



A two-phase method for a multi-skilled project scheduling problem with discounted cash flows

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Abstract. This paper considers a multi-skilled project scheduling problem that is a newly developed extension of the Resource-Constrained Project Scheduling Problem (RCPSP). The main difference in such problems, compared with classic scheduling problems, is associated with the given resources, which are only dependent on human type. Additionally, the net present value of a given project is considered by its cash in and out flow to guarantee project success. To solve the given problem, an enhanced two-phase method is proposed using genetic and path relinking algorithms, whose parameters are tuned by the Taguchi method to provide robust comparisons. Furthermore, the potential changes in the project execution method are considered for some of the mostly used payment methods. Finally, some different-sized instances are tested to check the performance and efficiency of the proposed method.

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1. Introduction

The Multi-Skill Project Scheduling Problem (MSPSP) was first addressed as a new scope in the development of project scheduling problems [1,2]. In other words, the MSPSP is an extended version of the resource-constrained project scheduling problem (RCPSP), in which different labor skills are needed to accomplish an activity. In a fairly similar extension, activities can be completed within different execution modes, which are referred to as multi-Mode Resource Constraint Project Scheduling Problems (MRCPSP). MSPSP can be mainly differentiated from MRCPSP in regard to resource types and activity requirements. Without loss of generality, staff members constitute the chief resource of the organization in the MSPSP, while each member owns different skills to complete project

activities. However, each activity can be performed by different execution modes in the MRCPSP in which a balance should be met with respect to mode selection and resource usage.

In the MSPSP, it is significant to find out how the staff members are designated to activity requirements. Each skill requirement should be satisfied by just one of the staff members potentially qualified. If it is aimed at establishing an association between the MSPSP and the MRCPSP, execution modes of an activity encompass a subset of qualified resources that can be assigned to it. In a broader sense, the number of modes of performing each activity in the MSPSP pertains to a subset of resources (i.e., staff members) qualified to deal with skilled requirements. Consequently, if it is to enumerate different alternatives of project execution, with respect to the corresponding skills, a large number of states can be developed, so that the problem may not be solved, even at medium size [3]. However, if the activities can be carried out just by mere skill, the MSPSP is then transformed into a classic RCPSP. Figure 1 shows a typical network of project activities

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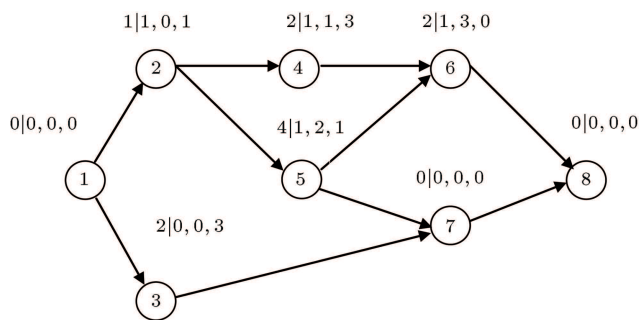


Figure 1. Precedence relations and activities requirement in an MSPSP.

in which three different skills are utilized to accomplish the project. The numbers written above each activity stand for the execution time and resource needs, respectively. The threesome of resource requirements is associated with three determined skills. For example, the numbers above activity 6 indicate that 2 time units are needed for each skill, once staff members 1 and 3 are needed for the first and second skills, respectively. Moreover, there is no need for the third skill. It can be assumed that the organization wants to assign its staff to the aforementioned project, while they are not identical in regard to the skills possessed (i.e., some of them have all three skills at once, while some may just possess a single skill). It is also evident that the number of assigned staff members and their qualifications directly influences the outcome.

The concept of the MSPSP can be incorporated by a job shop definition in which the jobs should be processed by multi-process machines [4]. On the other hand, the MSPSP can be addressed as the same MRCSPSP but with a noticeable raise in potential modes. Hence, the problem complexity increases, so that classic solution techniques cannot be used efficiently.

Many situations can be found in which the deliverables are dependent on human skills. Thus, the MSPSP importance can be highlighted better in such fields. For example, consulting firms, social security organizations, after-sale service centers, research-based organizations, information technology, engineering activities, and auditing institutes can all be archetypes of an MSPSP. Therefore, there are many different instances, in which the MSPSP can be applied. However, few research findings exist about this branch of project management in the literature. For example, Wu and Sun [5] (2006) presented a Mixed-Integer Non-Linear Programming (MINLP) model for project scheduling and staffing in addition to the learning effect. They considered no precedence relations amongst the activities and applied a Genetic Algorithm (GA) as the solution approach. Gutjahr et al. [6] (2008) also applied an MINLP model for staffing in project scheduling, with respect to the weighted average maximization of

project economic gain. A greedy priority-based heuristic was used to develop the scheduling. Valls et al. [7] (2009) dealt with task scheduling and multi-skilled workforce assignment under multi-criteria consideration for a service center. They proposed a hybrid GA approach as the solution methodology. Kazemipoor et al. [3] (2012) also addressed the portfolio scheduling of the MSPSP using a goal programming approach, and proposed the differential algorithm as the solution method.

In addition to above instances, the following are merely associated with the MSPSP. Bellenguez-Morineau and Néron [2] (2005) introduced the MSPSP considering the project makespan minimization. They proposed an integer Linear Programming (LP) model and took different skill levels for staff members. Moreover, Tabu Search (TS) was applied to solve the model. In a further study, Bellenguez-Morineau and Néron [8] (2007) presented a branch-and-bound algorithm for the problem in small and medium sizes, and studied different branching strategies. Bellenguez-Morineau [9] (2008) also applied TS in order to solve the MSPSP, and compared its performance with GAs in which TS could outperform them. Al-Anzi et al. [10] (2010) suggested a lower bound by LP based on the classical RCPSPs. Firat and Hurkens [11] (2012) applied a Mixed-Integer Programming (MIP) formulation to build schedules by repetitive usage of a flexible matching model. Yannibelli and Amandi [12] (2013) also addressed the effectiveness of human resources in carrying out a project in the light of an Objective Function (OF) in addition to makespan minimization.

Within the project completion process, resources are utilized in terms of activity requirements and their corresponding implementation times. As the project activities are completed, associated cash flow occurs. The issue can be addressed to cash out flow, as the contractor incurs expenses, along with each activity execution. Considering the financial perspective in project investigations has received much focus, since over 60 percentage of contracts encounter failure because of financial facets. Likewise, different financial factors (e.g., interest rate, credit limits, and payment condition) have been addressed as crucially influencing issues on timing the amount of resource usage. In fact, project yield maximization with respect to cash flow considerations can guarantee a reliable execution plan in which the project does not face failure. To do so, Barbosa and Pimentel [13] (2001) proposed a linear programming model for cash flow management in the Brazilian construction industry. Elazouni and Gab-Allah [14] (2004) presented profit maximization with respect to a credit limit. However, most papers have only considered positive cash flow, received after each phase, or when the whole project is delivered. They assumed that negative cash flow can be thoroughly

interpreted by just activities and there is no need to consider resource usage. In fact, the activities can be completed once sufficient resources are available and allocated to them. Thus, a resource cost can be taken into account as the crucial component of an activity cost. Likewise, it is advisable to bring cash outflow into calculation, so that the actual expenditure and resource assignment method can be reflected in the given scheduling problem.

Once the RCPSP is transformed into the MRCPSP with discounted cash flow, the given schedule is no longer necessarily optimal. In other words, the activity sequences may be altered to a large extent. This can be interpreted for certain circumstances in which different alternatives lead to the same minimum makespan; however, not all of them yield to the maximum Net Present Value (NPV). In a broader sense, maximizing the net NPV can be considered a makespan minimization, by summing all cash flow and putting it at the project completion time, for situations in which all cash flow is positive [15].

There are at least two different parties involved in each project for contraction purposes. The former is the client, which can be addressed as the project owner, and the latter is the contractor, who is in charge of project execution. Therefore, they should agree upon the payment method so that the contract can be signed. It is obvious that the client tends to deal with the whole payment at the project delivery due date, and the contractor inclines to receive the whole payment at the outset of project execution. However, it should be noted that in NPV maximization problems, the optimal approach is taken into consideration from the contractor's point of view. According to the extant literature, several types of contract and payment model have been developed. For instance, Dayanand and Padman [16] (1997) presented a comprehensive survey about payment methods. Chen et al. [17] (2005) also dealt with the impact of payment conditions and the accuracy of project cash flow. However, four payment methods have received much attention, in practice, amongst those existing. They can be listed as: Lump Sum Payment (LSP), Payment at Event Occurrences (PEO), payment at Equal Time Intervals (ETI), and Progress Payments (PP). In the LSP method, the whole payment is fulfilled at the end of the project when it is successfully delivered to the client. The contractor has to incur all financial burden of the project within the execution interval. However, the client may be strongly in favor of this method, as he/she can abide by his commitment by a single payment. Since LSP may be inappropriate in some situations, the other three methods can be substituted as reasonable choices in which negotiating parties decide on the project duration. Without loss of generality, in PEO, the payments are carried out

when specific events are completed. In ETI, the payments are fulfilled in $H-1$ equal time intervals and the H th payment is done at the completion time. In other words, the project time should be estimated first and the number of payments should be determined, afterwards. Finally, in the PP method, the payments are practiced in the course of project completion within regular time intervals. However, PP is different from ETI, as in the first one, the two parties concur with the length of the interval instead of the number of payments.

Ulusoy et al. [18] (2001) considered the time value of money in the NPV maximization of cash flow. They considered an MRCPSP with discounted cash flow, in which all renewable, non-renewable, and doubly constrained resource types were extant. A GA was used to find near-optimal solutions enhanced by a multi-component uniform order-based crossover. It was tested against local constraint-based analysis and proved efficient.

Mika et al. [15] (2005) addressed discounted cash flow maximization in an MRCPSP for an Activity-On-Arrow (AOA) network. They only took positive cash flow into account and assumed that executive costs are not dependent on time, but rather fixed and apart from the project duration. However, the issue is not true for all situations, as organizations can be investigated that may borrow additional aid from external experts or even outsource a specific set of activities. Simulated Annealing (SA) and TS were applied as the solution methodology and the results were compared. It was shown that SA could reach efficient results for large-sized problems for a fixed discount rate, while TS outperformed for a restricted number of activities.

Liu and Wang [19] (2011) considered profit maximization for project selection and scheduling problems with time-dependent resource constraints by constraint programming. They extended the problem into two distinctive scenarios including profit maximization with time-dependent budget limits and profit maximization with time-dependent renewable resource constraints, so that smoother budget consumption and resource usage can be realized.

The aforementioned papers indicate that MSPSP needs to be developed so that it can function better with respect to both its comprehensiveness and result quality. Hence, we consider the problem with the perspective of the NPV to provide a higher security margin for organization survival. Furthermore, we have tried to enhance the obtained schedules for a given payment method, to which both sides have concurred.

The rest of the paper is organized as follows. The problem definition and mathematical model is presented in Section 2. The next section is associated with

a solution representation and a two-phase enhanced GA in which Path Relinking (PR) is addressed as an improvement methodology for the GA output. The computational results are discussed in Section 4, in which the performance of the two-phase algorithm is compared with that of the GA. Finally, conclusions and future research directions are presented in the last section.

2. Problem definition

The problem definition is addressed in this section and the mathematical model is developed afterwards. As stated earlier, we aim to schedule activity execution so that staff members can be assigned appropriately to gain optimal cash flow. In other words, the payment method, number of personnel, and the number and frequency of extant skills can all directly influence the scheduling problem. In order to formulate the mathematical model, notations, parameters, and decision variables are introduced as follows.

2.1. Indices and notations

$i, j \in \{1, 2, \dots, N\}$	Counter of activities,
$k, k' \in \{1, 2, \dots, K\}$	Counter of skills,
$m \in \{1, 2, \dots, M\}$	Counter of resources,
$p \in \{1, 2, \dots, P\}$	Counter of payment occurrence.

2.2. Parameters

$G = (V, E)$	Precedence network where G represents the given graph. V and E stand for vertexes and edges, respectively;
$S = \{s_1, s_2, \dots, s_k\}$	Set of skills;
$R = \{r_1, r_2, \dots, r_M\}$	Set of resources (i.e., staff members);
b_{ik}	Required amount of the k th skill to do the i th activity
p_i	Execution time of the i th activity;
r	Rate of interest;
CF_i^-	Cash outflows (resource utilization cost) for the i th activity;
CF_p^+	Cash inflows (payments) for the p th payment;
T_p	Time of the p th payment occurrence;

$$r_{mk} = \begin{cases} 1 & \text{if resource } m \text{ has the } k\text{th skill} \\ 0 & \text{otherwise} \end{cases}$$

2.3. Decision variables

x_{ikm}	Start time of the i th activity by resource m and the k th skill
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$$y_{ikm} = \begin{cases} 1 & \text{if resource } m \text{ executes the } i\text{th} \\ & \text{activity with the } k\text{th skill} \\ 0 & \text{otherwise} \end{cases}$$

$$f_{ijkk'}^m = \begin{cases} 1 & \text{if } x_{ikm} \geq x_{jk'm} \\ 0 & \text{if } x_{ikm} < x_{jk'm} \end{cases}$$

Now, the mathematical model can be formulated, with regard to the previous definitions by Eqs. (1)–(7), in which Eq. (1) stands for the Objective Function (OF) and the rest constitute the model constraints:

$$\begin{aligned} \max Z = \text{NPV} = & \sum_{i=1}^N CF_i^-(1+r)^{-x_{ikm}} \\ & + \sum_{p=1}^P CF_p^+(1+r)^{-T_p}, \end{aligned} \quad (1)$$

s.t.:

$$\begin{aligned} x_{ikm} - x_{jk'm} & \geq (y_{ikm})(y_{jk'm})(p_j) - M f_{ijkk'}^m; \\ \forall i, k, m, \end{aligned} \quad (2)$$

$$\begin{aligned} x_{jk'm} - x_{ikm} & \geq (y_{ikm})(y_{jk'm})(p_i) - M(1 - f_{ijkk'}^m); \\ \forall i, k, m, \end{aligned} \quad (3)$$

$$\sum_{m=1}^M r_{mk} y_{ikm} = b_{ik}; \quad \forall i, k, \quad (4)$$

$$\begin{aligned} \min\{x_{jk'm'}\} - \max\{x_{ikm}\} & \geq p_i | y_{ikm}, y_{jk'm'} = 1; \\ \forall k, k', m, m', \end{aligned} \quad (5)$$

$$x_{ikm} \leq M y_{ikm}; \quad \forall i, k, m, \quad (6)$$

$$x_{ikm} \geq 0, \quad \text{and} \quad y_{ikm} \in \{0, 1\}. \quad (7)$$

Eq. (1) maximizes the NPV of project execution gain, which can be calculated by the difference between incurred expenditures and fulfilled payments. The corresponding costs are imposed on the system as the activities start; however, the payments are satisfied, along with determined milestones, according to the compromised payment method. The precedence relations are taken into account by Eqs. (2) and (3). They guarantee the constraint of non-preemptive assignment of resources to the activities. In other words, a resource is not allowed to be assigned to another activity at the same time if it is to deal with a specific activity skill. Eq. (4) states that the assigned resources to each activity should be equal to the required amount, with respect to the given skill. The next constraint, namely Eq. (5), guarantees that each work can start,

once sufficient resources are assigned to it. Eq. (6) expresses that the i th activity can be performed by the m th resource and the k th skill, only if it is assigned to it, and, finally, the variables nature is represented by Eq. (7). Moreover, M denotes the big M method.

It is obvious that the aforementioned model is non-linear; hence, more computational effort is needed to solve it. The intrinsic complexity increase of non-linear problems can be prevented by applying a linearization technique. Eqs. (2) and (3) can be substituted by Eqs. (8) and (9), respectively, in the linear equivalent model, where the binary variables are replaced by introducing an alternative variable, namely $z_{ijkk'm}$. It is also required to practice some further constraints on the given formulation to take the influence of the previous variables into account (i.e., Eqs. (10)–(12)). Moreover, Eq. (5) can be easily treated by Eq. (13), with regard to the precedence relations, as follows. In fact, it is obvious that a given activity can start just when all of the required skills of its prerequisites have been completed.

$$x_{ikm} - x_{jk'm} \geq z_{ijkk'm}p_j - Mf_{ijkk'}^m; \quad \forall i, k, m, \quad (8)$$

$$x_{jk'm} - x_{ikm} \geq z_{ijkk'm}p_i - M(1 - f_{ijkk'}^m); \quad \forall i, k, m, \quad (9)$$

$$z_{ijkk'm} - x_{ikm} - x_{jk'm} + 1.5 \geq 0; \quad \forall i, j, k, k', m, \quad (10)$$

$$1.5z_{ijkk'm} - x_{ikm} - x_{jk'm} + \leq 0; \quad \forall i, j, k, k', m, \quad (11)$$

$$z_{ijkk'm} \in \{0, 1\}. \quad (12)$$

3. Solution representation and generation scheme

In this section, a brief discussion is presented about GA and PR and the associated procedure, as well. It is first required to outline the applied solution representation and schedule generation approach in order to deal with the solution methodology. A preprocessing is carried out before the GA starts. This helps the applied algorithm search a smaller solution space. The reduction is obtained through the generation of initial solutions, in which infeasible schedules are not developed regarding the skill availability of the given resource.

Regarding the preprocessing phase, the GA starts by generating the initial population. Afterwards, the given individuals can be evaluated by transforming

them into the schedules. The following steps are repeated until the stop criterion is satisfied, once the fitness value of all initial population individuals is determined. A selection mechanism is applied in order to transform the set of better individuals to the next generation with a higher probability. The given population is sorted by random pairs of individuals and the pairs experience a crossover operation to generate new offspring. Meanwhile, some of the individuals are modified by a mutation operation to a specific probability. However, the operations should be performed so that the individuals may not be excluded from feasibility. As the termination criterion is met, the selected individuals are transformed into the improvement phase implemented by the PR algorithm. The aforementioned steps are described in more detail below.

3.1. Genetic Algorithm (GA)

The GA has received much favor in different combinatorial optimization problems since it was first introduced by Holland [20] (1975). It actually tries to mimic the biological evolution process to enhance solution quality. Referring to Darwinian natural selection and mutations in biological reproduction, a GA has been generalized to different modes, with respect to the evolution process. It has proved quite efficient in dealing with discrete optimization problems, as it can move toward high performance even in intricate search spaces [21–23]. Utilizing a crossover operator helps the algorithm explore different parts of the solution space, while the exploitation can also be fulfilled by the use of mutation. Applying mutation hampers the algorithm to experience premature convergence on a local optimum [24]. However, reaching good solutions highly depends on the proper representation of solutions.

As stated above, it is required to develop the genotype, namely the schedule representation, in order to start the GA. Kolisch and Hartmann [25] (1999) indicated five different schedule representations associated with the RCPSP. Amongst the stated representations, Activity List (AL) and Random-Key (RK) have been used more frequently. A priority structure is taken into consideration, apart from which of them is selected. However, the relative priority of an activity is determined in the AL representation, with respect to its position, compared with the other activities, while, in the RK representation, the position of an activity depends on the corresponding priority value assigned to it. A structured AL representation has been applied in this study, as the AL has proved efficient in a variety of related papers (e.g., [26–28]). The applied AL-based representation is illustrated by Figure 2 in which, for example, the first activity requires just a unit resource of the second skill executed by staff member 4 on

Skills	Activity 1			...	Activity N	
	(Staff number, start time)	(Staff number, start time)	(Staff number, start time)		(Staff number, start time)	(Staff number, start time)
1	(5,0)	(0,0)	(4,4)	...	(2,45)	(4,45)
2	(4,2)	(0,0)	(0,0)	...	(0,0)	(1,44)
⋮	⋮	⋮	⋮	⋮	⋮	⋮
K	(2,0)	(3,1)	(1,0)	...	(6,50)	(7,52)

Figure 2. Typical AL-based solution representation for the given project.

Repeat the following steps for the MSPSP, respectively.

- Generate random feasible individuals until their number equals to the population size.
- Begin the algorithm and continue so that the termination criterion, maximum iteration, can be met.
 - Evaluate each individual's fitness.
 - Determine the elite individuals.
 - Apply roulette wheel selection to select pairs for mating.
 - Replenish the population.
 - Apply crossover operator.
 - Apply mutation operator.
- Check for the termination criterion.
- Loop, if not terminated, otherwise

End.

Figure 3. Pseudo-code of the proposed GA.

start time 2. It is obvious that a required number of columns can be regarded for each activity, with respect to the maximum resource requirement. For instance, the first activity required three units of skill K and, therefore, three columns have been considered for it. Furthermore, the activities execution times have been considered by day units.

On the other hand, it is required to decode the genotype into phenotype carried out by a Scheduling Generation Scheme (SGS). Here, the serial SGS is chosen in which the individuals are directly transformed into their associated schedule. Without loss of generality, the SGS shows how a feasible schedule is obtained by assigning starting times to the different activities. More details can be studied in Kolisch [29] (1996), who provided a comprehensive gathering on SGSs. Finally, the pseudo-code of the proposed GA is shown by Figure 3.

3.2. Path Relinking (PR)

PR was first proposed by Glover and Laguna [30] (1997), as an integrated intensification and diversification strategy, to explore trajectories connecting elite solutions obtained by TS or Scatter Search (SS). More details can be found about the application of the PR algorithm to the combination of solutions in Glover et al. [31] (2000). In this algorithm, the paths leading to higher quality solutions are searched, taking two or more of the elite solutions into consideration. In other words, the search process starts from a high-fitted solution (namely, the initial solution) and is ended in another high-fitted solution (namely, the guiding solution). An important point in generating paths

is that just the moves representing the attributes in the guiding solution are picked out. This issue can be referred within the circumstances in which a given number of choices are allowed to be checked for the next move. The next move containing the guiding solution attribute is selected if it leads to a better OF value compared with the previous choice. This process is repeated until the whole path connecting the initial and guiding solutions is searched.

Different studies can be found about the application of PR as a complementary tool on the optimization of project scheduling problems. The widespread usage of PR denotes the noticeable efficiency in exploiting the solution space. For instance, Valls et al. [32] (2004) introduced PR as a combinatorial component for SS in the RCPSP in order to obtain high quality schedules. Yamashita et al. [33,34] used a PR mechanism to update the SS reference set in a project scheduling problem with a resource availability cost. In further research, Ranjbar et al. [26] (2008) addressed the PR approach in the resource availability problem by a modified GA. Ranjbar et al. [35] (2009) used a similar framework, namely SS and PR algorithms, in a discrete resource/time trade-off problem, where activities could be performed by different modes. Baradaran et al. [36] (2010) also utilized PR as an improvement method in the SS algorithm for the RCPSP in PERT networks. Alvarez-Valdes et al. [37] (2008) dealt with a combination of Greedy Randomized Adaptive Search Procedures (GRASP) and PR algorithms in scheduling projects with renewable resources. Tchao and Martins [38] (2008) applied PR as a post optimization method for the TS output, so that the connecting paths of TS elite solutions can be searched.

In order to apply PR in the aforementioned two-phase problem, some issues should be taken into account. The first underlying issue is the solution enhancement by the GA output. In other words, we do not encounter elite solutions; however, a set of high quality solutions is available. In fact, the GA output contains a gathering of individuals with the most fitted values, with respect to the fitness function. Therefore, all of the last generation individuals can be involved in the improvement phase. The second phase can be performed with regard to the population frequency, so that a pair of individuals can be selected randomly and their connecting trajectories are investigated. The

second issue corresponds to the feasibility preservation, which is of great importance. In other words, it is first required to check that the next move does not surpass the network precedence relations and, if it is a legal choice, then, it can be selected for further consideration. Afterwards, the next move is selected if it can yield to a better fitness value, and rejected, otherwise. However, the hopefully improving paths should be checked, with respect to the resource assignment method, apart from the activity sequences. The pseudo-code of the proposed PR is shown by Figure 4.

4. Computational study

In this section, the computational study is dealt with, in order to consider the model performance and effi-

Repeat the following steps for the MSPSP, respectively.

- Apply the solutions obtained from the last generation of the GA as the input of the PR algorithm.
- Begin the algorithm and continue so that the termination criterion, maximum iteration, can be met.
- Select a random pair of individuals as the initial and guiding solutions, respectively.
 - Consider the connecting trajectories between the individuals.
 - Perform the moves with respect to the number of the genes.
 - Accept the moves that have enhanced the fitness function maintaining the feasibility.
- Check for the termination criterion.
- Loop, if not terminated, otherwise

End.

Figure 4. Pseudo-code of the proposed PR algorithm.

ciency of the solution methodology. The required data set are generated randomly in a logical way regarding the rare accessibility to well-known test problems. A typical instance is taken into consideration in which discussed payment methods are compared with each other. Afterwards, some different-sized problems are investigated, so that the performance of the solution method can be highlighted. This leads to realization of how the improvement method can influence the final results for different problems. All calculations are run by C++ software on a Core i5PC with 2.0 GHz CPU and 4 GB of RAM.

Figure 5 shows a simple network to address the potential influence of each of the aforementioned payment methods on project execution. However, it is required to tune the parameters of the solution method so that robust results can be obtained. Therefore, the applied tuning approach is described below. Moreover, the data generation method is shown by Table 1.

4.1. Parameter tuning

The performance of the meta-heuristic methods can be highly influenced by their operators. Likewise, the GA

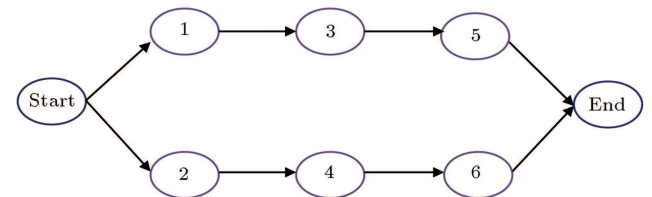


Figure 5. AON example of a project.

Table 1. Data generation method for the parameter values.

Organization	No. of resources (staff members)	Parameters	Corresponding random distribution
Type I	10	N (number of activities)	$\sim U[10, 40]$
		K (number of skills)	$\sim U[2, 6]$
		r_{mk}	$\sim U[0, 1]$
		b_{ik}	$\sim U[0, 5]$
		p_i	$\sim U[1, 5]$
		r	$\sim U[0.04, 0.06]$
		CF_i^- (\$)	$\sim U[5, 15]$
		CF_p^+ (\$)	1.2 times of the sum of the cost of the activities execution to ensure there is a positive NPV
Type II	50	N (number of activities)	$\sim U[20, 90]$
		K (number of skills)	$\sim U[2, 10]$
		r_{mk}	$\sim U[0, 1]$
		b_{ik}	$\sim U[0, 7]$
		p_i	$\sim U[1, 5]$
		r	$\sim U[0.04, 0.1]$
		CF_i^- (\$)	$\sim U[5, 15]$
		CF_p^+ (\$)	1.5 times of the sum of the cost of the activities execution to ensure there is a positive NPV

behavior can be dependent on its parameters to a large extent. Thus, selection of the most efficient choices by the appropriate methods is fundamental. There are different ways to run an experimental consideration. However, their performance can be compared with regard to the criteria influencing the computational efforts. For example, full factorial design is one of the most frequently applied methods in tuning meta-heuristic parameters [39]. However, it cannot be justified as an efficient approach, because a large amount of effort is needed once the frequency of factors increases, in particular [40–42]. Cochran and Cox [43] (1992) developed a fractional factorial experiment to moderate the number of essential tests. Likewise, Taguchi [44] (1986) addressed the fractional factorial experiment matrices that can decrease the number of required experiments and appropriate preservation of information. In other words, orthogonal arrays utilized in the Taguchi method help to study a broad amount of decision variables by the use of a small number of experiments. This method takes the factors into consideration in two major groups including the controllable and noise factors. The method concentrates on the minimization of the noise factors effect. Furthermore, it aims to determine the optimum values of the main controllable factors, with regard to the robustness concept, as the noise factors are unavoidable [45].

Likewise, it can identify the relative importance of each factor, with respect to its basic impact, on the total performance of the algorithm. Therefore, the Taguchi experimental design has created a remarkable demand for calibrating factors of the meta-heuristic algorithms [46].

The extant variation of the response variable is measured here by a Signal-to-Noise (S/N) ratio. The terms “signal” and “noise” represent the desirable (i.e., response variable) and undesirable (i.e., standard deviation) values, respectively. The given ratio can be taken into account as a robustness criterion in which the larger values indicate smaller variations of the desired value [47].

It is now required to deal with the most influencing factors, as well as their levels in the GA. To do so, five different factors of the GA are investigated of which four levels are taken into account. The factors entail the number of iterations as the stoppage criterion, population size as the configuration issue, and crossover, mutation, and reproduction percentage as the evolution factors. The details of the above-mentioned factors are presented in Table 2. As is obvious, the levels of the given factors are divided by the organization type in order to provide more precise performance.

The total degree of freedom should be determined

Table 2. Factors and factor levels of the GA.

Factor	Symbol	Level	Organization type	
			I	II
Number of iterations	A	4	A(1)-60	A(1)-150
			A(2)-80	A(2)-175
			A(3)-100	A(3)-200
			A(4)-120	A(4)-225
Population size	B	4	B(1)-40	B(1)-75
			B(2)-50	B(2)-100
			B(3)-60	B(3)-125
			B(4)-70	B(4)-150
Crossover rate	C	4	C(1)-75%	C(1)-75%
			C(2)-80%	C(2)-80%
			C(3)-85%	C(3)-85%
			C(4)-90%	C(4)-90%
Mutation rate	D	4	D(1)-10%	D(1)-10%
			D(2)-15%	D(2)-15%
			D(3)-20%	D(3)-20%
			D(4)-25%	D(4)-25%
Reproduction rate	E	4	E(1)-10%	E(1)-7.5%
			E(2)-15%	E(2)-10%
			E(3)-20%	E(3)-12.5%
			E(4)-25%	E(4)-15%

so that a well fitted orthogonal array can be selected. To do that, a degree of freedom for the total mean, and three degrees of freedom for each of the mentioned factors, should be taken to select the array. Hence, the total required degrees of freedom must incorporate at least 16 rows. Here, the orthogonal array, L_{16} , is chosen as an appropriate design, as shown in Table 3.

In order to find the most efficient factor levels for both organization types, each array is repeated five times to obtain the S/N ratio carried out by MINITAB 14. The best fitted levels of the GA are shown by Figures 6 and 7. As can be seen, the best GA factors, A, B, C, D and E, are 2, 2, 2, 3 and 2, and 3, 2, 2, 2 and 3 for organizations Types I and II, respectively.

Now, the problem is solved by the tuned proposed

Table 3. The proposed orthogonal array L_{16} for the GA.

Trial	Control factor level				
	A	B	C	D	E
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	1	4	4	4	4
5	2	1	2	3	4
6	2	2	1	4	3
7	2	3	4	1	2
8	2	4	3	2	1
9	3	1	3	4	2
10	3	2	4	3	1
11	3	3	1	2	4
12	3	4	2	1	3
13	4	1	4	2	3
14	4	2	3	1	4
15	4	3	2	4	1
16	4	4	1	3	2

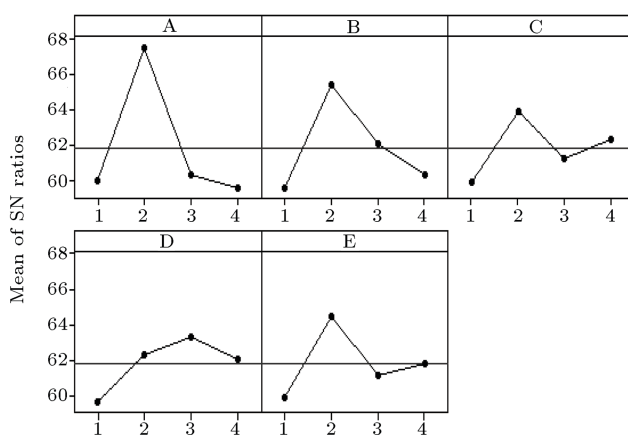


Figure 6. Mean S/N ratio plot for the levels of the GA factors in organizations Type I.

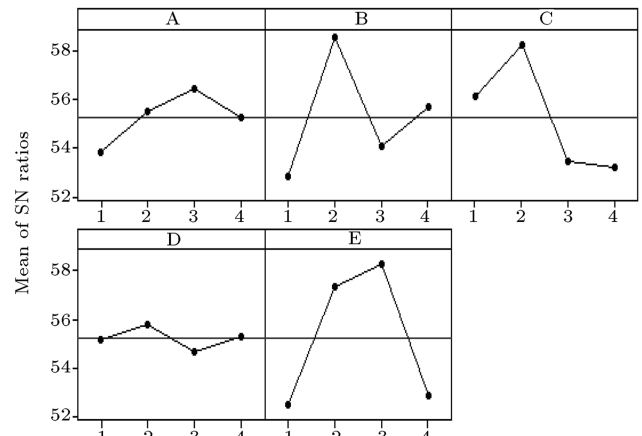


Figure 7. Mean S/N ratio plot for the levels of the GA factors in organizations Type II.

meta-heuristic approach and the results are compared with those obtained from the GAMS 22.1 solver. Moreover, the results are reflected once the PR has been applied at the second solution phase so that its improving impact can be realized. The comparison results are illustrated in Table 4.

According to Table 4, it can be observed that the OF value can change, regarding the payment method. However, the value is dependent on different issues like the contract details, and the optimum alternative should be selected with respect to the given problem. For example, the LSP obtained the minimum NPV, while ETI led to the maximum one. The GA can converge in a rather short time once the OF mean value shows a trivial difference, compared with the GAMS. Furthermore, it can yield to the final solution for the LSP. However, the slight deviation is noticeably retrieved in the second solution phase by the PR approach. The second phase can provide a precise searching possibility, so that the optimal solution can be reached.

Now, the model is tested by different instances for two types of organization. However, the comparisons are carried out just for the PEO and PP methods, since they are more favorable as a reasonable contract type. The comparisons are categorized, with respect to the payment method, and the organization type by Tables 5–8. The results show that GAMS do not reach the optimum solution for the first type organizations within the predefined time, and only an interval can be obtained for the OF value. The GA can obtain appropriate solutions with small variations, preserving the process time. The solutions can again be enhanced through the PR, with respect to both the OF mean and standard deviation values. It should be noted that the first phase lasts longer than the second, as it has to make more computational effort in searching the solution space.

On the other hand, GAMS is not successful

Table 4. Results obtained for the given network.

Payment method	GA			PR			GAMS	
	OF mean value	OF Std.	CPU time	OF mean value	OF Std.	CPU time	OF value	CPU time
LSP	155.57	0.000	11	155.57	0.000	< 5	155.57	54
PEO	155.91	0.029	12	155.93	0.004	7	155.94	56
ETI	156.09	0.018	12	156.11	0.000	< 5	156.11	54
PP	155.77	0.022	12	155.82	0.000	< 5	155.82	57

Table 5. Results obtained for PEO method and organizations Type I.

Problem No.	GA			PR			GAMS	
	OF mean value	OF Std.	CPU time	OF mean value	OF Std.	CPU time	OF value	CPU time
1	803.16	12.404	941	824.85	5.905	220	682-845	7200*
2	796.04	18.056	892	817.26	6.557	245	711-861	7200*
3	754.29	9.172	875	762.41	5.641	197	641-790	7200*
4	786.52	9.860	883	792.34	8.637	237	635-818	7200*
5	905.11	15.391	1017	917.73	7.610	294	732-944	7200*

*: The solution process is stopped after two hours.

Table 6. Results obtained for PP method and organization Type I.

Problem No.	GA			PR			GAMS	
	OF mean value	OF Std.	CPU time	OF mean value	OF Std.	CPU time	OF value	CPU time
1	965.20	27.135	1074	984.76	8.419	296	733-1040	7200*
2	850.82	24.622	1008	857.61	8.750	307	646-932	7200*
3	724.49	16.330	914	728.80	11.023	276	682-810	7200*
4	1014.73	37.606	1124	1037.33	10.842	314	833-1106	7200*
5	765.39	16.228	983	772.84	7.819	286	612-808	7200*

*: The solution process is stopped after two hours.

Table 7. Results obtained for PEO method and organizations Type II.

Problem No.	GA			PR			GAMS	
	OF mean value	OF Std.	CPU time	OF mean value	OF Std.	CPU time	OF value	CPU time
1	3416.49	42.215	4339	3452.07	14.464	1326	-	7200*
2	3352.00	43.846	4467	3388.46	13.505	1339	-	7200*
3	3324.39	42.157	4506	3352.17	16.109	1522	-	7200*
4	3576.43	58.564	4831	3619.73	22.614	1680	-	7200*
5	3552.20	66.076	4675	3594.48	21.345	1534	-	7200*

*: The solution process is stopped after two hours.

in finding even a solution interval for organization Type II. The intrinsic complexity of the problem prevents the conventional branch-and-bound method to perform efficiently. In other words, it cannot be applied to solve the problems of medium and large sizes. Therefore, the use of the two-phase algorithm

can be pinpointed in such circumstances. The results show that the PR algorithm could enhance the output of the GA to a remarkable extent, likewise. In both organization types, the second phase is thoroughly efficient and provides solutions with a small varying range.

Table 8. Results obtained for PP method and organizations Type II.

Problem No.	GA			PR			GAMS	
	OF mean value	OF Std.	CPU time	OF mean value	OF Std.	CPU time	OF value	CPU time
1	3288.09	55.647	4279	3330.71	16.227	1260	-	7200*
2	3416.94	62.778	4338	3462.30	19.808	1364	-	7200*
3	3407.82	61.786	4491	3455.82	25.610	1380	-	7200*
4	3422.73	51.686	4381	3463.55	16.175	1276	-	7200*
5	3680.07	84.145	4948	3758.70	36.782	1469	-	7200*

*: The solution process is stopped after two hours.

5. Conclusions

The MSPSP was addressed in this paper as a generalized version of the classic RCPSP. In this kind of project, the organization resources are only associated with human types, including technicians, engineers, and so on. Since many projects encounter serious financial problems during their execution, and may fail, the problem was taken into consideration with discounted cash flow. Four of the more well-known payment methods were presented and the probable changes in the optimum schedules were investigated. Regarding the hardness of such problems, a two-phase algorithm was applied in order to provide efficient solutions. First, a GA was used as a capable solution methodology, and a PR algorithm was used, so that the trajectories connecting efficient solutions could be searched, afterwards. The application of the second phase increases the chance of searching the parts of the solution space with higher eligibility in enhancing the solution quality. The GA parameters were tuned by the Taguchi method to enhance the results robustness. For a small-sized instance, the performance of the above-mentioned algorithm was tested for different payment methods against the GAMS solver and it proved to be good. Likewise, some further problems were presented for two typical types of organization.

The proposed problem can be of great interest for further research, regarding potential novelties. Thus, it can be taken into consideration with respect to different aspects. An interesting issue would be to apply other solution methods and compare the obtained results. For example, GA can be combined by other appropriate approaches. Another future research direction is to consider uncertainty in problem definition, as few events can be interpreted by deterministic states in real world conditions. For instance, the execution time of activities may be treated as a stochastic variable. Payments and client commitment can also be regarded as other uncertain facets. The authors aim to develop more comprehensive extensions of the MSPSP in future studies.

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