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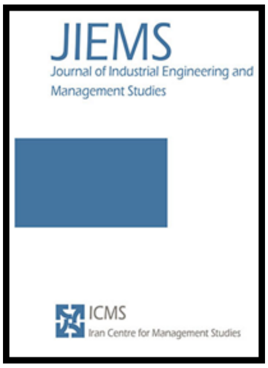

Project scheduling optimization for contractor's net present value maximization using meta-heuristic algorithms: A case study

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Abstract

Today's competitive conditions have caused the projects to be carried out in the least possible time with limited resources .Therefore, managing and scheduling a project is a necessity for the project. The timing of a project is to specify a sequence of times for a series of related activities. According to their priority and their latency, so that between the time the project is completed and the total cost is balanced. Given the balance between time and cost, and to achieve these goals, there are several options that should be considered among existing options and ultimately the best option to perform activities to complete the project. In this research, a mathematical model of project scheduling with multiple goals based on cost patterns and consideration of resource constraints is presented, and this problem is considered as a problem for NP-hard issues in family hybrid optimization. GA, PSO and SA Meta-heuristic algorithms are used to solve the proposed model in project scheduling and the results are compared with each other.

Keywords: project scheduling, NPV maximizing, payment patterns, resource constraints, meta-heuristic algorithms.

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1. Introduction

The scheduling and sequencing of operation is a decision making issue with a wide range of applications in manufacturing and service systems. In today's competitive atmosphere, an efficient scheduling and sequencing system is an essential and inevitable requirement for survival in the business environment. Scheduling and sequencing operations, as a decision making process, plays an integral role in most manufacturing and producing systems as well as most services environments. A survey of the relevant literature indicates that the issue of scheduling should be taken into account at different levels of decision making, whether short term, medium term and long term (Sadeghi et al., 2017).

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The resource-constrained project scheduling problem (RCPSP) is to schedule project activities in order to complete a project in the minimum possible time under the presence of precedence and resource constraints. Furthermore, precedence constraints are defined between activities (Kima et al., 2003). Blazewicz et al. (2010) have proven that the RCPSP is NP-hard in a strong sense. Numerous method algorithms have been proposed for solving the RCPSP (Baradaran et al., 2010). If the modes consist of a discrete set and the cost of an activity is decreasing in its processing time, we have a discrete time-cost tradeoff problem. Time-cost tradeoff problems are often classified according to objective function type (Yang et al., 2004). Many of the recent researches in project scheduling focus on maximizing the NPV of the project using the sum of positive and negative discounted cash flows throughout the life cycle of the project (Najafi et al., 2009). NPV is defined as the difference between cash inflows and outflows, taking into account the time value of money by discounting the cash flows. The presence of the NPV criterion results in a more complicated model called MRCPSP with discounted cash flows (Chen & Zhang, 2012).

The Contractor's cash outflows associated with an activity can occur anywhere throughout the activity. However, it is assumed here that they will be discounted to the starting time of the activity. The cash inflows for the contractor, which represent the cash outflows for the client, occur at predetermined equal time intervals. In this context, the earned value for the contractor corresponds to the payments regarding the activities completed within that specific period of time. If the project is completed earlier than the deadline, then the last payment occurs at the deadline. Crashing activities involves allocating more resources (such as materials, labor, and equipment) than planned in order to complete a project more quickly. In time–cost tradeoff problems, projects are not always completed as scheduled without reworking or modification. A project is a one-time task constrained by time, cost, and quality, and its success depends on how well these constraints are balanced. In the management of a project, it is often possible to compress the duration of some of the activities at an additional expense in order to reduce the total project's duration. This is known as time/cost tradeoff problem that addresses the issue as to ''which activity or activities in a project should be allocated additional resources in order to accelerate them and thus reducing the total project duration at a minimum level of additional resource expenses''. In the early time/cost tradeoff models the direct activity cost function was assumed to be a linear non-increasing function of its duration. The objective was usually to deliver the project within a specified deadline while minimizing the project's overall costs (Tareghian & Taheri, 2007).

In Research, the multi-mode resource-constrained project scheduling problem (MRCPSP), discrete time-cost trade-off problem (DTCTP) and also resource allocation and resource leveling problem (RLP) are considered simultaneously. This paper presents the multi-mode resource-constrained discrete time–cost-resource optimization (MRC-DTCRO) model in order to select starting the time and the execution mode of each activity satisfying all the project constraints. To solve these problems, non-domination based genetic algorithm (NSGA-II) is employed to search for the non-dominated solutions considering total project time, cost, and resources moment deviation as three objectives. The results of MRC-DTCRO model presented in this paper show that adding the resource leveling capability to the previously developed multi-mode resource-constrained discrete time-cost trade-off problem (MRC-DTCTP) models provides more practical solutions in terms of resource allocation and leveling, which makes this research applicable to both the construction industry and researchers.

2. Literature Review

The objective of time-cost trade-off problem is to identify the set of time–cost alternatives that will provide the optimal schedule (Sonmez & Bettemir, 2012). Mika et al. (2005) study, a positive flow is associated with each activity. The objective is to maximize the NPV of all cash flows of the project. They use two meta-heuristics that are widely used in research: Simulated Annealing (SA) and Tabu Search (TS). Rajeevan, M., Nagavinothini, R. (2015) This paper presents a method to minimize the duration of the project using a structured method by defining and evaluating multiple constraints such as precedence constraints, resource constraints and deadline constraints. Resource-Constrained Project Scheduling Problem (RCPSP) considers resources of limited availability and activities of known durations and resources requests, linked by precedence relations. The problem consists of finding a schedule of minimal duration by assigning a start time to each activity such that the precedence relations and the resource availabilities and deadline constraints are represented. Comparing to classical optimization techniques, meta-heuristic optimization techniques require less time to find the optimal solution for complex problems like RCPSP. Out of several meta-heuristic techniques, Genetic Algorithm is chosen for optimization. In this research, two problems from literature and two real life problems are chosen for time optimization using Genetic Algorithm.

Pellerin, et al.. (2020) surveyed the hybrid approaches for solving the Resource-Constrained Project Scheduling Problem (RCPSP) by a comparison of the results of the different hybrids on the well-known PSPLIB data instances. In this paper, the distinguishing features of the best hybrids are also discussed. Birjandi et al.. (2019) presented a new fuzzy mixed integer nonlinear programming (MINLP) model under uncertain conditions. A hybrid meta-heuristic approach is also proposed to minimize costs of project completion in this paper. Wang et al.. (2020) presented an integrated approach that enables fluent data flow from the information model to the RCPSP model for construction scheduling. Stiti and Driss (2019) proposed a new Particle Swarm Optimization-based solution to deal with this RCPSP variant aiming at minimizing the total project Makespan. The proposed algorithm uses a Valid Particle Generator to produce feasible schedules. Rahman et al. (2020) presented a genetic algorithm based memetic algorithm (MA) for solving RCPSP. This algorithm is initiated by a critical path-based heuristic and a variant of the Nawaz, Enscore, and Ham (NEH) heuristic.

Jia and Seo (2013) proposed an improved PSO method that treats the solutions of RCPSP as particle swarms and employs a double justification skill. It uses operator for the particles, in association with rank-priority-based representation, greedy random search, and serial scheduling scheme (Haji Akhundi et al. 2015). To solve the problem of project scheduling with the goal of minimizing the time of completion of the project with resource constraints, the frog mutation multifunctional algorithm has been used. The results indicate the proper and robust operation of this new meta-meta-algorithm. Shah Mohammadi and Kazemi (2015) have used a combined approach to the metamorphosed algorithm and an innovative method of eliminating and adding activities to solve these problems to solve the problem of scheduling a project with limited resources .By comparing the results obtained with sample problems and the results obtained in the articles, it shows the efficiency of the proposed algorithm (Maghsoudlou, H., et al. 2016). A new multi-skill multi-mode resource-constrained project scheduling problem with three objectives is studied in this paper. The objectives are: (1) minimizing project's makespan, (2) minimizing the total cost of allocating workers to skills, and (3) maximizing total quality of processing activities. A meta-heuristic algorithm called multi-objective invasive weeds optimization algorithm (MOIWO) with a new chromosome structure guaranteeing the feasibility of solutions is developed to solve the proposed problem. Two other meta-heuristic algorithms called non-dominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization algorithm (MOPSO) are used to validate the solutions obtained by the developed MOIWO. The parameters of the developed algorithms are calibrated using Taguchi method. The results of the experiments show that the MOIWO algorithm has better performance in terms of diversification metric, the MOPSO algorithm has better performance regarding mean ideal distance, while NSGA-II algorithm has better performance in terms of spread of non-dominance solution and spacing metrics.

Hosseininasab, S.M., et al. (2018) In Research, an integrated model for selecting, scheduling, and budgeting urban road construction projects is introduced as a multi-objective time-dependent bi-level network design problem. Three criteria are considered as upper-level objective functions: total travel time, user satisfaction over time, and spatial equity. Two new measures are developed to assess network design scenarios from the perspectives of user satisfaction over time and spatial equity. Given the great complexity of the intended problem, two multi-objective evolutionary approaches (an interactive and a-posteriori) are proposed to solve the model in a reasonable time. These two approaches are novel combinations of different techniques, such as: Genetic Algorithm (GA), Non-dominated Sorting Genetic Algorithm (NSGA-II), Frank-Wolfe algorithm, ordered logit model, and knees identification algorithm. Computational results for various test problems show that proposed approaches have acceptable performance in terms of both solution quality and solution time. To show the applicability of the proposed approach in large-sized networks, it is applied to a real case on Isfahan City in Iran.

3. Problem description and mathematical formulation

Our proposed model is categorized in resource-constrained project scheduling problem with discounted cash flows (RCPSPDCF) that can be defined as follows. A project consisting of n activities is represented by an activity-on-node network,$G = (J, E)$, $|J| = n$, where nodes and arcs correspond to activities and precedence constraints between activities, respectively. Nodes in graph G are topologic and numerically numbered, i.e. an activity has always a higher number than all its predecessors. No activity may be started before all its predecessors are finished. The duration of activity $j = (1,2, \dots, n)$ executed is d_j. There are R renewable resources (note that, Renewable resources is not in contradiction with constrain resources models in project scheduling problems. Since, this feature come back the kind of resources not the kind of problem). The number of available units of renewable resource $k = (k = 1,2, \dots, R)$ is R_k. Each activity j is executed requiring r_{jk} units of renewable resource $k = (k = 1,2, \dots, R)$ for its processing. A negative cash flow CF_j^- is associated with the execution of activity j. For each completed activity occurs a negative cash flow amount of until the completion time of a project. Finally, the contractor receives amount of cash flows CF_j^+ for each activity that has completed successfully. The value of the amount of money is a function of the time of receipt or disbursement of cash. Money received today is more valuable than money to be received some times in the future, since today's money can be invested immediately. In order to calculate the value of NPV, a discount rate i α has to be chosen, which represents the return following from investing in the project. The objective is to find an assignment of modes to activities as well as precedence and resource-feasible starting times for all activities such that the net present value (NPV) of the project is maximized. All the parameters are used in the proposed RCPSPDCF model are summarized in the Table 1.

Table 1. The parameters of the proposed RCPSPDCF model

N: Number of activities	G: Acyclic digraph representing the project
d_j: Duration of activity j executed	α: Discount rate
CF_j^+:Positive cash flow associated	CF_j^-:Negative cash flow associated
ST_j: Starting time of activity j	FT_j: Finishing time of activity j
EF_j: Earliest finishing time of activity j	LF_j: Latest finishing time of activity j
P_j:Set of all predecessors of activity j	R: Number of renewable resources
R_k:Number of available units of renewable resource k, $k = 1,2,\dots,R$	r_{jk}:Number of units of renewable resource k required by activity j executed
C_{max}: The maximum time for completion	T: Horizon of Project Scheduling
NPV: Net Present Value of the project	P_K: Paid the amount of k
K:The number of continuous payments	U: The total amount of payments
$X_{jt}=\begin{cases}1 & \text{If completed j activities at time t}\\ 0 & \text{Otherwise}\end{cases}$	$y_{jk}=\begin{cases}1 & \text{If payment k is done for j}\\ 0 & \text{Otherwise}\end{cases}$

By using the above notations, the proposed model can be formulated as the following mathematical programming problem:

$$\max NPV \tag{1}$$

$$\min c\max = \max(\sum_{t=EF_j}^{LF_j} tX_{jt}) \tag{2}$$

$st:$

$$\sum_{t=EF_j}^{LF_j} tx_{jt} \le \sum_{t=EF_j}^{LF_j} (t-d_j)x_{jt} \forall_{j,w} \in p_j \tag{3}$$

$$C_j = \sum_{t=EF_j}^{LF_j} tX_{jt} \forall_j = 1,2,\dots,n \tag{4}$$

$$C\max \ge C_j \forall_j = 1,2,\dots,n \tag{5}$$

$$T \le \sum_{j=1}^{n} \max(d_j) \tag{6}$$

$$C\max \le T \tag{7}$$

$$\sum_{j=1}^{n} r_{jk} \sum_{b=t}^{t+d_j-1} X_{jb} \le R_k, \forall_{k,t} \tag{8}$$

$$ES_1 = 0 \tag{9}$$

$$EF_i = ES_i + d_i, i = 1,2,\dots,n \tag{10}$$

$$ESj = \max\{EF_i\} \forall_i \in p_j, j = 1,2,\dots,n \tag{11}$$

$$d_0 = 0, d_{n+1} = 0 \tag{12}$$

$$\sum_{j=1}^{n} y_{jk} = 1, k = 1,2,\dots,k-1 \tag{13}$$

$$\sum_{k=1}^{k} y_{jk} \leq 1,\ j = 1,2,\ldots,n \tag{14}$$

$$\sum_{k=1}^{k} P_k = u,\ k = 1,2,\ldots,k \tag{15}$$

$$P_k \geq 0,\ k = 1,2,\ldots,k \tag{16}$$

Equation (1) represents the objective function is to maximize the net present value of the project and the contractor is calculated according to the method of payment. Equation (2) represents the objective function the maximum completion time of activity n +1 that should be minimized. The constraint set (3) makes sure that all precedence relations are satisfied. The Constraints set (4) shows the completion time of project activities. Constraint (5) calculates maximum project completion. Constraint (6) calculates project planning horizon which is equal to all project activities. Constraint (7) ensures that the project be completed before project planning horizon. Constraints (8) are for applying renewable resource constraints and in each period summation of consumption of all activities from each resource in each time unit cannot exceed from maximum amount of that resource (R_k) in its relevant time unit. Constraints (9) expresses project starts time. Constraints (10) are related to transposition relations (without delay) between project activities. In a way that no activity can start before end of all its prerequisite activities and from the other hand projects activities are continuous. Constraints (11) show that j the activity start time is equal or larger than its prerequisite activities end time. Constraints (12) show that 0 and n+1 activity are virtual activities. Constraints (13) shows number of payments K for certain event m. constraint (14) ensures that one payment be allocated at the end of event. Constraint (15) ensures that summations of all payments are equal to project contractor price. Constraint (16) shows that payments values always are positive.

As known, the Multi-objective RCPSPDCF comprises a series of cash inflows and cash outflows over the duration of the project. Cash outflows occur as project expenditures, which are determined by the product of resource unit costs and usages plus other costs. Cash inflows, on the other hand, occur as payments for completed activities. Furthermore, in this model, cash inflows occur at the beginning of each activity while cash outflows at the completion of each activity. The objective is to maximize the net present value and minimize project completion time according to the four models Payment that is described in the paper (Zareei et al., 2014). Four types of payment scheduling models are of particular interest in practice: Lump-sum payment, payment at event occurrences, payment at equal time intervals, and progress payment.

Lump-sum payment (LSP) is one of the more commonly used payment structures in the literature. Here, the whole payment is paid by the client to the contractor upon successful termination of the project. The LSP model represents the ideal situation for the client—he makes a single payment to the contractor only at the end of the project. However, in general, this shifts the entire financial burden on the contractor, which may not be acceptable in some project environments.

$$\begin{aligned} &\text{maxz} = CF_{lsp}(1+\alpha)^{-FT_n} - \sum_{i=1}^{n} \sum_{t=EF_i}^{LF_j} \sum_{m=1}^{M_j} \frac{CF_{jm}}{(1+\alpha)^t} \times X_{jmt} \\ &\text{CF}_{\text{lsp}} = \sum_{\text{j}=1}^{\text{n}} \text{CF}_{\text{j}}^{+} \end{aligned} \tag{17}$$

In the payments at event occurrences (PEO) model, payments are made at predetermined set of event nodes. The problem is to determine the amount and timing of these payments. PEO is a very reasonable model, where the contractor gets his payments for successful completion of each activity.

$$\max z = \sum_{j=1}^{n} CF_j^{+}(1+\alpha)^{-FT_j} - \sum_{j=1}^{n}\sum_{t=EF_i}^{LF_j}\sum_{m=1}^{M_j}\frac{CF_{jm}}{(1+\alpha)^t}\times X_{jmt} \qquad (18)$$

In the equal time intervals (ETI) model, the client makes H payments for the project. The first (H-1) of these payments are scheduled at equal time intervals over the duration of the project, and the final payment is scheduled on project completion. In the ETI model the client and the contractor agree about the number of payments over the course of the project. The payments are then made at equal time intervals.

$$\max z = \sum_{P=1}^{H} P_p(1+\alpha)^{-T_P} - \sum_{j=1}^{n}\sum_{t=EF_i}^{LF_j}\sum_{m=1}^{M_j}\frac{CF_{jm}}{(1+\alpha)^t}\times X_{jmt} \qquad (19)$$

In the progress payment (PP) model, the contractor receives the project payments from the client at regular time intervals until the project is completed. For example, the contractor might receive at the end of each month a payment for the work accomplished during that month multiplied by a profit rate agreed upon by both the client and the contractor. A similar situation concerns the PP model, where the payments are also made at regular time intervals, but in this case the two parties agree about the length of this interval, not the number of payments. The difference between the ETI and PP models is that in the latter case the number of payments is not known in advance.

$$\max z = (\sum_{P=1}^{H-1} P_p(1+\alpha_i)^{-PT} + P_H(1+\alpha_i)^{-FT_n}) - \sum_{j=1}^{n}\sum_{t=EF_i}^{LF_j}\sum_{m=1}^{M_j}\frac{CF_{jm}}{(1+\alpha)^t}\times X_{jmt} \qquad (20)$$

4. Multi-objective optimization methodology

In this paper a multi-objective function is presented. Therefore, a method for solving multi-objective should be provided accordingly, for optimizing multi-objective optimization problems, there are several methods that can be classified into five categories: numerical, interactive, fuzzy Methods, meta-heuristic techniques, and procedures decision support (Hassan-Pour et al., 2009). Considering that the desired problem is multi-objective and for the net present value of a project with project completion time are not of a type, In other words, they are was not the significant sum, Thus a solution of the objective function is uniform. For uniformization the objective function of convex a linear combination of the net present value and the completion time is used. Since the net present value and the completion time are different units; hence it is necessary for the value of the objective function is numeric. The convex linear combination follows as:

$$\varphi Z_1 - (1-\varphi)Z_2 \qquad ,0 \le \varphi \le 1$$

With respect to the value obtained for the first and second objective function, the total amount of the objective function is as follows:

$$Z_{opt} = \varphi(Z_1) - (1-\varphi)(Z_2)$$

In above equation, Z_1 is the net present value of the objective function value, and Z_2 is function of time, φ is a number between 0 and 1, and Z_{opt} is the value of the objective function.

5. The Model solution method

Project scheduling by desirable cost payment models with considering resource constraint problem, due to calculations complexities are considered as NP-Hard problems and solving them in a big scale by linear programming and existing applications are not possible or require a lot of time. Therefore Meta-heuristic methods are used for these kinds of problems. Also Meta-heuristic methods are very efficient to solve complex optimization rather than a precise algorithm and many other heuristic methods.

5.1. The Genetic algorithm

As it was mentioned in the literature, GA has a good performance in scheduling problem (Molavi and Rezaee Nik, 2016). The ability of the genetic algorithm to simultaneously search for different areas of a search space makes it possible to find an extensive set of solutions for difficult problems with the discontinuous, discontinuous, and even solution space. Genetic algorithm works with a set of answers (population) rather than a single solution. Therefore, by keeping a population of appropriate states and operators such as intersection and mutation, the probability of entanglement in the local minimum trap decreases significantly. On the other hand, in the subject literature, this algorithm has been used to solve the dispersion model, efficiency, and supply chain (Rahimi Nejad et al., 2014).

GA is a stochastic search approach inspired by natural evolution that involves crossover, mutation, and evaluation of survival fitness. Genetic operators work from initial generation to offspring in order to evolve an optimal solution through generations. Each individual of a generation generates a result for the problem and is represented as a string-named chromosome. The relatively straightforward and simple implementation procedure gives GA its exceptional flexibility to hybridize with domain-dependent heuristics to create effective implementation solutions tailored to specific problems. Based on these merits, the potential of using GA in optimization techniques has been studied intensively (Min-Yuan et al., 2009).

The Genetic algorithm must contain a practical genetic representation of the problem in order to work efficiently. Moreover, initial population as the generator of the following solutions, appropriate fitness function, genetic operators such as crossover and mutation and a procedure for tuning the genetic parameters such as crossover rate and mutation rate are the other essential characteristics of effective heuristic search (Fakhrzad and Alidoosti, 2018).

5.1.1. Updated the population

5.1.1.1. Crossover operator

p_c Parameter is considered as Crossover probability and for selecting parents chromosome in Crossover, we repeat the following process (pop-size $\times p_c$) times. For i=1, 2… pop-size, we use three Crossover types as one point and two points unified Crossover. This process is described as following. First we must select a stochastic number in one point crossover in [0, N-1] and then we break both parents at this point and by moving their sequence, we produce two new child. Then in two points Crossover we select two different random number in [0, N-1] interval and we break both generator in these two points and by moving points between two parts of both generators, we produce two children and then in unified intersection we produce two random numbers like V in [0, 1] interval and if $V \leq p_c$ (in the proposed algorithm is equal to 0.9), x_i chromosome is selected as a parent in Crossover operation. Then we reach the number of (pop-size) p_c parents for Crossover operation. We number them again from the start and specify them by the prime sign as (x'_1, x'_2, ...). In the next phase if we want to have an Crossover between two parents like $x'_1 = (x_1^{(1)}, x_2^{(1)}, \dots, x_n^{(1)}$, $x'_2 = (x_1^{(2)}, x_2^{(2)}, \dots, x_n^{(2)})$ we must first produce a random number in [0, 1] interval and then do the intersection operation by using the following equation which are new chromosome and named as child chromosome and are signed by ". If both Childs are feasible, then we replace parents with them. If one of the parents is possible then we keep that and repeat Crossover operations to reach another possible child. If both of them are not possible, we repeat the operation to two possible children.

5.1.1.2. Mutation operator

p_m Parameter is considered as probability of mutation. Parent chromosomes are selected by the same method which was mentioned in intersection operations. Parent chromosome are selected which are almost as many as (pop -size) p_m. Then mutation operation is applied as the following method. In this research, gussion method is used for producing mutants that for X variables which is X_{min} and X_{max}, new variable must have normal distribution with zero mean and σ^2 variance. That $X' = X + \Delta X$ and $\Delta X \sim N(X, \sigma^2)$. This means that a standard value is produced and multiplied by σ^2 and summed by X value and σ^2 is equal to $0.1 * (V_{max} - V_{min})$. Which σ^2 is equal to mutation steps. Therefor mu % (mutation ratio) is selected randomly and to have an integer value for mutants and at least one case be found, value are rounded up.

5.2. The Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a heuristic search technique that was proposed in 1995. This algorithm inspired by choreography of a bird flock. The position of each particle changes according to its own experience based on social-psychological tendency to emulate success of other individuals. A swarm consists of a set of particles and each particle represents a potential solution. $x^i[t]$ is the position of each particle that is defined by adding a velocity to a current position: $x^i[t+1] = x^i[t] + v^i[t+1]$

That the velocity vector is defined as fallow:

$v^i[t+1] = wv^i[t] + c_1 r_1 (x^{i.best}[t] - x^i[t] + c_2 r_2 (x^{g.best}[t] - x^i[t]$

Where $x^{i.best}[t]$ is position of the best particle member of the neighborhood of the given particle, $x^{g.best}[t]$ is the best position of the best particle member of the entire swarm (leader),w is inertia weight, c_1 is the cognitive learning factor and c_2 is the social learning factor (usually defined as constants) and , $r_1, r_2 \in [0,1]$ are random values (Ritwik & Paul, 2013) (Shams et al.. 2017).

Each member of the swarm knows the best position found by its best informant or by the group globally. This value is called gbest. Therefore, there are three fundamental elements for the calculation of the next displacement of a particle:

1) According to its own velocity.
2) Towards its best performance.
3) The best performance of its best informant.

The way in which these three vectors are combined linearly via confidence coefficients is the basis of all versions of the classic PSO (Hassanzadeh et al., 2015).

5.3. The simulated annealing

The SA algorithm, first proposed by Kirkpatrick et al., (1983), is a random search to find the optimal solution in stochastic combinatorial optimization problems. It is characterized by allowing hill climbing moves to escape the local optima and find global optimal solutions if the cooling schedule is slow enough. These approaches are based on the physical concepts of increasing temperature to reach a high value followed by a gradual cooling process and finally reaching to a state of a minimum potential energy (Zandieh and Asgari Tehrani, 2014). Simulated annealing (SA) is a stochastic search algorithm inspired by the physical process of annealing (Hassan-Pour et al., 2009). The SA algorithm starts with an initial solution for the given problem and repeats an iterative neighbor generation procedure that improves the objective function. During searching for the solution space and in order to escape from local minima, the SA algorithm offers the possibility to accept the worse neighbor solutions in a controlled manner. A neighboring solution (*S*′) of the current solution (*S*) is generated in each iteration of the inner loop. If the objective function value of *S*′ is better than *S*, then the generated solution replaces with the current one; otherwise, the solution can be also accepted with a probability $p = e^{-\frac{\Delta}{T}}$. Where T is the value of current temperature (i.e., higher values of T give a higher acceptance probability) and $\Delta = f(S) - f(S')$. The acceptance probability is compared to a number $y \in [0,1]$ generated randomly and *S*′ is accepted whenever $p > y$ (Chen et al., 2010) (Babaee Tirkolaee et al.., 2016)

6. Tuning the parameters for GA, PSO and SA algorithms

Here the aim is to find the levels of the GA parameters (as input variables) so that both the solution accuracy and the required CPU time to reach the solution (response variables) are optimized. As indicated previously, population size, crossover probability, Number of Off springs, mutation probability for genetic algorithm and Initial Temperature, Temperature Damping Rate, Set Initial Temperature for Simulated annealing and Inertia Weight, Personal Learning Coefficient, for Particle Swarm Optimization are considered as input variables. Therefore the Parameters values for the genetic algorithm and Particle Swarm Optimization and simulated annealing was used. Tables (2 to 4) present the control parameters for the GA, PSO, SA algorithms.

Table 2. Control parameters for the GA

Parameter	The parameters amount
Lower Bound of Variables	1
Upper Bound of Variables	0
Maximum Number of Iterations	200
Population Size	100
Crossover Percentage	0.9
Number of Off springs (Parents)	2*round(pc*nPop/2)
Mutation Percentage	0.3
Number of Mutants	round(pm*nPop)
Mutation Rate	0.02

Table 3. Control parameters for the SA algorithms

Parameter	The parameters amount
Maximum Number of Iterations	200
Maximum Number of Inner Iterations	10
Initial Temperature	10
Temperature Damping Rate	0.9
Set Initial Temperature	T=T0
Number of objective function evaluations (NFE)	1000

Table 4. Control parameters for the PSO algorithms

Parameter	The parameters amount
Maximum Number of Iterations	200
Lower Bound of Variables	0
Upper Bound of Variables	1
Population Size (Swarm Size)	100
Inertia Weight	0.3
Inertia Weight Damping Ratio	0.99
Personal Learning Coefficient	0.5
Global Learning Coefficient	1
Velocity Max	0.1*(VarMax-VarMin)
Velocity Min	-VelMax

7. Computational Results

Proposed method presented in this research is coded by using GA, PSO and SA algorithm proposed in MATLAB software. In this part, input parameters which consider general and control variables is presented and results of proposed algorithm solving are discussed and the proposed GA, PSO and SA algorithm is validated by GAMS. Availability required information for Bandar Abbas Gas Condensate Refinery Construction Project including activities time, prerequisite relations, required resources for activities and positive and negative financial flows for activities in the paper (Zareei et al., 2014). Which is shown in Figure 1 of the network for anticipation of activities in a part of the construction project of Bandar Abbas gas condensate refinery and in Table 5 information about the activities of the installation of steel structures.

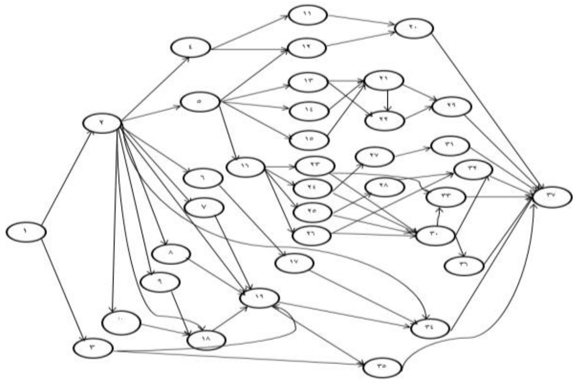

Figure 1. The network for anticipation of activities in a part of the construction project of Bandar Abbas gas condensate refinery

Table 5. Information about the activities of the installation of steel structures

Activities	duration	Prerequisite activities	Resource requirements		CF_j^-	CF_j^+
1	0	-	-	-	0	0
2	16	1	20	23	24800	55800
3	45	1	41	30	104400	234900
4	30	2	27	23	50700	114075
5	15	2	33	29	31650	71212.5
6	60	2	38	34	147600	332100
7	25	2	32	22	43500	97875
8	16	2	23	15	19360	43560
9	31	2	34	18	48980	110205
10	30	2	36	19	50100	112725
11	61	4	59	47	215330	484492.5
12	45	4,5	44	38	125100	281475
13	25	5,12	39	18	42000	94500
14	45	5	37	26	91800	206550
15	15	5	21	16	18300	41175
16	16	5	29	25	29280	65880
17	45	6	39	40	125100	281475
18	25	2,3,9	55	34	70000	157500
19	439	2,7,8	97	78	2569600	5781600
20	15	13,14,15	34	14	20700	46575
CF_j^+	Activities	duration	Prerequisite activities	Resource requirements	CF_j^-	CF_j^+
21	16	11,20	12	16	17680	39780
22	45	13,20	23	45	121950	274387.5
23	46	16	19	21	67210	151222.5
24	30	16	34	23	54900	123525
25	45	16,24	23	13	49950	112387.5
26	25	16,25	27	23	49010	110272.5
27	61	25	43	34	158720	357120
28	45	24	23	13	54390	122377.5
29	25	20,22	18	12	22080	49680
30	504	23,24,25,26	120	79	3321050	7472362.5
31	16	27,30	23	12	18020	40545

32	25	26,28,30	36	22	45500	102375
33	30	23,30	19	21	42900	96525
34	30	17,19	21	28	54600	122850
35	45	3,19	65	45	166850	375412.5
36	241	30	95	96	1654900	3723525
37	0	21,28,32,33,34,35,36	-	-	0	0

In relation to practice the algorithms, it is noted that the initially after entering general parameters of the problem, a initial solution is created by parallel scheduling production method which is considered as initial input of proposed algorithm. After defining and initialing control parameters, genetic algorithm, Particle Swarm Optimization and simulated annealing is applied. Finally, a set of solutions including a list of activities and executing order of activities and start and end of them and maximum time of project completion and project NPV is introduced as algorithm output and final solution. Amount of completion time and net present value projects for the main problem and for the Many problems in the form sample problems with number of 14 (Daneshpayeh, 2011), 18 (Rifat & Önder, 2012), 20 (Luong & Ario, 2008), and 25 (Kwan et al., 2003) activities for the four payments by using the GA, PSO and SA algorithms are shown in Tables 6 to 9.

Table 6. Amount completion time and NPV projects by using the GA

	types of payment	LSP		PEO		ETI		PP	
φ	problems with number activities	C_{max}	NPV	C_{max}	NPV	C_{max}	NPV	C_{max}	NPV
0.1	14	30	3714.29	30	4187.94	23	3761.305	27	1592.53
	18	242	66805.78	23	91935.68	41	72485.14	233	71682.34
	20	83	21159.43	83	22374.15	82	21124.54	81	10629.53
	25	86	18405.96	86	19437.28	84	18243.62	81	11028.49
	35	1660	255650.5	1580	5055782	1578	2942659.22	1544	963546.22
0.2	14	122	3753.2	123	4189.43	116	3810.53	123	1673.18
	18	228	67415.58	216	91281.58	237	72833.19	231	72261.22
	20	81	21210.81	79	22389.25	80	21200.26	77	10917.79
	25	84	18445.9	84	19438.73	82	18283.27	80	11378.61
	35	1628	323258.6	1563	5097745	1564	2956128.49	1528	969396.94
0.3	14	116	3782.62	120	4193.49	111	3837.63	117	1700.13
	18	220	68821.89	213	92015.72	234	73003.16	225	77362.28
	20	79	21227.73	75	22406.24	78	21274.34	75	11029.53
	25	82	18476.2	80	19438.83	78	18313.26	78	11758.29
	35	1578	522973	1522	5175565	1559	3016841.85	1527	1014759.77
0.4	14	111	3807.87	103	4199.02	106	3871.52	112	1704.40
	18	216	69324.97	210	92468.68	226	73218.29	219	77412.91
	20	77	21275.7	72	22422.68	75	21201.42	72	11251.14
	25	80	18509.12	79	19442.28	74	18401.43	75	12012.96
	35	1578	522973	1522	5175565	1547	3018279.76	1526	1032785.81
0.5	14	105	3836.43	98	4204.67	103	3901.59	111	1706.13
	18	211	70240.53	206	92163.41	220	73583.14	216	77629.12
	20	75	21302.42	70	22435.37	73	21310.46	69	11516.002
	25	78	18549.23	76	19452.05	71	18483.46	73	12078.49
	35	1556	617650.8	1511	5274138	1533	3038673.67	1512	1054547.38
0.6	14	99	3875.13	95	4205.19	96	3915.85	98	2764.53
	18	205	71252.27	202	92573	211	73731.47	214	77657.74
	20	72	21368.91	68	22465.85	69	21335.83	67	12015.41
	25	75	18604.85	73	19463.05	70	18506.3	71	12079.29
	35	1547	670599.6	1506	5299344	1517	3106890.43	1503	1198268.65
0.7	14	95	3895.16	91	4205.76	91	3923.62	92	2770.82
	18	195	72550.44	195	93099.41	199	73920.26	211	77819.81
	20	69	21441.33	67	22476	68	21400.26	65	12407.67
	25	72	18662.41	70	19479.5	68	18533.39	68	12944.61
	35	1534	727027	1501	5310492	1511	3194017.34	1496	1793895.45
0.8	14	90	3919.48	87	4213.42	85	3954.71	89	2772.83

	18	190	73489.38	188	93336.19	195	74284.07826	207	78132.18
	20	66	21518.41	65	22488.75	65	21578.53	64	13553.67
	25	68	18757.61	67	19501.77	66	18542.09	65	12968.16
	35	1523	792390.7	1488	5377051	1501	3204155.98	1490	2452668.24
0.9	14	86	3952.79	85	4214.3	83	3962	83	2780.51
	18	187	73816.44	187	93427.17	187	74791.85	187	78209.56
	20	64	21567.57	64	22502.48	63	21598.81	63	13642.08
	25	66	18812.52	65	19525.5	65	18555.29	64	13412.05
	35	1501	1030887	1472	5421284	1496	3459401.405	1481	2681276.7

Table 7. Amount completion time and NPV projects by using the PSO

	types of payment	LSP		PEO		ETI		PP	
φ	problems with number activities	C_{max}	NPV	C_{max}	NPV	C_{max}	NPV	C_{max}	NPV
0.1	14	130	3714.29	130	4187.942	127	3729.538	127	1654.29
	18	242	66991.25	229	91739.78	242	72061.75	235	72836.82
	20	83	21159.43	83	22374.32	82	21124.54	81	11367.38
	25	83	18471.58	86	19437.31	82	18413.76	81	11029.14
	35	1643	317986.1	1627	5144350	1612	4025217	1622	1006948
0.2	14	125	3741.283	123	4189.432	121	3761.544	123	1686.62
	18	233	68459.54	219	92282.42	238	72183.69	233	73926.19
	20	81	21210.81	81	22380.55	80	21200.26	79	11391.92
	25	82	18478.12	83	19441.73	79	18498.36	78	11379.67
	35	1606	419739.6	1618	5157401	1587	4091241	1616	1043729
0.3	14	118	3772.593	120	4193.49	116	3783.838	117	1700.131
	18	219	68887.35	216	92470.78	233	72253.96	227	76114.29
	20	79	21227.73	76	22407.58	78	21274.34	78	11451.54
	25	80	18517.08	79	19442.32	77	18499.21	76	11738.37
	35	1589	514062	1580	5167596	1550	4119094	1609	1133269
0.4	14	113	3796.684	110	4193.846	96	3771.671	114	1703.408
	18	214	70240.81	213	92496.76	231	73083.64	216	77916.33
	20	77	21275.7	74	22416.41	75	21296.59	69	11461.15
	25	77	18571.81	76	19452.68	74	18504.47	74	12018.94
	35	1571	622297.3	1563	5175072	1546	4129405	1554	1223734
0.5	14	110	3825.609	104	4203.12	92	3773.919	111	1706.135
	18	211	70408.02	206	92329.51	216	73738.05	211	78027.84
	20	74	21322.16	72	22427.88	73	21310.46	68	11506
	25	75	18610.74	73	19469.43	73	18515.06	73	12079.44
	35	1556	697280.9	1558	5199082	1540	4218754	1552	1577869
0.6	14	103	3867.024	98	4204.67	91	3780.888	96	2764.517
	18	207	70637.9	202	92573	209	74055.6	205	78197.56
	20	72	21368.91	69	22450.27	69	21335.83	67	11515.41
	25	72	18665.09	71	19488.45	70	18516.08	70	12082.57
	35	1544	760507.5	1534	5235346	1531	4227054	153	1603249
0.7	14	93	3907.526	90	4209.183	87	3916.867	92	2770.825
	18	199	71859.04	195	93108.35	200	74232.78	202	78331.16
	20	69	21441.33	68	22470.3	68	21400.26	66	12407.68
	25	69	18736.47	70	19491.69	68	18542.9	67	12947.55
	35	1526	886157.5	1518	5325881	1528	4332321	1531	1712763
0.8	14	87	3937.668	87	4213.425	85	3937.668	85	2776.839
	18	193	73031.06	188	93313.48	188	76209.77	188	78445.25
	20	66	21518.41	65	22488.75	65	21578.53	65	13583.68
	25	67	18799.73	67	19502.28	65	18557.4	65	12987.12
	35	1511	1051658	1508	5429219	1516	4452836	1530	1729430
0.9	14	83	3975.121	83	4215.9	83	3975.121	83	2780.516
	18	187	73864.16	187	93427.17	187	77852.39	187	78818.17
	20	63	21595.11	63	22522.66	63	21598.81	63	13612.09
	25	65	18837.14	65	19528.97	64	18608.64	64	13392.2
	35	1503	1070511	1497	5462359	1510	4590114	1523	2040748

Table 8. Amount completion time and NPV projects by using the SA

φ	types of payment problems with number activities	LSP C_{max}	LSP NPV	PEO C_{max}	PEO NPV	ETI C_{max}	ETI NPV	PP C_{max}	PP NPV
0.1	14	130	3714.29	130	4187.942	103	3901.59	123	1652.72
	18	242	66805.78	223	92440.07	211	73861.06	235	71691.68
	20	83	21159.46	83	22374.32	78	21274.34	78	11451.54
	25	86	18406.52	83	19440.99	78	18451.95	78	5218.26
	35	1659	293075.6	1573	5150189	1591	4035463	1565	1227021
0.2	14	125	3741.283	123	4189.432	99	3917.74	117	1700.345
	18	228	67415.58	214	92454.71	208	73868.37	233	73611.41
	20	79	21227.73	81	22380.47	75	21289.49	76	11473.28
	25	83	18459.74	79	19442.31	75	18465.36	74	5231.37
	35	1648	335549.5	1559	5162555	1586	4040525	1551	1262675
0.3	14	119	3771.592	120	4193.49	97	3924.28	112	1704.408
	18	220	68821.89	211	92468.68	203	73873.74	228	77650.51
	20	76	21294.04	77	22395.51	73	21307.1	72	11477.65
	25	80	18509.13	77	19451.63	74	18485.45	73	5237.639
	35	1612	409947.7	1543	5251535	1581	4056115	1545	1282225
0.4	14	115	3794.102	110	4193.666	94	3938.63	111	1706.135
	18	216	69324.97	202	92573	199	73880.08	214	77657.74
	20	74	21330.08	75	22410.46	70	21324.7	69	11481.07
	25	78	18549.23	76	19452.67	73	18492.32	70	5248.432
	35	1602	467000.1	1538	5268331	1533	4067493	1541	1292057
0.5	14	111	3807.872	103	4199.022	91	3953.95	98	2764.537
	18	211	70240.53	200	93025.45	195	74261.68	211	78048.59
	20	71	21392.81	72	22422.68	69	21335.41	68	11506
	25	75	18606.22	73	19463.06	71	18516.12	68	19560.2
	35	1586	510183.7	1534	5280256	1518	4172093	1535	1311329
0.6	14	105	3836.433	98	4204.67	90	3978.35	95	2766.429
	18	205	71252.27	197	93039.55	193	75154.03	207	78065.08
	20	69	21444.35	70	22435.37	68	21478.1	67	11515.41
	25	72	18665.8	70	19479.52	70	18539.85	67	5661.591
	35	1572	589093.4	1527	5303742	1517	4269926	1530	1353031
0.7	14	98	3875.898	91	4205.768	88	3993.85	91	2768.984
	18	199	71839.49	196	93118.22	191	75214.83	202	78242.19
	20	67	21484.85	67	22476.01	67	21522.38	65	13594.73
	25	70	18714.23	68	19497.75	68	18542.9	66	6916.905
	35	1550	711652.3	1517	5369675	1512	4280929	1526	1361570
0.8	14	92	3916.688	87	4213.425	85	4023.15	89	2772.839
	18	193	73066.23	188	93144.88	188	75309.18	196	78373.14
	20	65	21545.26	65	22488.75	65	21578.53	64	13612.31
	25	67	18799.73	67	19502.29	65	18547.16	64	17859. 73
	35	1527	824982.8	1511	5441611	1503	4356698	1518	1366569
0.9	14	83	3969.908	83	4216.604	83	4151.18	83	2780.516
	18	187	73816.44	187	93662.87	187	75364.61	187	78611.21
	20	63	21597.08	63	22524.54	63	21596.25	63	13626.72
	25	65	18837.14	65	19528.78	63	18711.27	65	8199.176
	35	1511	970441.1	1497	5456197	1502	4369480	1512	1386585

Table 9. Total amount of the objective function

	types of payment	LSP			PEO			ETI			PP		
φ	problems with number activities	GA	PSO	SA	GA	PSO	SA	GA	PSO	SA	GA	PSO	SA
0.1	14	3329.861	3329.861	3329.861	3756.146	3756.148	3756.148	3372.875	3343.884	3501.131	1420.577	1476.161	1475.148
	18	60101	60267.93	60101	82719.81	82542.9	83173.76	65212.53	64831.38	66453.85	64490.81	65529.64	64499.01
	20	19035.19	19035.19	19035.21	20128.44	20128.59	20128.59	19003.89	19003.89	19139.11	9558.482	10222.54	10298.59
	25	16556.76	16616.12	16557.27	17484.95	17484.98	17488.59	16410.86	16564.18	16598.96	9917.547	9918.126	4688.634
	35	229919.5	286023.2	263602.1	4550046	4629752	4635013	2648236	3622534	3631758	867037.2	906091	1104162
0.2	14	2978.16	2968.026	2968.026	3326.944	3326.946	3326.946	3025.23	2985.035	3114.392	1313.944	1324.696	1336.876
	18	53886.86	54721.03	53886.86	72982.06	73782.14	73920.97	58219.16	57699.35	59053.1	57762.78	59094.35	58842.53
	20	16952.45	16952.45	16966.38	17895.6	17888.24	17888.18	16944.21	16944.21	17016.59	8718.834	9097.736	9163.424
	25	14739.92	14766.1	14751.19	15534.18	15536.78	15538.05	14610.22	14782.89	14757.29	9086.891	9088.136	4170.296
	35	258281.3	335470.5	268110	4077883	4125597	4129732	2364590	3272675	3232103	775212	834660	1009830
0.3	14	2613.034	2605.415	2604.414	2899.443	2899.443	2899.443	2653.046	2613.887	2717.896	1154.991	1154.992	1159.486
	18	48109.32	48155.45	48109.32	64347.1	64664.75	64664.78	51032.01	50507.87	51650.72	54086.1	53211.9	54286.96
	20	14835.71	14835.71	14883.03	15661.87	15662.51	15653.76	14868.64	14868.64	14893.07	7698.175	7992.678	8012.755
	25	12908.74	12937.96	12932.39	13583.18	13585.92	13593.04	12795.89	12926.35	12917.62	8207.407	8194.059	3644.447
	35	365607.7	359366.7	286479.8	3622439	3616843	3675612	2111322	2882901	2838806	709873.7	792805.6	897094
0.4	14	2240.322	2232.81	2230.461	2478.212	2472.308	2472.2	2280.516	2224.603	2325.578	977.84	976.4448	979.281
	18	41508.58	42058.89	41508.58	55397.21	55412.86	55463	43840.58	43757.78	44248.45	46360.15	46663.4	46509.04
	20	12734.62	12734.62	12768.45	13424.81	13420.25	13416.28	12690.85	12747.95	12766.82	6721.888	6849.09	6861.042
	25	11073.47	11112.29	11098.34	11633.77	11641.21	11641.2	11011.26	11073.08	11066.19	7177.777	7181.764	3121.059
	35	313152.6	372750	279559.3	3104730	3104418	3160383	1810349	2477025	2439883	619061.1	733618.8	774617.8
0.5	14	1865.715	1857.805	1848.436	2053.335	2049.56	2048.011	1899.296	1840.96	1931.475	797.565	797.5675	1333.269
	18	35014.77	35098.51	35014.77	45978.71	46061.76	46412.73	36681.57	36761.03	37033.34	38706.56	38908.42	38918.8
	20	10613.71	10624.08	10660.91	11182.69	11177.94	11175.34	10618.73	10618.73	10633.21	5723.501	5719	5719
	25	9235.615	9267.87	9265.61	9688.025	9698.215	9695.03	9206.234	9221.03	9222.56	6002.748	6003.22	9746.1
	35	308047.4	347862.5	254298.9	2636314	2598762	2639361	1518570	2108607	2085288	526517.7	788158.5	654897
0.6	14	1490.652	1485.01	1471.573	1625.076	1623.068	1623.068	1508.742	1457.755	1537.34	1047.012	1048.207	1049.572
	18	28377.91	28130.96	28377.91	36908	36908	37097.62	29365.99	29496.84	29945.81	30934.7	31156.02	31101.83
	20	8504.364	8504.364	8536.34	8945.54	8938.708	8932.148	8492.932	8492.932	8550.44	4765.964	4565.964	4565.964
	25	7396.94	7422.836	7423.12	7741.42	7752.78	7749.808	7360.52	7364.432	7373.94	4789.12	4791.028	2224.436
	35	267311.6	303276.6	234694.2	2118834	2093218	2120581	1241846	1689903	1707060	478405.7	641207.8	540294.4
0.7	14	1102.048	1107.158	1094.169	1198.028	1199.755	1198.03	1113.388	1114.16	1136.555	766.846	766.8475	766.9952
	18	21628.63	21418.41	21412.55	27793.32	27796.01	27798.27	22036.78	22129.83	22430.75	23198.24	23357.95	23331.26
	20	6384.099	6384.099	6398.555	6695.9	6693.49	6695.903	6372.478	6372.478	6409.814	3676.803	3676.104	4032.919
	25	5548.323	5572.641	5565.269	5794.85	5798.507	5801.725	5512.418	5515.27	5515.27	3835.785	3837.365	2028.872
	35	217034.3	264779.1	212410.7	1592097	1596702	1609841	957147.5	1298627	1283220	537121.4	512757.2	407402.8
0.8	14	711.896	717.9336	709.7376	773.084	773.085	773.085	722.942	719.5336	736.63	483.366	487.3678	483.3678
	18	14545.88	14451.81	14458.85	18516.84	18512.3	18478.58	14700.82	15091.55	14911.44	15460.84	15538.65	15517.83
	20	4250.882	4250.882	4257.052	4445.75	4445.75	4445.75	4263.706	4263.706	4263.706	2659.534	2664.736	2671.262
	25	3697.122	3706.346	3706.346	3846.754	3846.856	3846.858	3655.619	3659.48	3657.432	2541.632	2545.424	3524.746
	35	157259.7	209122.8	163775	1074220	1084637	1087113	639630.4	889354.4	870137.2	489341.6	344662	272099.4
0.9	14	317.879	322.8121	322.2908	344.93	346.89	346.9604	321.5	322.8121	340.418	203.351	203.3516	203.3516
	18	7213.344	7218.116	7213.344	9174.417	9174.417	9197.987	7310.885	7616.939	7368.161	7652.656	7713.517	7692.821
	20	2099.157	2102.811	2103.008	2192.648	2195.566	2195.754	2103.181	2103.181	2102.925	1307.508	1304.509	1305.972
	25	1821.852	1825.214	1825.214	1894.05	1894.397	1894.378	1797.029	1803.264	1814.427	1283.605	1281.62	761.4176
	35	101737.8	105698.4	95684.21	540803.6	544888.6	544272.4	344593.7	457652.4	435596.2	266794.8	202704.1	137297.7

For proving the efficiency of the Meta-heuristic algorithms, solution of the GA, SA and PSO algorithms is compared. Therefore to prove efficiency of the algorithms, several sample problems in small scale including subsets of the real problem (with 10, 14, 18 and 20 activity) is solved by the proposed algorithms. Results and duration of executing GA, PSO and SA algorithm are shown and analyzed compared in the Tables 6-9. To compute means of differences percentage of the results of GA, SA and PSO, we use the following formulation and is shown in the Table 10.

Average difference percentage= ((GA result – SA result) / SA result) * 100.

Table 10. Percentage average differences between Results the GA, PSO and SA algorithms

	types of payment	LSP			PEO			ETI			PP		
φ	problems with number activities	GA, SA	GA, PSO	PSO, SA	GA, SA	GA, PSO	PSO, SA	GA, SA	GA, PSO	PSO, SA	GA, SA	GA, PSO	PSO, SA
0.1	14	0	0	0	5E-05	5E-05	0	3.8026	-0.86	4.703	3.8415	3.913	-0.069
	18	0	0.278	-0.277	0.549	-0.214	0.764	1.9035	-0.584	2.503	0.0127	1.611	-1.573
	20	1E-04	0	0.0001	7E-04	7E-04	0	0.7115	0	0.712	7.7429	6.947	0.7439
	25	0.003	0.359	-0.354	0.021	2E-04	0.021	1.1462	0.934	0.21	-52.724	0.006	-52.73
	35	14.65	24.4	-7.839	1.867	1.752	0.114	37.139	36.79	0.255	27.349	4.504	21.86
0.2	14	-0.34	-0.34	0	6E-05	6E-05	0	2.9473	-1.329	4.334	1.7453	0.818	0.9195
	18	0	1.548	-1.524	1.286	1.096	0.188	1.4324	-0.893	2.346	1.8693	2.305	-0.426
	20	0.082	0	0.0822	-0.04	-0.041	-3E-04	0.4272	0	0.427	5.0992	4.346	0.722
	25	0.076	0.178	-0.101	0.025	0.017	0.008	1.0066	1.182	-0.17	-54.106	0.014	-54.11
	35	3.805	29.89	-20.08	1.271	1.17	0.1	36.688	38.4	-1.24	30.265	7.669	20.987
0.3	14	-0.33	-0.292	-0.038	0	0	0	2.4444	-1.476	3.979	0.3892	9E-05	0.3891
	18	0	0.096	-0.096	0.494	0.494	5E-05	1.2124	-1.027	2.263	0.3714	-1.616	2.0203
	20	0.319	0	0.319	-0.05	0.004	-0.056	0.1643	0	0.164	4.0864	3.826	0.2512
	25	0.183	0.226	-0.043	0.073	0.02	0.052	0.9513	1.02	-0.07	-55.596	-0.163	-55.52
	35	-21.6	-1.707	-20.28	1.468	-0.154	1.625	34.456	36.54	-1.53	26.374	11.68	13.154
0.4	14	-0.44	-0.335	-0.105	-0.24	-0.238	-0.004	1.976	-2.452	4.539	0.1474	-0.143	0.2905
	18	0	1.326	-1.308	0.119	0.028	0.09	0.9303	-0.189	1.121	0.3212	0.654	-0.331
	20	0.266	0	0.2657	-0.06	-0.034	-0.03	0.5986	0.45	0.148	2.0702	1.892	0.1745
	25	0.225	0.351	-0.126	0.064	0.064	-9E-05	0.4989	0.561	-0.06	-56.518	0.056	-56.54
	35	-10.7	19.03	-25	1.793	-0.01	1.803	34.774	36.83	-1.5	25.128	18.51	5.5886
0.5	14	-0.93	-0.424	-0.504	-0.26	-0.184	-0.076	1.6943	-3.071	4.917	67.167	3E-04	67.167
	18	0	0.239	-0.239	0.944	0.181	0.762	0.959	0.217	0.741	0.5483	0.522	0.0267
	20	0.445	0.098	0.3467	-0.07	-0.042	-0.023	0.1364	0	0.136	-0.0786	-0.079	0
	25	0.325	0.349	-0.024	0.072	0.105	-0.033	0.1773	0.161	0.017	62.361	0.008	62.348
	35	-17.4	12.92	-26.9	0.116	-1.424	1.562	37.319	38.85	-1.11	24.383	49.69	-16.91
0.6	14	-1.28	-0.378	-0.905	-0.12	-0.124	0	1.8955	-3.379	5.459	0.2445	0.114	0.1302
	18	0	-0.87	0.8779	0.514	0	0.514	1.9745	0.446	1.522	0.5403	0.715	-0.174
	20	0.376	0	0.376	-0.15	-0.076	-0.073	0.6771	0	0.677	-4.1964	-4.196	0
	25	0.354	0.35	0.0038	0.108	0.147	-0.038	0.1823	0.053	0.129	-53.552	0.04	-53.57
	35	-12.2	13.45	-22.61	0.082	-1.209	1.307	37.461	36.08	1.015	12.936	34.03	-15.74
0.7	14	-0.71	0.464	-1.173	2E-04	0.144	-0.144	2.0808	0.069	2.01	0.0195	2E-04	0.0193
	18	-1	-0.972	-0.027	0.018	0.01	0.008	1.7878	0.422	1.36	0.5734	0.688	-0.114
	20	0.226	0	0.2264	4E-05	-0.036	0.036	0.5859	0	0.586	9.6855	-0.019	9.7063
	25	0.305	0.438	-0.132	0.119	0.063	0.055	0.0517	0.052	0	-47.107	0.041	-47.13
	35	-2.13	22	-19.78	1.115	0.289	0.823	34.067	35.68	-1.19	-24.151	-4.536	-20.55
0.8	14	-0.3	0.848	-1.142	1E-04	1E-04	0	1.8934	-0.471	2.376	0.0004	0.828	-0.821
	18	-0.6	-0.647	0.0487	-0.21	-0.025	-0.182	1.4327	2.658	-1.19	0.3686	0.503	-0.134
	20	0.145	0	0.1451	0	0	0	0	0	0	0.441	0.196	0.2449
	25	0.249	0.249	0	0.003	0.003	5E-05	0.0496	0.106	-0.06	38.68	0.149	38.474
	35	4.143	32.98	-21.68	1.2	0.97	0.228	36.037	39.04	-2.16	-44.395	-29.57	-21.05
0.9	14	1.388	1.552	-0.161	0.589	0.568	0.02	5.8843	0.408	5.454	0.0003	3E-04	0
	18	0	0.066	-0.066	0.257	0	0.257	0.7834	4.186	-3.27	0.5249	0.795	-0.268
	20	0.183	0.174	0.0094	0.142	0.133	0.009	-0.012	0	-0.01	-0.1175	-0.229	0.1121
	25	0.185	0.185	0	0.017	0.018	-0.001	0.9682	0.347	0.619	-40.681	-0.155	-40.59
	35	-5.95	3.893	-9.474	0.641	0.755	-0.113	26.409	32.81	-4.82	-48.538	-24.02	-32.27
difference percentage average		-1.07	3.599	-3.984	0.306	0.094	0.213	7.9935	7.301	0.808	-2.8105	2.052	-5.006

Total difference percentage average mean of SA algorithm to GA algorithm is 1.105 and the total difference percentage average mean of PSO algorithm to GA algorithm is 3.261 and total difference percentage average mean of -1.993. According to mentioned topics, GA algorithm has a better performance compared to SA, PSO algorithms and SA algorithm has better performance compared to PSO algorithm in obtaining wanted objectives. Therefor several sample problems in small scale including subsets of Reference are listed in addition Bandar Abbas Gas condensate Refinery project with number of 14 (Daneshpayeh, 2011), 18 (Rifat & Önder, 2012), 20 (Luong & Ario, 2008), and 25 (Kwan et al., 2003) activities is solved by the GA, SA and PSO proposed algorithms based on the four types of payments. With project implementation time increasing, the net present value for contractors for each of the four payment modes will be reduced. So the best option for contractors who are seeking a higher net present value this finish the project is less time and be able achieve to the higher net present value. LSP Payment for the client has the net present value highest. The method of ETI payment, whatever greater the number of payments, makes timeframe reduced payment Client to the contractor and as such the decrease the net present value for the Client. In PP payment mode, the net present value is increased for the Client, whatever is increased time intervals, therefore for the client it is better in this payments way, be more the interval. Completion time of the project and reaching to a solution time for different problems with different activities with the GA, SA and PSO algorithms is presented in Table 11 and Figure 2.

Table 11. Implementation time from the GA, PSO and SA

Problem / algorithms	J=14	J=18	J=20	J=25	J=35
GA	91.09	144.33	173.59	231.28	742.70
PSO	72.36	138.38	188.77	200.23	683.64
SA	8.56	14.29	19.17	23.79	58.09

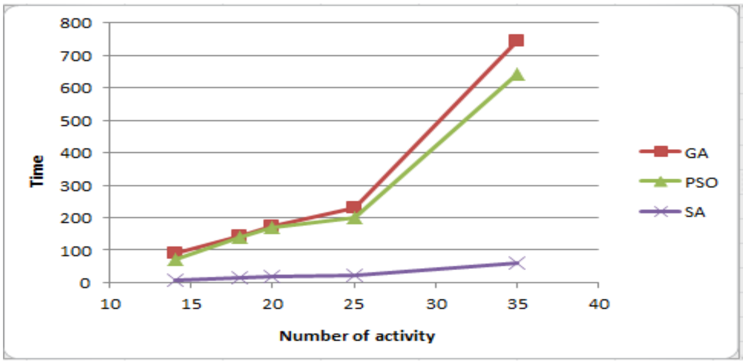

Fig 2. Time of sample problems solving by using GA, SA and PSO algorithms

Due to algorithm execution time, SA algorithm duration is less than GA and PSO algorithm but with regard to the total difference percentage average mean, GA algorithm has better performance than SA and PSO algorithms.

8. Conclusion

In this research Objects is considered are as following: Minimizing project completion time and maximizing the present net value of the project. It is impossible to reach global or local solution using classic optimization methods due to many constraints in the model and multiple objectives of the problem. Since the problem has complexity in calculation time and in other words it is classified as NP-hard problems, in this research GA, SA and PSO algorithms used for optimized scheduling. Then Bandar Abbas Gas Condensate Project and small sample cases scheduling results are compared using GA and SA and PSO algorithms. Results show that GA algorithm has better performance than SA and PSO algorithm but SA needs less time to solve problem than GA and PSO algorithms. According to the output results, LSP Payment for the Contractor has the lowest net present value and in the Payment ETI method, the net present value increases for the contractor by payments number increase and in PP payment method the net value of the contract decreases by time intervals increase.

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