Development of Construction Projects Scheduling with Evolutionary Algorithms

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ABSTRACT

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Evolutionary Algorithms (EAs) as appropriate tools to optimize multi-objective problems have been applied to optimize construction projects in the last two decades. However, studies on improving the convergence ratio and processing time in the most applied algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) in construction engineering and management domains remain poorly understood. Furthermore, hybrid algorithms such as Hybrid Genetic Algorithm-Particle Swarm Optimization (HGAPSO) and Shuffled Frog Leaping Algorithm (SFLA) have been presented in computational optimization and water resource management domains during recent years to prevent pitfalls of the aforementioned algorithms. In this dissertation, I present three studies on hybrid algorithms to show that our proposed hybrid approaches are superior than existing optimization algorithms in finding better project schedule solutions with less total project cost, shorter total project duration, and less total resources allocation moments. In the first, I present a HGAPSO approach to solve complex, TCRO problems in construction project planning. Our proposed approach uses the fuzzy set theory to characterize uncertainty about the input data (i.e., time, cost, and resources required to perform an activity). In the second, I present the SFLA algorithm to solve TCRO problems using splitting allowed during activities execution. The third study involves the evaluation of the inflation impact on resources unit price during execution of construction projects. This research presents the comprehensive TCRO model by comparing two hybrid algorithms, HGAPSO and SFLA, with the three most capable algorithms-GA, PSO and ACO-in

six different examples in terms of the structure of projects, construction assumptions and kinds of Time-Cost functions. Each of the three studies helps overcome parts of EAs problems and contributes to obtaining optimal project schedule solutions of total project duration, total project cost and total resources allocation moments of construction projects in the planning stage. The findings have significant implications in improving the scheduling of construction projects.

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New York, September 2011

Dedicated

To

My Respected Father, Mohammadhadi,

My Beloved Mother, Batool,

And

My Adore Wife, Setareh.

Chapter 1

Introduction and Background

Time, cost and resource management are three dimensions of project management in concepts of project control (PMBOK 2008). The Critical Path Method (Abraham et al. 1998; Shi et al. 2000; Lu and AbouRizk 2000; Galloway et al. 2006; Ibbs et al. 2007; and El-Rayes et al. 2009), Program Evaluation and Review Technique (Cottrell et al. 1999; AbouRizk et al. 2000; Lu et al. 2002 and; and Lee et al. 2006), and Graphical Evaluation and Review Technique (Pena-Mora and Park 2001) are three seminal methods for controlling the structure of projects including activities with various durations and budgets.

In the last two decades, much effort has focused on the optimization of scheduling by considering the impact of various activities of construction projects. Time-Cost Optimization (TCO), resource leveling, and resource allocation are the three most important problems that have been evaluated in construction engineering and management concepts. The increasing acceptance of different project delivery systems allows greater flexibility in construction duration, to the mutual benefit of both client and contractor. This also means that both construction time and cost should be considered concomitantly in the estimation and planning stages (Zheng et al. 2005). TCO is a process used to identify suitable construction activities for speeding up, and for deciding “by how much” so as to attain the best possible savings in both total duration and cost of projects (Zheng and Ng 2005). Resource allocation is used to assign available resources in an economic way or to schedule activities and the resources required by those activities while taking into consideration both the resource availability and the project time (PMBOK 2008). In addition, resource leveling is a project management process used to examine unbalanced use of resources over time, and for resolving over-allocations or conflicts (PMBOK 2008). However, the increase of project control importance in construction project makes it such that clients, contractors, and sponsors seek to improve their estimates and forecasting evaluations of project problems in the planning stage. Software packages such as Microsoft Project and Primavera and searching tools such as mathematical programming, heuristic models and evolutionary algorithms have been extensively applied to optimize the scheduling of construction projects. However, most of the construction projects scheduling software packages do not have the capability to set a limitation on resources for each activity over the duration of the project (Kim and Ellis 2010). Furthermore, the difficulties associated with using mathematical optimization on large-scale engineering problems have contributed to the development of alternative solutions (Elbeltagi et al. 2005). In addition, heuristic models quite possibly could provide good solutions, but do not guarantee optimality (Hegazy 1999). Since Evolutionary Algorithms (EAs) have greater capabilities in optimizing complex problems with widespread solutions, we apply EAs to construction problems. The main motivation for using EAs to solve multi-objective optimization problems is due to its capability for searching simultaneously with a set of possible solutions to find the optimal Pareto front with a fewest runs of algorithm. Moreover, EAs are less susceptible to the shape or continuity of the Pareto front (Coello Coello 2002).

EAs can be applied as multi-objective optimization tools to obtain the most appropriate solutions. In multi-objective problems, the decision maker is required to select a solution from a Pareto front solution by making compromises, which provide for acceptable performance over all objectives (Lamont et al. 2002). Cohon and Marks (1975) classified multi-objective methods in three categories: generating techniques with a posteriori articulation of preferences; techniques which rely on prior articulation of preferences; and techniques which rely on progressive articulation of preferences. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been extensively applied in optimization of construction problems. We briefly describe the algorithms in the following Sections:

1.1 Genetic Algorithm (GA)

As the first introduced evolutionary algorithm, GA has been used widely in various aspects of engineering problems such as constrained or unconstrained optimization, scheduling and reliability optimization. GA is a searching and optimization tool based on natural evolution. It directs the initial population toward the global optimum points according to the objective function. This method is presented by John Holland in 1997 and then developed by one of his students, David Goldberg, in 1989 for solving problems in controlling gas piping line transfers. A solution to a given problem is represented in the form of a string, called chromosome, consisting of a set of elements called genes that hold a set of values for the optimization variables (Goldberg 1989). In general, GA includes four important steps: (1) Generation of an initial population; (2) selection of the best chromosomes based on their fitness value; (3) crossover of the old chromosome to produce new chromosome in the next generation; (4) mutation of new chromosomes to extend the scope of searching. Usually some of the best chromosomes called an elitism genes go directly to the next generation. Based on the GA process, four important parameters including population size, $P_{crossover}$,$P_{mutation}$ and size of crowding distance have significant impact on the convergence ratio and quality of Pareto front solution (Goldberg 1989; Konak et al. 2006). Figure 1.1 shows GA optimization processes.

Some multi-objective algorithms initially have been applied to genetic algorithms. Schaffe (1985) introduces Vector Evaluated Genetic Algorithm (VEGA), which is the first method of genetic algorithm to optimize Pareto front with non-dominated solutions. Hajela and Lin (1992) introduce Weighted Based Genetic Algorithm (WBGA) with normalization of objective functions. Coello and Montes (2004) suggest the Niched Pareto Genetic Algorithm (NPGA) and Lu and Yen (2003) propose the Pareto Evolutionary Selective Algorithm (PESA) as genetic algorithms developed. Based on Deb's research (2000), each of the mentioned algorithms is suitable for the specific case studies; meanwhile, they have related problems in convergence speed to the final solution. However, the most applied multi-objective algorithm is the Non-dominated Sorting Genetic Algorithm (NSGA). The NSGA algorithm is first suggested by Goldberg (1989) and then implemented by Srinivas and Deb (1994). This algorithm uses the crowding technique to ensure diversity among non-dominated solutions. This method is computationally efficient and is capable of finding a good spread of Pareto optimal solutions (Deb et al. 2000). El-Rayes et al. (2006) improve multi-objective genetic algorithms to optimize resource utilization in large-scale construction projects.

GA has several limitations. Fogel (1995) present some deficiencies in GA performance, including premature convergence or a slow convergence process (requiring a large number of generations) have been also identified. Ng and Zheng (2008) state that despite the benefit of GA, the time taken by a GA model to generate a near-optimum solution can be excessive. Another major drawback of GAs has to do with genetic drift which is typified by the existence of multiple peaks of equal height. When genetic drift occurs, it will converge to a single peak due to stochastic errors during processing, which is undesirable for any multi-objective problems (Zheng et al. 2005).

1.2 Particle Swarm Optimization (PSO)

In comparison with GA, Particle Swarm Optimization (PSO) is a newer algorithm which is developed by Kennedy and Eberhart (1995). It is based on an analogy with the choreography of flight of a flock of birds. A large number of birds flock synchronously, change direction suddenly, and scatter and regroup together (Yin et al. 2005). Each particle adjust its flying from the experience of its own and that of the other members of the swarm during the search for food (Yin et al. 2005). Like the evolutionary algorithm, PSO search operates through updating swarms (population) of particle. There are some similarities between PSO and GA (Grosan et al 2005):

- Both techniques use a population of solutions from the search space which are initially randomly generated;
- Solutions belonging to the same population interact with each other during the search process;
- Solutions are evolved (their quality is improved) using techniques inspired from the real world.

On the basis of classical PSO, the algorithm maintains an elite set of non-dominated solutions and redefines the selections of guides during the optimization process (Yang 2007). In contrast to GA, PSO has the advantage of keeping the continuity between individuals to converge faster although it may easily get into the local optimum (Shahgholi et al 2006). In PSO, each particle corresponds to a candidate solution of the underlying problem. Unlike a GA that reproduces chromosomes of the next generation from unclassified survivals, PSO updates a population of particles with the internal velocity and attempts to profit from the discoveries of themselves and previous experiences of other companions.

In PSO, a population of particles is randomly initialized with position and velocities. A particle i is treated as a point in a multi-dimensional space j and status of the particle is characterized by its position and velocity (Kennedy and Eberhart 1995). During each PSO iteration, particle i adjusts its velocity v_{ij} and position vector $particle_{ij}$ through each dimension j by referring to, with random multipliers, the personal best vector $(pbest_{ij})$ and the swarm's best vector $(gbest_j)$. The updated functions for particle flying can be formulated as (Eberhart and Shi 1998):

$$v_{ij}(t+1) \xleftarrow{iteration} \omega v_{ij}(t) + c_1 r_1 (pbest_{ij}(t) - particle_{ij}(t)) + c_2 r_2 (gbest_j(t) - particle_{ij}(t)) \quad (1.1)$$

$$particle_{ij}(t+1) \xleftarrow{iteration} particle_{ij}(t) + v_{ij}(t+1)\Delta t \qquad (when \;\; \Delta t = 1) \quad (1.2)$$

where ω is inertia coefficient, which has an important role in balancing a global (a large value of ω) and local search (a small value of ω); c_1 and c_2 are the cognitive coefficients ; r_1 and r_2 are the uniform random real numbers in $(0,1)$, and the symbol $\xleftarrow{iteration}$ is used to show the updated values from iteration t to next iteration $t+1$. The parameters that have the most considerable impact on the convergence ratio and Pareto front are c_1, c_2 and ω. The inertia weight ω can be constant or varying with iteration. Varying inertia weight (from larger to smaller) use to be recommended to enhance global exploration for early iterations and to facilitate local exploration for last iterations (Zhang et al. 2006).

The basic PSO algorithm consists of three steps: generating particles' positions and velocities, velocity updating and position updating. Equation (1,1) is used to calculate a particle's new velocity according to its previous velocity and the distances of its current position from its local best and the global best. Equation (1,2) is used to calculate the new position of a particle by utilizing its previous experience (i.e., local best) and the experience for all particles (i.e., global best). These two equations also reflect the unique mechanism of operator PSO (Zhang et al. 2006).

The selection of $pbest(t)$ simply replaces the previous best experience by the current position if the former does not strongly dominate the latter. The selection of $gbest(t)$ is altered to promote population diversity without overlooking the edges and sparse areas (Yang 2007). Figure 1.1 shows the PSO concept in a 3D search space. Particle 1 moves to new position based on previous best experience (particle 6) and the best among the swarm (particle 5). In multi-objective PSO, multiple non-dominated solutions are usually sought. The main difference in the multi-objective approach is how the $pbest$ and $gbest$ vectors are defined (fitness evaluation), and given that these vectors are not unique anymore, what values of $pbest$ and $gbest$ are selected to be used in equation (1.1) are important (Baltar et al. 2008).

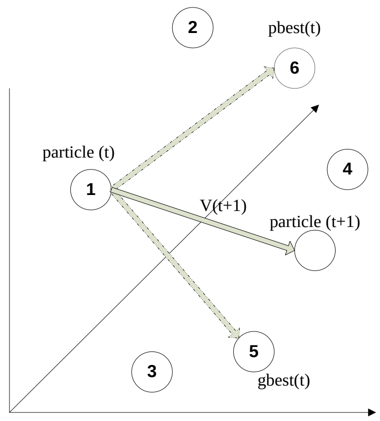


Figure 1.1 Schematic of the PSO Algorithm

1.3 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is proposed by Colorni (1991), which Dorigo and Maniezzo (1997) apply to travelling sales problems. Similar to PSO, ACO algorithm evolves not in their genetics but in their social behavior. As Figure 1.2 shows, ants can find the shortest path from their nest to food by laying pheromones on the ground as they move. The pheromone dissipates over time but it is strengthened when other ants travel on the same trail again. Those arriving subsequently choose the trails with denser pheromones, and they further intensify the pheromone on the preferred paths. Trails with less pheromone laid will eventually be abandoned, such that all the ants will converge to the same trail, which is in turn the shortest path from the nest to the food source (Dorigo and Gambardella 1996).

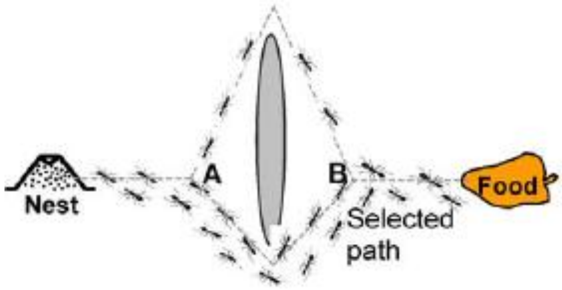


Figure 1.2 Schematic of the ACO algorithm

Based on Ng and Zhang's research (2008), ACO algorithm consists of three steps: (1) Generation of random solutions (initial population) that represent the travel of an ant from the first to last node so as to cover the whole network; (2) Selection probability corresponding to the pheromone is the basis for the different nodes selected by an ant. The ant k in node i selects an option j using the pseudorandom proportional action choice rule as follows: (Gambardella and Dorigo 1996)

$$P_{i,j}(k,t) = \frac{[\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}]^{\beta}}{\sum_{j\in(1,ni)}[\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}]^{\beta}} \tag{1.3}$$

where $P_{i,j}(k,t)$ represents the probability that $Option_{i,j}$ is chosen by Ant k for node i at iteration t; $\tau_{i,j}(t)$ is the total pheromone deposited on $Option_{i,j}$ in ant k at iteration t; $\tau_{i,j}$ changes with the iteration and is intended to indicate how useful it is to choose $Option_{i,j}$; $\eta_{i,j}$ is the heuristic function, which evaluates the utility of choosing $Option_{i,j}$. Usually, the heuristic values will help the first generations of ants finding good solutions. Moreover, α and β are weightings which show the relative importance of $\tau_{i,j}$ and $\eta_{i,j}$. Parameter β controls the relative influence of the heuristic values.

(3) Update Pheromone rule: After one solution is completed, pheromones will be added to the options of different nodes as selected by the ant during its journey as follows for local updating:

$$\tau_{i,j}(t+1) \xleftarrow{iteration} \rho\tau_{i,j}(t) + \Delta\tau_{i,j}$$

(1.4)

where $\rho \in (0,1)$ is a parameter that regulates the evaporation rate. Parameter ρ determines the convergence speed of the algorithm. In general, when the algorithm has time to generate a large number of solutions, a low value of ρ is profitable since the algorithm will explore different regions of the search space and does not focus the search too early on a small region (Merkle et al 2002).

Also $\Delta\tau_{i,j}$ represents the updating value of pheromone. After all ants have completed their travels, the pheromone value in options belonging to the best solution in that iteration are changed according the following global updating rule:

$$\Delta\tau_{i,j} = \begin{cases} R\ f_{best-iteration} & if\ \ option_{i,j} is\ traversed\ by\ the\ best\ ant \\ 0 & otherwise \end{cases} \tag{1.5}$$

where R is the constant representing the pheromone reward factor; and $f_{best-iteration}$ is the best value of objective function (the best ant) in each iteration.

Once the pheromone is updated after an iteration, the next iteration starts by changing the ants' paths (i.e. associated variable values) in a manner that respects pheromone concentration and also some heuristic preference (Elbeltagi et al. 2005). Figure 1.3 shows the flowchart of the ACO Algorithm.

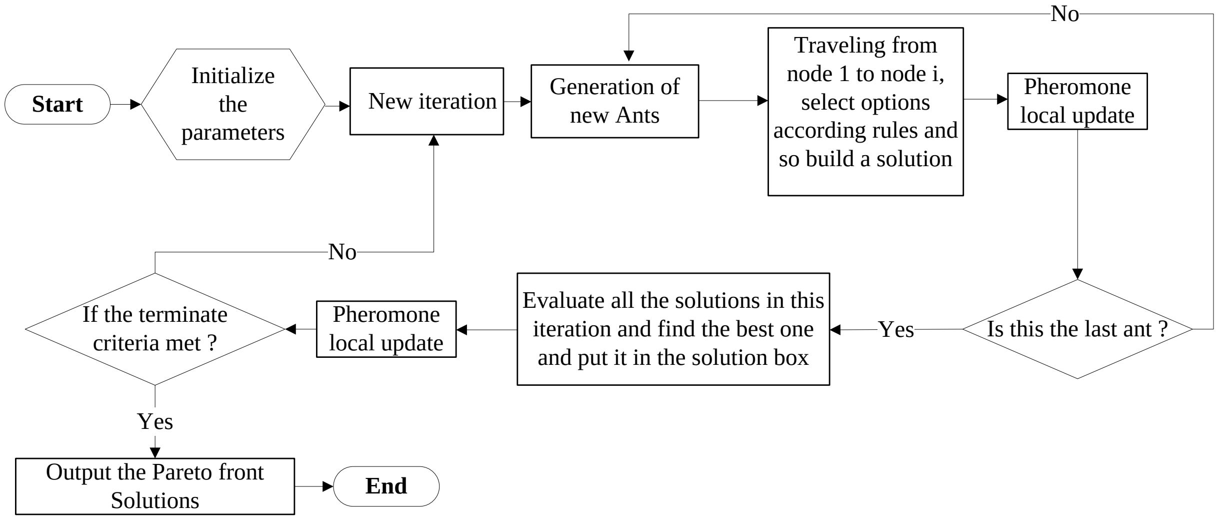


Figure 1.3 The flowchart of the ACO Algorithm

Two different approaches are usually used to terminate EAs iterations as for stopping criteria of searching: The lack of improvement of the best solutions over several generations; and the maximum number of iterations without any changes which is used in the proposed EAs due to its convenience and popularity.

In general, GA, PSO and ACO have been applied as three important evolutionary algorithms to solve multi-objective Time Cost Resource Optimization (TCRO) problems in construction project planning. Following Tables present some of important studies (Table 1.1 in time-cost tradeoff ; and Table 1.2 in resource management techniques) of optimization techniques with evolutionary algorithms.

Table 1.1 Selected important studies of time-cost tradeoff concepts with application of Evolutionary Algorithms

Previous Studies	Main Approach	Problem Type	Pre-Required Data	Selection Criterion	Optimal Solution
Feng et al. (1997)	GA and distance method	Deterministic	Crisp data for each option within each activity	Least cost & least time	Group of non-dominated solutions
Li & Love (1997)	Improved GA	Deterministic	Manually crafted linear time–cost curves	Least cost	Best solution
Zheng et al. (2004)	GA & adaptive weights	Deterministic	Crisp data for each option within each activity	Least cost & least time	Group of non-dominated solutions
Hegazy (1999)	GA	Deterministic	Crisp data for each option within each activity	Least cost	Best solution
Feng (2000)	Simulation techniques & GAs	Stochastic	Historical data to establish probability distribution of duration and cost	Least cost & least time	Group of non-dominated solutions
Leu et al. (2001)	Fuzzy logic & GAs	Stochastic	Experts' estimation of time in crash and normal situations; crisp unit cost in crash and normal situations.	Least cost	Best solution
Zheng et al. (2005)	Fuzzy logic & GAs	Stochastic	Crisp data for each option within each activity.	Least cost & least time	Group of non-dominated solutions
Yang (2007)	PSO	Deterministic	Continuous & Discrete Time-Cost Functions.	Least cost & least time	Group of non-dominated solutions
Rahimi & Iranmanesh (2008)	PSO	Deterministic	Crisp data for each option within each activity with Time-Cost-quality	Least cost & least time &best quality	Best solution
Zhang & Li (2010)	PSO	Deterministic	Crisp data for each option within each activity	Least cost & least time	Best solution
Ng & Zhang (2008)	ACO	Deterministic	Crisp data for each option within each activity	Least cost & least time	Group of non-dominated solutions
Xiong & Yaping (2008)	ACO	Deterministic	Crisp data for each option within each activity	Least cost & least time	Group of non-dominated solutions
Christodoulou (2010)	ACO	Stochastic	Crisp data for each activity in resource-constrained problems	Least time	Best solution

Table 1.2 Selected important studies of resource management concepts with application of Evolutionary Algorithms

Previous Studies	Main Approach	Pre-required Data	Selection Criterion	Optimal Solution
Matilla & Abraham (1998)	Linear Programming	Allocated Resources	Leveling	Best solution
Hegazy (1998)	GA	Priority Assigned to resources	Leveling & Allocation	Best solution
Leu & Yang (1999)	GA	Allocated Resources	Leveling , Least Time, Least Cost	Best solution
Hiyassat (2001)	Minimum Moment Method	Allocated Resources	Leveling	Best solution
Senouci &Eldin (2004)	GA	Pre-Required Data	Leveling &Least Cost	Best solution
Vaziri et al. (2007)	Simulated annealing	Pre-Required Stochastic Data	Leveling & Allocation	Optimized solution
El-Rayes & Jun (2009)	GA	Priority Assigned to resources	Leveling &Least Cost	Best solution

Judging from the progress of past research, it is necessary to develop more efficient algorithms to obtain better solutions with faster convergence (Konak et al. 2006). The concept of hybrid algorithms is presented in the last decades with computational optimization techniques. Two Hybrid Algorithms which are superior than existing optimization algorithms in finding better project schedule solutions with less total project cost, less total project duration, and less total variations of resource allocation have been applied in current research are introduced in the following Sections:

1.4 Hybrid Genetic Algorithm- Particle Swarm Optimization (HGAPSO)

Juang (2004) presents a new evolutionary learning algorithm based on a hybrid of GA and PSO called HGAPSO. In this hybrid algorithm, solutions in a new generation are created, not only by crossover and mutation operations as in GA, but also by PSO. The concept of elite strategy is adopted in HGAPSO, where the upper-half of the best-performing solutions in a population are regarded as elites. However, instead of being reproduced directly in the next generation, these elites are first enhanced. The group constituted by the elites is regarded as a swarm, and each elite corresponds to a particle within it. In this regard, the elites are enhanced by PSO, an operation which mimics the maturing phenomenon in nature. These enhanced elites constitute half of the population in the new generation, whereas the other half are generated by performing crossover and mutation operation on these enhanced elites.

1.5 Shuffled Frog Leaping Algorithm (SFLA)

The SFLA combines the benefits of the genetic-based Memetic Algorithm (MA) and the social behavior-based PSO (Elbeltagi et al. 2005). Instead of using genes in GA, SFLA uses memes to improve spreading and convergence ratio. In the SFLA, the population consists of a set of frogs (represent solution) that is partitioned into subsets referred to as memeplexes. SFLA, in essence, combines the benefit of the local search tool of PSO and the idea of mixing information from parallel local searches, to move toward a global solution which is called a Shuffled Complex Solution (SCE). The philosophy behind SCE is to treat the global search as a process of natural evolution (Duan et al 1992). The Equations (1.1), and (1.2) from PSO are applied in SFLA. After a defined number of memetic evolutionary steps, frogs are shuffled among memeplexes, enabling frogs to exchange messages among different memplexes and ensuring that they move to an optimal position, similar to particles in PSO (Eusuff and Lansey 2006).

1.6 Constraints of the Current Methodology

This research presents multi-objective optimization with evolutionary algorithms as previous studies have been applied. Our results show that our proposed hybrid optimization algorithms are good methods to solve construction project planning problems. Our approaches are appropriate methods to deal with project network problems including several activities with several temporal and logical relationships among activities. Our approaches can deal with the inherent complexity in these problems. These project planning problems are Time-Cost-Resource Optimization (TCRO) problems that require time-cost-resource tradeoff analysis. There are three objectives in these multi-objective optimization problems: minimize the project duration; minimize the total project cost; and minimize one of the total resource allocation moments. These problems are special kinds of complex, NP-hard problems. Our results show that our approach can provide better solutions (i.e., a frontier of optimal scheduling solutions) compared to existing optimization methods that are available for construction project planning problems.

The following limitations are identified for our proposed optimization methods:

- Our approach assumes that resources are available throughout the entire project duration. Interruptions in the availability of different resources are not considered in our optimization approach.
- Our approach assumes that resources are not prioritized. There is no weight considered for project resources when they are deployed to conduct project activities.
- Our method assumes that there is no priority in the execution of project activities.

In addition to the above limitations, our proposed algorithm cannot be used to solve stochastic optimization problems. For instance, our approach cannot be used to solve project planning problems under uncertainty, which have stochastic critical paths.

1.7 Format and Flow of this Dissertation

This dissertation is based on three journal papers. Chapters 2, 3 and 4 are each written according to the documents publishable in academic journals.

In Chapter 2 of this dissertation, the first paper presents a fuzzy enabled Hybrid Genetic Algorithm-Particle Swarm Optimization approach to develop Time-Cost-Resource Optimization in construction projects. Discretized and continuous fuzzy set theory are applied in three examples adopted from previous studies in GA, PSO, and fuzzy GA respectively to validate and compare the capabilities of proposed optimization approaches. The results have shown that processing time and optimal project schedule solutions will be improved with the proposed fuzzy enabled HGAPSO algorithm.

In Chapter 3 of this dissertation, the second paper presents applying the Shuffled Frog-Leaping Algorithm to the Time-Cost-Resource Optimization problems with activity splitting allowed. We present resources allocation while taking into account splitting during activities execution, in order to finish the project within budget and on time from the standpoints of contractors, sponsors, and the project client. Two examples have been used to demonstrate the impact of SFLA and splitting on the optimal project schedule solutions and to compare with previous algorithms.

In Chapter 4 of this dissertation, the third paper presents comparison of Evolutionary Algorithms in optimal project schedule solutions of the TCRO problems with evaluation of inflation impact. In this paper, we compare the results of three recent significant EAs: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and two hybrid algorithms (which have been applied in the previous two chapters) such as HGAPSO and SFLA on the TCRO problem. The algorithms are compared in terms of convergence ratio (number of required iterations to obtain optimal project schedule solutions and processing time) and quality of Pareto front in two examples. In addition, the inflation rate of resources unit price has been evaluated in the TCRO problems. Our results demonstrate that considering inflation has an important impact on the final solution and should be considered to make TCRO problem closer to approximating real projects.

Chapter 5 summarizes the contribution of the three papers of this dissertation and Chapter 6 includes the bibliographic information referenced in the dissertation.

Chapter 2

Time-Cost-Resource Optimization in Construction Project Planning:

A Fuzzy Enabled Hybrid Genetic Algorithm-Particle Swarm Optimization (HGAPSO) Approach

Abstract

One of the most challenging tasks of a construction project planner is to simultaneously minimize the total project cost and total project duration while considering issues related to optimal resource allocation and resource leveling. Therefore, project planners face complicated multivariate, Time-Cost-Resource Optimization (TCRO) problems that require time-cost-resource tradeoff analysis. We present a Hybrid Genetic Algorithm Particle Swarm Optimization (HGAPSO) approach to solve complex, TCRO problems in construction project planning. Our proposed approach uses the fuzzy set theory to characterize uncertainty about the input data (i.e., time, cost, and resources required to perform an activity) in this hybrid approach. We apply our fuzzy enabled HGAPSO approach to solve three optimization problems, which are found in the construction project planning literature. It is shown that our proposed fuzzy enabled HGAPSO approach is superior than existing optimization algorithms in finding better project schedule solutions with less total project cost, less total project duration, and less total variations of resource allocation. The results also show that our proposed approach is faster than existing methods in processing time for solving complex TCRO problems in construction project planning.

2.1 Introduction

One of the most challenging tasks of a construction project planner is to simultaneously minimize the total project cost and total project duration while considering issues related to optimal resource allocation and resource leveling. Project planners face complicated multivariate, Time-Cost-Resource Optimization (TCRO) problems that require time-cost-resource tradeoff analysis. Also, construction management decisions about time, cost, and required resources for conducting activities are made during the early planning stage of projects, yet many possible scenarios should be considered during the construction stage (Castro-Lacouture et al. 2009). This means that construction time, cost, and resources should be considered simultaneously in project planning and scheduling stages (Zheng and Ng 2005).

Three interrelated tasks should be performed as part of construction project planning: (1) time-cost tradeoff analysis; (2) constrained resource allocation; and (3) resource leveling (Leu and Yang 1999). It is found that the proper project planning through efficient project scheduling and appropriate resource allocation can significantly increase the possibility that a construction project is completed on time, within the budget, consistent with specifications, and with fewer problems (Mattila and Abraham 1998). Therefore, construction project scheduling should be performed under resource constraints with considering the flexibility for time and cost savings through the proper resource leveling. However, the conventional project scheduling methods and the most notably, Critical Path Method (CPM) has the limitation that they do not consider assigning resource constraints to project activities or the possibility of time and cost savings through changing project schedule and resource adjustments (Kim and Ellis 2010). The major problem is that the focus of these tools is on the local optimality at the activity level and not on the global optimality at the project level. Also, these tools are not capable of simultaneous time-cost-resource optimization.

Evolutionary algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been applied as advanced, computational optimization methods to overcome the above limitations of conventional methods and solve simultaneous TCRO problems in construction project planning. The Hybrid Genetic Algorithm Particle Swarm Optimization (HGAPSO) algorithm has been developed in computer science (Juang 2004) to utilize the strength of both GA and PSO algorithm in an integrated framework to solve complex optimization problems. In this chapter, we present a HGAPSO approach to solve TCRO problems in construction project planning. Our proposed approach also uses the fuzzy set theory to characterize uncertainty about the input data (i.e., time, cost, and resources required to perform an activity). Our objective is to create a superior optimization method than existing optimization algorithms to find better project schedule solutions with less total project costs, less total project durations, and less total variations of resource allocation.

In order to achieve this objective, this chapter is structured as follows. Research Background on existing optimization algorithms to solve TCRO problems in construction project planning is described in Section 2.2. The mathematical formulation of TCRO problems in construction project planning is presented in Section 2.3. Our fuzzy enabled HGAPSO approach is described in Section 2.4. In Section 2.5, we apply our proposed approach on three construction project planning problems, which are taken from the optimization literature in construction engineering and management. We compare the performance of our proposed approach with existing optimization algorithms in this Section. Conclusions are summarized at the end.

2.2 Research Background

TCRO problems in construction project planning are special kinds of general optimization problems recognized as NP-hard (non-deterministic polynomial-time hard) in the computational complexity theory (Colorni and Dorigo 1991; Merkle et al. 2002; Konak et al. 2006; Zavala 2008). NP-hard problems are one of the most difficult optimization problems. Typically there are three methods to solve these complex optimization problems:

(1) Heuristic approaches: these approaches are experience-based techniques that rely on the rules of thumb of decision-makers (Zheng et al. 2004). For instance, Moselhi (1993) develops a heuristic technique for construction project scheduling under time-cost constraints. Moselhi uses the least impact algorithm to allocate resources to a set or a group of activities simultaneously.

(2) Mathematical programming methods: these methods are mathematical techniques, which are applied to solve optimization problems where one seeks to minimize or maximize a real function by systematically choosing the values of real or integer variables within allowable sets (Avriel 2003). For instance, linear programming is used to solve TCRO problems through building time-cost linear relationships for activities in a construction project (Pagnoni 1990; Hendrickson and Au 1989). Also, Pena-Mora and Park (2001) use dynamic planning to develop Graphical Evaluation and Review Technique (GERT) in design-build, fast-track construction projects.

(3) Evolutionary algorithms: these algorithms are stochastic search methods that mimic the natural biological evolution and social behavior of species (Elbeltagi et al. 2005). GA (See Goldberg 1989 for a comprehensive review of GA techniques) and PSO (See Kennedy and Eberhart 1995 for a comprehensive review of PSO techniques) are two common evolutionary algorithms that have been used to solve TCRO problems in construction project planning. For instance, Kandil and El-Rayes (2006) apply multi-objective genetic algorithm to optimize resource allocation in a large-scale construction project. Also, Zahraie and Tavakolan (2009) use the Non-dominated Sorting Genetic Algorithm (NSGA-II) to solve a TCRO problem in a

harbor construction project. In addition, Yin (2005) applies the PSO algorithm for finding the optimal task assignment in distributed systems. Further, Yang (2007) modifies the PSO algorithm to facilitate the time-cost tradeoff analysis in construction project planning.

Heuristic approaches have been proven to be useful to solve complex, Time-Cost Optimization (TCO) problems. However, these methods just optimize a single objective function and cannot provide good solutions with the guaranteed optimality (Zheng et al. 2004; Ng et al. 2008). Mathematical programming, on the other hand, is applicable to constrained-resource, optimization problems. However, these methods are not able to generate a wide range of feasible solutions (Elbeltagi et al. 2005). Compared with heuristic and mathematical methods, evolutionary algorithms have a greater capability to optimize complex problems resulting in widespread solutions (Deb 2002; Zheng et al. 2004; Zitzler 2004; Konak 2006). For example, it is shown that GA can improve the convergence ratio in optimization processing and enhance the quality of solutions through considering the entire domain of feasible project schedule solutions (Srinivas 1995; El-Rayes 2001; Shi 2004; Senouci 2005; Zheng and Ng 2005; Ng et al. 2008).

Evolutionary algorithms like GA and PSO are proper methods to solve inherently complex TCRO problems in construction project planning. However, these methods are not without limitations. Ng et al. (2008) states that despite the benefit of GA, the time taken by GA to generate a near-optimum solution can be excessive. In addition, it may converge to a single peak due to stochastic errors during processing. These limitations are undesirable for solving multi-objective TCO problems (Zheng and Ng 2005).

To overcome the above limitations, Kandil and El-Rayes (2006) apply the multi-objective genetic algorithm to optimize the resource utilization in large-scale construction projects. However, Kandil and El-Rayes conclude that the large population size is necessary to find optimization solutions for complex projects without guaranteeing the optimality of solutions. Zahraie and Tavakolan (2009) present the TCRO optimization algorithm using the NSGA-II to solve TCRO problems in construction project planning. This algorithm obtains non-dominated solutions with the most desirable configurations of total project cost, total project duration, and total variations of resource allocation computed by the resource moment function. However, their model is unable to solve TCRO problems with limited resources. Also, their algorithm is relatively slow.

In comparison with GA, PSO is a newer algorithm based on an analogy with the choreography of the flight of a flock of birds. Although the PSO provides faster convergence, it does not perform well due to the early convergence and local optimal issues. In this chapter, we apply GA and PSO in a hybrid algorithm to solve TCRO problems in construction project planning. We use HGAPSO algorithm – developed by Juang (2004) in computer science to solve complex optimization problems – to solve TCRO problems in construction project planning. Our approach also utilizes the fuzzy set theory to characterize uncertainty about the input data (i.e., time, cost, and resources required to perform an activity) in this hybrid approach. Our fuzzy enabled HGAPSO approach improves the convergence ratio and facilitates the identification of Pareto front of optimal project schedule solutions in TCRO problems. Next, we describe the mathematical formulation of TCRO problems in construction planning, for which we develop the fuzzy enabled HGAPSO approach.

2.3 Mathematical Formulation of a Time-Cost-Resource Optimization (TCRO) Problem in Construction Project Planning

Consider a typical project planning problem consisting of N related activities: $A_1, A_2, ..., A_N$. There are several options to allocate S types of project resources $R_1, R_2, ..., R_S$ to perform an activity. Each project schedule option represents the time and cost of performing an activity with a combination of project resources. The values and ranges of time and direct cost for each activity are dependent variables based on Time-Cost function and defined by the project planners. Suppose $O_{i,j}$ represents the set of entire feasible schedule options that a project planner can choose from $option_j$ to perform activity $i = 1,2,...,N$:

$$O_i = \{\tilde{O}_{i,j_i} = Option_{j_i} \ for \ Time, Dircet \ Cost, \& \mathrm{Re}sources \ to \ Perform \ Activity_i = (T_{i,j_i}, C_{i,j_i}, (R_{1,j_1}, R_{2,j_1}, ..., R_{s,j_1})) \in Feasible \ Configurations \ of \ Time, \ Cost, \ and \ \mathrm{Re}sources \ to \ Perform \ Activity_i \}$$

This feasible option set of time and direct cost might be discrete or continuous depending on the number of possible alternatives available to perform an activity. Furthermore, direct cost is dependent on the resource allocation in each feasible schedule options (O_i) and is calculated based on the product of number of resources and fixed (without any interest or inflation) unit price of multiple resources. The proposed TCRO problem is also capable of considering two different modes of having non-limited and limited resources. The choices of time and cost for each activity in the later case are accepted only if the limited resources condition is satisfied. Figure 2.1 shows the flowchart of the proposed TCRO model.

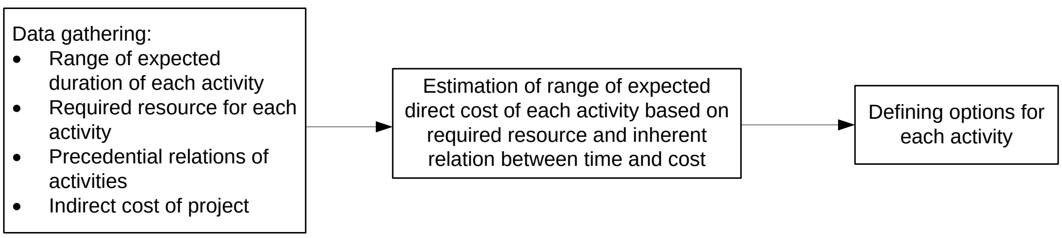


Figure 2.1 Flowchart of the proposed TCRO model

The project planner's problem is how to allocate project resources and schedule activities to minimize the total project cost and total project duration while maintaining daily resource limitations. Therefore, project planner's decision variables in this optimization problem are: (1) Start dates of project activities: $SD_1, SD_2, ..., SD_N$; and (2) Resource allocation options to perform project activities: $O_{1,j_1}, O_{2,j_2}, ..., O_{N,j_N}$. We assume that an activity cannot be split. Also, the resource allocation to an activity remains unchanged while the activity is in progress. The project planner's objective functions in this TCRO problem can be formulated as the simultaneous minimization of the total project cost, total project duration, and total variations of resource allocation as summarized below:

Z_1=Minimize total project cost (TC). The total project cost consists of total direct costs to perform project activities and indirect cost to complete the project. The total direct cost of the project is equal to the total costs of activities of a project which are proportional with the duration of activities. The indirect cost is usually considered to be equal to the summation of constant daily cost of project over the total time of project execution:

$$Z_1 = Min\ (TC) \tag{2.1}$$

Z_2=Minimize total project duration (TD). The total duration of the project is the time that it takes to complete critical activities that are on the critical path of project activity network:

$$Z_2 = Min\ (TD) \tag{2.2}$$

Z_3=Minimize the total variations of resource allocation. One of the most common indicators (i.e., moments) to measure variations of resource allocation is the Sum of Squares of

Resources (SSR) that are used over the total project duration (Hegazy 1999). The project planner should minimize this resource moment to achieve a better resource leveling:

$$Z_3 = Min\ (SSR) = Min\ \left(\sum_{k=1}^{TD} \sum_{n=1}^{S} (\mathrm{Re}\,source_{n,k})^2 \right) \tag{2.3}$$

where $\mathrm{Re}\,source_{n,k}$ is the number of $\mathrm{Re}\,source_n : n = 1,2...,S$ that is planned to use in day k of the project duration: $k = 1,2...,TD$.

A TCRO problem in construction project planning is subject to several constraints as:

1) Logical or physical dependencies between project activities as indicated by the diagram of the project activity network. Start-to-Start, Start-to-Finish, Finish-to-Start, and Finish-to-Finish relationships among project activities must be captured as appropriate constraints on activity start dates $SD_1, SD_2,..., SD_N$ and respective durations $T_1, T_2,..., T_N$.

2) (Any) limits on the total daily availability of resources: the total consumption of a particular resource among the entire project activities must not exceed the capacity of that resource at any point of time during the project.

Next, we present a fuzzy enabled HGAPSO approach to solve this TCRO Problem in construction project planning.

2.4 Fuzzy Enabled HGAPSO Approach to Solve TCRO Problems in Construction Project Planning

The capabilities of GA and PSO have been combined in a HGAPSO to achieve faster convergence rate and obtain better Pareto optimal solutions. HGAPSO is invented by Juang (2004) as a new evolutionary learning algorithm to solve complex optimization problems.

Juang's HGAPSO optimization algorithm is based on generating solutions within the feasible solution space and searching to improve current solutions through the crossover and mutation operations of GA combined with the elitism of PSO. The enhanced elites constitute half of the population in the new generation, whereas the other half are generated by performing crossover and mutation operation on these enhanced elites.

We apply Juang's HGAPSO algorithm to solve TCRO optimization problems in construction project planning. Particularly, we enable this algorithm for the specific context of construction project planning through using fuzzy input data. The fuzzy logic has been applied widely as an alternative approach to characterize uncertain variables in construction project planning (Zheng and Ng 2005; Shaheen et al. 2007; Castro-Lacouture et al. 2009). The specification of feasible options to allocate project resources to conduct an activity is subject to uncertainty. We use a standard triangular fuzzy membership function to characterize uncertainty about the cost and time to complete an activity. This specification is based on the range of possible time-cost configuration options as specified in the respective feasible set of resource allocation options. Suppose minimum, average, and maximum values of cost and time in the resource allocation option set are T_{min}, T_{avg}, and T_{max}, and C_{min}, C_{avg}, and C_{max}, respectively. These values are used to construct triangular cost and time fuzzy membership functions, respectively, as shown in Figures 2.2(a) and 2.1(b). Fuzzy time and cost membership functions – denoted by U(T) and U(C) – are summarized below.

$$U(T) = \begin{cases} \dfrac{T - T_{\min}}{T_{avg} - T_{\min}} & 0 \le T_{\min} \le T \le T_{avg}; \\ \dfrac{T_{\max} - T}{T_{\max} - T_{avg}} & T_{avg} \le T \le T_{\max}; and \\ 0 & otherwise \end{cases} \tag{2.4}$$

$$U(C)=\begin{cases}\dfrac{C-C_{\min}}{C_{avg}-C_{\min}} & 0\le C_{\min}\le C\le C_{avg};\\ \dfrac{C_{\max}-C}{C_{\max}-C_{avg}} & C_{avg}\le C\le C_{\max};and\\ 0 & otherwise\end{cases} \quad (2.5)$$

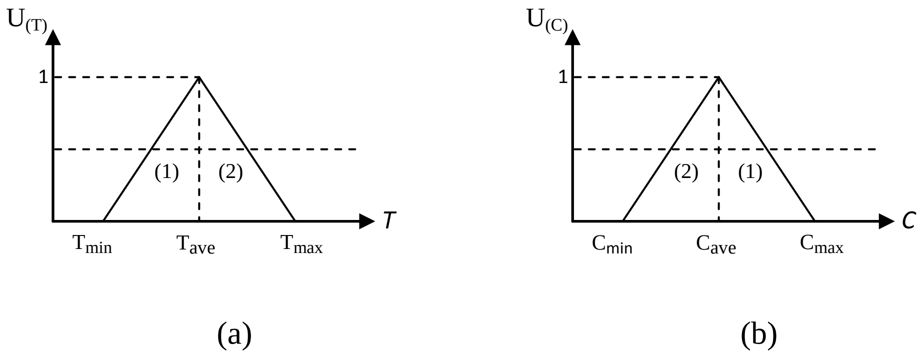


Figure 2.2 Fuzzy membership functions of (a) activity time; and (b) activity direct cost

The fuzzy enabled HGAPSO approach to solve the above TCRO problem consists of the following steps:

1) Set k=1; initialize a population set of feasible project schedule solutions:

$$P^{(K)}=\left\{\left((SD_1,\overline{O}_1),(SD_2,\overline{O}_2),...,(SD_N,\overline{O}_N)\right)\middle|\begin{array}{c}(SD_i,\overline{O}_N)\ is\ Randomly\ Selected\ \ from\ Entire\ Feasible\\ Set\ of\ Start\ Date\ and\ Time-Cost-\mathrm{Re}source\\ Allocation\ \ for\ Activity\ i:i=1,2,...,N\end{array}\right\}$$

This initial population set consists of $2N$ project schedule solutions, which are randomly drawn from feasible sets of start date and time-cost-resource allocation for project activities considering the logical and temporal relationships among project activities;

2) Compute the values of optimization objective functions for each feasible project schedule option in $P^{(k)}$: total project cost (Z_1), total project duration (Z_2), and total variations of resource allocation (Z_3);

3) Eliminate dominated project schedule solutions from the feasible set $P^{(k)}$: a dominated solution is a solution whose corresponding cost, duration, and resource variations are all greater than or equal to respective cost, duration, and resource variations of another feasible solution in the feasible set. Remove dominated project schedule options from the initial $P^{(K)}$ and update the project schedule solutions set $P^{(k)}$;

4) Compute average total project cost, average total project duration, and average total variations of resource allocation for the remaining project schedule solutions in the updated $P^{(k)}$: $\overline{Z}_1, \overline{Z}_2, and\ \overline{Z}_3$, respectively;

5) For each project schedule option in $P^{(k)}$, compute the normalized, distance in a three-dimensional objective space from the origin as:

$$D = \sqrt{\left(\frac{Z_1}{\overline{Z}_1}\right)^2 + \left(\frac{Z_2}{\overline{Z}_2}\right)^2 + \left(\frac{Z_3}{\overline{Z}_3}\right)^2} \ ;$$

6) Order project schedule options in $P^{(k)}$ from the greatest distance to the lowest distance. Split the ordered population set into two solution subsets: lower-half and upper-half (if the size of $P^{(k)}$ is even, the upper-half subset takes the middle point);

7) Apply the combined crossover and mutation operators of GA – see Zheng et al. (2004) for detailed description of these GA operators – to the current lower half subset to generate (possibly new, feasible) project schedule solutions. These (new) solutions belong to the next generation population set of project schedule options denoted by $P^{(k+1)}$;

8) Apply the movement operator of PSO – see Zhang et al. (2006) for detailed description of this PSO operator – to the current upper half subset to generate (possibly new, feasible) project schedule solutions. These (new) solutions also belong to the next generation population set of project schedule options denoted by $P^{(k+1)}$;

9) Repeat Steps 2 to 7 until no new project schedule solution can be found by conducting Steps 6 and 7; i.e., when the next generation population set of project schedule options is equal to the current generation set of project schedule options; and

10) The final population set represents a Pareto optimal set of project schedule solutions for the TCRO problem. Figure 2.3 summarizes the above steps.

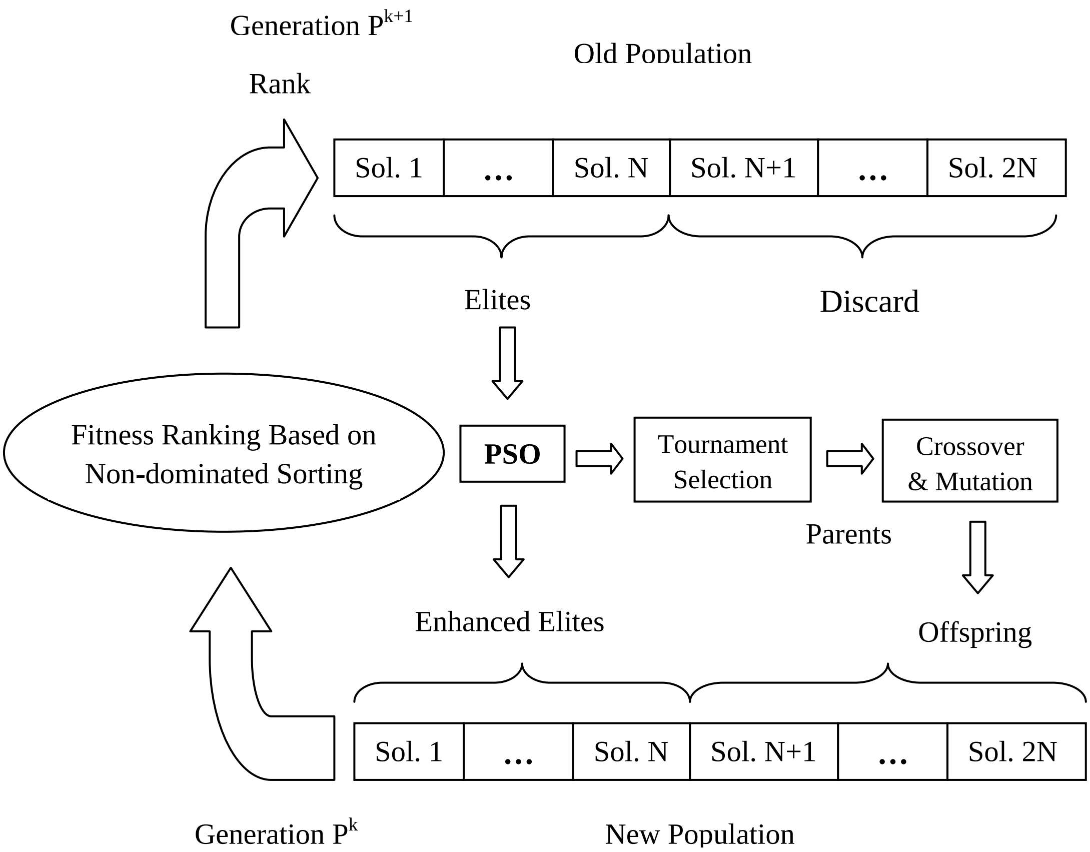


Figure 2.3 An overview of our proposed HGAPSO algorithm

Next, we demonstrate how the proposed fuzzy enabled HGAPSO approach can be used to solve TCRO problems in construction project planning and compare optimal project solutions found by our approach with the results of existing optimization algorithms.

2.5 Application of the Proposed Fuzzy Enabled HGAPSO Algorithm

We apply the proposed fuzzy enabled HGAPSO approach on three optimization problems, which we have found in the literature of construction project planning. These examples are selected to compare the results of our proposed HGAPSO approach with the results of existing methods. We use our approach to solve these project planning problems and find optimal project schedule solutions. We show that our proposed fuzzy enabled HGAPSO approach is superior than existing optimization algorithms to find better project schedule solutions with less total project costs, less total project durations, and less total variations of resource allocation. Also we show that our proposed approach is faster than existing methods in terms of the processing time for solving these optimization problems in construction project planning.

2.5.1 Example 2.1

The first example is presented in Zheng and Ng (2005). It is a project consisting of seven interrelated activities as shown in Activity On Node (AON) diagram in Figure 2.4. Seven resource types $R_1, R_2,...R_7$ are used in this project. There are several options to perform each activity using different configurations of these resources. For instance, Table 2.1 shows 11 configurations of time, direct cost, and resource allocation to perform activity 1. Also, indirect cost of this project is assumed to be $1,500 per day. Zheng and Ng (2005) use fuzzy GA algorithm to solve this project planning problem and find optimal project schedule solutions. Zahraie and Tavakolan (2009) revisit this problem and apply NSGA-II evolutionary algorithm to find the Pareto optimal front of project schedule solutions. We also apply our fuzzy enabled HGAPSO approach on this project planning problem to find the Pareto optimal front of project schedule solutions and then, compare our solutions with the results of the previous two algorithms. Figure 2.5 shows the discretized time and cost membership functions for the first activity of this project.

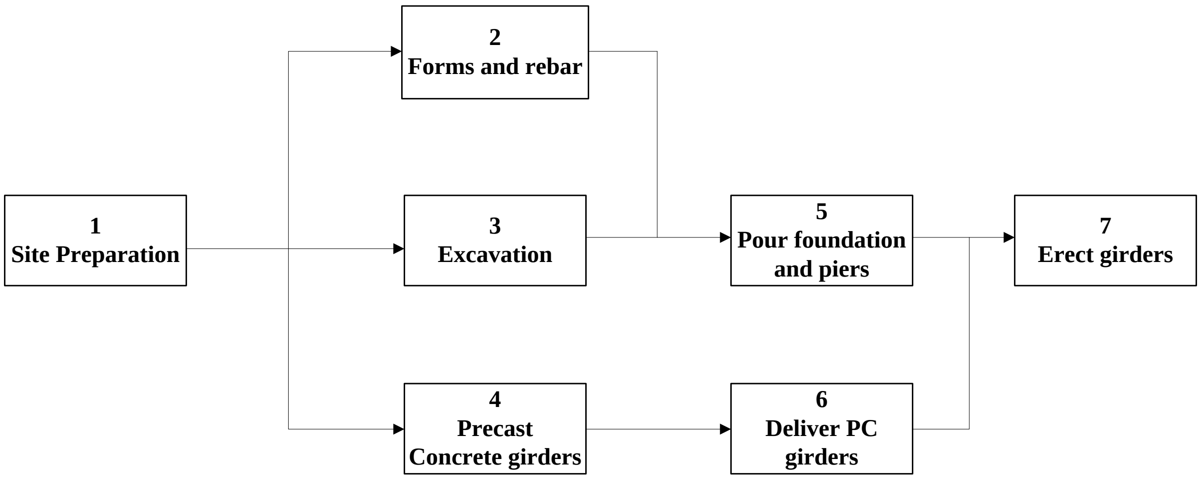


Figure 2.4 AON diagram of project activities in Example 2.1

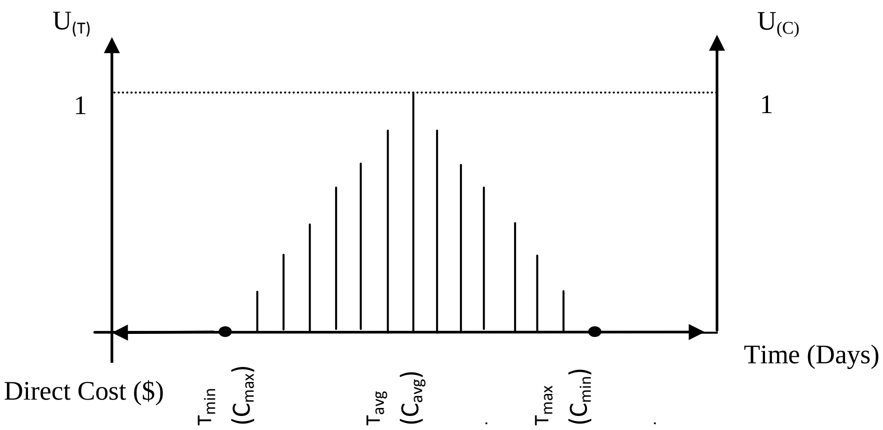


Figure 2.5 Discretized membership functions for duration and direct cost of activities

First, we compare our proposed HGAPSO approach with both Zheng and Ng's and Zahraie and Tavakolan's algorithms considering the simultaneous minimization of total project cost and total project duration. Zheng and Ng did not consider minimizing resource variations as one of their project planning objectives in this example. Figure 2.6 shows project schedule solutions on the Pareto optimal fronts for this TCRO problem in the 2-dimensional space of total project cost and total project time. These Pareto optimal points show total project costs and total project durations for non-dominated project schedule solutions, which are derived by our proposed fuzzy enabled HGAPSO approach as well as Zahraie and Tavakolan's (2009) algorithm. It can be seen that our proposed HGAPSO approach is able to find project schedule solutions with lower total project costs and total project durations, which were not found by any of the previous algorithms. In particular, the project schedule solution with the shortest total project duration (i.e., 64 days) and the project schedule solution with the least total project cost (i.e., $226,300) are just found by our proposed fuzzy enabled HGAPSO algorithm. Finding additional optimal project schedule solutions is one of the most significant contributions of our proposed algorithm over the existing optimization algorithms.

Next, we compare our proposed HGAPSO approach with Zahraie and Tavakolan's (2009) algorithm considering the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation. Figures 2.7(a) and 2.7(b) show project schedule solutions on the Pareto optimal fronts in the 3-dimensional space of project objectives: total project cost, total project duration, and total variations of resource allocation, which are derived by Zahraie and Tavakolan's NSGA-II algorithm and our proposed fuzzy enabled HGAPSO approach, respectively. These Pareto optimal points show total project costs, total project durations, and total variations of resource allocation for non-dominated project schedule solutions, which are derived by our proposed fuzzy enabled HGAPSO approach and Zahraie and Tavakolan's algorithm.

Table 2.1 Feasible project schedule options to perform Activity 1 in Example 2.1

Option No.	Duration (Days)	Required Resources (Numbers)							Direct Cost ($)
		$R_{1,1}$	$R_{1,2}$	$R_{1,3}$	$R_{1,4}$	$R_{1,5}$	$R_{1,6}$	$R_{1,7}$	
1	14	3	2	1	1	1	0	0	23,000
2	15	3	2	1	0	1	2	0	21,900
3	16	3	2	0	1	0	1	2	20,800
4	17	3	2	0	0	1	1	0	19,700
5	18	3	1	1	0	1	2	4	18,600
6	19	3	1	1	0	0	0	0	17,500
7	20	3	1	0	0	1	2	0	16,400
8	21	2	2	0	0	0	1	2	15,300
9	22	2	1	1	0	1	1	0	14,200
10	23	2	1	0	1	0	0	2	13,100
11	24	2	0	0	2	2	0	0	12,000

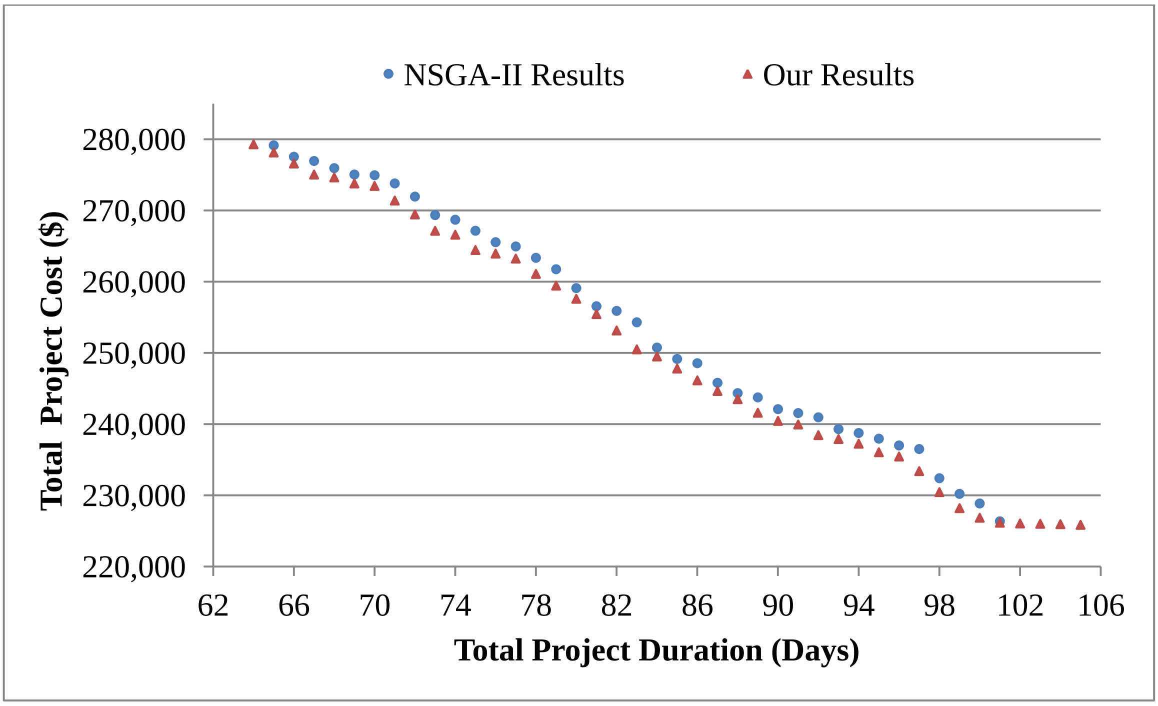
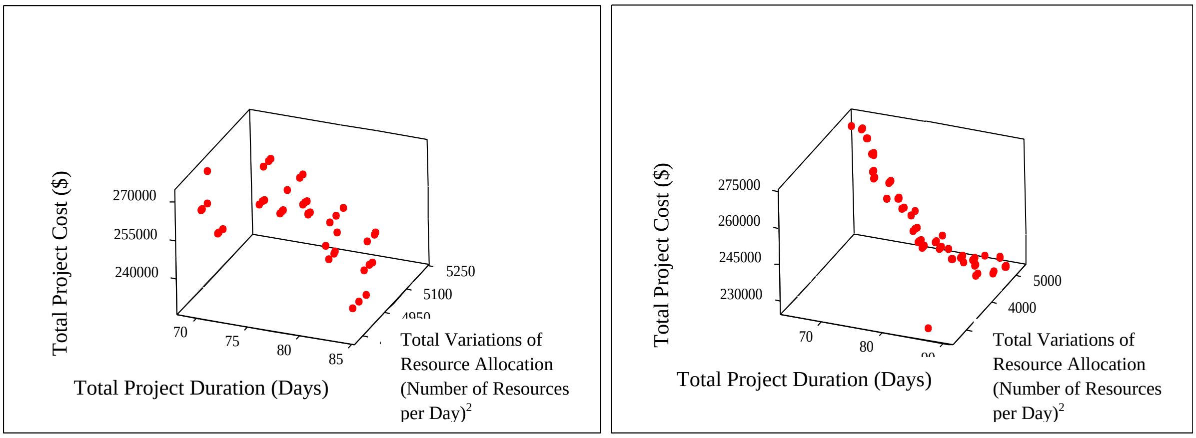


Figure 2.6 Optimal project schedule solutions in the 2-dimensional space of total project cost and total project duration found by our proposed HGAPSO, and Zahraie and Tavakolan's algorithms in Example 2.1

We also create Figures 2.8(a), 2.8(b), and 2.8(c) to better compare optimal project schedule solutions derived by these two algorithms in the 2-dimentional space of project planning objectives: total project cost and total project duration, and total project cost and total variations of resource allocation, and total project duration and total variations of resource allocation, respectively.



(a) (b)

Figure 2.7 Optimal project schedule solutions in the 3-dimensional space of total project cost, total project duration and total variations of resource allocation found by (a) NSGA-II approach; and (b) our proposed HGAPSO algorithm in Example 2.1

It can be seen that our proposed fuzzy enabled HGAPSO approach is able to find project schedule solutions with lower total project cost, total project duration, and total variations of resource allocation, which were not found by Zahraie and Tavakolan's NSGA-II algorithm. In particular, the shortest total project duration found by our approach (i.e., 64 days) is less than the shortest total project duration found by Zahraie and Tavakolan's algorithm (i.e., 69 days). The least total project cost found by our approach (i.e., $227,250) is less than the least total project cost found by Zahraie and Tavakolan's algorithm (i.e., $228,750). The least total variations of resource allocation found by our approach (i.e., 4,526 (Number of Resources per

Day)^2) is less than the least total variations of resource allocation found by Zahraie and Tavakolan's algorithm (i.e., 4,769 (Number of Resources per Day)^2). Finding additional optimal project schedule solutions with lower total project cost, total project durations, and total variations of resource allocation is one of the most significant contributions of our proposed approach over the previous Zahraie and Tavakolan's optimization algorithm. Further, our proposed approach also expedites the computational speed of solving TCRO problems in construction project planning. Our approach reduces the solution processing time by a factor of 3 compared to the previous Zahraie and Tavakolan's optimization algorithm.

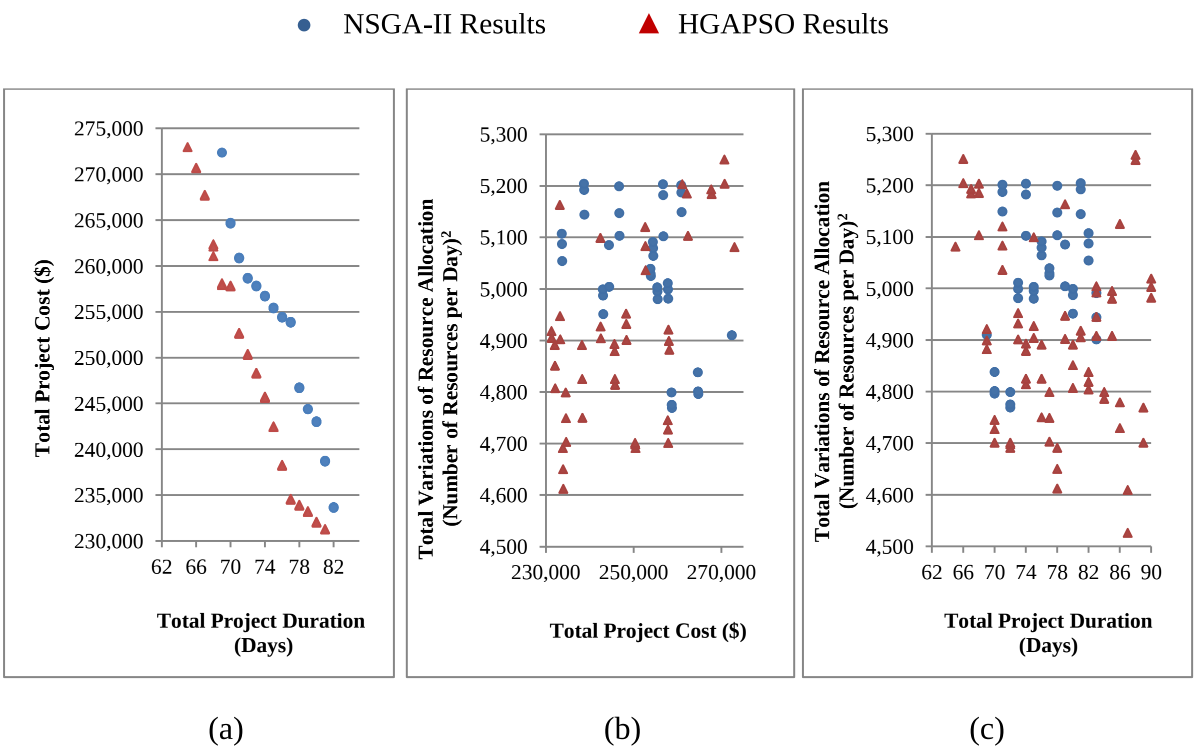


Figure 2.8 Optimal project schedule solutions in the 2-dimensional space of (a) total project cost and total project duration; (b) total project cost and total variations of resource allocation; and (c) total project duration and total variations of resource allocation found by the NSGA-II approach and our proposed HGAPSO algorithm in Example 2.1

2.5.2 Example 2.2

The second example is presented in Yang (2007). It is a fast-food outlet project consisting of fourteen interrelated activities as shown in AON diagram in Figure 2.9. This project consists of 14 activities. This project also uses 10 types of resources: $R_1, R_2, ...R_{10}$. There are several project schedule options to perform each activity considering various combinations of feasible resources, time, and cost. The project schedule options are described by several different continuous and discrete time-cost functions in Table 2.2. For instance, there are two project schedule options each defined by a continuous time-cost function to perform Activity 1. Figure 2.10 shows the continuous time and cost membership functions of this activity. In addition, each activity can be conducted using different sets of resources. For instance, Table 2.3 summarizes several examples of resource configurations to perform Activity 1. Each resource configuration corresponds to a specific time-cost configuration as identified in Table 2.3. Indirect cost of this project is assumed to be $600 per day.

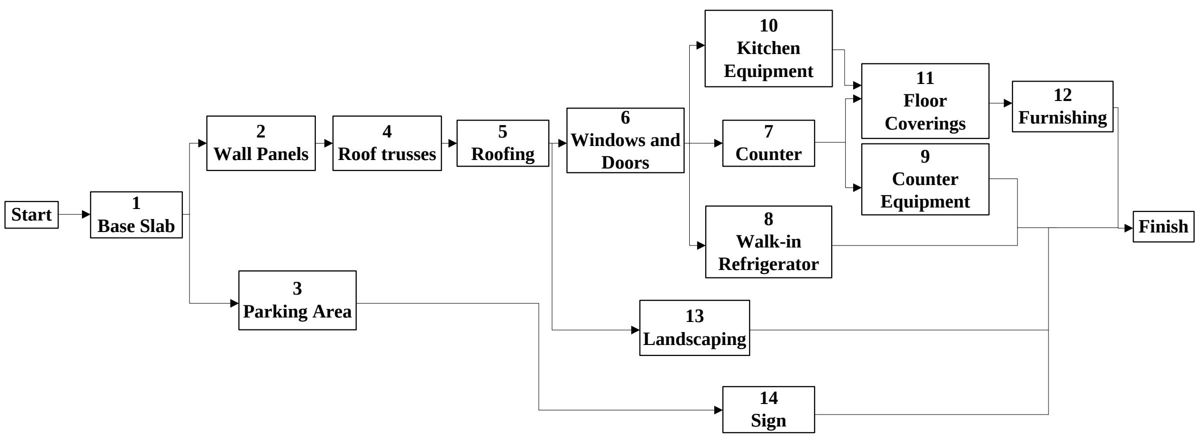


Figure 2.9 AON diagram of project activities in Example 2.2

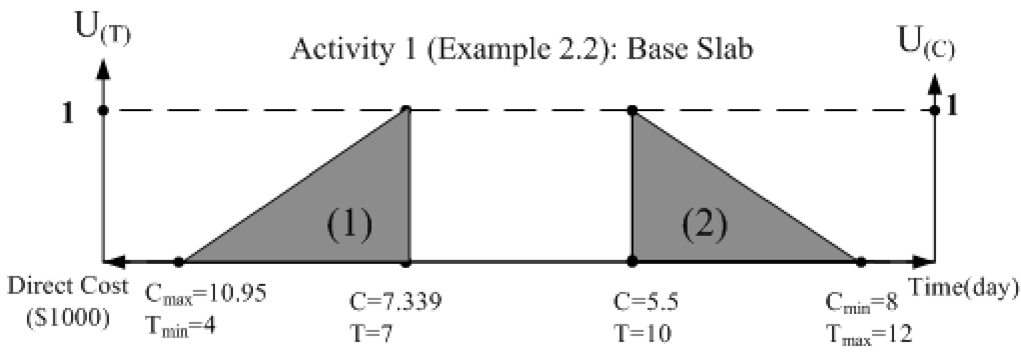


Figure 2.10 Continuous membership functions for duration and direct cost of activities

Yang (2007) uses the PSO algorithm to solve this project scheduling problem and find optimal project schedule solutions. Also, Zahraie and Tavakolan (2009) apply the NSGA-II algorithm to find optimal project schedule options in this problem. We apply our fuzzy enabled HGAPSO approach to solve this optimization problem and find the Pareto optimal front of project schedule solutions. Figure 2.11 shows project schedule solutions on the Pareto optimal fronts for this optimization problem in the 2-dimensional space of total project cost and total project time. These Pareto optimal points show total project costs and total project durations for non-dominated project schedule solutions, which are found by our proposed HGAPSO approach, and Zahraie and Tavakolan's NSGA-II algorithm. It can be seen that our proposed HGAPSO approach is able to find project schedule solutions with lower total project cost and total project duration, which were not found by Yang's and Zahraie and Tavakolan's algorithms. In particular, the shortest total project duration found by our approach (i.e., 21 days) is less than the shortest total project duration found by Yang's algorithm (i.e., 27 days) and total project duration found by the NSGA-II algorithm (i.e., 36 days). The least total project cost found by our approach (i.e., $81,265) is less than the least total project cost found by Yang's algorithm (i.e., $93,156) and the least total project cost found by the NSGA-II algorithm (i.e. $96,708). Finding additional optimal project schedule solutions with lower total project cost and shorter total project duration is one of the most significant contributions of our proposed approach over Yang's PSO and Zahraie and Tavakolan's NSGA-II algorithm.

Table 2.2 Cost-Time functions to perform project activities in Example 2.2

Activity ID	Cost (C)-Time (T) Functions	Time Range (Days)		Direct Cost Range (in thousands of dollars)	
		Minimum	Maximum	Minimum	Maximum
1	$C=0.33T^2-4.83T+25$	4	7	7.339	10.95
	$C=-0.25T^2+4.75T-17$	10	12	5.5	8
2	$C=0.5T^2-6.5T+27$	4	6	6	9
	C=4 if T=8	-	-	-	-
3	C=-T+20	8	12	8	12
	C=-0.5T+15	16	20	6	7
4	C=-0.067T+7.33	2	5	4	6
5	C=-T+6	1	4	2	5
6	C=-T+11	4	8	3	7
7	C=-0.4T+6.2	3	8	3	8
8	C=-0.4167T+8.83	2	8	5.5	8
9	C=-1.33T+8.33	1	4	3	7
10	C=-0.45T+9.32	4	15	2.5	7.5
11	C=-0.83T+9.67	2	8	3	8
12	C=-0.5T+12.5	5	15	5	10
13	C=10 if T=3	-	-	-	-
	C=8 if T=4	-	-	-	-
	C=7 if T=5	-	-	-	-
	C=5 if T=7	-	-	-	-
	C=4 if T=9	-	-	-	-
14	C=5 if T=3	-	-	-	-
	C=3 if T=5	-	-	-	-
	C=2 if T=6	-	-	-	-

Table 2.3 Examples of feasible project schedule options to perform Activity 1 in Example 2.2

Option No.	Duration (Days)	Required Resources (Numbers)										Direct Cost ($)
		$R_{1,1}$	$R_{1,2}$	$R_{1,3}$	$R_{1,4}$	$R_{1,5}$	$R_{1,6}$	$R_{1,7}$	$R_{1,8}$	$R_{1,9}$	$R_{1,10}$	
1	4	0	1	3	2	1	1	0	2	1	0	10,950
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
n	7	1	0	2	1	0	1	2	1	1	9	7,339
n+1	10	1	1	0	2	1	1	0	0	1	0	8,000
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
n+m	12	0	0	2	1	2	0	1	1	1	0	5,500

Yang's algorithm is not capable of solving this project planning problem considering the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation. Both our proposed fuzzy enable HGAPSO approach and Zahraie and Tavakolan's NSGA-II algorithm are capable of solving simultaneous TCRO problems with time-cost tradeoff functions. Figure 2.12 shows project schedule solutions on the Pareto optimal fronts for this TCRO problem in the 3-dimensional space of project objectives: total project cost, total project duration, and total variations of resource allocation. These Pareto optimal points show total project costs, total project durations, and total variations of resource allocation for non-dominated project schedule solutions, which are derived by our proposed fuzzy enabled HGAPSO approach and Zahraie and Tavakolan's NSGA-II algorithm. We also create Figures 2.13(a), 2.13(b), and 2.13(c) to better show optimal project schedule solutions derived by these two algorithms in the 2-dimentional space of project planning objectives: total project cost and total project duration, total project cost and total variations of resource allocation, and total project duration and total variations of resource allocation, respectively.

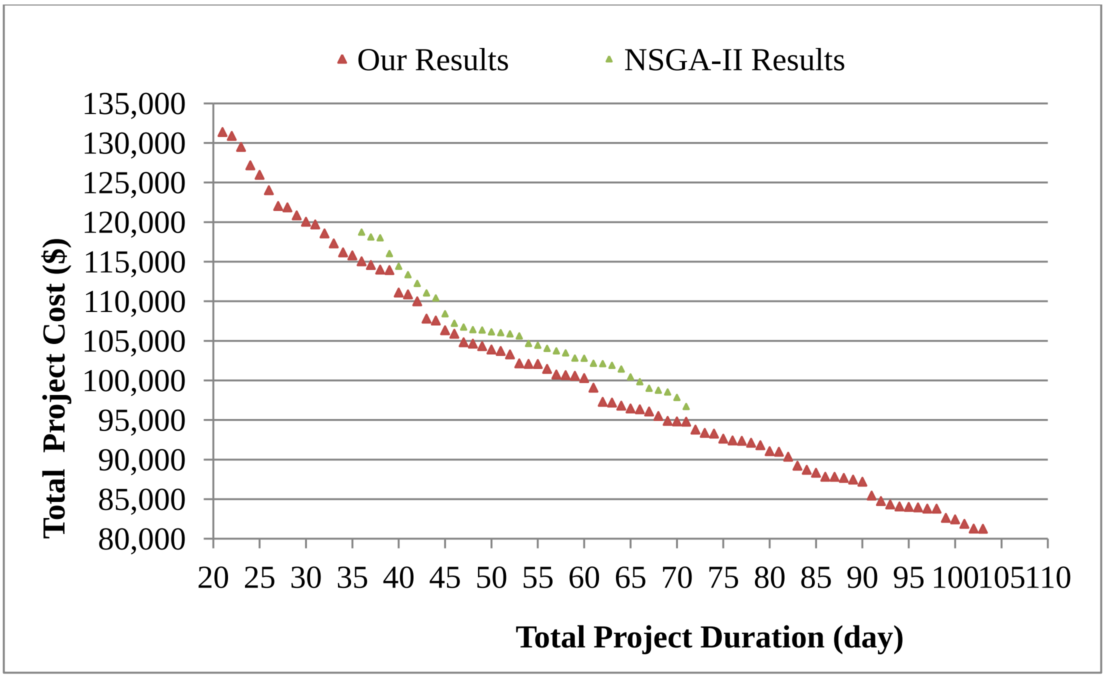
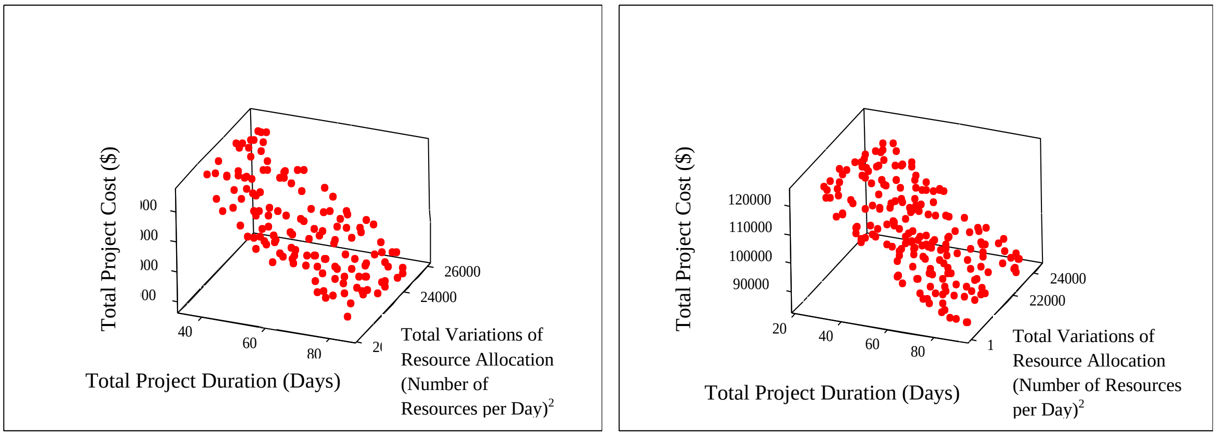


Figure 2.11 Optimal project schedule solutions in the 2-dimensional space of total project cost and total project duration by our proposed HGAPSO algorithm, and Zahraie and Tavakolan's NSGA-II algorithm in Example 2.2

It can be seen that our proposed fuzzy enabled HGAPSO approach is able to find project schedule solutions with lower total project cost, total project duration, and total variations of resource allocation, which were not found by Zahraie and Tavakolan's NSGA-II algorithm. In particular, the shortest total project duration found by our approach (i.e., 21 days) is less than the shortest total project duration found by Zahraie and Tavakolan's algorithm (i.e., 35 days). The least total project cost found by our approach (i.e., \$80,456) is less than the least total project cost found by Zahraie and Tavakolan's algorithm (i.e., \$95,581). The least total variations of resource allocation found by our approach (i.e., 18,078 (Number of Resources per Day)^2) is less than the least total variations of resource allocation found by Zahraie and Tavakolan's algorithm (i.e., 20,585 (Number of Resources per Day)^2).

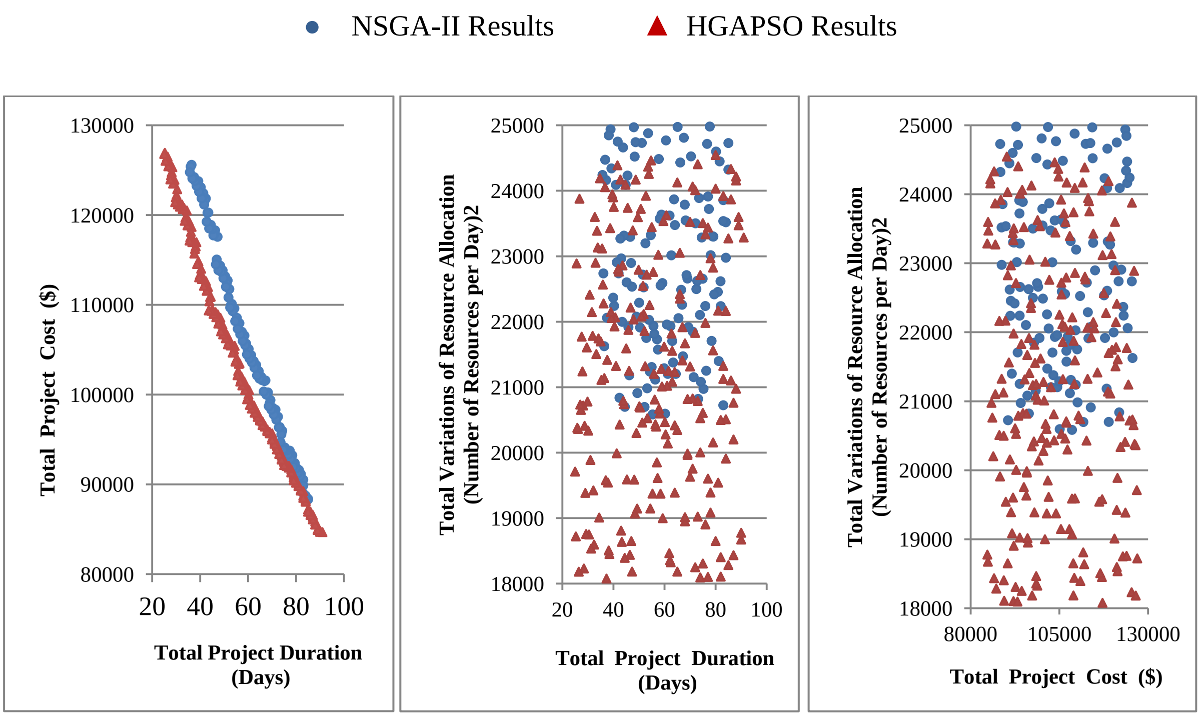


(a) (b)

Figure 2.12 Optimal project schedule solutions in the 3-dimensional space of total project cost, total project duration and total variations of resource allocation found by (a) NSGA-II approach; and (b) our proposed HGAPSO algorithm in Example 2.2

2.5.3 Example 2.3

The third example is presented in Ke et al. (2010). It is a project consisting of sixteen interrelated activities as shown in Activity On Arrow (AOA) diagram in Figure 2.14 This project also uses 5 types of resources: $R_1, R_2, ...R_5$. There are several project schedule options to perform each activity considering various combinations of feasible resources, time, and cost. Ke et al. use a symmetric fuzzy triangular function to describe the time and cost of conducting a project activity. Table 2.4 summarizes minimum and maximum values of time and direct cost are used to create symmetric time and cost fuzzy functions for project activities. Total number of resources to perform an activity is also identified in Table 2.4. In addition, it is assumed that this project does not have any indirect cost.



(a) (b) (c)

Figure 2.13 Optimal project schedule solutions in the 2-dimensional space of (a) total project cost and total project duration; (b) total project cost and total variations of resource allocation; and (c) total project duration and total variations of resource allocation found by the NSGA-II approach and our proposed HGAPSO algorithm in Example 2.2

Ke et al. apply the fuzzy GA algorithm to this problem and find the Pareto optimal project schedule solutions in the 2-dimensional space of total project cost and total project duration. We apply our fuzzy enabled HGAPSO approach to solve this optimization problem and find the Pareto optimal front of project schedule solutions. Figure 2.15 shows project schedule solutions on the Pareto optimal fronts for this optimization problem in the 2-dimensional space of total project cost and total project time. These Pareto optimal points show total project costs and total project durations for non-dominated project schedule solutions, which are derived by our proposed fuzzy enabled HGAPSO approach. It can be seen that our proposed HGAPSO approach is able to find project schedule solutions with lower total project cost and total project time, which were not found by Ke et al.'s algorithm.

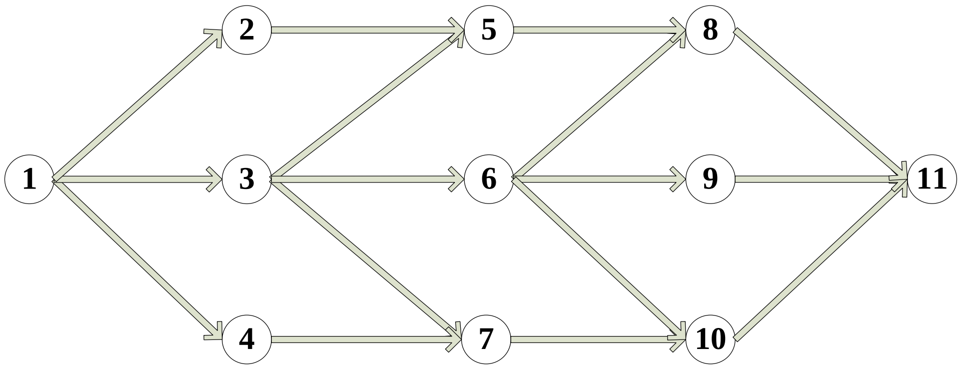


Figure 2.14 AOA diagram of project activities in Example 2.3

Table 2.4 Feasible project schedule options to perform project activities in Example 2.3

Activity (a,b)	Fuzzy Time Range (Days)		Fuzzy Direct Cost Range ($)		Total Number of Resources
	Minimum	Maximum	Minimum	Maximum	
(1,2)	7	12	170	370	3
(1,3)	4	8	300	580	4
(1,4)	7	12	45	115	3
(2,5)	4	9	270	570	2
(3,5)	8	13	35	85	2
(3,6)	7	10	25	55	4
(3,7)	6	11	150	250	2
(4,7)	5	8	600	1000	4
(5,8)	6	11	55	155	2
(6,8)	7	12	200	380	2
(6,9)	5	9	300	700	1
(6,10)	9	14	320	700	2
(7,10)	7	13	45	75	2
(8,11)	6	10	70	120	2
(9,11)	9	13	50	90	2
(10,11)	5	9	90	210	5

In addition, the shortest total project duration found by our approach (i.e., 34 days) is less than the shortest total project duration found by Ke et al.'s algorithm (i.e., 36 days). The least total project cost found by our approach (i.e., $17,625) is less than the least total project cost found by Ke et al.'s algorithm (i.e., $18,200). Finding additional optimal project schedule solutions with lower total project cost and shorter total project duration is one of the most significant contributions of our proposed approach over Ke et al.'s optimization algorithm.

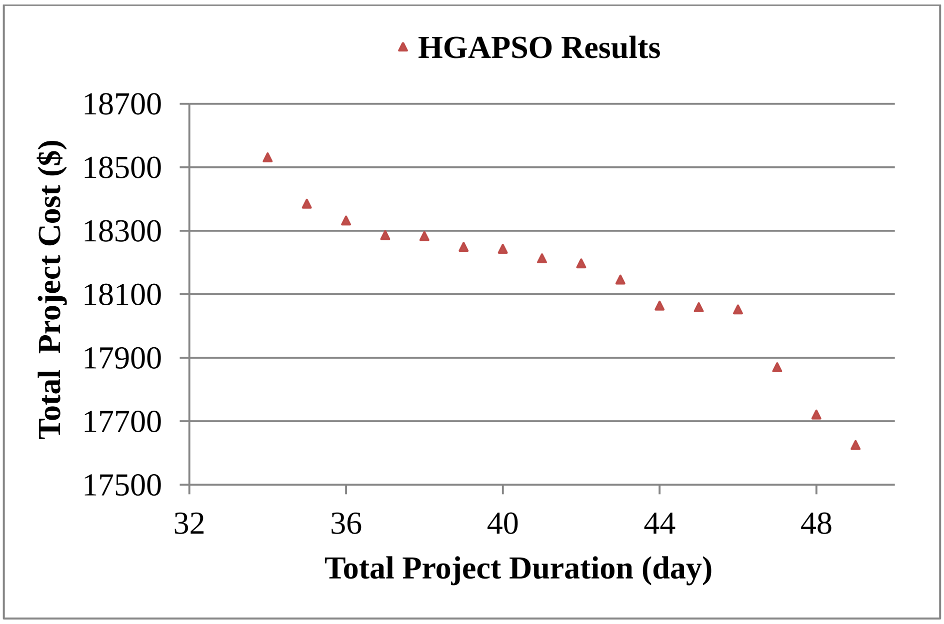


Figure 2.15 Optimal project schedule solutions in the 2-dimensional space of total project cost and total project duration by our proposed HGAPSO algorithm in Example 2.3

Ke et al.'s algorithm is not capable of solving this project planning problem considering the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation. Our proposed fuzzy enable HGAPSO approach is capable of solving simultaneous TCRO problems with continuous time-cost tradeoff functions. Figure 2.16 shows project schedule solutions on the Pareto optimal fronts for this TCRO problem in the 3-dimensional space of project objectives: total project cost, total project duration, and total variations of resource allocation. The shortest total project duration found by our approach is 32 days, the least total project cost is $17,581, and the least total variations of resource allocation is 5,509 (Number of Resources per Day)^2. These Pareto optimal points show total project costs, total project durations, and total variations of resource allocation for non-dominated project schedule solutions, which are derived by our proposed fuzzy enabled HGAPSO.

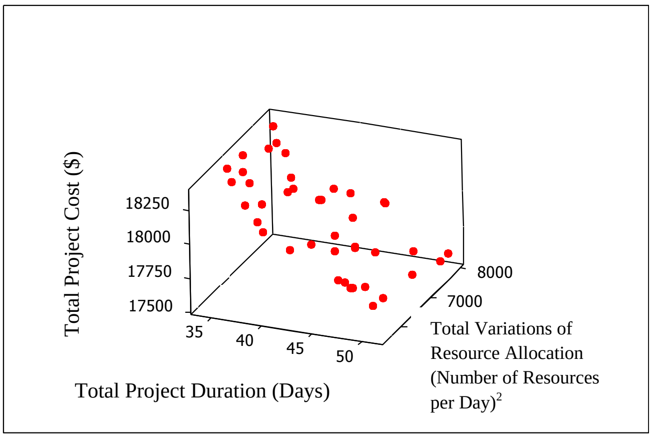


Figure 2.16 Optimal project schedule solutions in the 3-dimensional space of total project cost, total project duration and total variations of resource allocation found by our proposed HGAPSO algorithm in Example 2.3

2.6 Discussion

We compare the performance of our proposed HGAPSO algorithm with existing optimization algorithms in terms of processing time that it takes to solve project planning problems in Examples 2.1 and 2.2. Table 2.5 summarizes this processing time for our proposed approach and NSGA-II algorithm in Example 2.1 and PSO algorithm in Example 2.2. The processing time is the time that it takes to solve the optimization problem from the initiation to the final identification of optimal solutions. All algorithms are coded in the Delphi programming environment (the original Delphi code of the above algorithms is available to interested readers upon request). Optimization problems are solved on a personal computer with the Pentium Dual Core 2.5 GHz processor and the processing time is measured in minutes by the computer clock. The results show that in Example 2.1, our proposed HGAPSO algorithm is approximately 3.1 times faster than the NSGA-II algorithm in finding the frontier of optimal project schedule solutions. In Example 2.2, our proposed HGAPSO algorithm is approximately 2.6 times faster than the PSO algorithm in finding the frontier of optimal project schedule solutions.

No claim is made to generalize the results beyond comparing the performance of our approach to existing algorithms in these examples. However, we have applied our approach to several other project planning problems. Our approach outperforms existing algorithms in terms of processing time in those cases as well.

Table 2.5 Comparison of processing time (in minutes) to solve Examples 2.1 and 2.2 using our proposed Hybrid Genetic Algorithm-Particle Swarm Optimization approach and existing optimization algorithms

Examples	**Processing Time (in minutes)**	
Example 2.1	*NSGA-II Algorithm*	*Our Proposed Hybrid Genetic Algorithm-Particle Swarm Optimization Approach*
	18	5.8
Example 2.2	*PSO Algorithm*	*Our Proposed Hybrid Genetic Algorithm-Particle Swarm Optimization Approach*
	49	19

2.7 Conclusions

One of the most challenging tasks of a construction project planner is to simultaneously minimize total project cost, total project duration, and total variations of resource allocation. Therefore, project planners face complicated multivariate, TCRO problems that require time-cost-resource tradeoff analysis. We present a HGAPSO approach to solve complex, TCRO problems in construction project planning. Our proposed approach uses the fuzzy set theory to characterize uncertainty about the input data (i.e., time, cost, and resources required to perform an activity) in this hybrid approach. Triangular fuzzy functions are selected to represent variations in time and cost that it takes to complete a project activity in order to compare the results and performance of our approach to existing optimization algorithms. Example 2.1 (Zheng and Ng 2005), Example 2.2 (Yang 2007), and Example 2.3 (Ke et al.

2010) used triangular fuzzy functions. However, our proposed HGAPSO approach is flexible to other forms of fuzzy membership functions. We apply our fuzzy enabled HGAPSO approach to solve three optimization problems, which are found in the construction project planning literature.

It is shown that our proposed fuzzy enabled HGAPSO approach is superior than existing optimization algorithms in finding better project schedule solutions with less total project cost, less total project duration, and less total variations of resource allocation. Finding additional optimal project schedule solutions with lower total project cost, shorter total project duration, and lower total variations of resource allocation is one of the most significant contributions of our proposed approach over existing optimization algorithms: Ke et al.'s (2010) fuzzy GA algorithm, Zahraie and Tavakolan's (2009) NSGA-II algorithm, Yang's (2007) PSO algorithm, and Zheng and Ng's (2005) fuzzy GA algorithm. In addition, our proposed fuzzy enable HGAPSO approach is capable of solving simultaneous TCRO problems with continuous time-cost tradeoff functions. This is a major improvement over existing methods. Ke et al.'s fuzzy GA algorithm, Yang's PSO algorithm, and Zheng and Ng's fuzzy GA algorithm are not capable of solving project planning problems that require the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation.

Also, our results show that our proposed approach is faster than existing methods in processing time for solving complex TCRO problems in project planning. In particular, our proposed approach reduces the solution processing time by a factor of 3 compared to the previous Zahraie and Tavakolan's (2009) NSGA-II algorithm. Further research presented in next chapter, is needed to create advanced optimization algorithms that are capable of solving project scheduling problems that allow for activity splitting. Interrupting project activities and moving resources across project activities can be useful to achieve better project planning and resource leveling.

Chapter 3

Applying the Shuffled Frog-Leaping Algorithm to Time-Cost-Resource Optimization Problems with Activity Splitting Allowed

Abstract

In situation of contractors competing to finish a given project with the shortest duration and least cost, acquiring the ability to improve the project quality properties seems essential for project planners. Evolutionary Algorithm (EAs) such as the Genetic Algorithm and Particle Swarm Optimization have been applied as suitable algorithms to develop the multi-objective Time-Cost-Resource Optimization (TCRO) in the last two decades. In this chapter, we present the Shuffled Frog Leaping Algorithm (SFLA) to solve complex, Time-Cost-Resource Optimization (TCRO) problems in construction project planning. Our proposed approach uses splitting allowed during execution of activities as a significant reality of actual construction projects in this hybrid algorithm. We apply our SFLA approach to solve two optimization problems, which are found in the construction project planning literature. It is shown that our proposed SFLA algorithm is superior than existing optimization algorithms in finding better project schedule solutions with less total project cost, less total project duration, and less total variations of resource allocation or total time utilizations of resource allocation. The results also show that our proposed approach is faster than existing methods in processing time for solving complex TCRO problems in construction project planning.

3.1 Introduction

Project control plays an important role for project contractors for scheduling, cost analysis and resource evaluation. Project planners face complicated multivariate, Time-Cost-Resource Optimization (TCRO) problems that require time-cost-resource tradeoff analysis. From the researchers' point of view, developing highly efficient and robust algorithms to solve highly complex TCRO problems is still a challenging subject (Afshar et al. 2009). Also, construction management decisions to optimize resources variation and resources utilization in order to meet the project milestones are still challenging (Senouci and Eldin 2004). This means that resource availability constraints may postpone activity start time, extend activity duration, and hence prolong the total project duration (Lu and Lam 2008).

One of the significant factors on total project duration and cost is delay. Delays are acts or events that extend the time necessary to finish activities under a contract (Stumpf 2000). If a project is delayed beyond its due date, a financial penalty is incurred by the contractor (Vaziri et al. 2007). Delays during execution of projects can happen at the start of each activity or during activities. Delays at the start of activity change the initiation from early start to late start. If an activity is placed on CPM or delay duration is longer than total float, then delay postpones total project duration. We call it "splitting allowed" if delay happens during activity execution. It effects on total duration of activity, however, the active duration of activity will not be varied. Split can happen due to: (1) Weather variation; (2) Insufficient budget (or other financial problems); (3) Unpredicted manpower problems: In construction projects, manpower planning decisions represent a major challenge because skilled workers represent limited and expensive resources (Vaziri et al 2007); (4) Resource limitations (Machinery, Manpower, etc.); (5) Non working days (weekend, holidays) and; (6) Due to properties of activity; For instance, an activity such as concrete curing intrinsically cannot be completed continuously.

Accordingly, the key question is how to allocate resources to activities while taking into account splitting, in order to finish the project within budget and on time from the standpoints of contractors, sponsors, and the project client.

The main objectives of current methodology are:

- Applying Splitting Allowed by interrupting project activities and moving resources across project activities to achieve better project planning and resource leveling;
- Applying Shuffled Frog Leaping Algorithm (SFLA) to achieve better project schedule solutions of TCRO model.

In order to achieve these objectives, this chapter is structured as follows. Research Background on existing optimization algorithms for solving TCRO problems in construction project planning is described in Section 3.2. We present the mathematical formulation of Time-Cost-Resource Optimization (TCRO) problems in construction project planning in Section 3.3. We present our presented Shuffled Frog Leaping Algorithm (SFLA) in Section 3.4. In Section 3.5, we apply our proposed algorithm on two construction project planning problems taken from the optimization literature in construction engineering and management. We compare the performance of our proposed approach with existing optimization algorithms in this Section. Conclusions are summarized at the end.

3.2 Research Background

A number of Time-Cost tradeoff models (Leu and Yang 1999; Feng et al. 2000; Hegazi 1999; Moussourakis 2004; Zheng et al. 2004; Ammar 2005; Lacouture 2009) and resource leveling and allocation models (Chang 1990; Hegazy 1999; Zayed 2004; Ellis 2005; Ibbs and Nguyen 2007; Vaziri et al. 2007; El-Rayes and Jun 2009; Christodoulou 2010) with various methods of optimization have been developed to reduce total project duration, total project cost and to optimize required resources. However, to avoid delays attributable to implementations of resources on a project, the schedule for the work should reflect the allocation of available resources (Aslani 2007). In order to accomplish this purpose, Resource Constrained Scheduling Problems (RCSPs) have been introduced and improved during last decade. Kim and Garza (2003) present a resource-constrained critical path method to improve the CPM and resource constrained scheduling techniques. Senouci and Eldin (2004) apply an augmented Lagrangian genetic algorithm model to solve RCSPs problems. Aslani (2007) applies dynamic programming in RCSPs to optimize the allocation of resources and minimize the project's duration. Christodoulu (2010) evaluates RCSPs as non-deterministic polynomial-time hard problems and applies resource moment methods for resource leveling using entropy maximization.

However, most of the models have some deficiencies. The various mentioned methods used to level resources incorporated into software do not guarantee an optimal solution (Son and Mattila 2004, Zheng et al. 2004, Ng et al. 2008). Therefore, using the appropriate tool to optimize these problems can play an important role to obtaining better answers (Deb 2002; Zheng et al. 2004; Zitzler et al. 2000; Konak et al. 2006). Furthermore, all the mentioned research assumed that project activities cannot be split. Only Son and Mattila, (2004) present an exact method using binary programming which allows splitting the activities of small networks. Considering splitting in duration of activities is a fundamental step to make models better approximate real projects (Hashemi Doulabi et al. 2011). Although this is not a necessary constraint for all activities, it is unavoidable in many real cases. The use of activity splitting has also been applied in RCSPs in order to shorten the project makespan (Hashemi Doulabi et al. 2011; Buddhakulsomsiri and Kim 2007; Peteghem and Vanhoucke 2010).

In an attempt to reduce processing time and improve the quality of solutions, particularly to avoid being trapped in local optima, Evolutionary Algorithms (EAs) have been introduced during last decade (Elbeltagi et al. 2005; Zheng and Ng 2008; El-Rayes and Kandil 2005). EAs are stochastic search methods that mimic natural biological evolution and social behavior of species. Elbeltagi et al. (2005) compare the results of five recent EAs, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Memetic Alogrithm (MA) and SFLA in two mathematic continuous functions problem and Time-Cost discrete optimization problem. They evaluate the performance of the different algorithms based on three criteria: (1) the percentage of success, as represented by the number of trials required for the objective function to reach its known target value; (2) the average value of the solution obtained in all trials; and (3) the processing time to reach the optimum target value. Based on their results, SFLA algorithm has the best results among the other EAs.

There are a few papers that addressed the SFLA algorithm (Rahimi-Vahed 2007). Eusuff and Lansey (2006) test SFLA algorithm to optimize several mathematical test functions and water distribution system designs. Finally, the results demonstrate that SFLA produces better results than the GA in terms of effectiveness and efficiency for all problems. Rahimi-Vahed (2007) applies Multi-objective-SFLA to solve a bi-criteria permutation flow-shop problem. When comparing results with three multi-objective genetic algorithms: PSNC-GA, NSGA-II and SPEA-II, his computational results show that SFLA improves the number of Pareto front solutions, the processing time, and the error ratio of different algorithms. He extends his work in 2009 by applying Hybrid Multi-objective Shuffled Frog Leaping Algorithm (HMSFLA) to improve the solution quality and diversity level of various test problems. The success rate of the algorithm is satisfactory and encouraging. In computational optimization techniques, Mashhadi Kashtiban (2009) proposes various strategies for partitioning memeplexes in

SFLA, since partitioning is one of the most stages of optimization in the SFLA. He introduces random and geometric partitioning in addition to cost partitioning. A comparison among the results of three methods demonstrates geometric partitioning has a better performance in problem-solving with continuous domain spaces. In addition, a combination of SFLA and GA is applied by Yang (2008) for gene selection to compare 11 classification problems. His results also demonstrate that the accuracy of solutions obtained by the proposed SFLA is higher than the other methods.

We use Shuffled Frog Leaping Algorithm (SFLA) algorithm – developed by Eusuff and Lansey (2003) in water resource planning management to solve complex optimization problems – to solve TCRO problems in construction project planning. Our approach also utilizes splitting to enable model to find the shortest total project duration and the least total project cost in this hybrid algorithm. Our proposed SFLA algorithm improves the convergence ratio and facilitates the identification of Pareto front of optimal project schedule solutions in TCRO problems. Next, we describe the mathematical formulation of time-cost-resource optimization problems in construction planning, for which we develop the SFLA algorithm.

3.3 Mathematical Formulation of Time-Cost-Resource Optimization (TCRO) Problems with Activity Splitting Allowed in Construction Project Planning

Consider a typical project planning problem consisting of N related activities: $A_1, A_2, ..., A_N$. There are finite options to allocate S types of project resources $R_1, R_2, ..., R_S$ to perform an activity; each option represents number of different resources as well as respective time and cost to complete an activity. Suppose $O_{i,j}$ represents the entire feasible option set available to project planner to choose from $option_j$ to perform activity $i = 1,2,...,N$:

$$O_i = \{\tilde{O}_{i,j_i} = Option_{j_i} \ for \ Time, Dircet \ Cost, \& \ \mathrm{Re}sources \ to \ Perform \ Activity_i = (T_{i,j_i}, C_{i,j_i}, (R_{1,j_1}, R_{2,j_1}, ..., R_{s,j_1})) \in Feasible \ Configurations \ of \ Time, \ Cost, \ and \ \mathrm{Re}sources \ to \ Perform \ Activity_i \ \}$$

In case of splitting allowed, we suppose λ_{ij} for each activity A_i : $\sum_{j=1}^{T_i+TF_i} \lambda_{ij} = T_i$ to put splitting between activity duration; splitting is applied only in activities in which final results of TCRO model is improved. If the activity's possible occupying position is decided, each position is assigned to one or zero (the values of λ) and the sum of these positions must equal the duration of the activity (Son and Mattila 2004). As an example, Equation (3.1) is used in Figures 3.1 and 3.2:

$$\sum_{j=1}^{5} \lambda_{ij} = 3 \qquad (3.1)$$

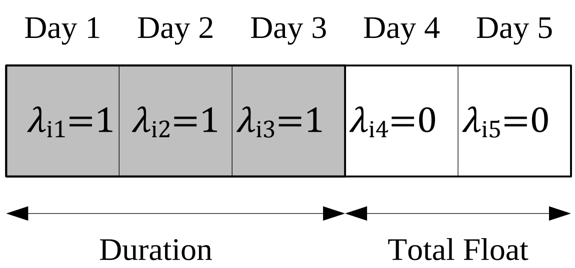


Figure 3.1 Occupying positions of activity i based on ES_i (without Splitting)

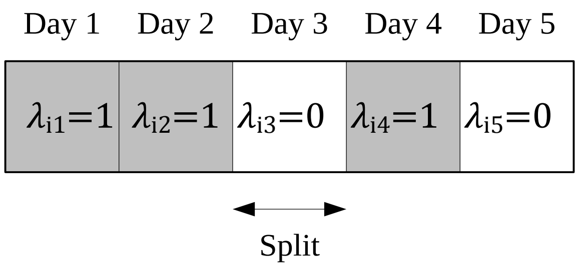


Figure 3.2 Occupying positions of activity i (with splitting)

The project planner's problem is how to allocate project resources and schedule activities to minimize total project cost and total project duration while maintaining daily resource limitations. Therefore, project planner's decision variables in this optimization problem are: (1) Start dates of project activities: $SD_1, SD_2, ..., SD_N$; (2) resource allocation options to perform project activities: $O_{1,j_1}, O_{2,j_2}, ..., O_{N,j_N}$; (3) Total Float of project activities: $TF_1, TF_2, ..., TF_N$; and (4) Free Float of project activities: $FF_1, FF_2, ..., FF_N$.

The sequence of solutions should be consistent with the order of activities in priority relations between activities. Each solution contains the information of one project based on the different chosen option of activities. The solution containing non-critical activities are candidates for using splitting. However, based on the total float and free float for each candidate, splitting is applied to obtain better solutions with the shortest total project duration, least total project cost and resource allocations. Also, the resource leveling condition should be satisfied in the model in cases of limited resources.

3.3.1 Objective Functions

The project planner's objective functions in this TCRO problem can be formulated as simultaneous minimization of total project cost, total project duration, and resource allocations as summarized below:

Z_1 =Minimize total project cost (TC): total project cost consists of total direct costs to perform project activities and indirect cost to complete the project.

$$Z_1 = Min \ (TC) \tag{3.2}$$

Z_2 =Minimize total project duration (TD): total duration of the project is the time that takes to complete critical activities on the critical path.

$$Z_2 = Min \ (TD) \tag{3.3}$$

Both of the above mentioned objectives and one of the following resource allocation objectives are the three objective functions of the optimization model:

Z_3 =Minimize the total variations in resource allocation: one of the most common indicators (i.e., moments) to measure variations in resource allocation is sum of squares of daily resources (SSR) consumed to perform the entire activities over the total project length (Hegazy 1999). Project planner should minimize this resource moment to achieve a better resource leveling:

$$Z_3 = Min \ (SSR) = Min \ \left(\sum_{k=1}^{TD} \sum_{n=1}^{S} (\mathrm{Re}\,source_{n,k})^2 \right) \tag{3.4}$$

Z_4 = Minimize total time utilizations of resource allocation: Both high duration of resources utilization and late release time of resources can increase the value of this resource moment which is suitable to minimize continuous and expensive consumed resources such as machinery in the construction projects. The project planner can get rid of expenses of specified resources by measuring sum of products of daily resources and date number (from the start date of project) of resources consuming (SPD):

$$Z_4 = Min\ \ (SPD) = Min\ \left(\sum_{k=1}^{TD} \sum_{n=1}^{S} (\text{Re}\,source_{n,k} \times n) \right) \tag{3.5}$$

where $\text{Re}\,source_{n,k}$ is the number of $\text{Re}\,source_n : n = 1,2...,S$ that is planned to use in day k of the project duration: $k = 1,2...,TD$.

3.3.2 Constraints of the Model

A TCRO problem in construction project planning is subject to several constraints as:

(1) Logical or physical dependencies between project activities as indicated by the diagram of the project activity network. Start-to-Start, Start-to-Finish, Finish-to-Start, and Finish-to-Finish relationships among project activities must be captured as appropriate constraints on activities' start dates $SD_1, SD_2, ..., SD_N$ and durations $T_1, T_2, ..., T_N$. Since we have only "Finish to Start" relationships between activities, the following constraint precludes the situation that the successor has started before the predecessor is finished by considering TF and FF of all activities in one solution. Following constraint should be satisfied in case of splitting allowed:

$$(TF_i - FF_i - m + 1) \times \lambda_{(i+1)m} + \lambda_{i(T_i + FF_i + m)} + \lambda_{i(T_i + FF_i + m + 1)} + ... + \lambda_{i(T_i + TF_i)} \leq (TF_i - FF_i - m + 1) \tag{3.6}$$

where $m = 1,2,...,TF_i - FF_i$.

Consider Figure 3.3 from Son and Mattila's study (2004) as an example. "*A noncritical activity k has a predecessor activity p. Each activity's duration is 3 days.* FF_P *is 1 day,* TF_P

is 4 days, and TF_k is 4 days. The value of λ_{P1}, λ_{P2}, λ_{P3}, and λ_{P4} does not affect the value of any λ_{kj}, where $j = 1,2,...,7$ because there is no overlap of activities p and k during that time period. However, the value of λ_{P5}, λ_{P6} and λ_{P7} has an effect on the value of λ_{kj}, where j=1, 2, and 3 because of the potential overlap and the requirement that p precedes k. For example, if λ_{P5} is 1, λ_{k1} must be 0 to maintain the relationship logic. If λ_{P6} is 1, λ_{k1} and λ_{k2} must be 0. If λ_{P7} is 1, λ_{k1}, λ_{k2}, and λ_{k3} must be 0."

Following constraints of this example can be expressed as:

$$3\lambda_{k1} + \lambda_{p5} + \lambda_{p6} + \lambda_{p7} \leq 3 \tag{3.7}$$

$$2\lambda_{k2} + \lambda_{p6} + \lambda_{p6} + \lambda_{p7} \leq 2 \tag{3.8}$$

$$\lambda_{k3} + \lambda_{p7} \leq 1 \tag{3.9}$$

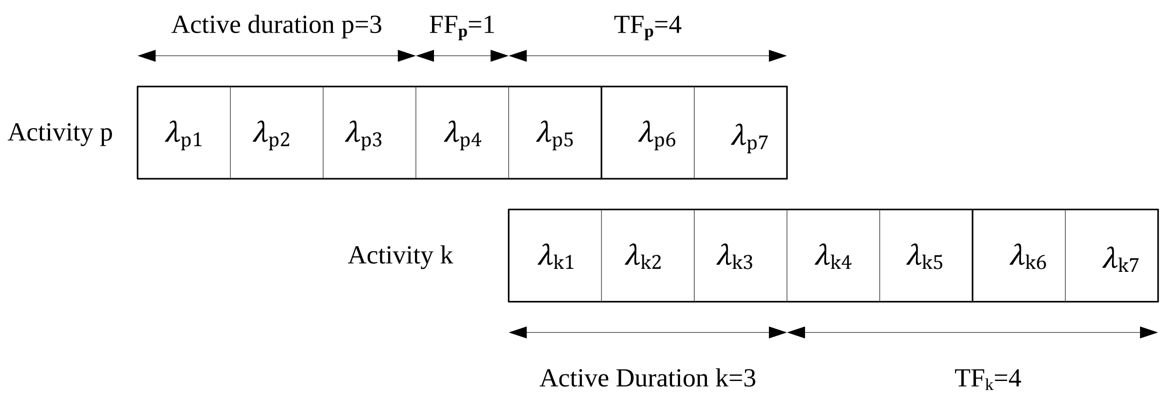


Figure 3.3 Example of a relationship constraint

(2) (Any) limits on the total daily availability of resources: the total consumption of a particular resource among the entire project activities must not exceed the capacity of that resource at any point of time during the project.

Next, we present a Shuffled Frog Leaping Algorithm (SFLA) algorithm to solve this Time-Cost-Resource Optimization (TCRO) Problem with activity splitting allowed in construction project planning.

3.4 Shuffled Frog Leaping Algorithm (SFLA) Algorithm to Solve TCRO Problems in Construction Project Planning

The capabilities of Particle Swarm Optimization (PSO) as the local search tool and Shuffled Complex Evolution Algorithm (SCE) as the operator of mixing information from parallel local searches to move toward a global solution have been combined in the Shuffled Frog Leaping Algorithm (SFLA) Algorithm to achieve faster convergence rate and obtain better Pareto optimal solutions**.** SFLA presented by Eusuff and Lansey (2003) is a meta-heuristic iterative method inspired from the memetic evolution of a group of frogs when seeking for food (Huynh and Nguyen 2009). Instead of using genes in GA, SFLA uses memes to improve spreading and convergence ratio to Pareto front solutions. The main difference between a gene and a meme is related to its transmission ability. Genes can only be transmitted from parents or a parent in the case of asexual reproduction to offspring. Memes can be transmitted between any two individuals (Eusuff et al. 2006).

Eusuff and Lansey's SFLA optimization algorithm is based on generating solutions within the wide scan of a large feasible solution space with a deep search of promising locations for a global optimum (Elbeltagi et al. 2006). The whole population of solution is distributed within a different subset called a memeplex. Figure 3.4 illustrates the memeplex partitioning process.

Each memeplex performs an independent local search with PSO operator. Within searching each solution can be influenced by other solutions and evolve through a process of memetic evolution (Eusuff and Lansey 2003). After a defined number of evolutionary steps, solutions are shuffled among memeplexes, enabling solutions to interchange feasible options among different activities and ensuring that they move to an optimal position. The local search and the shuffling processes continue until defined convergence criteria are satisfied (Eusuff et al. 2006).

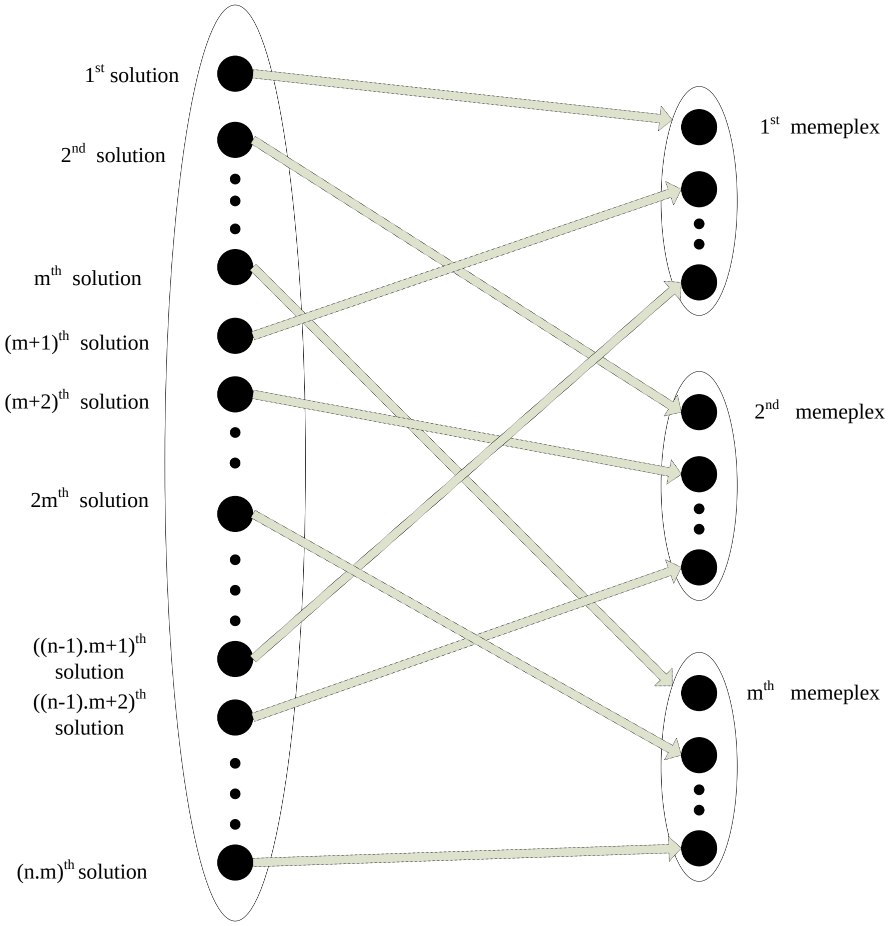


Figure 3.4 The memeplex partitioning process

We apply Eusuff and Lansey's SFLA algorithm to solve TCRO optimization problem with splitting allowed in construction project planning. This algorithm consists of the following steps:

1. Set k=1; initialize a population set of feasible project schedule solutions:

$$P_{m,n}^{(k)} = \left\{ \left((SD_1, \overline{O}_1, TF_1, FF_1), \ldots, (SD_N, \overline{O}_N, TF_N, FF_N) \right) \middle| \begin{array}{c} \left(SD_i, \overline{O}_i, TF_i, FF_i \right) \ is \ Randomly \ Selected \\ from \ Entire \ Feasible \ Set \ of \ Start \ Date \\ and \ Time - Cost - \mathrm{Re}source \ Allocation \\ Activity \ \ i : i = 1, 2, \ldots, N \end{array} \right\}$$

This initial population set consists of $m \times n$ project schedule solutions, where m is the number of memeplexes and n is the number of solutions in each memeplex. They are randomly drawn from feasible sets of start dates and time-cost-resources allocation (and free float and total float in case of splitting allowed) for project activities considering the logical and temporal relationships among project activities;

2. Partition solutions in to $P_{m,n}^{(k)}$. The population of solution is partitioned into a number of parallel communities (memeplexes) that are permitted to evolve independently to search the solution space in different directions;
3. Compute the values of optimization objective functions for each feasible project schedule option in each $P_{m,n}^{(k)}$: total project cost (Z_1), total project duration (Z_2), and one of the total variations of resource allocation (Z_3) or total time utilizations of resource allocation (Z_4);
4. Eliminate dominated project schedule solutions from the feasible set $P_{m,n}^{(k)}$: a dominated solution is a solution whose corresponding cost, duration, and resource variations are greater than or equal to respective cost, duration, and resource variations of another feasible solution in the feasible set. Remove dominated project schedule options and update the project schedule solutions in each $P_{m,n}^{(k)}$;

5. Compute average total project cost, average total project duration, and average total variations of resource allocation for the remaining project schedule solutions in the updated $P_{m,n}{}^{(k)}$: $\overline{Z}_1$, $\overline{Z}_2$,and one of the $\overline{Z}_3$ or $\overline{Z}_4$,respectively;

6. For each project schedule option in $P_{m,n}{}^{(k)}$, compute the normalized, distance in a three-dimensional objective space from the origin as:

$$D = \sqrt{\left(\frac{Z_1}{\overline{Z}_1}\right)^2 + \left(\frac{Z_2}{\overline{Z}_2}\right)^2 + \left(\frac{Z_3}{\overline{Z}_3}\right)^2} \quad \text{or} \quad D = \sqrt{\left(\frac{Z_1}{\overline{Z}_1}\right)^2 + \left(\frac{Z_2}{\overline{Z}_2}\right)^2 + \left(\frac{Z_4}{\overline{Z}_4}\right)^2};$$

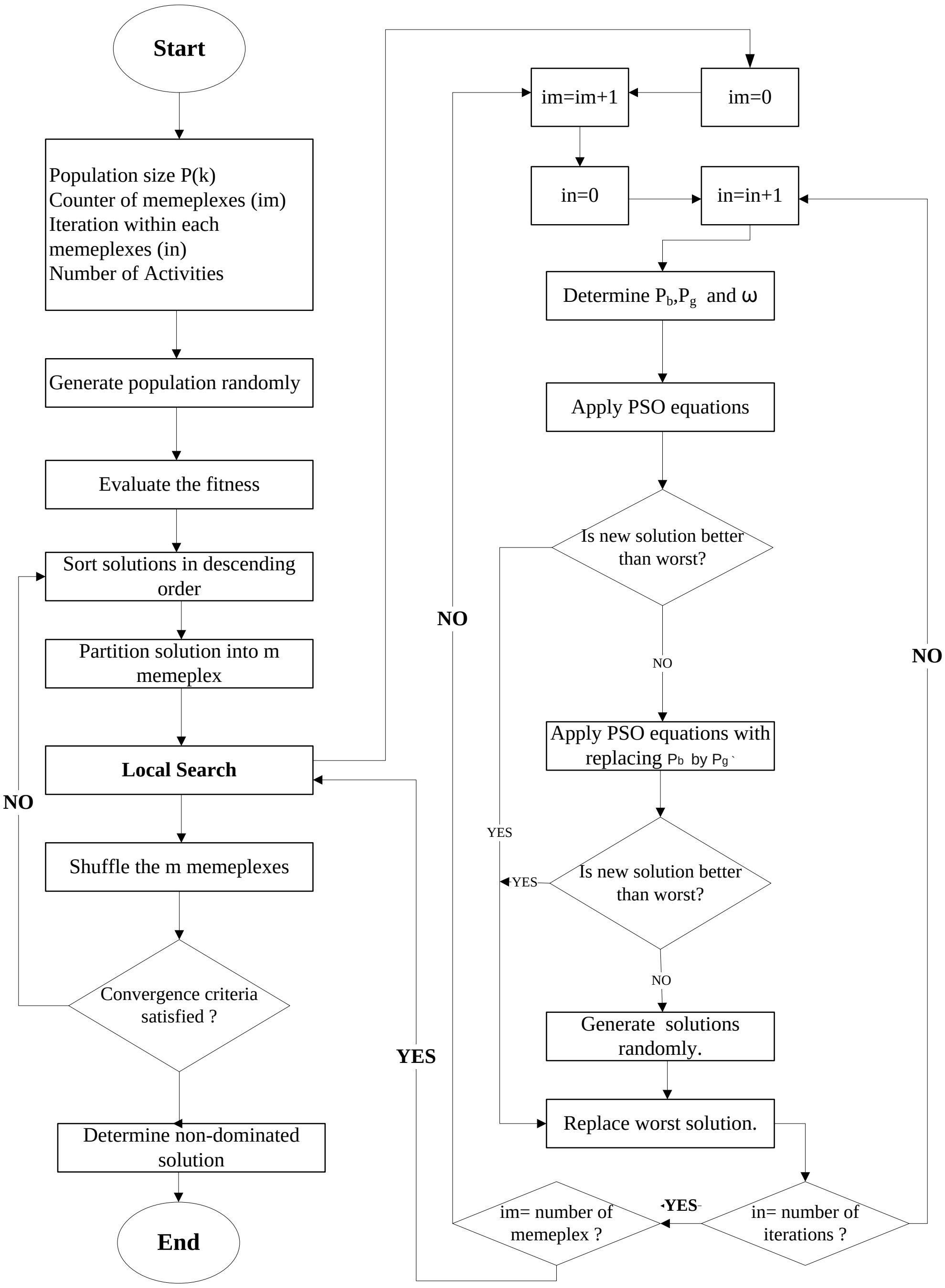
7. Order project schedule options in $P_{m,n}{}^{(k)}$ from the greatest distance to the lowest distance. Apply movement operator in PSO – see Zhang et al. (2006) for detailed description of this PSO operator – to the current solutions set $P_{m,n}{}^{(k)}$;

8. After the $P_{m,n}{}^{(k)}$ have been evolved, the algorithm returns to the global exploration for shuffling (apply shuffling operator in SCE- see Eusuff and Lansey (2003) for detailed description of this SCE operator) and update the population the best solution position in $P^{(k)}$. These (new) solutions also belong to the next generation population set of project schedule options denoted by $P^{(k+1)}$;

9. Repeat Steps 2 to 8 until no new project schedule solution can be found by conducting Steps 7 and 8; i.e., when the next generation population set of project schedule options is equal to the current generation set of project schedule options; and

10. The final population set represents a Pareto optimal set of project schedule solutions for this TCRO problem.

Figure 3.5 demonstrates the flowchart of the SFLA. Next, we demonstrate how the proposed SFLA algorithm can be used to solve TCRO problems in construction project planning and compare the results with existing optimization algorithms.



P_b: The best previous solution in solution *i*; P_g: global best solution in current population;

ω: inertia weight

Figure 3.5 The flowchart of the SFLA algorithm

3.5 Application of the Proposed SFLA Algorithm

We apply the proposed SFLA algorithm on two optimization problems, which we have found in the literature of construction project planning. These examples are selected to compare the results of our proposed SFLA algorithm before and after splitting allowed with the results of existing methods. We use our algorithm to solve these project planning problems and find optimal project schedule solutions. We show that our proposed SFLA algorithm with splitting allowed is superior than existing optimization algorithms to find better project schedule solutions with less total project costs, less total project durations, and less total variations of resource allocation or less total time utilizations of resource allocation. We also show that our proposed approach is faster than existing methods in terms of the processing time for solving these optimization problems in construction project.

3.5.1 Example 3.1

The first example is adopted from Zheng et al. (2004). It is a project consisting of seven interrelated activities as described in Table 3.1. Seven resource types $R_1, R_2, ..., R_7$ with fixing unit costs (ranges from \$50 to \$4000) are used in this project. In total, 80 options have been considered for activities of the project using different configurations of resources. For instance, Table 2.1 shows 11 configurations of time, direct cost, and resource allocation to perform activity 1. Also, indirect cost of this project is assumed to be \$1,500 per day. Zheng et al. (2004) use GA algorithm to solve this project planning problem and find optimal project schedule solutions. Zahraie and Tavakolan (2009) revisit this problem and apply NSGA-II evolutionary algorithm to find the Pareto optimal front of project schedule solutions. We also apply our enabled SFLA algorithm with splitting allowed on this project planning problem to find the Pareto optimal front of project schedule solutions and then, compare our solutions with the results of the previous two algorithms before and after splitting allowed.

Table 3.1 Details of Example 3.1

Activity Description	Activity ID	Precedent Activities	No. of Options	Types of Required Resources
Site preparation	1	-	11	7
Forms and rebar	2	1	11	4
Excavation	3	1	19	4
Precast concrete girder	4	1	9	7
Pour foundation and piers	5	2,3	9	7
Deliver PC girders	6	4	11	7
Erect girders	7	5,6	10	7

First, we compare our proposed SFLA algorithm with both Zheng et al.'s and Zahraie and Tavakolan's algorithms considering the simultaneous minimization of total project cost and total project duration. Zheng et al. (2004) did not consider minimizing resource variations as one of their project planning objectives in this example. Figure 3.6 shows project schedule solutions on the Pareto optimal fronts for this TCRO problem in the 2-dimensional space of total project cost and total project time before and after splitting allowed. These Pareto optimal points show total project costs and total project durations for non-dominated project schedule solutions, which are derived by our proposed SFLA algorithm as well as Zheng et al.'s (2004) and Zahraie and Tavakolan's (2009) approaches. It can be seen that our proposed SFLA approach is able to find project schedule solutions with lower total project costs and total project durations, which were not found by any of the previous algorithms. In particular, the project schedule solution with the shorter total project duration (i.e., 64 days) and the project schedule solution with lower total project cost (i.e., $226,300) before splitting allowed and the shortest total project duration (i.e., 62 days) and the lowest total project cost (i.e., $225,450) after splitting allowed are just found by our proposed SFLA algorithm. Finding additional optimal project schedule solutions is one of the most significant contributions of our proposed algorithm over the existing optimization approaches.

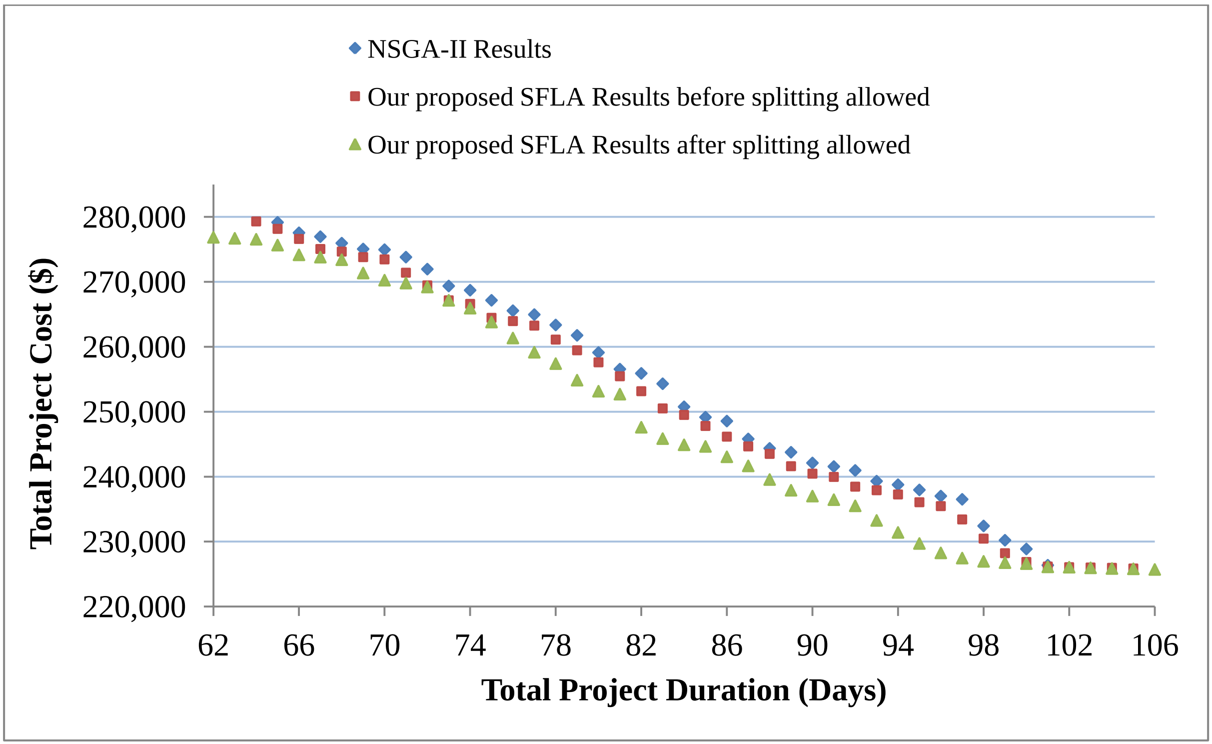
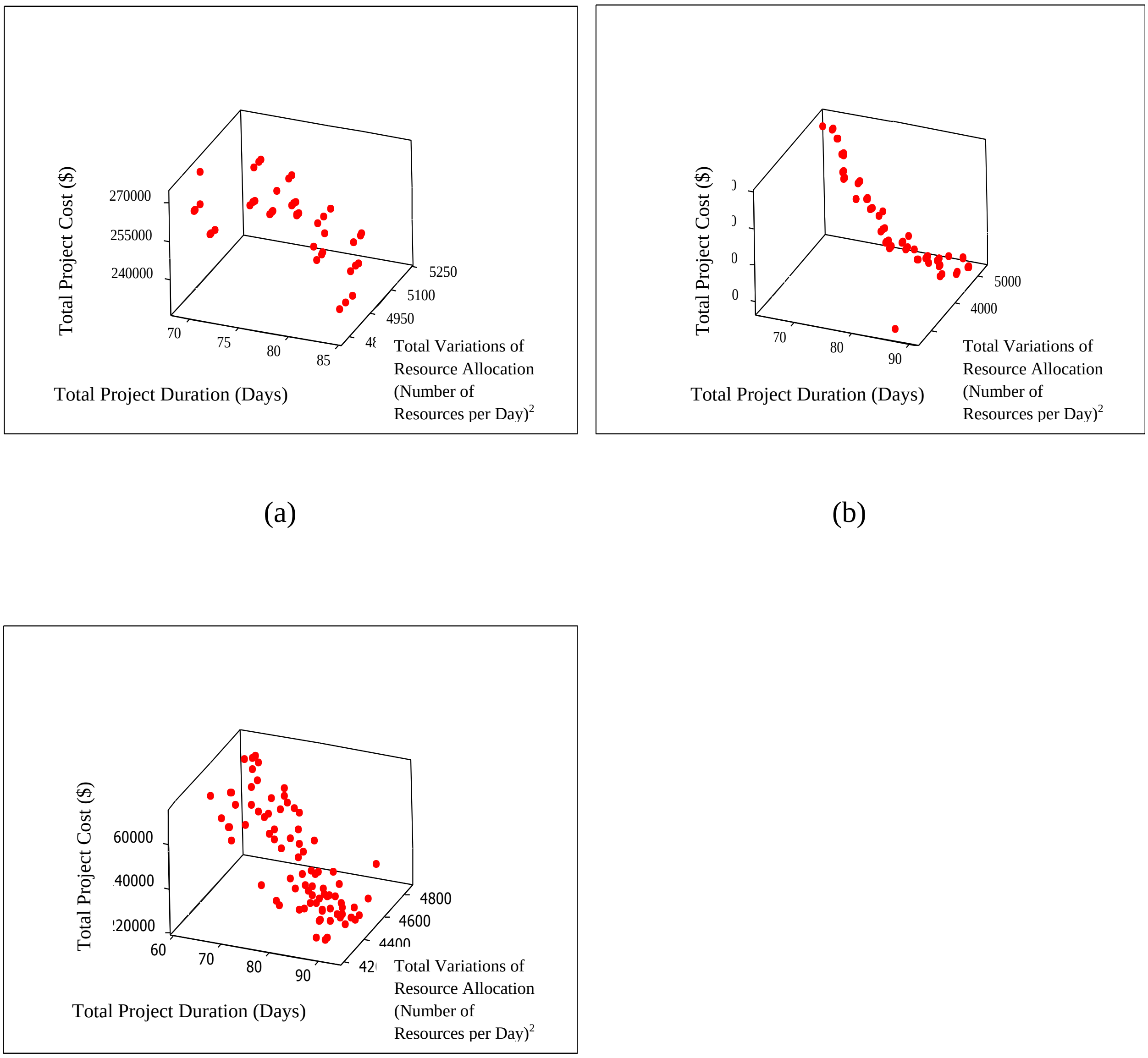


Figure 3.6 Optimal project schedule solutions in the 2-dimensional space of total project cost and total project duration found by our proposed SFLA algorithm (before and after splitting allowed), and Zahraie and Tavakolan's algorithms in Example 3.1

Next, we compare our proposed SFLA algorithm with Zahraie and Tavakolan's (2009) algorithm considering the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation. Figures 3.7(a), 3.7(b), and 3.7(c) show project schedule solutions on the Pareto optimal fronts in the 3-dimensional space of project objectives: total project cost, total project duration, and total variations of resource allocation, which are derived by Zahraie and Tavakolan's NSGA-II and our proposed SFLA algorithm, before and after splitting allowed, respectively. Since one of the resource moments (Z_3 or Z_4) is considered with Z_1 and Z_2 as objective functions of TCRO model, the same approach can be seen in the 3-dimensional space of project objectives: total project cost, total project duration, and total time utilizations of resource allocation in Figures 3.8(a), 3.8(b), and 3.8(c).

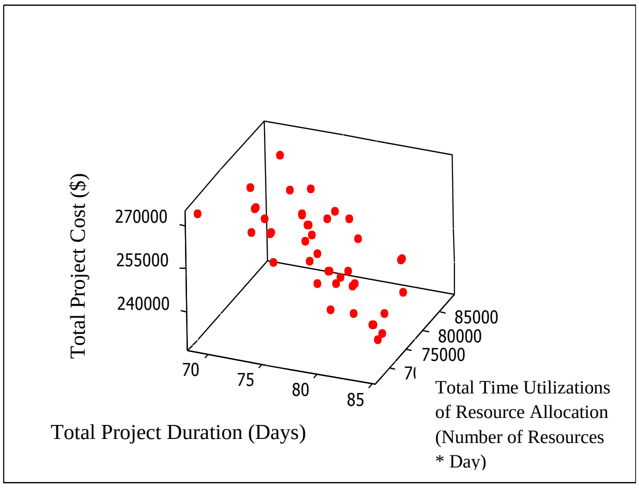
We also create the other Figures to better compare optimal project schedule solutions derived by these two algorithms in the 2-dimentional space of project planning objectives: total project cost and total project duration in both space of total variations of resource allocation (Figure 3.9(a)) and total time utilizations of resource allocation (Figure 3.9(b)), and total project duration and total variations of resource allocation (Figure 3.10(a)) and total project duration and total time utilizations of resource allocation (Figure 3.10(b)), and total project cost and total variations of resource allocation (Figure 3.11(a)) and total project cost and total time utilizations of resource allocation (Figure 3.11(b)), respectively.



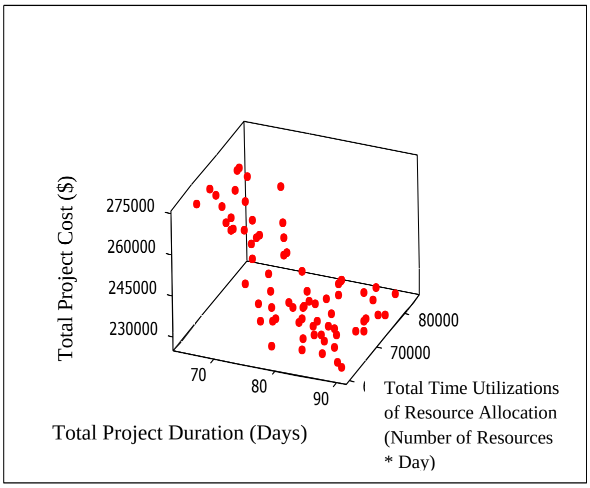
(a) (b)

(c)

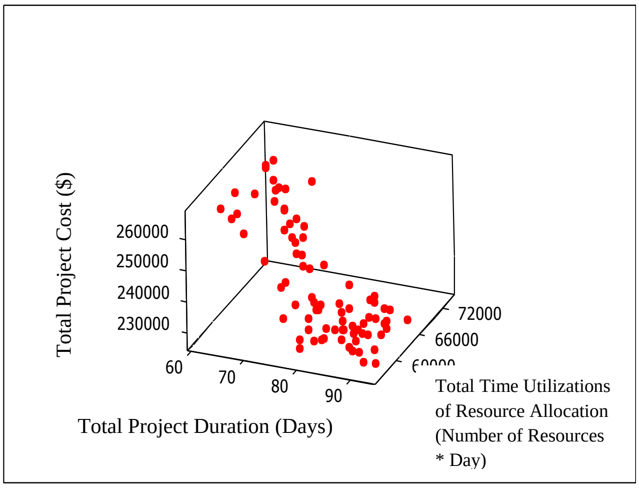
Figure 3.7 Optimal project schedule solutions in the 3-dimensional space of total project cost, total project duration and total variations of resource allocation found by (a) NSGA-II approach; and (b) our proposed SFLA algorithm before splitting allowed; and (c) our proposed SFLA algorithm after splitting allowed in Example 3.1



(a)

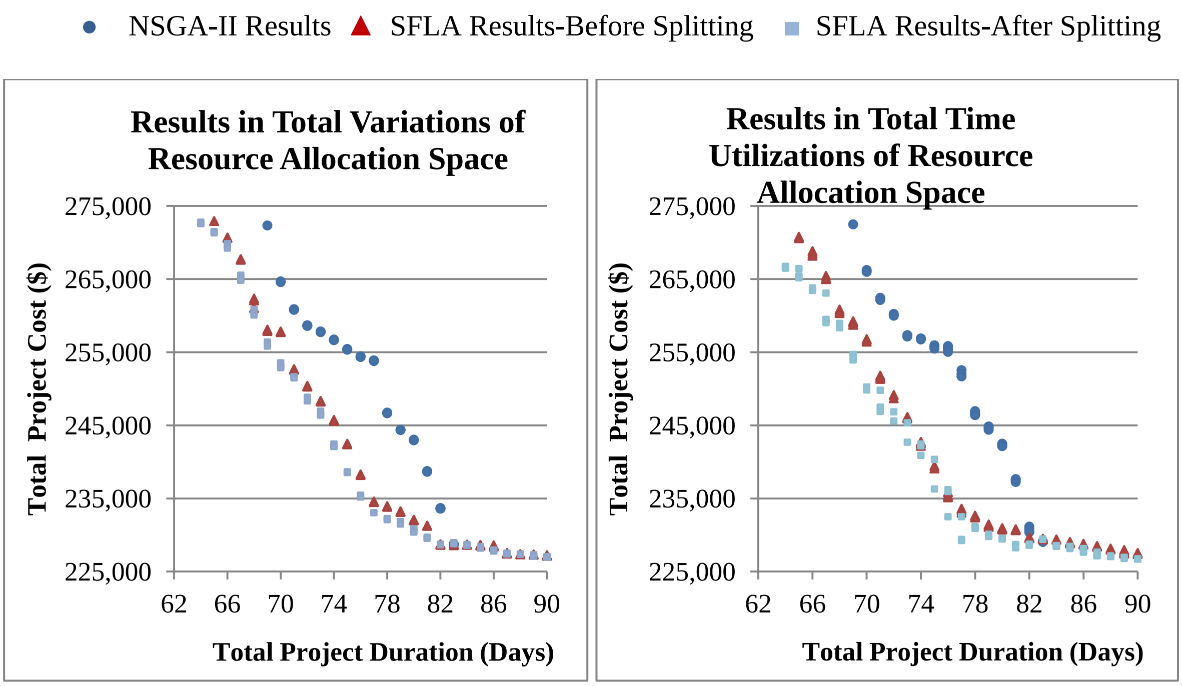


(b)



(c)

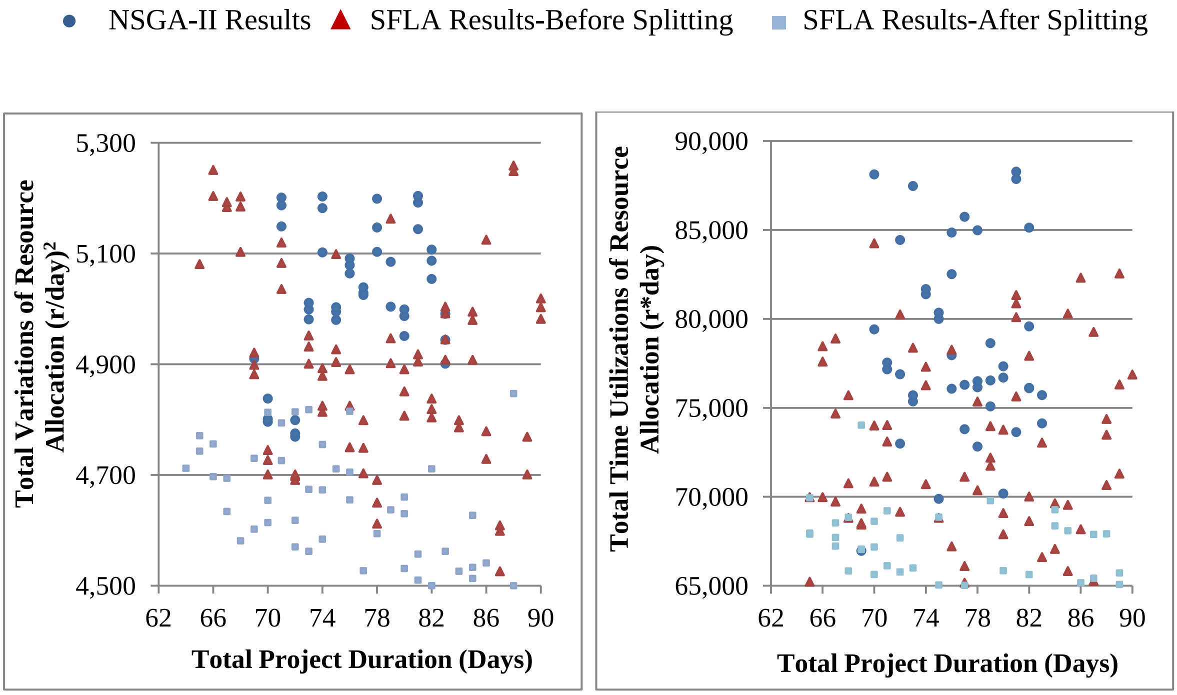
Figure 3.8 Optimal project schedule solutions in the 3-dimensional space of total project cost, total project duration and total time utilizations of resource allocation found by (a) NSGA-II approach; and (b) our proposed SFLA algorithm before splitting allowed; and (c) our proposed SFLA algorithm after splitting allowed in Example 3.1



(a) (b)

Figure 3.9 Optimal project schedule solutions found by the NSGA-II approach and our proposed SFLA algorithm (before and after splitting allowed) in the 2-dimensional space of total project cost and total project duration; (a) in space of total variations of resource allocation; and (b) in space of total time utilizations of resource allocation in Example 3.1

It also can be seen that our proposed SFLA algorithm with splitting allowed is able to find project scheduling solutions with the shortest total project duration (i.e., 64 days compared to 69 days provided by NSGA-II algorithm and 65 days provided by SFLA algorithm before splitting allowed), the lowest total project cost (i.e., \$266,500 compared to \$272,550 provided by NSGA-II algorithm and \$270,600 provided by SFLA algorithm before splitting allowed) and less total variations of resources allocation (Z_3) (i.e., 4,601 (Number of Resources per Day)^2 compared to 4,769 (Number of Resources per Day)^2 provided by NSGA-II algorithm and 4,637 (Number of Resources per Day)^2 provided by SFLA algorithm before splitting allowed) and less total time utilizations of resources allocation (Z_4) (i.e., 53,361 (Number of Resources*Day) compared to 54,585 (Number of Resources*Day)



(a) (b)

Figure 3.10 Optimal project schedule solutions found by the NSGA-II approach and our proposed SFLA algorithm (before and after splitting allowed) in the 2-dimensional space of (a) total project duration and total variations of resource allocation; (b) and total project duration and total time utilizations of resource allocation in Example 3.1

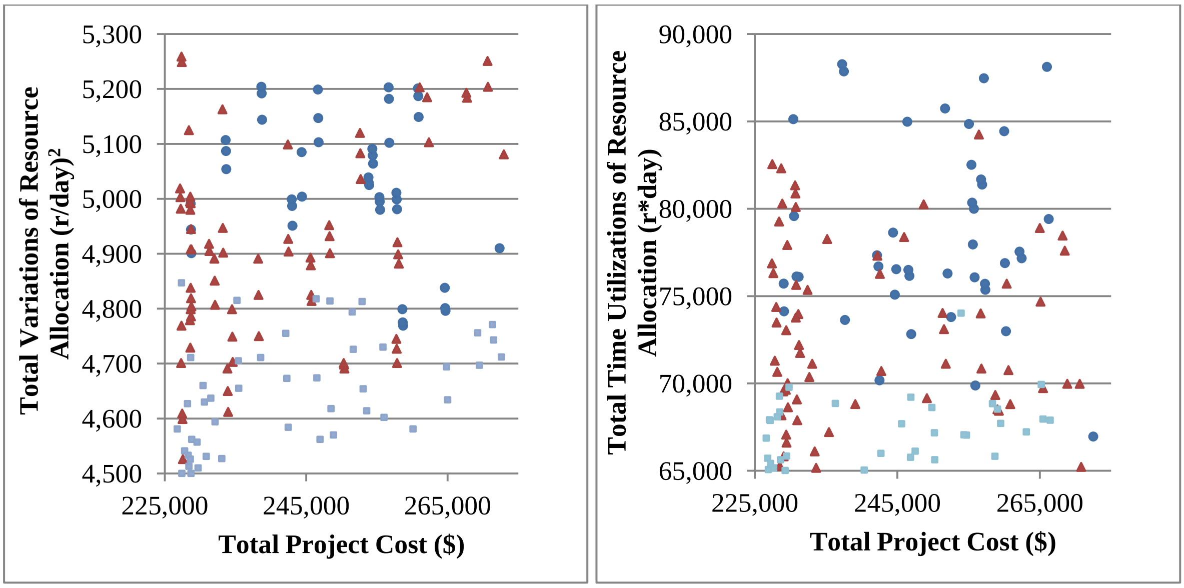


Figure 3.11 Optimal project schedule solutions found by the NSGA-II approach and our proposed SFLA algorithm (before and after splitting allowed) in the 2-dimensional space of (a) total project cost and total variations of resource allocation; (b) and total project cost and total time utilizations of resource allocation in Example 3.1

provided by NSGA-II algorithm and, 53,843 (Number of Resources*Day) provided by SFLA algorithm before splitting allowed).

Finding additional optimal project schedule solutions with lower total project cost, total project durations, and total variations of resource allocation or total time utilizations of resource allocation before and after splitting allowed is one of the most significant contributions of our proposed algorithm over the previous Zahraie and Tavakolan's optimization approach. Further, our proposed algorithm also expedites the computational speed of solving TCRO problems in construction project planning. Our approach reduces the solution processing time by a factor of 3 compared to the previous Zahraie and Tavakolan's optimization approach (the original Delphi code of SFLA optimization algorithm is available to interested readers upon request).

3.5.2 Example 3.2

The second example is adopted from Elbeltagi et al. (2005) included 18 activities as shown in Activity On Node (AON) diagram in Figure 3.12. First, Feng et al. (1997) apply GA to solve construction time-cost tradeoff in this problem. Later, Zheng et al. (2005) also utilize this example to applying Pareto ranking and niche formation of time-cost optimization by multi-objective GA. El-Rayes and Kandil (2005) also apply it in time-cost-quality tradeoff analysis for highway construction. Ng and Zhang (2008) use this example to optimize construction time and cost using Ant Colony Optimization (ACO) approach.

Elbeltagi et al. (2005) compare five Evolutionary Algorithms in terms of processing time, convergence ratio and quality of results by using both continuous and discrete optimization problem. Based on their results, the SFLA computational speed is the least among all algorithms in Time-Cost Optimization. We apply the same example by considering the same parameters such as indirect cost ($500) and various discretized options for each activity. Elbeltagi et al. (2005) consider 65 options for 18 activities of project. We extend the options of activities by considering the discretized options for every day between the minimum and maximum durations. Overall, we consider 196 options for activities of the project. A higher number of options create more flexibility in order to find a better solution with the shortest total project duration and the least total project cost and the fewest resource moments with the study by Elbeltagi et al. (2005). We also uses 14 resources; $R_1, R_2, ...R_{14}$. The fixing price for various resources is shown in Table 3.2. There are several project schedule options to perform each activity considering various combinations of feasible resources, time, and cost. The project schedule options for the first activity are described in details in Table 3.3. More details about the second example are presented in Table 3.4.

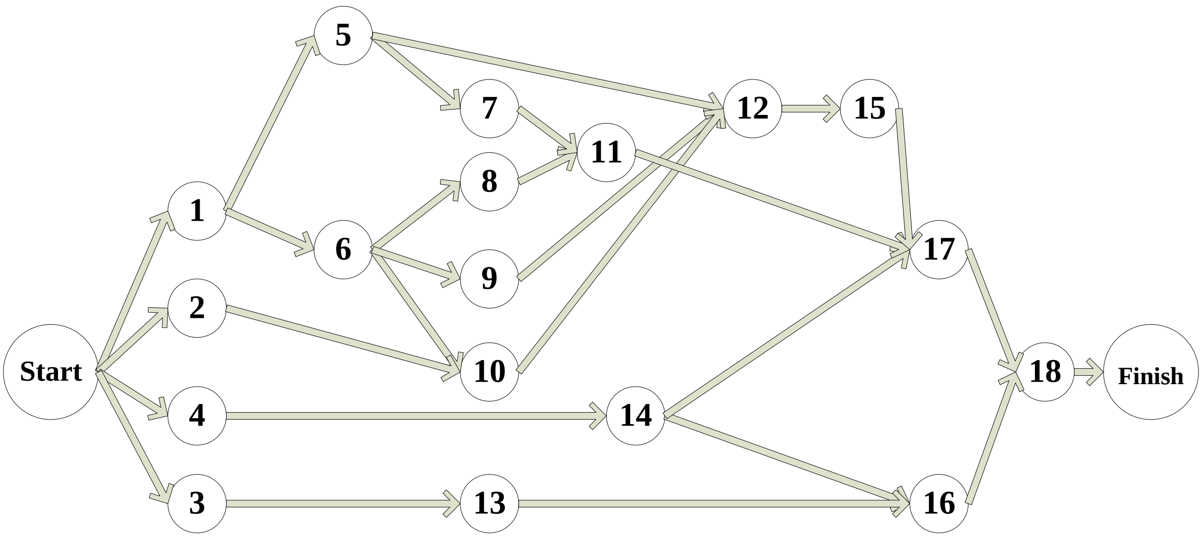


Figure 3.12 Activity on Node (AON) Network of Example 3.2

Table 3.2 The fixing unit price of resources in Example 3.2

Required Resources	**Unit Cost ($)**
R_1	7500
R_2	4500
R_3	2500
R_4	1500
R_5	1000
R_6	800
R_7	500
R_8	350
R_9	200
R_{10}	100
R_{11}	50
R_{12}	20
R_{13}	10
R_{14}	2

Table 3.3 Different options for the first activity in Example 3.2

Option No.	Duration (Days)	Required Resources (Numbers)														Total Direct Cost($)
		$R_{1,1}$	$R_{1,2}$	$R_{1,3}$	$R_{1,4}$	$R_{1,5}$	$R_{1,6}$	$R_{1,7}$	$R_{1,8}$	$R_{1,9}$	$R_{1,10}$	$R_{1,11}$	$R_{1,12}$	$R_{1,13}$	$R_{1,14}$	
1	14	0	0	0	0	1	1	0	0	1	2	3	2	1	0	2400
2	15	0	0	0	1	0	0	1	0	0	2	1	1	1	0	2280
3	16	0	0	0	0	2	0	0	0	0	1	1	0	1	0	2160
4	17	0	0	0	0	0	2	0	1	0	0	1	0	4	0	2040
5	18	0	0	0	1	0	0	0	1	0	0	1	0	1	5	1920
6	19	0	0	0	0	1	0	1	0	1	1	0	0	0	0	1800
7	20	0	0	0	0	0	0	0	0	5	4	3	4	5	0	1680
8	21	0	0	0	0	1	0	1	0	0	0	1	0	1	0	1560
9	22	0	0	0	0	0	0	1	2	1	0	0	1	2	0	1440
10	23	0	0	0	0	0	0	2	0	1	1	0	0	1	5	1320
11	24	0	0	0	0	0	0	0	3	0	1	1	0	0	0	1200

Table 3.4 The detailed information of activities in Example 3.2

Activity ID	No. of Options	Types of Required Resources
1	11	11
2	11	10
3	19	12
4	9	14
5	9	11
6	11	11
7	10	13
8	11	4
9	10	8
10	19	7
11	9	7
12	9	10
13	11	11
14	10	10
15	5	6
16	11	7
17	11	8
18	10	9

We apply our SFLA algorithm to solve this optimization problem and find the Pareto optimal front of project schedule solutions. Figure 3.13 shows project schedule solutions on the Pareto optimal fronts for this optimization problem in the 2-dimensional space of total project cost and total project time before and after splitting allowed. These Pareto optimal points show total project costs and total project durations for non-dominated project schedule solutions, which are found by our proposed SFLA algorithm before and after splitting allowed. It can be seen that our proposed SFLA approach is able to find project schedule solutions with lower total project cost and total project duration, which were not found by the other studies algorithms.

In particular, the shorter total project duration found by our approach (i.e., 106 days) before splitting allowed and the shortest total project duration (i.e., 99 days) after splitting allowed is less than the shortest total project duration found by Elbeltagi et al.'s approach (i.e., 113 days by GA and PSO, and 112 days by SFLA), Zheng et al.'s (i.e.,115 days), El-Rayes and Kandil's (i.e., 124 days) and Ng and Zheng's algorithm (i.e., 110 days). The lower total project cost found by our approach (i.e., $161,802) before splitting allowed and the lowest total project cost (i.e., $160,970) after splitting allowed is less than the least total project cost found by Elbeltagi et al.'s approach (i.e., $162,270 by GA, $162,300 by PSO, and $162,020 by SFLA), Zheng et al.'s (i.e., $210,000), El-Rayes and Kandil's (i.e., $206,320) and Ng and Zheng's algorithm (i.e., $203,720). Finding additional optimal project schedule solutions with lower total project cost and shorter total project duration is one of the most significant contributions of our proposed algorithm over the other studies algorithms.

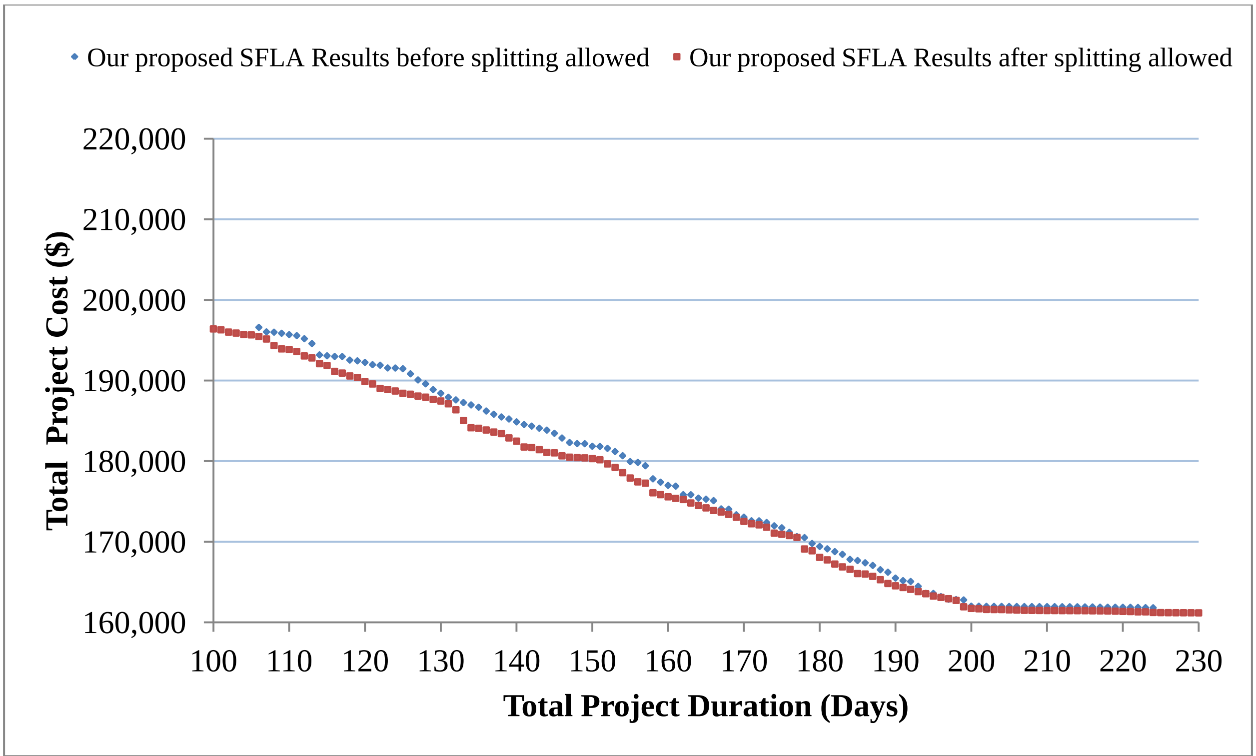
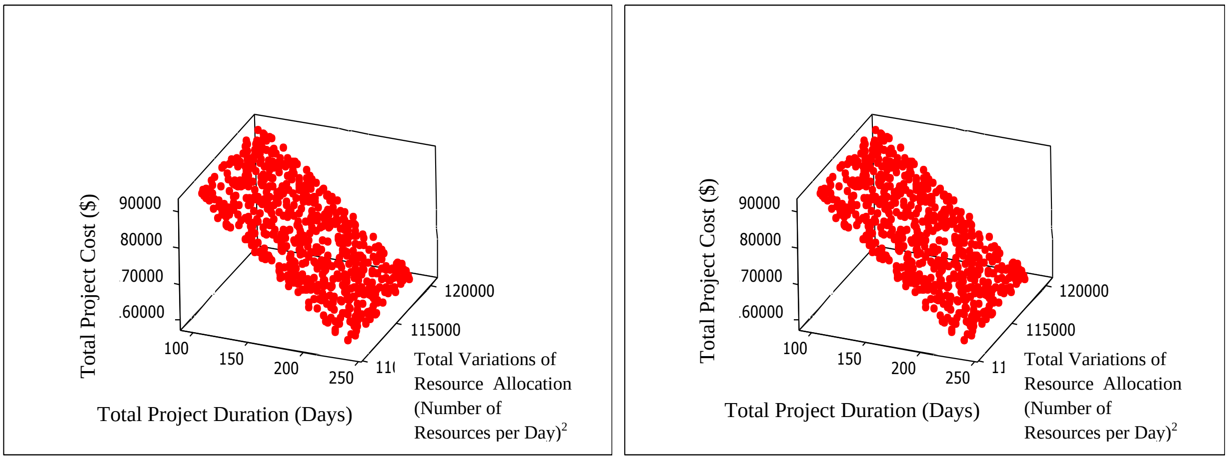


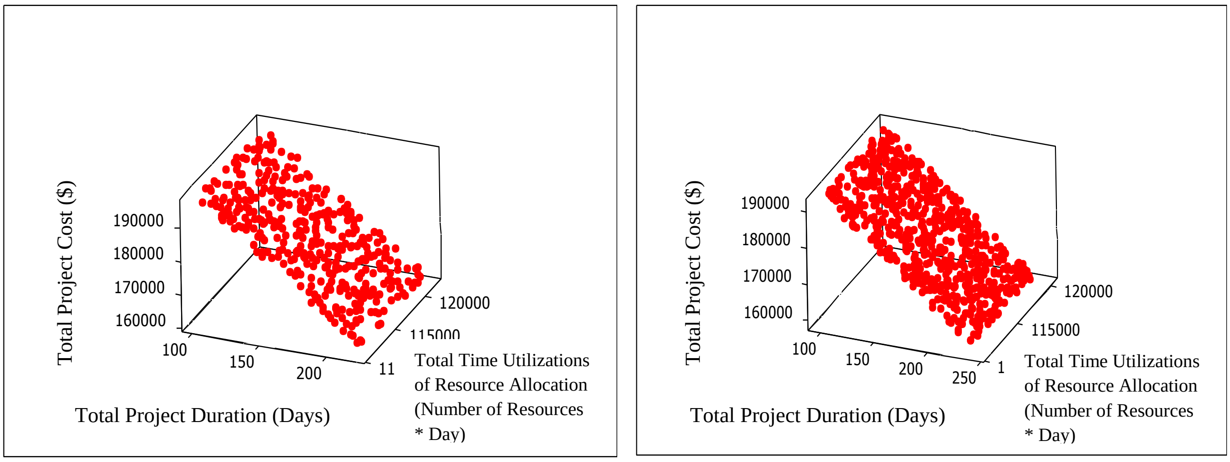
Figure 3.13 Optimal project schedule solutions in the 2-dimensional space of total project cost and total project duration found by our proposed SFLA algorithm before and after splitting allowed in Example 3.2

Elbeltagi et al.'s, El-Rayes and Kandil's, Zheng et al.'s, Ng and Zheng's algorithms are not capable of solving this project planning problem considering the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation. Our proposed SFLA algorithm is capable of solving simultaneous time-cost-resource optimization problems with time-cost tradeoff functions. Figure 3.14 and 3.15 show Pareto optimal front of this TCRO problem in the 3-dimensional space of project objectives before and after splitting allowed. These Pareto optimal points show the values of total project cost, duration, and total variation of resource allocation (Z_3) or total time utilizations of resource allocation (Z_4) for non-dominated project schedule solutions derived by our SFLA algorithm. The shortest total project time, the lowest total project cost and the fewest resource moments of the TCRO model are found in case of splitting allowed.



(a) (b)

Figure 3.14 Optimal project schedule solutions in the 3-dimensional space of total project cost, total project duration and total variations of resource allocation found by (a) our proposed SFLA algorithm before splitting allowed; and (b) our proposed SFLA algorithm after splitting allowed in Example 3.2

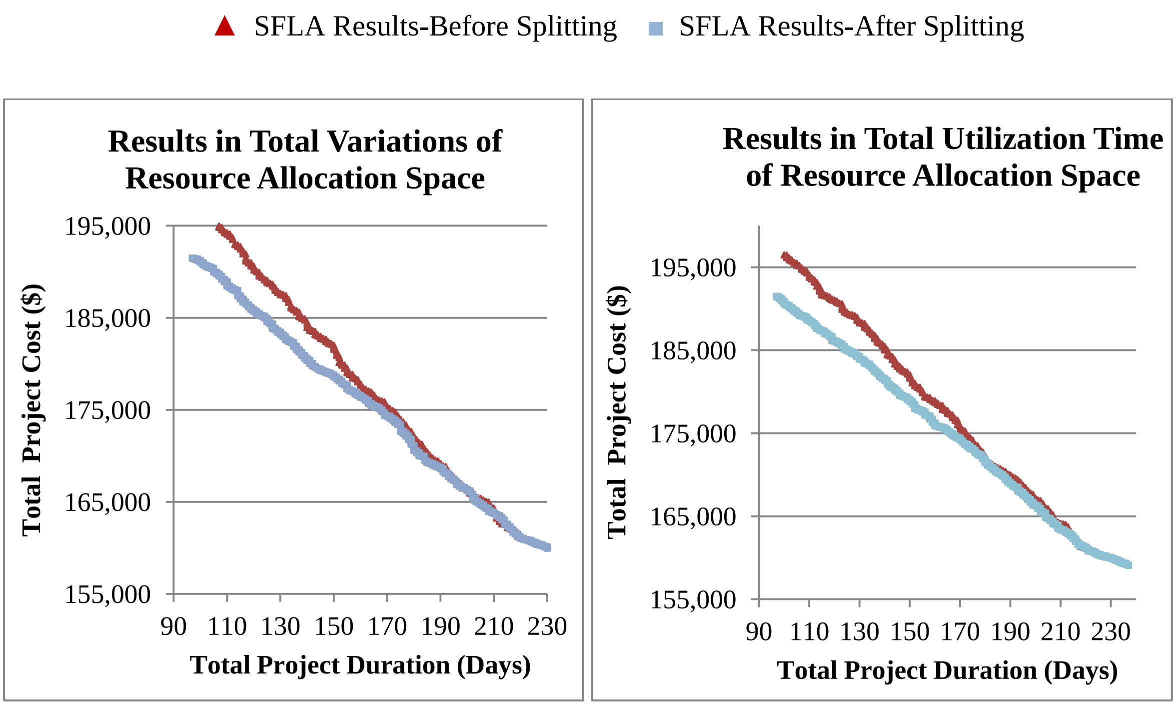


(a) (b)

Figure 3.15 Optimal project schedule solutions in the 3-dimensional space of total project cost, total project duration and total time utilizations of resource allocation found by (a) our proposed SFLA algorithm before splitting allowed; and (b) our proposed SFLA algorithm after splitting allowed in Example 3.2

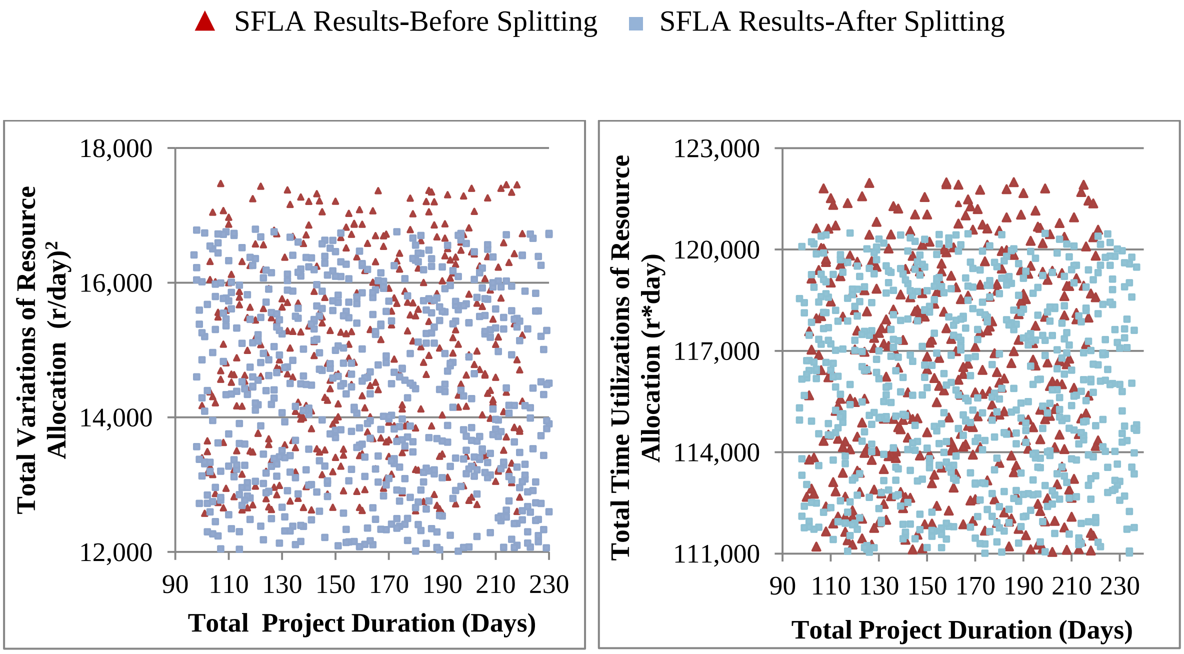
We also create the other Figures to better compare optimal project schedule solutions derived by SFLA algorithm before and after splitting allowed in the 2-dimentional space of project planning objectives: total project cost and total project duration in both space of total variations of resource allocation (Figure 3.16(a)) and total time utilizations of resource allocation (Figure 3.16(b)), and total project duration and total variations of resource allocation (Figure 3.17(a)) and total project duration and total time utilizations of resource allocation (Figure 3.17(b)), and total project cost and total variations of resource allocation (Figure 3.18(a)) and total project cost and total time utilizations of resource allocation (Figure 3.18(b)), respectively. It also can be seen that our proposed SFLA algorithm with splitting allowed is able to find project scheduling solutions with the shortest total project duration (i.e., 97 days compared to 100 days before splitting allowed), the lowest total project cost (i.e., \$159,114 compared to \$161,124 before splitting allowed) and less total variations of resources allocation (Z_3) (i.e., 12,013 (Number of Resources per Day)^2 compared to 12,576

(Number of Resources per Day)^2 before splitting allowed) and less total time utilizations of resources allocation (Z_4) (i.e., 111,011 (Number of Resources*Day) compared to 111,050 (Number of Resources*Day) before splitting allowed). Finding additional optimal project schedule solutions with lower total project cost, total project durations, and total variations of resource allocation or total time utilizations of resource allocation after splitting allowed is one of the most significant contributions of splitting impact over the previous studies optimization approach without splitting allowed. It shows that better non-dominated project schedule solutions could be achieved by interrupting project activities and moving resources across project activities.



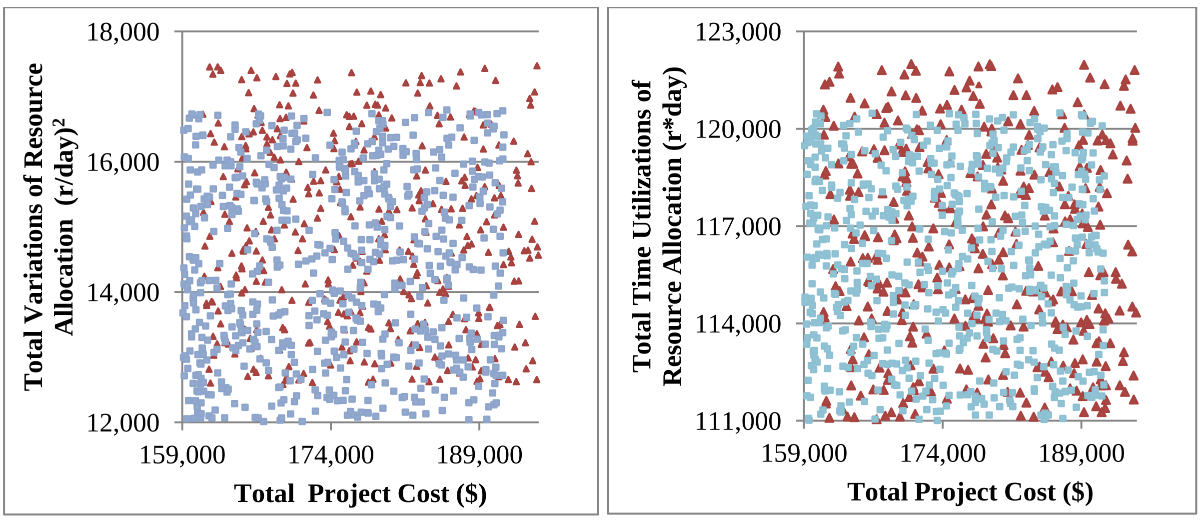
(a) (b)

Figure 3.16 Optimal project schedule solutions found by the NSGA-II approach and our proposed SFLA algorithm (before and after splitting allowed) in the 2-dimensional space of total project cost and total project duration; (a) in space of total variations of resource allocation; and (b) in space of total time utilizations of resource allocation in Example 3.2



(a) (b)

Figure 3.17 Optimal project schedule solutions found by our proposed SFLA algorithm (before and after splitting allowed) in the 2-dimensional space of (a) total project duration and total variations of resource allocation; (b) and total project duration and total time utilizations of resource allocation in Example 3.2



(a) (b)

Figure 3.18 Optimal project schedule solutions found by our proposed SFLA algorithm (before and after splitting allowed) in the 2-dimensional space of (a) total project cost and total variations of resource allocation; (b) and total project cost and total time utilizations of resource allocation in Example 3.2

3.6 Conclusions

In the past few years, many project planners have been forced to evaluate their projects by using heterogeneous technologies in order to remain competitive in a construction world. Therefore, project planners face complicated multivariate, Time-Cost-Resource Optimization (TCRO) problems that require time-cost-resource tradeoff analysis. We present the Shuffled Frog Leaping Algorithm (SFLA) to solve complex, Time-Cost-Resource Optimization (TCRO) problems in construction project planning. Our proposed algorithm uses advantages of two algorithms (PSO operator in the local searching and SCE operator in the competitive mixing of global searching) simultaneously. Furthermore, one of the problems of previous research in construction project planning is that that project activities cannot be split. We apply our proposed SFLA approach with activity splitting allowed to solve two optimization problems, which are found in the construction project planning literature.

It is shown that our proposed SFLA algorithm is superior than existing optimization algorithms in finding better project schedule solutions with less total project cost, less total project duration, and less total variations of resource allocation or total time utilizations of resource allocation. Finding additional optimal project schedule solutions with lower total project cost, shorter total project duration, and lower total variations of resource allocation or total time utilizations of resource allocation is one of the most significant contributions of our proposed algorithm over existing optimization algorithms: Zheng et al.'s (2004) GA algorithm, Zahraie and Tavakolan's (2009) NSGA-II algorithm, Zheng et al.'s (2005) GA algorithm, El-Rayes and Kandil's (2005) GA algorithm, Elbeltagi et al.'s (2005) GA, PSO and SFLA algorithms, and Ng and Zheng's (2008) ACO algorithm. In addition, our proposed SFLA algorithm is capable of solving simultaneous time-cost-resource optimization problems with activity splitting allowed. This is a major improvement over existing methods. Mentioned previous studies are not capable of solving project planning problems that require the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation.

Also, our results show that our proposed approach is faster than existing methods in processing time for solving complex TCRO problems in project planning. In particular, our proposed algorithm reduces the solution processing time by a factor of 3 compared to the previous Zahraie and Tavakolan’s (2009) NSGA-II algorithm. In next chapter, we present the model to create advanced optimization algorithms that are consistent with actual project scheduling problems that consider resources unit price inflation impact on the final results of the TCRO model.

Chapter 4

Comparison of Evolutionary Algorithms in Non-dominated Solutions of Time-Cost-Resource Optimization Problems with Evaluation of Inflation Impact

Abstract

In recent years, most research on project control concepts have been focused to optimizing simultaneously minimize the total project cost and total project duration while considering issues related to optimal resource allocation and resource leveling. Therefore, project planners face complicated multivariate, Time-Cost-Resource Optimization (TCRO) problems that require time-cost-resource tradeoff analysis to make models closer to actual projects. Project planner should consider the impact of inflation rate during project implementation to obtain the closer approximate actual cost of project. This subject has not been considered in recent studies. We apply two Hybrid approaches- Hybrid Genetic Algorithm Particle Swarm Optimization (HGAPSO), and Shuffled Frog Leaping Algorithm (SFLA)- of Evolutionary Algorithms (EAs) presented in previous chapters to solve complex, TCRO problems with considering the inflation impact on unit resources price in construction project planning. We also apply our hybrid approaches to solve two optimization problems, which are found in the construction project planning literature. It is shown that our proposed hybrid approaches are superior than existing optimization algorithms such as presented Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), before and after inflation impact in finding better project schedule solutions with less total project cost, less total project duration, and less total resources allocation. The results also show that hybrid

approaches are faster than existing methods in processing time for solving complex TCRO problems in construction project planning. The findings also show that inflation has significant impact on non-dominated solutions of TCRO problems.

4.1 Introduction

The challenge in project control concepts is to face complicated multivariate, Time-Cost-Resource Optimization (TCRO) problems. Selection of construction methods, which provides the optimal balance of time and cost and a time-cost curve demonstrating the relationship between total project duration and cost, are the results of TCRO problems (Xiong and Kuang 2008). Generally, the unavailability of resources in resource allocation analysis can be due to resource limits and resource calendars (Lu and Lam 2008). The goal of resource leveling is to minimize the incremental demands that cause fluctuation of resources, and thus avoid undesirable cycle hiring and firing during project scheduling (Senouci and Eldin 2004).This means that construction time, cost, and resources should be considered simultaneously in the estimation and planning stages to optimize resource allocation and keep the extension of the total project duration and total project cost to a minimum (Hegazy 1999; Lu et al. 2003). In the case of multi-objective optimization, the definition of optimal project schedule solutions is substantially more complex than for single-objective optimization problems, because the optimization goal itself consists of multiple objectives (Zitzler et al 2000):

- The distance of the resulting non-dominated set to the Pareto-optimal front should be minimized.
- A good (in most cases uniform) distribution of the solutions found is desirable. The assessment of this criterion might be based on a certain distance metric.

- The extent of the obtained non-dominated front should be maximized, i.e., for each objective, a wide range of values should be covered by the non-dominated solutions.

Traditional TCRO analysis assumes constant value of activities cost along the project time span (Ammar 2011). In previous research, the unit price of resources has been considered in fix values without any variation during construction period. However, it can vary during the period of construction, especially in infrastructure projects that take longer than one month (Levitt et al. 2010; Gibson et al. 2010). Every month, Engineering News-Record (ENR) publishes the Construction Cost Index (CCI), which is a weighted aggregate index of the 20-city average prices of construction activities (Ashuri and Lu 2010). It includes the latest rates of inflation for different resources used in construction projects. These values can be changed every month based on various factors such as economic and political conditions, and availability of resources (Smyth 1992; Ling and Hoang 2010; Wong and Ng 2010). Resources such as materials, machinery, and manpower have different rates of inflation during construction of projects (Reed-Scott 1985). Table 4.1 shows rates of inflation for various resources based on latest information from ENR in September 2010. In this chapter, we consider the inflation rate for resources unit price in two examples so that we may make a model closer to the actual surrounding conditions of construction project in the planning stage. The inflation rate of resources unit price can be varied based on the changes of project duration (ENR 2010).

In this chapter, the comprehensive comparison approaches of optimization algorithms is presented to solve Time-Cost-Resource Optimization (TCRO) problems in construction project planning. Our proposed approaches apply inflation rate to resources unit price of construction projects in three recent significant EAs: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and two hybrid algorithms. Our objective is to find

Table 4.1 Recent Values of Inflation of Resources (ENR)

Items	Sept 2010 Index Value	% Change Month	% Change Year
Construction Cost	8857.40	+0.2	+3.2
Common Labor	8857.40	+0.2	+3.2
Wage ($/hr)	8857.40	+0.2	+3.2
Building Cost	4910.41	+0.1	+3.1
Skilled Labor	8517.21	+0.2	+3.2
Wage ($/hr)	47.27	+0.2	+3.2
Materials	2703.53	-0.7	+2.8
Cement $/ton	102.90	+0.2	+1.5
Steel $/cwt	45.22	0.0	+3.8

superior optimization methods than existing optimization algorithms in finding better project schedule solutions with less total project costs, less total project durations, and less total resources allocation. The main objectives of this chapter include:

- Evaluation of three EAs- GA, PSO, and ACO- in terms of convergence ratio in required number of iterations and processing time, and quality of Pareto front to obtain optimal project schedule solutions;
- Evaluation of resources unit prices inflation impact on the TCRO problems;
- Comparison of the above three algorithms results with presented hybrid algorithms such as SFLA and HGAPSO in any type of time-cost functions such as continuous, discrete or linear and non-linear forms;
- Obtain the most significant parameters of different algorithms based on the project size in order to optimize non-dominated solutions in the shortest processing time.

In order to achieve these objectives, this chapter is structured as follows. Research Background on existing optimization algorithms to solve TCRO problems in construction project planning is described in Section 4.2. The approach of how to compute the inflation rates is presented in Section 4.3. In Section 4.4, we apply our proposed approaches on two construction project planning problems, which are taken from the optimization literature in construction engineering and management. We compare the performance of our proposed approach with existing optimization algorithms in this Section. In Section 4.5, we present the values of significant parameters of Evolutionary Algorithms in both examples. Conclusions are summarized at the end.

4.2 Research Background

In the last few decades a number of mathematical methods (Feng et al 1997; Li and Love 1997), dynamic programming (Pena-Mora 2001) and neural networks (Senouci and Adeli 2001) have been applied to optimize scheduling of construction projects. However, previous models have suffered in terms of speed of convergence in complex problems (Zheng et al. 2005), or they have been easily trapped in local optima (Afshar et al. 2009) or problems related to the assumption of models which make them ineffective and different from real construction projects. In addition, some previous studies did not consider every dimension of effective parameters for the final output of their models. For example, Adeli's model dealt with continuous variables only and did not consider the case of discrete variables (Senouci and Eldin 2004). Researchers have developed Evolutionary Algorithms as highly efficient and robust algorithms to optimize various problems (Konak et al. 2006). Recently, researches try to solve time-cost trade off and resource constrained scheduling with using different EAs (El-Rayes and Kandil 2005; Ng and Zhang 2008).

Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are known as the famous optimization approaches of EAs. In general, we can classify algorithms based on the method of evolution. GA population evolves throughout each subsequent population of chromosomes; however, PSO and ACO updates their population based on social

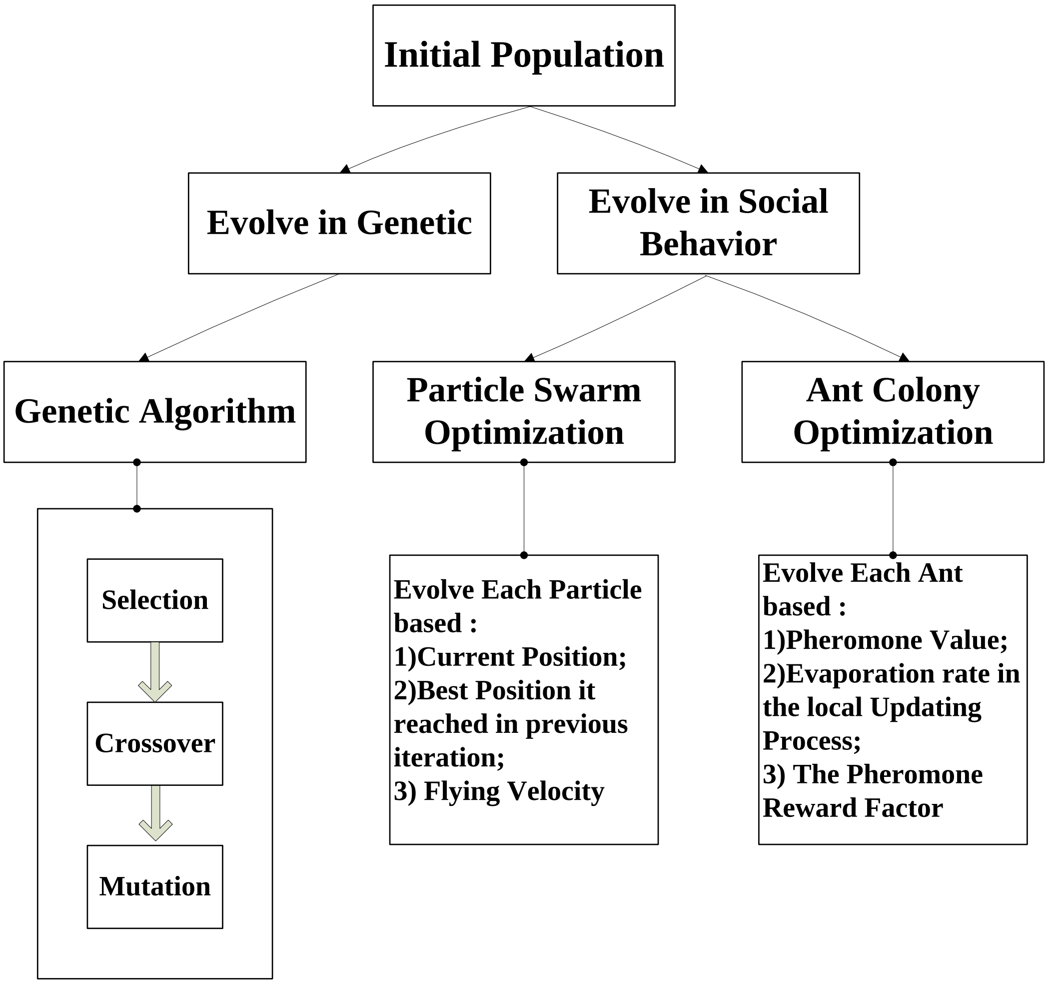


Figure 4.1 The evolution process of three EAs (GA, PSO, ACO)

behavior. Figure 4.1 demonstrates the entire process of optimization in three Evolutionary Algorithms.

Four important parameters of GA algorithm including: (1) population size; (2) $P_{crossover}$; (3) $P_{mutation}$; and (4) size of crowding distance. They have significant impact on the convergence ratio and quality of Pareto front solution (Goldberg 1989; Konak et al. 2006). Three important parameters of PSO algorithm including: positive constant of c_1, c_2 as learning factors; and ω as an inertia weight to control the impact of the previous solutions convergence on the current velocity. The operator ω plays the role of balancing the global search and the local search in PSO algorithm (Shi and Eberhart 1998). Finally, five important parameters of ACO algorithm are: (1) ρ is pheromone evaporation rate between $(0,1)$. Parameter ρ determines the convergence speed of the algorithm. In general, when the algorithm has time to generate a large number of solutions, a low value of ρ is profitable since the algorithm will explore different regions of the search space and does not focus the search too early on a small region (Merkle et al 2002); (2) η is the heuristic function, which evaluates the utility of choosing each option. Usually, the heuristic values will help the first generations of ants finding good solutions; (3) α and (4) β are weightings which control the relative influence of the heuristic values; and (5) R is a constant called the pheromone reward factor.

Mathematical formulation of Time-Cost-Resource Optimization (TCRO) problems in construction project planning presented in Section 2.3 is also applied in this chapter. The only difference is to consider two resource moments (Z_4-presented also in Section 3.3.1) and Z_5. In order to reduce fluctuations of resource utilization and release of resources in the least possible time, we minimize the total resources allocation:

$$Z_5 = Min(SSR + SPD) \tag{4.1}$$

where $SSR = \left(\sum_{k=1}^{TD} \sum_{n=1}^{S} (\text{Re}\,source_{n,k})^2 \right)$; and $SPD = \left(\sum_{k=1}^{TD} \sum_{n=1}^{S} (\text{Re}\,source_{n,k} \times n) \right)$

Both of the objectives of minimizing total project cost and total project duration and one of the three resource allocation objectives are the three objective functions of the optimization model. Also a TCRO problem in construction project planning is subject to the same constraints of logical or physical dependencies between project activities; and any limits on the total daily availability of resources as described in detail in Section 2.3.

4.3 Computation of Inflation

Based on Table 4.1, we consider three kinds of resources: material, manpower and machinery. The average rates of inflation for material and machinery are considered as 0.2, and for manpower considered 0.3, respectively. In addition, since these values are calculated monthly, they should be varied based on the duration of activities. Table 4.2 states the equivalent factor of inflation rates based on the kind of resources and duration of activities. It is calculated based on the future value of money concept.

Table 4.2 Details of Calculation of Inflation Rate

The Equivalent Factor	Kind of Resources		
	Material	Machinery	Manpower
Duration < 1 month	1	1	1
Duration < 2 months	$(1+0.2)^1$	$(1+0.2)^1$	$(1+0.3)^1$
Duration < 3 months	$(1+0.2)^2$	$(1+0.2)^2$	$(1+0.3)^2$
Duration < 4 months	$(1+0.2)^3$	$(1+0.2)^3$	$(1+0.3)^3$
Duration < 5 months	$(1+0.2)^4$	$(1+0.2)^4$	$(1+0.3)^4$

4.4 Application of the Proposed Hybrid Algorithms with Inflation rate of Resources Unit Price

We apply the proposed HGAPSO and SFLA algorithms on two optimization problems, which we have found in the literature of construction project planning. These examples are selected to compare the results of our proposed hybrid algorithms with the results of existing methods. We use our algorithms to solve these project planning problems and find optimal project schedule solutions. We show that our proposed hybrid algorithms are superior than existing optimization algorithms to find better project schedule solutions before and after inflation impact with less total project costs, less total project durations, and less total variations of resource allocation, or less total time utilizations of resource allocation or less total resource allocation. Also we show that our hybrid approaches are faster than existing methods in terms of the processing time for solving these optimization problems in construction project planning.

4.4.1 Example 4.1

The first example is adopted from Senouci and Eldin (2004). This project consists of 12 activities as shown in Activity On Node (AON) diagram in Figure 4.2. This project also uses 5 types of resources: $R_1, R_2, ...R_5$. There are several project schedule options to perform each activity considering various combinations of feasible resources, time, and cost. The project schedule options are described in details by different continuous and discrete time-direct cost functions in Table 4.3. For instance, there are project schedule options defined by continuous time-cost functions to perform Activity A. In addition, each activity can be conducted using different sets of resources. Table 4.4 summarizes several examples of resource configurations to perform Activity A. Each resource configuration corresponds to a specific time-direct cost configuration as identified in Table 4.4. Also, indirect cost of this project is assumed to be \$2,500 per day. Senouci and Eldin (2004) use GA algorithm to solve this project planning problem and find optimal resource schedule solutions. The objective of their problem is to optimize the total cost of the project by assigning different numbers for one resource to various activities of project. In this project, any relation types between activities contain Start to Start, Start to Finish, Finish to Start, and Finish to Finish are applied for various activities of the project. Furthermore, using lag time and any relation type between activities promote the TCRO problem and make it closer to the actual projects. We also apply our hybrid algorithms on this project planning problem to find the Pareto optimal front of project schedule solutions and then, compare our solutions with the results of the previous algorithms. In order to make our results comparable with Senouci and Eldin's study, we utilize the same values of lag time as they used for various activities of the project. Since inflation in TCRO model is effective for period of one month, we change the scale of duration in Senouci and Eldin's assumption from day to month.

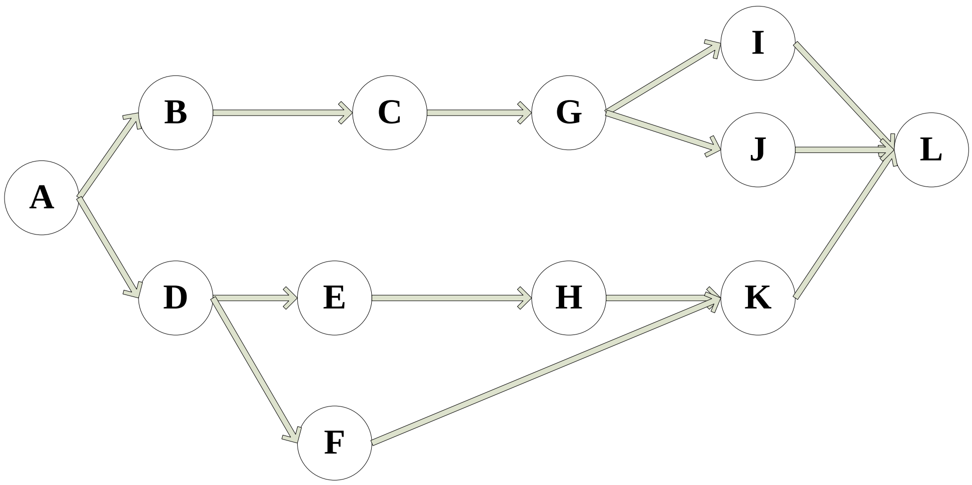


Figure 4.2 Activity on Node (AON) Network of Example 4.1

Senouci and Eldin (2004) use the GA algorithm to solve this project scheduling problem and find optimal project schedule solutions. We apply our hybrid algorithms to solve this optimization problem and find the Pareto optimal front of project schedule solutions. Since ACO algorithm is not suitable for continuous problems (Elbeltagi et al. 2005), we evaluate the other algorithms capabilities in this example. We evaluate the impact of population size of EAs on the quality of non-dominated solutions, and the iteration numbers needed to obtain the solution. Although the percentage of improvement of results are different among all of EAs, we conclude that selecting the appropriate population size (which is 300 in this example) has a significant impact on decreasing processing time to obtain optimal project schedule solutions with a suitable range of Pareto front from the shortest total project duration and the least total project cost to the longest total project duration and the highest total project cost. Figure 4.3 shows project schedule solutions on the Pareto optimal fronts for this optimization problem in the 2-dimensional space of total project cost and total project time. These Pareto optimal points show total project costs and total project durations for non-dominated project schedule solutions, which are found by our proposed hybrid algorithms, NSGA-II, and PSO.

Table 4.3 Cost-Time functions to perform project activities in Example 4.1

Activity ID	Precedence Activities	Relation Type	Lag time (Months)	Time Ranges (Months)		Direct Cost (C)-Time (T) Functions ($)	Direct Cost Range ($)	
				Minimum	Maximum		Minimum	Maximum
A	-	-	-	1	2	$3,000-100T-50T^2$	2,600	2,850
B	A	Start-Start	2	4	5	$7,000-300T-75T^2$	3,625	4,600
C	B	Finish-Finish	3	1	3	$6,000-500T-25T^2$	4,275	5,475
D	A	Start-Start	2	1	2	$8,000-600T-50T^2$	6,600	7,350
E	D	Start-Finish	2	2	4	$11,000-400T-20T^2$	9,080	10,120
F	D	Finish-Finish	4	2	3	$11,000-400T-75T^2$	9,125	9,900
G	C	Finish-Start	0	1	2	$7,000-500T-100T^2$	5,600	6,400
H	E	Start-Start	1	1	2	$3,500-300T-75T^2$	2,600	3,125
I	G	Finish-Finish	4	2	4	$3,500-300T-50T^2$	1,500	2,700
J	G	Finish-Finish	2	7	8	$2,500-100T-15T^2$	740	1,065
K	F,H	Finish-Start	0,2	4	6	$5,000-200T-25T^2$	2,900	3,800
L	I,J,K	Finish-Start	1,0,0	2	3	$2,000-200T-30T^2$	1,130	1,480

Table 4.4 Feasible project schedule options to perform Activity A in Example 4.1

Option No.	**Duration (Days)**	**Required Resources (Numbers)**					**Direct Cost ($)**
		$\mathbf{R_{1,1}}$	$\mathbf{R_{1,2}}$	$\mathbf{R_{1,3}}$	$\mathbf{R_{1,4}}$	$\mathbf{R_{1,5}}$	
1	1	1	3	1	3	0	2,850
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
n	30	1	2	2	4	0	2,600

It can be seen that our proposed hybrid approach is able to find project schedule solutions with lower total project cost and total project duration, which were not found by the other algorithms. In particular, the shortest total project duration found by our approach (i.e., 14 month and 25 days) is less than the shortest total project duration found by Senouci and Eldin's approach (i.e., 18 months) and total project duration found by NSGA-II (i.e., 15 months and 25 days), and by PSO algorithm (i.e., 15 months and 17 days). The least total project cost found by our approach (i.e., $95,505) is less than the least total project cost found by Senouci and Eldin's approach (i.e., $102,675) and the least total project cost found by NSGA-II (i.e. $97,963), and by PSO algorithm (i.e. $96,888). Finding additional optimal project schedule solutions with lower total project cost and shorter total project duration is one of the most significant contributions of our proposed algorithms over NSGA-II and PSO algorithms and Senouci and Eldin's GA results.

In the next step, we apply inflation impact on resources unit price on TCRO problem. It can be seen that the shortest total project duration and the least total project cost found by algorithms are increased compared with the previous results. In this case also, it can be seen that our proposed hybrid approach is able to find project schedule solutions with lower total project cost and total project duration, which are not found by the other algorithms. In particular, the shortest total project duration found by our approach (i.e., 22 months and 13 days) is less than the shortest total project duration found by NSGA-II (i.e., 25 months and 17 days), and by PSO algorithm (24 months and 3 days). Also the least total project cost found by our approach (i.e., $107,906) is less than the least total project cost found by NSGA-II (i.e. $109,863), and by PSO algorithm ($109,147). Figure 4.4 shows project schedule solutions after applying inflation impact on the Pareto optimal fronts for this optimization problem in the 2-dimensional space of total project cost and total project time.

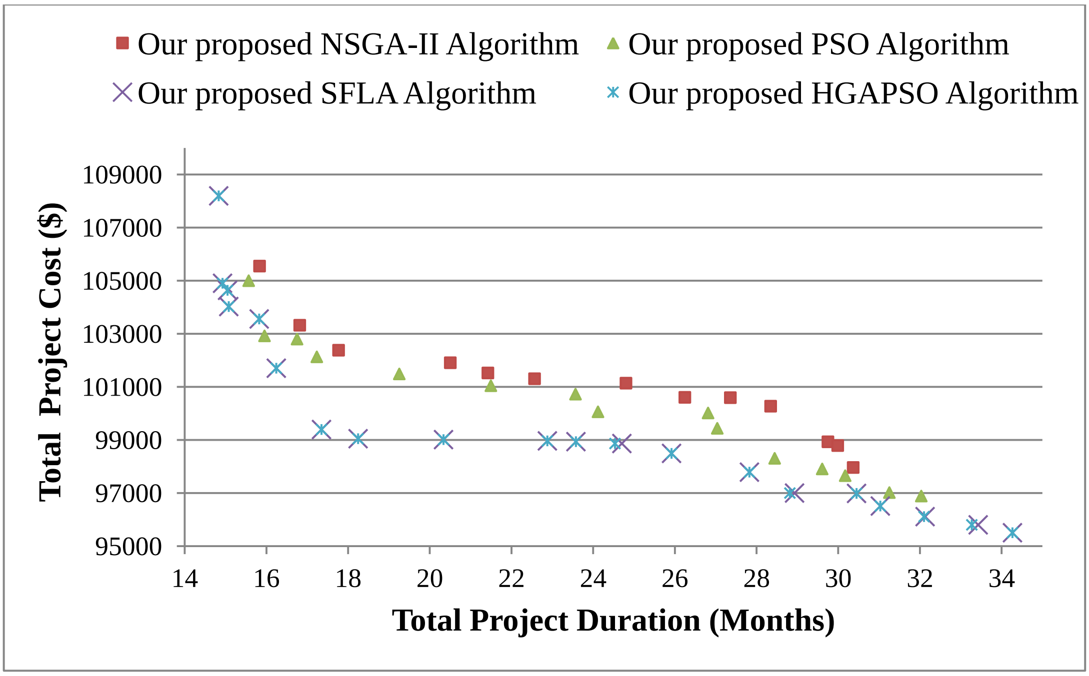


Figure 4.3 Optimal project schedule solutions before applying inflation in the 2-dimensional space of total project cost and total project duration found by our proposed hybrid algorithms, our proposed GA and PSO in Example 4.1

Senouci and Eldin's algorithm is not capable of solving this project planning problem considering the simultaneous minimization of total project cost, total project duration, and total resource allocations. Both our proposed hybrid algorithms and NSGA-II and PSO algorithms are capable of solving simultaneous time-cost-resource optimization problems with time-cost tradeoff functions. Figures 4.5, 4.6, and 4.7 show project schedule solutions after inflation impact on the Pareto optimal fronts for this TCRO problem in the 3-dimensional space of project objectives: total project cost, total project duration, and total variations of resource allocation; total project cost, total project duration, and total time utilizations of resource allocation; and total project cost, total project duration, and total resources allocation. These Pareto optimal points show total project costs, total project durations, and total resource allocation moments for non-dominated project schedule solutions, which are derived by our proposed hybrid algorithms, NSGA-II and PSO algorithms.

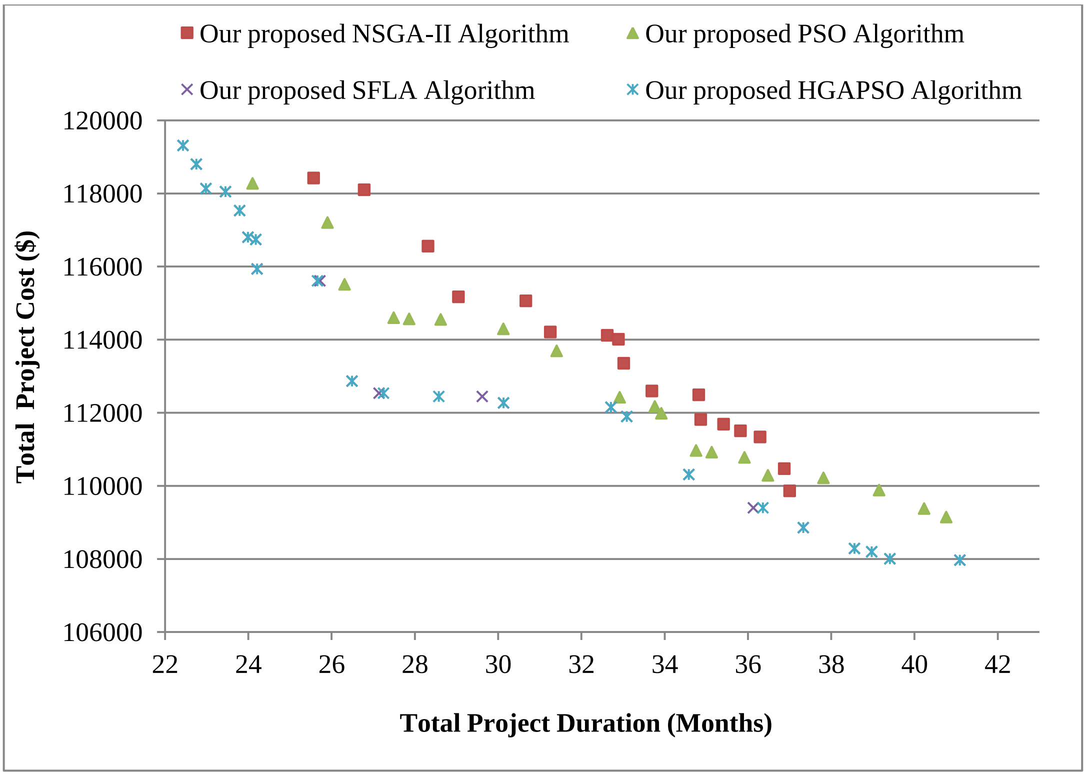
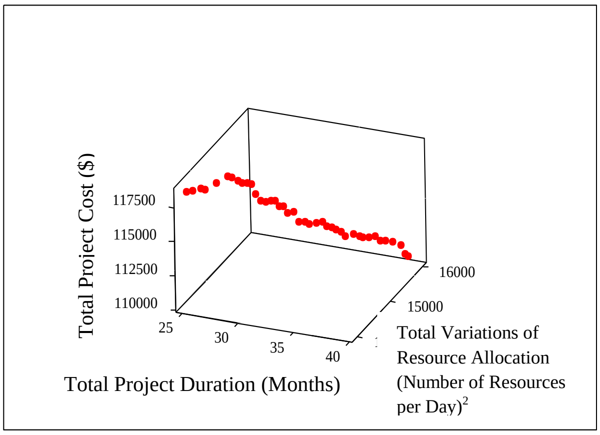


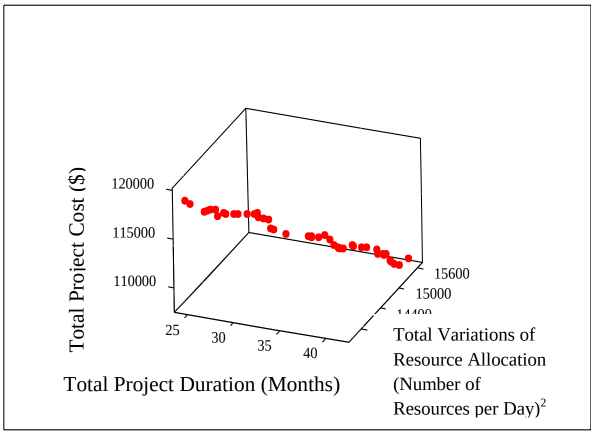
Figure 4.4 Optimal project schedule solutions after applying inflation in the 2-dimensional space of total project cost and total project duration found by our proposed hybrid algorithms, and our proposed GA and PSO in Example 4.1

We also create Figures 4.8(a), 4.8(b), and 4.8(c) to better show optimal project schedule solutions derived by our proposed four algorithms in the 2-dimentional space of project planning objectives: total project cost and total project duration in three spaces of total variations resource allocation, total time utilizations of resource allocation, and total resources allocation. Figures 4.8(d), 4.8(e), and 4.8(f) demonstrate optimal project schedule solutions derived by our four algorithms in the 2-dimentional space of total project duration and one of the total variations of resource allocation, total time utilizations of resource allocation, and total resources allocation. Also Figures 4.8(g), 4.8(h), and 4.8(i) show optimal project schedule solutions derived by these four algorithms in the 2-dimentional space of total project cost and one of the total variations of resource allocation, total time utilizations of resource allocation, and total resources allocation, respectively.

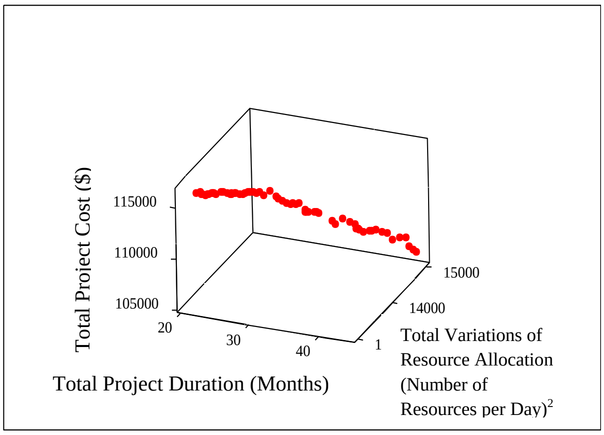
It can be seen that our proposed hybrid approaches are able to find project schedule solutions with lower total project cost, total project duration, and total variations of resource allocation, which are not found by two other algorithms. In particular, the shortest total project duration found by our approach (i.e., 22 months) is less than the shortest total project duration found by NSGA-II (i.e., 25 months and 10 days), and PSO algorithm (i.e., 23 months and 5 days). The least total project cost found by our approach (i.e., $116,369) is less than the least total project cost found by NSGA-II (i.e., $118,410), and PSO algorithm (i.e., $118,588). The least total variations of resource allocation found by our approach (i.e., 13,008 (Number of Resources per Day)^2) is less than the values found by NSGA-II (i.e., 13,945 (Number of Resources per Day)^2), and PSO algorithm (i.e., 13,513 (Number of Resources*Day)). Moreover, the least total time utilizations of resource allocation found by our approach (i.e., 88,003 (Number of Resources*Day)) is less than the values found by NSGA-II (i.e., 93,137 (Number of Resources*Day)), and PSO algorithm (i.e., 91,156 (Number of Resources*Day)). Also, the least total resource allocation found by our approach (i.e., 60,387) is less than the values found by NSGA-II (i.e., 62,110), and PSO algorithm (i.e., 61,645). Our presented hybrid approach reduces the solution processing time by a factor of 2.6 compared to the previous Zahraie and Tavakolan's NSGA-II algorithm, and 2.1 to the PSO algorithm and 2 to the ACO algorithm.



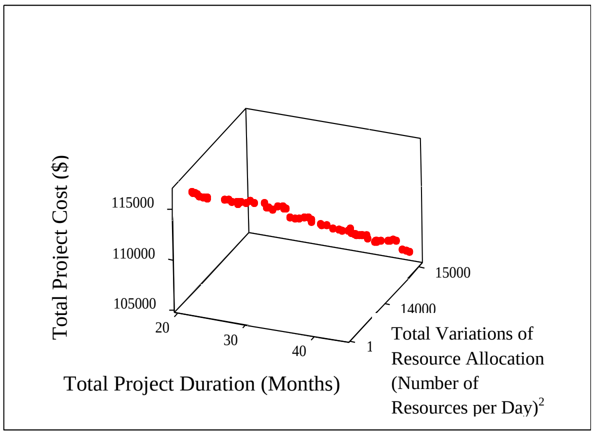
(a) NSGA-II Results



(b) PSO Results

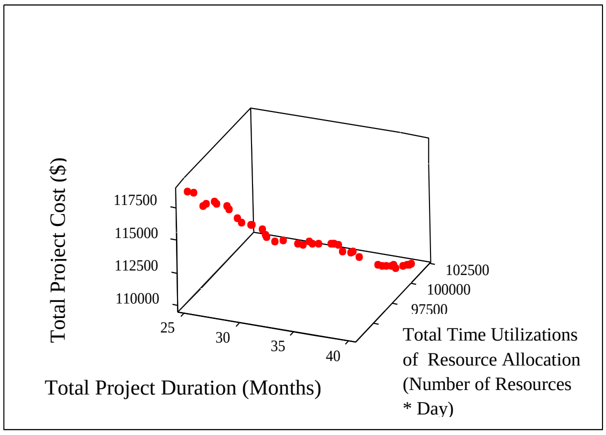


(c) SFLA Results

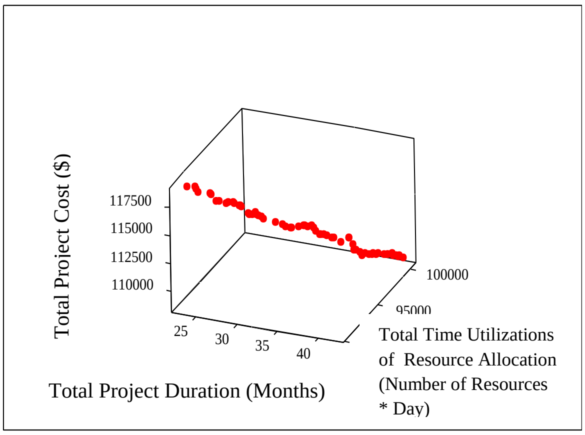


(d) HGAPSO Results

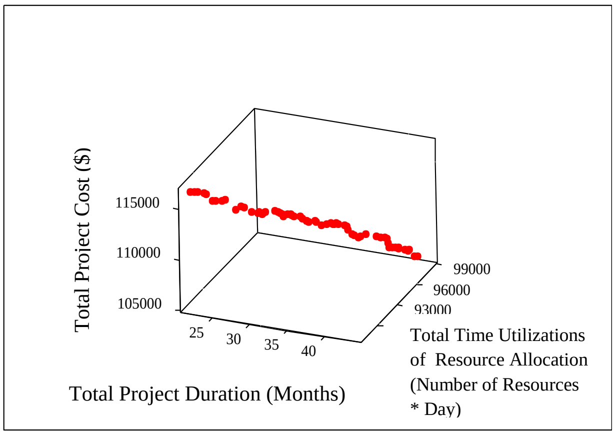
Figure 4.5 Optimal project schedule solutions found by the (a) NSGA-II, (b) PSO, (c) SFLA, and (d) HGAPSO algorithms after applying inflation in the 3-dimensional space of total project cost, total project duration and total resource allocation (Z_3) in Example 4.1



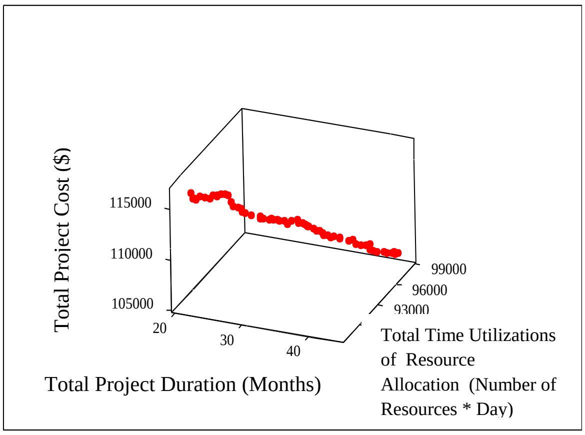
(a) NSGA-II Results



(b) PSO Results

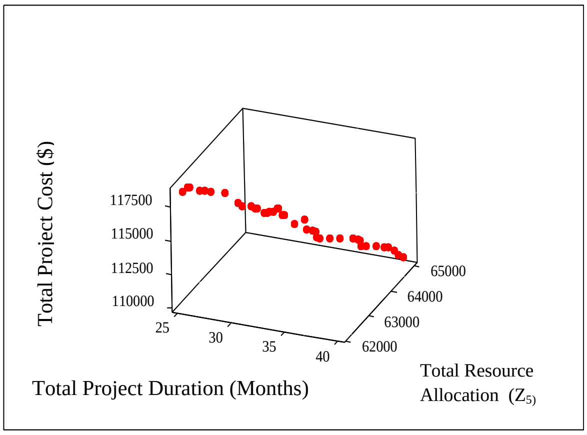


(c) SFLA Results

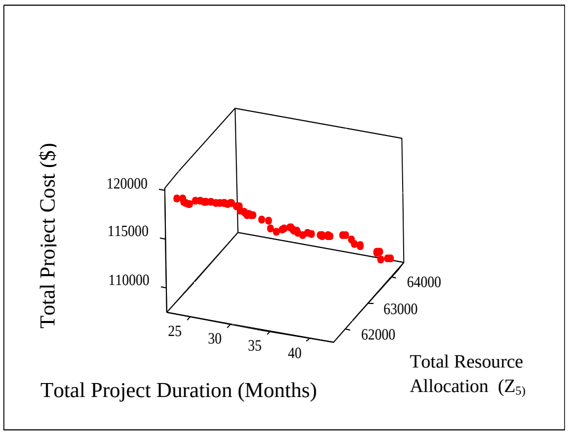


(d) HGAPSO Results

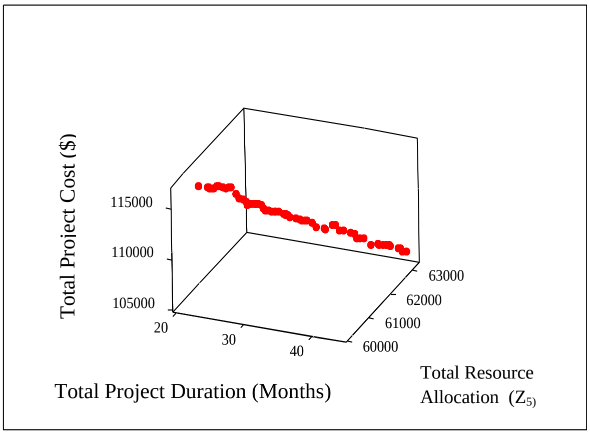
Figure 4.6 Optimal project schedule solutions found by the (a) NSGA-II, (b) PSO, (c) SFLA, and (d) HGAPSO algorithms after applying inflation in the 3-dimensional space of total project cost, total project duration and total resource allocation (Z_4) in Example 4.1



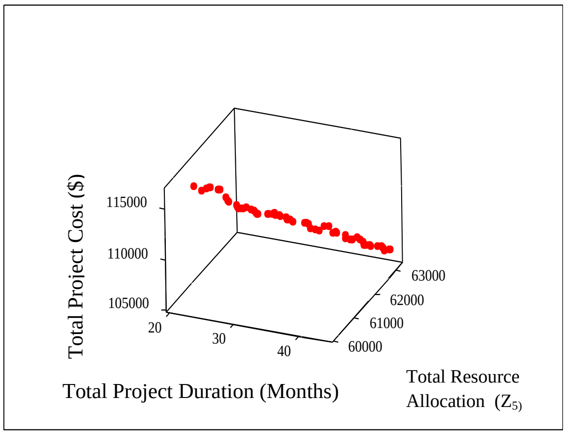
(a) NSGA-II Results



(b) PSO Results

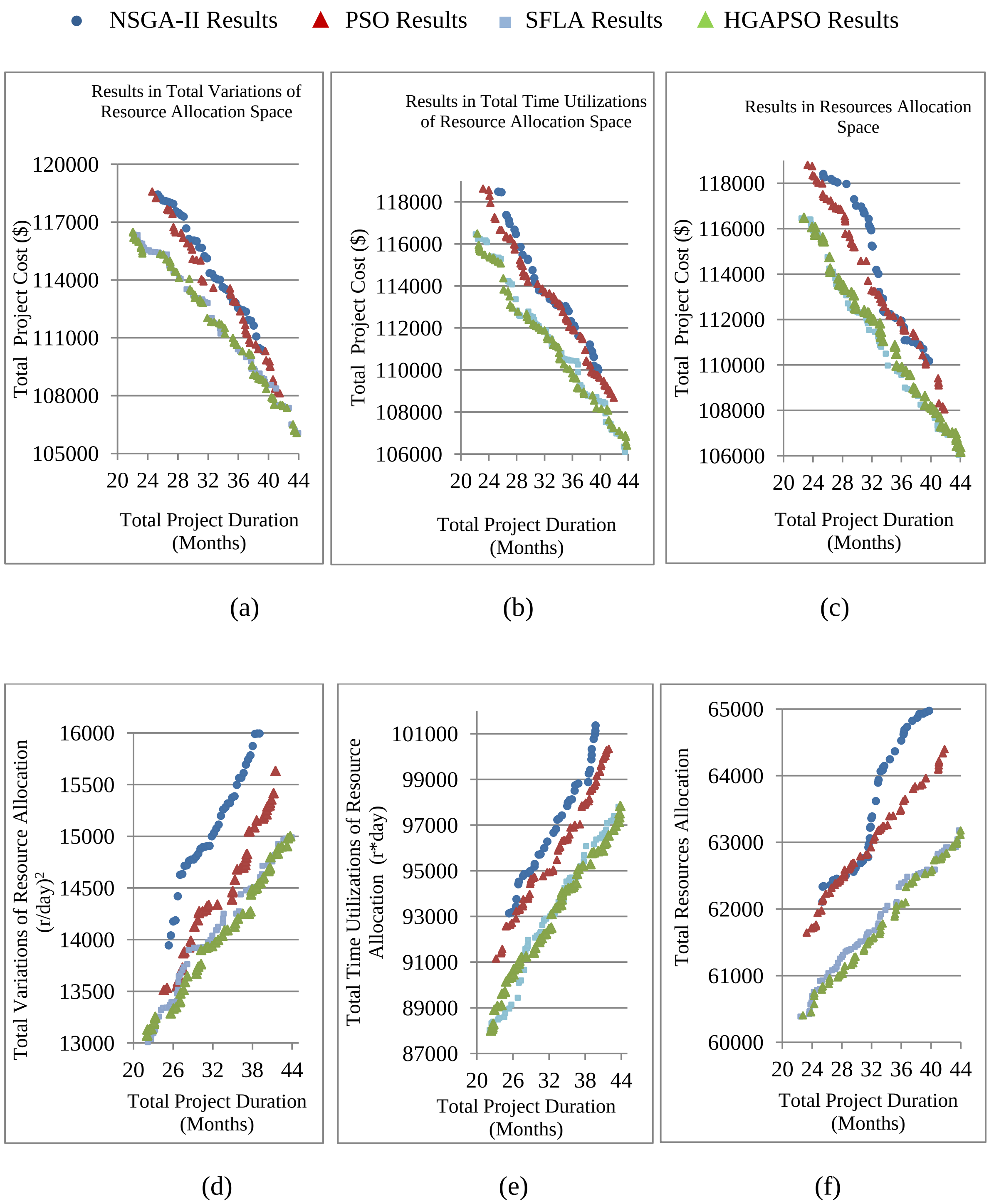


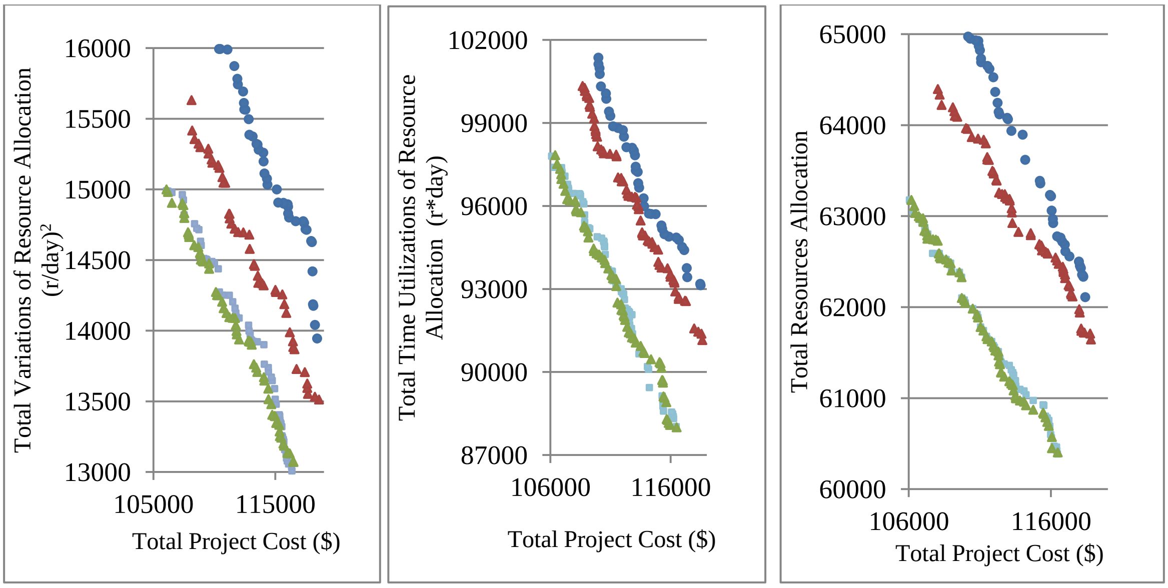
(c) SFLA Results



(d) HGAPSO Results

Figure 4.7 Optimal project schedule solutions found by the (a) NSGA-II, (b) PSO, (c) SFLA, and (d) HGAPSO algorithms after applying inflation in the 3-dimensional space of total project cost, total project duration and total resource allocation (Z_5) in Example 4.1


NSGA-II Results
PSO Results
SFLA Results
HGAPSO Results
Results in Total Variations of Resource Allocation Space
Total Project Cost ($)
120000
117000
114000
111000
108000
105000
20 24 28 32 36 40 44
Total Project Duration (Months)
(a)
Results in Total Time Utilizations of Resource Allocation Space
Total Project Cost ($)
118000
116000
114000
112000
110000
108000
106000
20 24 28 32 36 40 44
Total Project Duration (Months)
(b)
Results in Resources Allocation Space
Total Project Cost ($)
118000
116000
114000
112000
110000
108000
106000
20 24 28 32 36 40 44
Total Project Duration (Months)
(c)
Total Variations of Resource Allocation (r/day)2
16000
15500
15000
14500
14000
13500
13000
20 26 32 38 44
Total Project Duration (Months)
(d)
Total Time Utilizations of Resource Allocation (r*day)
101000
99000
97000
95000
93000
91000
89000
87000
20 26 32 38 44
Total Project Duration (Months)
(e)
Total Resources Allocation
65000
64000
63000
62000
61000
60000
20 24 28 32 36 40 44
Total Project Duration (Months)
(f)

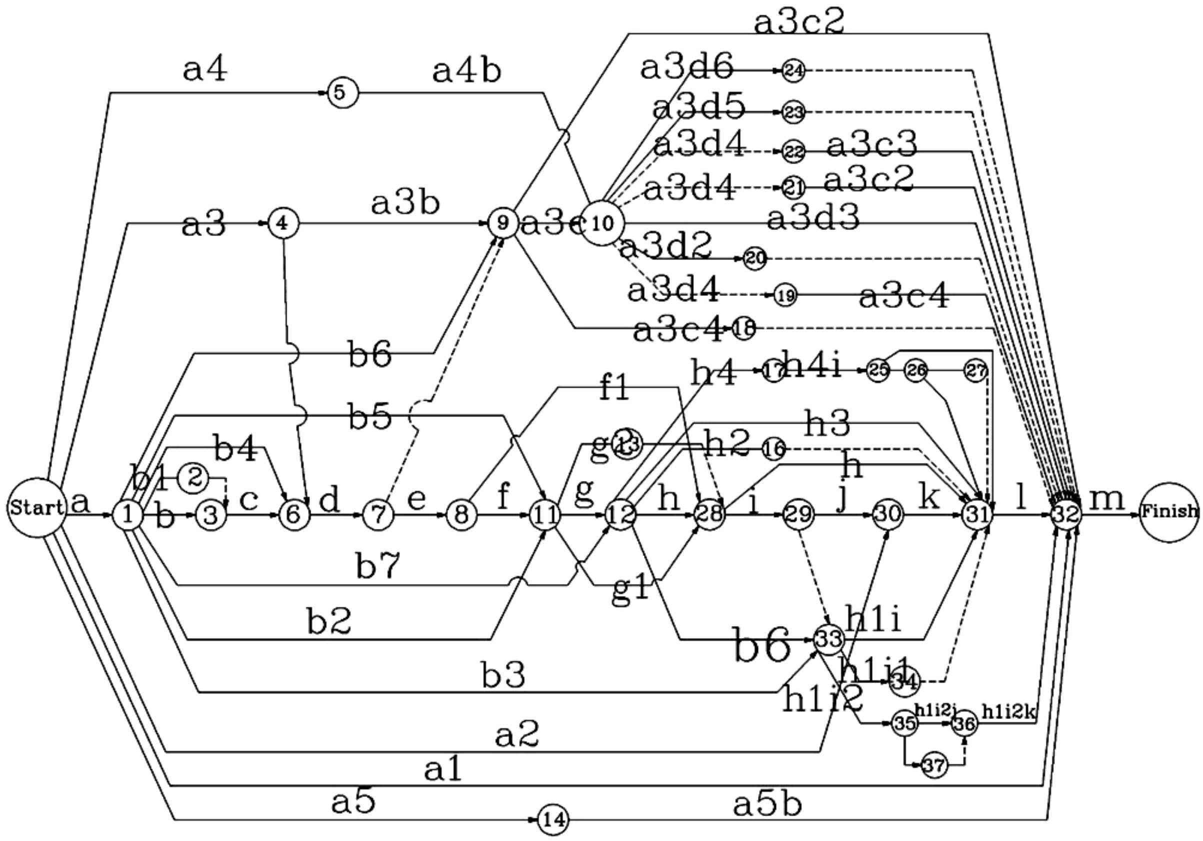


(g) (h) (i)

Figure 4.8 Optimal project schedule solutions found by the NSGA-II, PSO, SFLA, and HGAPSO algorithms (after applying inflation) in the 2-dimensional space of total project cost and total project duration; (a) in space of total variations of resource allocation; and (b) in space of total time utilizations of resource allocation; and (c) in resource allocation space; (d) total project duration and total variations of resource allocation; (e) and total project duration and total time utilizations of resource allocation; and (f) total project duration and total resources allocation; (g) total project cost and total variations of resource allocation; (h) and total project cost and total time utilizations of resource allocation; and (i) total project cost and total resources allocation in Example 4.1

4.4.2 Example 4.2

Usually, construction projects have a complex structure with more activities (Halfawy and Froese 2005; Wideman 1990). Most construction projects last at least six months by adding the duration of site equipment (Martin et al. 2006). Since the uncertainty associated with variable predictions increases monotonically with time (Chiara 2006), we choose the real complex project (with average duration of 750 days) in Shahidrajaee Port in South of Iran which is adopted from Kazemi (2006). Zahraie and Tavakolan (2009) present this project consisting of sixty three interrelated activities as shown in Activity On Arrow (AOA) diagram in Figure 4.9. Eighteen resource types $R_1, R_2, ...R_{18}$ are used in this project. Zahraie and Tavakolan (2009) apply NSGA-II evolutionary algorithm to find the Pareto optimal front of project schedule solutions. There are several options to perform each activity using different configurations of these resources. For instance, Table 4.5 shows 11 configurations of time, direct cost, and resource allocation to perform activity 1. Also, indirect cost of this project is assumed to be $1,500 per day. Thirty three of project activities last more than one month and both of them have duration of up to sixteen months. These activities are the subject of inflation in execution of project. We apply our proposed hybrid approaches on this project planning problem to find the Pareto optimal front of project schedule solutions and then, compare our solutions with the results of NSGA-II algorithm presented by Zahraie and Tavakolan, and two algorithms: PSO, and ACO. We select the same initial population (1200), the same as Zahraie and Tavakolan’s study (2009). We also evaluate the impact of indirect cost on the variation of TCRO results by considering two values of indirect cost: $1,500 (same value as in 2009 research) and $3,000.



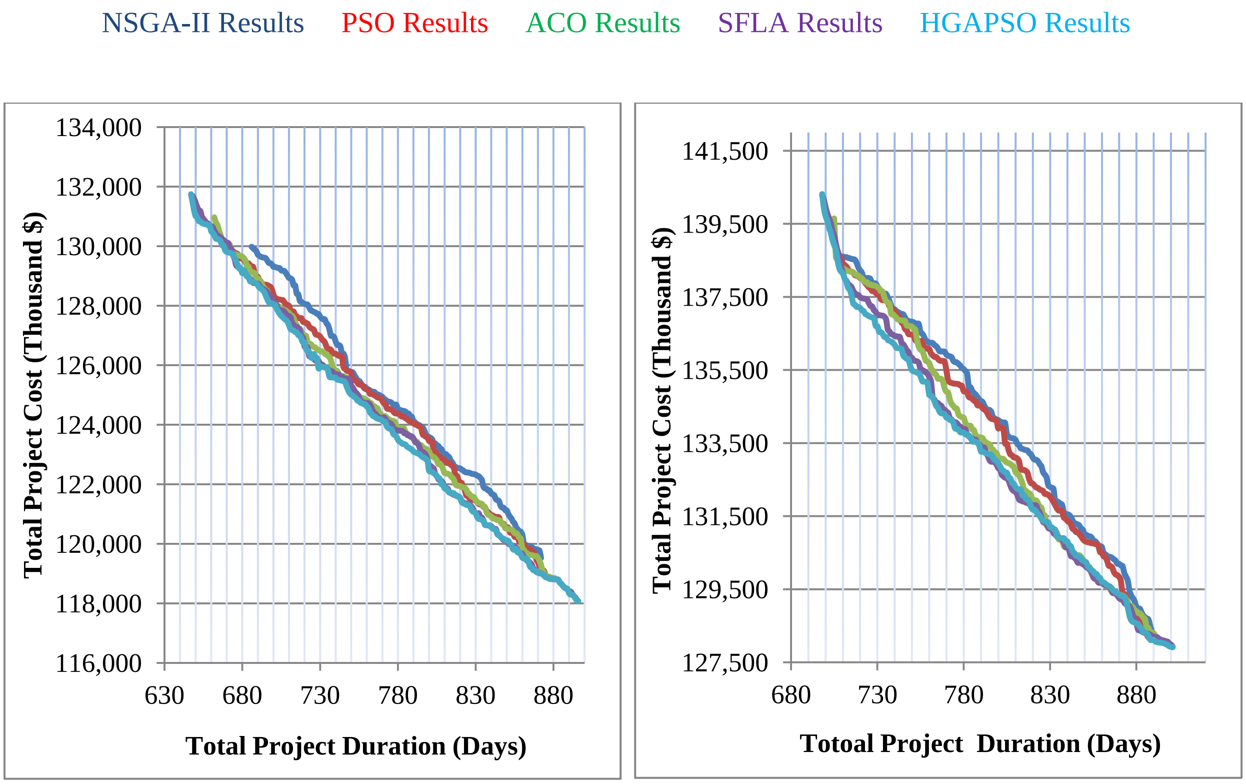
Legend: a4 —— (5)   a4 : Activity name   (5) : Node Number

Figure 4.9 Activity On Arrow (AOA) Network of Example 4.2

First, we compare our proposed hybrid approaches with Zahraie and Tavakolan's algorithms, and PSO and ACO algorithms considering the simultaneous minimization of total project cost and total project duration. Figures 4.10(a), 4.10(b) show project schedule solutions on the Pareto optimal fronts for this TCRO problem before and after applying inflation in the 2-dimensional space of total project cost and total project time. These Pareto optimal points show total project costs and total project durations for non-dominated project schedule solutions, which are derived by our proposed hybrid approaches as well as Zahraie and Tavakolan's (2009) algorithms. It can be seen that our proposed hybrid approaches are able to find project schedule solutions with lower total project costs and total project durations, which were not found by any of the previous algorithms. In particular, the project schedule solution with the shortest total project duration (i.e., 702 days) and the project schedule solution with the least total project cost (i.e., 128,579 Thousand Dollars) are just found by our proposed hybrid algorithms. Finding additional optimal project schedule solutions is one of the most significant contributions of our proposed algorithms over the existing optimization algorithms.

Table 4.5 Feasible project schedule options to perform Activity 1 in Example 4.2

Option No.	Duration (Days)	Required Resources (Numbers)																		Direct Cost ($)
		$R_{1,1}$	$R_{1,2}$	$R_{1,3}$	$R_{1,4}$	$R_{1,5}$	$R_{1,6}$	$R_{1,7}$	$R_{1,8}$	$R_{1,9}$	$R_{1,10}$	$R_{1,11}$	$R_{1,12}$	$R_{1,13}$	$R_{1,14}$	$R_{1,15}$	$R_{1,16}$	$R_{1,17}$	$R_{1,18}$	
1	62	0	0	0	0	5	3	2	1	2	0	0	1	5	3	5	4	2	8	148,648
2	63	0	0	0	0	5	3	2	1	2	0	0	1	1	0	1	2	0	6	147,296
3	64	0	0	0	0	5	3	2	1	1	1	0	1	1	1	2	2	0	4	145,944
4	65	0	0	0	0	5	3	2	1	1	0	0	3	5	4	2	3	6	2	144,592
5	66	0	0	0	0	5	3	2	1	1	0	0	2	2	1	3	3	5	5	143,240
6	67	0	0	0	0	5	3	2	1	1	0	0	0	0	1	3	5	6	8	141,888
7	68	0	0	0	0	5	3	2	1	0	1	0	1	0	0	0	1	3	1	140536
8	69	0	0	0	0	5	3	2	1	0	0	0	3	2	4	5	5	5	9	139,184
9	70	0	0	0	0	5	3	2	1	0	0	0	1	2	2	3	3	4	2	137,832
10	71	0	0	0	0	5	3	2	0	1	0	0	3	2	2	5	5	5	5	136,480
11	72	0	0	0	0	5	3	2	0	1	0	0	1	2	1	1	3	4	4	135,134

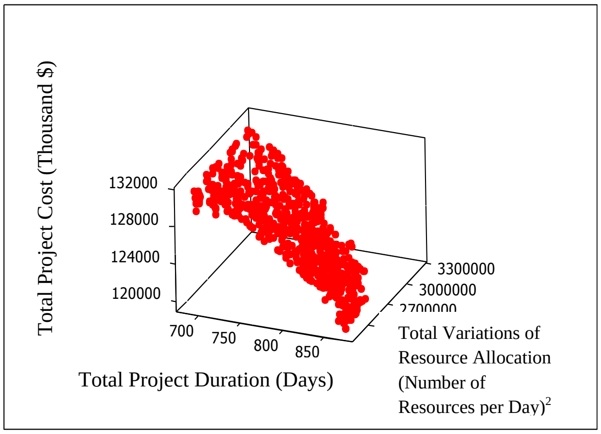


(a) (b)

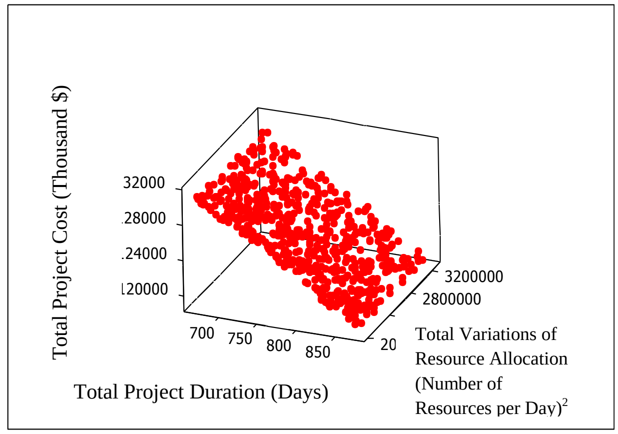
Figure 4.10 Optimal project schedule solutions found by the NSGA-II, PSO, SFLA, and HGAPSO algorithms in the 2-dimensional space of total project cost and total project duration, (a) before applying inflation, and (b) after applying inflation with indirect cost= $1,500 in Example 4.2

Next, we compare our proposed hybrid approaches with Zahraie and Tavakolan's (2009) algorithm considering the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation, or total time utilizations of resource allocation, or total resource allocation. Figures 4.11, 4.12, and 4.13 show project schedule solutions on the Pareto optimal fronts in the 3-dimensional space of project objectives: total project cost, total project duration, and total variations of resource allocation, or total time utilizations of resource allocation, or total resource allocation which are derived by Zahraie and Tavakolan's NSGA-II algorithm, our proposed hybrid approaches, and PSO and ACO algorithms, respectively. These Pareto optimal points show total project costs, total project durations, and total variations of resource allocation, or total time utilizations of resource allocation, or total resource allocation for non-dominated project schedule solutions, which are derived by our proposed hybrid approaches and Zahraie and Tavakolan's algorithm, PSO and ACO algorithm.

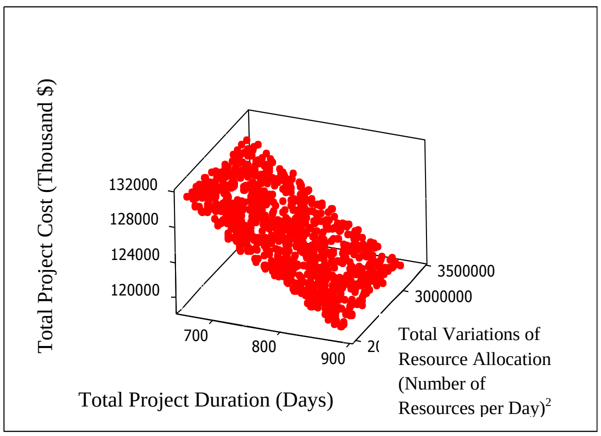
It can be seen that our proposed hybrid approaches are able to find project schedule solutions with lowest total project cost, total project duration, and total variations of resource allocation, or total time utilizations of resource allocation, or total resource allocation which were not found by Zahraie and Tavakolan's NSGA-II algorithm, PSO and ACO algorithms. In particular, the shortest total project duration found by our approaches (i.e., 698 days) is less than the shortest total project duration found by Zahraie and Tavakolan's algorithm (i.e., 729 days), PSO (i.e., 721 days), and ACO (i.e., 720 days). The least total project cost found by our approach (i.e., 127,909 Thousand Dollars) is less than the least total project cost found by Zahraie and Tavakolan's algorithm (i.e., 128,346 Thousand Dollars), PSO (i.e., 128,111 Thousand Dollars), and ACO (i.e., 128,056 Thousand Dollars) . The least total variations of resource allocation found by our approach (i.e., 2,283,073 (Number of Resources per Day)^2) is less than the least total variations of resource allocation found by Zahraie and Tavakolan's algorithm (i.e., 2,298,307 (Number of Resources per Day)^2), the values by PSO algorithm (i.e., 2,296,374 (Number of Resources per Day)^2), and ACO algorithm (i.e., 2,295,676 (Number of Resources per Day)^2). Also, the least total time utilizations of resource allocation found by our approaches (i.e., 47,149,973 (Number of Resources per Day)^2) is less than the least total time utilizations of resource allocation found by Zahraie and Tavakolan's algorithm (i.e., 47,152,906 (Number of Resources*Day)), the values by PSO algorithm (i.e., 47,152,158 (Number of Resources*Day)), and ACO algorithm (i.e., 47,151,171 (Number of Resources*Day)). The same approaches also can be seen in total resources allocation. The least total time utilizations of resource allocation found by our approaches (i.e., 5,190,683) is less than the least total resources allocation found by Zahraie and Tavakolan's algorithm (i.e., 5,199,735), and the values by PSO algorithm (i.e., 5,196,349), and ACO algorithm (i.e., 5,195,926). Finding additional optimal project schedule solutions with lower total project cost, total project durations, and total variations of resource allocation, or total time utilizations of resource allocation, or total resources allocation is one of the most significant contributions of our proposed approaches over the previous Zahraie and Tavakolan's optimization algorithm, PSO, and ACO algorithms. Further, our proposed approach also expedites the computational speed of solving TCRO problems in construction project planning. Our approach reduces the solution processing time by a factor of 3.2 compared to the previous Zahraie and Tavakolan's NSGA-II algorithm, 2.8 to the PSO algorithm and 2.5 to the ACO algorithm.



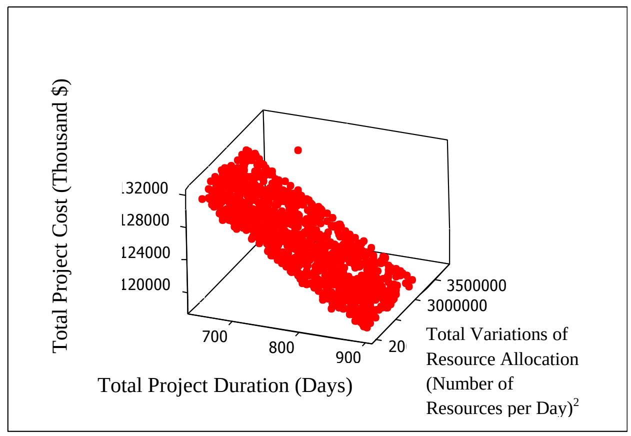
(a) NSGA-II Results



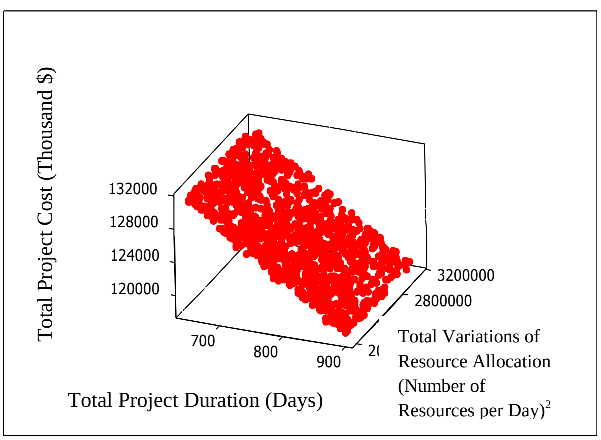
(b) PSO Results



(c) ACO Results

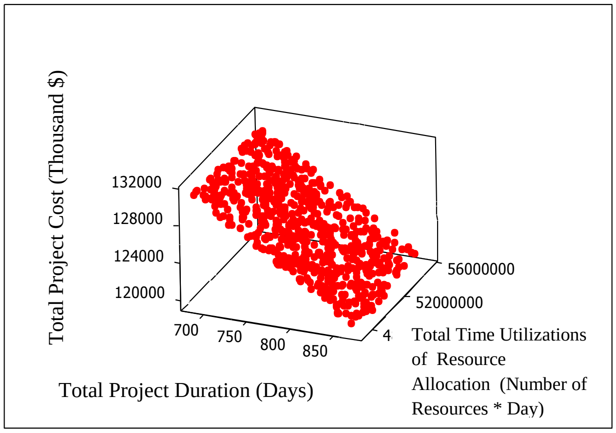


(d) SFLA Results

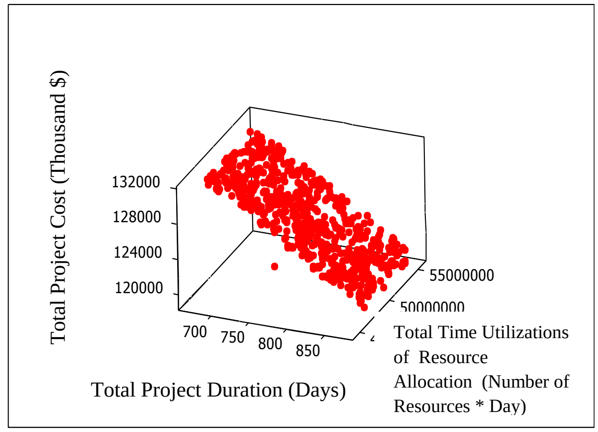


(e) HGAPSO Results

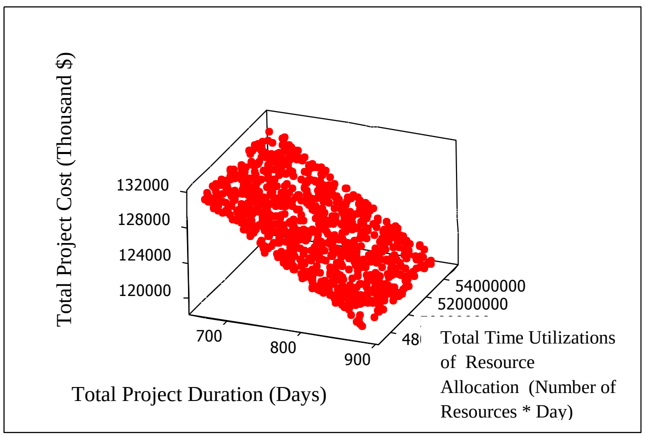
Figure 4.11 Optimal project schedule solutions found by the (a) NSGA-II, (b) PSO, (c) ACO, (d) SFLA, and (e) HGAPSO algorithms after applying inflation in the 3-dimensional space of total project cost, total project duration and total variations of resources allocation (Z_3) with indirect cost= $1,500 in Example 4.2



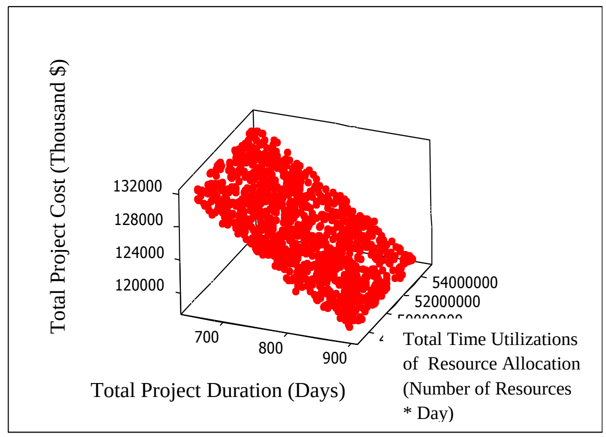
(a) NSGA-II Results



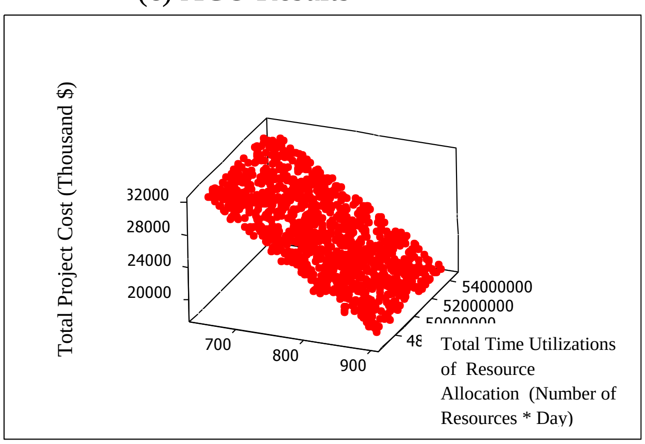
(b) PSO Results



(c) ACO Results

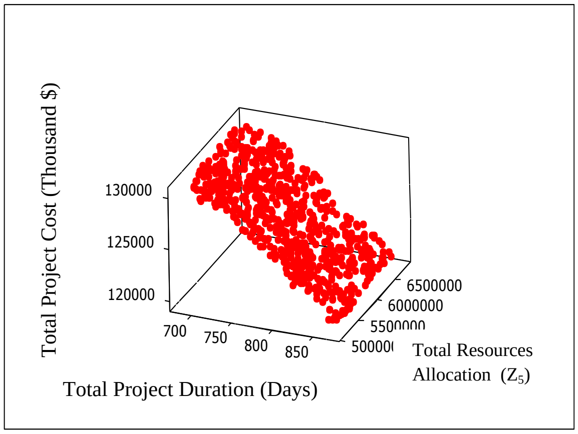


(d) SFLA Results

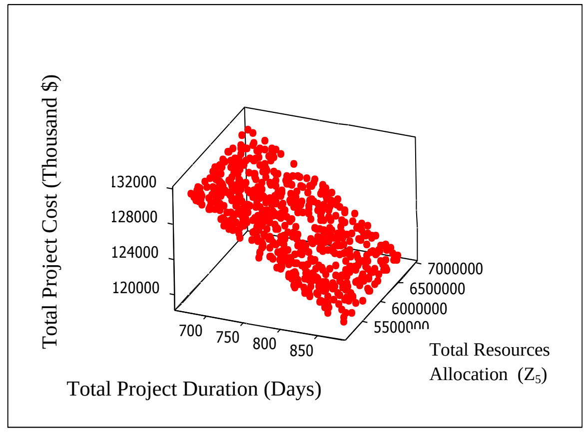


(e) HGAPSO Results

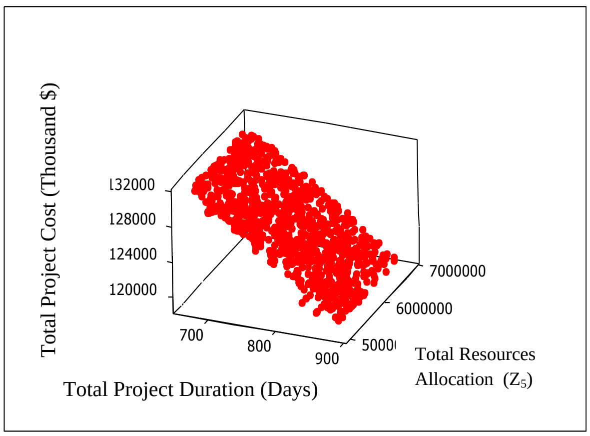
Figure 4.12 Optimal project schedule solutions found by the (a) NSGA-II, (b) PSO, (c) ACO, (d) SFLA, and (e) HGAPSO algorithms after applying inflation in the 3-dimensional space of total project cost, total project duration and total time utilizations of resource allocation (Z_4) with indirect cost= $1,500 in Example 4.2



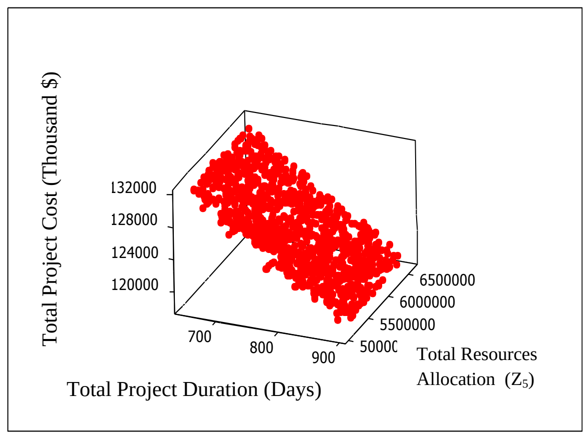
(a) NSGA-II Results



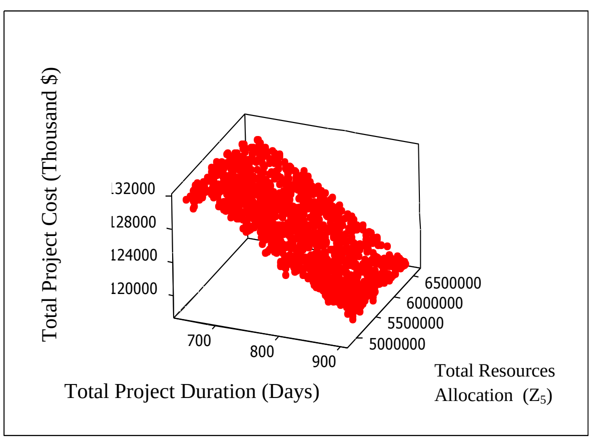
(b) PSO Results



(c) ACO Results



(d) SFLA Results



(e) HGAPSO Results

Figure 4.13 Optimal project schedule solutions found by the (a) NSGA-II, (b) PSO, (c) ACO, (d) SFLA, and (e) HGAPSO algorithms after applying inflation in the 3-dimensional space of total project cost, total project duration and total resource allocation (Z_5) with indirect cost= $1,500 in Example 4.2

It can be seen that by doubling the indirect cost from \$1,500 to \$3,000, the shortest total project duration found by optimization algorithms essentially stayed unchanged; however, considerable changes can be observed in the total project cost solutions. The changes in non-dominated solutions are presented in Table 4.6. Table 4.7 shows the comparison of required number iterations of five studied Evolutionary Algorithms to obtain optimal project schedule solutions in two examples.

Table 4.6 The increases of cost solutions when indirect cost= \$3,000 against \$1,500 in Example 4.2

Algorithm	Inflation	The least Cost	The highest Cost
NSGA-II	Applied	1.40%*	2.46%
PSO	-	0.81%	1.46%
	Applied	1.48%	2.32%
ACO	-	0.61%	0.88%
	Applied	1.36%	1.88%
SFLA	-	1.03%	1.49%
	Applied	1.16%	1.51%
HGA-PSO	-	1.04%	1.64%
	Applied	1.16%	1.62%

*:

$$\frac{(The\ least\ \cos t\ when\ indirect\ \cos t = \$3{,}000) - (The\ least\ \cos t\ when\ indirect\ \cos t = \$1{,}500)}{(The\ least\ \cos t\ when\ indirect\ \cos t = \$1{,}500)}$$

Table 4.7 The comparison of required iteration numbers by Evolutionary Algorithms in Examples: 4.1, and 4.2

Case studies	**Algorithms**				
	NSGA-II	**PSO**	**ACO**	**SFLA**	**HGAPSO**
Example 4.1 (with population size of 100)	1100	850	830	420	420
Example 4.1 (with population size of 300)	950	700	680	260	260
Example 4.2	5500	5350	5300	3100	3100

4.5 Comparison of Significant Parameters of Evolutionary Algorithms

We evaluate various algorithms in two examples with different sizes and structure of activities. If a project includes N activities, each with n_i number of options, then the total number of possible combinations is equal to $\prod_{i=1}^{M} n_i$ (Afshar et al. 2009). However, only the number of iterations takes into consideration the number of activities in a project. In other words, the larger the project scale is the more iterations would be needed to search for optimal solutions (Ng and Zhang 2008). In two examples, we are looking to optimize the number of iterations. Furthermore, we carry out trial and error on the significant parameters of GA, PSO and ACO. Clearly, the convergence speed of the model and quality of Pareto front will be changed by changing these parameters. The same parameters are used in hybrid algorithms in order to compare their capabilities correctly with the other EAs. By trial and error, we present the most suitable values for parameters to promote processing time and to obtain optimal project schedule solutions. Simultaneously, our optimization approach is to obtain the widest ranges of total project duration and total project cost solutions and finding the optimal values for resource allocation values which is one of the most important contribution of this study. Table 4.8

illustrates the values of parameters for three mentioned algorithms, which have been applied for both examples. The same values of parameters of GA and PSO are used for hybrid algorithms.

Table 4.8 The values of significant parameters of EAs in both Examples

Examples	Significant Factors									
	GA		**PSO**			**ACO**				
	P_{cr}	P_{mu}	C_1	C_2	ω	ρ	η	α	β	R
Example 4.1	0.35	0.1	1.5	1.5	0.8	-	-	-	-	-
Example 4.2	0.3	0.1	1	1	0.98	0.05	1.1	0.95	1.5	30

4.6 Conclusions

This chapter presents the comprehensive model of Time-Cost-Resource Optimization with evaluation of the capabilities and robustness of three Evolutionary Algorithms and two hybrid algorithms in terms of obtaining the shortest total project duration, the least total project cost, and the least resource moments in the least processing time and the fewest required number of iterations. We present HGAPSO and SFLA approaches to solve complex, TCRO problems in construction project planning. Our proposed approach uses the inflation impact on resources unit price to in TCRO problems. We apply HGAPSO and SFLA approaches to solve two optimization problems, which are found in the construction project planning literature. In each example, according to the project size, we evaluate the significant parameters of each algorithm to obtain the optimal project schedule solutions. We also evaluate the impact of initial population (Example 4.1) and indirect cost (Example 4.2) on the results of optimal project solutions.

It is shown that our proposed hybrid approaches are superior than existing optimization algorithms in finding better project schedule solutions with less total project cost, less total project duration, and less total variations of resource allocation, or less total time utilizations of resource allocation, or less total resources allocation. Finding additional optimal project schedule solutions with lower total project cost, shorter total project duration, and lower three resource allocation moments is one of the most significant contributions of our proposed approach over existing optimization algorithms: Senouci and Eldin’s GA (2004), Zahraie and Tavakolan’s (2009) NSGA-II algorithm, PSO algorithm, and ACO algorithm. In addition, our proposed approaches are capable of solving simultaneous TCRO problems with considering the inflation impact. This is a major improvement over existing methods: Senouci and Eldin’s GA algorithm, Zahraie and Tavakolan’s NSGA-II algorithm, and previous studies in GA, PSO, and ACO algorithms which are not capable of solving project planning problems by considering the inflation impact that require the simultaneous minimization of total project cost, total project duration, and total variations of resource allocation, or total time utilizations of resource allocation, or total resources allocation. Considering the lag time and any relation types between activities (SS,SF,FS,FF) in the TCRO problem are the other improvements of current study. Also, our results show that our proposed hybrid approaches are faster than existing methods in processing time for solving complex TCRO problems in project planning.

Chapter 5

Conclusions and Future Works

In this chapter, I provide a summary of conclusions and future works for this thesis. This study starts with the introduction of Time-Cost-Resource Optimization problems. In the last two decades (1990s to 2010s), Time-Cost tradeoff and resource leveling and allocation have been favored for conceptualizing optimization techniques. These optimization models have meaningful outputs including the ranges of non-dominated solutions of total project duration, total project cost, and total resources allocation moments. The results of TCRO problems have great importance for construction project planners. One of the most efficacious tools to optimize these kinds of problems is Evolutionary Algorithms, which are applied and compared in this dissertation. The three studies in this thesis contribute to a comprehensive model from the standpoints of construction project planning and computational optimization techniques. In this thesis, we present two hybrid optimization approaches to solve six optimization problems, which are found in the construction project planning literature. In each example, we evaluate the impact of significant parameters of EAs such as population size and parameters of the TCRO problem, such as indirect costs of the construction project, on the non-dominated solutions of the TCRO problem. It is shown that our proposed hybrid approaches are superior than existing optimization algorithms in finding better project schedule solutions with less total project cost, less total project duration, and less total values of resources allocation moments. The results also show that our proposed approaches are faster than existing methods in processing time for solving complex TCRO problems in construction project planning.

In addition, we present closer model to real construction problems and see their impact on the optimal project solutions by applying: (1) splitting during the execution of project activities as an internal factor in all construction projects; and (2) the rate of inflation in the resources unit price during the execution of the project as an external factor in all construction projects. I present the most important contributions from each of the three studies in this thesis below.

In Chapter 2, I present the Hybrid Genetic Algorithm-Particle Swarm Optimization (HGAPSO) with application of fuzzy set theory to improve the convergence rates and optimal project solutions of TCRO problems. Our proposed approach uses the fuzzy set theory to characterize uncertainty about the input data (i.e., time, cost, and resources required to perform an activity) in this hybrid approach. Both discrete and various mathematical types of continuous time-cost functions, such as nonlinear, linear, and hybrid convex/concave shapes, are applied for the construction project activities in three examples adopted from previous studies in GA, fuzzy GA, and PSO. The optimal project schedule solutions found by the HGAPSO algorithm in the 2-dimensional space of total project cost and total project duration, and the 3-dimensional space of total project cost, total project duration, and total variations of resource allocation demonstrate the improvement of the optimal Pareto front of project schedule solutions to obtain the shortest total project duration, the least total project cost, and the fewest total variations of resource allocation.

In Chapter 3, I apply another hybrid algorithm, the Shuffled Frog-Leaping Algorithm (SFLA) to the TCRO problem with activity splitting allowed. The shuffling of TCRO solutions in various memeplexes in each solution population, and use of memes capabilities (instead of genes in GA) are the most significant reasons to improve the optimal project schedule solutions. In addition, using the advantages of two algorithms (PSO and SCE) simultaneously in the optimization process improves the speed of convergence to the non-dominated solutions. In previous studies, the splitting impact during activities execution has been disregarded on the optimal project schedule solutions. Our proposed approach uses splitting allowed to obtain the project schedule solutions of the TCRO problems. The results of the 2-dimensional space of total project cost and total project duration, and the 3-dimensional space of total project cost and total project duration, and total variations of resource allocation, or total time utilizations of resource allocation demonstrate that applying splitting to the non-critical construction project activities will make model superior than existing optimization algorithms in finding better project schedule solutions in the TCRO problems. It also can be seen that keeping track of the splitting allowed at activities execution permits the construction project planner to know in which activities they can use splitting to obtain the shortest total project duration and the least total project cost for the construction project. The results in two construction projects also show that our proposed SFLA approach is faster than existing methods in processing time for solving complex TCRO problems in construction project planning.

In Chapter 4, we compare the three most applied Evolutionary Algorithms (GA, PSO, ACO) as previously presented optimization technique tools in the concept of construction engineering and management problems. We evaluate the capabilities of mentioned algorithms in terms of convergence ratio and quality of Pareto front of project schedule solutions in the TCRO problems and compare them with the two hybrid algorithms, HGAPSO and SFLA which have been presented in Chapters 2 and 3, respectively. Based on the kinds of resources (manpower, machinery and material) and the activities duration, the various inflation rates are considered for resources unit price during the execution of construction project activities. We present an equivalent factor for monthly inflation rate based on the future value of money concept on two TCRO problems, which are found in the construction project planning literature. Considering the inflation rates on the resources of the TCRO problem as a reality in actual construction projects is another significant contribution of our proposed model over previous optimization approaches. Two examples (the second example is the actual and large-scale construction project with the complex structure of activities dependencies) are adopted from the construction project planning literature, in order to evaluate the robustness of optimal project schedule solutions in all EAs. We evaluate the impact of significant parameters of GA, PSO, and ACO algorithms in these examples. We present the most suitable values for the parameters to promote processing time and to obtain the optimal project schedule solutions. We also evaluate the impact of population size (as an important effective factor of EAs) and indirect cost (as an important factor of construction projects) on the Pareto front of non-dominated solutions. The results of the 2-dimensional space of total project cost and total project duration and the 3-dimensional space of total project cost and total project duration, and total variations of resource allocation, or total time utilizations of resource allocation, or total resources allocation demonstrate that hybrid algorithms have the best performance in terms of the shortest total project duration, the least total project cost, and the fewest values of resource allocation moments, in the least processing time.

This research contains several limitations that should be addressed in future research of TCRO models. It is suggested that for empirical results of TCRO problems, the actual case studies of construction projects be applied in the model. It is obvious that considering actual case studies (with more than 500 activities) interferes with other effective factors in the stage of construction projects planning. The validity and reliability of TCRO problems depend on the constraints of actual case studies. It is recommended to consider the bonus values in case of completing the project before the deadline or the penalty values in case of completing the project after the deadline. Since these values are dependent on total project duration, they will change the results of the TCRO problem. Furthermore, the impact of interest rates on direct or indirect costs of project can be considered in the TCRO problem. Another limitation of the models is considering the other objective functions such as quality (Time-Cost-Resource-Quality) for the current models.

Chapter 6

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