time-resource trade-offs and activity splitting. Furthermore, the model combines the three main objectives of project scheduling under one objective function. These objectives include minimum completion time, minimum project total cost, and minimum variation on resource levels. The main significance of the model is that the computational time for duration and cost problems are drastically reduced with regards the other previously presented algorithms, which don't take into consideration resource leveling.

Mattila and Abraham [25] develop an integer linear programming method to level resources for linear projects. Linear projects are characterized by having a set of activities that are repeated in different locations. Examples of linear projects include highways, pipelines, and tunnels. The method assumes that the project is planned and scheduled using a linear scheduling method. In addition, the controlling activity path is determined by using linear schedule models, and not the critical path method (CPM), because research has indicated that it is ineffective to use networks in scheduling linear projects. The formulation of the presented model relies on the ideas of rate float and activity float.

Senouci and Adeli [26] develop a mathematical model that uses the Neural Dynamic Model, developed by Adeli and Park, for resource scheduling. The model takes into consideration precedence relationships, multiple crew-strategies, and time cost trade-off, which are scheduling techniques that were ignored in prior research. In addition, the main objective of the model's formulation is to minimize the total project cost, rather than only minimizing the project duration. Moreover, the model performs resource-

leveling and resource-allocation simultaneously, rather than independently, for resource scheduling. The model can be used for large projects and is very efficient for resource scheduling.

In most of the previous research, it is always assumed that an activity may not be interrupted, that is once an activity starts, it will continue until it's finished. However, in the following two papers, the researchers have taken an extra step for resource leveling in which activity splitting is allowed. In other words, an activity can be stopped and restarted during the project's duration.

Son and Matilla [27] formulate a binary linear programming model to level resources with activity splitting. The values of the decision variables, whether to split an activity or not, are only restricted to zero and one. The model relies on CPM to identify the critical and non-critical activities. Like other traditional models, this model also shifts the non-critical activities within their free-float to level resources. The main objective of the model is to measure the usage level of the resources. In addition, the model allows the practitioners to select certain activities to be split, to mimic the actual process. The model showed more realistic results when compared with results obtained from commercial software in which activity splitting was not allowed. However, their model did not consider the cost of splitting.

Hariga and El-Sayegh [4] propose an optimization model which uses a mixed binary-integer programming for resource leveling. The model takes into consideration activity splitting when leveling resource usage over the project life. This is achieved by moving the non-critical activities within their float. The objective of the paper is to minimize the costs associated with the splitting, the starting and stopping of activities, and the moving of the resources. The model assumes that the resources are unlimited; the resource rate for each activity remains constant over its duration. Although, an optimum solution is achieved through this model, large numbers of calculations are required.

2.4 Meta Heuristics

Leu and Yang [28] present a genetic algorithm based technique to schedule resource-constrained projects. The technique allocates multiple resources to a single project. Its main objective is to provide an optimum or near optimum project duration, while taking into consideration the resource constraints. One of the main drawbacks of using genetic algorithms for project scheduling is their sequencing; Leu and Yang overcome this problem by using crossover and mutation operators. Like heuristic models, genetic-based algorithms do not always provide optimum solutions.

Leu and Hung [29] establish a schedule simulation model based on genetic algorithms for scheduling resource-constrained projects. The model also takes into consideration variable activity durations because in reality activity durations are uncertain due to external environments such as weather, resource availability, and space congestion. The model uses probability distribution to come up with these uncertain activity durations. Along with providing the optimal project duration, the model is capable of providing the optimal averaged project duration and the cumulative project completion probabilities. The model may be improved to allow for resource leveling and time/cost trade-off for uncertain activity durations.

Dawood and Sriprasert [30] develop a genetic algorithm for the optimization of multi-constrained construction schedules. Examples of constraints include resource availability, execution space, physical dependency of construction products, and client instructions. The objective of the algorithm is to provide an optimum or near-optimum set of project duration, cost, and a smooth resource profile (resource-leveling). The results are achieved by altering the two sets of the chromosome string (one for the priority level assigned to each activity and the other for the options of construction methods assigned to the activity). The algorithm provides a schedule with acceptable searching time.

Montoya-Torres et al. [31] present yet another model based on genetic algorithms to schedule projects with limited resources. Unlike prior research, this research uses object-oriented programming to represent the chromosomes, which may allow the design of efficient decision support systems. Compared with other models, this model is effective and in many cases may find results in less computational time. The model does not take into consideration the activity costs. The authors suggest that further research is

required to investigate the various formulation techniques for the multi-objective optimization problems.

Senouci and Eldin [32] present a model based on genetic algorithms for resource scheduling. This model performs resource leveling along with resource allocation simultaneously, unlike prior research in which they were performed independently. Moreover, this model takes into consideration the different precedence relationships (Start-Start, Start-Finish, Finish-Start, Finish-Finish), total project cost minimization, and time-cost trade-off. The model results in optimum or near optimum total costs. Also, to optimize the project schedule and the total cost, this model could be used along with CPM while performing resource leveling. The model can solve large project sizes with a large number of activities efficiently.

Christodoulou [33] presents a methodology using algorithms based on Ant Colony Optimization (ACO) artificial agents to schedule resource-constrained and resource-unconstrained projects. Also, the method can search for longest paths which are useful for solving direct network topologies. The method uses intelligent selection procedures to perform the path-route calculations. The algorithms have an advantage over the traditional CPM methods, due to its capability to calculate the shortest and longest paths. The presented methodology may further consider resource leveling and activity splitting.

Zhang et al. [11] introduce a Particle Swarm Optimization (PSO) approach to schedule resource-constrained projects. The objective of this approach is to minimize the project's duration. With PSO, a search is conducted to find the best location for each activity among a group of activities. The priorities of the activities are represented by particles and the group of activities is represented as a swarm. The solution achieved from these particles is transformed to a feasible solution using a parallel scheme. The approach takes into consideration the precedence and resource constraints. Through computational analysis, it has been shown that this approach is more efficient than genetic algorithm based approaches due to its search mechanism. The approach may be further improved to include resource leveling and multi-objectives.

Zhang et al. [34] introduce, yet another, methodology based on Particle Swarm Optimization (PSO) for scheduling resource constrained activities with activity splitting and break. The method assumes that activities are interrupted during non-working periods and are not necessarily resumed at the next working period. This because limited resources may be reallocated during their breaks and may not be back in time for the next working period. The main objective of this method is to minimize the project's duration while exploiting preemption and break of resource constrained projects. Using PSO, the solution is represented by the particle position which is then transformed into a feasible preemptive schedule using a parallel scheme. The authors verify the effectiveness of their method through computational analyses. Although this method takes into consideration activity splitting, it does not attempt to level resources, as to achieve a smooth resource profile.

Son and Skibniewski [35] develop a technique for resource leveling with the objective of minimizing the difference between the required resources and the desired resource profile. Their technique is based on local optimizers and a hybrid model. The local optimizer is developed by designing four independent algorithms, in which each algorithm uses combinations of different schemes for the order of shifting non-critical activities. A local optimal is obtained from each algorithm and the minimum optimal is chosen as the solution for the model. However, in order to enhance the performance of the local optimizers, the authors have decided to develop a hybrid model which combines the local optimizers with Simulated Annealing (SA). The model assumes that the project's duration is fixed and that once an activity starts, it should continue until it is completed. Hence, this model does not take into consideration activity splitting.

Zhang et al. [36] take a step further to present a model based on Particle Swarm Optimization (PSO) for scheduling resource constrained projects using a permutation based scheme. The priority for scheduling an activity is determined by its order in the permutation. The activity must be placed after its predecessors in the permutation to take into consideration the precedent constraint. The main objective of this model is to minimize the project's duration. This permutation based model does not lead to combinatorial explosion or is problem-dependent effectiveness, and thus, it is considered

more robust than heuristic methods. The model has demonstrated its effectiveness through computational experiments. This model may be further extended to include multiple objectives and to consider activity interruption.

Khanesar [37] introduces a modified discrete particle swarm optimization approach, with the aim of retaining the original definitions of the continuous PSO parameters. The velocity of the particle is interpreted as the rate at which the particle changes its bits' value. Also, the previous direction and previous state of each particle is taken into account upon updating a particle's position. The previous velocities of a particle contain information about the direction to previous local best and global bests of the particle which help in attaining better and faster solutions. This approach can be used in numerous applications which require a discrete search space.

Jun and Chang [38] present a binary mixture particle swarm algorithm to be used to solve discrete optimization problems. The algorithm combines the original binary particle swarm optimization with simulated annealing to avoid traps in the local optimal solution and improve the overall search capabilities of the algorithm. Moreover, the algorithm replaces PSOs update operation for particle velocity and position with the cross-operation of the genetic algorithm in order to simplify the algorithm's structure. The algorithm demonstrated that it is very efficient and has a fast convergence rate when tested against other PSO algorithms.

Liao et al. [39] present a discrete PSO algorithm which is applied to the flowshop scheduling problem. The proposed algorithm redefines the particle's position and velocity and utilizes an efficient approach which is based on frequency based memory to move the particle to a new position. The algorithm is tested against a continuous PSO algorithm and two genetic algorithms and has showed to be very competitive. Moreover, the authors extended their research to include PSO-LS, a local search scheme into the proposed algorithm, which performed well for the flowshop problem, but required more computational time.

Yang et al. [40] propose a discrete particle swarm optimization algorithm based on quantum theory, where the minimum unit which carries information is known as a

qubit, and holds the value 0 or 1. This concept is applied to the PSO, where each bit of the particle position is either 0 or 1, and that the velocity of a particle represents the probability that the j^{th} bit of the i^{th} particle being zero. Note that the algorithm does not rely on the sigmoid function to achieve binary values, but rather generates a random number which dictates the value of the bit when compared to the velocity. The algorithm has been tested against other meta-heuristic approaches such as Genetic Algorithm and discrete PSO algorithms which use the sigmoid function. It has been proved that the proposed algorithm is simple, efficient, and converges at a fast rate.

As it can be noted from the above comprehensive literature review, resource leveling problem with activity splitting was not addressed using any heuristic approach. Most of the research tackled the resource-constrained problem. And a few took one step further to solve resource-constrained problems with activity splitting. Son and Skibniewski [35] develop a technique to minimize the difference between the required resources and the desired resources for resource leveling, as activity splitting was not taken into consideration. Moreover, none of the discrete PSO techniques developed by the other researchers tackle the resource-leveling problem.

2.5 Chapter Summary

This chapter presented a summary of the related literature that dealt with project resource leveling techniques. The techniques are grouped into three categories: heuristics, optimization and meta-heuristics. Based on this extensive review, it is clear that there is a need for a new resource leveling method that is computationally efficient and allows splitting of activities.

Chapter 3: Resource Leveling – Optimization Approach

3.1 Introduction

This chapter presents the optimization model developed by Hariga and El-Sayegh [4] to level resources with activity splitting. The model formulation is explained and a sample problem is demonstrated in the subsequent sections. Further, the model is used on several test problems, which serve as benchmarks, and are later used to assess the quality of the proposed heuristic procedure.

3.2 Optimization Model

Hariga and El-Sayegh [4] propose an optimization model for resource leveling while taking into consideration activity splitting by using a mixed binary-integer programming. In addition, the model aims at minimizing the costs associated with the shutdown and restart of the activities as well as the activities' dependent costs incurred because of the splitting. The latter type of costs is the result of work disruption such as labor inefficiency (loss of learning efficiency) due to the demobilization and subsequent remobilization [4]. As with other models, this proposed model relies on CPM to identify the critical and non-critical activities. The model assumes that the resources are unlimited, the resource rate for each activity remains constant over its duration, and that only non-critical activities can be split. Furthermore, this model allows for activity splitting and multi-resource leveling. Although, an optimum solution is achieved through this model, large numbers of calculations are required.

All optimization models consist of the following elements:

- State the assumptions
- Define the terms, parameters, and decision variables;
- Define the constraints to be met
- Set the objective function

The model considers that a project has n activities and P resource types. Each activity has a fixed duration represented by, $T_j, j = 1, 2, \dots, n$. After performing CPM calculations, the early start (ES_j), late start (LS_j), early finish (EF_j), late finish (LF_j) as

well as the total float (TF_j) for each activity is determined. The critical (nc) and non-critical (nn) activities are determined. The model reschedules the non-critical activities (nn) within the interval $[ES_j, LF_j]$, thus not altering the project's duration.

The model requires that the below-mentioned set of assumptions to be satisfied at all times:

- There are P resource types available for running the project.
- The resource requirement rate for each activity remains constant over its duration.
- A non-critical activity can be split with an associated cost.
- The time to setup an activity prior to restarting activity is small enough such that it is carried out at the end of the split period.
- A non-critical activity resumes with the same resource requirement rate after preemption.
- The precedence relationships for activities that are split must be satisfied.

The model consists of two types of parameters: problem parameters and problem decision variables.

Problem Parameters

r_{ip} Number of units of resource type p ($p = 1, 2, \dots, P$) needed to run activity $i = 1, 2, \dots, n$.

Z_{ti} Binary parameter equal to one when critical activity i is active from period ES_i to period EF_i and zero otherwise, $i = 1, 2, \dots, nc$ and $t = 1, 2, \dots, T$.

CI_p Cost of acquiring one unit of resource type p ($p = 1, \dots, P$).

CD_p Cost of releasing one unit of resource type p ($p = 1, \dots, P$).

CS_j Cost of splitting non-critical activity j , $j = 1, 2, \dots, nn$.

Problem Decision Variables

y_{ij} Binary variable equal to one when non-critical activity j is active (running) during period t and zero otherwise, $t = ES_j, ES_j+1, \dots, LF_j$ and $j = 1, 2, \dots, nn$.

- S_j Start time of non-critical activity $j, j = 1, 2, \dots, nn$.
- F_j Finish time of non-critical activity $j, j = 1, 2, \dots, nn$.
- L_{tj} Non-negative variable to determine whether activity j is split in period $t + 1$.
- NL_j Number of times activity j is split, $j = 1, 2, \dots, nn$.
- I_{tp} Number of units of resource type p ($p = 1, \dots, P$) acquired during period $t, t = 1, 2, \dots, T$.
- D_{tp} Number of units of resource type p ($p = 1, \dots, P$) released during period $t, t = 1, 2, \dots, T$.
- R_{tp} Requirement for resource type p ($p = 1, \dots, P$) on period $t, t = 1, 2, \dots, T$.

The following is the cost optimization model for the resource leveling problem with allowed activity splitting:

$$\text{Minimize } \sum_{p=1}^P \left[CI_p \sum_{t=1}^T I_{tp} + CD_p \sum_{t=1}^T D_{tp} \right] + \sum_{j=1}^{nn} CS_j NL_j \quad (1)$$

subject to:

$$R_{tp} - R_{(t-1)p} + D_{tp} - I_{tp} = 0, \quad t = 1, 2, \dots, T \text{ and } p = 1, 2, \dots, P \quad (2)$$

$$R_{tp} = \sum_{i=1}^{nc} r_{ip} z_{ti} + \sum_{j=1}^{nn} r_{jp} y_{tj}, \quad t = 1, 2, \dots, T \text{ and } p = 1, 2, \dots, P \quad (3)$$

$$\sum_{t=ES_j}^{LF_j} y_{tj} = T_j, \quad j = 1, 2, \dots, nn \quad (4)$$

$$S_j = (T + 1) - \max\{(T + 1 - t)y_{tj} : t = ES_j, ES_j + TF_j\}, \quad j = 1, 2, \dots, nn \quad (5)$$

$$F_j = \max\{ty_{tj} : T = LF_j - TF_j, LF_j\}, \quad j = 1, 2, \dots, nn \quad (6)$$

$$S_k \geq F_j + 1, \quad j = 1, 2, \dots, nn \text{ and } k \in Succ(j) \quad (7)$$

$$L_{tj} = Max(y_{tj} - y_{(t+1)j}, 0), \quad j = 1, 2, \dots, nn \text{ and } t = ES_j, LF_j \quad (8)$$

$$NL_j = \sum_{t=ES_j}^{LF_j} L_{tj} - 1, \quad j = 1, 2, \dots, nn \quad (9)$$

$$y_{tj} \in \{0, 1\}, \quad j = 1, 2, \dots, nn \text{ and } t = ES_j, LF_j$$

$$L_{tj} \geq 0, \quad j = 1, 2, \dots, nn \text{ and } t = ES_j, LF_j$$

$$I_t, D_t \geq 0, \quad t = 1, 2, \dots, T - 1$$

$$y_{(T+1)j} = 0, \quad j = 1, 2, \dots, n$$

In this model, there are three types of constraints: resource balance constraint, duration constraint, and network logic constraint.

Equation 3 expresses the resource requirement decision variable, R_{tp} , as a function of the binary variables, y_{tj} and z_t , which is used in the resource balance constraint which guarantees that the requirement for resource type p at time t plus the amount of the same resource acquired during period t is equal to the requirement for resource type p at time $t+1$ plus the amount of the same resource released during time t (equation 2).

Equation 4 represents the duration constraint which is required to ensure that the total number of active periods for a non-critical activity j is equal to its duration T_j .

The network logic constraint is required to ensure that the network logic relationships between the non-critical activities are maintained. Since the critical activities have zero float and will not be moved, there is no need to include them in the network logic constraint.

To construct the network logic constraint, the starting time (S_j) and finishing time (F_j) for non-critical activity j can be determined as a function of binary variables using equations 5 and 6. Equation 7 represents the network logic constraint which ensures that

the starting time of a successor activity is greater than or equal to the finishing time of its predecessor.

Finally, equation 1 represents the cost function of the optimization model, in which its objective is to minimize the sum of costs resulting from the fluctuations in resource usage over the project life as well as the total costs of splitting the non-critical activities. Note that equation 9 calculates the number of times that activity j is split.

As formulated, the model contains $\sum_{j=1}^m (LF_j - ES_j + 1)$ binary variables and at most $[2PT + \sum_{j=1}^m (LF_j - ES_j + 1) + 2nn]$ continuous variables. Moreover, the model has at most $[P(T-1) + nn + \sum_{j=1}^m (LF_j - ES_j + 1) + 2 \sum_{j=1}^m (TF_j + 1) + \sum_{j=1}^m nn_j]$ constraints, where nn_j is the number of immediate successors of activity j . This proves that as the number of non-critical activities increase, the computational time of the model will increase as well.

3.3 Illustrative Example

In this section, an example of a project having 11 activities with 6 different resource types is illustrated using the optimization model developed by Hariga and El-Sayegh [4]. Figure 3 shows the project network for this illustrative example. After performing the CPM calculations, the ES , EF , LS , LF times and the slack for each activity are determined. Moreover, the critical and non-critical activities are identified as A, C, H, and K and B, D, E, F, G, I, and J, respectively. Note that the project's duration is 15 time periods which will be unchanged since only the non-critical activities can be delayed within their float in order to achieve smooth the resource profiles. The CPM results are taken as input in the model, along with the resource requirements, resource costs for acquiring and releasing, and splitting costs. Table 1 shows the data entered into the model with respect to the illustrative example.

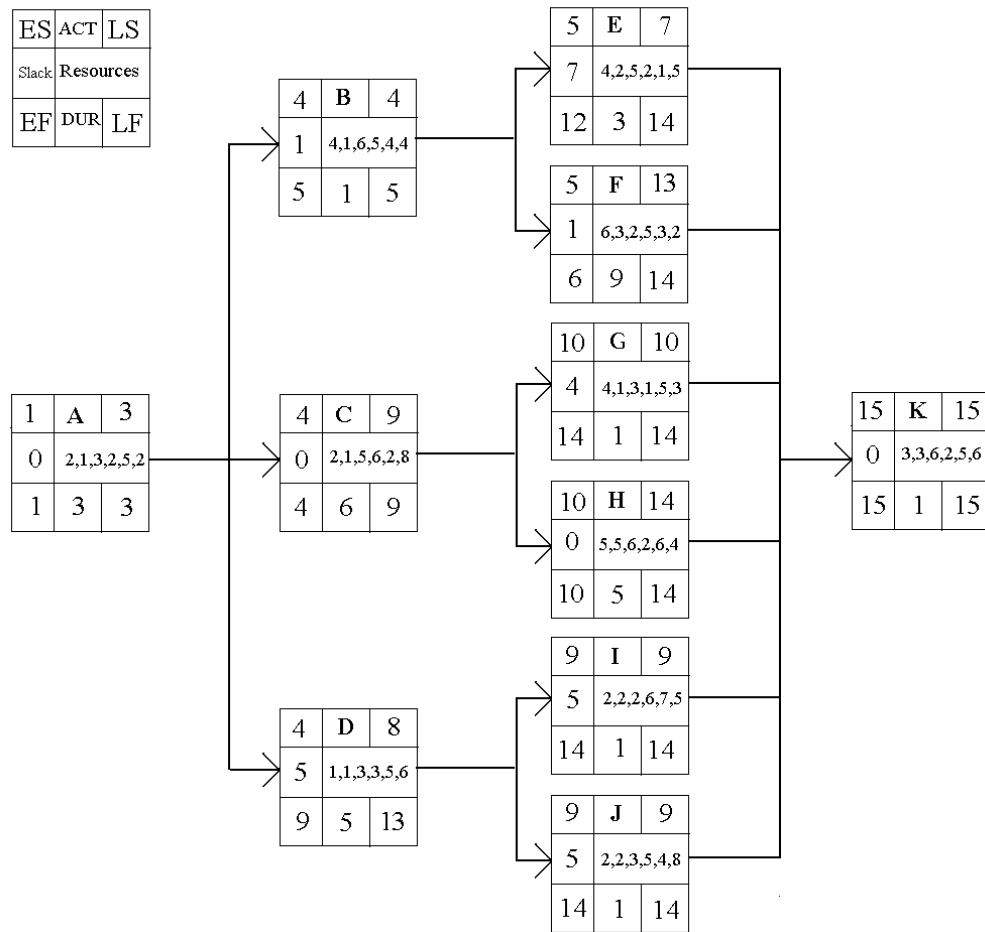


Figure 3: Project Network Example

Table 1: Data Input for the Illustrative Example

| Activity | Duration | ES | LF | Slack | R1 | R2 | R3 | R4 | R5 | R6 | CS |
|----------|----------|----|----|-------|----|----|----|----|----|----|----|
| A | 3 | 1 | 3 | 0 | 2 | 1 | 3 | 2 | 5 | 2 | 0 |
| B | 1 | 4 | 5 | 1 | 4 | 1 | 6 | 5 | 4 | 4 | 2 |
| C | 6 | 4 | 9 | 0 | 2 | 1 | 5 | 6 | 2 | 8 | 0 |
| D | 5 | 4 | 13 | 5 | 1 | 1 | 3 | 3 | 5 | 6 | 2 |
| E | 3 | 5 | 14 | 7 | 4 | 2 | 5 | 2 | 1 | 5 | 3 |
| F | 9 | 5 | 14 | 1 | 6 | 3 | 2 | 5 | 3 | 2 | 5 |
| G | 1 | 10 | 14 | 4 | 4 | 1 | 3 | 1 | 5 | 3 | 1 |
| H | 5 | 10 | 14 | 0 | 5 | 5 | 6 | 2 | 6 | 4 | 0 |
| I | 1 | 9 | 14 | 5 | 2 | 2 | 2 | 6 | 7 | 5 | 7 |
| J | 1 | 9 | 14 | 5 | 2 | 2 | 3 | 5 | 4 | 8 | 4 |
| K | 1 | 15 | 15 | 0 | 3 | 3 | 6 | 2 | 5 | 6 | 0 |

| Cost | |
|----------|----------|
| Acquired | Required |
| 1 | 1 |
| 2 | 3 |
| 3 | 2 |
| 5 | 2 |
| 3 | 2 |
| 3 | 1 |

After inputting all the required data and running the model, the following Gantt chart is produced (Table 2). Table 2 displays the y_{ij} for each activity, which indicate the active and inactive periods and are used to in calculating the optimal cost. The chart shows that activity F is stopped (inactive) in time period 11, and that is why the y_{ij} for $j = 11$ is zero. Activity F resumes it work at period 12.

Table 2: y_{ij} of each activity in the Illustrative Example

| Activities | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|------------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|
| A | 1 | 1 | 1 | | | | | | | | | | | | |
| B | | | | 1 | 0 | | | | | | | | | | |
| C | | | | 1 | 1 | 1 | 1 | 1 | 1 | | | | | | |
| D | | | | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | | |
| E | | | | | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| F | | | | | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | |
| G | | | | | | | | | | 0 | 0 | 0 | 0 | 1 | |
| H | | | | | | | | | | 1 | 1 | 1 | 1 | 1 | |
| I | | | | | | | | | 0 | 0 | 1 | 0 | 0 | 0 | |
| J | | | | | | | | | 0 | 1 | 0 | 0 | 0 | 0 | |
| K | | | | | | | | | | | | | | | 1 |

Based on Table 2, the duration constraints are satisfied for all the non-critical activities, for example, for activity F,

$$\sum_{t=5}^{14} y_{tj} = (1 + 1 + 1 + 1 + 1 + 1 + 0 + 1 + 1 + 1) = 9$$

Once the y_{ij} values are determined, the problem decision variables can be calculated (Table 3). For example, R_{tp} , I_{tp} , and D_{tp} for resource type 2 at period 9, can be calculated as follows:

$$R_{9,2} = (1 * 1) + (1 * 1) + (0 * 2) + (1 * 3) + (0 * 2) + (0 * 2) = 5$$

Since $R_{10,2} - R_{9,2} = 10 - 5 > 0$, $I_{9,2} = 5$, and $D_{9,2} = 0$.

Table 3: R_{tp} , I_{tp} , D_{tp} for the Illustrative Example

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|-------------------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|
| # of Acquired | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| # of Released | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| Total Resources 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|-------------------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|
| # of Acquired | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| # of Released | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| Total Resources 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|-------------------|---|---|---|----|---|---|---|---|----|----|----|----|----|----|----|
| # of Acquired | 1 | 3 | 7 | 0 | 1 | 1 | 1 | 7 | 0 | 0 | 1 | 9 | 0 | 1 | |
| # of Released | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 0 | 3 | 1 | 0 | 0 | 7 | 0 | |
| Total Resources 3 | 1 | 2 | 5 | 12 | 5 | 6 | 7 | 8 | 15 | 12 | 11 | 12 | 21 | 14 | 15 |

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|-------------------|---|---|---|----|---|---|---|---|----|----|----|----|----|----|----|
| # of Acquired | 1 | 3 | 7 | 0 | 1 | 1 | 1 | 7 | 0 | 0 | 1 | 9 | 0 | 1 | |
| # of Released | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 0 | 3 | 1 | 0 | 0 | 7 | 0 | |
| Total Resources 4 | 1 | 2 | 5 | 12 | 5 | 6 | 7 | 8 | 15 | 12 | 11 | 12 | 21 | 14 | 15 |

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|-------------------|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| # of Acquired | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| # of Released | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| Total Resources 5 | 6 | 10 | 14 | 28 | 36 | 40 | 44 | 48 | 52 | 54 | 58 | 59 | 63 | 65 | 66 |

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|-------------------|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| # of Acquired | 3 | 39 | 3 | 0 | 3 | 3 | 3 | 21 | 0 | 9 | 0 | 27 | 6 | 0 | |
| # of Released | 0 | 0 | 0 | 33 | 0 | 0 | 0 | 0 | 9 | 0 | 9 | 0 | 0 | 24 | |
| Total Resources 6 | 3 | 6 | 45 | 48 | 15 | 18 | 21 | 24 | 45 | 36 | 45 | 36 | 63 | 69 | 45 |

The resource balance constraint is satisfied for all R_{tp} , for $t = 0, 1, \dots, T$ and $p = 1, 2, \dots, P$. For example, $R_{9,2}$ is $5 - 10 - 0 + 5 = 0$.

Moreover, the network logic constraints for all the non-critical activities are satisfied. The starting times and finishing times can be easily computed using the equations mention in the previous section. For example, the starting time for activity F is

$$S_j = 15 - \max\{11 \times 0, 10 \times 1\} = 15 - 10 = 5.$$

$$F_j = \max\{13 \times 1, 14 \times 1\} = 14.$$

Figure 4 shows the resource utilization for the six different resource types used in this example before leveling while Figure 5 displays the resource utilization for the six different resource types after leveling. Each graph plots the resource requirements against the time period. Notice that the resource profile for each of the resources has improved after leveling. For resource type 2, the peak has dropped from 21 to 14 in addition to minimizing the fluctuations.

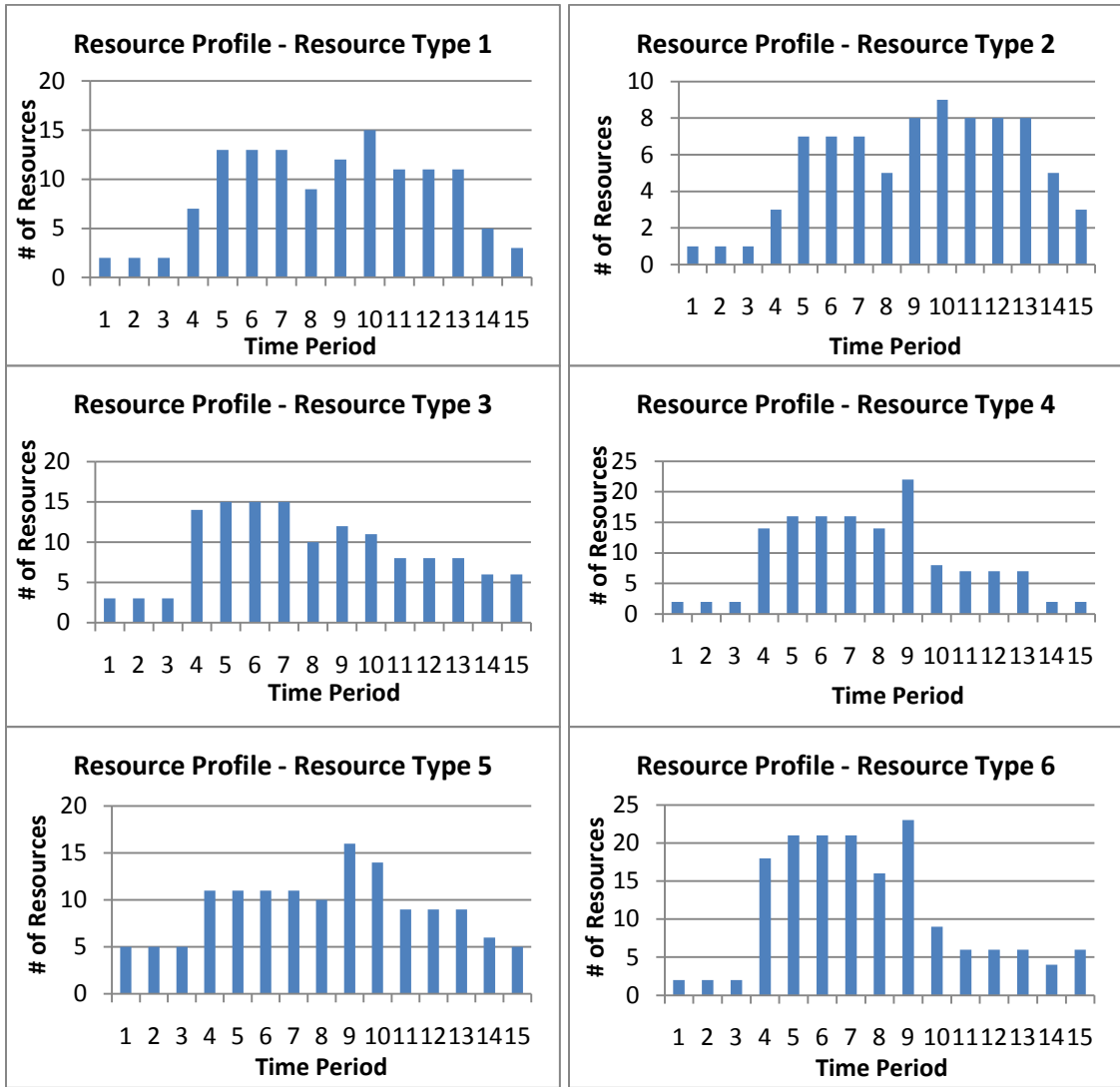


Figure 4: Resource Utilization for Illustrative Example (Before Resource Leveling)

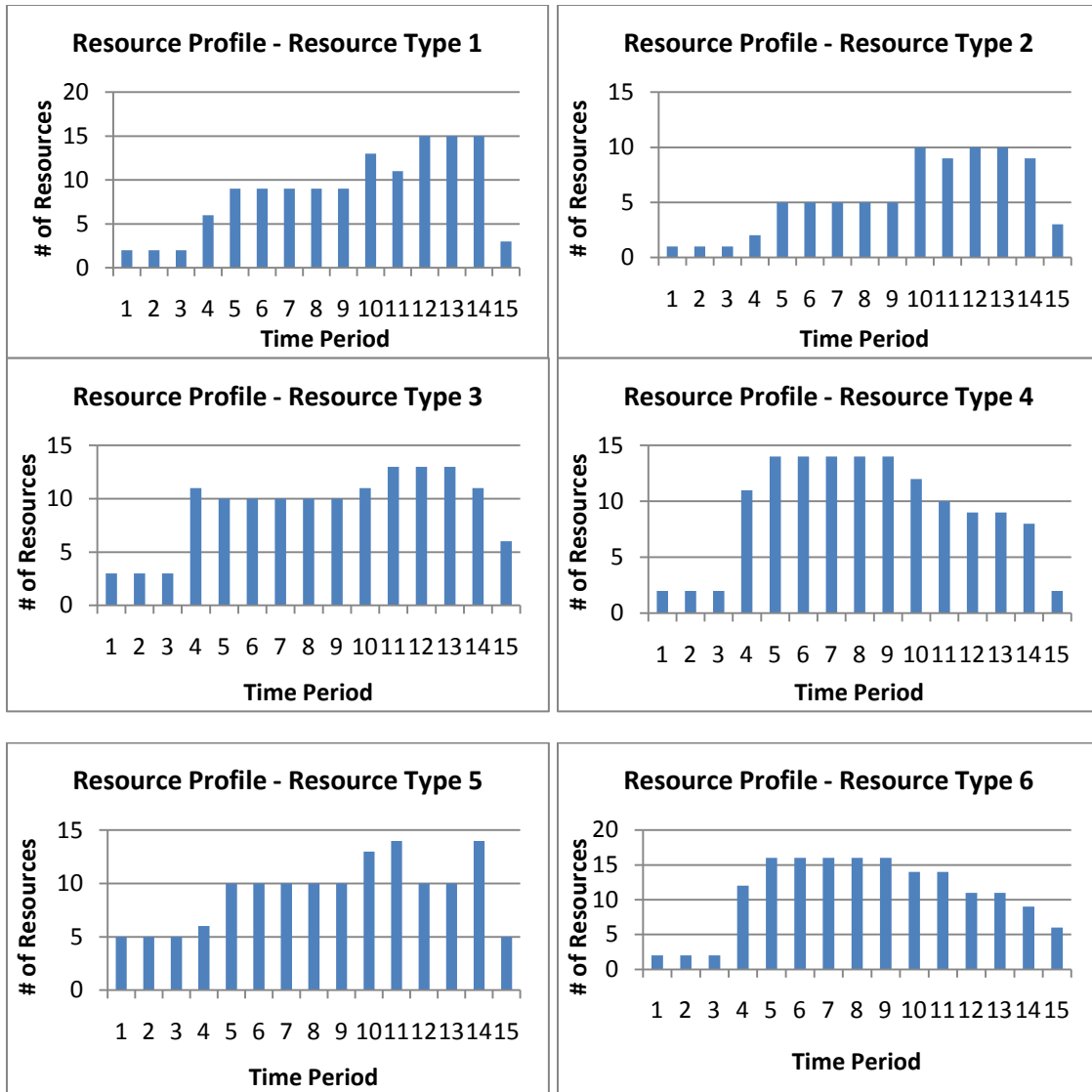


Figure 5: Resource Utilization for Illustrative Example (After Resource Leveling)

Finally, the optimal solution generated by this model has a total cost of 328 which is attained using the objective function of the model whose objective is to minimize total cost.

3.4 Benchmark Problems

As there are no benchmark problems available in the project scheduling literature, a set of test instances are developed to assess the solution quality of the proposed meta-heuristic approach. The test problems are generated by varying the number of non-critical activities, nn , and number of resource types, P . For each combination of $nn \in \{2, 4, 7, 8, 9, 10\}$ and $P \in \{2, 4, 6\}$, 10 instances with different problem parameters (i.e. varying the

resource utilization rates and costs) are created. Each of the 180 problem instances are setup in Microsoft Excel with the application of the cost optimization model of Hariga and El-Sayegh[4] and are then solved using What'sBest 9 from LINDO Systems. These obtained optimal solutions are later used as benchmarks to evaluate the cost performance of the proposed heuristic procedure. Appendix A contains the network diagrams and Appendix B contains the optimal cost and the computational time for the 180 instances.

3.5 Chapter Summary

For large number of non-critical activities and long activity scheduling intervals (difference between the latest finishing time and earliest starting time), the model becomes a large mixed binary linear program requiring a large number of calculations to produce an optimum solution. Therefore, one of the objectives of this research work is to develop a heuristic procedure that is computationally efficient and generates high quality solutions. In the next two chapters, the Particle Swarm Optimization and Simulated Annealing models for leveling resources with activity splitting are presented, respectively.

Chapter 4: Particle Swarm Optimization Based Solution for the Multi-Resource Problem with Activity Splitting

4.1 Introduction

The chapter begins with an overview of the original Particle Swarm Optimization (PSO), discrete PSO and quantum discrete PSO. Next, the particle swarm optimization search procedure is implemented for the resource leveling problem with activity splitting. Six heuristic techniques based on different PSO search procedures are then presented. Subsequently, the six procedures are assessed based on the cost and time performance using the 180 test problems generated in Chapter 3. Finally, the chapter concludes with a summary of the findings.

4.2 Overview of Particle Swarm Optimization

The PSO technique consists of a population of particles whereby each particle is represented by a position in n -dimensional space and a velocity. The velocity corresponds to the speed and direction at which the particle is moving. The particles update their positions and velocities using their own previous best positions, cognitive learning, and the best previous position of all the particles, social learning, which are known as local best positions and global best position, respectively. The following subsections describe three previously developed PSO models.

4.2.1 Continuous PSO

The PSO method is first developed by Kennedy and Eberhart [10] as a continuous PSO in which the positions of the particles are represented as real numbers. The PSO model consists of a population of P particles in the swarm, where each particle is initialized with a random position and velocity. Next, the PSO procedure searches iteratively for the best position (near or optimum) by updating each particle's velocity and position using its own previous best position and best position of all particles. The local and global bests are determined through the assessment of each particle's fitness values. The search continues until convergence is attained which is either when the allowed maximum number of iterations, K , is exceeded or a relatively steady position is reached (i.e. the algorithm is trapped in one of the local optimum).

The particle's position and velocity are represented by $X_i(k)$ and $V_i(k)$, for $i = 1, 2, \dots, P$ and $k = 1, 2, \dots, K$. The N -dimensional position for the i^{th} particle at the k^{th} iteration is denoted by

$$X_i(k) = [x_{i1}(k), x_{i2}(k), \dots, x_{iN}(k)]$$

where,

$x_{ij}(k)$ represents the j^{th} coordinate of the i^{th} particle for $j = 1, 2, \dots, N$.

Similarly, the particle's velocity for the i^{th} particle at the k^{th} iteration is represented by

$$V_i(k) = [v_{i1}(k), v_{i2}(k), \dots, v_{iN}(k)]$$

The updating mechanism of the i^{th} particle's velocity and position at the k^{th} iteration is performed using the following two equations, respectively [11]

$$V_i(k) = wV_i(k-1) + c_1r_1[X_i^L - X_i(k-1)] + c_2r_2[X^G - X_i(k-1)]$$

$$X_i(k) = V_i(k) + X_i(k-1)$$

where,

X_i^L is the local best position of the i^{th} particle found after the last $k-1$ iteration.

X^G is the global best position among all particles in the swarm visited so far.

w is the inertia weight used to reduce the impact of previous velocities on the current velocity so that it does not go out of control.

c_1 and c_2 are two positive parameters representing the cognition and social learning factors, respectively. If c_1 is large, then the particles tend to move towards their own local best, but if c_2 is large, then the particles tend to move towards the known global best so far.

r_1 and r_2 are random numbers between 0 and 1.

The velocity of any particle is restricted in the interval $[V_{min}, V_{max}]$. If the new velocity, V_{ij} is smaller than V_{min} , then V_{ij} is set to V_{min} . Similarly, if the new velocity, V_{ij} is larger than V_{max} , then V_{ij} is set to V_{max} .

4.2.2 Discrete PSO

Kennedy and Eberhart [12] developed a discrete binary PSO. The particles are represented as binary variables holding values of 0 or 1. Moreover, the velocities of the particle no longer represent the speed but rather represent either the probability of a position changing its value to one or the probability of a position being 0 [37, 41]. Thus, the values of the velocities are restricted to the interval [0, 1].

In discrete PSO, the particle's velocity is updated the same way as in the continuous PSO. However, a normalization function is used to transform the real numbers to binary numbers. This is done using the sigmoid function that is stated as follows:

$$v'_{ij}(k) = \text{sig}(v_{ij}(k)) = \frac{1}{1 + e^{-v_{ij}(k)}}$$

Once the velocity is normalized (i.e. its value is between 0 and 1), it is then used to update the position of the particle using the following equation:

$$x_{ij}(k+1) = \begin{cases} 1 & \text{if } r_{ij} < \text{sig}(v_{ij}(k+1)) \\ 0 & \text{otherwise} \end{cases}$$

where, r_{ij} is a random number between [0,1].

4.2.3 Quantum Discrete PSO

Yang et al. [40] proposed the quantum discrete PSO, which is based on quantum theory. In the quantum theory, the quantum particle position, $X_i(k)$, consists of qubits, where each qubit (or bit) holds the values of 0 or 1. A quantum particle vector, $V_i(k)$, denotes the particle's velocity, v_{ij} , which represents the probability that the j^{th} bit of the i^{th} particle being 0.

The quantum discrete PSO uses the following equations to update the velocity of the particle and to obtain a new binary position:

$$\begin{aligned} V_i^L(k) &= \alpha X_i^L(k) + \beta(1 - X_i^L(k)) \\ V_i^G(k) &= \alpha X_i^G(k) + \beta(1 - X_i^G(k)) \\ V_i(k) &= wV_i(k-1) + c_1 V_i^L(k) + c_2 V_i^G(k) \end{aligned}$$

$$X_i(k) = \begin{cases} 0 & \text{if } (rand < V_i(k)) \\ 1 & \text{otherwise} \end{cases}$$

where,

α and β are control parameters which indicate the control degree of V , with $\alpha + \beta = 1$ and $0 \leq \alpha, \beta \leq 1$.

w , c_1 , and c_2 represent the inertia weight, and the cognitive and social learning factors, respectively; where $w + c_1 + c_2 = 1$ and $0 \leq w, c_1, c_2 \leq 1$.

$rand$ is a random number generated between $[0, 1]$.

4.3 Implementation of PSO to the Resource Leveling Problem with Activity Splitting

In this research, a particle within the PSO population denotes a feasible schedule for a project having n activities and p resource types. Therefore, a particle represents the set of non-critical activities since the critical activities are not changed when leveling the resources.

Hereafter, each PSO particle consists of a number of bits, each representing the y_{ij} value of a given non-critical activity. Recall that the y_{ij} indicates if activity j is active at time period t . To illustrate this representation, consider a particle composed of the y_{ij} values of the example introduced in Chapter 3 (refer to the project's schedule in Table 2).

$$X_i(k) = [x_{i1}(k), x_{i2}(k), \dots, x_{iN}(k)]$$

where,

$$x_{ij}(k) = \{y_{tj} \text{ values of the } j^{\text{th}} \text{ non-critical activity of the } i^{\text{th}} \text{ particle at the } k^{\text{th}} \text{ iteration}\}$$

For example, referring to Table 2, the i^{th} particle, which is composed of 7 non-critical activities, is represented as

$$X_i(k) = \{x_{i1}(k), x_{i2}(k), \dots, x_{i7}(k)\}$$

$$X_i(k) = \left\{ (1, 0), (0, 1, 1, 1, 1, 1, 0, 0, 0, 0), (0, 0, 0, 0, 0, 0, 1, 1, 1, 0), (1, 1, 1, 1, 1, 1, 0, 1, 1, 1), (0, 0, 0, 0, 1), (0, 0, 1, 0, 0, 0), (0, 1, 0, 0, 0, 0) \right\}$$

Note that the dimension, or the total number of bits, of $X_i(k)$ is calculated as

$$\sum_{j=1}^N (LF_j - ES_j + 1)$$

Figure 6, below, depicts the pseudo-code for the PSO algorithm which consists of mainly two phases: initialization and searching for best particle. In the initialization phase, P particles with feasible schedules are first generated. In this research the first particle is composed of the project schedule resulting from the CPM method; i.e. a feasible schedule without splitting. As for the remaining $P - 1$ particles, they are randomly generated using the algorithm described in section 4.3.1, which ensures that the particles are feasible. Next, K and $maxK_{imp}$ are initialized to the maximum number of iterations and the maximum number of iterations without any cost improvement, respectively. Finally, k , the iteration counter is set to 1 and k_{imp} , the iteration improvement counter, is initialized to 0.

In the second phase, the particles' positions are assessed. First, the fitness, $F(X_i(k))$, of each particle, i , at the k^{th} iteration is computed. Next, $F(X_i(k))$ is compared with the fitness of the best local position for particle i , $F(X_i^L)$. If $F(X_i(k))$ is a better fit than $F(X_i^L)$, then X_i^L is set to $X_i(k)$ and $F(X_i^L)$ is set to $F(X_i(k))$. Similarly, $F(X_i(k))$ is compared with the fitness of the global best position, $F(X^G)$. If $F(X_i(k))$ has a better cost performance than the global best position, then the global best position, $F(X^G)$, is set to $F(X_i(k))$ and k_{imp} is initialized to zero since a new global best is found; otherwise k_{imp} is incremented. Afterwards, the velocity, $V_i(k)$, and the position, $X_i(k)$, of the i^{th} particle are updated. Finally, iteration counter, k , is incremented. The search for the best particle continues until either the iteration counter, k , reaches the maximum number of iterations, K , or k_{imp} reaches the maximum number of steady state iterations.

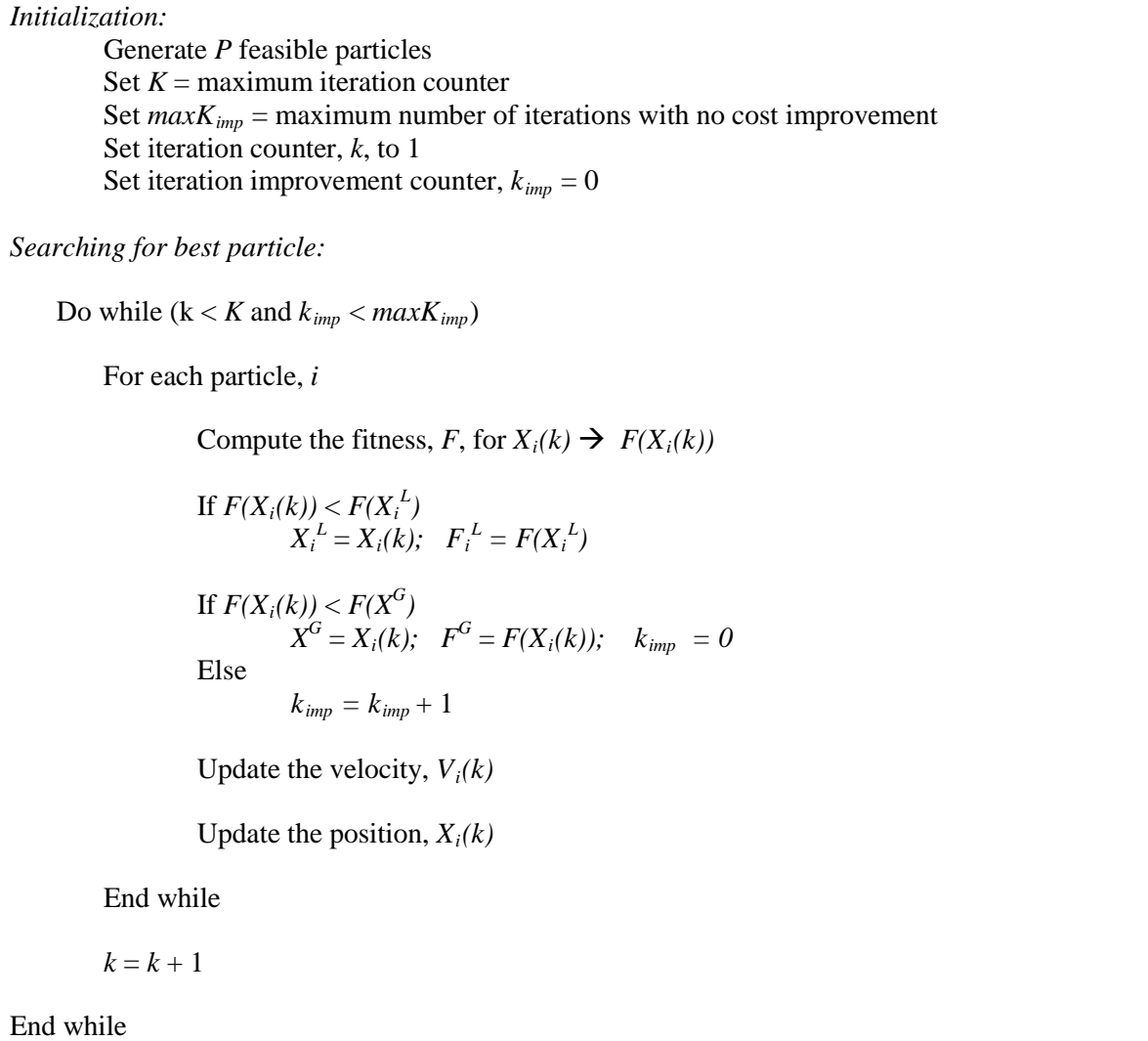


Figure 6: Pseudo-code for PSO Algorithm

4.3.1 Generation of the Initial Particle Positions

The initial particles of a population are generated such that each particle represents a feasible project schedule. A project schedule is feasible if it meets the duration constraint, where the sum of the y_{ij} values of each activity is equal to its duration, and the network logic constraint, where each activity starts once all of its predecessors are finished. (Refer to section 3.2 for more details) The first two steps of the algorithm ensure that the network logic constraints of the schedule are satisfied, and step 3 makes sure that the duration constraint is satisfied.

For each non-critical activity, j , within particle, i , the following steps are taken:

Step 1: If activity, j , does not have any non-critical activity as its predecessor:

- Generate a discrete random number between ES_j and $ES_j + TF_j - 1$.
- Set the starting time of activity j , S_j , to the generated random number.
- Set $y_{ij} = 0$, for all $ES_j, ES_j + 1, \dots, S_{j-1}$.
- Go to step 3

Step 2: If activity, j , does have some non-critical activities as predecessors:

- Find the finishing times of the non-critical predecessors, which have been already determined, and set F as the largest finishing time.
- Set $S_j = F + 1$
- Set $y_{ij} = 0$, for all $t < S_j$.
- Go to step 3.

Step 3:

- Generate T_j discrete random numbers between S_j and LF_j .
- Set the cells (y_{ij}) corresponding to these random numbers to 1 and the remaining y_{ij} values to 0.

Figure 7: Pseudo-code for the Generation of Feasible Particle Algorithm

4.3.2 Generation of the Initial Particle Velocities

For each of the particle, a position and a velocity is determined. The initial velocities, $V_{ij}(0)$, are created, by randomly generating numbers between the lower and upper bounds defined for the velocity. In this research, the lower and upper bounds are set as $V_{min} = 0$ and $V_{max} = 1$, respectively. This ensures that the velocity, which denotes a probability, is restricted to values between 0 and 1.

4.3.3 Transformation of a Particle's Position into a Feasible Particle's Position

Once a particle's position is updated, it is possible that the new position does not represent a feasible solution. Therefore, the algorithm below is applied to transform the updated particle's position into a particle representing a feasible project schedule.

For each non-critical activity, j , in the i^{th} particle,

1. If activity, j , does not have any non-critical activities as predecessors, go to step 6; otherwise continue to step 2.
2. Find the starting time for activity j , S_j , using equation 5 in chapter 3.
3. Calculate the finishing times of activity j 's predecessors and set F as the latest finishing time.
4. If $F > S_j$, then set $S_j = F + 1$.
5. For all $t < S_j$, set $y_{tj} = 0$.
6. Count the number of y_{tj} values that are equal to 1 between S_j and LF_j . If the sum of the ones is less than the activity's duration, T_j , continue on to step 7, otherwise go to step 12.
7. For $t \geq S_j$, count the number of y_{tj} values that are equal to zero, say z , and assign an equal probability for each, $\frac{1}{z}$.
8. Randomly choose a number between $[0,1]$, r .
9. If $r \in \left[\frac{u-1}{z}, \frac{u}{z} \right]$, where $u = 1, 2, \dots, z$, then set the u^{th} bit of the particle that has a value of 0 to 1.
10. Increment the count by 1.
11. Repeat steps 8-10 until the sum of the y_{tj} values that is equal to the activity's duration, T_j , and skip to step 17.
12. For $t \geq S_j$, count the number of y_{tj} values that are equal to one, say z , and assign an equal probability for each, $\frac{1}{z}$.
13. Randomly choose a number between $[0,1]$, r .
14. If $r \in \left[\frac{u-1}{z}, \frac{u}{z} \right]$ where $u = 1, 2, \dots, z$, then set the u^{th} bit of the particle that has a value of 1 to 0.
15. Decrement the count by 1.
16. Repeat steps 13-15 until the sum of the y_{tj} values is equal to the activity's duration, T_j .
17. Stop.

Figure 8: Pseudo-code for the Transformation of a Particle into a Feasible Particle Algorithm

Upon completing the afore-mentioned steps for all the non-critical activities, a feasible solution is attained. Note that if activity, j , has no predecessors, steps 2 – 5 are not required.

For example, assume that there are two activities A and B, where A is the predecessor of B. Activity A has duration of 2 and Activity B has duration of 3. Note that in the figure below, activity B does not meet the duration constraint. Therefore, the algorithm detailed above is utilized to attain a feasible solution as illustrated in Figures 9 and 10.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| A | 1 | 0 | 0 | 1 | | | | | |
| B | | | | 1 | 1 | 1 | 1 | 1 | 1 |

Figure 9: Example – Infeasible Solution

| | | | | | | | | | |
|---|---|---|---|-----|----------------|-----------------|-----------------|------------------|-----------|
| A | 1 | 0 | 0 | 1 | ES | | | | LF |
| B | | | | ± 0 | 1 | ± 0 | 1 | 1 | |
| Must be set to 0 to satisfy the precedence constraint | | | | | 0-25% u = 1 | 25-50% u = 2 | 50-75% u = 3 | 75-100% u = 4 | |

Figure 10: Example - Feasible Solution

Equal percentage ranges of $\frac{1}{4}$ are set for each y_{ij} having a value of 1 as shown in the figure above. A random number, r , is generated, and the range it falls within is determined. The value of y_{ij} having that range is set to 0. This procedure is repeated until the sum of the y_{ij} of Activity B becomes 3.

In order to calculate the cost for a particle, the bits of the particle’s position which consists of the y_{ij} values of the non-critical activities are input into the project’s schedule, and all of the cost components are computed. (Refer to section 3.2 for more information regarding the cost function.)

4.4 PSO Heuristic Procedures

In this research, six different PSO procedures are proposed, whereby in each procedure a different mechanism to update a particle’s velocity and/or position is employed. All of the six procedures utilize the PSO algorithm, summarized in section 4.3, to solve the 180 instance problems developed for this research.

Several experiments for each of the heuristic procedures are conducted; each with a different parameter setting (i.e. number of particles, maximum number of iterations, and maximum number of steady iterations). Based on the experiments, it is observed that the

PSO has more chances to hit the optimal solution for large numbers of particles; however, the optimal solution is generated at the expense of its time efficiency. Therefore, the size of the particle's population should balance the cost and time efficiencies of the PSO algorithm. In this study, the number of particles is problem dependent and is set equal to twice the number of binary variables; contrary to the PSO literature, where the number of particles is assumed to be fixed regardless of the size of the problem to be solved. Recall that for all problems the number of binary variables is equal to $\sum_{j=1}^{nn} (LF_j - ES_j + 1)$ which is small compared to the total number of possible solutions which is computed as

$$\# \text{ of possible solutions} = \prod_{j=1}^{nn} \binom{LF_j - ES_j + 1}{1}$$

Note that for each heuristic procedure, the maximum number of iterations is set to 400 with a steady position of no more than 100 iterations. (I.e. the global best position does not change in the last 100 iterations).

In the following subsections, a description of each heuristic procedure, which includes the update velocity and position mechanism, is presented. For illustrative purposes, each procedure is conducted for the project schedule example introduced in chapter 3. For each of the proposed heuristic procedures, the PSO algorithm is performed 10 times with the constant parameters representing the cognitive and social learning, c_1 and c_2 , are both set to 0.25 and the inertia weight, w , is set to 0.50. For each run, the global best particle position and its cost are recorded. After completing the 10 runs, the particle with the least cost among the global best positions of the 10 runs becomes the best solution of the resource leveling problem. Moreover, the computational time to complete the 10 runs is recorded. The results of the heuristics are summarized at the end of the section.

4.4.1 PSO Procedure 1

This heuristic is based on the continuous PSO model presented by Kenedy and Eberhart [10], where the new velocity of the i^{th} particle, $V_i(k)$, which is restricted to $[0, 1]$, is achieved using the equation:

$$V_i(k) = wV_i(k-1) + c_1r_1[X_i^L - X_i(k-1)] + c_2r_2[X^G - X_i(k-1)]$$

The particle's position is updated using

$$x_{ij}(k) = \begin{cases} 0 & \text{if } v_{ij}(k) < 0.5 \\ 1 & \text{otherwise} \end{cases}$$

Note that in this procedure the velocity is defined as the probability that the particle holds the value of 0 or 1. It is assumed that there is a 50-50 % chance for the particle to hold the values 0 or 1.

4.4.2 PSO Procedure 2

This heuristic is also based on the continuous PSO model presented by Kenedy and Eberhart [10]. However, the velocity is defined as the probability that the particle changes its value. The following mechanism is used to update the particle's position

$$x_{ij}(k) = \begin{cases} x_{ij}(k-1) & \text{if } v_{ij}(k) < 0.5 \\ 1 - x_{ij}(k-1) & \text{otherwise} \end{cases}$$

4.4.3 PSO Procedure 3

This procedure is based on the quantum discrete PSO algorithm, where the position of the particle contains only binary values. However, in this procedure the velocity is defined as the probability that the particle holds the value of 0 or 1. It is assumed that there is a 50-50 % chance for the particle to hold the values 0 or 1.

The new velocity of the i^{th} particle, $V_i(t)$, is achieved using the following set of equations:

$$V_i^L(k) = \alpha X_i^L(k) + \beta(1 - X_i^L(k))$$

$$V_i^G(k) = \alpha X^G(k) + \beta(1 - X^G(k))$$

$$V_i(k) = wV_i(k-1) + c_1V_i^L(k) + c_2V_i^G(k)$$

where,

α and β are random variables which indicate the control degree of V , with $\alpha + \beta = 1$ and $0 \leq \alpha, \beta \leq 1$.

w , c_1 , and c_2 represent the inertia weight, and the **cognitive and social learning** factors, respectively; where $w + c_1 + c_2 = 1$ and $0 \leq w, c_1, c_2 \leq 1$.

Next, the new position of the particle is determined as follows:

$$x_{ij}(k) = \begin{cases} 0 & \text{if } v_{ij}(k) < 0.5 \\ 1 & \text{otherwise} \end{cases}$$

4.4.4 PSO Procedure 4

This procedure also relies on the quantum discrete PSO algorithm, and therefore, uses the same set of equations to update the velocity. However, the velocity is defined as the probability that the particle changes its value. The new position of the particle is determined as follows:

$$x_{ij}(k) = \begin{cases} x_{ij}(k-1) & \text{if } v_{ij}(k) < 0.5 \\ 1 - x_{ij}(k-1) & \text{otherwise} \end{cases}$$

4.4.5 PSO Procedure 5

In this procedure, a new PSO discrete algorithm is introduced, which extends the discrete PSO of Kennedy and Eberhart. This procedure presents a newly developed mechanism which calculates the new velocity of a particle and uses the same algorithm as the one presented in PSO Procedure 4 to update the particle's position.

The following equations are used to update the velocity of a particle:

$$V_i^L(k) = \alpha * X_i^L(k) + (1 - \alpha) * (1 - X_i^L(k))$$

$$V_i^G(k) = \beta * X^G(k) + (1 - \beta) * (1 - X^G(k))$$

$$V_{New} = w * V_i(k-1) + c_1 * V_i^L(k) + c_2 * V_i^G(k)$$

where,

α and β are random variables which indicate the control degree of $V_i^l(k)$ and $V_i^r(k)$, with $0 \leq \alpha, \beta \leq 1$.

w , c_1 , and c_2 represent the inertia weight, and the cognitive and social learning factors, respectively; where $w + c_1 + c_2 = 1$ and $0 \leq w, c_1, c_2 \leq 1$.

The particle's position is updated using

$$x_{ij}(k) = \begin{cases} 0 & \text{if } v_{ij}(k) < 0.5 \\ 1 & \text{otherwise} \end{cases}$$

4.4.6 PSO Procedure 6

In this procedure, the same PSO algorithm presented in PSO Procedure 5 is conducted but with the following slight change to the update mechanism of the particle's position.

$$x_{ij}(k) = \begin{cases} x_{ij}(k-1) & \text{if } v_{ij}(k) < 0.5 \\ 1 - x_{ij}(k-1) & \text{otherwise} \end{cases}$$

Table 4 shows the summary of the results in terms of cost and computational time after performing each of the above-mentioned six heuristic procedures on the illustrative example of Chapter 3.

Table 4: Results of PSO Heuristic Procedures

| PSO Procedure | Cost | Computational Time (seconds) | Percentage Difference |
|--------------------|------|------------------------------|-----------------------|
| Optimization Model | 328 | 84 | 0% |
| PSO Procedure 1 | 382 | 27 | 16% |
| PSO Procedure 2 | 440 | 99 | 34% |
| PSO Procedure 3 | 368 | 5 | 12% |
| PSO Procedure 4 | 379 | 181 | 16% |
| PSO Procedure 5 | 390 | 54 | 19% |
| PSO Procedure 6 | 401 | 37 | 22% |

From Table 4, it can be noted that none of the PSO procedures were able to attain the optimal solution generated by the optimization model presented in Chapter 3 for this particular example. However, PSO Procedure 3 generated the nearest solution with a cost of 368 in 5 seconds, a 12% cost difference between the generated solution and the optimal.

4.5 Performance Analysis of the Six Heuristic Procedures

Each of the proposed six heuristic procedures is assessed using the 180 test problems generated in Chapter 3. The heuristic procedures are programmed in Java and are run on an HP Pavilion Notebook PC 2.13 GHz with 3.0 GB RAM. The same set of initial PSO particles, generated by setting the seed of the random number to “123456789”, is used for all of the procedures.

For each procedure, c_1 and c_2 are initially varied between [0.05, 0.95] with an increment of 0.05 (ie. $c_1 = 0.05$ and $c_2 = 0.05$, $c_1 = 0.05$ and $c_2 = 0.10$... $c_1 = 0.95$ and $c_2 = 0.05$). Upon running the six procedures with the different values of c_1 and c_2 , it is noted that when the value of c_1 is equal to the value of c_2 and are in the range of [0.20, 0.50] better results are obtained. In other words, when the particles move with equal probability to the best global solution, each heuristic procedure generates better results. Therefore, it is decided to analyze the results of the procedures when the values of c_1 and c_2 are equal to each other and vary in the interval [0.25, 0.45], with an increment of 0.05.

The performance of each heuristic procedure is based on the percentage deviation of its cost from the optimal solution and the CPU time. Appendix C contains the complete results (cost and CPU time) of the heuristic procedures assessed using all 180 test problems.

The cost quality of each heuristic is also assessed using the number of problems resulting in 0% cost deviation and the number of problems having a cost deviation of less than or equal to 2%, 5%, and 10%. Moreover, for each variation in c_1 and c_2 , the minimum, maximum, and average cost percentage difference for all the procedures are calculated.

Tables 5 to 10 report the results of the six PSO procedures when conducted for c_1 , c_2 equal to {0.25, 0.30, 0.35, 0.40, and 0.45}. The highlighted row in each table shows the best cost performance of the corresponding heuristic.

Table 5: PSO Procedure 1 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 15.47 | 47.72 | 59 | 61 | 74 | 78 |
| 0.30 | 0 | 16.48 | 47.72 | 53 | 57 | 68 | 72 |
| 0.35 | 0 | 15.61 | 58.33 | 52 | 57 | 66 | 70 |
| 0.40 | 0 | 13.47 | 37.70 | 52 | 56 | 66 | 73 |
| 0.45 | 0 | 13.52 | 53.33 | 51 | 54 | 67 | 79 |

Table 6: PSO Procedure 2 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 38.20 | 162.50 | 27 | 27 | 29 | 34 |
| 0.30 | 0 | 49.65 | 136.36 | 1 | 1 | 4 | 6 |
| 0.35 | 0 | 49.65 | 136.36 | 1 | 1 | 4 | 6 |
| 0.40 | 0 | 49.65 | 136.36 | 1 | 1 | 4 | 6 |
| 0.45 | 0 | 49.65 | 136.36 | 1 | 1 | 4 | 6 |

Table 7: PSO Procedure 3 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 7.74 | 34.51 | 57 | 66 | 91 | 114 |
| 0.30 | 0 | 8.89 | 38.64 | 51 | 61 | 78 | 105 |
| 0.35 | 0 | 7.50 | 35.29 | 63 | 69 | 90 | 116 |
| 0.40 | 0 | 7.76 | 31.11 | 66 | 72 | 89 | 110 |
| 0.45 | 0 | 7.85 | 33.33 | 63 | 69 | 89 | 112 |

Table 8: PSO Procedure 4 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 16.84 | 58.33 | 40 | 42 | 57 | 63 |
| 0.30 | 0 | 16.31 | 58.33 | 41 | 44 | 56 | 67 |
| 0.35 | 0 | 18.57 | 58.33 | 40 | 42 | 52 | 62 |
| 0.40 | 0 | 15.99 | 47.06 | 43 | 47 | 58 | 65 |
| 0.45 | 0 | 16.53 | 58.33 | 39 | 43 | 59 | 69 |

Table 9: PSO Procedure 5 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 19.48 | 60.00 | 39 | 40 | 45 | 54 |
| 0.30 | 0 | 20.96 | 100.00 | 36 | 36 | 42 | 53 |
| 0.35 | 0 | 22.53 | 67.24 | 31 | 31 | 33 | 43 |
| 0.40 | 0 | 23.97 | 109.09 | 30 | 31 | 34 | 41 |
| 0.45 | 0 | 24.21 | 81.81 | 31 | 32 | 36 | 41 |

Table 10: PSO Procedure 6 - Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 16.86 | 58.33 | 41 | 47 | 59 | 63 |
| 0.30 | 0 | 16.68 | 50.00 | 40 | 45 | 57 | 68 |
| 0.35 | 0 | 17.37 | 58.83 | 41 | 44 | 54 | 64 |
| 0.40 | 0 | 16.96 | 50.00 | 40 | 42 | 56 | 61 |
| 0.45 | 0 | 16.26 | 58.33 | 37 | 39 | 55 | 66 |

By comparing the results of the heuristic procedures conducted for all the test problems, it can be concluded that PSO Procedure 3 has generated the best results, in terms of percentage difference between the optimal and the yielded results. The generated project schedules have resulted in near optimum solutions, with an average percentage difference of 7.5%. Moreover, 116 problems have a percentage difference of less than or equal to 10%. PSO Procedure 2 has generated the worst results where in some instances only one problem out of the 180 had a percentage difference of 0.

For large size problems, the computational time is significantly less when performing resource leveling using the proposed heuristic procedures. Moreover, it can be noted that most runs of the PSO algorithms ended upon reaching 100 iterations, which means that the particles were trapped in local optimal and were unable to reach the global optimal solutions. Therefore, the need to combine Particle Swarm Optimization with Simulated Annealing is required to avoid having particles trapped in local optimum, and thus generate improved results (i.e. near optimum project schedules).

4.6 Chapter Summary

An overview of the original PSO, discrete PSO and quantum discrete PSO are presented. Furthermore, the particle swarm optimization model for resource leveling with activity splitting is discussed along with the algorithms to initialize particle positions and velocities as well as transforming particles into feasible project schedules. The constraints related to resource leveling have been discussed whereby a particle must satisfy the duration constraints and the network logic constraints. Moreover, six different heuristic procedures were presented and analyzed; each with a newly developed PSO approach. PSO Procedure 3 has shown good results with an average cost deviation of 7.5%. In the next chapter, each of the proposed PSO procedures is combined with Simulated Annealing to avoid particles from becoming trapped in local optimum and hence generate better results.

Chapter 5: Hybrid Particle Swarm Optimization and Simulated Annealing Solution to the Multi-Resource Leveling Problem with Activity Splitting

5.1 Introduction

The Particle Swarm Optimization heuristic has many advantages; some of these include its simplicity in coding, ease of implementation with fewer parameters to adjust and its consistency in performance, along with its local and global search abilities. However, one drawback of PSO is the possibility of being trapped in local optima. Therefore, PSO is combined with Simulated Annealing (SA) to overcome this deficiency.

This chapter begins with an overview of Simulated Annealing. Next, the Simulated Annealing search procedure is presented. Then, each of the six heuristic procedures presented in Chapter 4 is run for the illustrative example using PSO combined with SA. After that, the six heuristic procedures are assessed based on their cost and time performance. Finally, the chapter concludes with a summary of the findings.

5.2 Overview of Simulated Annealing

Simulated Annealing (SA) is a probabilistic based search meta-heuristic to locate a good solution to a global optimization problem with multiple local optimal. Simulated annealing was introduced by various researchers in the mid 1980s [42]. The concept of simulated annealing is based on the analogy between the simulation of the annealing of solids and the problem of solving large combinatorial optimization problems [8]. Annealing refers to the process in which the particles of a solid are randomly arranged once the solid turns to liquid at high temperatures. Technically speaking, as the temperature rises, the particles of a solid tend to move around each other faster to make new forms. One of the main advantages of simulated annealing is its ability to find good solutions without being trapped in a local optimum.

The Simulated Annealing search procedure consists of two phases: initialization and searching for the best neighboring solution. The initialization phase begins by setting an initial solution as the best solution found so far, *sbest*. The initial solution is usually the best solution generated by another search procedure. Also, the initial temperature,

$temp_0$, is set to a fixed or calculated temperature. $temp$ is first set to the initial temperature which decreases at a rate of λ as the procedure iterates to search for a good solution in the next phase.

In the second phase, the procedure iterates until it finds a candidate solution. During each iteration, a neighboring solution, s' , is generated from the neighborhood of s . Next, the fitness of the neighboring solution is computed, $F(s')$ and is compared to the fitness of the current solution s , $F(s)$, where their difference is stored as Δ . The neighboring solution is considered as a candidate for s_{best} if it is either a better solution than the one found so far or the probability of accepting a worse solution is high. This probability relies on the variable, $temp$, which represents the temperature in the annealing process. The higher the value of $temp$, the more chances a solution is accepted (i.e. more randomness). The following is a pseudo-code for the classical simulated annealing search procedure.

```

Initialization:
    Get initial solution,  $s$ 
    Set  $s_{best} = s$ 
    Set  $Temp_o =$  initial temperature
    Set  $Temp_f =$  final temperature
    Set  $Temp = Temp_o$ 
Searching for best neighboring solution:
    Do while  $Temp < Temp_f$ 
        Do while  $r < R$  (Perform the following steps  $R$  times)
            Generate randomly a neighboring solution  $s'$  from neighborhood of  $s$ 
            Compute fitness of  $s'$ 
            Compute  $\Delta =$  fitness ( $s'$ ) – fitness ( $s$ )
            If ( $\Delta \leq 0$ ,)
                 $s'$  is accepted and  $s_{best} = s'$ 
            Else
                If ( $rand < \exp(-\Delta/Temp)$ )
                     $s'$  is accepted and  $s_{best} = s'$ 
             $r \leftarrow r + 1$ 

```

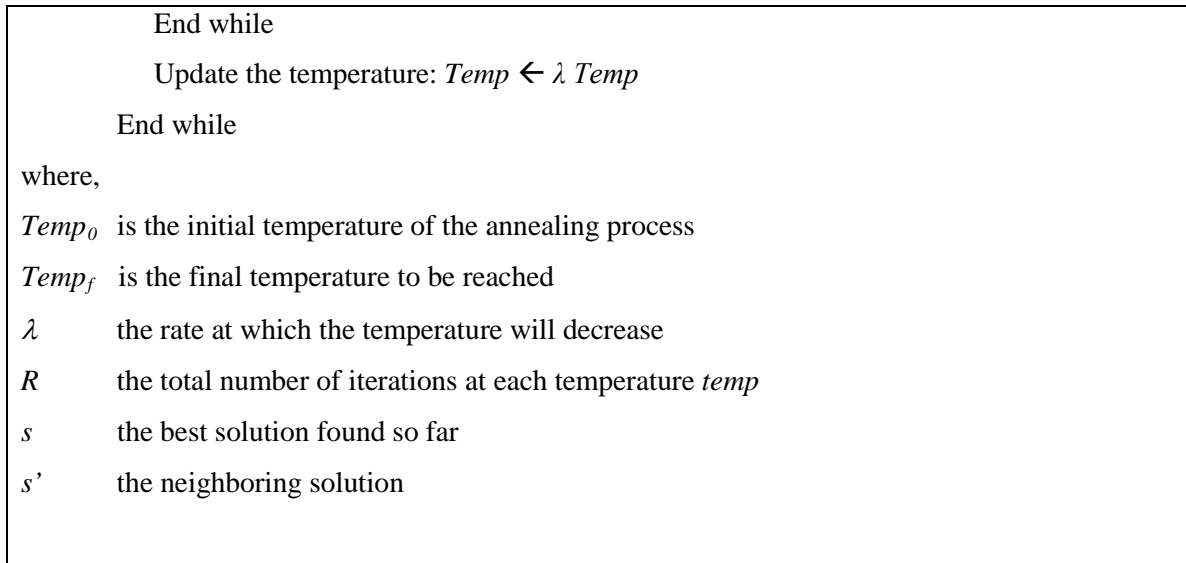


Figure 11: Pseudo-code for SA

5.3 Simulated Annealing for the Multi-Resource Leveling Problem with Activity Splitting

In this research, the Simulated Annealing algorithm is slightly modified in order to increase the chances of achieving a near optimum solution in less time. At each change in temperature, 10 neighboring solutions are generated as opposed to the general algorithm in which only one neighbor is generated. Next, the fitness is calculated for each of the neighboring solutions, and the neighboring solution with the best fit (s') is compared to the best solution found so far (s). Note that each neighboring solution represents a feasible project schedule which is generated using the neighborhood selection algorithm and the control parameter settings described in the subsequent subsections.

5.3.1 Neighborhood Selection

In this research, each neighboring solution represents a feasible project schedule, which is composed of the y_{ij} values of the non-critical activities. A neighboring solution is generated by swapping a random pair of y_{ij} 's having different values, for each of the non-critical activities within the particle. The pairs are determined using a discrete probability algorithm.

Prior to determining the pair to be swapped, the y_{ij} values of the non-critical activity must first satisfy the duration and the network logic constraints. In other words,

the sum of the y_{ij} values of the activity should be equal to its duration and that the y_{ij} 's of the activity are only active between its calculated start and finish times. Refer to section 4.3 for more details on how to transform an activity to a feasible activity.

For each feasible non-critical activity, two discrete random numbers between its starting and finishing times are generated, say u and v . If the values of y_{uj} and y_{vj} are different, then they are swapped. However, in case the two y_{ij} values are equal, two new random numbers are generated until they correspond to different y_{ij} values. This process is repeated for all of the non-critical activities within a particle, and thus, a new neighboring solution is generated.

5.3.2 Control Parameter Settings

The SA algorithm has several parameters. The main three parameters are $Temp_0$, $Temp_f$, and λ . $Temp_0$ denotes the initial temperature and $Temp_f$ is the final temperature. At each iteration of the algorithm, the temperature is decreased at a constant rate, λ , which is between 0 and 1. The smaller the value of λ , the slower the algorithm reaches the final temperature, and thus, increases the chances of finding a better solution. However, a slow search increases the computational time. Therefore, it is very important to choose wisely the settings of the parameters.

In this research, it is decided to vary the initial temperature depending on the problem's characteristic. In general, a neighboring solution at the n th iteration is accepted if it is a better fit (less cost) than the best generated solution so far or if it is near to the best solution by a certain probability, $e^{-\Delta/temp_n}$.

Let Δ denote the change in the fitness between the best solution, $F(s)$, and the neighboring solution, $F(s')$; $temp_n$ represent the current temperature, which is equivalent to $\lambda^n temp_0$; and P_{max} denote the maximum probability to accept a neighboring solution. Therefore, the initial temperature is determined using the acceptance probability as follows:

$$P_{max} = e^{-\Delta/temp_n}$$

$$P_{max} = e^{-\frac{\Delta}{\lambda^n temp_0}}$$

$$temp_0 = -\frac{\Delta}{\lambda^n \ln(P_{max})} > -\frac{\Delta}{\lambda \ln(P_{max})}$$

In this research, the initial temperature, $temp_0$, is calculated given that a neighboring solution is accepted with a maximum probability, P_{max} , of 80% and if there is an increase in the cost performance of no more than 20%. Thus,

$$\Delta = 0.20 * F(s)$$

Furthermore, since there is a tradeoff between the computational time and a good solution, the initial temperature is set as

$$temp_0 = -\frac{0.2 F(s)}{0.9 \ln(0.8)}$$

to reduce the computation time. Also, λ is set as 0.90, so that the temperature descends at a slower rate where there are more chances of finding a good solution.

5.4 Implementation of PSO and SA Search Procedure

The PSO/SA search procedure is composed of three stages. In the first stage, only the PSO search procedure is performed, with the number of particles equal to twice the number of y_{ij} values. During the run the local positions of each of the particles is updated along with the global best position of all the particles. The PSO search procedure stops by either reaching the maximum number of iterations or becoming stuck in local optimum.

In the next stage, the local best particle positions obtained from the previous stage are input in the SA search procedure. For each local best particle, 10 feasible neighboring solutions are generated. The neighboring solution with the least cost is selected to be compared to the best local solution of that particle. The selected neighboring solution is accepted as a good solution if it reduces the cost of the particle or if its cost is not greater than 20% of the best SA position. Once Simulated Annealing procedure ends by reaching the final temperature at 0.01, the global best PSO position is updated only if the SA has produced a better cost performance.

Finally, in the last stage, the PSO search procedure is performed one more time with SA output as initial particles. This procedure (PSO-SA-PSO) is repeated 10 times and the best global position is returned. (Refer to Figure 12)

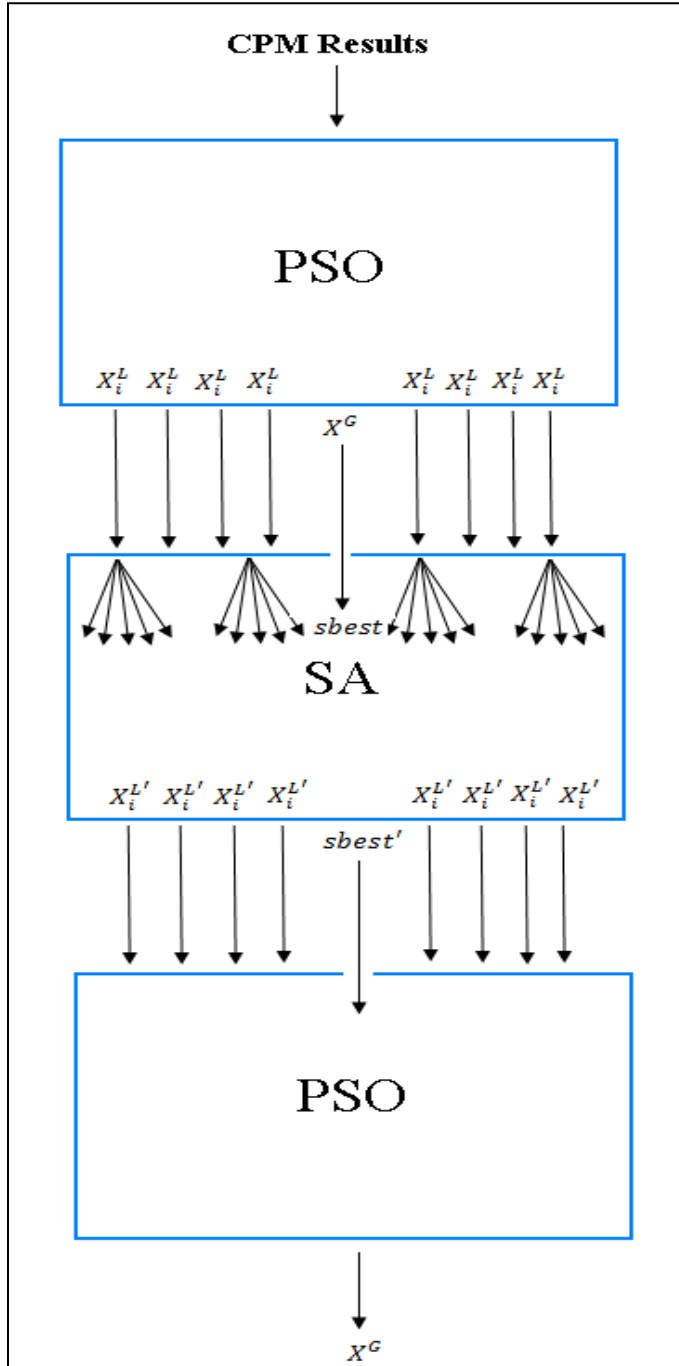


Figure 12: PSO-SA-PSO Search Procedure

5.5 PSO/SA Illustrative Examples

In this section, the six heuristic procedures, presented in Chapter 4, are extended to demonstrate the improvement resulting by incorporating the SA algorithm. Table 11 shows the results of the PSO heuristic procedures with SA that are attained for the illustrative example used throughout this research where $c_1 = c_2 = 0.25$.

Table 11: Results of PSO Heuristic Procedures with SA

| PSO/SA Procedure | PSO Results | | | PSO/SA Results | | |
|--------------------|-------------|------------------------------|-----------------------|----------------|------------------------------|-----------------------|
| | Cost | Computational Time (seconds) | Percentage Difference | Cost | Computational Time (seconds) | Percentage Difference |
| PSO/SA Procedure 1 | 382 | 27 | 16% | 335 | 222 | 2% |
| PSO/SA Procedure 2 | 440 | 99 | 34% | 348 | 239 | 6% |
| PSO/SA Procedure 3 | 368 | 5 | 12% | 328 | 264 | 0% |
| PSO/SA Procedure 4 | 379 | 181 | 16% | 345 | 432 | 5% |
| PSO/SA Procedure 5 | 390 | 54 | 19% | 343 | 174 | 5% |
| PSO/SA Procedure 6 | 401 | 37 | 22% | 343 | 269 | 5% |

By combining the PSO with SA, a better project schedule is generated, in terms of cost, for each of the six heuristic procedures. PSO/SA Procedure 3 actually generated the optimal solution having a cost of 328 within 264 seconds.

5.6 Performance Analysis for the Combined PSO/SA Search Procedure

Each of the six heuristic procedures is assessed using the 180 generated test problems. The PSO/SA procedure consists of three stages. In the first stage, only the PSO search procedure is performed. In the next stage, the local best particle positions obtained from the previous stage are input in the SA search procedure. For each local best particle, 10 feasible neighboring solutions are generated. The neighboring solution with the least cost is selected to be compared to the best local solution of that particle. The selected neighboring solution is accepted as a good solution if it reduces the cost of the particle or if its cost is not greater than 20% of the best SA position. Note that the search is reduced to neighboring solutions that will only result in an increase in cost of no more than 20%.

This will help to determine a good starting value of the temperature as discussed in section 5.3.2. Once the final temperature, which is set to 0.01, is reached, the global best PSO position is updated only if the Simulated Annealing has produced a better cost performance. Finally, in the last stage, the PSO search procedure is performed one more time with SA output as initial particles. This procedure (PSO-SA-PSO) is repeated 10 times and the best global position is returned.

5.6.1 Cost Performance of PSO/SA

For each procedure, the cost of the generated solution is recorded, in which the minimum, maximum, and average percentage difference on cost for all the procedures is calculated. The analysis performed is based upon the percentage difference of cost between the optimal solution and the generated solutions. Tables 12 to 17 report the results of the six PSO procedures combined with SA when conducted for c_1, c_2 equal to {0.25, 0.30, 0.35, 0.40, and 0.45}. The highlighted row in each table shows the best cost performance of the corresponding heuristic. Note that when $c_1, c_2 = 0.25$, PSO/SA procedure 3 resulted with an average cost difference of 4.23% and the costs of 147 out of the 180 problems were within 10% of the optimal ones.

Table 12: PSO/SA Procedure 1 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 6.85 | 23.53 | 67 | 77 | 89 | 115 |
| 0.30 | 0 | 6.94 | 23.53 | 58 | 69 | 85 | 116 |
| 0.35 | 0 | 7.39 | 23.53 | 56 | 66 | 77 | 112 |
| 0.40 | 0 | 7.02 | 22.41 | 57 | 70 | 79 | 117 |
| 0.45 | 0 | 7.31 | 22.22 | 57 | 65 | 77 | 114 |

Table 13: PSO/SA Procedure 2 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 9.67 | 47.06 | 46 | 55 | 71 | 95 |
| 0.30 | 0 | 10.11 | 58.33 | 46 | 53 | 74 | 99 |
| 0.35 | 0 | 10.11 | 58.33 | 46 | 53 | 74 | 99 |
| 0.40 | 0 | 10.11 | 58.33 | 46 | 53 | 74 | 99 |
| 0.45 | 0 | 10.11 | 58.33 | 46 | 53 | 74 | 99 |

Table 14: PSO/SA Procedure 3 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 4.23 | 18.18 | 87 | 95 | 113 | 147 |
| 0.30 | 0 | 4.79 | 18.18 | 74 | 88 | 107 | 143 |
| 0.35 | 0 | 4.47 | 20.00 | 84 | 95 | 112 | 147 |
| 0.40 | 0 | 4.29 | 22.41 | 82 | 95 | 111 | 149 |
| 0.45 | 0 | 4.85 | 19.82 | 75 | 88 | 108 | 144 |

Table 15: PSO/SA Procedure 4 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 7.94 | 45.83 | 53 | 61 | 75 | 102 |
| 0.30 | 0 | 7.72 | 24.24 | 56 | 60 | 72 | 107 |
| 0.35 | 0 | 8.67 | 39.39 | 56 | 65 | 79 | 104 |
| 0.40 | 0 | 7.73 | 22.15 | 53 | 58 | 70 | 104 |
| 0.45 | 0 | 7.78 | 33.33 | 55 | 64 | 73 | 109 |

Table 16: PSO/SA Procedure 5 – Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 8.37 | 34.09 | 48 | 57 | 70 | 102 |
| 0.30 | 0 | 8.23 | 58.33 | 50 | 59 | 73 | 105 |
| 0.35 | 0 | 8.65 | 33.33 | 45 | 54 | 75 | 103 |
| 0.40 | 0 | 8.61 | 47.73 | 43 | 52 | 70 | 106 |
| 0.45 | 0 | 9.19 | 58.33 | 44 | 57 | 72 | 103 |

Table 17: PSO/SA Procedure 6 - Results

| c1, c2 | % Difference | | | Frequency | | | |
|--------|--------------|---------|---------|-----------|------|------|-------|
| | Minimum | Average | Maximum | = 0% | ≤ 2% | ≤ 5% | ≤ 10% |
| 0.25 | 0 | 8.21 | 35.29 | 56 | 62 | 71 | 103 |
| 0.30 | 0 | 8.54 | 41.67 | 55 | 62 | 73 | 103 |
| 0.35 | 0 | 8.53 | 35.29 | 56 | 59 | 71 | 100 |
| 0.40 | 0 | 8.16 | 33.33 | 53 | 62 | 71 | 105 |
| 0.45 | 0 | 8.28 | 32.32 | 53 | 62 | 75 | 103 |

The combination of Particle Swarm Optimization with Simulated Annealing has allowed the particles to search for solutions in different spaces rather than becoming trapped in local optimum. By analyzing the results of the heuristic procedures assessed using the 180 test problems, it can be concluded that PSO/SA Procedure 3 has generated the best results, in terms of percentage difference between the optimal and generated results. The generated project schedules have resulted in near optimum solutions, with an average percentage difference of only 4.23%. Furthermore, 81.67% of the test problems have a percentage difference of less or to 10%.

5.6.2 Computation Time Performance of PSO/SA

For each heuristic, the time required to generate a solution, also known as the computational time, is recorded. The table below displays the computation times recorded for test problems 151 – 180, with 178 binary variables, using the exact optimization procedure and the PSO/SA Procedure 3, which generated the best results. (Refer to Appendix D for full results).

Table 18: Exact Procedure vs Best Heuristic Computation Times

| Problem # | Exact Time (seconds) | Best Heuristic Time (seconds) |
|-----------|----------------------|-------------------------------|
| 151 | 1189 | 487 |
| 152 | 1479 | 560 |
| 153 | 861 | 501 |
| 154 | 1299 | 505 |
| 155 | 1355 | 498 |
| 156 | 1937 | 541 |
| 157 | 2549 | 520 |
| 158 | 1789 | 563 |
| 159 | 728 | 517 |
| 160 | 621 | 528 |
| 161 | 5359 | 569 |
| 162 | 8861 | 560 |
| 163 | 6899 | 589 |
| 164 | 2544 | 588 |
| 165 | 6551 | 537 |
| 166 | 6121 | 617 |
| 167 | 2384 | 596 |
| 168 | 1680 | 626 |
| 169 | 4673 | 593 |
| 170 | 9064 | 617 |
| 171 | 5955 | 560 |
| 172 | 10785 | 638 |
| 173 | 4236 | 592 |
| 174 | 5935 | 603 |
| 175 | 4480 | 580 |
| 176 | 6492 | 609 |
| 177 | 2609 | 653 |
| 178 | 7153 | 630 |
| 179 | 5445 | 603 |
| 180 | 4743 | 626 |

It should be mentioned here that an odd time performance is noticed for the *What's Best* application utilized to solve the 180 procedures with the exact procedure. In some problem instances, the computation time of a given large size problem is smaller than another problem with fewer number of binary variables. For example, it takes

What's Best 15211 seconds to solve a problem with 130 binary variables. However, an optimal solution for a problem with 178 binary variables and the same number of resources is obtained after 2384 seconds. Moreover, the average computation times for problems with 130 and 178 binary variables are 6563 and 4192 seconds, respectively. This abnormal observation is explained by the fact that the time performance of *What's Best* depends on the initial solution entered in the Excel sheet. Obviously, if such initial solution is close to the optimal one, it will take shorter time to terminate. Consequently, it is decided to assess the time performance of PSO/SA only for large size problems with 178 binary variables. Note that from the above table that the computational time recorded using PSO/SA Procedure 3 is far less than the computational time of the optimization model. The average reduction in computation time for the large size problems is 7 times, where in some problems a computation time reduction of 15 times is attained.

To further illustrate the significance of the proposed heuristic procedure and to show the extent of time savings for larger problems, two relatively large problems with 25 activities, of which 15 are non-critical, are created. These two problems, having 320 binary variables, are solved using the exact and the proposed heuristic procedures. When solved for the exact procedure, the *What's Best* solver was interrupted after having computation times of more than 24 hours, and hence, no optimal solution is generated. However, when the two problems are run using the best PSO/SA heuristic approach (PSO Procedure 3), solutions are generated in 1380 and 1512 seconds, which is equivalent to 23 and 25 minutes, respectively. This proves that heuristic procedures are more computationally time efficient for large sized project schedules.

In conclusion, even with the implementation of Simulated Annealing along with the PSO model, the computational time is indeed significantly less the optimization model presented in Chapter 3 for large size problems. Moreover, the computational time of PSO/SA can be further reduced by carefully designing a time efficient mechanism for the update of the particles' position which does not affect the feasibility of the particles. In fact, through the experimentations of the PSO/SA search procedures, it can be noted that much of the computation time of the search procedures is taken in making the

particle feasible. The feasibility algorithm, introduced in section 4.3, is run for each particle after updating its position and at each iteration. This observation and its suggestion could be the subject of future research.

5.7 Chapter Summary

In this chapter each of the Particle Swarm Optimization heuristic procedures is combined with Simulated Annealing to overcome PSO's drawback of having particles being trapped in local optimum. First, an overview of Simulated Annealing is presented, which is followed by a description of the Simulated Annealing search procedure. Afterwards, a summary of the results of the heuristic PSO procedures with SA for the illustrative example are presented. The heuristic procedures were assessed using all the 180 problems, where it was evident that PSO/SA Procedure 3 has generated the best results with the lowest average in percentage change and the most number of problems with a percentage difference of less than or equal to 10%.

Chapter 6: Conclusion and Recommendations

Resource leveling is an important technique that is applied by project managers in order to improve the resource profile by minimizing the fluctuations in resource requirements. Most resource leveling techniques assumes that activities are continuous. A recent research proposed a new method to level resources while allowing activity splitting using optimization techniques. Optimization techniques allow reaching the optimum solution but it is time-consuming especially for large projects. Based on the review of the literature, it is clear that there is a need for a search procedure for the multi-resource leveling problem with activity splitting that is computationally efficient. This thesis presents Particle Swarm Optimization search procedures complemented with Simulated Annealing for the resource leveling of project schedules with activity splitting.

The first step in this research was to develop a set of 180 test problems to serve as benchmark problems in order to assess the performance of the proposed meta-heuristics. Each of the 180 problems was solved using the optimization model, where the cost and computation time were recorded. It was noted that as the size of the problem increased, the computation time increased dramatically. For example, a problem with 178 binary variables took an average of 4193 seconds to generate the optimal solution.

One of the main advantages of meta-heuristics is their ability to find near – optimum solutions in a short time period. The Particle Swarm Optimization procedure consists of a population of particles; each having a position and a velocity. The particles' positions and velocities are updated using their own previous best positions and the best position of all the other particles. In resource leveling terms, the particle's positions are represented by the y_{ij} values of the non-critical activities of a feasible project schedule.

In this research, six PSO heuristic approaches were developed; each having different approaches to update the particle's velocity and position. Each of the search procedures with different parameter settings were assessed using the 180 benchmark problems. The results were analyzed by calculating the minimum, average, and maximum percentage difference in costs for all the procedures. In addition, the cost quality of each heuristic was also assessed using the number of problems resulting in 0% cost deviation

and the number of problems having a cost deviation of less than or equal to 2%, 5%, and 10%.

By analyzing the results of the heuristic procedures conducted for all the test problems with variations in the parameters, it can be concluded that PSO Procedure, which is based on the quantum discrete PSO, has generated the best results, with an average percentage cost difference of 7.5%. Moreover, 116 out of the 180 problems have a percentage cost difference of less than or equal to 10%. As for the computation time, all the heuristic procedures were able to generate solutions in less time than the optimization procedure, especially for large problems. For example, a problem with 130 binary variables generated an optimal solution in 4382 seconds while the heuristic procedure generated a solution with a 2% cost difference in 130 seconds.

However, it was noticed that for large size problems the heuristics were trapped in local optimum and the search discontinued. Therefore, it was decided to take the PSO search procedure a step further to combine it with Simulated Annealing. The main purpose of Simulated Annealing is to move particles to different search spaces without being trapped in local optimum. In SA, a neighboring solution is determined by swapping one pair of distinct y_{ij} values for each non-critical activity within a particle.

The six heuristic procedures, along with their different parameter variations, were assessed using the 180 benchmark problems. For each heuristic procedure, the minimum, maximum, and average cost is calculated along with the percentage cost difference. PSO/SA Procedure 3, having $c_1 = c_2 = 0.25$, has attained the best results with an average cost difference of 4.23% and the costs of 147 out of the 180 problems were within 10% of the optimal ones. Furthermore, 81.67% of the test problems have a percentage difference of less than or equal to 10%. As for the computation time, the heuristic procedures generated solutions in less time as compared to the optimization model. The average reduction in computation time for the large size problems is 7 times, where in some problems a computation time reduction of 15 times is attained.

Furthermore, to illustrate the significance of the proposed heuristic procedure, two project schedules having 25 activities, of which 15 are non-critical, were created. These

two problems, having 320 binary variables, were solved using the exact and the proposed heuristic procedures. The exact procedure was unable to generate solutions for both of these schedules within a 24 hour time period. However, the proposed heuristic procedure generated results within 25 minutes; a large saving in the time. Therefore, this proves that heuristic procedures are more computationally time efficient.

This research is an important additional step in the ongoing research on resource leveling. The proposed heuristic procedure offers several improvements over the current resource leveling techniques. The proposed procedure allows for activity splitting, which is more realistic and results in better resource profile. The new procedure takes advantage of combining Particle Swarm Optimization with Simulated Annealing to reach the optimum or near optimum solution in a short period. The proposed procedure allows planners to consider the tradeoff between the cost of activity splitting and the cost of resource fluctuations resulting in a minimum overall project cost.

It is recommended that a software program is developed that enables the use of this procedure by leading scheduling software such as Primavera and Microsoft project. This will make it easier for practitioners to use this technique. Another recommendation for future research is to use this technique to solve the combined problem of resource leveling and time-cost tradeoff with and without allowed activity splitting. The improvement of the computation time of the hybrid PSO/SA is another line of future research. Indeed, based on our numerical experimentation with the proposed heuristics, the mechanism for particle position's update can be redesigned so that it does not affect the feasibility of the algorithm. Finally, one more topic for future research is to compare the proposed PSO/SA search procedure with other meta-heuristics such as genetic or tabu search procedures.

References

- [1] PMBOK, *A Guide to the Project Management Body of Knowledge*, 4th Edition, Project Management Institute, 2008.
- [2] H. Kerzner, *Project Management: A System Approach to Planning, Scheduling, and Controlling*, 9th Edition, John Wiley & Sons Inc., 2009.
- [3] W. S. Herroelen, “Resource-Constrained Project Scheduling – The State of the Art,” *Operational Research Quarterly*, vol. 23, no. 3, pp. 261-275, September 1972.
- [4] M. Hariga and S. M. El-Sayegh, “Cost Optimization for the Multi-Resource Leveling Problem with Allowed Activity Splitting,” *Journal of Construction Engineering and Management*, ASCE, vol. 137, no. 1, pp. 56-64, January 2011.
- [5] F. S. Hillier and G. J. Lieberman, *Introduction to Operations Research*, 9th Edition, New York: McGraw – Hill International Edition, 2010.
- [6] S. M. Easa, “Resource Leveling in Construction by Optimization,” *Journal of Construction Engineering and Management*, ASCE, vol. 115, no. 2, June 1989.
- [7] F. Glover, “Future Paths for Integer Programming and Links to Artificial Intelligence,” *Computers and Operations Research*, vol. 5, pp. 533-549, 1986.
- [8] P. Laarhoven and E. Aarts. *Simulated Annealing: Theory and Applications*. Dordrecht, The Netherlands: Kluwer Academic Publisher, 1987.
- [9] A. P. Engelbrecht, *Fundamentals of Computational Swarm Intelligence*, John Wiley & Sons Ltd, Chichester, England, 1995.
- [10] J. Kennedy and R. Eberhart, “Particle Swarm Optimization,” *IEEE International Conference in Neural Networks*, vol. 4, pp. 1942-1948, 1995.
- [11] H. Zhang, H. Li, and C. M. Tam, “Particle Swarm Optimization for Resource-Constrained Project Scheduling,” *International Journal of Project Management*, vol. 24, pp. 83-92, 2006.

- [12] J. Kennedy and R. Eberhart, "A Discrete Binary Version of the Particle Swarm Algorithm", *IEEE International Conference on Systems, Man, and Cybernetics*, vol. 5, pp.4104-4108, 1997.
- [13] C. F. Gray and E. W. Larson, *Project Management: The Managerial Process*, 4th Edition, New York: McGraw-Hill Irwin, 2008.
- [14] J. W. Hinze, *Construction Planning and Scheduling*, 3rd Edition. New Jersey: Pearson Prentice Hall, 2008.
- [15] T. Hegazy, *Computer-based Construction Project Management*, New Jersey: Prentice Hall, 2002.
- [16] R. B. Harris, *Precedence and Arrow networking Techniques for Construction*, New York: Wiley, 1978.
- [17] M. A. Hiyassat, "Modification of Minimum Moment Approach in Resource Leveling," *Journal of Construction Engineering and Management*, vol. 126, no. 4, July/August 2000.
- [18] M. A. Hiyassat, "Applying Modified Minimum Moment Method to Multiple Resource Leveling," *Journal of Construction Engineering and Management*, vol. 127, no. 3, May/June 2001.
- [19] R. B. Harris, "Packing Method for Resource Leveling (PACK)," *Journal of Construction Engineering and Management*, vol. 116, no. 2, June 1990.
- [20] H. Zhang, H. Li, and C. M. Tam, "Heuristic Scheduling of Resource-Constrained, Multiple Mode and Repetitive Projects," *Construction Management and Economics*, vol. 24, pp. 159-169, February 2006.
- [21] A. B. Pritsker, L. J. Watters, and P. M. Wolfe, "Multi-Project Scheduling with Limited Resources: A Zero-One Programming Approach," *Management Science*, vol. 16, no. 1, September 1969.

- [22] R. N. Ramlogan and I. C. Goulter, "Mixed Integer Model for Resource Allocation in Project Management," *Engineering Optimization*, vol. 15, pp. 97-111, 1989.
- [23] M. Bandelloni, M. Tucci, and R. Rinaldi, "Optimal Resource Leveling using Non-Serial Dynamic Programming," *European Journal of Operational Research*, vol. 78, pp. 162-177, 1994.
- [24] N. Nudtasomboon and S. U. Randhawa, "Resource-Constrained Project Scheduling with Renewable and Non-Renewable Resources and Time-Resource Tradeoffs," *Computers and Industrial Engineering*, vol. 32, no. 1, pp. 227-242, 1997.
- [25] K. G. Mattila and D. M. Abraham, "Resource Leveling of Linear Schedules Using Integer Linear Programming," *Journal of Construction Engineering and Management*, ASCE, vol. 124, no. 3, May/June 1998.
- [26] A. B. Senouci and H. Adeli, "Resource Scheduling Using Neural Dynamics Model of Adeli and Park", *Journal of Construction Engineering and Management*, ASCE, vol. 127, no. 1, January/February 2001.
- [27] J. Son and K. G. Mattila, "Binary Resource Leveling Model: Activity Splitting Allowed," *Journal of Construction Engineering and Management*, ASCE, vol. 130, no. 6, December 2004.
- [28] S. S. Leu and C. H. Yang, "A Genetic-Algorithm-Based Resource-Constrained Construction Scheduling System," *Construction Management and Economics*, vol. 17, pp. 767-776, 1999.
- [29] S. S. Leu and T. H. Hung, "A Genetic Algorithm-Based Optimal Resource-Constrained Scheduling Simulation Model," *Construction Management and Economics*, vol. 20, pp. 131-141, 2002.
- [30] N. Dawood and E. Sriprasert, "Construction Scheduling Using Multi-Constraint and Genetic Algorithms Approach," *Construction Management and Economics*, vol. 24, pp. 19-30, January 2006.

- [31] J. R. Montoya-Torres, E. Gutierrez-Franco, and C. Pirachicán-Mayorga, "Project Scheduling with Limited Resources Using a Genetic Algorithm," *International Journal of Project Management*, vol. 28, no. 6, pp. 619-628, August 2010.
- [32] A. B. Senouci and N. N. Eldin, "Use of Genetic Algorithms in Resource Scheduling of Construction Projects," *Journal of Construction Engineering and Management*, ASCE, vol. 130, no. 6, December 2004.
- [33] S. Christodoulou, "Scheduling Resource-Constrained Projects with Ant Colony Optimization Artificial Agents," *Journal of Computing in Civil Engineering*, vol. 24, no. 1, January 2010.
- [34] H. Zhang, H. Li, and C. M. Tam, "Particle Swarm Optimization for Preemptive Scheduling under Break and Resource-Constraints," *Journal of Construction Engineering and Management*, ASCE, vol. 132, no. 3, March 2006.
- [35] J. Son and M. J. Skibniewski, "Multiheuristic Approach for Resource Leveling Problem in Construction Engineering: Hybrid Approach," *Journal of Construction Engineering and Management*, ASCE, vol. 125, no. 1, January/February 1999.
- [36] H. Zhang, H. Li, and C. M. Tam, "Permutation-Based Particle Swarm Optimization for Resource-Constrained Project Scheduling," *Journal of Computing in Civil Engineering*, vol. 20, no. 2, March 2006.
- [37] M. A. Khanesar, "A Novel Binary Particle Swarm Optimization," *Proceedings of the 15th Mediterranean Conference on Control & Automation*, Athens, Greece, T33-001, July 2007.
- [38] X. Jun and H. Chang, "The Discrete Binary Version of the Improved Particle Swarm Optimization Algorithm," *International Conference on Management and Service Science*, pp. 1-6, September 2009.
- [39] C. J. Liao, C. T. Tseng, and P. Luarn, "A Discrete Version of Particle Swarm Optimization for Flowshop Scheduling Problems," *Computers & Operations Research*, vol. 34, no. 10, pp. 3099-3111, 2007.

[40] S. Yang, M. Wang, and L. Jiao, "A Quantum Particle Swarm Optimization," *Congress on Evolutionary Computations*, pp 320-324, 2004.

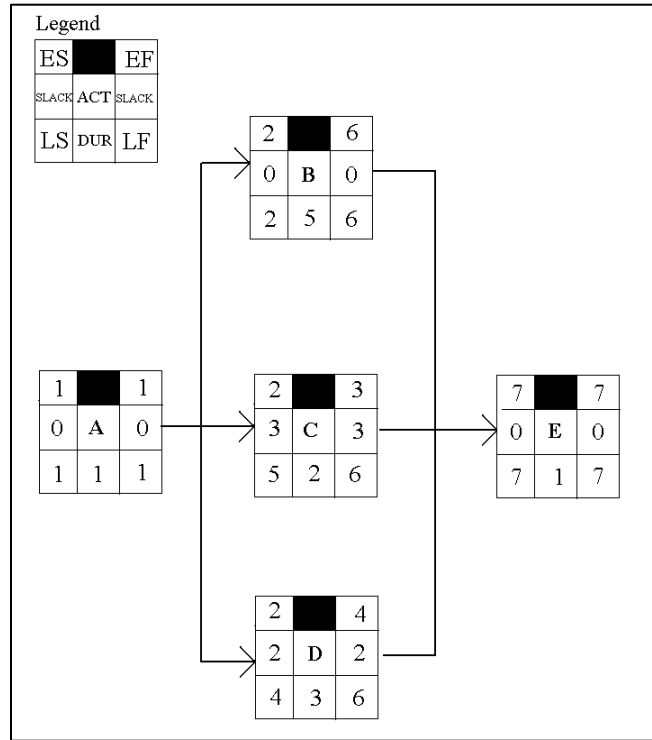
[41] A. Chen, G. Yang, and Z. Wu, "Hybrid Discrete Particle Swarm Optimization algorithm for Capacitated Vehicle Routing Problem," *Journal of Zhejiang University Science A*, vol. 7, no. 4, pp. 607-614, 2006.

[42] S. Luke, *Essentials of Metaheuristics*, 2009. [E-book]
Available: <http://cs.gmu.edu/~sean/book/metaheuristics>.

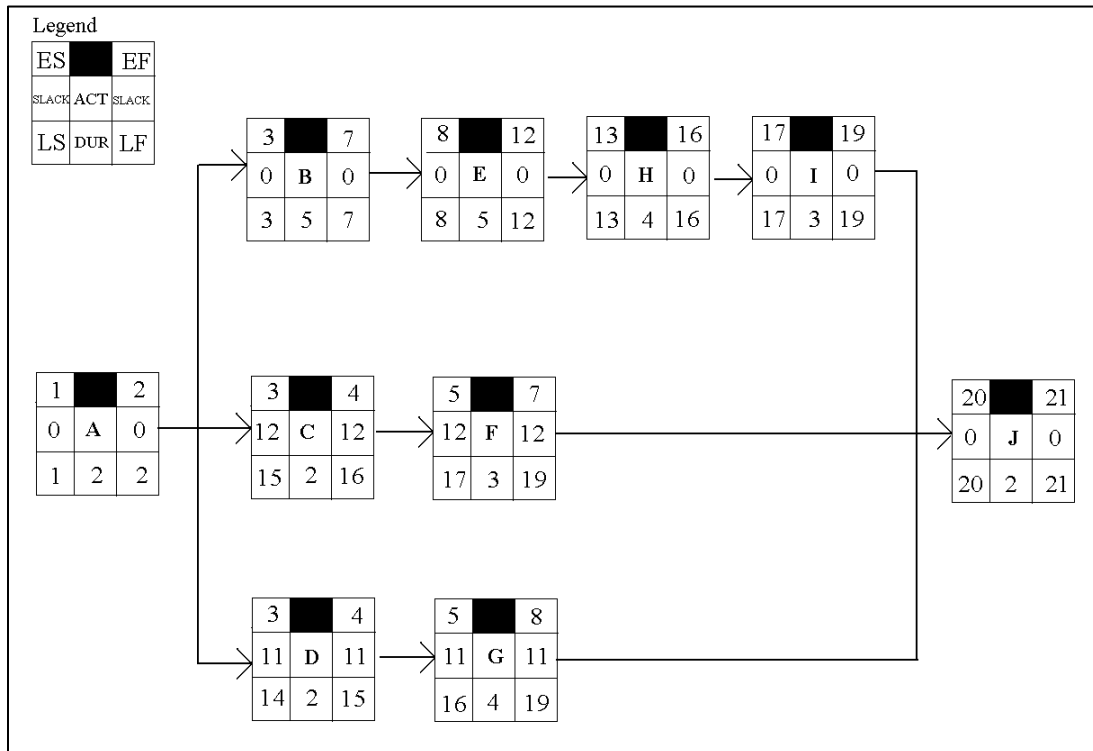
Appendix A

Network Diagrams for the 180 Test Problems

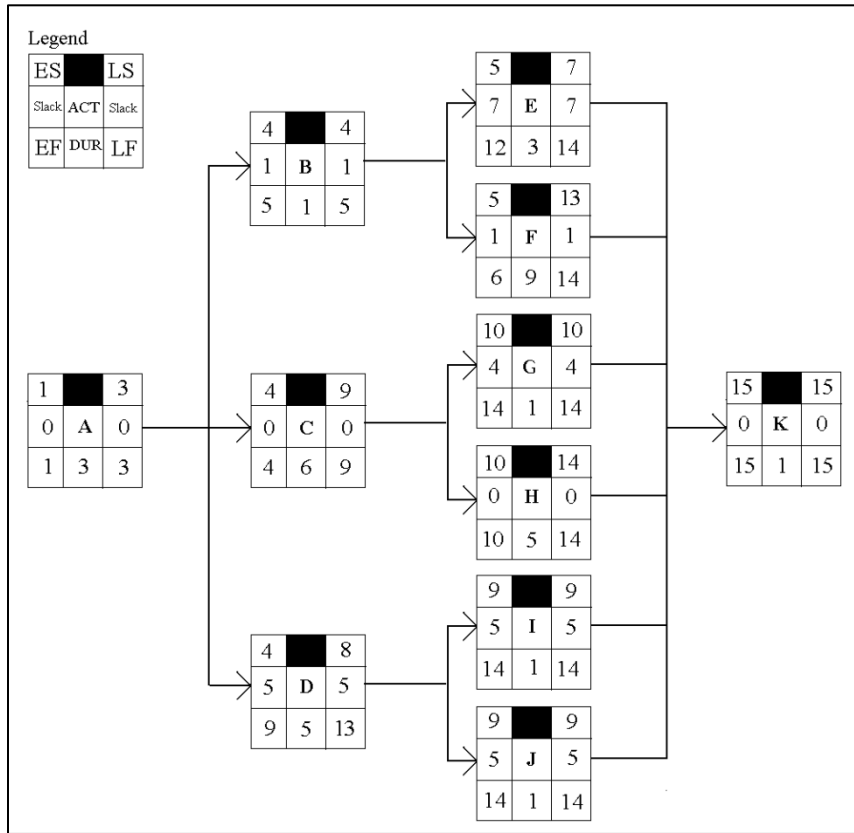
Number of Non-Critical Activities: 2



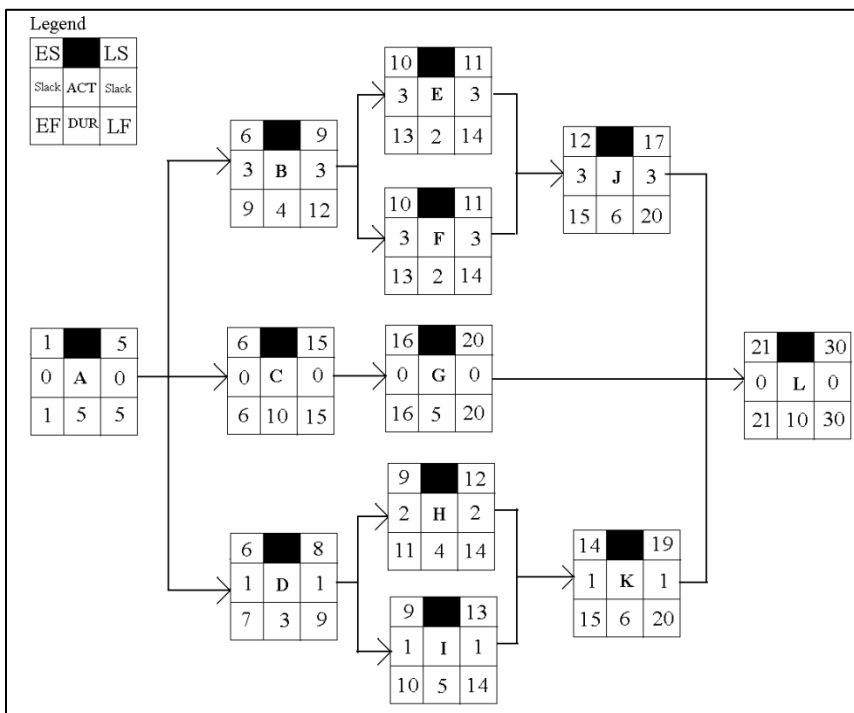
Number of Non-Critical Activities: 4



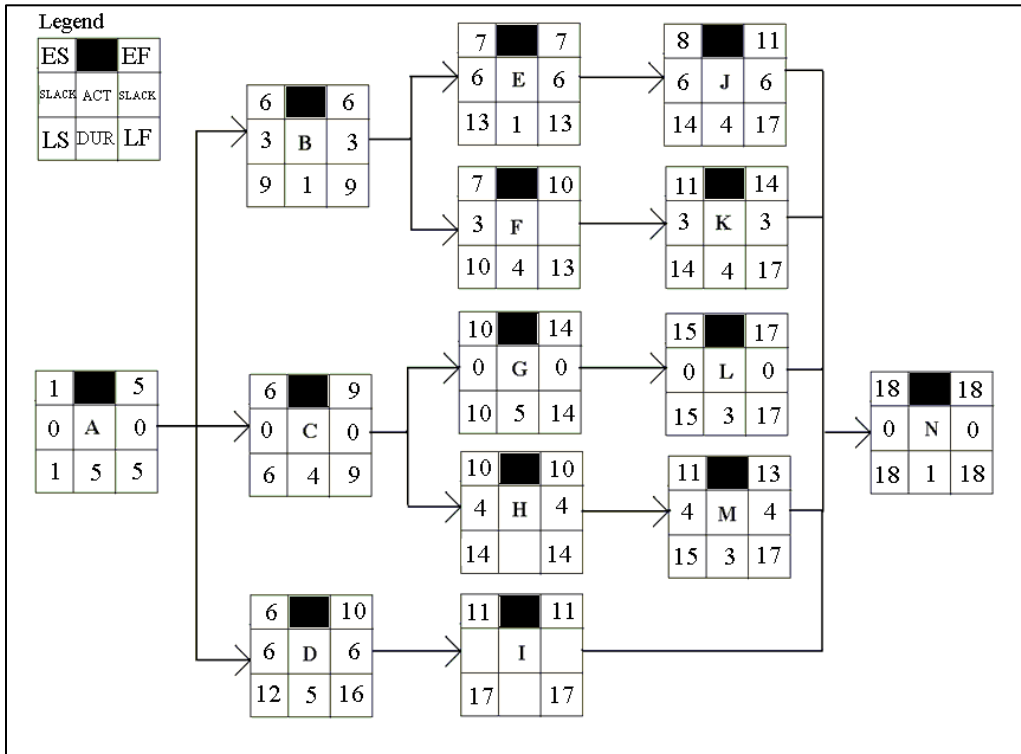
Number of Non-Critical Activities: 7



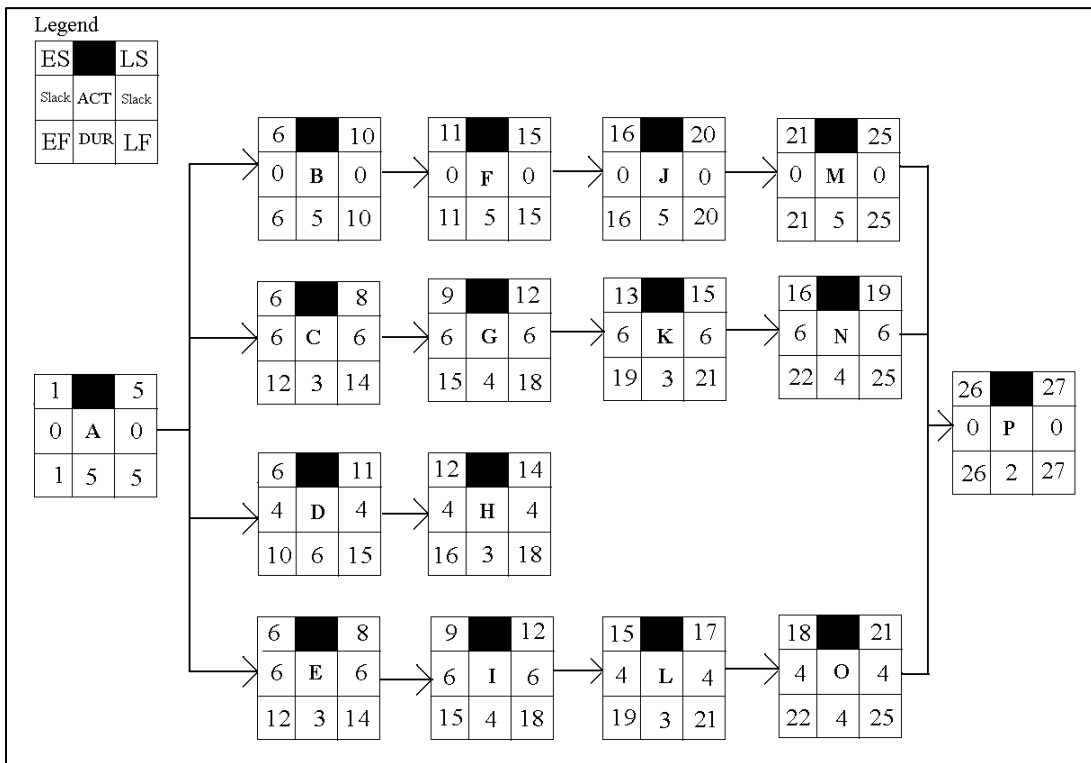
Number of Non-Critical Activities: 8



Number of Non-Critical Activities: 9



Number of Non-Critical Activities: 10



Appendix B Optimization Results for 180 Test Problems

| Problem # | # of Non-Critical Activities | # of Resources | Instance # | # of Binary Variables | Optimal Cost | Time in Seconds |
|-----------|------------------------------|----------------|------------|-----------------------|--------------|-----------------|
| 1 | 2 | 2 | 1 | 20 | 7.00 | 0 |
| 2 | 2 | 2 | 2 | 20 | 14.00 | 0 |
| 3 | 2 | 2 | 3 | 20 | 9.00 | 0 |
| 4 | 2 | 2 | 4 | 20 | 7.00 | 0 |
| 5 | 2 | 2 | 5 | 20 | 16.00 | 0 |
| 6 | 2 | 2 | 6 | 20 | 14.00 | 0 |
| 7 | 2 | 2 | 7 | 20 | 9.00 | 0 |
| 8 | 2 | 2 | 8 | 20 | 16.00 | 0 |
| 9 | 2 | 2 | 9 | 20 | 11.00 | 0 |
| 10 | 2 | 2 | 10 | 20 | 17.00 | 0 |
| 11 | 2 | 4 | 1 | 20 | 18.00 | 0 |
| 12 | 2 | 4 | 2 | 20 | 61.00 | 0 |
| 13 | 2 | 4 | 3 | 20 | 49.00 | 0 |
| 14 | 2 | 4 | 4 | 20 | 48.00 | 0 |
| 15 | 2 | 4 | 5 | 20 | 61.00 | 0 |
| 16 | 2 | 4 | 6 | 20 | 49.00 | 0 |
| 17 | 2 | 4 | 7 | 20 | 92.00 | 0 |
| 18 | 2 | 4 | 8 | 20 | 92.00 | 0 |
| 19 | 2 | 4 | 9 | 20 | 44.00 | 0 |
| 20 | 2 | 4 | 10 | 20 | 54.00 | 0 |
| 21 | 2 | 6 | 1 | 20 | 35.00 | 0 |
| 22 | 2 | 6 | 2 | 20 | 95.00 | 0 |
| 23 | 2 | 6 | 3 | 20 | 82.00 | 0 |
| 24 | 2 | 6 | 4 | 20 | 35.00 | 0 |
| 25 | 2 | 6 | 5 | 20 | 95.00 | 0 |
| 26 | 2 | 6 | 6 | 20 | 82.00 | 0 |
| 27 | 2 | 6 | 7 | 20 | 142.00 | 0 |
| 28 | 2 | 6 | 8 | 20 | 142.00 | 0 |
| 29 | 2 | 6 | 9 | 20 | 98.00 | 0 |
| 30 | 2 | 6 | 10 | 20 | 113.00 | 0 |
| 31 | 4 | 2 | 1 | 114 | 17.00 | 6 |
| 32 | 4 | 2 | 2 | 114 | 33.00 | 3 |
| 33 | 4 | 2 | 3 | 114 | 24.00 | 4 |
| 34 | 4 | 2 | 4 | 114 | 17.00 | 5 |
| 35 | 4 | 2 | 5 | 114 | 33.00 | 5 |
| 36 | 4 | 2 | 6 | 114 | 24.00 | 4 |
| 37 | 4 | 2 | 7 | 114 | 40.00 | 2 |
| 38 | 4 | 2 | 8 | 114 | 54.00 | 5 |
| 39 | 4 | 2 | 9 | 114 | 44.00 | 4 |
| 40 | 4 | 2 | 10 | 114 | 99.00 | 8 |
| 41 | 4 | 4 | 1 | 114 | 67.00 | 16 |
| 42 | 4 | 4 | 2 | 114 | 239.00 | 85 |
| 43 | 4 | 4 | 3 | 114 | 220.00 | 93 |
| 44 | 4 | 4 | 4 | 114 | 67.00 | 23 |
| 45 | 4 | 4 | 5 | 114 | 334.00 | 84 |
| 46 | 4 | 4 | 6 | 114 | 239.00 | 67 |
| 47 | 4 | 4 | 7 | 114 | 220.00 | 94 |
| 48 | 4 | 4 | 8 | 114 | 334.00 | 18 |
| 49 | 4 | 4 | 9 | 114 | 220.00 | 30 |
| 50 | 4 | 4 | 10 | 114 | 191.00 | 10 |
| 51 | 4 | 6 | 1 | 114 | 108.00 | 181 |
| 52 | 4 | 6 | 2 | 114 | 326.00 | 176 |
| 53 | 4 | 6 | 3 | 114 | 298.00 | 129 |
| 54 | 4 | 6 | 4 | 114 | 108.00 | 49 |
| 55 | 4 | 6 | 5 | 114 | 520.00 | 48 |

| | | | | | | |
|-----|---|---|----|-----|--------|-----|
| 56 | 4 | 6 | 6 | 114 | 326.00 | 186 |
| 57 | 4 | 6 | 7 | 114 | 298.00 | 134 |
| 58 | 4 | 6 | 8 | 114 | 426.00 | 167 |
| 59 | 4 | 6 | 9 | 114 | 332.00 | 58 |
| 60 | 4 | 6 | 10 | 114 | 380.00 | 326 |
| 61 | 7 | 2 | 1 | 98 | 33.00 | 1 |
| 62 | 7 | 2 | 2 | 98 | 65.00 | 1 |
| 63 | 7 | 2 | 3 | 98 | 58.00 | 1 |
| 64 | 7 | 2 | 4 | 98 | 33.00 | 1 |
| 65 | 7 | 2 | 5 | 98 | 65.00 | 1 |
| 66 | 7 | 2 | 6 | 98 | 58.00 | 0 |
| 67 | 7 | 2 | 7 | 98 | 90.00 | 0 |
| 68 | 7 | 2 | 8 | 98 | 79.00 | 1 |
| 69 | 7 | 2 | 9 | 98 | 97.00 | 1 |
| 70 | 7 | 2 | 10 | 98 | 122.00 | 1 |
| 71 | 7 | 4 | 1 | 98 | 83.00 | 6 |
| 72 | 7 | 4 | 2 | 98 | 263.00 | 24 |
| 73 | 7 | 4 | 3 | 98 | 241.00 | 29 |
| 74 | 7 | 4 | 4 | 98 | 84.00 | 2 |
| 75 | 7 | 4 | 5 | 98 | 263.00 | 7 |
| 76 | 7 | 4 | 6 | 98 | 241.00 | 6 |
| 77 | 7 | 4 | 7 | 98 | 420.00 | 17 |
| 78 | 7 | 4 | 8 | 98 | 208.00 | 3 |
| 79 | 7 | 4 | 9 | 98 | 392.00 | 13 |
| 80 | 7 | 4 | 10 | 98 | 250.00 | 4 |
| 81 | 7 | 6 | 1 | 98 | 141.00 | 19 |
| 82 | 7 | 6 | 2 | 98 | 380.00 | 58 |
| 83 | 7 | 6 | 3 | 98 | 346.00 | 53 |
| 84 | 7 | 6 | 4 | 98 | 142.00 | 8 |
| 85 | 7 | 6 | 5 | 98 | 382.00 | 15 |
| 86 | 7 | 6 | 6 | 98 | 348.00 | 10 |
| 87 | 7 | 6 | 7 | 98 | 588.00 | 45 |
| 88 | 7 | 6 | 8 | 98 | 539.00 | 25 |
| 89 | 7 | 6 | 9 | 98 | 328.00 | 84 |
| 90 | 7 | 6 | 10 | 98 | 503.00 | 99 |
| 91 | 8 | 2 | 1 | 98 | 41.00 | 6 |
| 92 | 8 | 2 | 2 | 98 | 78.00 | 5 |
| 93 | 8 | 2 | 3 | 98 | 74.00 | 6 |
| 94 | 8 | 2 | 4 | 98 | 42.00 | 4 |
| 95 | 8 | 2 | 5 | 98 | 80.00 | 4 |
| 96 | 8 | 2 | 6 | 98 | 76.00 | 4 |
| 97 | 8 | 2 | 7 | 98 | 106.00 | 7 |
| 98 | 8 | 2 | 8 | 98 | 114.00 | 7 |
| 99 | 8 | 2 | 9 | 98 | 100.00 | 5 |
| 100 | 8 | 2 | 10 | 98 | 162.00 | 4 |
| 101 | 8 | 4 | 1 | 98 | 86.00 | 31 |
| 102 | 8 | 4 | 2 | 98 | 260.00 | 34 |
| 103 | 8 | 4 | 3 | 98 | 236.00 | 33 |
| 104 | 8 | 4 | 4 | 98 | 86.00 | 6 |
| 105 | 8 | 4 | 5 | 98 | 260.00 | 4 |
| 106 | 8 | 4 | 6 | 98 | 236.00 | 5 |
| 107 | 8 | 4 | 7 | 98 | 410.00 | 8 |
| 108 | 8 | 4 | 8 | 98 | 212.00 | 9 |
| 109 | 8 | 4 | 9 | 98 | 218.00 | 6 |
| 110 | 8 | 4 | 10 | 98 | 430.00 | 8 |
| 111 | 8 | 6 | 1 | 98 | 139.00 | 27 |
| 112 | 8 | 6 | 2 | 98 | 373.00 | 14 |
| 113 | 8 | 6 | 3 | 98 | 356.00 | 15 |
| 114 | 8 | 6 | 4 | 98 | 139.00 | 6 |
| 115 | 8 | 6 | 5 | 98 | 603.00 | 15 |
| 116 | 8 | 6 | 6 | 98 | 373.00 | 7 |
| 117 | 8 | 6 | 7 | 98 | 356.00 | 9 |
| 118 | 8 | 6 | 8 | 98 | 598.00 | 12 |

| | | | | | | |
|-----|----|---|----|-----|---------|-------|
| 119 | 8 | 6 | 9 | 98 | 528.00 | 15 |
| 120 | 8 | 6 | 10 | 98 | 751.00 | 17 |
| 121 | 9 | 2 | 1 | 130 | 45.00 | 167 |
| 122 | 9 | 2 | 2 | 130 | 94.00 | 481 |
| 123 | 9 | 2 | 3 | 130 | 90.00 | 448 |
| 124 | 9 | 2 | 4 | 130 | 50.00 | 194 |
| 125 | 9 | 2 | 5 | 130 | 236.00 | 539 |
| 126 | 9 | 2 | 6 | 130 | 151.00 | 349 |
| 127 | 9 | 2 | 7 | 130 | 143.00 | 412 |
| 128 | 9 | 2 | 8 | 130 | 226.00 | 605 |
| 129 | 9 | 2 | 9 | 130 | 149.00 | 107 |
| 130 | 9 | 2 | 10 | 130 | 195.00 | 254 |
| 131 | 9 | 4 | 1 | 130 | 99.00 | 4496 |
| 132 | 9 | 4 | 2 | 130 | 279.00 | 2267 |
| 133 | 9 | 4 | 3 | 130 | 289.00 | 5146 |
| 134 | 9 | 4 | 4 | 130 | 104.00 | 1604 |
| 135 | 9 | 4 | 5 | 130 | 468.00 | 4382 |
| 136 | 9 | 4 | 6 | 130 | 289.00 | 7514 |
| 137 | 9 | 4 | 7 | 130 | 299.00 | 15211 |
| 138 | 9 | 4 | 8 | 130 | 480.00 | 9382 |
| 139 | 9 | 4 | 9 | 130 | 490.00 | 5610 |
| 140 | 9 | 4 | 10 | 130 | 529.00 | 9041 |
| 141 | 9 | 6 | 1 | 130 | 180.00 | 30725 |
| 142 | 9 | 6 | 2 | 130 | 433.00 | 7457 |
| 143 | 9 | 6 | 3 | 130 | 443.00 | 9550 |
| 144 | 9 | 6 | 4 | 130 | 188.00 | 10688 |
| 145 | 9 | 6 | 5 | 130 | 695.00 | 16826 |
| 146 | 9 | 6 | 6 | 130 | 440.00 | 3955 |
| 147 | 9 | 6 | 7 | 130 | 450.00 | 5925 |
| 148 | 9 | 6 | 8 | 130 | 702.00 | 13175 |
| 149 | 9 | 6 | 9 | 130 | 450.00 | 18051 |
| 150 | 9 | 6 | 10 | 130 | 1469.00 | 12334 |
| 151 | 10 | 2 | 1 | 178 | 59.00 | 1189 |
| 152 | 10 | 2 | 2 | 178 | 214.00 | 1479 |
| 153 | 10 | 2 | 3 | 178 | 122.00 | 861 |
| 154 | 10 | 2 | 4 | 178 | 118.00 | 1299 |
| 155 | 10 | 2 | 5 | 178 | 60.00 | 1355 |
| 156 | 10 | 2 | 6 | 178 | 128.00 | 1937 |
| 157 | 10 | 2 | 7 | 178 | 124.00 | 2549 |
| 158 | 10 | 2 | 8 | 178 | 299.00 | 1789 |
| 159 | 10 | 2 | 9 | 178 | 174.00 | 728 |
| 160 | 10 | 2 | 10 | 178 | 178.00 | 621 |
| 161 | 10 | 4 | 1 | 178 | 104.00 | 5359 |
| 162 | 10 | 4 | 2 | 178 | 316.00 | 8861 |
| 163 | 10 | 4 | 3 | 178 | 285.00 | 6899 |
| 164 | 10 | 4 | 4 | 178 | 302.00 | 2544 |
| 165 | 10 | 4 | 5 | 178 | 107.00 | 6551 |
| 166 | 10 | 4 | 6 | 178 | 288.00 | 6121 |
| 167 | 10 | 4 | 7 | 178 | 305.00 | 2384 |
| 168 | 10 | 4 | 8 | 178 | 483.00 | 1680 |
| 169 | 10 | 4 | 9 | 178 | 489.00 | 4673 |
| 170 | 10 | 4 | 10 | 178 | 525.00 | 9064 |
| 171 | 10 | 6 | 1 | 178 | 153.00 | 5955 |
| 172 | 10 | 6 | 2 | 178 | 338.00 | 10785 |
| 173 | 10 | 6 | 3 | 178 | 385.00 | 4236 |
| 174 | 10 | 6 | 4 | 178 | 408.00 | 5935 |
| 175 | 10 | 6 | 5 | 178 | 153.00 | 4480 |
| 176 | 10 | 6 | 6 | 178 | 640.00 | 6492 |
| 177 | 10 | 6 | 7 | 178 | 697.00 | 2609 |
| 178 | 10 | 6 | 8 | 178 | 460.00 | 7153 |
| 179 | 10 | 6 | 9 | 178 | 344.00 | 5445 |
| 180 | 10 | 6 | 10 | 178 | 700.00 | 4743 |

Appendix C PSO Heuristic Procedures – Results

PSO Heuristic Procedure 1

| | | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | | | | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | |
|-----------|-----------|-----------------------|-----------|-----------------------|-----------|-----------------------|-----------|-----------------------|-----------|-----------------------|-----------|-----------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|
| Problem # | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Problem # | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 91 | 42 | 5 | 42 | 5 | 42 | 5 | 42 | 5 | 42 | 5 | 42 | 6 |
| 2 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 1 | 14 | 0 | 92 | 80 | 208 | 80 | 93 | 79 | 156 | 80 | 86 | 79 | 156 | 79 | 156 |
| 3 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 93 | 76 | 133 | 75 | 157 | 76 | 112 | 76 | 27 | 76 | 5 | 76 | 5 |
| 4 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 94 | 42 | 5 | 42 | 5 | 42 | 9 | 42 | 6 | 42 | 6 | 42 | 6 |
| 5 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 95 | 80 | 5 | 80 | 6 | 80 | 5 | 80 | 5 | 82 | 5 | 82 | 5 |
| 6 | 14 | 1 | 14 | 1 | 14 | 0 | 14 | 0 | 14 | 0 | 96 | 76 | 5 | 76 | 5 | 76 | 5 | 76 | 5 | 78 | 24 | 78 | 24 |
| 7 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 97 | 111 | 169 | 111 | 141 | 111 | 5 | 111 | 133 | 111 | 79 | 111 | 79 |
| 8 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 98 | 114 | 5 | 114 | 5 | 114 | 5 | 114 | 6 | 114 | 5 | 114 | 5 |
| 9 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 99 | 101 | 6 | 101 | 6 | 101 | 5 | 101 | 5 | 101 | 9 | 101 | 9 |
| 10 | 17 | 1 | 17 | 0 | 17 | 0 | 17 | 0 | 17 | 0 | 100 | 164 | 157 | 177 | 143 | 169 | 5 | 177 | 147 | 169 | 223 | 169 | 223 |
| 11 | 18 | 1 | 18 | 0 | 18 | 0 | 18 | 0 | 18 | 1 | 101 | 86 | 6 | 86 | 5 | 86 | 5 | 86 | 7 | 86 | 7 | 86 | 7 |
| 12 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 102 | 260 | 6 | 260 | 6 | 260 | 6 | 260 | 5 | 260 | 6 | 260 | 6 |
| 13 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 103 | 236 | 5 | 236 | 6 | 236 | 5 | 236 | 5 | 236 | 6 | 236 | 6 |
| 14 | 48 | 0 | 48 | 0 | 48 | 0 | 48 | 0 | 48 | 0 | 104 | 86 | 5 | 86 | 5 | 86 | 5 | 86 | 5 | 86 | 6 | 86 | 6 |
| 15 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 105 | 260 | 6 | 260 | 5 | 260 | 6 | 260 | 6 | 260 | 5 | 260 | 5 |
| 16 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 1 | 106 | 236 | 5 | 236 | 6 | 236 | 6 | 236 | 5 | 236 | 5 | 236 | 5 |
| 17 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 107 | 410 | 5 | 410 | 6 | 410 | 6 | 410 | 5 | 410 | 6 | 410 | 6 |
| 18 | 92 | 0 | 92 | 1 | 92 | 0 | 92 | 0 | 92 | 1 | 108 | 212 | 6 | 212 | 6 | 212 | 5 | 212 | 7 | 212 | 6 | 212 | 6 |
| 19 | 44 | 0 | 44 | 0 | 44 | 0 | 44 | 0 | 44 | 0 | 109 | 218 | 5 | 218 | 5 | 218 | 6 | 218 | 6 | 218 | 6 | 218 | 6 |
| 20 | 54 | 0 | 54 | 0 | 54 | 0 | 54 | 0 | 54 | 0 | 110 | 430 | 5 | 430 | 6 | 430 | 5 | 430 | 6 | 430 | 7 | 430 | 7 |
| 21 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 111 | 144 | 10 | 145 | 88 | 145 | 91 | 142 | 134 | 144 | 8 | 144 | 8 |
| 22 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 112 | 386 | 202 | 384 | 69 | 379 | 220 | 379 | 66 | 386 | 143 | 386 | 143 |
| 23 | 82 | 0 | 82 | 1 | 82 | 0 | 82 | 1 | 82 | 1 | 113 | 369 | 202 | 362 | 222 | 367 | 116 | 356 | 91 | 362 | 128 | 362 | 128 |
| 24 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 114 | 145 | 6 | 145 | 5 | 145 | 179 | 147 | 56 | 145 | 193 | 145 | 193 |
| 25 | 95 | 1 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 115 | 632 | 37 | 612 | 133 | 612 | 127 | 612 | 38 | 620 | 180 | 620 | 180 |
| 26 | 82 | 0 | 82 | 0 | 82 | 1 | 82 | 1 | 82 | 0 | 116 | 383 | 247 | 383 | 147 | 386 | 121 | 388 | 161 | 383 | 120 | 383 | 120 |
| 27 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 117 | 366 | 247 | 369 | 93 | 356 | 41 | 366 | 248 | 356 | 35 | 356 | 35 |
| 28 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 118 | 630 | 205 | 620 | 118 | 638 | 119 | 612 | 139 | 598 | 155 | 598 | 155 |
| 29 | 98 | 0 | 98 | 0 | 98 | 0 | 98 | 0 | 98 | 1 | 119 | 548 | 37 | 546 | 69 | 537 | 225 | 548 | 146 | 528 | 10 | 528 | 10 |
| 30 | 113 | 0 | 113 | 0 | 113 | 0 | 113 | 1 | 113 | 0 | 120 | 773 | 6 | 774 | 31 | 773 | 6 | 773 | 5 | 773 | 60 | 773 | 60 |
| 31 | 20 | 40 | 19 | 52 | 19 | 31 | 19 | 32 | 18 | 65 | 121 | 57 | 8 | 61 | 245 | 57 | 242 | 57 | 194 | 57 | 70 | 57 | 70 |
| 32 | 37 | 61 | 40 | 31 | 36 | 92 | 39 | 29 | 33 | 44 | 122 | 120 | 9 | 126 | 201 | 115 | 281 | 119 | 113 | 114 | 9 | 114 | 9 |
| 33 | 35 | 31 | 35 | 31 | 38 | 26 | 24 | 28 | 28 | 3 | 123 | 107 | 143 | 122 | 200 | 120 | 235 | 107 | 75 | 121 | 40 | 121 | 40 |
| 34 | 21 | 60 | 25 | 25 | 25 | 79 | 23 | 3 | 25 | 78 | 124 | 64 | 38 | 62 | 66 | 60 | 8 | 60 | 260 | 60 | 8 | 60 | 8 |
| 35 | 36 | 21 | 47 | 78 | 44 | 2 | 37 | 4 | 36 | 71 | 125 | 291 | 112 | 262 | 141 | 291 | 114 | 285 | 48 | 300 | 179 | 300 | 179 |
| 36 | 29 | 40 | 29 | 40 | 34 | 103 | 28 | 4 | 35 | 15 | 126 | 184 | 114 | 163 | 142 | 186 | 50 | 188 | 8 | 173 | 70 | 173 | 70 |
| 37 | 44 | 21 | 44 | 21 | 44 | 21 | 44 | 21 | 44 | 22 | 127 | 176 | 113 | 184 | 116 | 179 | 17 | 184 | 115 | 155 | 149 | 155 | 149 |
| 38 | 76 | 30 | 76 | 29 | 70 | 30 | 68 | 4 | 60 | 21 | 128 | 304 | 251 | 284 | 288 | 302 | 212 | 294 | 308 | 284 | 105 | 284 | 105 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 39 | 65 | 28 | 65 | 28 | 65 | 28 | 49 | 69 | 54 | 62 | 129 | 190 | 114 | 176 | 142 | 190 | 115 | 200 | 36 | 171 | 221 |
| 40 | 111 | 21 | 135 | 28 | 143 | 43 | 111 | 30 | 111 | 33 | 130 | 248 | 324 | 260 | 337 | 244 | 102 | 241 | 73 | 212 | 41 |
| 41 | 67 | 22 | 85 | 3 | 79 | 3 | 77 | 80 | 85 | 3 | 131 | 132 | 105 | 119 | 305 | 111 | 38 | 119 | 138 | 117 | 198 |
| 42 | 300 | 3 | 300 | 3 | 271 | 4 | 290 | 3 | 258 | 129 | 132 | 324 | 204 | 365 | 166 | 342 | 295 | 348 | 141 | 311 | 9 |
| 43 | 281 | 3 | 246 | 138 | 259 | 79 | 271 | 3 | 259 | 85 | 133 | 365 | 46 | 345 | 111 | 327 | 87 | 321 | 229 | 321 | 9 |
| 44 | 67 | 22 | 79 | 126 | 79 | 3 | 81 | 3 | 79 | 3 | 134 | 126 | 169 | 116 | 134 | 122 | 44 | 120 | 37 | 116 | 116 |
| 45 | 334 | 21 | 334 | 21 | 334 | 21 | 424 | 3 | 424 | 3 | 135 | 577 | 82 | 582 | 245 | 570 | 12 | 584 | 41 | 543 | 41 |
| 46 | 300 | 3 | 239 | 22 | 279 | 3 | 279 | 4 | 279 | 2 | 136 | 326 | 86 | 365 | 84 | 360 | 48 | 314 | 151 | 340 | 165 |
| 47 | 281 | 3 | 281 | 3 | 260 | 4 | 260 | 19 | 260 | 3 | 137 | 363 | 197 | 349 | 88 | 377 | 235 | 324 | 338 | 329 | 161 |
| 48 | 334 | 21 | 394 | 127 | 394 | 3 | 424 | 3 | 334 | 21 | 138 | 642 | 165 | 590 | 89 | 594 | 45 | 546 | 47 | 570 | 42 |
| 49 | 220 | 22 | 220 | 22 | 220 | 22 | 280 | 3 | 261 | 2 | 139 | 604 | 47 | 583 | 126 | 596 | 124 | 583 | 125 | 623 | 223 |
| 50 | 253 | 3 | 191 | 22 | 215 | 3 | 215 | 3 | 219 | 3 | 140 | 639 | 84 | 618 | 126 | 619 | 276 | 615 | 337 | 577 | 192 |
| 51 | 108 | 22 | 118 | 141 | 133 | 2 | 133 | 2 | 133 | 132 | 141 | 220 | 39 | 217 | 74 | 211 | 341 | 201 | 336 | 201 | 48 |
| 52 | 326 | 22 | 385 | 3 | 359 | 4 | 326 | 22 | 326 | 22 | 142 | 533 | 128 | 482 | 84 | 512 | 5 | 510 | 288 | 485 | 38 |
| 53 | 298 | 23 | 354 | 130 | 298 | 22 | 298 | 22 | 357 | 3 | 143 | 511 | 213 | 543 | 47 | 552 | 40 | 496 | 292 | 505 | 6 |
| 54 | 108 | 22 | 134 | 4 | 134 | 3 | 128 | 120 | 128 | 131 | 144 | 204 | 140 | 226 | 286 | 204 | 150 | 202 | 148 | 204 | 186 |
| 55 | 520 | 23 | 520 | 22 | 609 | 3 | 520 | 22 | 520 | 23 | 145 | 862 | 128 | 799 | 9 | 811 | 7 | 799 | 11 | 834 | 155 |
| 56 | 326 | 22 | 366 | 142 | 326 | 23 | 326 | 22 | 355 | 80 | 146 | 533 | 48 | 501 | 281 | 488 | 311 | 498 | 162 | 498 | 12 |
| 57 | 298 | 22 | 298 | 22 | 298 | 23 | 354 | 5 | 354 | 2 | 147 | 515 | 211 | 525 | 154 | 508 | 127 | 498 | 86 | 525 | 155 |
| 58 | 426 | 22 | 426 | 22 | 530 | 131 | 426 | 23 | 506 | 134 | 148 | 890 | 169 | 898 | 331 | 802 | 7 | 786 | 91 | 782 | 220 |
| 59 | 332 | 22 | 332 | 22 | 332 | 22 | 410 | 3 | 332 | 23 | 149 | 509 | 117 | 499 | 281 | 515 | 153 | 530 | 44 | 485 | 310 |
| 60 | 380 | 22 | 380 | 22 | 466 | 130 | 380 | 23 | 380 | 22 | 150 | 1820 | 302 | 1864 | 127 | 1686 | 260 | 1759 | 89 | 1775 | 49 |
| 61 | 43 | 4 | 43 | 175 | 44 | 154 | 38 | 44 | 44 | 61 | 151 | 73 | 183 | 76 | 382 | 68 | 355 | 73 | 73 | 76 | 16 |
| 62 | 85 | 125 | 86 | 43 | 83 | 88 | 86 | 42 | 76 | 109 | 152 | 279 | 203 | 279 | 187 | 263 | 70 | 253 | 314 | 256 | 387 |
| 63 | 77 | 5 | 76 | 65 | 78 | 26 | 62 | 85 | 78 | 162 | 153 | 159 | 126 | 173 | 10 | 159 | 442 | 141 | 24 | 147 | 11 |
| 64 | 41 | 95 | 45 | 98 | 47 | 154 | 43 | 5 | 43 | 23 | 154 | 159 | 70 | 169 | 11 | 141 | 20 | 141 | 449 | 143 | 11 |
| 65 | 84 | 5 | 83 | 25 | 82 | 48 | 76 | 46 | 84 | 155 | 155 | 86 | 65 | 68 | 371 | 70 | 463 | 76 | 12 | 92 | 10 |
| 66 | 77 | 4 | 77 | 5 | 71 | 65 | 71 | 24 | 77 | 83 | 156 | 185 | 12 | 188 | 66 | 169 | 61 | 156 | 410 | 158 | 197 |
| 67 | 126 | 43 | 118 | 5 | 118 | 62 | 110 | 5 | 122 | 22 | 157 | 181 | 11 | 181 | 11 | 167 | 117 | 167 | 12 | 155 | 454 |
| 68 | 107 | 129 | 105 | 124 | 99 | 46 | 95 | 44 | 103 | 89 | 158 | 386 | 118 | 386 | 119 | 386 | 117 | 365 | 146 | 365 | 88 |
| 69 | 120 | 25 | 132 | 166 | 120 | 25 | 127 | 4 | 126 | 196 | 159 | 216 | 231 | 204 | 126 | 222 | 279 | 194 | 179 | 208 | 57 |
| 70 | 159 | 5 | 159 | 120 | 164 | 48 | 168 | 64 | 159 | 165 | 160 | 206 | 417 | 222 | 73 | 220 | 171 | 206 | 300 | 226 | 12 |
| 71 | 104 | 64 | 101 | 26 | 98 | 94 | 101 | 194 | 98 | 27 | 161 | 130 | 340 | 121 | 372 | 130 | 76 | 121 | 377 | 126 | 56 |
| 72 | 312 | 156 | 311 | 176 | 311 | 67 | 327 | 203 | 313 | 140 | 162 | 386 | 244 | 412 | 290 | 388 | 122 | 362 | 146 | 390 | 79 |
| 73 | 290 | 26 | 286 | 110 | 296 | 5 | 290 | 161 | 306 | 87 | 163 | 383 | 60 | 393 | 10 | 343 | 156 | 370 | 78 | 341 | 369 |
| 74 | 106 | 172 | 104 | 27 | 100 | 4 | 100 | 94 | 100 | 27 | 164 | 382 | 303 | 410 | 10 | 386 | 413 | 363 | 241 | 372 | 306 |
| 75 | 336 | 89 | 337 | 90 | 337 | 116 | 341 | 70 | 315 | 164 | 165 | 145 | 10 | 137 | 20 | 127 | 182 | 143 | 398 | 125 | 56 |
| 76 | 301 | 4 | 293 | 162 | 282 | 45 | 309 | 46 | 293 | 26 | 166 | 382 | 360 | 380 | 298 | 393 | 9 | 350 | 356 | 346 | 364 |
| 77 | 530 | 88 | 530 | 88 | 526 | 131 | 520 | 4 | 436 | 98 | 167 | 397 | 303 | 387 | 239 | 399 | 356 | 397 | 17 | 355 | 172 |
| 78 | 252 | 111 | 258 | 147 | 253 | 25 | 247 | 67 | 251 | 118 | 168 | 618 | 122 | 613 | 392 | 658 | 10 | 658 | 10 | 658 | 10 |
| 79 | 476 | 209 | 494 | 213 | 501 | 49 | 476 | 208 | 489 | 170 | 169 | 625 | 306 | 623 | 242 | 586 | 62 | 585 | 150 | 591 | 425 |
| 80 | 303 | 4 | 318 | 112 | 250 | 96 | 307 | 132 | 301 | 90 | 170 | 661 | 69 | 623 | 70 | 664 | 62 | 623 | 152 | 659 | 19 |
| 81 | 159 | 134 | 167 | 47 | 165 | 26 | 159 | 85 | 165 | 32 | 171 | 198 | 233 | 202 | 17 | 192 | 434 | 194 | 133 | 193 | 135 |
| 82 | 482 | 54 | 476 | 186 | 445 | 47 | 445 | 207 | 457 | 26 | 172 | 430 | 213 | 430 | 211 | 445 | 157 | 463 | 86 | 456 | 552 |
| 83 | 416 | 26 | 435 | 214 | 448 | 54 | 419 | 73 | 368 | 153 | 173 | 509 | 412 | 493 | 356 | 543 | 10 | 525 | 128 | 543 | 9 |
| 84 | 174 | 5 | 168 | 27 | 166 | 156 | 172 | 46 | 170 | 176 | 174 | 524 | 70 | 566 | 10 | 566 | 10 | 511 | 187 | 528 | 302 |
| 85 | 450 | 47 | 482 | 191 | 470 | 5 | 454 | 218 | 470 | 117 | 175 | 193 | 454 | 221 | 11 | 203 | 74 | 201 | 181 | 201 | 72 |
| 86 | 438 | 96 | 431 | 77 | 440 | 172 | 431 | 47 | 423 | 24 | 176 | 827 | 199 | 863 | 130 | 849 | 152 | 861 | 16 | 773 | 71 |
| 87 | 680 | 133 | 762 | 54 | 700 | 219 | 748 | 224 | 644 | 129 | 177 | 914 | 93 | 914 | 91 | 925 | 126 | 856 | 454 | 890 | 94 |
| 88 | 678 | 93 | 676 | 5 | 675 | 96 | 544 | 154 | 667 | 194 | 178 | 600 | 187 | 614 | 409 | 612 | 345 | 614 | 399 | 566 | 452 |
| 89 | 382 | 27 | 416 | 134 | 404 | 117 | 367 | 133 | 392 | 142 | 179 | 462 | 10 | 452 | 366 | 421 | 30 | 425 | 66 | 421 | 220 |
| 90 | 649 | 97 | 624 | 74 | 628 | 69 | 561 | 162 | 654 | 173 | 180 | 951 | 23 | 895 | 436 | 947 | 363 | 859 | 20 | 841 | 101 |

PSO Heuristic Procedure 2

| Problem # | c1 = c2 = 0.25 | | c1 = c2 = 0.30 | | c1 = c2 = 0.35 | | c1 = c2 = 0.40 | | c1 = c2 = 0.45 | | Problem # | c1 = c2 = 0.25 | | c1 = c2 = 0.30 | | c1 = c2 = 0.35 | | c1 = c2 = 0.40 | | c1 = c2 = 0.45 | |
|-----------|----------------|-----------------------|----------------|-----------------------|----------------|-----------------------|----------------|-----------------------|----------------|-----------------------|-----------|----------------|-----------------------|----------------|-----------------------|----------------|-----------------------|----------------|-----------------------|----------------|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 91 | 48 | 72 | 43 | 112 | 43 | 114 | 43 | 113 | 43 | 116 |
| 2 | 14 | 0 | 19 | 0 | 19 | 0 | 19 | 0 | 19 | 1 | 92 | 90 | 192 | 94 | 19 | 94 | 19 | 94 | 19 | 94 | 19 |
| 3 | 9 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 93 | 82 | 51 | 83 | 18 | 83 | 19 | 83 | 19 | 83 | 20 |
| 4 | 11 | 1 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 94 | 42 | 182 | 52 | 1 | 52 | 2 | 52 | 1 | 52 | 1 |
| 5 | 16 | 0 | 22 | 0 | 22 | 0 | 22 | 0 | 22 | 1 | 95 | 94 | 5 | 88 | 18 | 88 | 19 | 88 | 19 | 88 | 19 |
| 6 | 22 | 0 | 22 | 0 | 22 | 0 | 22 | 0 | 22 | 0 | 96 | 78 | 75 | 82 | 18 | 82 | 18 | 82 | 19 | 82 | 19 |
| 7 | 17 | 0 | 17 | 0 | 17 | 0 | 17 | 0 | 17 | 0 | 97 | 132 | 103 | 121 | 54 | 121 | 55 | 121 | 55 | 121 | 56 |
| 8 | 16 | 0 | 26 | 0 | 26 | 0 | 26 | 0 | 26 | 0 | 98 | 114 | 76 | 114 | 19 | 114 | 19 | 114 | 19 | 114 | 20 |
| 9 | 19 | 0 | 19 | 0 | 19 | 0 | 19 | 0 | 19 | 0 | 99 | 108 | 76 | 103 | 156 | 103 | 159 | 103 | 159 | 103 | 161 |
| 10 | 17 | 0 | 28 | 0 | 28 | 0 | 28 | 0 | 28 | 0 | 100 | 195 | 79 | 193 | 20 | 193 | 21 | 193 | 21 | 193 | 20 |
| 11 | 18 | 0 | 24 | 0 | 24 | 0 | 24 | 0 | 24 | 0 | 101 | 92 | 5 | 105 | 2 | 105 | 2 | 105 | 1 | 105 | 1 |
| 12 | 61 | 0 | 73 | 0 | 73 | 0 | 73 | 0 | 73 | 0 | 102 | 282 | 32 | 320 | 2 | 320 | 2 | 320 | 2 | 320 | 2 |
| 13 | 49 | 0 | 61 | 0 | 61 | 1 | 61 | 0 | 61 | 0 | 103 | 265 | 5 | 296 | 1 | 296 | 2 | 296 | 2 | 296 | 2 |
| 14 | 48 | 0 | 62 | 0 | 62 | 0 | 62 | 0 | 62 | 0 | 104 | 100 | 54 | 108 | 20 | 108 | 20 | 108 | 20 | 108 | 20 |
| 15 | 61 | 0 | 77 | 0 | 77 | 0 | 77 | 0 | 77 | 0 | 105 | 292 | 5 | 323 | 2 | 323 | 2 | 323 | 2 | 323 | 2 |
| 16 | 49 | 1 | 65 | 0 | 65 | 0 | 65 | 0 | 65 | 0 | 106 | 268 | 5 | 299 | 2 | 299 | 2 | 299 | 2 | 299 | 2 |
| 17 | 92 | 0 | 110 | 0 | 110 | 0 | 110 | 0 | 110 | 0 | 107 | 459 | 6 | 509 | 2 | 509 | 1 | 509 | 2 | 509 | 2 |
| 18 | 92 | 0 | 114 | 0 | 114 | 0 | 114 | 0 | 114 | 0 | 108 | 226 | 5 | 259 | 2 | 259 | 2 | 259 | 2 | 259 | 1 |
| 19 | 44 | 0 | 58 | 0 | 58 | 0 | 58 | 1 | 58 | 0 | 109 | 254 | 32 | 266 | 1 | 266 | 2 | 266 | 2 | 266 | 2 |
| 20 | 54 | 0 | 76 | 0 | 76 | 0 | 76 | 0 | 76 | 0 | 110 | 508 | 33 | 522 | 2 | 522 | 2 | 522 | 2 | 522 | 2 |
| 21 | 35 | 0 | 43 | 0 | 43 | 0 | 43 | 0 | 43 | 1 | 111 | 154 | 61 | 142 | 22 | 142 | 22 | 142 | 22 | 142 | 22 |
| 22 | 95 | 0 | 110 | 1 | 110 | 0 | 110 | 0 | 110 | 0 | 112 | 436 | 6 | 447 | 2 | 447 | 2 | 447 | 2 | 447 | 2 |
| 23 | 82 | 0 | 97 | 0 | 97 | 0 | 97 | 0 | 97 | 0 | 113 | 397 | 259 | 430 | 2 | 430 | 2 | 430 | 2 | 430 | 2 |
| 24 | 35 | 0 | 47 | 0 | 47 | 0 | 47 | 0 | 47 | 0 | 114 | 157 | 32 | 173 | 1 | 173 | 2 | 173 | 1 | 173 | 2 |
| 25 | 95 | 0 | 114 | 0 | 114 | 0 | 114 | 0 | 114 | 0 | 115 | 707 | 272 | 710 | 190 | 710 | 188 | 710 | 187 | 710 | 188 |
| 26 | 82 | 0 | 101 | 0 | 101 | 0 | 101 | 0 | 101 | 0 | 116 | 435 | 149 | 450 | 2 | 450 | 2 | 450 | 2 | 450 | 2 |
| 27 | 142 | 0 | 164 | 0 | 164 | 0 | 164 | 0 | 164 | 0 | 117 | 368 | 178 | 400 | 24 | 400 | 24 | 400 | 24 | 400 | 24 |
| 28 | 142 | 0 | 168 | 0 | 168 | 0 | 168 | 0 | 168 | 0 | 118 | 630 | 93 | 728 | 2 | 728 | 2 | 728 | 2 | 728 | 2 |
| 29 | 98 | 0 | 122 | 0 | 122 | 0 | 122 | 0 | 122 | 0 | 119 | 650 | 64 | 631 | 96 | 631 | 94 | 631 | 93 | 631 | 94 |
| 30 | 113 | 0 | 143 | 0 | 143 | 0 | 143 | 0 | 143 | 0 | 120 | 849 | 35 | 913 | 30 | 913 | 167 | 913 | 166 | 913 | 168 |
| 31 | 31 | 2 | 32 | 1 | 32 | 2 | 32 | 1 | 32 | 1 | 121 | 73 | 123 | 81 | 3 | 81 | 2 | 81 | 2 | 81 | 3 |
| 32 | 48 | 68 | 60 | 2 | 60 | 1 | 60 | 2 | 60 | 2 | 122 | 158 | 102 | 160 | 270 | 160 | 269 | 160 | 268 | 160 | 269 |
| 33 | 47 | 27 | 51 | 51 | 51 | 52 | 51 | 52 | 51 | 52 | 123 | 137 | 199 | 153 | 120 | 153 | 121 | 153 | 120 | 153 | 121 |
| 34 | 31 | 2 | 35 | 2 | 35 | 1 | 35 | 1 | 35 | 1 | 124 | 62 | 65 | 88 | 2 | 88 | 2 | 88 | 3 | 88 | 3 |
| 35 | 57 | 54 | 62 | 14 | 62 | 14 | 62 | 14 | 62 | 14 | 125 | 394 | 39 | 445 | 3 | 445 | 3 | 445 | 3 | 445 | 3 |
| 36 | 63 | 107 | 55 | 1 | 55 | 2 | 55 | 1 | 55 | 1 | 126 | 232 | 138 | 284 | 2 | 284 | 3 | 284 | 3 | 284 | 2 |
| 37 | 78 | 2 | 86 | 66 | 86 | 67 | 86 | 66 | 86 | 67 | 127 | 200 | 239 | 263 | 283 | 263 | 283 | 263 | 281 | 263 | 283 |
| 38 | 84 | 1 | 100 | 1 | 100 | 1 | 100 | 1 | 100 | 2 | 128 | 342 | 178 | 412 | 35 | 412 | 35 | 412 | 35 | 412 | 35 |
| 39 | 95 | 96 | 104 | 106 | 104 | 108 | 104 | 106 | 104 | 108 | 129 | 243 | 71 | 269 | 96 | 269 | 96 | 269 | 95 | 269 | 96 |
| 40 | 187 | 31 | 184 | 15 | 184 | 15 | 184 | 15 | 184 | 15 | 130 | 314 | 4 | 287 | 194 | 287 | 194 | 287 | 193 | 287 | 194 |
| 41 | 106 | 2 | 113 | 1 | 113 | 1 | 113 | 2 | 113 | 1 | 131 | 139 | 4 | 152 | 181 | 152 | 183 | 152 | 181 | 152 | 181 |
| 42 | 385 | 2 | 457 | 47 | 457 | 49 | 457 | 48 | 457 | 49 | 132 | 370 | 111 | 439 | 135 | 439 | 136 | 439 | 135 | 439 | 136 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 43 | 366 | 2 | 367 | 1 | 367 | 1 | 367 | 1 | 367 | 2 | 133 | 380 | 39 | 439 | 69 | 439 | 69 | 439 | 69 | 439 | 69 |
| 44 | 107 | 2 | 113 | 1 | 113 | 1 | 113 | 1 | 113 | 2 | 134 | 138 | 167 | 156 | 182 | 156 | 183 | 156 | 181 | 156 | 183 |
| 45 | 525 | 2 | 564 | 1 | 564 | 1 | 564 | 1 | 564 | 2 | 135 | 622 | 341 | 751 | 142 | 751 | 142 | 751 | 142 | 751 | 142 |
| 46 | 367 | 2 | 386 | 1 | 386 | 2 | 386 | 1 | 386 | 2 | 136 | 429 | 146 | 393 | 3 | 393 | 3 | 393 | 3 | 393 | 2 |
| 47 | 348 | 1 | 367 | 1 | 367 | 1 | 367 | 2 | 367 | 2 | 137 | 403 | 4 | 479 | 136 | 479 | 136 | 479 | 135 | 479 | 136 |
| 48 | 529 | 2 | 564 | 2 | 564 | 1 | 564 | 2 | 564 | 2 | 138 | 674 | 228 | 654 | 3 | 654 | 2 | 654 | 2 | 654 | 3 |
| 49 | 361 | 2 | 364 | 1 | 364 | 2 | 364 | 2 | 364 | 2 | 139 | 665 | 193 | 723 | 2 | 723 | 2 | 723 | 2 | 723 | 2 |
| 50 | 304 | 2 | 331 | 1 | 331 | 1 | 331 | 1 | 331 | 1 | 140 | 711 | 230 | 809 | 108 | 809 | 109 | 809 | 107 | 809 | 108 |
| 51 | 169 | 63 | 164 | 1 | 164 | 2 | 164 | 2 | 164 | 1 | 141 | 249 | 146 | 280 | 293 | 280 | 298 | 280 | 94 | 280 | 294 |
| 52 | 492 | 2 | 492 | 1 | 492 | 1 | 492 | 2 | 492 | 1 | 142 | 587 | 5 | 633 | 215 | 633 | 218 | 633 | 214 | 633 | 215 |
| 53 | 464 | 2 | 470 | 51 | 470 | 52 | 470 | 52 | 470 | 52 | 143 | 596 | 118 | 597 | 285 | 597 | 289 | 597 | 285 | 597 | 285 |
| 54 | 164 | 2 | 164 | 1 | 164 | 2 | 164 | 2 | 164 | 1 | 144 | 268 | 108 | 258 | 3 | 258 | 3 | 258 | 2 | 258 | 3 |
| 55 | 792 | 1 | 792 | 1 | 792 | 1 | 792 | 2 | 792 | 2 | 145 | 938 | 43 | 990 | 2 | 990 | 3 | 990 | 3 | 990 | 2 |
| 56 | 492 | 1 | 492 | 1 | 492 | 1 | 492 | 2 | 492 | 2 | 146 | 616 | 156 | 615 | 179 | 615 | 180 | 615 | 179 | 615 | 179 |
| 57 | 464 | 1 | 464 | 1 | 464 | 2 | 464 | 2 | 464 | 2 | 147 | 602 | 80 | 600 | 215 | 600 | 217 | 600 | 214 | 600 | 216 |
| 58 | 632 | 1 | 696 | 86 | 696 | 88 | 696 | 87 | 696 | 88 | 148 | 958 | 242 | 990 | 2 | 990 | 3 | 990 | 2 | 990 | 2 |
| 59 | 500 | 2 | 500 | 1 | 500 | 1 | 500 | 2 | 500 | 1 | 149 | 673 | 270 | 642 | 179 | 642 | 180 | 642 | 178 | 642 | 180 |
| 60 | 576 | 1 | 576 | 1 | 576 | 2 | 576 | 2 | 576 | 1 | 150 | 2056 | 46 | 2426 | 239 | 2426 | 239 | 2426 | 237 | 2426 | 238 |
| 61 | 54 | 58 | 55 | 31 | 55 | 32 | 55 | 32 | 55 | 32 | 151 | 89 | 146 | 92 | 4 | 92 | 4 | 92 | 4 | 92 | 5 |
| 62 | 95 | 24 | 110 | 34 | 110 | 35 | 110 | 35 | 110 | 35 | 152 | 323 | 10 | 333 | 177 | 333 | 178 | 333 | 177 | 333 | 178 |
| 63 | 84 | 43 | 79 | 1 | 79 | 1 | 79 | 1 | 79 | 1 | 153 | 179 | 158 | 230 | 127 | 230 | 128 | 230 | 126 | 230 | 127 |
| 64 | 57 | 22 | 65 | 17 | 65 | 17 | 65 | 17 | 65 | 17 | 154 | 178 | 10 | 208 | 86 | 208 | 87 | 208 | 86 | 208 | 86 |
| 65 | 109 | 103 | 105 | 68 | 105 | 71 | 105 | 69 | 105 | 70 | 155 | 104 | 426 | 92 | 5 | 92 | 4 | 92 | 4 | 92 | 5 |
| 66 | 93 | 62 | 85 | 1 | 85 | 2 | 85 | 1 | 85 | 1 | 156 | 203 | 57 | 199 | 4 | 199 | 4 | 199 | 4 | 199 | 4 |
| 67 | 134 | 24 | 146 | 70 | 146 | 71 | 146 | 71 | 146 | 72 | 157 | 178 | 9 | 195 | 5 | 195 | 5 | 195 | 4 | 195 | 4 |
| 68 | 118 | 165 | 107 | 2 | 107 | 1 | 107 | 1 | 107 | 2 | 158 | 440 | 9 | 443 | 49 | 443 | 49 | 443 | 48 | 443 | 48 |
| 69 | 148 | 24 | 146 | 19 | 146 | 18 | 146 | 19 | 146 | 19 | 159 | 264 | 355 | 296 | 172 | 296 | 171 | 296 | 171 | 296 | 173 |
| 70 | 186 | 109 | 194 | 18 | 194 | 19 | 194 | 19 | 194 | 19 | 160 | 280 | 208 | 268 | 340 | 268 | 338 | 268 | 344 | 268 | 341 |
| 71 | 118 | 170 | 118 | 1 | 118 | 1 | 118 | 1 | 118 | 1 | 161 | 162 | 107 | 182 | 46 | 182 | 46 | 182 | 47 | 182 | 46 |
| 72 | 348 | 141 | 382 | 159 | 382 | 162 | 382 | 161 | 382 | 163 | 162 | 432 | 61 | 490 | 416 | 490 | 414 | 490 | 423 | 490 | 416 |
| 73 | 334 | 95 | 357 | 40 | 357 | 41 | 357 | 41 | 357 | 42 | 163 | 382 | 9 | 434 | 233 | 434 | 231 | 434 | 237 | 434 | 233 |
| 74 | 106 | 3 | 120 | 1 | 120 | 1 | 120 | 1 | 120 | 1 | 164 | 424 | 337 | 410 | 5 | 410 | 4 | 410 | 5 | 410 | 4 |
| 75 | 361 | 49 | 404 | 81 | 404 | 82 | 404 | 82 | 404 | 83 | 165 | 161 | 110 | 145 | 5 | 145 | 5 | 145 | 4 | 145 | 5 |
| 76 | 353 | 140 | 369 | 60 | 369 | 62 | 369 | 62 | 369 | 62 | 166 | 482 | 435 | 393 | 371 | 393 | 367 | 393 | 377 | 393 | 371 |
| 77 | 556 | 3 | 660 | 43 | 660 | 43 | 660 | 43 | 660 | 43 | 167 | 500 | 161 | 410 | 4 | 410 | 4 | 410 | 5 | 410 | 5 |
| 78 | 278 | 161 | 341 | 176 | 341 | 179 | 341 | 179 | 341 | 179 | 168 | 738 | 459 | 832 | 388 | 832 | 387 | 832 | 392 | 832 | 388 |
| 79 | 567 | 75 | 594 | 169 | 594 | 172 | 594 | 171 | 594 | 172 | 169 | 723 | 397 | 830 | 196 | 830 | 196 | 830 | 197 | 830 | 196 |
| 80 | 339 | 209 | 360 | 21 | 360 | 22 | 360 | 21 | 360 | 21 | 170 | 802 | 63 | 895 | 435 | 895 | 437 | 895 | 438 | 895 | 436 |
| 81 | 190 | 3 | 224 | 153 | 224 | 156 | 224 | 156 | 224 | 157 | 171 | 243 | 168 | 265 | 274 | 265 | 275 | 265 | 276 | 265 | 274 |
| 82 | 566 | 27 | 570 | 85 | 570 | 87 | 570 | 87 | 570 | 87 | 172 | 543 | 121 | 523 | 149 | 523 | 151 | 523 | 151 | 523 | 151 |
| 83 | 477 | 3 | 476 | 43 | 476 | 45 | 476 | 44 | 476 | 44 | 173 | 620 | 60 | 596 | 347 | 596 | 348 | 596 | 349 | 596 | 347 |
| 84 | 202 | 205 | 218 | 21 | 218 | 21 | 218 | 21 | 218 | 21 | 174 | 550 | 295 | 647 | 152 | 647 | 152 | 647 | 152 | 647 | 151 |
| 85 | 509 | 100 | 550 | 65 | 550 | 66 | 550 | 66 | 550 | 66 | 175 | 255 | 220 | 263 | 94 | 263 | 95 | 263 | 95 | 263 | 94 |
| 86 | 483 | 3 | 546 | 191 | 546 | 193 | 546 | 194 | 546 | 195 | 176 | 979 | 123 | 921 | 463 | 921 | 465 | 921 | 465 | 921 | 463 |
| 87 | 860 | 179 | 882 | 178 | 882 | 181 | 882 | 181 | 882 | 182 | 177 | 976 | 547 | 1176 | 159 | 1176 | 159 | 1176 | 160 | 1176 | 158 |
| 88 | 687 | 128 | 761 | 23 | 761 | 24 | 761 | 23 | 761 | 24 | 178 | 694 | 416 | 734 | 153 | 734 | 154 | 734 | 154 | 734 | 153 |
| 89 | 440 | 99 | 473 | 104 | 473 | 106 | 473 | 106 | 473 | 108 | 179 | 513 | 177 | 533 | 439 | 533 | 441 | 533 | 441 | 533 | 439 |
| 90 | 680 | 151 | 760 | 88 | 760 | 89 | 760 | 89 | 760 | 90 | 180 | 1039 | 488 | 1234 | 415 | 1234 | 416 | 1234 | 418 | 1234 | 415 |

PSO Heuristic Procedure 3

| Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | | Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | |
|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 1 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 91 | 42 | 6 | 42 | 9 | 42 | 6 | 42 | 60 | 42 | 5 |
| 2 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 92 | 80 | 6 | 82 | 25 | 80 | 149 | 81 | 4 | 81 | 45 |
| 3 | 9 | 0 | 9 | 0 | 9 | 1 | 9 | 0 | 9 | 0 | 93 | 76 | 118 | 78 | 4 | 76 | 170 | 76 | 23 | 76 | 88 |
| 4 | 7 | 0 | 7 | 0 | 7 | 1 | 7 | 0 | 7 | 0 | 94 | 42 | 5 | 42 | 3 | 42 | 4 | 42 | 5 | 42 | 78 |
| 5 | 16 | 0 | 16 | 0 | 16 | 1 | 16 | 0 | 16 | 0 | 95 | 85 | 4 | 82 | 8 | 80 | 4 | 80 | 4 | 80 | 5 |
| 6 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 96 | 81 | 5 | 76 | 30 | 76 | 4 | 76 | 4 | 76 | 5 |
| 7 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 97 | 111 | 117 | 111 | 27 | 112 | 26 | 111 | 25 | 111 | 65 |
| 8 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 1 | 98 | 114 | 26 | 114 | 5 | 114 | 3 | 114 | 4 | 114 | 6 |
| 9 | 11 | 0 | 11 | 1 | 11 | 1 | 11 | 0 | 11 | 0 | 99 | 101 | 8 | 101 | 5 | 101 | 5 | 101 | 6 | 101 | 5 |
| 10 | 17 | 0 | 17 | 0 | 17 | 0 | 17 | 0 | 17 | 0 | 100 | 169 | 29 | 169 | 27 | 169 | 4 | 169 | 71 | 169 | 111 |
| 11 | 18 | 0 | 18 | 0 | 18 | 1 | 18 | 0 | 18 | 0 | 101 | 87 | 5 | 87 | 6 | 87 | 27 | 86 | 6 | 98 | 4 |
| 12 | 61 | 0 | 61 | 0 | 61 | 1 | 61 | 0 | 61 | 1 | 102 | 265 | 8 | 260 | 9 | 265 | 5 | 260 | 5 | 265 | 6 |
| 13 | 49 | 0 | 49 | 1 | 49 | 0 | 49 | 0 | 49 | 0 | 103 | 241 | 8 | 236 | 9 | 241 | 5 | 236 | 5 | 241 | 5 |
| 14 | 48 | 0 | 48 | 0 | 48 | 1 | 48 | 0 | 48 | 0 | 104 | 90 | 7 | 86 | 9 | 90 | 26 | 86 | 27 | 86 | 46 |
| 15 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 105 | 268 | 35 | 265 | 4 | 268 | 6 | 260 | 4 | 260 | 6 |
| 16 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 106 | 244 | 7 | 241 | 4 | 244 | 6 | 236 | 4 | 236 | 6 |
| 17 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 107 | 419 | 32 | 410 | 12 | 496 | 4 | 419 | 6 | 410 | 4 |
| 18 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 108 | 214 | 4 | 214 | 5 | 212 | 27 | 212 | 6 | 242 | 4 |
| 19 | 44 | 0 | 44 | 0 | 44 | 0 | 44 | 0 | 44 | 0 | 109 | 221 | 5 | 221 | 6 | 238 | 7 | 218 | 7 | 248 | 4 |
| 20 | 54 | 0 | 54 | 0 | 54 | 0 | 54 | 0 | 54 | 0 | 110 | 436 | 4 | 436 | 5 | 496 | 28 | 430 | 7 | 490 | 4 |
| 21 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 111 | 139 | 10 | 142 | 13 | 139 | 31 | 139 | 31 | 142 | 6 |
| 22 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 112 | 373 | 37 | 402 | 106 | 373 | 217 | 373 | 105 | 405 | 7 |
| 23 | 82 | 0 | 82 | 0 | 82 | 1 | 82 | 0 | 82 | 0 | 113 | 363 | 40 | 376 | 119 | 356 | 55 | 368 | 29 | 356 | 33 |
| 24 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 114 | 139 | 10 | 151 | 6 | 149 | 5 | 139 | 77 | 151 | 5 |
| 25 | 95 | 0 | 95 | 1 | 95 | 0 | 95 | 0 | 95 | 1 | 115 | 632 | 93 | 623 | 7 | 623 | 6 | 623 | 4 | 652 | 161 |
| 26 | 82 | 0 | 82 | 0 | 82 | 1 | 82 | 0 | 82 | 0 | 116 | 398 | 63 | 386 | 122 | 391 | 31 | 373 | 188 | 373 | 6 |
| 27 | 142 | 0 | 142 | 0 | 142 | 1 | 142 | 0 | 142 | 1 | 117 | 366 | 88 | 356 | 122 | 356 | 117 | 392 | 191 | 356 | 7 |
| 28 | 142 | 1 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 118 | 620 | 93 | 634 | 38 | 598 | 196 | 620 | 5 | 620 | 80 |
| 29 | 98 | 0 | 98 | 0 | 98 | 0 | 98 | 0 | 98 | 0 | 119 | 541 | 62 | 548 | 5 | 544 | 189 | 541 | 7 | 543 | 4 |
| 30 | 113 | 0 | 113 | 0 | 113 | 1 | 113 | 0 | 113 | 0 | 120 | 765 | 35 | 762 | 60 | 770 | 254 | 762 | 36 | 762 | 6 |
| 31 | 20 | 8 | 20 | 21 | 17 | 8 | 17 | 41 | 17 | 17 | 121 | 53 | 107 | 56 | 9 | 54 | 229 | 51 | 6 | 53 | 6 |
| 32 | 40 | 41 | 33 | 13 | 33 | 68 | 33 | 36 | 33 | 4 | 122 | 101 | 7 | 126 | 79 | 105 | 186 | 106 | 10 | 100 | 70 |
| 33 | 28 | 95 | 24 | 12 | 24 | 68 | 28 | 38 | 24 | 4 | 123 | 97 | 7 | 100 | 84 | 102 | 8 | 98 | 141 | 97 | 134 |
| 34 | 21 | 37 | 17 | 24 | 23 | 3 | 17 | 83 | 17 | 8 | 124 | 56 | 44 | 58 | 38 | 58 | 5 | 52 | 159 | 54 | 98 |
| 35 | 33 | 30 | 36 | 20 | 33 | 42 | 33 | 158 | 33 | 22 | 125 | 246 | 237 | 290 | 118 | 243 | 8 | 245 | 261 | 243 | 346 |
| 36 | 24 | 24 | 24 | 67 | 32 | 8 | 24 | 45 | 32 | 5 | 126 | 154 | 353 | 154 | 13 | 154 | 12 | 154 | 7 | 196 | 41 |
| 37 | 40 | 94 | 44 | 24 | 40 | 87 | 40 | 6 | 45 | 49 | 127 | 146 | 124 | 146 | 12 | 146 | 12 | 146 | 7 | 146 | 210 |
| 38 | 54 | 28 | 62 | 19 | 54 | 39 | 62 | 146 | 54 | 102 | 128 | 304 | 115 | 244 | 84 | 262 | 359 | 254 | 7 | 264 | 148 |
| 39 | 44 | 4 | 61 | 57 | 44 | 22 | 44 | 21 | 54 | 8 | 129 | 171 | 9 | 168 | 230 | 168 | 233 | 171 | 8 | 168 | 190 |
| 40 | 99 | 9 | 99 | 8 | 99 | 25 | 116 | 54 | 99 | 5 | 130 | 243 | 48 | 225 | 5 | 225 | 6 | 220 | 255 | 225 | 8 |
| 41 | 80 | 21 | 77 | 163 | 67 | 37 | 77 | 20 | 80 | 3 | 131 | 109 | 8 | 111 | 115 | 104 | 185 | 106 | 320 | 107 | 177 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 42 | 267 | 64 | 239 | 99 | 278 | 4 | 239 | 97 | 278 | 3 | 132 | 311 | 7 | 319 | 350 | 311 | 168 | 306 | 76 | 311 | 5 |
| 43 | 220 | 25 | 252 | 151 | 220 | 23 | 220 | 59 | 220 | 91 | 133 | 327 | 223 | 321 | 7 | 321 | 6 | 321 | 4 | 321 | 5 |
| 44 | 67 | 27 | 81 | 3 | 81 | 3 | 81 | 100 | 83 | 37 | 134 | 112 | 8 | 110 | 190 | 112 | 7 | 112 | 5 | 112 | 5 |
| 45 | 374 | 24 | 394 | 43 | 394 | 4 | 394 | 5 | 376 | 76 | 135 | 479 | 130 | 523 | 6 | 543 | 293 | 512 | 6 | 523 | 195 |
| 46 | 239 | 86 | 279 | 4 | 279 | 3 | 279 | 4 | 239 | 40 | 136 | 323 | 14 | 306 | 45 | 314 | 4 | 314 | 5 | 314 | 4 |
| 47 | 260 | 4 | 260 | 4 | 246 | 79 | 260 | 4 | 260 | 3 | 137 | 333 | 14 | 324 | 113 | 324 | 5 | 316 | 75 | 324 | 4 |
| 48 | 334 | 86 | 384 | 82 | 399 | 21 | 374 | 169 | 334 | 23 | 138 | 530 | 131 | 526 | 8 | 526 | 5 | 568 | 78 | 524 | 121 |
| 49 | 261 | 6 | 258 | 77 | 220 | 58 | 245 | 46 | 259 | 4 | 139 | 618 | 354 | 576 | 264 | 541 | 98 | 550 | 5 | 550 | 5 |
| 50 | 215 | 4 | 215 | 3 | 191 | 61 | 215 | 3 | 215 | 3 | 140 | 577 | 8 | 577 | 7 | 577 | 5 | 573 | 232 | 577 | 5 |
| 51 | 108 | 46 | 118 | 112 | 108 | 7 | 108 | 6 | 127 | 21 | 141 | 195 | 219 | 187 | 203 | 193 | 50 | 199 | 122 | 187 | 210 |
| 52 | 355 | 50 | 326 | 23 | 326 | 147 | 326 | 45 | 326 | 44 | 142 | 494 | 303 | 482 | 129 | 470 | 139 | 462 | 257 | 481 | 47 |
| 53 | 354 | 104 | 357 | 22 | 339 | 181 | 354 | 138 | 298 | 46 | 143 | 481 | 6 | 471 | 254 | 492 | 84 | 514 | 6 | 495 | 166 |
| 54 | 108 | 25 | 118 | 114 | 128 | 55 | 134 | 3 | 108 | 124 | 144 | 198 | 49 | 190 | 88 | 200 | 6 | 190 | 6 | 198 | 150 |
| 55 | 520 | 136 | 520 | 169 | 596 | 63 | 520 | 128 | 596 | 44 | 145 | 760 | 12 | 740 | 180 | 791 | 177 | 763 | 95 | 779 | 47 |
| 56 | 326 | 112 | 326 | 46 | 365 | 145 | 326 | 79 | 362 | 32 | 146 | 539 | 90 | 473 | 16 | 519 | 130 | 473 | 138 | 473 | 10 |
| 57 | 298 | 9 | 338 | 117 | 336 | 86 | 358 | 122 | 320 | 84 | 147 | 486 | 358 | 478 | 62 | 482 | 290 | 510 | 288 | 483 | 11 |
| 58 | 426 | 140 | 495 | 64 | 426 | 64 | 448 | 84 | 426 | 62 | 148 | 746 | 91 | 786 | 270 | 802 | 346 | 766 | 59 | 782 | 49 |
| 59 | 368 | 70 | 344 | 125 | 332 | 85 | 332 | 129 | 344 | 142 | 149 | 503 | 174 | 514 | 291 | 485 | 168 | 467 | 218 | 472 | 238 |
| 60 | 445 | 25 | 422 | 63 | 445 | 126 | 464 | 184 | 380 | 173 | 150 | 1634 | 7 | 1634 | 225 | 1720 | 8 | 1634 | 6 | 1634 | 6 |
| 61 | 35 | 172 | 42 | 4 | 42 | 3 | 36 | 61 | 41 | 41 | 151 | 67 | 344 | 67 | 102 | 61 | 146 | 66 | 399 | 62 | 222 |
| 62 | 68 | 194 | 68 | 185 | 68 | 89 | 76 | 6 | 68 | 69 | 152 | 246 | 512 | 226 | 162 | 226 | 206 | 258 | 263 | 253 | 11 |
| 63 | 61 | 76 | 61 | 94 | 61 | 124 | 61 | 102 | 61 | 144 | 153 | 131 | 269 | 144 | 109 | 132 | 441 | 146 | 370 | 153 | 10 |
| 64 | 37 | 89 | 39 | 40 | 33 | 4 | 33 | 3 | 33 | 146 | 154 | 139 | 15 | 147 | 362 | 141 | 51 | 127 | 363 | 137 | 296 |
| 65 | 68 | 190 | 81 | 172 | 75 | 126 | 65 | 124 | 68 | 11 | 155 | 68 | 11 | 68 | 10 | 68 | 52 | 74 | 182 | 68 | 49 |
| 66 | 68 | 10 | 71 | 146 | 61 | 166 | 71 | 4 | 61 | 11 | 156 | 149 | 128 | 146 | 9 | 133 | 204 | 137 | 217 | 149 | 200 |
| 67 | 106 | 73 | 110 | 109 | 114 | 4 | 118 | 167 | 106 | 43 | 157 | 133 | 319 | 142 | 9 | 136 | 197 | 139 | 148 | 129 | 154 |
| 68 | 93 | 34 | 91 | 79 | 91 | 118 | 83 | 50 | 91 | 150 | 158 | 313 | 290 | 313 | 177 | 358 | 8 | 347 | 9 | 342 | 154 |
| 69 | 115 | 60 | 127 | 194 | 101 | 50 | 116 | 4 | 115 | 46 | 159 | 198 | 230 | 194 | 17 | 198 | 146 | 212 | 53 | 194 | 10 |
| 70 | 129 | 81 | 152 | 91 | 129 | 138 | 145 | 144 | 129 | 46 | 160 | 202 | 56 | 206 | 409 | 202 | 105 | 206 | 285 | 212 | 441 |
| 71 | 83 | 10 | 95 | 48 | 83 | 109 | 95 | 4 | 95 | 4 | 161 | 111 | 420 | 120 | 467 | 119 | 9 | 134 | 245 | 112 | 466 |
| 72 | 269 | 60 | 269 | 25 | 309 | 143 | 305 | 188 | 269 | 71 | 162 | 348 | 511 | 360 | 65 | 362 | 471 | 336 | 329 | 358 | 17 |
| 73 | 285 | 30 | 318 | 3 | 241 | 80 | 269 | 73 | 288 | 71 | 163 | 346 | 86 | 343 | 341 | 343 | 235 | 351 | 429 | 315 | 20 |
| 74 | 84 | 102 | 104 | 130 | 90 | 53 | 86 | 115 | 100 | 5 | 164 | 380 | 131 | 335 | 506 | 360 | 322 | 332 | 72 | 332 | 20 |
| 75 | 263 | 165 | 263 | 216 | 272 | 121 | 302 | 96 | 263 | 27 | 165 | 123 | 349 | 125 | 316 | 125 | 14 | 113 | 384 | 117 | 56 |
| 76 | 260 | 176 | 250 | 72 | 264 | 169 | 277 | 187 | 248 | 69 | 166 | 318 | 85 | 357 | 502 | 353 | 415 | 363 | 342 | 359 | 263 |
| 77 | 452 | 137 | 468 | 29 | 420 | 84 | 484 | 32 | 420 | 26 | 167 | 342 | 497 | 363 | 71 | 354 | 332 | 364 | 10 | 357 | 176 |
| 78 | 243 | 99 | 208 | 169 | 208 | 189 | 209 | 4 | 247 | 200 | 168 | 587 | 278 | 530 | 21 | 576 | 184 | 573 | 77 | 536 | 399 |
| 79 | 481 | 114 | 482 | 54 | 392 | 57 | 458 | 77 | 447 | 169 | 169 | 623 | 546 | 581 | 9 | 568 | 298 | 585 | 166 | 581 | 10 |
| 80 | 250 | 109 | 250 | 122 | 293 | 142 | 294 | 53 | 250 | 7 | 170 | 603 | 244 | 605 | 224 | 558 | 359 | 605 | 343 | 614 | 166 |
| 81 | 160 | 189 | 146 | 29 | 151 | 93 | 142 | 165 | 142 | 26 | 171 | 183 | 393 | 184 | 122 | 181 | 14 | 181 | 72 | 184 | 162 |
| 82 | 400 | 89 | 400 | 215 | 382 | 31 | 427 | 31 | 380 | 152 | 172 | 373 | 518 | 399 | 76 | 371 | 71 | 394 | 444 | 405 | 70 |
| 83 | 419 | 29 | 374 | 7 | 410 | 150 | 361 | 8 | 433 | 118 | 173 | 427 | 194 | 463 | 189 | 459 | 15 | 439 | 400 | 473 | 402 |
| 84 | 142 | 114 | 142 | 191 | 142 | 174 | 142 | 5 | 144 | 118 | 174 | 489 | 491 | 448 | 277 | 482 | 15 | 462 | 172 | 506 | 66 |
| 85 | 489 | 59 | 433 | 157 | 390 | 221 | 382 | 104 | 470 | 225 | 175 | 157 | 264 | 191 | 12 | 179 | 445 | 179 | 14 | 181 | 402 |
| 86 | 362 | 85 | 434 | 82 | 366 | 225 | 348 | 107 | 348 | 175 | 176 | 768 | 247 | 751 | 324 | 750 | 9 | 760 | 12 | 766 | 80 |
| 87 | 588 | 185 | 676 | 184 | 658 | 106 | 680 | 85 | 588 | 105 | 177 | 823 | 491 | 800 | 535 | 800 | 190 | 784 | 73 | 823 | 120 |
| 88 | 560 | 36 | 586 | 211 | 608 | 38 | 597 | 113 | 554 | 158 | 178 | 582 | 394 | 552 | 14 | 544 | 123 | 552 | 11 | 544 | 15 |
| 89 | 368 | 5 | 333 | 82 | 333 | 182 | 392 | 201 | 333 | 223 | 179 | 443 | 439 | 406 | 7 | 387 | 302 | 417 | 234 | 401 | 181 |
| 90 | 517 | 7 | 580 | 29 | 514 | 174 | 514 | 10 | 591 | 186 | 180 | 855 | 376 | 841 | 505 | 841 | 13 | 804 | 123 | 889 | 132 |

PSO Heuristic Procedure 4

| Problem # | c ₁ = c ₂ = 0.25 | | c ₁ = c ₂ = 0.30 | | c ₁ = c ₂ = 0.35 | | c ₁ = c ₂ = 0.40 | | c ₁ = c ₂ = 0.45 | | Problem # | c ₁ = c ₂ = 0.25 | | c ₁ = c ₂ = 0.30 | | c ₁ = c ₂ = 0.35 | | c ₁ = c ₂ = 0.40 | | c ₁ = c ₂ = 0.45 | | |
|-----------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|-----------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|-----------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost |
| 1 | 7 | 1 | 7 | 0 | 7 | 0 | 7 | 1 | 7 | 0 | 91 | 42 | 12 | 42 | 11 | 42 | 7 | 42 | 9 | 43 | 6 | 6 |
| 2 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 92 | 80 | 15 | 80 | 18 | 80 | 118 | 80 | 11 | 80 | 11 | 11 |
| 3 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 93 | 75 | 142 | 76 | 55 | 75 | 198 | 76 | 353 | 76 | 91 | 91 |
| 4 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 94 | 42 | 14 | 44 | 7 | 44 | 45 | 44 | 6 | 42 | 11 | 11 |
| 5 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 95 | 82 | 6 | 80 | 7 | 80 | 53 | 80 | 9 | 80 | 7 | 7 |
| 6 | 14 | 1 | 14 | 1 | 14 | 0 | 14 | 0 | 14 | 1 | 96 | 78 | 6 | 76 | 7 | 78 | 7 | 76 | 8 | 76 | 10 | 10 |
| 7 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 97 | 111 | 227 | 111 | 13 | 108 | 284 | 111 | 91 | 111 | 356 | 356 |
| 8 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 98 | 114 | 11 | 114 | 11 | 114 | 83 | 114 | 13 | 114 | 7 | 7 |
| 9 | 11 | 0 | 11 | 0 | 11 | 1 | 11 | 0 | 11 | 0 | 99 | 101 | 8 | 101 | 10 | 103 | 7 | 101 | 10 | 101 | 7 | 7 |
| 10 | 17 | 1 | 17 | 0 | 17 | 1 | 17 | 1 | 17 | 0 | 100 | 169 | 391 | 169 | 293 | 177 | 349 | 169 | 258 | 169 | 89 | 89 |
| 11 | 18 | 0 | 18 | 0 | 18 | 0 | 18 | 0 | 18 | 0 | 101 | 86 | 13 | 86 | 13 | 92 | 6 | 92 | 7 | 86 | 10 | 10 |
| 12 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 1 | 102 | 266 | 10 | 266 | 14 | 260 | 23 | 260 | 9 | 265 | 76 | 76 |
| 13 | 49 | 0 | 49 | 0 | 49 | 1 | 49 | 0 | 49 | 0 | 103 | 242 | 10 | 242 | 14 | 236 | 25 | 236 | 9 | 238 | 18 | 18 |
| 14 | 48 | 0 | 48 | 1 | 48 | 0 | 48 | 1 | 48 | 1 | 104 | 86 | 17 | 92 | 7 | 86 | 11 | 92 | 7 | 92 | 7 | 7 |
| 15 | 61 | 0 | 61 | 1 | 61 | 0 | 61 | 1 | 61 | 1 | 105 | 275 | 10 | 260 | 13 | 267 | 13 | 265 | 9 | 260 | 7 | 7 |
| 16 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 106 | 251 | 9 | 236 | 13 | 251 | 55 | 241 | 9 | 236 | 8 | 8 |
| 17 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 1 | 92 | 0 | 107 | 410 | 9 | 420 | 8 | 410 | 7 | 412 | 10 | 420 | 10 | 10 |
| 18 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 1 | 108 | 217 | 12 | 224 | 13 | 212 | 8 | 214 | 7 | 222 | 20 | 20 |
| 19 | 44 | 1 | 44 | 0 | 44 | 0 | 44 | 1 | 44 | 0 | 109 | 218 | 12 | 218 | 10 | 233 | 7 | 218 | 10 | 221 | 11 | 11 |
| 20 | 54 | 1 | 54 | 0 | 54 | 1 | 54 | 0 | 54 | 0 | 110 | 440 | 10 | 460 | 6 | 460 | 7 | 430 | 17 | 430 | 18 | 18 |
| 21 | 35 | 1 | 35 | 1 | 35 | 1 | 35 | 0 | 35 | 0 | 111 | 142 | 228 | 147 | 421 | 145 | 6 | 139 | 416 | 143 | 414 | 414 |
| 22 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 1 | 95 | 0 | 112 | 373 | 61 | 379 | 12 | 393 | 444 | 373 | 17 | 400 | 347 | 347 |
| 23 | 82 | 0 | 82 | 1 | 82 | 0 | 82 | 0 | 82 | 1 | 113 | 369 | 268 | 362 | 11 | 384 | 6 | 356 | 16 | 368 | 56 | 56 |
| 24 | 35 | 1 | 35 | 1 | 35 | 0 | 35 | 1 | 35 | 1 | 114 | 139 | 102 | 145 | 95 | 143 | 183 | 153 | 310 | 145 | 52 | 52 |
| 25 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 1 | 115 | 603 | 434 | 603 | 188 | 603 | 62 | 603 | 12 | 633 | 157 | 157 |
| 26 | 82 | 0 | 82 | 0 | 82 | 1 | 82 | 1 | 82 | 0 | 116 | 386 | 301 | 373 | 316 | 373 | 396 | 373 | 158 | 388 | 60 | 60 |
| 27 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 1 | 117 | 381 | 71 | 356 | 171 | 378 | 7 | 368 | 57 | 371 | 258 | 258 |
| 28 | 142 | 0 | 142 | 1 | 142 | 0 | 142 | 1 | 142 | 0 | 118 | 598 | 111 | 612 | 111 | 626 | 6 | 598 | 309 | 638 | 112 | 112 |
| 29 | 98 | 1 | 98 | 0 | 98 | 1 | 98 | 0 | 98 | 0 | 119 | 546 | 185 | 528 | 171 | 541 | 11 | 541 | 369 | 544 | 101 | 101 |
| 30 | 113 | 0 | 113 | 1 | 113 | 0 | 113 | 0 | 113 | 0 | 120 | 785 | 12 | 773 | 312 | 751 | 263 | 785 | 160 | 774 | 169 | 169 |
| 31 | 20 | 79 | 21 | 159 | 24 | 65 | 25 | 116 | 17 | 94 | 121 | 53 | 15 | 58 | 88 | 58 | 334 | 58 | 141 | 60 | 13 | 13 |
| 32 | 36 | 171 | 40 | 137 | 47 | 315 | 47 | 56 | 40 | 17 | 122 | 119 | 222 | 111 | 161 | 115 | 13 | 119 | 85 | 122 | 321 | 321 |
| 33 | 38 | 287 | 27 | 285 | 31 | 12 | 27 | 152 | 38 | 214 | 123 | 108 | 166 | 120 | 160 | 111 | 13 | 122 | 279 | 128 | 319 | 319 |
| 34 | 21 | 224 | 25 | 98 | 23 | 85 | 19 | 9 | 21 | 34 | 124 | 60 | 376 | 56 | 345 | 64 | 288 | 62 | 494 | 58 | 83 | 83 |
| 35 | 38 | 239 | 38 | 139 | 47 | 80 | 38 | 246 | 39 | 270 | 125 | 282 | 571 | 307 | 459 | 295 | 75 | 309 | 421 | 300 | 654 | 654 |
| 36 | 38 | 31 | 38 | 165 | 38 | 6 | 29 | 142 | 32 | 71 | 126 | 184 | 18 | 198 | 80 | 197 | 606 | 189 | 616 | 200 | 588 | 588 |
| 37 | 45 | 71 | 44 | 233 | 60 | 246 | 44 | 15 | 44 | 82 | 127 | 189 | 558 | 187 | 351 | 189 | 72 | 180 | 364 | 189 | 335 | 335 |
| 38 | 62 | 160 | 58 | 274 | 74 | 219 | 60 | 10 | 78 | 183 | 128 | 294 | 386 | 282 | 424 | 310 | 210 | 304 | 545 | 294 | 94 | 94 |
| 39 | 49 | 326 | 66 | 78 | 66 | 233 | 49 | 158 | 49 | 93 | 129 | 193 | 388 | 200 | 343 | 203 | 90 | 190 | 327 | 196 | 614 | 614 |
| 40 | 143 | 70 | 111 | 83 | 143 | 166 | 111 | 44 | 116 | 10 | 130 | 225 | 427 | 244 | 555 | 238 | 73 | 264 | 9 | 251 | 12 | 12 |
| 41 | 75 | 40 | 77 | 7 | 79 | 7 | 80 | 6 | 78 | 138 | 131 | 122 | 70 | 133 | 9 | 124 | 75 | 114 | 72 | 119 | 26 | 26 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|------|------|------|------|------|
| 42 | 275 | 203 | 278 | 7 | 278 | 157 | 278 | 9 | 278 | 204 | 132 | 362 | 465 | 359 | 270 | 378 | 595 | 354 | 503 | 350 | 288 |
| 43 | 259 | 8 | 259 | 6 | 259 | 6 | 246 | 245 | 259 | 11 | 133 | 367 | 159 | 370 | 87 | 386 | 282 | 374 | 159 | 385 | 231 |
| 44 | 79 | 13 | 79 | 72 | 81 | 267 | 79 | 9 | 81 | 9 | 134 | 132 | 11 | 120 | 139 | 128 | 11 | 130 | 9 | 116 | 125 |
| 45 | 394 | 18 | 384 | 345 | 395 | 15 | 384 | 78 | 394 | 7 | 135 | 602 | 292 | 591 | 167 | 582 | 10 | 567 | 12 | 571 | 99 |
| 46 | 279 | 48 | 271 | 79 | 275 | 12 | 279 | 6 | 279 | 7 | 136 | 392 | 379 | 353 | 510 | 336 | 169 | 336 | 156 | 321 | 620 |
| 47 | 260 | 12 | 260 | 10 | 260 | 104 | 260 | 7 | 260 | 7 | 137 | 365 | 696 | 356 | 79 | 382 | 370 | 356 | 366 | 352 | 99 |
| 48 | 394 | 12 | 384 | 11 | 394 | 108 | 389 | 42 | 384 | 199 | 138 | 570 | 14 | 606 | 10 | 630 | 615 | 626 | 686 | 576 | 165 |
| 49 | 247 | 87 | 259 | 191 | 254 | 171 | 259 | 10 | 258 | 73 | 139 | 595 | 243 | 589 | 388 | 603 | 598 | 583 | 538 | 583 | 595 |
| 50 | 215 | 8 | 215 | 9 | 215 | 7 | 215 | 77 | 215 | 6 | 140 | 693 | 400 | 700 | 702 | 615 | 532 | 577 | 407 | 603 | 543 |
| 51 | 130 | 178 | 128 | 148 | 120 | 7 | 118 | 335 | 118 | 249 | 141 | 211 | 86 | 209 | 149 | 208 | 512 | 209 | 363 | 211 | 354 |
| 52 | 385 | 115 | 382 | 311 | 382 | 136 | 382 | 117 | 401 | 240 | 142 | 524 | 263 | 495 | 640 | 554 | 694 | 489 | 719 | 521 | 173 |
| 53 | 339 | 318 | 331 | 240 | 331 | 128 | 354 | 7 | 357 | 222 | 143 | 544 | 19 | 523 | 335 | 560 | 224 | 552 | 298 | 522 | 247 |
| 54 | 118 | 288 | 118 | 228 | 118 | 319 | 134 | 9 | 118 | 70 | 144 | 202 | 97 | 214 | 437 | 204 | 14 | 220 | 221 | 194 | 489 |
| 55 | 578 | 11 | 604 | 12 | 609 | 7 | 604 | 10 | 556 | 237 | 145 | 831 | 406 | 862 | 19 | 799 | 629 | 873 | 404 | 804 | 252 |
| 56 | 382 | 259 | 364 | 159 | 389 | 7 | 367 | 13 | 382 | 11 | 146 | 493 | 472 | 488 | 13 | 528 | 616 | 492 | 547 | 507 | 321 |
| 57 | 332 | 155 | 336 | 317 | 354 | 8 | 332 | 233 | 339 | 122 | 147 | 587 | 87 | 487 | 157 | 571 | 224 | 561 | 469 | 567 | 309 |
| 58 | 506 | 10 | 466 | 130 | 501 | 231 | 437 | 117 | 466 | 48 | 148 | 868 | 660 | 866 | 334 | 812 | 477 | 870 | 238 | 862 | 245 |
| 59 | 405 | 109 | 392 | 323 | 368 | 237 | 350 | 82 | 362 | 18 | 149 | 550 | 389 | 482 | 329 | 502 | 249 | 527 | 433 | 522 | 613 |
| 60 | 422 | 246 | 422 | 351 | 422 | 208 | 450 | 221 | 450 | 154 | 150 | 1750 | 20 | 1760 | 576 | 1776 | 655 | 1892 | 326 | 1760 | 16 |
| 61 | 44 | 305 | 42 | 43 | 38 | 113 | 44 | 182 | 44 | 41 | 151 | 80 | 32 | 78 | 676 | 69 | 402 | 77 | 323 | 70 | 104 |
| 62 | 86 | 172 | 82 | 187 | 77 | 44 | 79 | 80 | 84 | 264 | 152 | 267 | 124 | 273 | 170 | 274 | 314 | 298 | 19 | 278 | 32 |
| 63 | 73 | 244 | 79 | 343 | 80 | 189 | 79 | 4 | 75 | 109 | 153 | 153 | 35 | 165 | 230 | 172 | 578 | 147 | 532 | 157 | 277 |
| 64 | 49 | 4 | 45 | 11 | 47 | 37 | 45 | 155 | 47 | 276 | 154 | 142 | 305 | 165 | 920 | 141 | 29 | 168 | 604 | 152 | 55 |
| 65 | 83 | 152 | 85 | 77 | 96 | 35 | 84 | 16 | 88 | 122 | 155 | 78 | 16 | 70 | 19 | 92 | 100 | 86 | 19 | 76 | 32 |
| 66 | 82 | 214 | 85 | 5 | 81 | 97 | 66 | 203 | 78 | 219 | 156 | 155 | 15 | 148 | 31 | 172 | 632 | 170 | 247 | 164 | 842 |
| 67 | 122 | 8 | 126 | 286 | 126 | 5 | 114 | 286 | 114 | 118 | 157 | 175 | 388 | 144 | 33 | 160 | 27 | 161 | 347 | 173 | 21 |
| 68 | 101 | 185 | 105 | 135 | 109 | 40 | 95 | 245 | 103 | 45 | 158 | 389 | 469 | 401 | 142 | 408 | 722 | 395 | 239 | 387 | 760 |
| 69 | 119 | 189 | 129 | 287 | 134 | 267 | 129 | 46 | 129 | 314 | 159 | 240 | 325 | 248 | 146 | 220 | 872 | 220 | 507 | 222 | 389 |
| 70 | 164 | 193 | 159 | 88 | 159 | 209 | 152 | 7 | 164 | 97 | 160 | 206 | 37 | 222 | 244 | 232 | 21 | 216 | 45 | 226 | 32 |
| 71 | 107 | 220 | 97 | 50 | 105 | 155 | 101 | 169 | 102 | 122 | 161 | 138 | 16 | 131 | 650 | 139 | 537 | 124 | 241 | 136 | 664 |
| 72 | 318 | 51 | 324 | 135 | 316 | 50 | 302 | 262 | 331 | 145 | 162 | 384 | 832 | 360 | 257 | 410 | 137 | 416 | 899 | 392 | 665 |
| 73 | 287 | 186 | 299 | 47 | 311 | 166 | 273 | 93 | 277 | 94 | 163 | 374 | 251 | 370 | 124 | 378 | 15 | 378 | 854 | 371 | 635 |
| 74 | 102 | 160 | 116 | 308 | 102 | 48 | 102 | 7 | 104 | 41 | 164 | 383 | 124 | 377 | 161 | 395 | 18 | 368 | 19 | 380 | 485 |
| 75 | 329 | 145 | 323 | 53 | 306 | 144 | 332 | 272 | 304 | 354 | 165 | 139 | 108 | 131 | 547 | 139 | 100 | 135 | 572 | 145 | 17 |
| 76 | 310 | 7 | 263 | 393 | 292 | 58 | 307 | 228 | 293 | 52 | 166 | 351 | 853 | 346 | 880 | 374 | 18 | 360 | 938 | 380 | 670 |
| 77 | 526 | 99 | 504 | 230 | 542 | 187 | 488 | 241 | 516 | 265 | 167 | 383 | 781 | 407 | 118 | 394 | 319 | 413 | 335 | 403 | 33 |
| 78 | 263 | 94 | 252 | 92 | 268 | 392 | 248 | 356 | 242 | 172 | 168 | 631 | 926 | 617 | 961 | 624 | 16 | 615 | 149 | 647 | 597 |
| 79 | 518 | 190 | 496 | 359 | 489 | 240 | 490 | 249 | 514 | 48 | 169 | 623 | 24 | 591 | 925 | 652 | 604 | 591 | 1016 | 630 | 519 |
| 80 | 304 | 370 | 312 | 306 | 294 | 304 | 263 | 82 | 297 | 356 | 170 | 632 | 490 | 624 | 43 | 673 | 293 | 606 | 21 | 694 | 400 |
| 81 | 175 | 8 | 176 | 136 | 173 | 367 | 178 | 6 | 171 | 382 | 171 | 210 | 119 | 202 | 757 | 219 | 472 | 199 | 715 | 205 | 789 |
| 82 | 455 | 319 | 444 | 93 | 448 | 145 | 451 | 277 | 400 | 10 | 172 | 456 | 182 | 484 | 28 | 466 | 821 | 479 | 18 | 432 | 451 |
| 83 | 457 | 240 | 416 | 317 | 411 | 139 | 461 | 279 | 433 | 366 | 173 | 523 | 740 | 517 | 426 | 518 | 234 | 510 | 815 | 490 | 1073 |
| 84 | 174 | 95 | 166 | 14 | 168 | 218 | 178 | 187 | 178 | 88 | 174 | 478 | 351 | 516 | 25 | 553 | 1087 | 513 | 25 | 524 | 337 |
| 85 | 459 | 331 | 456 | 143 | 461 | 14 | 464 | 55 | 465 | 7 | 175 | 215 | 124 | 211 | 877 | 231 | 853 | 203 | 323 | 219 | 211 |
| 86 | 463 | 224 | 423 | 325 | 424 | 110 | 493 | 5 | 438 | 141 | 176 | 820 | 132 | 867 | 244 | 833 | 837 | 797 | 657 | 847 | 1059 |
| 87 | 724 | 97 | 728 | 193 | 680 | 103 | 742 | 361 | 766 | 285 | 177 | 894 | 761 | 905 | 324 | 932 | 442 | 954 | 434 | 921 | 509 |
| 88 | 672 | 238 | 695 | 192 | 666 | 284 | 665 | 236 | 658 | 420 | 178 | 624 | 678 | 570 | 751 | 598 | 817 | 588 | 494 | 606 | 25 |
| 89 | 379 | 181 | 390 | 8 | 400 | 282 | 401 | 227 | 411 | 414 | 179 | 460 | 459 | 458 | 887 | 444 | 131 | 433 | 585 | 421 | 319 |
| 90 | 629 | 232 | 630 | 428 | 634 | 281 | 636 | 383 | 632 | 12 | 180 | 934 | 357 | 965 | 255 | 978 | 138 | 925 | 781 | 971 | 617 |

PSO Heuristic Procedure 5

| Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | | Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | |
|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 0 | 7 | 1 | 7 | 0 | 7 | 1 | 7 | 0 | 91 | 44 | 3 | 43 | 17 | 45 | 75 | 42 | 16 | 46 | 18 |
| 2 | 14 | 0 | 14 | 0 | 14 | 1 | 14 | 0 | 14 | 0 | 92 | 80 | 64 | 83 | 18 | 82 | 141 | 82 | 65 | 82 | 18 |
| 3 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 93 | 79 | 109 | 77 | 92 | 81 | 34 | 86 | 3 | 76 | 125 |
| 4 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 94 | 48 | 3 | 44 | 118 | 46 | 2 | 52 | 3 | 48 | 3 |
| 5 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 95 | 80 | 80 | 85 | 81 | 86 | 2 | 94 | 3 | 80 | 141 |
| 6 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 96 | 76 | 50 | 76 | 63 | 82 | 3 | 80 | 18 | 78 | 18 |
| 7 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 97 | 118 | 3 | 113 | 34 | 115 | 48 | 118 | 51 | 122 | 3 |
| 8 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 98 | 114 | 49 | 114 | 49 | 114 | 131 | 120 | 19 | 120 | 3 |
| 9 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 99 | 101 | 31 | 105 | 110 | 105 | 3 | 101 | 127 | 103 | 66 |
| 10 | 17 | 0 | 17 | 0 | 17 | 0 | 17 | 0 | 17 | 0 | 100 | 178 | 134 | 169 | 102 | 178 | 134 | 177 | 53 | 196 | 153 |
| 11 | 18 | 0 | 18 | 0 | 18 | 0 | 18 | 0 | 18 | 0 | 101 | 86 | 3 | 86 | 3 | 98 | 2 | 100 | 2 | 100 | 19 |
| 12 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 102 | 309 | 3 | 283 | 3 | 320 | 2 | 320 | 2 | 309 | 21 |
| 13 | 49 | 1 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 103 | 285 | 3 | 259 | 3 | 296 | 2 | 296 | 2 | 285 | 3 |
| 14 | 48 | 0 | 48 | 0 | 48 | 0 | 48 | 0 | 48 | 0 | 104 | 102 | 2 | 98 | 3 | 104 | 3 | 102 | 3 | 104 | 3 |
| 15 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 105 | 310 | 2 | 305 | 3 | 323 | 3 | 323 | 2 | 310 | 21 |
| 16 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 49 | 0 | 106 | 286 | 2 | 281 | 3 | 299 | 3 | 259 | 21 | 286 | 3 |
| 17 | 92 | 0 | 92 | 1 | 92 | 0 | 92 | 0 | 92 | 0 | 107 | 495 | 3 | 472 | 2 | 509 | 3 | 509 | 3 | 495 | 3 |
| 18 | 92 | 1 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 108 | 212 | 3 | 212 | 3 | 241 | 3 | 229 | 20 | 241 | 2 |
| 19 | 44 | 0 | 44 | 0 | 44 | 0 | 44 | 0 | 44 | 0 | 109 | 218 | 2 | 218 | 3 | 247 | 2 | 253 | 3 | 248 | 2 |
| 20 | 54 | 0 | 54 | 0 | 54 | 0 | 54 | 0 | 54 | 1 | 110 | 430 | 3 | 430 | 3 | 486 | 3 | 498 | 3 | 486 | 2 |
| 21 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 111 | 149 | 91 | 157 | 3 | 153 | 38 | 165 | 75 | 162 | 145 |
| 22 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 112 | 406 | 22 | 413 | 100 | 447 | 3 | 447 | 3 | 406 | 3 |
| 23 | 82 | 0 | 82 | 0 | 82 | 0 | 82 | 0 | 82 | 1 | 113 | 389 | 2 | 381 | 100 | 430 | 3 | 407 | 41 | 443 | 62 |
| 24 | 35 | 0 | 35 | 0 | 41 | 0 | 35 | 0 | 35 | 0 | 114 | 143 | 38 | 151 | 92 | 163 | 3 | 173 | 3 | 149 | 3 |
| 25 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 115 | 682 | 107 | 620 | 63 | 709 | 24 | 667 | 187 | 612 | 84 |
| 26 | 82 | 0 | 82 | 0 | 82 | 0 | 82 | 0 | 82 | 0 | 116 | 395 | 60 | 422 | 43 | 391 | 121 | 418 | 82 | 424 | 23 |
| 27 | 142 | 0 | 142 | 1 | 142 | 0 | 142 | 0 | 142 | 1 | 117 | 366 | 139 | 429 | 23 | 409 | 178 | 424 | 22 | 390 | 22 |
| 28 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 118 | 646 | 146 | 658 | 104 | 696 | 23 | 702 | 103 | 662 | 144 |
| 29 | 98 | 0 | 98 | 0 | 98 | 0 | 98 | 0 | 98 | 0 | 119 | 548 | 24 | 618 | 64 | 528 | 143 | 543 | 124 | 585 | 64 |
| 30 | 113 | 0 | 113 | 0 | 113 | 0 | 113 | 0 | 113 | 0 | 120 | 785 | 25 | 851 | 126 | 849 | 44 | 773 | 45 | 773 | 65 |
| 31 | 22 | 55 | 24 | 57 | 22 | 99 | 24 | 80 | 19 | 56 | 121 | 59 | 162 | 75 | 70 | 61 | 4 | 73 | 49 | 69 | 90 |
| 32 | 39 | 24 | 40 | 105 | 40 | 82 | 45 | 96 | 44 | 105 | 122 | 126 | 27 | 129 | 222 | 126 | 50 | 123 | 198 | 120 | 146 |
| 33 | 27 | 69 | 48 | 3 | 31 | 82 | 31 | 25 | 37 | 47 | 123 | 116 | 77 | 97 | 170 | 124 | 26 | 126 | 30 | 116 | 99 |
| 34 | 17 | 3 | 23 | 23 | 19 | 14 | 25 | 35 | 27 | 3 | 124 | 80 | 116 | 58 | 167 | 66 | 118 | 66 | 25 | 68 | 26 |
| 35 | 48 | 49 | 43 | 26 | 54 | 3 | 49 | 27 | 60 | 83 | 125 | 306 | 217 | 317 | 136 | 308 | 162 | 331 | 212 | 359 | 82 |
| 36 | 34 | 2 | 38 | 3 | 32 | 47 | 39 | 97 | 38 | 2 | 126 | 196 | 159 | 193 | 132 | 223 | 199 | 187 | 5 | 204 | 55 |
| 37 | 57 | 3 | 49 | 61 | 49 | 2 | 60 | 27 | 60 | 26 | 127 | 200 | 233 | 195 | 27 | 176 | 201 | 250 | 233 | 194 | 177 |
| 38 | 68 | 27 | 74 | 49 | 60 | 50 | 68 | 63 | 80 | 3 | 128 | 284 | 163 | 316 | 33 | 312 | 29 | 294 | 240 | 310 | 210 |
| 39 | 61 | 3 | 66 | 15 | 58 | 89 | 92 | 75 | 59 | 14 | 129 | 206 | 104 | 172 | 28 | 203 | 132 | 190 | 207 | 184 | 80 |
| 40 | 127 | 90 | 124 | 26 | 124 | 41 | 128 | 40 | 164 | 105 | 130 | 254 | 165 | 250 | 163 | 259 | 132 | 263 | 31 | 298 | 234 |
| 41 | 80 | 3 | 80 | 3 | 93 | 3 | 77 | 3 | 80 | 2 | 131 | 127 | 29 | 129 | 55 | 132 | 177 | 121 | 207 | 132 | 51 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 42 | 295 | 4 | 280 | 31 | 278 | 3 | 360 | 3 | 280 | 136 | 132 | 329 | 120 | 387 | 3 | 317 | 83 | 355 | 4 | 355 | 245 |
| 43 | 276 | 4 | 259 | 3 | 259 | 3 | 261 | 74 | 259 | 3 | 133 | 373 | 141 | 316 | 143 | 366 | 251 | 354 | 59 | 366 | 194 |
| 44 | 77 | 55 | 99 | 4 | 93 | 3 | 77 | 2 | 77 | 40 | 134 | 112 | 2 | 138 | 4 | 152 | 30 | 126 | 29 | 134 | 3 |
| 45 | 374 | 87 | 385 | 90 | 385 | 123 | 384 | 3 | 435 | 139 | 135 | 628 | 63 | 548 | 232 | 593 | 87 | 573 | 257 | 571 | 181 |
| 46 | 270 | 120 | 279 | 3 | 279 | 3 | 361 | 3 | 279 | 2 | 136 | 369 | 61 | 353 | 63 | 351 | 166 | 314 | 194 | 374 | 55 |
| 47 | 301 | 3 | 260 | 3 | 290 | 129 | 342 | 3 | 260 | 3 | 137 | 335 | 198 | 352 | 87 | 384 | 3 | 340 | 137 | 387 | 110 |
| 48 | 399 | 3 | 399 | 3 | 464 | 2 | 419 | 137 | 399 | 3 | 138 | 584 | 262 | 574 | 260 | 616 | 31 | 558 | 232 | 616 | 3 |
| 49 | 220 | 45 | 277 | 35 | 261 | 3 | 251 | 73 | 298 | 103 | 139 | 582 | 186 | 595 | 118 | 598 | 60 | 645 | 117 | 718 | 211 |
| 50 | 259 | 124 | 215 | 3 | 215 | 3 | 248 | 3 | 215 | 3 | 140 | 681 | 218 | 693 | 181 | 580 | 58 | 637 | 87 | 658 | 31 |
| 51 | 133 | 32 | 127 | 3 | 124 | 132 | 127 | 47 | 133 | 2 | 141 | 226 | 85 | 211 | 58 | 221 | 159 | 217 | 4 | 240 | 191 |
| 52 | 362 | 65 | 382 | 3 | 372 | 18 | 377 | 126 | 385 | 108 | 142 | 493 | 120 | 494 | 62 | 487 | 35 | 604 | 89 | 519 | 207 |
| 53 | 357 | 3 | 341 | 17 | 357 | 3 | 331 | 52 | 429 | 92 | 143 | 491 | 162 | 522 | 63 | 518 | 240 | 535 | 36 | 534 | 237 |
| 54 | 144 | 3 | 120 | 98 | 152 | 17 | 120 | 2 | 134 | 3 | 144 | 212 | 4 | 228 | 87 | 230 | 3 | 228 | 111 | 214 | 98 |
| 55 | 701 | 3 | 673 | 148 | 672 | 87 | 596 | 140 | 609 | 65 | 145 | 819 | 3 | 851 | 98 | 812 | 33 | 862 | 95 | 836 | 33 |
| 56 | 365 | 32 | 392 | 92 | 449 | 125 | 389 | 5 | 372 | 50 | 146 | 581 | 150 | 519 | 184 | 519 | 125 | 517 | 33 | 567 | 60 |
| 57 | 369 | 142 | 408 | 3 | 354 | 3 | 361 | 6 | 408 | 127 | 147 | 583 | 274 | 507 | 69 | 504 | 266 | 506 | 234 | 571 | 61 |
| 58 | 503 | 19 | 466 | 4 | 463 | 55 | 503 | 39 | 536 | 82 | 148 | 878 | 33 | 880 | 279 | 802 | 123 | 834 | 4 | 900 | 3 |
| 59 | 387 | 35 | 387 | 61 | 398 | 115 | 387 | 65 | 386 | 20 | 149 | 567 | 93 | 572 | 61 | 523 | 277 | 522 | 215 | 556 | 3 |
| 60 | 445 | 64 | 536 | 139 | 536 | 18 | 445 | 21 | 466 | 3 | 150 | 1874 | 5 | 1840 | 130 | 1820 | 164 | 1960 | 3 | 1774 | 290 |
| 61 | 42 | 54 | 43 | 93 | 45 | 119 | 47 | 97 | 40 | 93 | 151 | 80 | 267 | 81 | 198 | 82 | 75 | 67 | 74 | 81 | 134 |
| 62 | 89 | 58 | 82 | 114 | 88 | 16 | 83 | 60 | 85 | 88 | 152 | 250 | 125 | 226 | 295 | 271 | 247 | 280 | 169 | 274 | 15 |
| 63 | 85 | 111 | 79 | 72 | 78 | 86 | 79 | 2 | 88 | 30 | 153 | 156 | 185 | 160 | 244 | 166 | 40 | 150 | 44 | 155 | 15 |
| 64 | 45 | 107 | 43 | 2 | 51 | 54 | 59 | 16 | 43 | 55 | 154 | 163 | 8 | 162 | 72 | 153 | 77 | 165 | 112 | 151 | 115 |
| 65 | 92 | 72 | 88 | 45 | 88 | 16 | 107 | 134 | 85 | 72 | 155 | 70 | 6 | 82 | 75 | 90 | 6 | 72 | 5 | 88 | 99 |
| 66 | 76 | 29 | 85 | 2 | 97 | 30 | 93 | 32 | 96 | 30 | 156 | 164 | 183 | 182 | 111 | 158 | 82 | 202 | 146 | 166 | 15 |
| 67 | 118 | 103 | 118 | 104 | 138 | 31 | 126 | 2 | 124 | 60 | 157 | 152 | 14 | 170 | 144 | 159 | 175 | 164 | 10 | 162 | 49 |
| 68 | 111 | 116 | 122 | 16 | 118 | 120 | 127 | 91 | 107 | 31 | 158 | 353 | 316 | 402 | 42 | 399 | 5 | 365 | 10 | 394 | 201 |
| 69 | 127 | 60 | 135 | 60 | 131 | 75 | 144 | 32 | 149 | 17 | 159 | 208 | 10 | 236 | 224 | 224 | 45 | 254 | 5 | 254 | 5 |
| 70 | 175 | 77 | 164 | 134 | 158 | 48 | 171 | 108 | 182 | 48 | 160 | 218 | 42 | 206 | 111 | 246 | 144 | 262 | 223 | 272 | 75 |
| 71 | 99 | 119 | 118 | 2 | 111 | 47 | 125 | 133 | 120 | 136 | 161 | 134 | 327 | 147 | 41 | 140 | 217 | 135 | 247 | 137 | 42 |
| 72 | 341 | 2 | 333 | 85 | 387 | 1 | 375 | 36 | 351 | 86 | 162 | 408 | 48 | 384 | 7 | 416 | 208 | 372 | 49 | 444 | 217 |
| 73 | 299 | 68 | 311 | 85 | 336 | 69 | 333 | 155 | 346 | 102 | 163 | 339 | 127 | 380 | 50 | 375 | 7 | 394 | 47 | 365 | 281 |
| 74 | 116 | 32 | 126 | 120 | 118 | 63 | 112 | 19 | 118 | 137 | 164 | 392 | 353 | 359 | 198 | 399 | 46 | 386 | 362 | 380 | 6 |
| 75 | 365 | 2 | 390 | 35 | 354 | 102 | 314 | 123 | 372 | 86 | 165 | 133 | 148 | 129 | 6 | 139 | 6 | 129 | 6 | 129 | 6 |
| 76 | 339 | 19 | 321 | 136 | 314 | 2 | 291 | 119 | 363 | 68 | 166 | 368 | 160 | 349 | 202 | 356 | 165 | 393 | 210 | 347 | 353 |
| 77 | 532 | 72 | 526 | 72 | 618 | 72 | 508 | 57 | 604 | 19 | 167 | 400 | 45 | 420 | 327 | 410 | 130 | 381 | 6 | 381 | 6 |
| 78 | 273 | 148 | 247 | 149 | 258 | 151 | 268 | 103 | 262 | 100 | 168 | 630 | 176 | 623 | 207 | 668 | 136 | 591 | 338 | 602 | 131 |
| 79 | 503 | 37 | 532 | 161 | 489 | 91 | 526 | 55 | 489 | 72 | 169 | 653 | 126 | 729 | 88 | 639 | 7 | 716 | 216 | 597 | 84 |
| 80 | 313 | 136 | 327 | 69 | 307 | 36 | 360 | 53 | 341 | 19 | 170 | 627 | 295 | 622 | 174 | 674 | 6 | 705 | 305 | 664 | 330 |
| 81 | 164 | 3 | 185 | 131 | 175 | 65 | 193 | 130 | 181 | 2 | 171 | 194 | 44 | 185 | 156 | 191 | 215 | 211 | 6 | 185 | 375 |
| 82 | 446 | 37 | 453 | 73 | 545 | 160 | 538 | 20 | 506 | 159 | 172 | 474 | 168 | 415 | 6 | 486 | 6 | 464 | 131 | 466 | 332 |
| 83 | 444 | 160 | 477 | 160 | 512 | 143 | 489 | 125 | 482 | 125 | 173 | 508 | 348 | 555 | 329 | 535 | 217 | 565 | 172 | 526 | 47 |
| 84 | 202 | 67 | 184 | 82 | 202 | 50 | 190 | 146 | 204 | 65 | 174 | 509 | 50 | 517 | 263 | 537 | 48 | 563 | 130 | 549 | 7 |
| 85 | 466 | 20 | 552 | 2 | 452 | 73 | 529 | 1 | 508 | 38 | 175 | 217 | 82 | 185 | 7 | 201 | 88 | 197 | 196 | 207 | 358 |
| 86 | 485 | 161 | 508 | 72 | 502 | 2 | 499 | 20 | 501 | 161 | 176 | 750 | 344 | 825 | 259 | 751 | 242 | 799 | 217 | 831 | 367 |
| 87 | 822 | 78 | 786 | 93 | 818 | 20 | 824 | 39 | 822 | 131 | 177 | 845 | 6 | 830 | 276 | 959 | 327 | 838 | 137 | 899 | 101 |
| 88 | 649 | 2 | 640 | 111 | 655 | 2 | 680 | 166 | 850 | 149 | 178 | 596 | 7 | 628 | 90 | 638 | 7 | 604 | 95 | 630 | 270 |
| 89 | 390 | 54 | 439 | 2 | 406 | 2 | 431 | 89 | 473 | 124 | 179 | 457 | 129 | 462 | 91 | 460 | 354 | 419 | 261 | 418 | 330 |
| 90 | 717 | 112 | 693 | 94 | 681 | 38 | 614 | 2 | 677 | 93 | 180 | 983 | 226 | 980 | 91 | 855 | 93 | 922 | 50 | 992 | 263 |

PSO Heuristic Procedure 6

| Problem # | c ₁ = c ₂ = 0.25 | | c ₁ = c ₂ = 0.30 | | c ₁ = c ₂ = 0.35 | | c ₁ = c ₂ = 0.40 | | c ₁ = c ₂ = 0.45 | | Problem # | c ₁ = c ₂ = 0.25 | | c ₁ = c ₂ = 0.30 | | c ₁ = c ₂ = 0.35 | | c ₁ = c ₂ = 0.40 | | c ₁ = c ₂ = 0.45 | | |
|-----------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|-----------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|-----------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost |
| 1 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 1 | 91 | 42 | 4 | 42 | 8 | 42 | 7 | 42 | 6 | 42 | 4 | 4 |
| 2 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 1 | 14 | 0 | 92 | 81 | 4 | 81 | 5 | 80 | 6 | 80 | 30 | 80 | 7 | 7 |
| 3 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 93 | 76 | 53 | 76 | 26 | 76 | 6 | 76 | 113 | 76 | 51 | 51 |
| 4 | 7 | 1 | 7 | 0 | 7 | 0 | 7 | 0 | 7 | 0 | 94 | 42 | 4 | 42 | 6 | 42 | 7 | 44 | 4 | 42 | 8 | 8 |
| 5 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 95 | 80 | 6 | 80 | 9 | 82 | 5 | 80 | 4 | 80 | 5 | 5 |
| 6 | 14 | 1 | 14 | 0 | 14 | 0 | 14 | 0 | 14 | 0 | 96 | 76 | 6 | 76 | 9 | 76 | 25 | 76 | 4 | 76 | 5 | 5 |
| 7 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 9 | 0 | 97 | 111 | 28 | 111 | 27 | 111 | 49 | 111 | 117 | 111 | 30 | 30 |
| 8 | 16 | 1 | 16 | 0 | 16 | 0 | 16 | 0 | 16 | 0 | 98 | 114 | 5 | 114 | 5 | 114 | 7 | 114 | 6 | 114 | 6 | 6 |
| 9 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 11 | 0 | 99 | 101 | 27 | 101 | 8 | 101 | 5 | 101 | 4 | 101 | 8 | 8 |
| 10 | 17 | 1 | 17 | 0 | 17 | 0 | 17 | 0 | 17 | 0 | 100 | 169 | 5 | 169 | 4 | 162 | 6 | 169 | 31 | 169 | 85 | 85 |
| 11 | 18 | 0 | 18 | 0 | 18 | 0 | 18 | 0 | 18 | 0 | 101 | 89 | 9 | 89 | 6 | 86 | 9 | 86 | 9 | 88 | 31 | 31 |
| 12 | 61 | 1 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 102 | 262 | 12 | 265 | 8 | 265 | 12 | 272 | 5 | 266 | 6 | 6 |
| 13 | 49 | 0 | 49 | 0 | 49 | 1 | 49 | 0 | 49 | 1 | 103 | 238 | 12 | 241 | 8 | 241 | 12 | 248 | 5 | 242 | 6 | 6 |
| 14 | 48 | 0 | 48 | 0 | 48 | 0 | 48 | 0 | 48 | 0 | 104 | 94 | 7 | 88 | 8 | 86 | 11 | 86 | 4 | 86 | 9 | 9 |
| 15 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 61 | 0 | 105 | 265 | 37 | 265 | 9 | 260 | 7 | 270 | 6 | 267 | 7 | 7 |
| 16 | 49 | 0 | 49 | 1 | 49 | 1 | 49 | 0 | 49 | 0 | 106 | 243 | 9 | 241 | 9 | 236 | 6 | 246 | 6 | 243 | 7 | 7 |
| 17 | 92 | 1 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 107 | 418 | 20 | 410 | 5 | 425 | 5 | 431 | 4 | 417 | 5 | 5 |
| 18 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 92 | 0 | 108 | 212 | 42 | 216 | 7 | 229 | 5 | 216 | 5 | 223 | 4 | 4 |
| 19 | 44 | 0 | 44 | 0 | 44 | 0 | 44 | 0 | 44 | 1 | 109 | 223 | 6 | 223 | 8 | 236 | 5 | 218 | 4 | 223 | 7 | 7 |
| 20 | 54 | 0 | 54 | 1 | 54 | 1 | 54 | 0 | 54 | 0 | 110 | 440 | 35 | 430 | 5 | 436 | 4 | 430 | 5 | 430 | 7 | 7 |
| 21 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 35 | 0 | 111 | 139 | 94 | 139 | 94 | 139 | 60 | 144 | 103 | 143 | 12 | 12 |
| 22 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 1 | 95 | 0 | 112 | 379 | 119 | 394 | 4 | 373 | 189 | 383 | 7 | 401 | 191 | 191 |
| 23 | 82 | 0 | 82 | 0 | 82 | 0 | 82 | 0 | 82 | 0 | 113 | 368 | 257 | 374 | 97 | 384 | 63 | 356 | 129 | 369 | 13 | 13 |
| 24 | 35 | 0 | 35 | 0 | 35 | 1 | 35 | 0 | 35 | 0 | 114 | 139 | 147 | 145 | 109 | 147 | 55 | 145 | 111 | 145 | 35 | 35 |
| 25 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 95 | 0 | 115 | 603 | 66 | 612 | 132 | 603 | 6 | 623 | 100 | 633 | 103 | 103 |
| 26 | 82 | 1 | 82 | 0 | 82 | 0 | 82 | 0 | 82 | 1 | 116 | 373 | 35 | 386 | 6 | 410 | 150 | 397 | 257 | 404 | 35 | 35 |
| 27 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 1 | 142 | 0 | 117 | 366 | 36 | 356 | 68 | 369 | 92 | 397 | 94 | 369 | 165 | 165 |
| 28 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 142 | 0 | 118 | 598 | 7 | 638 | 4 | 638 | 156 | 598 | 101 | 598 | 121 | 121 |
| 29 | 98 | 1 | 98 | 0 | 98 | 0 | 98 | 0 | 98 | 0 | 119 | 544 | 4 | 528 | 154 | 551 | 8 | 543 | 43 | 560 | 11 | 11 |
| 30 | 113 | 0 | 113 | 0 | 113 | 0 | 113 | 0 | 113 | 0 | 120 | 751 | 6 | 751 | 44 | 770 | 97 | 751 | 6 | 802 | 74 | 74 |
| 31 | 20 | 151 | 24 | 150 | 23 | 6 | 23 | 84 | 23 | 59 | 121 | 50 | 215 | 53 | 256 | 55 | 14 | 57 | 77 | 58 | 235 | 235 |
| 32 | 37 | 39 | 47 | 130 | 41 | 121 | 39 | 20 | 39 | 41 | 122 | 120 | 241 | 125 | 13 | 117 | 6 | 124 | 235 | 135 | 265 | 265 |
| 33 | 38 | 4 | 27 | 171 | 27 | 27 | 31 | 164 | 35 | 170 | 123 | 122 | 117 | 120 | 280 | 115 | 150 | 122 | 197 | 107 | 47 | 47 |
| 34 | 23 | 109 | 25 | 112 | 25 | 36 | 23 | 20 | 23 | 37 | 124 | 66 | 185 | 66 | 158 | 56 | 40 | 64 | 6 | 62 | 7 | 7 |
| 35 | 47 | 129 | 39 | 148 | 44 | 156 | 38 | 141 | 41 | 21 | 125 | 316 | 134 | 308 | 288 | 285 | 247 | 300 | 260 | 267 | 248 | 248 |
| 36 | 27 | 5 | 34 | 7 | 38 | 107 | 32 | 103 | 38 | 4 | 126 | 200 | 314 | 190 | 218 | 197 | 6 | 188 | 117 | 200 | 214 | 214 |
| 37 | 50 | 108 | 53 | 94 | 50 | 4 | 44 | 24 | 60 | 58 | 127 | 185 | 286 | 164 | 231 | 174 | 46 | 195 | 321 | 183 | 293 | 293 |
| 38 | 68 | 6 | 72 | 110 | 78 | 60 | 68 | 4 | 60 | 76 | 128 | 304 | 169 | 294 | 215 | 294 | 81 | 284 | 9 | 304 | 344 | 344 |
| 39 | 59 | 24 | 66 | 54 | 59 | 41 | 66 | 75 | 52 | 24 | 129 | 203 | 118 | 188 | 239 | 222 | 6 | 200 | 10 | 198 | 6 | 6 |
| 40 | 124 | 118 | 111 | 4 | 131 | 58 | 123 | 76 | 131 | 139 | 130 | 260 | 333 | 250 | 8 | 261 | 241 | 264 | 380 | 258 | 12 | 12 |
| 41 | 79 | 6 | 79 | 4 | 79 | 8 | 79 | 8 | 79 | 6 | 131 | 122 | 49 | 113 | 207 | 124 | 199 | 120 | 196 | 113 | 273 | 273 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 42 | 278 | 7 | 258 | 7 | 278 | 4 | 278 | 4 | 278 | 6 | 132 | 323 | 94 | 323 | 392 | 323 | 87 | 375 | 163 | 347 | 6 |
| 43 | 259 | 128 | 239 | 6 | 259 | 123 | 259 | 4 | 259 | 6 | 133 | 389 | 174 | 382 | 138 | 326 | 8 | 327 | 165 | 357 | 56 |
| 44 | 77 | 5 | 79 | 6 | 79 | 4 | 79 | 4 | 79 | 4 | 134 | 126 | 7 | 142 | 44 | 112 | 119 | 130 | 180 | 116 | 42 |
| 45 | 365 | 134 | 394 | 8 | 384 | 115 | 394 | 150 | 385 | 73 | 135 | 594 | 137 | 591 | 315 | 598 | 141 | 584 | 93 | 531 | 232 |
| 46 | 279 | 4 | 279 | 4 | 279 | 4 | 279 | 5 | 279 | 4 | 136 | 320 | 295 | 369 | 273 | 314 | 134 | 371 | 226 | 377 | 50 |
| 47 | 260 | 4 | 260 | 4 | 260 | 4 | 260 | 5 | 260 | 4 | 137 | 348 | 96 | 377 | 302 | 363 | 43 | 324 | 358 | 371 | 256 |
| 48 | 394 | 6 | 394 | 5 | 399 | 150 | 399 | 4 | 394 | 7 | 138 | 536 | 405 | 572 | 57 | 594 | 102 | 618 | 274 | 526 | 97 |
| 49 | 247 | 155 | 259 | 5 | 259 | 6 | 261 | 6 | 261 | 6 | 139 | 638 | 8 | 534 | 194 | 598 | 141 | 606 | 351 | 550 | 221 |
| 50 | 215 | 5 | 215 | 5 | 215 | 4 | 215 | 4 | 215 | 5 | 140 | 675 | 261 | 618 | 6 | 684 | 143 | 635 | 11 | 699 | 416 |
| 51 | 124 | 166 | 128 | 7 | 133 | 145 | 120 | 87 | 127 | 136 | 141 | 203 | 93 | 215 | 58 | 201 | 137 | 201 | 258 | 195 | 300 |
| 52 | 359 | 197 | 385 | 4 | 369 | 178 | 385 | 5 | 382 | 7 | 142 | 559 | 175 | 581 | 47 | 554 | 305 | 557 | 317 | 485 | 273 |
| 53 | 354 | 6 | 357 | 4 | 354 | 4 | 354 | 179 | 354 | 6 | 143 | 495 | 289 | 503 | 281 | 563 | 5 | 569 | 426 | 522 | 59 |
| 54 | 134 | 5 | 118 | 114 | 128 | 4 | 120 | 143 | 118 | 91 | 144 | 202 | 136 | 200 | 54 | 208 | 44 | 212 | 10 | 226 | 214 |
| 55 | 609 | 6 | 596 | 5 | 556 | 79 | 603 | 209 | 556 | 31 | 145 | 867 | 193 | 862 | 202 | 882 | 369 | 855 | 14 | 871 | 237 |
| 56 | 366 | 138 | 389 | 26 | 382 | 116 | 382 | 7 | 382 | 198 | 146 | 546 | 262 | 541 | 250 | 488 | 139 | 535 | 178 | 533 | 416 |
| 57 | 339 | 138 | 354 | 89 | 339 | 200 | 358 | 154 | 338 | 6 | 147 | 575 | 273 | 503 | 23 | 555 | 271 | 547 | 379 | 547 | 317 |
| 58 | 501 | 4 | 501 | 81 | 530 | 4 | 498 | 96 | 506 | 163 | 148 | 872 | 280 | 826 | 283 | 890 | 266 | 802 | 424 | 786 | 188 |
| 59 | 387 | 6 | 381 | 81 | 392 | 74 | 387 | 25 | 383 | 157 | 149 | 482 | 294 | 482 | 105 | 554 | 278 | 542 | 135 | 502 | 102 |
| 60 | 450 | 27 | 450 | 5 | 415 | 126 | 450 | 7 | 443 | 122 | 150 | 1788 | 242 | 1722 | 450 | 1776 | 163 | 1840 | 59 | 1810 | 107 |
| 61 | 42 | 68 | 44 | 48 | 44 | 190 | 41 | 24 | 42 | 22 | 151 | 69 | 25 | 77 | 20 | 82 | 268 | 72 | 312 | 71 | 175 |
| 62 | 85 | 165 | 85 | 47 | 85 | 50 | 76 | 132 | 77 | 164 | 152 | 285 | 193 | 285 | 17 | 256 | 22 | 282 | 17 | 321 | 10 |
| 63 | 75 | 54 | 78 | 206 | 75 | 69 | 69 | 31 | 78 | 50 | 153 | 169 | 18 | 149 | 233 | 167 | 65 | 162 | 341 | 155 | 73 |
| 64 | 47 | 126 | 45 | 24 | 43 | 4 | 49 | 5 | 47 | 71 | 154 | 146 | 231 | 141 | 168 | 141 | 149 | 162 | 11 | 139 | 283 |
| 65 | 89 | 183 | 81 | 217 | 91 | 181 | 94 | 88 | 87 | 24 | 155 | 82 | 12 | 90 | 399 | 88 | 314 | 82 | 387 | 86 | 365 |
| 66 | 89 | 90 | 80 | 6 | 81 | 6 | 80 | 116 | 72 | 74 | 156 | 163 | 9 | 160 | 10 | 160 | 79 | 165 | 120 | 156 | 297 |
| 67 | 122 | 5 | 128 | 47 | 114 | 5 | 126 | 115 | 118 | 28 | 157 | 161 | 299 | 159 | 294 | 151 | 142 | 160 | 289 | 174 | 250 |
| 68 | 105 | 165 | 104 | 26 | 105 | 4 | 105 | 162 | 105 | 65 | 158 | 382 | 352 | 354 | 427 | 402 | 116 | 374 | 359 | 374 | 504 |
| 69 | 125 | 98 | 121 | 164 | 125 | 166 | 133 | 25 | 120 | 29 | 159 | 228 | 15 | 236 | 406 | 232 | 452 | 224 | 128 | 222 | 15 |
| 70 | 167 | 27 | 159 | 145 | 156 | 97 | 162 | 221 | 152 | 215 | 160 | 206 | 13 | 246 | 306 | 210 | 182 | 222 | 12 | 206 | 246 |
| 71 | 103 | 106 | 92 | 75 | 105 | 99 | 101 | 168 | 104 | 198 | 161 | 138 | 194 | 132 | 14 | 133 | 13 | 126 | 472 | 130 | 14 |
| 72 | 309 | 59 | 328 | 210 | 338 | 127 | 331 | 185 | 307 | 193 | 162 | 398 | 330 | 360 | 135 | 360 | 121 | 372 | 72 | 370 | 423 |
| 73 | 289 | 88 | 306 | 245 | 313 | 112 | 288 | 168 | 302 | 5 | 163 | 351 | 76 | 365 | 208 | 371 | 71 | 369 | 136 | 368 | 335 |
| 74 | 110 | 48 | 104 | 197 | 108 | 74 | 108 | 72 | 110 | 98 | 164 | 387 | 575 | 382 | 440 | 389 | 369 | 364 | 76 | 382 | 154 |
| 75 | 344 | 243 | 306 | 183 | 323 | 186 | 321 | 239 | 304 | 216 | 165 | 125 | 30 | 137 | 343 | 137 | 24 | 151 | 60 | 143 | 372 |
| 76 | 310 | 8 | 297 | 219 | 287 | 34 | 292 | 127 | 282 | 167 | 166 | 375 | 336 | 349 | 566 | 389 | 261 | 374 | 497 | 354 | 246 |
| 77 | 516 | 33 | 540 | 148 | 508 | 11 | 484 | 67 | 530 | 107 | 167 | 384 | 440 | 411 | 129 | 407 | 278 | 385 | 16 | 366 | 87 |
| 78 | 243 | 34 | 262 | 130 | 261 | 203 | 252 | 161 | 260 | 80 | 168 | 599 | 327 | 609 | 493 | 615 | 11 | 590 | 85 | 561 | 162 |
| 79 | 507 | 213 | 517 | 33 | 498 | 245 | 483 | 191 | 479 | 261 | 169 | 675 | 72 | 622 | 441 | 560 | 407 | 621 | 443 | 615 | 383 |
| 80 | 316 | 30 | 316 | 10 | 330 | 137 | 304 | 80 | 304 | 255 | 170 | 649 | 394 | 614 | 232 | 650 | 290 | 659 | 197 | 606 | 12 |
| 81 | 161 | 81 | 163 | 10 | 163 | 58 | 173 | 32 | 169 | 220 | 171 | 192 | 316 | 204 | 20 | 199 | 541 | 199 | 397 | 198 | 81 |
| 82 | 464 | 36 | 459 | 87 | 455 | 186 | 462 | 64 | 427 | 135 | 172 | 453 | 265 | 440 | 338 | 471 | 220 | 462 | 83 | 472 | 260 |
| 83 | 428 | 233 | 365 | 175 | 443 | 223 | 413 | 212 | 433 | 268 | 173 | 492 | 548 | 519 | 207 | 497 | 605 | 498 | 232 | 489 | 404 |
| 84 | 160 | 240 | 180 | 4 | 170 | 27 | 182 | 216 | 156 | 233 | 174 | 519 | 469 | 515 | 212 | 538 | 81 | 507 | 335 | 532 | 13 |
| 85 | 481 | 151 | 488 | 160 | 497 | 250 | 456 | 255 | 476 | 61 | 175 | 201 | 207 | 205 | 139 | 209 | 297 | 201 | 242 | 221 | 9 |
| 86 | 425 | 70 | 460 | 66 | 454 | 57 | 444 | 175 | 471 | 194 | 176 | 827 | 216 | 766 | 17 | 827 | 203 | 828 | 133 | 776 | 25 |
| 87 | 688 | 206 | 712 | 177 | 778 | 92 | 672 | 45 | 620 | 118 | 177 | 921 | 19 | 908 | 494 | 972 | 12 | 902 | 658 | 870 | 87 |
| 88 | 702 | 4 | 657 | 60 | 692 | 138 | 668 | 177 | 625 | 71 | 178 | 590 | 80 | 632 | 68 | 594 | 594 | 546 | 399 | 630 | 336 |
| 89 | 401 | 37 | 348 | 116 | 387 | 135 | 382 | 116 | 366 | 109 | 179 | 415 | 13 | 440 | 195 | 428 | 585 | 435 | 325 | 404 | 11 |
| 90 | 615 | 9 | 587 | 116 | 576 | 115 | 570 | 251 | 634 | 221 | 180 | 967 | 460 | 920 | 293 | 881 | 223 | 989 | 341 | 947 | 88 |

Appendix D PSO Heuristic Procedures with SA – Results

PSO/SA Heuristic Procedure 1

| Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | | Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | |
|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 6 | 7 | 6 | 7 | 6 | 7 | 6 | 7 | 6 | 91 | 42 | 202 | 42 | 202 | 42 | 200 | 42 | 218 | 42 | 216 |
| 2 | 14 | 7 | 14 | 7 | 14 | 7 | 14 | 7 | 14 | 7 | 92 | 79 | 225 | 79 | 217 | 79 | 216 | 79 | 205 | 79 | 216 |
| 3 | 9 | 6 | 9 | 6 | 9 | 6 | 9 | 6 | 9 | 6 | 93 | 75 | 216 | 75 | 215 | 75 | 213 | 75 | 213 | 76 | 215 |
| 4 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 94 | 42 | 208 | 42 | 199 | 42 | 211 | 42 | 206 | 42 | 207 |
| 5 | 16 | 6 | 16 | 6 | 16 | 7 | 16 | 7 | 16 | 7 | 95 | 80 | 222 | 80 | 217 | 80 | 215 | 80 | 208 | 80 | 206 |
| 6 | 14 | 7 | 14 | 7 | 14 | 7 | 14 | 7 | 14 | 6 | 96 | 76 | 211 | 76 | 217 | 76 | 220 | 76 | 214 | 76 | 213 |
| 7 | 9 | 7 | 9 | 7 | 9 | 6 | 9 | 6 | 9 | 7 | 97 | 109 | 230 | 107 | 228 | 107 | 225 | 109 | 216 | 107 | 235 |
| 8 | 16 | 7 | 16 | 7 | 16 | 7 | 16 | 7 | 16 | 6 | 98 | 114 | 225 | 114 | 225 | 114 | 227 | 114 | 230 | 114 | 227 |
| 9 | 11 | 6 | 11 | 6 | 11 | 6 | 11 | 6 | 11 | 7 | 99 | 101 | 236 | 101 | 219 | 101 | 217 | 101 | 222 | 101 | 230 |
| 10 | 17 | 7 | 17 | 7 | 17 | 7 | 17 | 7 | 17 | 6 | 100 | 164 | 247 | 164 | 229 | 164 | 244 | 164 | 232 | 165 | 241 |
| 11 | 18 | 8 | 18 | 7 | 18 | 7 | 18 | 7 | 18 | 7 | 101 | 86 | 236 | 86 | 240 | 86 | 233 | 86 | 234 | 86 | 228 |
| 12 | 61 | 8 | 61 | 8 | 61 | 8 | 61 | 8 | 61 | 8 | 102 | 260 | 295 | 260 | 273 | 260 | 265 | 260 | 252 | 260 | 263 |
| 13 | 49 | 8 | 49 | 8 | 49 | 8 | 49 | 8 | 49 | 8 | 103 | 236 | 286 | 236 | 273 | 236 | 252 | 236 | 252 | 236 | 256 |
| 14 | 48 | 8 | 48 | 8 | 48 | 8 | 48 | 7 | 48 | 8 | 104 | 86 | 230 | 86 | 229 | 86 | 269 | 86 | 224 | 86 | 232 |
| 15 | 61 | 8 | 61 | 8 | 61 | 8 | 61 | 8 | 61 | 7 | 105 | 260 | 273 | 260 | 260 | 260 | 247 | 260 | 259 | 260 | 245 |
| 16 | 49 | 8 | 49 | 8 | 49 | 8 | 49 | 8 | 49 | 8 | 106 | 236 | 261 | 236 | 260 | 236 | 260 | 236 | 252 | 236 | 257 |
| 17 | 92 | 8 | 92 | 8 | 92 | 8 | 92 | 8 | 92 | 8 | 107 | 410 | 277 | 410 | 276 | 410 | 269 | 410 | 271 | 410 | 262 |
| 18 | 92 | 9 | 92 | 9 | 92 | 8 | 92 | 9 | 92 | 9 | 108 | 212 | 261 | 212 | 260 | 212 | 257 | 212 | 254 | 212 | 263 |
| 19 | 44 | 8 | 44 | 8 | 44 | 8 | 44 | 7 | 44 | 7 | 109 | 218 | 261 | 218 | 253 | 218 | 250 | 218 | 251 | 218 | 252 |
| 20 | 54 | 8 | 54 | 8 | 54 | 8 | 54 | 8 | 54 | 8 | 110 | 430 | 267 | 430 | 267 | 430 | 256 | 430 | 268 | 430 | 286 |
| 21 | 35 | 8 | 35 | 8 | 35 | 8 | 35 | 8 | 35 | 8 | 111 | 142 | 253 | 139 | 269 | 142 | 268 | 139 | 250 | 142 | 258 |
| 22 | 95 | 9 | 95 | 8 | 95 | 8 | 95 | 8 | 95 | 8 | 112 | 379 | 282 | 373 | 287 | 379 | 264 | 379 | 273 | 373 | 271 |
| 23 | 82 | 8 | 82 | 9 | 82 | 9 | 82 | 9 | 82 | 9 | 113 | 362 | 284 | 362 | 266 | 362 | 273 | 356 | 276 | 362 | 291 |
| 24 | 35 | 8 | 35 | 8 | 35 | 8 | 35 | 8 | 35 | 8 | 114 | 145 | 240 | 145 | 240 | 143 | 251 | 143 | 258 | 139 | 233 |
| 25 | 95 | 9 | 95 | 9 | 95 | 8 | 95 | 8 | 95 | 8 | 115 | 612 | 297 | 603 | 296 | 612 | 292 | 612 | 296 | 603 | 304 |
| 26 | 82 | 9 | 82 | 9 | 82 | 9 | 82 | 9 | 82 | 9 | 116 | 383 | 266 | 383 | 284 | 384 | 279 | 384 | 257 | 383 | 274 |
| 27 | 142 | 9 | 142 | 9 | 142 | 9 | 142 | 9 | 142 | 9 | 117 | 366 | 266 | 356 | 294 | 356 | 281 | 366 | 267 | 356 | 282 |
| 28 | 142 | 9 | 142 | 9 | 142 | 9 | 142 | 9 | 142 | 8 | 118 | 612 | 282 | 612 | 281 | 612 | 279 | 612 | 267 | 598 | 295 |
| 29 | 98 | 9 | 98 | 9 | 98 | 9 | 98 | 8 | 98 | 9 | 119 | 528 | 273 | 537 | 268 | 537 | 298 | 536 | 269 | 528 | 290 |
| 30 | 113 | 9 | 113 | 9 | 113 | 8 | 113 | 9 | 113 | 9 | 120 | 762 | 300 | 762 | 271 | 762 | 308 | 762 | 281 | 762 | 289 |
| 31 | 20 | 131 | 19 | 124 | 19 | 119 | 19 | 128 | 18 | 119 | 121 | 53 | 297 | 53 | 303 | 53 | 323 | 53 | 303 | 53 | 316 |
| 32 | 37 | 134 | 37 | 134 | 36 | 130 | 36 | 134 | 33 | 129 | 122 | 111 | 321 | 109 | 326 | 107 | 335 | 110 | 330 | 108 | 358 |
| 33 | 28 | 131 | 28 | 130 | 28 | 136 | 24 | 124 | 27 | 127 | 123 | 107 | 320 | 105 | 329 | 104 | 324 | 107 | 323 | 105 | 344 |
| 34 | 21 | 117 | 21 | 122 | 21 | 115 | 17 | 113 | 19 | 111 | 124 | 58 | 291 | 58 | 306 | 60 | 307 | 56 | 283 | 60 | 307 |
| 35 | 36 | 131 | 38 | 130 | 33 | 130 | 37 | 121 | 36 | 127 | 125 | 262 | 309 | 262 | 339 | 262 | 363 | 264 | 352 | 276 | 350 |
| 36 | 29 | 129 | 29 | 124 | 27 | 124 | 28 | 122 | 27 | 122 | 126 | 163 | 349 | 163 | 332 | 174 | 354 | 163 | 338 | 173 | 339 |
| 37 | 44 | 134 | 44 | 137 | 44 | 138 | 44 | 136 | 44 | 139 | 127 | 155 | 348 | 155 | 353 | 167 | 347 | 155 | 349 | 155 | 340 |
| 38 | 62 | 131 | 62 | 131 | 62 | 134 | 54 | 133 | 60 | 136 | 128 | 270 | 344 | 266 | 348 | 266 | 350 | 254 | 335 | 270 | 347 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 39 | 54 | 130 | 54 | 134 | 49 | 123 | 49 | 130 | 49 | 123 | 129 | 176 | 349 | 176 | 325 | 176 | 351 | 174 | 327 | 171 | 348 |
| 40 | 111 | 147 | 116 | 138 | 111 | 147 | 111 | 139 | 111 | 146 | 130 | 231 | 349 | 223 | 363 | 231 | 335 | 225 | 327 | 212 | 335 |
| 41 | 67 | 148 | 79 | 138 | 79 | 135 | 77 | 130 | 79 | 128 | 131 | 109 | 331 | 110 | 330 | 111 | 324 | 110 | 324 | 111 | 319 |
| 42 | 278 | 154 | 278 | 154 | 271 | 151 | 278 | 143 | 258 | 140 | 132 | 317 | 368 | 311 | 380 | 311 | 362 | 311 | 347 | 311 | 369 |
| 43 | 259 | 162 | 246 | 150 | 239 | 149 | 259 | 149 | 252 | 136 | 133 | 321 | 360 | 318 | 362 | 327 | 375 | 321 | 365 | 321 | 351 |
| 44 | 67 | 146 | 75 | 138 | 79 | 132 | 79 | 129 | 79 | 130 | 134 | 114 | 331 | 116 | 330 | 108 | 340 | 114 | 318 | 112 | 347 |
| 45 | 334 | 166 | 334 | 164 | 334 | 156 | 394 | 149 | 374 | 146 | 135 | 523 | 370 | 515 | 393 | 523 | 389 | 523 | 357 | 523 | 355 |
| 46 | 279 | 160 | 239 | 157 | 279 | 142 | 279 | 141 | 279 | 140 | 136 | 321 | 371 | 314 | 372 | 319 | 393 | 314 | 347 | 319 | 376 |
| 47 | 260 | 156 | 260 | 154 | 260 | 144 | 252 | 140 | 260 | 137 | 137 | 330 | 374 | 324 | 357 | 328 | 370 | 324 | 363 | 329 | 366 |
| 48 | 334 | 156 | 374 | 156 | 394 | 149 | 394 | 145 | 334 | 154 | 138 | 534 | 393 | 526 | 375 | 526 | 397 | 534 | 356 | 526 | 369 |
| 49 | 220 | 157 | 220 | 154 | 220 | 154 | 259 | 146 | 259 | 142 | 139 | 550 | 382 | 536 | 379 | 550 | 386 | 550 | 374 | 536 | 369 |
| 50 | 215 | 156 | 191 | 155 | 215 | 143 | 215 | 141 | 215 | 135 | 140 | 599 | 377 | 568 | 386 | 568 | 380 | 587 | 364 | 577 | 382 |
| 51 | 108 | 153 | 118 | 152 | 128 | 145 | 128 | 138 | 118 | 144 | 141 | 197 | 358 | 193 | 359 | 194 | 368 | 193 | 361 | 195 | 365 |
| 52 | 326 | 162 | 378 | 161 | 359 | 161 | 326 | 162 | 326 | 162 | 142 | 485 | 402 | 482 | 379 | 485 | 377 | 475 | 407 | 485 | 369 |
| 53 | 298 | 173 | 338 | 161 | 298 | 160 | 298 | 157 | 354 | 149 | 143 | 495 | 393 | 492 | 384 | 492 | 379 | 495 | 398 | 492 | 368 |
| 54 | 108 | 153 | 128 | 146 | 128 | 142 | 120 | 146 | 118 | 144 | 144 | 200 | 353 | 196 | 343 | 196 | 346 | 198 | 342 | 192 | 337 |
| 55 | 520 | 180 | 520 | 169 | 604 | 162 | 520 | 161 | 520 | 162 | 145 | 783 | 391 | 788 | 385 | 779 | 385 | 783 | 368 | 779 | 379 |
| 56 | 326 | 173 | 366 | 171 | 326 | 161 | 326 | 162 | 355 | 156 | 146 | 492 | 373 | 488 | 386 | 488 | 376 | 488 | 387 | 478 | 377 |
| 57 | 298 | 162 | 298 | 163 | 298 | 160 | 354 | 153 | 354 | 152 | 147 | 495 | 400 | 498 | 369 | 483 | 376 | 495 | 380 | 490 | 380 |
| 58 | 426 | 174 | 426 | 168 | 493 | 162 | 426 | 166 | 493 | 163 | 148 | 788 | 391 | 782 | 400 | 792 | 391 | 786 | 385 | 782 | 399 |
| 59 | 332 | 163 | 332 | 162 | 332 | 158 | 392 | 154 | 332 | 156 | 149 | 474 | 403 | 482 | 389 | 489 | 367 | 490 | 392 | 485 | 375 |
| 60 | 380 | 163 | 380 | 162 | 436 | 161 | 380 | 156 | 380 | 155 | 150 | 1611 | 416 | 1629 | 416 | 1629 | 415 | 1611 | 392 | 1587 | 421 |
| 61 | 36 | 182 | 35 | 188 | 36 | 195 | 38 | 194 | 38 | 180 | 151 | 66 | 543 | 62 | 506 | 62 | 478 | 62 | 527 | 66 | 503 |
| 62 | 76 | 198 | 69 | 197 | 73 | 197 | 69 | 202 | 76 | 195 | 152 | 229 | 567 | 229 | 543 | 246 | 534 | 229 | 589 | 241 | 540 |
| 63 | 69 | 199 | 69 | 198 | 69 | 195 | 62 | 201 | 63 | 195 | 153 | 131 | 533 | 131 | 553 | 131 | 538 | 131 | 558 | 141 | 518 |
| 64 | 39 | 182 | 35 | 185 | 39 | 185 | 39 | 184 | 39 | 187 | 154 | 127 | 507 | 137 | 535 | 127 | 510 | 131 | 527 | 127 | 524 |
| 65 | 78 | 200 | 78 | 199 | 79 | 199 | 76 | 193 | 68 | 203 | 155 | 68 | 528 | 68 | 486 | 68 | 494 | 70 | 473 | 68 | 491 |
| 66 | 71 | 196 | 71 | 199 | 71 | 196 | 71 | 186 | 69 | 194 | 156 | 145 | 554 | 137 | 543 | 137 | 511 | 137 | 492 | 137 | 541 |
| 67 | 110 | 201 | 110 | 192 | 110 | 198 | 110 | 204 | 110 | 195 | 157 | 141 | 547 | 141 | 536 | 133 | 529 | 133 | 489 | 133 | 538 |
| 68 | 83 | 199 | 95 | 200 | 93 | 195 | 93 | 203 | 93 | 201 | 158 | 318 | 546 | 318 | 577 | 318 | 543 | 318 | 556 | 318 | 597 |
| 69 | 117 | 201 | 101 | 204 | 103 | 199 | 116 | 209 | 112 | 211 | 159 | 184 | 523 | 184 | 541 | 184 | 522 | 184 | 532 | 184 | 528 |
| 70 | 143 | 203 | 138 | 215 | 145 | 221 | 145 | 199 | 138 | 201 | 160 | 188 | 497 | 188 | 541 | 188 | 537 | 188 | 538 | 198 | 556 |
| 71 | 84 | 210 | 92 | 206 | 89 | 212 | 84 | 208 | 90 | 208 | 161 | 111 | 530 | 111 | 561 | 118 | 544 | 111 | 512 | 118 | 514 |
| 72 | 275 | 217 | 269 | 215 | 263 | 214 | 282 | 220 | 282 | 220 | 162 | 336 | 547 | 336 | 556 | 336 | 555 | 336 | 582 | 356 | 559 |
| 73 | 258 | 216 | 249 | 215 | 248 | 226 | 247 | 217 | 260 | 215 | 163 | 315 | 586 | 333 | 552 | 315 | 608 | 315 | 575 | 315 | 585 |
| 74 | 92 | 209 | 84 | 204 | 90 | 198 | 90 | 207 | 86 | 214 | 164 | 350 | 586 | 332 | 563 | 350 | 580 | 332 | 556 | 332 | 580 |
| 75 | 270 | 235 | 272 | 213 | 285 | 224 | 263 | 220 | 286 | 226 | 165 | 123 | 504 | 123 | 497 | 117 | 519 | 117 | 538 | 117 | 514 |
| 76 | 273 | 223 | 249 | 222 | 256 | 220 | 263 | 222 | 273 | 227 | 166 | 321 | 582 | 321 | 575 | 321 | 549 | 339 | 583 | 328 | 557 |
| 77 | 420 | 215 | 432 | 222 | 452 | 213 | 420 | 230 | 436 | 232 | 167 | 338 | 584 | 357 | 554 | 343 | 555 | 338 | 574 | 355 | 544 |
| 78 | 223 | 216 | 222 | 231 | 208 | 207 | 209 | 208 | 223 | 228 | 168 | 536 | 592 | 536 | 613 | 536 | 586 | 536 | 567 | 559 | 569 |
| 79 | 392 | 227 | 416 | 230 | 418 | 230 | 418 | 225 | 404 | 231 | 169 | 544 | 593 | 539 | 585 | 544 | 596 | 544 | 589 | 574 | 574 |
| 80 | 272 | 222 | 274 | 222 | 250 | 221 | 270 | 213 | 270 | 216 | 170 | 558 | 554 | 558 | 561 | 558 | 574 | 589 | 625 | 558 | 580 |
| 81 | 141 | 218 | 144 | 213 | 141 | 212 | 150 | 230 | 150 | 218 | 171 | 177 | 537 | 173 | 531 | 182 | 532 | 173 | 574 | 179 | 555 |
| 82 | 382 | 238 | 393 | 227 | 400 | 236 | 400 | 224 | 400 | 222 | 172 | 406 | 578 | 405 | 613 | 414 | 572 | 413 | 574 | 410 | 591 |
| 83 | 346 | 238 | 349 | 232 | 366 | 238 | 361 | 236 | 368 | 237 | 173 | 434 | 563 | 434 | 557 | 434 | 559 | 449 | 582 | 434 | 608 |
| 84 | 142 | 214 | 144 | 210 | 154 | 217 | 150 | 208 | 142 | 214 | 174 | 457 | 565 | 457 | 601 | 457 | 571 | 457 | 603 | 457 | 575 |
| 85 | 397 | 238 | 400 | 233 | 396 | 236 | 387 | 235 | 387 | 230 | 175 | 181 | 549 | 187 | 567 | 179 | 537 | 179 | 560 | 179 | 560 |
| 86 | 363 | 238 | 368 | 238 | 358 | 231 | 366 | 234 | 366 | 231 | 176 | 718 | 571 | 742 | 609 | 718 | 636 | 718 | 596 | 719 | 624 |
| 87 | 588 | 256 | 620 | 243 | 620 | 237 | 636 | 241 | 596 | 241 | 177 | 811 | 617 | 784 | 610 | 784 | 579 | 784 | 612 | 784 | 610 |
| 88 | 567 | 232 | 556 | 245 | 572 | 235 | 544 | 253 | 560 | 234 | 178 | 540 | 567 | 522 | 595 | 540 | 617 | 538 | 635 | 540 | 629 |
| 89 | 335 | 222 | 336 | 221 | 346 | 227 | 336 | 250 | 343 | 222 | 179 | 392 | 577 | 377 | 571 | 377 | 600 | 377 | 600 | 392 | 549 |
| 90 | 503 | 234 | 506 | 240 | 517 | 242 | 507 | 249 | 519 | 243 | 180 | 804 | 617 | 827 | 597 | 827 | 589 | 804 | 645 | 841 | 653 |

PSO/SA Heuristic Procedure 2

| Problem # | c ₁ = c ₂ = 0.25 | | c ₁ = c ₂ = 0.30 | | c ₁ = c ₂ = 0.35 | | c ₁ = c ₂ = 0.40 | | c ₁ = c ₂ = 0.45 | | Problem # | c ₁ = c ₂ = 0.25 | | c ₁ = c ₂ = 0.30 | | c ₁ = c ₂ = 0.35 | | c ₁ = c ₂ = 0.40 | | c ₁ = c ₂ = 0.45 | |
|-----------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|-----------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 6 | 7 | 6 | 7 | 7 | 7 | 6 | 7 | 6 | 91 | 42 | 222 | 42 | 157 | 42 | 160 | 42 | 159 | 42 | 163 |
| 2 | 14 | 7 | 14 | 8 | 14 | 7 | 14 | 7 | 14 | 8 | 92 | 79 | 233 | 79 | 169 | 79 | 172 | 79 | 171 | 79 | 173 |
| 3 | 9 | 7 | 9 | 7 | 9 | 7 | 9 | 7 | 9 | 7 | 93 | 75 | 230 | 77 | 168 | 77 | 171 | 77 | 171 | 77 | 174 |
| 4 | 7 | 7 | 7 | 6 | 7 | 7 | 7 | 7 | 7 | 6 | 94 | 42 | 222 | 44 | 156 | 44 | 159 | 44 | 158 | 44 | 161 |
| 5 | 16 | 8 | 16 | 8 | 16 | 7 | 16 | 8 | 16 | 8 | 95 | 82 | 235 | 82 | 168 | 82 | 172 | 82 | 171 | 82 | 173 |
| 6 | 14 | 7 | 14 | 7 | 14 | 8 | 14 | 7 | 14 | 7 | 96 | 78 | 233 | 76 | 167 | 76 | 170 | 76 | 170 | 76 | 173 |
| 7 | 9 | 7 | 9 | 7 | 9 | 7 | 9 | 7 | 9 | 8 | 97 | 107 | 244 | 109 | 176 | 109 | 179 | 109 | 178 | 109 | 181 |
| 8 | 16 | 8 | 16 | 8 | 16 | 7 | 16 | 8 | 16 | 7 | 98 | 114 | 238 | 114 | 174 | 114 | 177 | 114 | 176 | 114 | 180 |
| 9 | 11 | 7 | 11 | 7 | 11 | 7 | 11 | 7 | 11 | 7 | 99 | 104 | 237 | 103 | 172 | 103 | 175 | 103 | 174 | 103 | 177 |
| 10 | 17 | 8 | 17 | 8 | 17 | 8 | 17 | 8 | 17 | 8 | 100 | 164 | 248 | 171 | 183 | 171 | 187 | 171 | 187 | 171 | 190 |
| 11 | 18 | 7 | 18 | 7 | 18 | 8 | 18 | 7 | 18 | 8 | 101 | 86 | 244 | 86 | 180 | 86 | 183 | 86 | 182 | 86 | 185 |
| 12 | 61 | 9 | 61 | 9 | 61 | 8 | 61 | 9 | 61 | 9 | 102 | 260 | 269 | 260 | 205 | 260 | 207 | 260 | 206 | 260 | 209 |
| 13 | 49 | 8 | 49 | 9 | 49 | 9 | 49 | 9 | 49 | 8 | 103 | 236 | 269 | 236 | 202 | 236 | 206 | 236 | 205 | 236 | 209 |
| 14 | 48 | 9 | 48 | 9 | 48 | 9 | 48 | 9 | 48 | 9 | 104 | 86 | 247 | 86 | 178 | 86 | 181 | 86 | 180 | 86 | 183 |
| 15 | 61 | 8 | 61 | 9 | 61 | 9 | 61 | 9 | 61 | 9 | 105 | 260 | 269 | 260 | 208 | 260 | 206 | 260 | 205 | 260 | 209 |
| 16 | 49 | 9 | 49 | 8 | 49 | 9 | 49 | 9 | 49 | 9 | 106 | 236 | 267 | 236 | 208 | 236 | 206 | 236 | 204 | 236 | 207 |
| 17 | 92 | 9 | 92 | 10 | 92 | 9 | 92 | 9 | 92 | 9 | 107 | 410 | 282 | 410 | 221 | 410 | 217 | 410 | 216 | 410 | 219 |
| 18 | 92 | 10 | 92 | 9 | 92 | 9 | 92 | 9 | 92 | 10 | 108 | 212 | 265 | 212 | 205 | 212 | 202 | 212 | 201 | 212 | 202 |
| 19 | 44 | 8 | 44 | 9 | 44 | 9 | 44 | 9 | 44 | 9 | 109 | 218 | 267 | 218 | 204 | 218 | 202 | 218 | 201 | 218 | 202 |
| 20 | 54 | 9 | 54 | 9 | 54 | 9 | 54 | 9 | 54 | 8 | 110 | 430 | 279 | 430 | 219 | 430 | 217 | 430 | 215 | 430 | 217 |
| 21 | 35 | 9 | 35 | 8 | 35 | 9 | 35 | 9 | 35 | 9 | 111 | 139 | 266 | 142 | 203 | 142 | 200 | 142 | 199 | 142 | 201 |
| 22 | 95 | 9 | 95 | 10 | 95 | 9 | 95 | 9 | 95 | 10 | 112 | 379 | 289 | 380 | 225 | 380 | 223 | 380 | 222 | 380 | 223 |
| 23 | 82 | 10 | 82 | 10 | 82 | 10 | 82 | 10 | 82 | 10 | 113 | 362 | 283 | 363 | 225 | 363 | 222 | 363 | 221 | 363 | 222 |
| 24 | 35 | 9 | 35 | 9 | 35 | 9 | 35 | 9 | 35 | 9 | 114 | 145 | 263 | 145 | 202 | 145 | 200 | 145 | 198 | 145 | 200 |
| 25 | 95 | 9 | 95 | 10 | 95 | 10 | 95 | 10 | 95 | 10 | 115 | 612 | 297 | 612 | 235 | 612 | 232 | 612 | 231 | 612 | 233 |
| 26 | 82 | 10 | 82 | 9 | 82 | 10 | 82 | 9 | 82 | 9 | 116 | 385 | 286 | 385 | 225 | 385 | 222 | 385 | 221 | 385 | 222 |
| 27 | 142 | 10 | 142 | 11 | 142 | 10 | 142 | 11 | 142 | 11 | 117 | 368 | 286 | 367 | 223 | 367 | 221 | 367 | 221 | 367 | 221 |
| 28 | 142 | 10 | 142 | 10 | 142 | 10 | 142 | 10 | 142 | 10 | 118 | 612 | 293 | 620 | 234 | 620 | 232 | 620 | 231 | 620 | 232 |
| 29 | 98 | 10 | 98 | 10 | 98 | 10 | 98 | 10 | 98 | 10 | 119 | 541 | 294 | 537 | 235 | 537 | 231 | 537 | 229 | 537 | 231 |
| 30 | 113 | 10 | 113 | 10 | 113 | 10 | 113 | 10 | 113 | 10 | 120 | 762 | 298 | 762 | 240 | 762 | 236 | 762 | 235 | 762 | 237 |
| 31 | 25 | 123 | 25 | 117 | 25 | 119 | 25 | 117 | 25 | 119 | 121 | 53 | 299 | 55 | 276 | 55 | 273 | 55 | 271 | 55 | 273 |
| 32 | 43 | 132 | 47 | 126 | 47 | 126 | 47 | 126 | 47 | 128 | 122 | 111 | 322 | 109 | 298 | 109 | 296 | 109 | 295 | 109 | 296 |
| 33 | 32 | 129 | 32 | 124 | 32 | 126 | 32 | 125 | 32 | 127 | 123 | 102 | 324 | 102 | 296 | 102 | 296 | 102 | 294 | 102 | 296 |
| 34 | 25 | 124 | 25 | 121 | 25 | 121 | 25 | 120 | 25 | 122 | 124 | 58 | 300 | 60 | 275 | 60 | 275 | 60 | 274 | 60 | 275 |
| 35 | 46 | 132 | 38 | 126 | 38 | 127 | 38 | 127 | 38 | 129 | 125 | 270 | 354 | 260 | 328 | 260 | 327 | 260 | 326 | 260 | 329 |
| 36 | 32 | 131 | 38 | 125 | 38 | 127 | 38 | 126 | 38 | 128 | 126 | 173 | 337 | 182 | 311 | 182 | 312 | 182 | 311 | 182 | 312 |
| 37 | 48 | 135 | 56 | 130 | 56 | 131 | 56 | 129 | 56 | 131 | 127 | 161 | 335 | 159 | 312 | 159 | 312 | 159 | 310 | 159 | 312 |
| 38 | 78 | 137 | 78 | 132 | 78 | 132 | 78 | 132 | 78 | 134 | 128 | 270 | 347 | 266 | 323 | 266 | 323 | 266 | 322 | 266 | 324 |
| 39 | 59 | 135 | 64 | 131 | 64 | 133 | 64 | 131 | 64 | 134 | 129 | 182 | 335 | 187 | 311 | 187 | 311 | 187 | 310 | 187 | 312 |
| 40 | 135 | 145 | 136 | 139 | 136 | 140 | 136 | 139 | 136 | 141 | 130 | 229 | 344 | 231 | 319 | 231 | 318 | 231 | 317 | 231 | 319 |
| 41 | 79 | 144 | 79 | 137 | 79 | 140 | 79 | 140 | 79 | 141 | 131 | 111 | 322 | 111 | 298 | 111 | 301 | 111 | 297 | 111 | 298 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 42 | 278 | 160 | 275 | 154 | 275 | 158 | 275 | 156 | 275 | 159 | 132 | 316 | 357 | 316 | 333 | 316 | 334 | 316 | 332 | 316 | 334 |
| 43 | 259 | 160 | 259 | 154 | 259 | 157 | 259 | 156 | 259 | 158 | 133 | 326 | 356 | 332 | 333 | 332 | 333 | 332 | 332 | 332 | 334 |
| 44 | 79 | 145 | 79 | 138 | 79 | 141 | 79 | 140 | 79 | 142 | 134 | 114 | 326 | 112 | 300 | 112 | 300 | 112 | 298 | 112 | 300 |
| 45 | 394 | 165 | 394 | 158 | 394 | 161 | 394 | 160 | 394 | 162 | 135 | 539 | 374 | 523 | 348 | 523 | 349 | 523 | 348 | 523 | 350 |
| 46 | 279 | 161 | 279 | 154 | 279 | 158 | 279 | 156 | 279 | 159 | 136 | 325 | 357 | 319 | 333 | 319 | 333 | 319 | 333 | 319 | 334 |
| 47 | 260 | 160 | 260 | 154 | 260 | 157 | 260 | 157 | 260 | 158 | 137 | 329 | 360 | 324 | 334 | 324 | 335 | 324 | 333 | 324 | 334 |
| 48 | 394 | 165 | 394 | 159 | 394 | 161 | 394 | 160 | 394 | 163 | 138 | 534 | 374 | 534 | 351 | 534 | 350 | 534 | 348 | 534 | 351 |
| 49 | 259 | 160 | 259 | 154 | 259 | 158 | 259 | 157 | 259 | 159 | 139 | 539 | 376 | 574 | 350 | 574 | 352 | 574 | 349 | 574 | 350 |
| 50 | 215 | 161 | 215 | 152 | 215 | 154 | 215 | 153 | 215 | 156 | 140 | 602 | 376 | 577 | 352 | 577 | 357 | 577 | 350 | 577 | 353 |
| 51 | 125 | 154 | 128 | 149 | 128 | 153 | 128 | 151 | 128 | 153 | 141 | 196 | 350 | 194 | 323 | 194 | 328 | 194 | 356 | 194 | 324 |
| 52 | 382 | 171 | 382 | 165 | 382 | 168 | 382 | 167 | 382 | 169 | 142 | 484 | 377 | 489 | 354 | 489 | 358 | 489 | 352 | 489 | 355 |
| 53 | 354 | 170 | 337 | 165 | 337 | 167 | 337 | 167 | 337 | 169 | 143 | 495 | 377 | 491 | 353 | 491 | 358 | 491 | 353 | 491 | 353 |
| 54 | 128 | 153 | 128 | 149 | 128 | 153 | 128 | 151 | 128 | 154 | 144 | 200 | 348 | 196 | 325 | 196 | 329 | 196 | 323 | 196 | 326 |
| 55 | 604 | 175 | 604 | 172 | 604 | 175 | 604 | 174 | 604 | 176 | 145 | 760 | 394 | 783 | 369 | 783 | 374 | 783 | 368 | 783 | 370 |
| 56 | 382 | 170 | 382 | 166 | 382 | 168 | 382 | 168 | 382 | 170 | 146 | 487 | 379 | 477 | 353 | 477 | 355 | 477 | 353 | 477 | 354 |
| 57 | 354 | 168 | 354 | 164 | 354 | 168 | 354 | 167 | 354 | 169 | 147 | 502 | 379 | 495 | 355 | 495 | 358 | 495 | 353 | 495 | 356 |
| 58 | 506 | 172 | 505 | 169 | 505 | 172 | 505 | 170 | 505 | 174 | 148 | 790 | 394 | 786 | 369 | 786 | 372 | 786 | 368 | 786 | 369 |
| 59 | 392 | 168 | 392 | 164 | 392 | 166 | 392 | 166 | 392 | 168 | 149 | 490 | 380 | 493 | 354 | 493 | 355 | 493 | 352 | 493 | 355 |
| 60 | 450 | 169 | 450 | 166 | 450 | 170 | 450 | 169 | 450 | 171 | 150 | 1629 | 416 | 1629 | 394 | 1629 | 396 | 1629 | 392 | 1629 | 394 |
| 61 | 38 | 184 | 39 | 152 | 39 | 155 | 39 | 154 | 39 | 155 | 151 | 62 | 454 | 66 | 377 | 66 | 378 | 66 | 374 | 66 | 379 |
| 62 | 76 | 198 | 78 | 164 | 78 | 167 | 78 | 167 | 78 | 169 | 152 | 246 | 517 | 229 | 432 | 229 | 434 | 229 | 430 | 229 | 433 |
| 63 | 69 | 196 | 62 | 163 | 62 | 166 | 62 | 165 | 62 | 167 | 153 | 131 | 492 | 131 | 409 | 131 | 411 | 131 | 407 | 131 | 410 |
| 64 | 39 | 189 | 41 | 157 | 41 | 159 | 41 | 159 | 41 | 161 | 154 | 127 | 489 | 127 | 408 | 127 | 411 | 127 | 408 | 127 | 409 |
| 65 | 76 | 199 | 76 | 168 | 76 | 171 | 76 | 170 | 76 | 171 | 155 | 68 | 462 | 70 | 380 | 70 | 378 | 70 | 377 | 70 | 381 |
| 66 | 58 | 198 | 71 | 166 | 71 | 169 | 71 | 168 | 71 | 169 | 156 | 137 | 490 | 137 | 410 | 137 | 406 | 137 | 408 | 137 | 411 |
| 67 | 102 | 207 | 102 | 172 | 102 | 176 | 102 | 175 | 102 | 176 | 157 | 140 | 488 | 141 | 410 | 141 | 407 | 141 | 407 | 141 | 410 |
| 68 | 93 | 202 | 93 | 169 | 93 | 172 | 93 | 170 | 93 | 172 | 158 | 338 | 523 | 318 | 445 | 318 | 441 | 318 | 441 | 318 | 443 |
| 69 | 116 | 205 | 116 | 173 | 116 | 175 | 116 | 176 | 116 | 176 | 159 | 184 | 494 | 184 | 420 | 184 | 416 | 184 | 416 | 184 | 420 |
| 70 | 143 | 210 | 143 | 177 | 143 | 180 | 143 | 179 | 143 | 181 | 160 | 188 | 499 | 188 | 419 | 188 | 417 | 188 | 425 | 188 | 420 |
| 71 | 89 | 209 | 90 | 175 | 90 | 178 | 90 | 178 | 90 | 178 | 161 | 111 | 494 | 118 | 415 | 118 | 411 | 118 | 422 | 118 | 415 |
| 72 | 281 | 230 | 273 | 198 | 273 | 201 | 273 | 200 | 273 | 201 | 162 | 336 | 535 | 336 | 457 | 336 | 455 | 336 | 465 | 336 | 458 |
| 73 | 242 | 231 | 260 | 197 | 260 | 201 | 260 | 200 | 260 | 202 | 163 | 315 | 535 | 337 | 458 | 337 | 454 | 337 | 465 | 337 | 458 |
| 74 | 90 | 208 | 84 | 176 | 84 | 179 | 84 | 179 | 84 | 179 | 164 | 332 | 546 | 341 | 459 | 341 | 454 | 341 | 467 | 341 | 458 |
| 75 | 290 | 231 | 274 | 200 | 274 | 202 | 274 | 201 | 274 | 203 | 165 | 123 | 492 | 117 | 416 | 117 | 413 | 117 | 424 | 117 | 417 |
| 76 | 241 | 230 | 268 | 197 | 268 | 201 | 268 | 201 | 268 | 202 | 166 | 321 | 536 | 321 | 459 | 321 | 454 | 321 | 465 | 321 | 458 |
| 77 | 432 | 241 | 420 | 209 | 420 | 211 | 420 | 210 | 420 | 212 | 167 | 357 | 530 | 350 | 459 | 350 | 454 | 350 | 466 | 350 | 459 |
| 78 | 223 | 224 | 214 | 194 | 214 | 197 | 214 | 197 | 214 | 197 | 168 | 564 | 561 | 536 | 479 | 536 | 480 | 536 | 484 | 536 | 480 |
| 79 | 392 | 240 | 404 | 209 | 404 | 212 | 404 | 212 | 404 | 213 | 169 | 544 | 554 | 564 | 479 | 564 | 479 | 564 | 481 | 564 | 479 |
| 80 | 266 | 229 | 271 | 197 | 271 | 200 | 271 | 199 | 271 | 200 | 170 | 558 | 555 | 558 | 479 | 558 | 480 | 558 | 481 | 558 | 479 |
| 81 | 144 | 223 | 149 | 190 | 149 | 194 | 149 | 193 | 149 | 194 | 171 | 173 | 529 | 173 | 449 | 173 | 450 | 173 | 451 | 173 | 448 |
| 82 | 396 | 242 | 380 | 210 | 380 | 213 | 380 | 213 | 380 | 214 | 172 | 406 | 569 | 404 | 483 | 404 | 485 | 404 | 486 | 404 | 484 |
| 83 | 381 | 242 | 356 | 210 | 356 | 214 | 356 | 213 | 356 | 214 | 173 | 434 | 567 | 448 | 488 | 448 | 490 | 448 | 491 | 448 | 489 |
| 84 | 146 | 224 | 146 | 191 | 146 | 194 | 146 | 194 | 146 | 194 | 174 | 457 | 571 | 457 | 490 | 457 | 491 | 457 | 492 | 457 | 490 |
| 85 | 397 | 244 | 400 | 211 | 400 | 215 | 400 | 213 | 400 | 215 | 175 | 185 | 529 | 185 | 450 | 185 | 451 | 185 | 452 | 185 | 450 |
| 86 | 366 | 242 | 368 | 210 | 368 | 213 | 368 | 213 | 368 | 215 | 176 | 718 | 586 | 730 | 509 | 730 | 511 | 730 | 511 | 730 | 510 |
| 87 | 620 | 251 | 596 | 221 | 596 | 224 | 596 | 224 | 596 | 226 | 177 | 784 | 596 | 811 | 512 | 811 | 514 | 811 | 517 | 811 | 512 |
| 88 | 558 | 249 | 539 | 217 | 539 | 221 | 539 | 220 | 539 | 223 | 178 | 522 | 588 | 544 | 495 | 544 | 497 | 544 | 497 | 544 | 495 |
| 89 | 348 | 239 | 343 | 206 | 343 | 210 | 343 | 209 | 343 | 213 | 179 | 392 | 563 | 377 | 482 | 377 | 485 | 377 | 484 | 377 | 483 |
| 90 | 521 | 248 | 521 | 217 | 521 | 219 | 521 | 219 | 521 | 222 | 180 | 804 | 597 | 824 | 513 | 824 | 515 | 824 | 516 | 824 | 513 |

PSO/SA Heuristic Procedure 3

| Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | | Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | |
|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 8 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 91 | 42 | 201 | 42 | 195 | 42 | 186 | 42 | 185 | 42 | 192 |
| 2 | 14 | 8 | 14 | 8 | 14 | 7 | 14 | 7 | 14 | 7 | 92 | 79 | 221 | 79 | 204 | 79 | 203 | 79 | 200 | 79 | 197 |
| 3 | 9 | 8 | 9 | 7 | 9 | 7 | 9 | 7 | 9 | 7 | 93 | 75 | 220 | 75 | 199 | 75 | 208 | 76 | 191 | 75 | 201 |
| 4 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 94 | 42 | 200 | 42 | 184 | 42 | 184 | 42 | 188 | 42 | 185 |
| 5 | 16 | 8 | 16 | 8 | 16 | 8 | 16 | 8 | 16 | 8 | 95 | 80 | 208 | 80 | 199 | 80 | 197 | 80 | 198 | 80 | 196 |
| 6 | 14 | 8 | 14 | 8 | 14 | 8 | 14 | 8 | 14 | 7 | 96 | 76 | 208 | 76 | 200 | 76 | 198 | 76 | 200 | 76 | 193 |
| 7 | 9 | 8 | 9 | 7 | 9 | 7 | 9 | 7 | 9 | 7 | 97 | 107 | 222 | 107 | 209 | 107 | 209 | 107 | 206 | 107 | 212 |
| 8 | 16 | 8 | 16 | 8 | 16 | 7 | 16 | 8 | 16 | 8 | 98 | 114 | 221 | 114 | 206 | 114 | 201 | 114 | 201 | 114 | 209 |
| 9 | 11 | 8 | 11 | 8 | 11 | 8 | 11 | 7 | 11 | 8 | 99 | 101 | 217 | 101 | 213 | 101 | 205 | 101 | 206 | 101 | 203 |
| 10 | 17 | 8 | 17 | 8 | 17 | 7 | 17 | 8 | 17 | 7 | 100 | 169 | 231 | 169 | 213 | 165 | 214 | 169 | 218 | 169 | 212 |
| 11 | 18 | 9 | 18 | 8 | 18 | 8 | 18 | 8 | 18 | 8 | 101 | 86 | 229 | 86 | 214 | 86 | 219 | 86 | 214 | 86 | 212 |
| 12 | 61 | 9 | 61 | 9 | 61 | 10 | 61 | 9 | 61 | 10 | 102 | 260 | 259 | 260 | 249 | 260 | 239 | 260 | 236 | 260 | 239 |
| 13 | 49 | 10 | 49 | 10 | 49 | 8 | 49 | 9 | 49 | 9 | 103 | 236 | 253 | 236 | 244 | 236 | 243 | 236 | 237 | 236 | 234 |
| 14 | 48 | 9 | 48 | 9 | 48 | 10 | 48 | 9 | 48 | 9 | 104 | 86 | 237 | 86 | 223 | 86 | 210 | 86 | 217 | 86 | 206 |
| 15 | 61 | 10 | 61 | 9 | 61 | 9 | 61 | 10 | 61 | 9 | 105 | 260 | 259 | 260 | 247 | 260 | 243 | 260 | 231 | 260 | 232 |
| 16 | 49 | 10 | 49 | 9 | 49 | 9 | 49 | 9 | 49 | 9 | 106 | 236 | 251 | 236 | 245 | 236 | 241 | 236 | 232 | 236 | 233 |
| 17 | 92 | 10 | 92 | 10 | 92 | 10 | 92 | 9 | 92 | 10 | 107 | 410 | 265 | 410 | 270 | 410 | 241 | 410 | 247 | 410 | 248 |
| 18 | 92 | 10 | 92 | 12 | 92 | 9 | 92 | 10 | 92 | 9 | 108 | 212 | 255 | 212 | 226 | 212 | 230 | 212 | 230 | 212 | 223 |
| 19 | 44 | 10 | 44 | 9 | 44 | 9 | 44 | 9 | 44 | 9 | 109 | 218 | 246 | 218 | 237 | 218 | 249 | 218 | 240 | 218 | 226 |
| 20 | 54 | 10 | 54 | 9 | 54 | 9 | 54 | 9 | 54 | 9 | 110 | 430 | 265 | 430 | 255 | 430 | 246 | 430 | 252 | 430 | 248 |
| 21 | 35 | 9 | 35 | 9 | 35 | 9 | 35 | 9 | 35 | 9 | 111 | 139 | 258 | 142 | 240 | 139 | 234 | 139 | 240 | 142 | 238 |
| 22 | 95 | 11 | 95 | 10 | 95 | 10 | 95 | 10 | 95 | 10 | 112 | 373 | 278 | 379 | 262 | 373 | 263 | 373 | 252 | 380 | 273 |
| 23 | 82 | 10 | 82 | 10 | 82 | 10 | 82 | 10 | 82 | 10 | 113 | 363 | 276 | 356 | 277 | 356 | 267 | 362 | 253 | 356 | 259 |
| 24 | 35 | 10 | 35 | 9 | 35 | 9 | 35 | 9 | 35 | 9 | 114 | 139 | 247 | 145 | 237 | 145 | 228 | 139 | 240 | 145 | 239 |
| 25 | 95 | 11 | 95 | 11 | 95 | 10 | 95 | 10 | 95 | 11 | 115 | 603 | 292 | 613 | 277 | 603 | 269 | 613 | 275 | 612 | 263 |
| 26 | 82 | 10 | 82 | 10 | 82 | 10 | 82 | 10 | 82 | 9 | 116 | 385 | 274 | 373 | 280 | 385 | 253 | 373 | 273 | 373 | 258 |
| 27 | 142 | 11 | 142 | 11 | 142 | 11 | 142 | 11 | 142 | 11 | 117 | 366 | 268 | 356 | 270 | 356 | 259 | 356 | 261 | 356 | 256 |
| 28 | 142 | 12 | 142 | 10 | 142 | 10 | 142 | 10 | 142 | 10 | 118 | 598 | 289 | 620 | 268 | 598 | 269 | 620 | 273 | 618 | 263 |
| 29 | 98 | 11 | 98 | 11 | 98 | 10 | 98 | 10 | 98 | 11 | 119 | 528 | 284 | 541 | 262 | 537 | 267 | 541 | 268 | 541 | 268 |
| 30 | 113 | 12 | 113 | 10 | 113 | 11 | 113 | 11 | 113 | 10 | 120 | 751 | 288 | 762 | 266 | 751 | 276 | 762 | 268 | 762 | 272 |
| 31 | 17 | 182 | 17 | 172 | 17 | 155 | 17 | 160 | 17 | 152 | 121 | 52 | 341 | 53 | 318 | 54 | 313 | 51 | 304 | 53 | 308 |
| 32 | 33 | 187 | 33 | 173 | 33 | 159 | 33 | 165 | 33 | 150 | 122 | 101 | 355 | 106 | 351 | 105 | 345 | 106 | 358 | 100 | 334 |
| 33 | 24 | 180 | 24 | 167 | 24 | 158 | 24 | 165 | 24 | 156 | 123 | 97 | 372 | 100 | 342 | 102 | 352 | 98 | 339 | 97 | 331 |
| 34 | 17 | 176 | 17 | 156 | 17 | 156 | 17 | 152 | 17 | 151 | 124 | 56 | 340 | 54 | 303 | 54 | 308 | 52 | 303 | 54 | 302 |
| 35 | 33 | 190 | 33 | 161 | 33 | 171 | 33 | 169 | 33 | 158 | 125 | 246 | 387 | 244 | 366 | 243 | 381 | 245 | 374 | 243 | 375 |
| 36 | 24 | 171 | 24 | 160 | 24 | 168 | 24 | 174 | 24 | 154 | 126 | 154 | 382 | 154 | 365 | 154 | 368 | 154 | 368 | 154 | 343 |
| 37 | 40 | 186 | 40 | 163 | 40 | 164 | 40 | 175 | 45 | 152 | 127 | 146 | 373 | 146 | 363 | 146 | 371 | 146 | 366 | 146 | 344 |
| 38 | 54 | 182 | 54 | 169 | 54 | 165 | 54 | 160 | 54 | 163 | 128 | 256 | 379 | 244 | 377 | 248 | 389 | 254 | 361 | 264 | 356 |
| 39 | 44 | 191 | 44 | 175 | 44 | 165 | 44 | 167 | 44 | 168 | 129 | 168 | 384 | 168 | 375 | 168 | 369 | 168 | 356 | 168 | 357 |
| 40 | 99 | 201 | 99 | 184 | 99 | 173 | 99 | 182 | 99 | 177 | 130 | 225 | 389 | 225 | 367 | 225 | 368 | 217 | 352 | 225 | 353 |
| 41 | 77 | 182 | 75 | 177 | 67 | 172 | 77 | 166 | 79 | 163 | 131 | 109 | 368 | 109 | 347 | 104 | 354 | 106 | 347 | 107 | 344 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 42 | 239 | 203 | 239 | 186 | 278 | 183 | 239 | 185 | 278 | 177 | 132 | 306 | 406 | 299 | 380 | 306 | 395 | 306 | 385 | 306 | 365 |
| 43 | 220 | 197 | 220 | 187 | 220 | 188 | 220 | 181 | 220 | 179 | 133 | 316 | 425 | 316 | 384 | 316 | 373 | 316 | 393 | 316 | 375 |
| 44 | 67 | 188 | 79 | 177 | 79 | 168 | 77 | 162 | 77 | 162 | 134 | 112 | 381 | 110 | 353 | 112 | 353 | 112 | 323 | 112 | 327 |
| 45 | 374 | 206 | 384 | 191 | 394 | 187 | 394 | 187 | 376 | 183 | 135 | 479 | 413 | 523 | 391 | 512 | 409 | 512 | 399 | 508 | 382 |
| 46 | 239 | 198 | 279 | 187 | 279 | 187 | 279 | 181 | 239 | 184 | 136 | 314 | 393 | 306 | 378 | 314 | 376 | 314 | 382 | 314 | 370 |
| 47 | 260 | 198 | 260 | 184 | 220 | 186 | 260 | 185 | 260 | 176 | 137 | 324 | 424 | 324 | 368 | 324 | 377 | 316 | 384 | 324 | 376 |
| 48 | 334 | 206 | 334 | 204 | 334 | 193 | 374 | 184 | 334 | 188 | 138 | 522 | 409 | 526 | 405 | 526 | 387 | 524 | 370 | 524 | 384 |
| 49 | 259 | 194 | 258 | 187 | 220 | 183 | 220 | 196 | 259 | 178 | 139 | 540 | 432 | 513 | 432 | 541 | 405 | 526 | 406 | 550 | 374 |
| 50 | 215 | 198 | 215 | 184 | 191 | 181 | 215 | 182 | 215 | 175 | 140 | 577 | 424 | 577 | 383 | 577 | 392 | 561 | 376 | 577 | 377 |
| 51 | 108 | 201 | 118 | 181 | 108 | 187 | 108 | 177 | 120 | 180 | 141 | 187 | 419 | 187 | 380 | 193 | 369 | 193 | 378 | 187 | 378 |
| 52 | 326 | 212 | 326 | 198 | 326 | 201 | 326 | 197 | 326 | 196 | 142 | 470 | 449 | 470 | 413 | 470 | 420 | 462 | 420 | 478 | 413 |
| 53 | 331 | 213 | 298 | 204 | 320 | 198 | 298 | 204 | 298 | 199 | 143 | 481 | 416 | 471 | 406 | 492 | 397 | 484 | 418 | 480 | 396 |
| 54 | 108 | 208 | 118 | 182 | 118 | 183 | 128 | 181 | 108 | 174 | 144 | 190 | 407 | 190 | 382 | 200 | 368 | 190 | 369 | 190 | 363 |
| 55 | 520 | 225 | 520 | 205 | 596 | 205 | 520 | 204 | 596 | 197 | 145 | 760 | 463 | 740 | 435 | 751 | 424 | 763 | 411 | 739 | 404 |
| 56 | 326 | 213 | 326 | 196 | 365 | 200 | 326 | 194 | 362 | 207 | 146 | 485 | 411 | 473 | 418 | 469 | 404 | 473 | 404 | 473 | 408 |
| 57 | 298 | 217 | 337 | 191 | 336 | 200 | 298 | 201 | 320 | 197 | 147 | 486 | 430 | 478 | 416 | 482 | 404 | 473 | 423 | 483 | 419 |
| 58 | 426 | 215 | 426 | 210 | 426 | 199 | 448 | 211 | 426 | 216 | 148 | 746 | 448 | 782 | 435 | 774 | 421 | 766 | 423 | 766 | 421 |
| 59 | 368 | 214 | 344 | 200 | 332 | 202 | 332 | 204 | 344 | 196 | 149 | 486 | 421 | 482 | 405 | 485 | 399 | 467 | 408 | 472 | 386 |
| 60 | 380 | 220 | 422 | 197 | 380 | 203 | 380 | 201 | 380 | 208 | 150 | 1634 | 469 | 1611 | 438 | 1576 | 450 | 1634 | 422 | 1634 | 425 |
| 61 | 35 | 204 | 35 | 204 | 38 | 186 | 35 | 184 | 37 | 186 | 151 | 62 | 487 | 62 | 448 | 61 | 446 | 62 | 431 | 62 | 420 |
| 62 | 68 | 230 | 68 | 200 | 68 | 201 | 76 | 202 | 68 | 207 | 152 | 226 | 560 | 226 | 504 | 226 | 495 | 226 | 522 | 229 | 500 |
| 63 | 61 | 219 | 61 | 209 | 61 | 202 | 61 | 200 | 61 | 195 | 153 | 131 | 501 | 131 | 477 | 132 | 478 | 130 | 455 | 131 | 446 |
| 64 | 37 | 208 | 39 | 181 | 33 | 181 | 33 | 181 | 33 | 177 | 154 | 137 | 505 | 128 | 509 | 127 | 506 | 127 | 489 | 127 | 465 |
| 65 | 68 | 230 | 76 | 206 | 68 | 201 | 65 | 198 | 68 | 199 | 155 | 68 | 498 | 68 | 433 | 64 | 474 | 64 | 444 | 68 | 438 |
| 66 | 61 | 232 | 66 | 205 | 61 | 202 | 71 | 195 | 61 | 192 | 156 | 137 | 541 | 145 | 467 | 133 | 477 | 137 | 488 | 137 | 483 |
| 67 | 106 | 233 | 94 | 204 | 94 | 203 | 90 | 202 | 106 | 199 | 157 | 133 | 520 | 133 | 507 | 133 | 493 | 129 | 468 | 129 | 470 |
| 68 | 91 | 239 | 83 | 232 | 91 | 208 | 83 | 203 | 91 | 203 | 158 | 313 | 563 | 313 | 531 | 318 | 539 | 338 | 492 | 318 | 480 |
| 69 | 101 | 234 | 101 | 219 | 101 | 217 | 101 | 207 | 115 | 199 | 159 | 184 | 517 | 194 | 504 | 190 | 504 | 190 | 487 | 184 | 488 |
| 70 | 129 | 242 | 129 | 223 | 129 | 216 | 129 | 202 | 129 | 203 | 160 | 188 | 528 | 188 | 498 | 188 | 490 | 188 | 464 | 190 | 487 |
| 71 | 83 | 233 | 83 | 219 | 83 | 208 | 83 | 216 | 90 | 205 | 161 | 111 | 569 | 111 | 503 | 118 | 484 | 111 | 478 | 108 | 503 |
| 72 | 269 | 243 | 269 | 245 | 263 | 231 | 264 | 230 | 269 | 228 | 162 | 346 | 560 | 336 | 524 | 350 | 515 | 336 | 517 | 356 | 517 |
| 73 | 241 | 255 | 247 | 226 | 241 | 235 | 247 | 232 | 253 | 227 | 163 | 315 | 589 | 315 | 529 | 333 | 540 | 315 | 583 | 315 | 528 |
| 74 | 84 | 227 | 84 | 211 | 84 | 217 | 86 | 208 | 84 | 210 | 164 | 332 | 588 | 335 | 548 | 332 | 524 | 332 | 560 | 332 | 527 |
| 75 | 263 | 259 | 263 | 234 | 272 | 232 | 263 | 228 | 263 | 232 | 165 | 117 | 537 | 117 | 511 | 123 | 479 | 113 | 468 | 117 | 484 |
| 76 | 241 | 251 | 250 | 232 | 241 | 230 | 241 | 228 | 241 | 220 | 166 | 318 | 617 | 333 | 544 | 321 | 567 | 321 | 539 | 338 | 517 |
| 77 | 452 | 269 | 420 | 246 | 420 | 252 | 420 | 242 | 420 | 225 | 167 | 342 | 596 | 338 | 567 | 354 | 534 | 338 | 542 | 331 | 519 |
| 78 | 208 | 252 | 208 | 240 | 208 | 228 | 209 | 212 | 212 | 218 | 168 | 564 | 626 | 530 | 573 | 539 | 582 | 536 | 587 | 536 | 553 |
| 79 | 392 | 283 | 392 | 254 | 392 | 242 | 404 | 251 | 424 | 239 | 169 | 544 | 593 | 544 | 542 | 568 | 560 | 544 | 557 | 544 | 525 |
| 80 | 250 | 254 | 250 | 235 | 250 | 232 | 250 | 229 | 250 | 230 | 170 | 558 | 617 | 589 | 521 | 558 | 556 | 558 | 559 | 558 | 527 |
| 81 | 141 | 254 | 142 | 231 | 142 | 235 | 142 | 224 | 142 | 220 | 171 | 173 | 560 | 173 | 574 | 173 | 535 | 173 | 555 | 173 | 521 |
| 82 | 399 | 285 | 400 | 257 | 382 | 251 | 390 | 251 | 380 | 245 | 172 | 355 | 638 | 399 | 587 | 371 | 563 | 394 | 543 | 405 | 537 |
| 83 | 348 | 267 | 348 | 270 | 348 | 247 | 348 | 246 | 349 | 238 | 173 | 427 | 592 | 434 | 550 | 434 | 548 | 439 | 553 | 434 | 553 |
| 84 | 142 | 271 | 142 | 230 | 142 | 216 | 142 | 218 | 142 | 225 | 174 | 450 | 603 | 448 | 623 | 457 | 603 | 462 | 557 | 457 | 562 |
| 85 | 382 | 278 | 382 | 260 | 390 | 240 | 382 | 241 | 382 | 276 | 175 | 157 | 580 | 179 | 545 | 179 | 538 | 179 | 506 | 159 | 496 |
| 86 | 361 | 267 | 366 | 251 | 356 | 245 | 348 | 246 | 348 | 241 | 176 | 718 | 609 | 718 | 608 | 742 | 592 | 718 | 594 | 718 | 556 |
| 87 | 588 | 284 | 596 | 254 | 588 | 252 | 588 | 265 | 588 | 250 | 177 | 784 | 653 | 800 | 582 | 800 | 597 | 784 | 591 | 784 | 569 |
| 88 | 560 | 283 | 547 | 257 | 550 | 257 | 541 | 269 | 554 | 254 | 178 | 522 | 630 | 522 | 592 | 522 | 553 | 522 | 583 | 522 | 535 |
| 89 | 328 | 264 | 333 | 252 | 333 | 250 | 345 | 244 | 333 | 242 | 179 | 377 | 603 | 377 | 575 | 351 | 570 | 377 | 568 | 377 | 532 |
| 90 | 517 | 278 | 524 | 254 | 514 | 241 | 514 | 259 | 528 | 255 | 180 | 816 | 626 | 804 | 606 | 804 | 574 | 804 | 589 | 804 | 570 |

PSO/SA Heuristic Procedure 4

| Problem # | c ₁ = c ₂ = 0.25 | | c ₁ = c ₂ = 0.30 | | c ₁ = c ₂ = 0.35 | | c ₁ = c ₂ = 0.40 | | c ₁ = c ₂ = 0.45 | | Problem # | c ₁ = c ₂ = 0.25 | | c ₁ = c ₂ = 0.30 | | c ₁ = c ₂ = 0.35 | | c ₁ = c ₂ = 0.40 | | c ₁ = c ₂ = 0.45 | | | |
|-----------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|-----------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|--|-----------------------|-----------|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 12 | 7 | 12 | 7 | 12 | 7 | 13 | 7 | 11 | 91 | 42 | 376 | 42 | 372 | 42 | 348 | 42 | 379 | 42 | 373 | 42 | 374 |
| 2 | 14 | 15 | 14 | 13 | 14 | 13 | 14 | 12 | 14 | 12 | 92 | 80 | 390 | 80 | 401 | 79 | 373 | 80 | 393 | 80 | 393 | 80 | 381 |
| 3 | 9 | 16 | 9 | 13 | 9 | 14 | 9 | 11 | 9 | 12 | 93 | 75 | 403 | 75 | 398 | 75 | 386 | 75 | 382 | 75 | 382 | 75 | 388 |
| 4 | 7 | 13 | 7 | 12 | 7 | 13 | 7 | 12 | 7 | 11 | 94 | 42 | 384 | 42 | 369 | 42 | 364 | 42 | 365 | 42 | 365 | 42 | 361 |
| 5 | 16 | 13 | 16 | 13 | 16 | 13 | 16 | 16 | 16 | 12 | 95 | 80 | 394 | 80 | 383 | 80 | 388 | 80 | 381 | 80 | 381 | 80 | 382 |
| 6 | 14 | 15 | 14 | 14 | 14 | 15 | 14 | 21 | 14 | 13 | 96 | 76 | 390 | 76 | 384 | 76 | 375 | 76 | 393 | 76 | 393 | 76 | 382 |
| 7 | 9 | 13 | 9 | 13 | 9 | 13 | 9 | 21 | 9 | 12 | 97 | 107 | 429 | 111 | 410 | 108 | 397 | 107 | 413 | 109 | 413 | 109 | 386 |
| 8 | 16 | 13 | 16 | 14 | 16 | 13 | 16 | 23 | 16 | 12 | 98 | 114 | 407 | 114 | 383 | 114 | 388 | 114 | 404 | 114 | 404 | 114 | 395 |
| 9 | 11 | 11 | 11 | 13 | 11 | 13 | 11 | 21 | 11 | 12 | 99 | 101 | 401 | 101 | 393 | 101 | 444 | 101 | 388 | 101 | 388 | 101 | 389 |
| 10 | 17 | 13 | 17 | 13 | 17 | 14 | 17 | 21 | 17 | 13 | 100 | 165 | 423 | 164 | 403 | 165 | 425 | 164 | 418 | 164 | 418 | 164 | 400 |
| 11 | 18 | 13 | 18 | 14 | 18 | 14 | 18 | 20 | 18 | 12 | 101 | 86 | 437 | 86 | 415 | 86 | 420 | 86 | 422 | 86 | 422 | 86 | 422 |
| 12 | 61 | 14 | 61 | 18 | 61 | 15 | 61 | 28 | 61 | 15 | 102 | 260 | 460 | 260 | 447 | 260 | 482 | 260 | 469 | 260 | 469 | 260 | 476 |
| 13 | 49 | 16 | 49 | 15 | 49 | 16 | 49 | 26 | 49 | 14 | 103 | 236 | 465 | 236 | 479 | 236 | 485 | 236 | 456 | 236 | 456 | 236 | 476 |
| 14 | 48 | 16 | 48 | 16 | 48 | 16 | 48 | 32 | 48 | 16 | 104 | 86 | 421 | 86 | 421 | 86 | 407 | 86 | 413 | 86 | 413 | 86 | 429 |
| 15 | 61 | 15 | 61 | 17 | 61 | 16 | 61 | 31 | 61 | 20 | 105 | 260 | 457 | 260 | 475 | 260 | 454 | 260 | 476 | 260 | 476 | 260 | 473 |
| 16 | 49 | 15 | 49 | 15 | 49 | 15 | 49 | 27 | 49 | 18 | 106 | 236 | 498 | 236 | 475 | 236 | 466 | 236 | 447 | 236 | 447 | 236 | 446 |
| 17 | 92 | 17 | 92 | 17 | 92 | 17 | 92 | 29 | 92 | 25 | 107 | 410 | 482 | 410 | 495 | 410 | 495 | 410 | 465 | 410 | 465 | 410 | 482 |
| 18 | 92 | 17 | 92 | 17 | 92 | 17 | 92 | 32 | 92 | 19 | 108 | 212 | 462 | 212 | 450 | 212 | 450 | 212 | 484 | 212 | 484 | 212 | 464 |
| 19 | 44 | 16 | 44 | 16 | 44 | 15 | 44 | 29 | 44 | 20 | 109 | 218 | 458 | 218 | 448 | 218 | 444 | 218 | 452 | 218 | 452 | 218 | 456 |
| 20 | 54 | 15 | 54 | 15 | 54 | 16 | 54 | 23 | 54 | 17 | 110 | 430 | 464 | 430 | 498 | 430 | 480 | 430 | 476 | 430 | 476 | 430 | 450 |
| 21 | 35 | 15 | 35 | 16 | 35 | 16 | 35 | 21 | 35 | 15 | 111 | 142 | 438 | 139 | 463 | 142 | 444 | 139 | 448 | 139 | 448 | 139 | 448 |
| 22 | 95 | 16 | 95 | 17 | 95 | 17 | 95 | 28 | 95 | 16 | 112 | 373 | 493 | 373 | 501 | 379 | 480 | 373 | 516 | 379 | 516 | 379 | 482 |
| 23 | 82 | 18 | 82 | 17 | 82 | 19 | 82 | 25 | 82 | 16 | 113 | 356 | 501 | 362 | 474 | 356 | 450 | 356 | 523 | 362 | 523 | 362 | 485 |
| 24 | 35 | 17 | 35 | 16 | 35 | 15 | 35 | 26 | 35 | 15 | 114 | 139 | 439 | 139 | 440 | 143 | 452 | 139 | 444 | 139 | 444 | 139 | 454 |
| 25 | 95 | 17 | 95 | 18 | 95 | 17 | 95 | 26 | 95 | 17 | 115 | 603 | 523 | 603 | 524 | 603 | 493 | 603 | 420 | 603 | 420 | 603 | 493 |
| 26 | 82 | 22 | 82 | 17 | 82 | 18 | 82 | 27 | 82 | 16 | 116 | 373 | 487 | 373 | 501 | 373 | 478 | 373 | 486 | 373 | 486 | 373 | 489 |
| 27 | 142 | 31 | 142 | 17 | 142 | 18 | 142 | 29 | 142 | 18 | 117 | 356 | 520 | 356 | 481 | 367 | 475 | 368 | 483 | 356 | 483 | 356 | 511 |
| 28 | 142 | 23 | 142 | 19 | 142 | 17 | 142 | 28 | 142 | 17 | 118 | 598 | 500 | 598 | 500 | 612 | 502 | 598 | 505 | 598 | 505 | 598 | 511 |
| 29 | 98 | 19 | 98 | 17 | 98 | 18 | 98 | 32 | 98 | 16 | 119 | 528 | 525 | 528 | 515 | 528 | 500 | 536 | 521 | 537 | 537 | 484 | |
| 30 | 113 | 25 | 113 | 20 | 113 | 17 | 113 | 35 | 113 | 17 | 120 | 762 | 529 | 751 | 518 | 751 | 503 | 751 | 506 | 751 | 506 | 751 | 499 |
| 31 | 20 | 297 | 21 | 287 | 22 | 305 | 19 | 464 | 17 | 286 | 121 | 53 | 602 | 50 | 627 | 54 | 616 | 54 | 593 | 53 | 593 | 53 | 611 |
| 32 | 36 | 341 | 37 | 319 | 39 | 337 | 36 | 413 | 36 | 322 | 122 | 111 | 661 | 111 | 717 | 108 | 625 | 111 | 627 | 108 | 627 | 108 | 653 |
| 33 | 28 | 310 | 27 | 306 | 31 | 289 | 27 | 337 | 27 | 344 | 123 | 108 | 669 | 101 | 609 | 111 | 617 | 107 | 659 | 107 | 659 | 107 | 638 |
| 34 | 21 | 269 | 21 | 285 | 23 | 258 | 19 | 268 | 21 | 279 | 124 | 56 | 606 | 56 | 645 | 58 | 553 | 56 | 599 | 58 | 599 | 58 | 595 |
| 35 | 38 | 294 | 36 | 332 | 46 | 257 | 38 | 292 | 39 | 290 | 125 | 255 | 698 | 271 | 725 | 274 | 701 | 271 | 687 | 269 | 687 | 269 | 707 |
| 36 | 35 | 249 | 29 | 330 | 32 | 271 | 29 | 269 | 32 | 298 | 126 | 160 | 657 | 165 | 717 | 154 | 656 | 170 | 667 | 173 | 667 | 173 | 648 |
| 37 | 45 | 326 | 44 | 353 | 52 | 273 | 44 | 286 | 44 | 321 | 127 | 158 | 681 | 170 | 678 | 165 | 636 | 157 | 682 | 159 | 682 | 159 | 681 |
| 38 | 62 | 293 | 58 | 298 | 66 | 309 | 60 | 297 | 60 | 294 | 128 | 256 | 717 | 264 | 682 | 274 | 677 | 240 | 666 | 276 | 666 | 276 | 687 |
| 39 | 49 | 349 | 49 | 323 | 61 | 283 | 49 | 281 | 49 | 293 | 129 | 171 | 600 | 177 | 675 | 174 | 669 | 182 | 644 | 173 | 644 | 173 | 668 |
| 40 | 116 | 356 | 111 | 343 | 124 | 321 | 111 | 334 | 111 | 317 | 130 | 225 | 694 | 228 | 680 | 231 | 674 | 231 | 651 | 231 | 651 | 231 | 689 |
| 41 | 75 | 314 | 77 | 320 | 79 | 284 | 79 | 289 | 78 | 315 | 131 | 109 | 650 | 113 | 655 | 109 | 614 | 111 | 649 | 109 | 649 | 109 | 647 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|------|------|------|------|------|
| 42 | 275 | 319 | 278 | 344 | 265 | 309 | 278 | 314 | 275 | 338 | 132 | 317 | 730 | 316 | 676 | 311 | 650 | 316 | 699 | 308 | 707 |
| 43 | 259 | 344 | 259 | 335 | 259 | 298 | 246 | 340 | 259 | 390 | 133 | 326 | 708 | 321 | 711 | 321 | 690 | 321 | 712 | 327 | 724 |
| 44 | 79 | 346 | 77 | 322 | 77 | 292 | 79 | 324 | 79 | 324 | 134 | 114 | 672 | 116 | 632 | 112 | 622 | 116 | 666 | 116 | 621 |
| 45 | 384 | 393 | 384 | 371 | 394 | 320 | 384 | 421 | 394 | 357 | 135 | 531 | 719 | 523 | 744 | 523 | 713 | 531 | 713 | 531 | 749 |
| 46 | 270 | 354 | 271 | 350 | 275 | 317 | 279 | 327 | 279 | 330 | 136 | 314 | 744 | 314 | 714 | 314 | 714 | 325 | 703 | 314 | 747 |
| 47 | 260 | 396 | 260 | 348 | 251 | 312 | 260 | 329 | 260 | 309 | 137 | 324 | 750 | 324 | 722 | 322 | 720 | 324 | 721 | 329 | 713 |
| 48 | 394 | 472 | 384 | 362 | 374 | 328 | 389 | 359 | 384 | 321 | 138 | 522 | 759 | 534 | 750 | 526 | 742 | 540 | 742 | 534 | 767 |
| 49 | 247 | 379 | 258 | 360 | 254 | 320 | 245 | 371 | 258 | 316 | 139 | 550 | 757 | 550 | 744 | 531 | 730 | 527 | 737 | 550 | 731 |
| 50 | 215 | 344 | 215 | 337 | 215 | 314 | 213 | 330 | 215 | 301 | 140 | 577 | 791 | 561 | 760 | 577 | 737 | 577 | 766 | 577 | 763 |
| 51 | 120 | 345 | 118 | 353 | 120 | 345 | 118 | 359 | 118 | 341 | 141 | 197 | 708 | 197 | 696 | 195 | 707 | 197 | 689 | 190 | 709 |
| 52 | 360 | 350 | 366 | 381 | 372 | 457 | 362 | 369 | 364 | 386 | 142 | 489 | 806 | 470 | 775 | 485 | 756 | 483 | 776 | 482 | 767 |
| 53 | 339 | 379 | 331 | 378 | 331 | 369 | 354 | 370 | 339 | 359 | 143 | 495 | 812 | 495 | 767 | 492 | 724 | 492 | 726 | 495 | 740 |
| 54 | 118 | 346 | 118 | 359 | 118 | 343 | 128 | 344 | 118 | 332 | 144 | 202 | 691 | 200 | 692 | 196 | 666 | 196 | 707 | 194 | 687 |
| 55 | 578 | 397 | 604 | 387 | 596 | 374 | 604 | 383 | 556 | 386 | 145 | 779 | 810 | 787 | 816 | 780 | 756 | 783 | 767 | 783 | 795 |
| 56 | 364 | 399 | 364 | 473 | 382 | 357 | 367 | 371 | 367 | 366 | 146 | 493 | 754 | 488 | 730 | 481 | 771 | 492 | 755 | 477 | 744 |
| 57 | 332 | 367 | 336 | 386 | 354 | 368 | 332 | 373 | 339 | 370 | 147 | 504 | 757 | 487 | 746 | 502 | 721 | 498 | 768 | 491 | 723 |
| 58 | 466 | 380 | 466 | 394 | 468 | 371 | 437 | 360 | 466 | 387 | 148 | 782 | 793 | 792 | 781 | 766 | 754 | 794 | 771 | 786 | 759 |
| 59 | 362 | 369 | 362 | 403 | 368 | 370 | 350 | 337 | 362 | 383 | 149 | 492 | 745 | 482 | 767 | 493 | 718 | 490 | 713 | 485 | 754 |
| 60 | 422 | 389 | 422 | 378 | 422 | 380 | 415 | 361 | 415 | 382 | 150 | 1611 | 799 | 1629 | 803 | 1634 | 794 | 1629 | 814 | 1611 | 833 |
| 61 | 38 | 333 | 38 | 344 | 38 | 338 | 38 | 342 | 39 | 347 | 151 | 66 | 973 | 62 | 939 | 62 | 876 | 62 | 947 | 62 | 913 |
| 62 | 68 | 395 | 76 | 349 | 76 | 364 | 76 | 368 | 75 | 376 | 152 | 229 | 1024 | 229 | 1070 | 229 | 965 | 229 | 1024 | 229 | 1019 |
| 63 | 65 | 333 | 69 | 370 | 71 | 379 | 69 | 348 | 65 | 361 | 153 | 141 | 968 | 131 | 970 | 131 | 954 | 131 | 973 | 131 | 1008 |
| 64 | 41 | 322 | 41 | 360 | 39 | 322 | 39 | 352 | 39 | 338 | 154 | 127 | 1004 | 127 | 1014 | 137 | 909 | 127 | 987 | 137 | 983 |
| 65 | 79 | 367 | 78 | 373 | 75 | 326 | 78 | 407 | 76 | 366 | 155 | 70 | 939 | 70 | 908 | 68 | 867 | 68 | 862 | 70 | 931 |
| 66 | 71 | 394 | 71 | 360 | 72 | 329 | 66 | 384 | 71 | 362 | 156 | 145 | 956 | 145 | 978 | 137 | 955 | 137 | 981 | 137 | 904 |
| 67 | 110 | 451 | 106 | 397 | 110 | 366 | 106 | 390 | 110 | 378 | 157 | 133 | 1003 | 141 | 1000 | 133 | 928 | 133 | 996 | 140 | 896 |
| 68 | 91 | 353 | 89 | 395 | 93 | 376 | 95 | 390 | 87 | 382 | 158 | 327 | 1053 | 330 | 1093 | 330 | 1016 | 318 | 1042 | 318 | 1042 |
| 69 | 116 | 358 | 107 | 391 | 116 | 377 | 116 | 373 | 116 | 378 | 159 | 184 | 986 | 184 | 1052 | 184 | 941 | 184 | 959 | 184 | 896 |
| 70 | 143 | 377 | 131 | 400 | 143 | 395 | 129 | 380 | 129 | 396 | 160 | 198 | 1052 | 188 | 1013 | 198 | 884 | 198 | 967 | 188 | 970 |
| 71 | 86 | 358 | 90 | 402 | 83 | 385 | 89 | 401 | 83 | 378 | 161 | 111 | 1011 | 118 | 953 | 111 | 858 | 111 | 1054 | 111 | 905 |
| 72 | 269 | 386 | 282 | 434 | 264 | 417 | 281 | 428 | 264 | 435 | 162 | 336 | 1115 | 336 | 1008 | 336 | 1016 | 356 | 1095 | 336 | 1289 |
| 73 | 247 | 452 | 249 | 439 | 247 | 416 | 251 | 438 | 260 | 448 | 163 | 322 | 1095 | 333 | 1028 | 315 | 954 | 315 | 1154 | 328 | 1025 |
| 74 | 94 | 398 | 86 | 390 | 84 | 379 | 90 | 386 | 90 | 373 | 164 | 332 | 1070 | 332 | 1256 | 332 | 1087 | 332 | 1211 | 332 | 951 |
| 75 | 270 | 444 | 274 | 417 | 263 | 424 | 292 | 433 | 272 | 428 | 165 | 123 | 920 | 117 | 1057 | 123 | 849 | 117 | 909 | 123 | 1125 |
| 76 | 267 | 426 | 241 | 426 | 250 | 415 | 260 | 437 | 260 | 435 | 166 | 321 | 1036 | 321 | 958 | 340 | 979 | 321 | 1017 | 339 | 1078 |
| 77 | 428 | 454 | 436 | 458 | 440 | 443 | 420 | 456 | 452 | 428 | 167 | 338 | 1074 | 338 | 1001 | 338 | 1007 | 338 | 1249 | 356 | 1122 |
| 78 | 212 | 423 | 208 | 425 | 208 | 427 | 229 | 385 | 208 | 421 | 168 | 536 | 1101 | 536 | 1167 | 564 | 1072 | 536 | 1113 | 536 | 1005 |
| 79 | 404 | 455 | 405 | 487 | 392 | 443 | 404 | 397 | 424 | 451 | 169 | 544 | 1071 | 572 | 1107 | 552 | 1003 | 544 | 1085 | 544 | 1148 |
| 80 | 276 | 448 | 250 | 416 | 250 | 421 | 263 | 402 | 250 | 427 | 170 | 558 | 1092 | 589 | 1102 | 558 | 1396 | 605 | 1034 | 558 | 1225 |
| 81 | 147 | 401 | 146 | 411 | 145 | 403 | 151 | 419 | 149 | 413 | 171 | 173 | 1121 | 173 | 1057 | 181 | 1092 | 179 | 1029 | 180 | 1057 |
| 82 | 397 | 447 | 393 | 448 | 400 | 457 | 393 | 446 | 400 | 448 | 172 | 413 | 1118 | 413 | 1258 | 415 | 992 | 406 | 1183 | 406 | 1102 |
| 83 | 346 | 459 | 366 | 439 | 349 | 427 | 368 | 454 | 349 | 452 | 173 | 434 | 1200 | 448 | 1220 | 454 | 997 | 434 | 1079 | 448 | 1254 |
| 84 | 146 | 416 | 150 | 417 | 142 | 411 | 150 | 425 | 150 | 416 | 174 | 471 | 1089 | 457 | 1062 | 452 | 1397 | 457 | 1149 | 457 | 1087 |
| 85 | 392 | 450 | 406 | 446 | 400 | 452 | 397 | 446 | 392 | 447 | 175 | 179 | 1000 | 179 | 946 | 185 | 1393 | 179 | 950 | 187 | 974 |
| 86 | 388 | 444 | 366 | 446 | 366 | 462 | 366 | 437 | 361 | 448 | 176 | 718 | 1131 | 718 | 1055 | 718 | 1080 | 718 | 1055 | 718 | 1499 |
| 87 | 620 | 453 | 620 | 479 | 640 | 460 | 652 | 443 | 640 | 459 | 177 | 784 | 1205 | 822 | 1047 | 784 | 1024 | 816 | 1135 | 784 | 1547 |
| 88 | 550 | 466 | 554 | 458 | 554 | 461 | 560 | 446 | 560 | 455 | 178 | 548 | 1109 | 538 | 1054 | 522 | 1027 | 522 | 1159 | 522 | 1507 |
| 89 | 345 | 432 | 347 | 422 | 342 | 445 | 335 | 448 | 333 | 448 | 179 | 377 | 1072 | 377 | 1060 | 397 | 1286 | 377 | 1107 | 395 | 991 |
| 90 | 507 | 448 | 518 | 469 | 528 | 455 | 519 | 464 | 528 | 462 | 180 | 804 | 1177 | 804 | 1114 | 804 | 1277 | 804 | 1073 | 804 | 1234 |

PSO/SA Heuristic Procedure 5

| Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | | Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | |
|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 5 | 7 | 5 | 7 | 4 | 7 | 6 | 7 | 5 | 91 | 43 | 145 | 42 | 144 | 42 | 146 | 42 | 141 | 43 | 145 |
| 2 | 14 | 5 | 14 | 6 | 14 | 6 | 14 | 5 | 14 | 6 | 92 | 79 | 153 | 79 | 153 | 80 | 153 | 79 | 154 | 79 | 152 |
| 3 | 9 | 5 | 9 | 5 | 9 | 5 | 9 | 5 | 9 | 5 | 93 | 75 | 153 | 76 | 150 | 77 | 153 | 75 | 151 | 75 | 153 |
| 4 | 7 | 5 | 7 | 5 | 7 | 5 | 7 | 5 | 7 | 5 | 94 | 44 | 143 | 42 | 144 | 44 | 143 | 44 | 142 | 44 | 144 |
| 5 | 16 | 6 | 16 | 6 | 16 | 6 | 16 | 6 | 16 | 6 | 95 | 80 | 154 | 80 | 155 | 80 | 152 | 82 | 153 | 80 | 154 |
| 6 | 14 | 5 | 14 | 5 | 14 | 5 | 14 | 6 | 14 | 5 | 96 | 76 | 153 | 76 | 152 | 78 | 153 | 78 | 153 | 78 | 154 |
| 7 | 9 | 5 | 9 | 5 | 9 | 5 | 9 | 5 | 9 | 5 | 97 | 107 | 161 | 107 | 157 | 107 | 155 | 109 | 161 | 112 | 160 |
| 8 | 16 | 6 | 16 | 6 | 16 | 6 | 16 | 6 | 16 | 6 | 98 | 114 | 157 | 114 | 158 | 114 | 159 | 116 | 159 | 116 | 158 |
| 9 | 11 | 5 | 11 | 5 | 11 | 5 | 11 | 5 | 11 | 5 | 99 | 101 | 155 | 101 | 154 | 101 | 159 | 101 | 155 | 101 | 159 |
| 10 | 17 | 6 | 17 | 6 | 17 | 6 | 17 | 6 | 17 | 6 | 100 | 165 | 165 | 169 | 164 | 164 | 164 | 169 | 165 | 164 | 167 |
| 11 | 18 | 6 | 18 | 6 | 18 | 6 | 18 | 6 | 18 | 6 | 101 | 86 | 164 | 86 | 164 | 86 | 165 | 86 | 161 | 86 | 166 |
| 12 | 61 | 6 | 61 | 7 | 61 | 7 | 61 | 6 | 61 | 7 | 102 | 260 | 185 | 260 | 184 | 260 | 182 | 260 | 184 | 260 | 184 |
| 13 | 49 | 7 | 49 | 6 | 49 | 6 | 49 | 7 | 49 | 6 | 103 | 236 | 182 | 236 | 182 | 236 | 181 | 236 | 181 | 236 | 184 |
| 14 | 48 | 7 | 48 | 7 | 48 | 7 | 48 | 7 | 48 | 7 | 104 | 86 | 164 | 86 | 162 | 86 | 163 | 86 | 162 | 86 | 164 |
| 15 | 61 | 7 | 61 | 7 | 61 | 7 | 61 | 7 | 61 | 7 | 105 | 260 | 182 | 260 | 183 | 260 | 182 | 260 | 183 | 260 | 182 |
| 16 | 49 | 6 | 49 | 6 | 49 | 7 | 49 | 7 | 49 | 7 | 106 | 236 | 181 | 236 | 183 | 236 | 181 | 236 | 180 | 236 | 182 |
| 17 | 92 | 7 | 92 | 8 | 92 | 7 | 92 | 7 | 92 | 7 | 107 | 410 | 193 | 410 | 190 | 410 | 190 | 410 | 192 | 410 | 192 |
| 18 | 92 | 8 | 92 | 7 | 92 | 7 | 92 | 7 | 92 | 7 | 108 | 212 | 178 | 212 | 178 | 212 | 181 | 212 | 179 | 212 | 180 |
| 19 | 44 | 6 | 44 | 6 | 44 | 7 | 44 | 7 | 44 | 6 | 109 | 218 | 179 | 218 | 179 | 218 | 180 | 218 | 179 | 218 | 180 |
| 20 | 54 | 7 | 54 | 7 | 54 | 6 | 54 | 7 | 54 | 7 | 110 | 430 | 191 | 430 | 189 | 430 | 190 | 430 | 190 | 430 | 190 |
| 21 | 35 | 7 | 35 | 7 | 35 | 7 | 35 | 7 | 35 | 7 | 111 | 142 | 178 | 142 | 177 | 142 | 178 | 142 | 179 | 142 | 178 |
| 22 | 95 | 7 | 95 | 7 | 95 | 8 | 95 | 7 | 95 | 7 | 112 | 380 | 195 | 379 | 195 | 379 | 195 | 380 | 196 | 380 | 195 |
| 23 | 82 | 8 | 82 | 8 | 82 | 7 | 82 | 8 | 82 | 8 | 113 | 363 | 195 | 362 | 196 | 363 | 193 | 362 | 195 | 362 | 197 |
| 24 | 35 | 6 | 35 | 6 | 35 | 7 | 35 | 7 | 35 | 7 | 114 | 143 | 178 | 139 | 179 | 145 | 176 | 145 | 178 | 145 | 176 |
| 25 | 95 | 8 | 95 | 8 | 95 | 7 | 95 | 7 | 95 | 7 | 115 | 603 | 208 | 613 | 203 | 612 | 204 | 603 | 204 | 612 | 203 |
| 26 | 82 | 7 | 82 | 7 | 82 | 8 | 82 | 8 | 82 | 7 | 116 | 385 | 194 | 385 | 196 | 384 | 197 | 383 | 196 | 385 | 195 |
| 27 | 142 | 8 | 142 | 8 | 142 | 7 | 142 | 8 | 142 | 8 | 117 | 366 | 195 | 368 | 195 | 368 | 195 | 368 | 192 | 368 | 194 |
| 28 | 142 | 8 | 142 | 8 | 142 | 8 | 142 | 8 | 142 | 8 | 118 | 618 | 203 | 618 | 201 | 612 | 201 | 612 | 202 | 598 | 202 |
| 29 | 98 | 7 | 98 | 8 | 98 | 8 | 98 | 7 | 98 | 8 | 119 | 536 | 216 | 536 | 203 | 528 | 201 | 537 | 203 | 541 | 201 |
| 30 | 113 | 8 | 113 | 7 | 113 | 8 | 113 | 8 | 113 | 7 | 120 | 762 | 214 | 762 | 205 | 762 | 207 | 762 | 207 | 762 | 206 |
| 31 | 22 | 107 | 19 | 108 | 22 | 107 | 19 | 111 | 19 | 108 | 121 | 54 | 232 | 54 | 221 | 51 | 221 | 54 | 226 | 55 | 221 |
| 32 | 39 | 112 | 37 | 114 | 40 | 114 | 36 | 116 | 41 | 114 | 122 | 111 | 257 | 106 | 243 | 108 | 235 | 100 | 242 | 111 | 240 |
| 33 | 27 | 111 | 27 | 113 | 31 | 112 | 31 | 111 | 35 | 111 | 123 | 107 | 243 | 97 | 239 | 112 | 237 | 108 | 244 | 107 | 242 |
| 34 | 17 | 109 | 23 | 107 | 19 | 112 | 23 | 109 | 23 | 109 | 124 | 58 | 228 | 58 | 230 | 56 | 225 | 58 | 231 | 58 | 223 |
| 35 | 36 | 113 | 43 | 112 | 44 | 114 | 41 | 118 | 41 | 115 | 125 | 275 | 266 | 261 | 264 | 263 | 256 | 261 | 263 | 262 | 262 |
| 36 | 29 | 110 | 38 | 112 | 29 | 112 | 29 | 116 | 38 | 112 | 126 | 169 | 257 | 166 | 252 | 160 | 247 | 171 | 252 | 169 | 254 |
| 37 | 44 | 114 | 49 | 116 | 49 | 116 | 49 | 119 | 48 | 117 | 127 | 166 | 255 | 168 | 246 | 161 | 249 | 165 | 256 | 166 | 254 |
| 38 | 60 | 119 | 54 | 119 | 60 | 118 | 68 | 120 | 78 | 119 | 128 | 264 | 264 | 264 | 267 | 274 | 266 | 264 | 263 | 266 | 259 |
| 39 | 59 | 119 | 44 | 118 | 58 | 122 | 65 | 122 | 59 | 118 | 129 | 165 | 253 | 172 | 249 | 185 | 252 | 173 | 253 | 181 | 252 |
| 40 | 127 | 125 | 116 | 126 | 124 | 125 | 128 | 126 | 128 | 129 | 130 | 221 | 268 | 230 | 260 | 231 | 264 | 217 | 257 | 225 | 256 |
| 41 | 79 | 123 | 79 | 126 | 79 | 130 | 77 | 126 | 79 | 129 | 131 | 107 | 248 | 112 | 249 | 109 | 247 | 109 | 252 | 109 | 245 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 42 | 278 | 147 | 271 | 144 | 278 | 144 | 278 | 146 | 265 | 149 | 132 | 299 | 286 | 316 | 271 | 311 | 268 | 317 | 274 | 321 | 269 |
| 43 | 259 | 145 | 259 | 150 | 259 | 143 | 253 | 149 | 259 | 148 | 133 | 321 | 278 | 316 | 276 | 326 | 275 | 331 | 275 | 321 | 277 |
| 44 | 77 | 132 | 79 | 132 | 79 | 132 | 77 | 131 | 77 | 135 | 134 | 112 | 247 | 114 | 251 | 116 | 260 | 112 | 246 | 112 | 248 |
| 45 | 374 | 146 | 385 | 148 | 385 | 149 | 384 | 148 | 334 | 151 | 135 | 532 | 292 | 499 | 286 | 532 | 279 | 531 | 282 | 531 | 291 |
| 46 | 270 | 145 | 279 | 146 | 279 | 153 | 279 | 148 | 279 | 146 | 136 | 325 | 284 | 319 | 278 | 314 | 269 | 314 | 271 | 322 | 272 |
| 47 | 260 | 142 | 260 | 147 | 255 | 141 | 260 | 145 | 260 | 149 | 137 | 331 | 278 | 329 | 277 | 324 | 273 | 331 | 272 | 334 | 276 |
| 48 | 394 | 142 | 394 | 148 | 394 | 141 | 374 | 149 | 394 | 146 | 138 | 526 | 288 | 534 | 284 | 534 | 282 | 524 | 286 | 526 | 279 |
| 49 | 220 | 137 | 258 | 148 | 259 | 144 | 251 | 142 | 258 | 144 | 139 | 550 | 300 | 550 | 288 | 550 | 282 | 548 | 290 | 550 | 296 |
| 50 | 191 | 135 | 215 | 139 | 215 | 140 | 215 | 144 | 215 | 142 | 140 | 577 | 302 | 588 | 292 | 577 | 282 | 577 | 282 | 602 | 289 |
| 51 | 127 | 142 | 127 | 136 | 124 | 144 | 127 | 141 | 128 | 137 | 141 | 197 | 275 | 196 | 277 | 197 | 267 | 197 | 265 | 196 | 268 |
| 52 | 362 | 153 | 382 | 152 | 372 | 152 | 377 | 154 | 359 | 149 | 142 | 482 | 304 | 485 | 292 | 484 | 294 | 487 | 291 | 486 | 290 |
| 53 | 354 | 152 | 341 | 155 | 354 | 150 | 331 | 154 | 344 | 153 | 143 | 491 | 307 | 491 | 293 | 492 | 297 | 492 | 305 | 492 | 291 |
| 54 | 128 | 139 | 120 | 136 | 112 | 138 | 120 | 145 | 128 | 140 | 144 | 204 | 271 | 196 | 286 | 200 | 263 | 196 | 270 | 200 | 280 |
| 55 | 604 | 159 | 520 | 161 | 596 | 165 | 596 | 171 | 575 | 156 | 145 | 779 | 313 | 783 | 300 | 787 | 300 | 787 | 306 | 783 | 304 |
| 56 | 365 | 154 | 372 | 152 | 372 | 157 | 382 | 159 | 372 | 153 | 146 | 485 | 295 | 485 | 295 | 483 | 298 | 490 | 289 | 477 | 291 |
| 57 | 339 | 154 | 354 | 151 | 354 | 156 | 354 | 157 | 344 | 157 | 147 | 502 | 299 | 493 | 305 | 500 | 291 | 495 | 288 | 498 | 291 |
| 58 | 503 | 151 | 466 | 152 | 463 | 163 | 503 | 167 | 501 | 161 | 148 | 790 | 308 | 774 | 308 | 798 | 302 | 790 | 300 | 794 | 303 |
| 59 | 387 | 150 | 387 | 147 | 368 | 162 | 387 | 165 | 386 | 159 | 149 | 493 | 301 | 492 | 299 | 497 | 302 | 482 | 297 | 490 | 288 |
| 60 | 380 | 150 | 445 | 152 | 445 | 160 | 445 | 166 | 450 | 159 | 150 | 1623 | 326 | 1629 | 325 | 1611 | 319 | 1629 | 322 | 1608 | 319 |
| 61 | 39 | 129 | 38 | 130 | 38 | 130 | 35 | 135 | 36 | 129 | 151 | 64 | 329 | 62 | 318 | 66 | 332 | 64 | 325 | 62 | 328 |
| 62 | 69 | 140 | 69 | 140 | 69 | 141 | 68 | 143 | 76 | 141 | 152 | 229 | 389 | 226 | 365 | 229 | 386 | 229 | 400 | 229 | 386 |
| 63 | 61 | 136 | 61 | 139 | 62 | 140 | 69 | 141 | 69 | 139 | 153 | 131 | 352 | 131 | 340 | 131 | 357 | 131 | 362 | 131 | 361 |
| 64 | 39 | 132 | 39 | 134 | 39 | 131 | 35 | 134 | 35 | 134 | 154 | 137 | 356 | 127 | 350 | 133 | 342 | 133 | 346 | 127 | 344 |
| 65 | 76 | 141 | 78 | 143 | 81 | 141 | 78 | 147 | 78 | 141 | 155 | 68 | 320 | 68 | 321 | 70 | 344 | 70 | 337 | 68 | 315 |
| 66 | 71 | 138 | 69 | 138 | 71 | 138 | 71 | 147 | 72 | 140 | 156 | 137 | 349 | 144 | 344 | 137 | 366 | 137 | 369 | 137 | 386 |
| 67 | 102 | 145 | 94 | 145 | 110 | 146 | 110 | 148 | 110 | 145 | 157 | 141 | 346 | 140 | 349 | 133 | 343 | 141 | 354 | 133 | 360 |
| 68 | 95 | 143 | 93 | 145 | 89 | 146 | 90 | 150 | 93 | 144 | 158 | 329 | 381 | 318 | 362 | 318 | 370 | 318 | 386 | 318 | 385 |
| 69 | 117 | 145 | 116 | 146 | 116 | 146 | 117 | 150 | 117 | 146 | 159 | 194 | 358 | 184 | 363 | 184 | 355 | 184 | 367 | 184 | 368 |
| 70 | 140 | 150 | 139 | 147 | 131 | 153 | 129 | 151 | 143 | 151 | 160 | 198 | 370 | 188 | 356 | 188 | 356 | 188 | 355 | 188 | 352 |
| 71 | 90 | 146 | 91 | 150 | 84 | 149 | 84 | 146 | 83 | 149 | 161 | 111 | 357 | 119 | 367 | 115 | 361 | 111 | 345 | 117 | 358 |
| 72 | 281 | 167 | 280 | 166 | 269 | 165 | 287 | 170 | 269 | 168 | 162 | 354 | 395 | 336 | 387 | 336 | 398 | 336 | 379 | 336 | 396 |
| 73 | 259 | 167 | 271 | 164 | 252 | 167 | 260 | 171 | 260 | 167 | 163 | 333 | 395 | 315 | 399 | 333 | 400 | 315 | 402 | 315 | 401 |
| 74 | 94 | 150 | 94 | 149 | 84 | 152 | 90 | 154 | 90 | 150 | 164 | 350 | 386 | 332 | 378 | 350 | 404 | 332 | 394 | 350 | 404 |
| 75 | 292 | 166 | 263 | 166 | 271 | 168 | 290 | 173 | 272 | 168 | 165 | 117 | 350 | 117 | 364 | 123 | 359 | 117 | 375 | 117 | 345 |
| 76 | 258 | 167 | 256 | 168 | 260 | 166 | 256 | 167 | 248 | 166 | 166 | 321 | 389 | 321 | 385 | 339 | 388 | 321 | 397 | 321 | 385 |
| 77 | 436 | 175 | 468 | 175 | 452 | 175 | 420 | 179 | 428 | 175 | 167 | 338 | 385 | 338 | 398 | 345 | 400 | 338 | 396 | 338 | 392 |
| 78 | 224 | 163 | 208 | 163 | 208 | 165 | 224 | 167 | 209 | 164 | 168 | 536 | 413 | 544 | 404 | 536 | 429 | 564 | 415 | 565 | 412 |
| 79 | 418 | 174 | 424 | 177 | 416 | 178 | 392 | 180 | 424 | 175 | 169 | 572 | 397 | 544 | 399 | 544 | 416 | 544 | 429 | 544 | 411 |
| 80 | 269 | 166 | 263 | 165 | 272 | 166 | 272 | 167 | 263 | 166 | 170 | 568 | 406 | 558 | 409 | 558 | 415 | 558 | 419 | 558 | 403 |
| 81 | 145 | 162 | 144 | 161 | 145 | 159 | 144 | 160 | 148 | 160 | 171 | 182 | 372 | 181 | 374 | 179 | 395 | 173 | 401 | 181 | 406 |
| 82 | 402 | 178 | 395 | 177 | 399 | 176 | 397 | 178 | 393 | 175 | 172 | 406 | 413 | 415 | 426 | 413 | 416 | 406 | 431 | 406 | 407 |
| 83 | 365 | 175 | 365 | 176 | 359 | 177 | 381 | 175 | 362 | 177 | 173 | 448 | 423 | 434 | 409 | 457 | 423 | 449 | 423 | 449 | 427 |
| 84 | 150 | 162 | 146 | 160 | 146 | 161 | 148 | 161 | 152 | 161 | 174 | 471 | 417 | 469 | 420 | 457 | 431 | 457 | 423 | 457 | 429 |
| 85 | 400 | 176 | 387 | 176 | 414 | 177 | 400 | 178 | 397 | 176 | 175 | 181 | 382 | 185 | 383 | 179 | 388 | 181 | 383 | 181 | 389 |
| 86 | 368 | 176 | 376 | 176 | 368 | 177 | 366 | 178 | 366 | 177 | 176 | 718 | 423 | 718 | 424 | 718 | 460 | 718 | 431 | 718 | 446 |
| 87 | 604 | 186 | 616 | 183 | 604 | 185 | 620 | 184 | 640 | 184 | 177 | 784 | 438 | 784 | 455 | 784 | 463 | 784 | 435 | 784 | 440 |
| 88 | 560 | 183 | 567 | 182 | 560 | 181 | 569 | 182 | 547 | 186 | 178 | 522 | 425 | 522 | 416 | 548 | 427 | 522 | 422 | 522 | 430 |
| 89 | 343 | 174 | 343 | 175 | 343 | 173 | 351 | 174 | 333 | 175 | 179 | 377 | 405 | 377 | 426 | 377 | 431 | 377 | 418 | 377 | 413 |
| 90 | 529 | 182 | 536 | 180 | 506 | 182 | 524 | 183 | 532 | 181 | 180 | 804 | 434 | 827 | 425 | 804 | 432 | 804 | 456 | 824 | 433 |

PSO/SA Heuristic Procedure 6

| Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | | Problem # | $c_1 = c_2 = 0.25$ | | $c_1 = c_2 = 0.30$ | | $c_1 = c_2 = 0.35$ | | $c_1 = c_2 = 0.40$ | | $c_1 = c_2 = 0.45$ | |
|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|-----------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|--------------------|-----------------------|
| | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds | Min. Cost | Total Time in Seconds |
| 1 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 8 | 91 | 42 | 215 | 42 | 218 | 42 | 209 | 42 | 212 | 42 | 210 |
| 2 | 14 | 8 | 14 | 8 | 14 | 8 | 14 | 8 | 14 | 8 | 92 | 80 | 238 | 80 | 226 | 80 | 231 | 79 | 230 | 79 | 234 |
| 3 | 9 | 8 | 9 | 8 | 9 | 8 | 9 | 8 | 9 | 7 | 93 | 75 | 226 | 75 | 230 | 75 | 226 | 75 | 221 | 75 | 223 |
| 4 | 7 | 8 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 8 | 94 | 42 | 216 | 42 | 215 | 42 | 214 | 42 | 220 | 42 | 212 |
| 5 | 16 | 8 | 16 | 8 | 16 | 8 | 16 | 8 | 16 | 8 | 95 | 80 | 233 | 80 | 228 | 80 | 224 | 80 | 222 | 80 | 232 |
| 6 | 14 | 9 | 14 | 8 | 14 | 8 | 14 | 8 | 14 | 8 | 96 | 76 | 228 | 76 | 237 | 76 | 223 | 76 | 223 | 76 | 230 |
| 7 | 9 | 8 | 9 | 8 | 9 | 8 | 9 | 8 | 9 | 8 | 97 | 107 | 244 | 107 | 232 | 107 | 234 | 109 | 233 | 107 | 237 |
| 8 | 16 | 11 | 16 | 8 | 16 | 8 | 16 | 8 | 16 | 8 | 98 | 114 | 225 | 114 | 239 | 114 | 235 | 114 | 236 | 114 | 237 |
| 9 | 11 | 9 | 11 | 8 | 11 | 8 | 11 | 8 | 11 | 8 | 99 | 101 | 232 | 101 | 233 | 101 | 222 | 101 | 224 | 101 | 235 |
| 10 | 17 | 10 | 17 | 8 | 17 | 8 | 17 | 8 | 17 | 8 | 100 | 169 | 242 | 169 | 249 | 162 | 241 | 165 | 238 | 164 | 246 |
| 11 | 18 | 9 | 18 | 8 | 18 | 9 | 18 | 8 | 18 | 9 | 101 | 86 | 263 | 86 | 256 | 86 | 248 | 86 | 254 | 86 | 245 |
| 12 | 61 | 12 | 61 | 10 | 61 | 10 | 61 | 10 | 61 | 9 | 102 | 260 | 285 | 260 | 290 | 260 | 271 | 260 | 276 | 260 | 285 |
| 13 | 49 | 11 | 49 | 9 | 49 | 10 | 49 | 9 | 49 | 10 | 103 | 236 | 277 | 236 | 281 | 236 | 276 | 236 | 283 | 236 | 279 |
| 14 | 48 | 11 | 48 | 10 | 48 | 9 | 48 | 9 | 48 | 10 | 104 | 86 | 260 | 86 | 259 | 86 | 246 | 86 | 259 | 86 | 267 |
| 15 | 61 | 10 | 61 | 9 | 61 | 10 | 61 | 10 | 61 | 10 | 105 | 260 | 280 | 260 | 276 | 260 | 262 | 260 | 276 | 260 | 280 |
| 16 | 49 | 10 | 49 | 10 | 49 | 10 | 49 | 9 | 49 | 9 | 106 | 236 | 313 | 236 | 287 | 236 | 268 | 236 | 279 | 236 | 280 |
| 17 | 92 | 11 | 92 | 10 | 92 | 10 | 92 | 10 | 92 | 10 | 107 | 410 | 300 | 410 | 287 | 410 | 284 | 410 | 303 | 410 | 286 |
| 18 | 92 | 11 | 92 | 10 | 92 | 10 | 92 | 10 | 92 | 10 | 108 | 212 | 299 | 212 | 279 | 212 | 277 | 212 | 267 | 212 | 263 |
| 19 | 44 | 10 | 44 | 9 | 44 | 9 | 44 | 10 | 44 | 10 | 109 | 218 | 272 | 218 | 265 | 218 | 275 | 218 | 262 | 218 | 292 |
| 20 | 54 | 11 | 54 | 10 | 54 | 10 | 54 | 9 | 54 | 10 | 110 | 430 | 282 | 430 | 289 | 430 | 282 | 430 | 285 | 430 | 290 |
| 21 | 35 | 10 | 35 | 9 | 35 | 10 | 35 | 9 | 35 | 9 | 111 | 139 | 274 | 139 | 266 | 139 | 273 | 142 | 265 | 142 | 272 |
| 22 | 95 | 12 | 95 | 11 | 95 | 10 | 95 | 11 | 95 | 11 | 112 | 379 | 281 | 379 | 289 | 373 | 303 | 380 | 290 | 373 | 324 |
| 23 | 82 | 11 | 82 | 10 | 82 | 10 | 82 | 10 | 82 | 10 | 113 | 356 | 281 | 356 | 316 | 356 | 297 | 356 | 299 | 362 | 300 |
| 24 | 35 | 10 | 35 | 10 | 35 | 10 | 35 | 10 | 35 | 10 | 114 | 139 | 276 | 139 | 262 | 139 | 271 | 139 | 259 | 139 | 282 |
| 25 | 95 | 11 | 95 | 10 | 95 | 11 | 95 | 10 | 95 | 10 | 115 | 603 | 296 | 612 | 314 | 603 | 308 | 603 | 308 | 603 | 321 |
| 26 | 82 | 12 | 82 | 11 | 82 | 11 | 82 | 10 | 82 | 11 | 116 | 373 | 285 | 383 | 308 | 373 | 290 | 383 | 310 | 373 | 294 |
| 27 | 142 | 12 | 142 | 11 | 142 | 11 | 142 | 11 | 142 | 11 | 117 | 366 | 289 | 356 | 314 | 356 | 313 | 366 | 299 | 356 | 312 |
| 28 | 142 | 11 | 142 | 11 | 142 | 11 | 142 | 11 | 142 | 11 | 118 | 598 | 304 | 620 | 299 | 618 | 303 | 598 | 318 | 598 | 306 |
| 29 | 98 | 11 | 98 | 10 | 98 | 10 | 98 | 11 | 98 | 11 | 119 | 537 | 301 | 528 | 294 | 528 | 308 | 528 | 310 | 538 | 302 |
| 30 | 113 | 12 | 113 | 11 | 113 | 11 | 113 | 10 | 113 | 11 | 120 | 751 | 330 | 751 | 315 | 751 | 319 | 751 | 301 | 762 | 318 |
| 31 | 20 | 180 | 19 | 164 | 23 | 161 | 20 | 166 | 19 | 173 | 121 | 50 | 351 | 53 | 355 | 55 | 330 | 53 | 353 | 54 | 378 |
| 32 | 37 | 194 | 37 | 185 | 37 | 190 | 39 | 177 | 39 | 175 | 122 | 109 | 374 | 115 | 396 | 109 | 349 | 105 | 377 | 105 | 377 |
| 33 | 31 | 207 | 27 | 183 | 27 | 177 | 27 | 177 | 27 | 183 | 123 | 106 | 370 | 104 | 385 | 107 | 356 | 107 | 369 | 107 | 371 |
| 34 | 23 | 173 | 23 | 158 | 21 | 160 | 19 | 161 | 21 | 167 | 124 | 56 | 353 | 58 | 377 | 56 | 347 | 58 | 357 | 60 | 348 |
| 35 | 33 | 175 | 39 | 178 | 41 | 172 | 38 | 170 | 41 | 192 | 125 | 275 | 447 | 268 | 410 | 259 | 400 | 256 | 406 | 267 | 406 |
| 36 | 27 | 179 | 34 | 173 | 32 | 175 | 32 | 162 | 30 | 173 | 126 | 170 | 381 | 165 | 407 | 170 | 394 | 163 | 381 | 175 | 417 |
| 37 | 44 | 195 | 44 | 185 | 45 | 172 | 44 | 177 | 44 | 193 | 127 | 160 | 388 | 164 | 379 | 161 | 379 | 157 | 393 | 167 | 400 |
| 38 | 68 | 182 | 72 | 176 | 60 | 178 | 68 | 183 | 60 | 183 | 128 | 270 | 420 | 270 | 418 | 264 | 383 | 270 | 418 | 272 | 419 |
| 39 | 59 | 173 | 59 | 181 | 58 | 179 | 49 | 175 | 52 | 173 | 129 | 168 | 376 | 177 | 383 | 179 | 389 | 173 | 413 | 177 | 394 |
| 40 | 124 | 190 | 111 | 182 | 124 | 193 | 123 | 180 | 131 | 196 | 130 | 229 | 407 | 231 | 394 | 225 | 397 | 228 | 413 | 231 | 403 |
| 41 | 79 | 194 | 79 | 192 | 79 | 189 | 79 | 190 | 79 | 203 | 131 | 113 | 381 | 109 | 396 | 111 | 384 | 109 | 384 | 112 | 382 |

| | | | | | | | | | | | | | | | | | | | | | |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-----|------|-----|------|-----|------|-----|------|-----|
| 42 | 278 | 203 | 258 | 199 | 278 | 196 | 278 | 200 | 278 | 206 | 132 | 311 | 419 | 317 | 424 | 311 | 408 | 311 | 399 | 311 | 426 |
| 43 | 256 | 202 | 239 | 198 | 254 | 197 | 259 | 197 | 259 | 205 | 133 | 326 | 421 | 326 | 424 | 321 | 406 | 327 | 412 | 316 | 414 |
| 44 | 77 | 199 | 79 | 185 | 79 | 193 | 79 | 190 | 79 | 201 | 134 | 116 | 393 | 114 | 383 | 112 | 373 | 112 | 401 | 116 | 395 |
| 45 | 365 | 217 | 394 | 221 | 384 | 220 | 374 | 209 | 385 | 219 | 135 | 523 | 443 | 531 | 438 | 523 | 428 | 523 | 429 | 523 | 446 |
| 46 | 279 | 205 | 279 | 197 | 279 | 194 | 270 | 202 | 279 | 198 | 136 | 320 | 423 | 314 | 428 | 314 | 413 | 314 | 420 | 319 | 432 |
| 47 | 260 | 201 | 260 | 201 | 260 | 196 | 260 | 196 | 260 | 201 | 137 | 329 | 432 | 324 | 418 | 329 | 392 | 324 | 430 | 329 | 425 |
| 48 | 394 | 217 | 394 | 210 | 384 | 212 | 394 | 208 | 394 | 221 | 138 | 526 | 439 | 534 | 442 | 534 | 436 | 526 | 454 | 526 | 450 |
| 49 | 247 | 209 | 259 | 203 | 259 | 208 | 259 | 206 | 259 | 214 | 139 | 550 | 434 | 534 | 448 | 550 | 436 | 550 | 433 | 550 | 443 |
| 50 | 215 | 199 | 215 | 196 | 215 | 195 | 215 | 193 | 215 | 198 | 140 | 577 | 441 | 587 | 439 | 591 | 431 | 577 | 434 | 587 | 458 |
| 51 | 124 | 201 | 128 | 206 | 127 | 205 | 120 | 203 | 127 | 212 | 141 | 196 | 414 | 193 | 430 | 195 | 420 | 197 | 413 | 195 | 410 |
| 52 | 359 | 236 | 382 | 216 | 369 | 215 | 382 | 215 | 382 | 216 | 142 | 482 | 436 | 478 | 440 | 482 | 437 | 470 | 441 | 485 | 449 |
| 53 | 338 | 225 | 354 | 221 | 354 | 211 | 344 | 217 | 354 | 232 | 143 | 495 | 461 | 487 | 443 | 496 | 443 | 492 | 460 | 495 | 447 |
| 54 | 128 | 204 | 118 | 214 | 128 | 202 | 120 | 197 | 118 | 213 | 144 | 202 | 414 | 200 | 411 | 204 | 394 | 204 | 408 | 196 | 423 |
| 55 | 604 | 233 | 596 | 228 | 556 | 232 | 603 | 226 | 556 | 240 | 145 | 787 | 462 | 783 | 463 | 780 | 453 | 782 | 465 | 784 | 456 |
| 56 | 366 | 227 | 366 | 223 | 375 | 221 | 355 | 214 | 381 | 215 | 146 | 488 | 429 | 488 | 463 | 488 | 428 | 488 | 441 | 488 | 451 |
| 57 | 339 | 220 | 339 | 212 | 339 | 216 | 353 | 216 | 332 | 223 | 147 | 506 | 444 | 503 | 460 | 503 | 440 | 500 | 460 | 495 | 452 |
| 58 | 463 | 221 | 501 | 233 | 506 | 220 | 448 | 231 | 473 | 226 | 148 | 782 | 445 | 784 | 460 | 788 | 444 | 782 | 460 | 786 | 457 |
| 59 | 387 | 226 | 381 | 242 | 383 | 225 | 387 | 213 | 383 | 220 | 149 | 482 | 469 | 482 | 441 | 490 | 447 | 487 | 438 | 485 | 452 |
| 60 | 443 | 231 | 450 | 225 | 415 | 230 | 450 | 225 | 443 | 225 | 150 | 1565 | 475 | 1611 | 488 | 1629 | 481 | 1629 | 400 | 1658 | 484 |
| 61 | 35 | 210 | 38 | 213 | 38 | 208 | 38 | 195 | 35 | 206 | 151 | 66 | 549 | 66 | 513 | 62 | 511 | 62 | 510 | 62 | 529 |
| 62 | 76 | 232 | 76 | 223 | 76 | 217 | 76 | 215 | 68 | 223 | 152 | 229 | 597 | 246 | 570 | 229 | 569 | 246 | 605 | 229 | 590 |
| 63 | 68 | 228 | 62 | 222 | 69 | 215 | 69 | 225 | 62 | 229 | 153 | 131 | 576 | 131 | 559 | 139 | 555 | 131 | 550 | 131 | 579 |
| 64 | 37 | 216 | 41 | 208 | 39 | 200 | 39 | 209 | 39 | 217 | 154 | 127 | 558 | 127 | 519 | 127 | 591 | 137 | 566 | 127 | 560 |
| 65 | 78 | 225 | 78 | 234 | 78 | 225 | 75 | 215 | 79 | 233 | 155 | 70 | 506 | 68 | 555 | 68 | 506 | 68 | 526 | 68 | 512 |
| 66 | 71 | 218 | 69 | 224 | 71 | 220 | 69 | 230 | 72 | 224 | 156 | 137 | 580 | 145 | 574 | 137 | 583 | 137 | 561 | 137 | 569 |
| 67 | 110 | 219 | 102 | 227 | 110 | 224 | 110 | 219 | 102 | 224 | 157 | 133 | 552 | 138 | 577 | 133 | 565 | 133 | 560 | 133 | 601 |
| 68 | 87 | 230 | 93 | 215 | 91 | 233 | 91 | 222 | 93 | 226 | 158 | 318 | 562 | 327 | 582 | 318 | 548 | 318 | 594 | 318 | 611 |
| 69 | 103 | 231 | 114 | 229 | 118 | 228 | 116 | 216 | 115 | 242 | 159 | 194 | 569 | 184 | 567 | 184 | 549 | 184 | 537 | 194 | 595 |
| 70 | 143 | 234 | 143 | 236 | 145 | 234 | 142 | 239 | 131 | 233 | 160 | 198 | 565 | 188 | 575 | 188 | 567 | 198 | 568 | 188 | 582 |
| 71 | 90 | 246 | 83 | 233 | 90 | 228 | 89 | 230 | 91 | 239 | 161 | 111 | 570 | 111 | 536 | 111 | 552 | 111 | 562 | 111 | 552 |
| 72 | 282 | 274 | 287 | 254 | 269 | 257 | 274 | 257 | 263 | 268 | 162 | 336 | 627 | 354 | 596 | 336 | 589 | 336 | 605 | 356 | 653 |
| 73 | 241 | 260 | 241 | 268 | 247 | 261 | 241 | 264 | 249 | 274 | 163 | 333 | 606 | 333 | 629 | 315 | 613 | 315 | 598 | 333 | 654 |
| 74 | 90 | 229 | 92 | 238 | 84 | 230 | 90 | 236 | 96 | 234 | 164 | 332 | 619 | 339 | 599 | 332 | 608 | 332 | 616 | 350 | 658 |
| 75 | 282 | 265 | 270 | 261 | 271 | 255 | 285 | 261 | 263 | 261 | 165 | 123 | 584 | 117 | 537 | 123 | 564 | 117 | 530 | 117 | 591 |
| 76 | 260 | 262 | 241 | 262 | 248 | 264 | 250 | 245 | 250 | 263 | 166 | 328 | 659 | 321 | 610 | 321 | 614 | 339 | 600 | 321 | 595 |
| 77 | 436 | 275 | 448 | 277 | 448 | 283 | 448 | 275 | 436 | 256 | 167 | 338 | 611 | 338 | 618 | 357 | 631 | 350 | 616 | 345 | 623 |
| 78 | 224 | 277 | 209 | 259 | 224 | 249 | 208 | 251 | 208 | 249 | 168 | 536 | 608 | 536 | 597 | 536 | 612 | 536 | 657 | 561 | 637 |
| 79 | 424 | 292 | 404 | 267 | 405 | 268 | 404 | 264 | 421 | 282 | 169 | 544 | 658 | 574 | 612 | 560 | 641 | 544 | 683 | 544 | 622 |
| 80 | 275 | 273 | 250 | 261 | 272 | 257 | 263 | 254 | 268 | 278 | 170 | 558 | 620 | 558 | 673 | 589 | 640 | 558 | 613 | 605 | 623 |
| 81 | 141 | 256 | 146 | 244 | 145 | 250 | 149 | 264 | 145 | 263 | 171 | 179 | 594 | 182 | 651 | 182 | 584 | 179 | 627 | 180 | 614 |
| 82 | 397 | 316 | 400 | 266 | 400 | 259 | 380 | 292 | 390 | 271 | 172 | 406 | 636 | 406 | 642 | 406 | 668 | 414 | 644 | 413 | 611 |
| 83 | 363 | 280 | 365 | 283 | 372 | 273 | 348 | 303 | 374 | 289 | 173 | 434 | 656 | 442 | 631 | 434 | 659 | 448 | 680 | 454 | 655 |
| 84 | 142 | 259 | 142 | 255 | 150 | 240 | 154 | 267 | 154 | 252 | 174 | 472 | 643 | 457 | 628 | 457 | 656 | 457 | 634 | 457 | 645 |
| 85 | 400 | 287 | 400 | 269 | 402 | 272 | 400 | 278 | 416 | 272 | 175 | 181 | 618 | 181 | 568 | 179 | 590 | 181 | 572 | 179 | 600 |
| 86 | 382 | 289 | 366 | 278 | 348 | 265 | 392 | 279 | 359 | 275 | 176 | 718 | 646 | 718 | 673 | 718 | 641 | 718 | 654 | 718 | 712 |
| 87 | 596 | 299 | 620 | 283 | 628 | 274 | 592 | 291 | 612 | 284 | 177 | 784 | 683 | 784 | 673 | 784 | 666 | 811 | 708 | 784 | 657 |
| 88 | 569 | 309 | 547 | 283 | 558 | 267 | 541 | 278 | 544 | 293 | 178 | 522 | 662 | 546 | 626 | 522 | 645 | 540 | 649 | 540 | 652 |
| 89 | 343 | 269 | 343 | 274 | 338 | 257 | 346 | 271 | 336 | 269 | 179 | 377 | 640 | 392 | 650 | 377 | 631 | 392 | 635 | 377 | 636 |
| 90 | 503 | 273 | 528 | 275 | 528 | 267 | 511 | 273 | 514 | 274 | 180 | 804 | 650 | 827 | 665 | 824 | 669 | 804 | 690 | 804 | 679 |

Vita

Hadeel Y. Al Sayegh was born in 1982, in Dubai, United Arab Emirates. She attended Al Mawakeb School in Dubai before moving to Canada. She graduated from St. Patrick's High School in 2000. She enrolled in the University of Ottawa in Ontario, Canada, from which she graduated with magna cum laude, in 2004. Her degree was a Bachelor of Science in Information and Management Systems from the School of Information Technology and Engineering (SITE).

In 2008, Ms. Al Sayegh began a master's program in Engineering Systems Management at the American University of Sharjah. She earned the Master of Science degree in Engineering Systems Management in 2011.