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RESEARCH ARTICLE

Finding Optimum Resource Allocation to Optimizing Construction Project Time/Cost through Combination of Artificial Agents CPM and GA

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Abstract

In order to plan a construction project, computer simulations are frequently used to predict the performance of the operations through simulating the process flows and resource selection procedure. However, for finding the optimum resource allocation of the construction activities, all possible combinations must be tested through simulation study. If the number of activities and allocated resources are high, the numbers of these combinations become too large, then this process would not be economical task to do. Therefore, simulation analysis is no longer considered through an optimization technique. Using of Genetic Algorithms (GA) is one of the simple and widely used tools for optimizing heavy intensive engineering problems which can covers various areas of research. With keeping this in mind, this study presented a new hybrid model which integrated agent based modeling with CPM and GA to find out the best resource allocation combination for the construction project's activities. Based on the results obtained, this new hybrid model can effectively find the optimum resource allocation with respect to time, cost, or any combination of time-cost.

Keywords

Resource Allocation · CPM · Agent based Modeling · Genetic Algorithm · Time/Cost optimization

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1 Introduction

Despite the fact that different robust methods have been developed for project scheduling and planning, in the construction industry, Critical Path Method (CPM) is still the most popular method. The first major cause of this popularity is the simplicity of the CPM. On the other hand, for finding the optimum allocation, planners must test all of the alternate construction technologies and resource allocations, including crew sizes for all of the project activities. In each activity, each of its alternatives cause specific duration and cost. In the complicated projects, with increase in the number of activities and the types of resources, these alternatives increase progressively. Therefore, the effective technique is necessary to analyze and determine the optimal resource allocation to complete a project with the minimum cost or time. Several researchers have used discrete event simulation (DES) to develop such a technique for analyzing the effect of different resource allocations. Examples include evaluating the effect of different resource allocation on the concrete batching operations, [1], earthmoving operations [2], residential construction inspection process [3], precast concrete workshops [4], and tunnel planning [5].

Although these simulation techniques could find optimum resource allocation, examination of all resource allocation combinations to determine the best solution is too lengthy. Therefore, sensitivity analysis was proposed by [6] to facilitate such enumerations. However, with increase in the complexity of simulation model and number of available resource combinations, sensitivity analysis becomes an extremely time-consuming process. In this regard, different researchers have used heuristic algorithms (HAs) to efficiently search for appropriate resource allocation under specified objectives. For instance, AbouRizk and Shi (1994) used a heuristic algorithm (HA) to find the best resource allocation in the simulation system [7]. Several researchers proposed a hybrid model with combining genetic algorithms (GAs) and simulation for optimizing resource allocation regarding minimum unit cost or maximum productivity rate of the simulation model [8–10]. Senouci and Adeli (2001) used dynamic neural network to optimize resource allocation subjected to project network and available resource constrains that was neglected in the previous research [11]. Cheng and Yan (2009) combined messy genetic algorithms (GAs) and DES to select best resource utilization schemes relative to production rate or unit cost. [12].

Most of these methods are suitable for construction projects with highly repetitive tasks [9]. As mentioned earlier, the major reason that planners use CPM is its simplicity. However, using these methods need a high experience for simulation via DES software, since it could be complicated. In addition, in the traditional network planning techniques, such as CPM, PERT, and their derivatives, it is assumed that the duration of activities was almost known or had a pre-determined probability distribution. In practice, there are many cases where these conditions are not met.

In the CPM, the focus of concern is on the duration and cost of the project's activities. In practice, the duration and cost of each activity is determined through a three-way interaction among activity, its assigned resources, and the project environment. The attributes of activity, quantity and quality of resources, and environmental factors directly affect these interactions.

With this in mind, the very purpose of this study was to come up with a model which these interactions are of concern, and the model procedure is simple and easily comprehensible like CPM. To achieve this contribution, in this study, GA, CPM, and Agent Base Modeling (ABM) were combined. Genetic algorithm is a known issue in civil engineering and can easily be combined with other methods. So, it is used in different areas in civil engineering, such as cost estimation [13], design of a long-span suspension bridge [14], life cycle optimization of buildings [15], resource leveling model for line of balance schedules [16], and etc.

Agent-based modeling (ABM) is a recently developed approach to model complex systems. ABM has a broad range of application in many areas and fields including stock market [17], supply chains [18], adaptive immune system [19], understanding consumer purchasing behavior [20], military application [21], modeling fuzzy group decision making [22], and etc.

Having laid the ground, to achieve its objectives, this study is arranged as follows:

In section 2 and 3, ABM and Support Vector Regression (SVR) is introduced; the problem statement is described in section 4; section 5 describes the modeling procedure and methodology; the case study is described in section 6; in section 7 the results and discussion are presented; finally, the study is closed through the conclusion part.

2 ABM introduction

If a complex system is created from interacting, autonomous 'agents', then one of the recently developed approach to model it is ABM. The behavior of these Agents are affected by their characteristic and interactions with one another agents, learning from their experiences, and adaptation to their environment for better matching. By modelling of agents individually, the effects of their behavioral varieties with respect to their attributes can be traced. If this is accomplished, the behavior of the whole system can be predicted. In the agent based modeling, through system decomposition, agent-by-agent and interaction-by-interaction, model accuracy is improved [23].

2.1 Structure of an agent-based model

Typically an agent-based model contains three basic elements: [23]:

- A set of agents with their attributes and behaviors, where these attributes can be static or dynamic with respect to time or to simulation.
- A set of agent correlations and ways of interaction, where through model topology, constrains of the selecting and interacting mode are fixed.
- The agents' environment: agents interact within their environment as of other agents.

"The single most important defining characteristic of an agent is its capability to act autonomously, that is, to act on its own without external direction in response to situations it encounters. Typically, agents are active, initiating their actions to achieve their internal goals, rather than merely passive, reactively responding to other agents and the environment" [23]. The independence of the agent contributes to their decision making. The agent attributes could have a dynamic or a static due time.

In order to model the agent's interactions, it is necessary to establish two important issues:

1 Which agent could be connected to which one of its kind?

2 The manners of the interactions.

Both issues must be addressed in developing agent-based models. As in real-world systems, each agent interacts with other agents, yet not necessarily in a direct manner or simultaneously with all of them. Typically, every agent interacts with its neighbors, where it obtains information and becomes aware of its vicinity. ABM topology determines the agent's neighborhoods.

One of the simplest topologies in ABM is cellular automata. This topology splits the system environment to cells with grid lines. The cells that immediately surround an agent make up its neighborhood (Fig. 1-a).Another representation of ABM topology is network. Here, the agent's neighborhood could be defined in a general sense (Fig. 1-b). In such networks, each agent can communicate with other connected agents through the links.

Agents' environment affect their behavior. The environment could have both dynamic and static attributes.

In order to run, ABM model needs a computational engine. This engine approximates the output of the agents' interactions with one another and the system environment. This computational engine can range from simplistic and reactive if-then-rule engines to complex models run by adaptive Artificial Intelligence (AI) techniques [23]. In the proposed model we used SVR

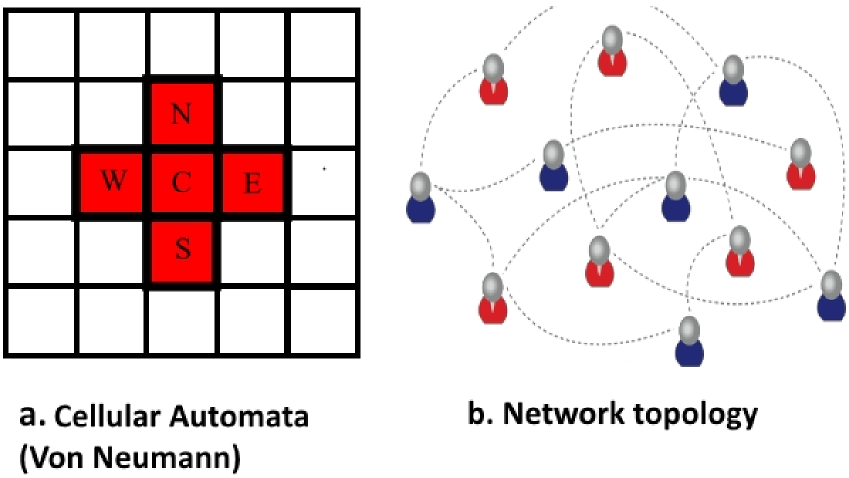

Fig. 1. Schematic of some ABM topologies

as ABM computational engine to approximate the output of the agents' interactions with one another and the system environment. The most important reason for using SVR is its unique structure in solving all related problems.

3 Support Vector Regression (SVR) introduction

Support vector machine (SVM) is a supervised learning method for analyzing the data for classification and regression problems. Vapnik proposed ε-support vector regression (SVR) by introducing an alternative ε-insensitive loss function [24, 25].The purpose of the SVR is to find best function for approximating the outputs of given training data and have to be as flat as possible [26]. A summary of the SVR methodology is presented as follows:

Let input x_i with n component have output y_i. $F(x)$ is a set of real functions that contains the regression function $f_0(x)$. Considering linear regression ($f(x) = (w \cdot x) + b$) with the set of data $\{(x_1, y_1), \ldots, (x_n, y_n)\}$. The optimal regression function can be found by minimizing the empirical risk R:

$$R = \frac{1}{n} \sum_{i=1}^{n} |y_i - f(x_i)|_{\varepsilon} \tag{1}$$

With ε-insensitive loss function:

$$|y - f(x)|_{\varepsilon} = \begin{cases} \text{if } |y - f(x)| \leq \varepsilon 0 \\ \text{otherwise } |y - f(x)| - \varepsilon \end{cases} \tag{2}$$

Now the function $f(x)$ must be found, that has minimum deviation of ε from the actual outputs y_i for all the training data and at the same time is as flat as possible.

This is equivalent to minimizing the following function:

$$R(w) = \frac{\left\|w^2\right\|}{2} + C \times \frac{1}{n} \sum_{i=1}^{n} |y_i - f(x_i)|_{\varepsilon} \tag{3}$$

Where flatness of function considering through $\left(\frac{\|w^2\|}{2}\right)$ and empirical risk was calculated the through second term $\left(\frac{1}{n} \sum_{i=1}^{n} |y_i - f(x_i)|_{\varepsilon}\right)$. C is a penalty value that trades off empirical risk against flatness of approximation function. The larger value of C decreases the training error but decreases generalization performance of the function as well. Eq. (3) could be represented as the dual optimization problem and this optimization problem can be solved by Lagrange method as follows:

$$\begin{aligned} L_2 = {} & \sum_{i=1}^{l} y_i \left(\alpha_i^* - \alpha_i\right) - \varepsilon \times \sum_{i=1}^{l} \left(\alpha_i^* + \alpha_i\right) - \\ & - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \left(\alpha_i^* - \alpha_i\right)\left(\alpha_j^* - \alpha_j\right)\left(x_i \cdot x_j\right) \end{aligned} \tag{4}$$

Subject to these constrains:

$$\sum \alpha_i^* = \sum \alpha_i; 0 \leq \alpha_i^* \leq C; 0 \leq \alpha_i \leq C \tag{5}$$

The training data with nonzero Lagrangian multipliers (α_i, α_i^*) are called support vectors.

The final solution could be as follows:

$$f(x) = \sum_{i=1}^{nsv} \left(\alpha_i^* - \alpha_i\right) x_i + b \tag{6}$$

Where nsv is the number of support vectors

However, in reality, as in the case of most engineering applications, linear regression is uncommon. Therefore, SVR maps out the input data x into a high-dimensional feature space by a non-linear map that in this space linear regression can be done [27].

To avoid computing explicitly in this feature space, a nonlinear kernel $K\left(x_i \cdot x_j\right)$ is used to map out the data. Once the optimum values α_i and α_i^* are obtained, then the regression function is given by

$$f(x) = \sum_{i=1}^{NSV} \left(\alpha_i^* - \alpha_i\right) K\left(x_i \cdot x\right) + b \tag{7}$$

Any function which satisfies Mercer condition can be used as the kernel function [24]. Some of these kernel functions are presented in Table 1. Choosing the kernel parameters is an important issue because they have important and direct effect in accuracy and complexity of SVR.

Tab. 1. Different types of kernel function

Type of classification	Kernel Function
Polynomial degree	$K(x \cdot x_i) = \left[\left(x^T \cdot x_i\right) + 1\right]^d$
Gaussian	$K(x \cdot x_i) = e^{-\frac{\|x - x_i\|^2}{\sigma^2}}$
Multi-layer perceptron	$K(x \cdot x_i) = \tanh\left[\left(x^T \cdot x_i\right) + b\right]$

It should be noted that tuning of SVR parameters is a heuristic process and the parameters specified by user are (1) type of kernel function and the parameters, (2) the value of the penalty factor C and (3) the value of ε-insensitive. More information about the SVM method can be found in [28–30]

4 Problem statement

For the purpose of this study, an Activity on Node (AON) project containing n activities is considered. The first and n^{th} activities represent the start and the finish points, respectively.

Assumptions:

1 Loop or circle is not allowed. This is a feedforward network.

2 No split is allowed.

3 Activities are ready to perform if the preceding activity completed.

4 Activity relationships are known and given based on the nature of the works to be performed.

The split of the activities is not considered in this study. Mathematical presentation of the CPM is:

$$\min f_n \tag{8}$$

Subject to:

$$f_1 = 0 \tag{9}$$

$$f_j - d_j \geq f_i \forall (i, j) \in H \tag{10}$$

Where d_i is the duration of activity i, f_i is the finish time of activity i, H is the subset of activities that are predecessors of activity I, and f_n is the duration of project.

As observed, $f_n$is the function of d_i. In the traditional CPM, d_i is the value based on experts' or project team's judgment. If the activity duration is deterministic, the CPM can be a very useful tool in managing project schedule. However, in practice, uncertainties in the project environment and variation in the quality of resources cause activity duration to become indeterministic. As mentioned earlier, the duration and cost of every activity is consequence of a three-way interaction among the given activity properties, its assigned resources, and the project environment. Obscurity of this interaction can cause uncertainty in the activities' duration and cost. CPM cannot face these uncertainties in an efficient manner. In cases, where the system outputs depend on the system's components and their interactions, one of the applicable methods in predicting these outcomes is ABM. However, to overcome some of the mentioned deficiencies in a more efficient manner, the combination of CPM and ABM adoption was proposed. In the proposed model, d_i is determined through considering three-way interaction among activity i, its assigned resources, and the project environment. Consequently, the project's duration, f_n depends on the interaction between its participated resources, activities, and environmental attributes.

Therefore, in this study, CPM is combined with ABM to generate the hybrid model. The attempt is made to make this model consider this three-way interaction in a direct manner. Then, the model is combined with GA to find optimal resource allocation for activities subjected to minimization project's total cost, duration, or time-cost tradeoff.

5 Modeling procedure and methodology

All projects have three basic elements: labor, activity, and environment. To achieve the study's objectives, these elements were mapped into ABM as follows:

1 Labors: every labor is an agent who is described through his/her attributes and characteristics.

2 Activity: Every activity has two parts, agent and environment. Agent part contains the natural attributes of the activity, and it is independent of the activity location in the project, such as the complexity. Environment part contains activity properties that depend on the location of the activity in the project, such as the accessibility to the activity material.

3 Environment: It contains the project properties that cover project spaces such as management conditions.

Model topology defines the correlation of agents with one another and with the environment. In this proposed model, the agents that are participated in an activity interact with one another, with the agent part of the activity, and with both the environment of the activity and that of the project. The restriction of the topology is similar to that of the activity. A schematic view of the model's topology is presented in Fig. 2.

An AI engine was selected as ABM computational engine to predict the possible results obtained from the agents' interactions with one another and with the environment [23]. To do this, the AI engine must be trained to find the best among agents' and environment attributes as inputs, and result of their interactions as outputs. This trained engine maps the agents' attributes and environment parameters onto the result of the interaction of agents with one another and with the environment. As mentioned earlier, in this study, SVR was chosen as an AI engine.

For making the crews, several resource pool must be defined. Each resource pool contains unlimited amount of resources (artificial agents) with similar characteristics. In the resource allocation step, agents were selected from these resource pools, and the crew properties were calculated based on these selections.

For optimizing the work crews, the proposed model had two important sections:

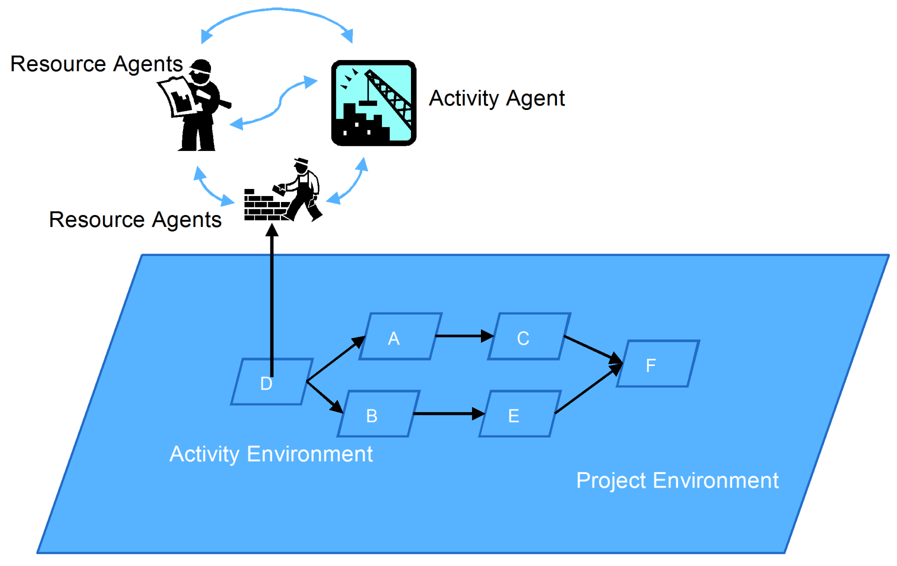

Fig. 2. Schematic view of the model topology

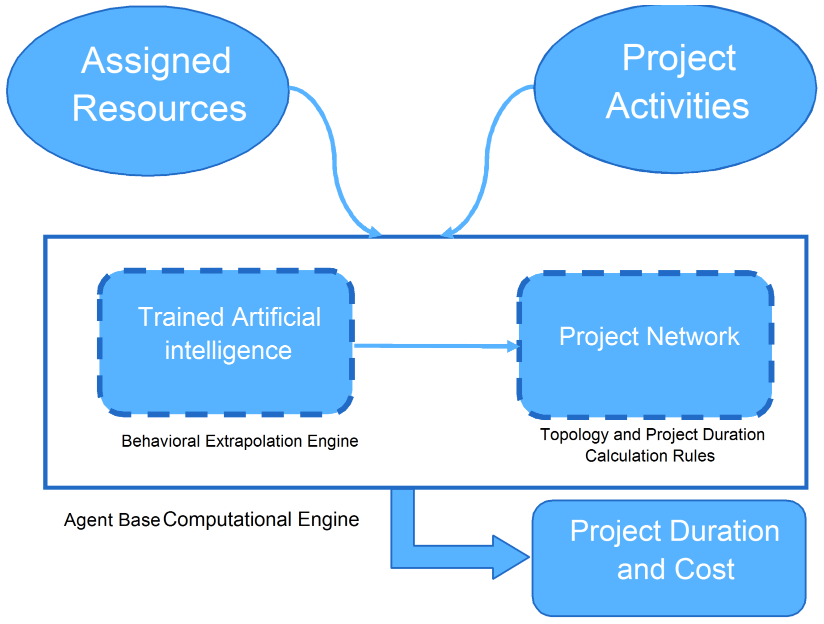

Fig. 3. Schematic of procedure of project duration and cost calculation

1 The project duration and cost calculation engine. This section was done through combining CPM and ABM

2 Optimizing the work crews to minimize time, cost, or time-cost. This section was completed via GA.

The step by step procedure of project duration and cost calculation engine includes:

1 Defining the labors and their behavioral attributes

2 Defining activities and their attributes and environmental factors

3 Defining and evaluating project environment factors

4 Collecting historical data based on previously defined parameters. These data contained the evaluation of activities and their assigned labor attributes as inputs, and the average workrate as output

5 Training SVR with collected data to predict new situations

6 Assigning labors to work crew of each activity from resource pools.

7 Approximating activities' durations using trained AI and activities' volume

8 Calculating network events based on predicted durations

The schematic view of this proposed model is illustrated in Fig. 3

In the optimization phase, the model must find the best taskforce arrangement for each activity to minimize project time, cost, or both of them. Therefore, the traditional CPM Eqs. (8)-(10) convert to these equations:

$$\min f_n \tag{11}$$

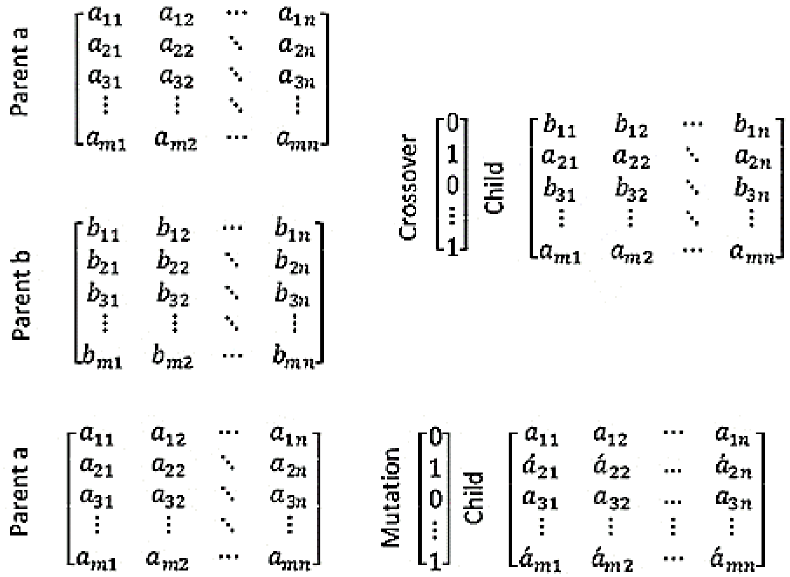

Fig. 4. Chromosome, Crossover and Mutation function representation

Subject to:

$$f_1 = 0 \tag{12}$$

$$f_j - d_j \geq f_i \forall\, (i, j) \in H \tag{13}$$

$$d_j = G(wc_j A_j E) \tag{14}$$

In the above mathematical model, Eq. (11) implies the objective function which is minimization of the total time of the project. Eq. (12) represents the first activity will be started at time zero. Eq. (13), presenting the relationships among the activities and models preceding relationships of all activities. Eq. (14), calculate the duration of activity based on three-way interaction among the given activity properties, its assigned resources, and the project environment

G is the function that calculates activity duration, wc_j is the properties of assigned work crew to activity j, A_j is the properties of activity j, and E is the environmental parameters of the project.

In the proposed model, each chromosome contains a $[m \times n]$ matrix which n is the number of resource pools and m is the number of activities The schematic view of chromosome was shown in Fig. 4

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as the former process may be very time-consuming. In the proposed model The Stochastic universal sampling was used as selection function [31]

In the proposed model, the crossover function creates a random $[m \times 1]$ binary vector and selects the row where the vector is a 1 from the first parent, and the row where the vector is a 0 from the second parent, then combines the genes to form the child. The mutation function generated a random $[m \times 1]$ binary vector for selecting individuals; where the vector is a 1, the corresponding row regenerates, and where the vector is a 0, the corresponding row remains unchanged. In Fig. 4 example cases of crossover and mutation functions are presented.

The model can be run in either one or multi objective optimizations. The fitness of each individual is calculated based on cost, time, or the combination of both of them through previously mentioned steps. The graphic view of the modeling procedure is presented in Fig. 5.

In the next section, the hypothetical problem is solved with the proposed method in both one and multi objective conditions.

The obtained results are near optimal solutions. In order to avoid falling in a local trap, mutation operator has been defined in the developed genetic algorithm.

6 Case Study

For estimating the abilities of this proposed model, a simple case problem was solved through hypothetical data. In this case, problem, the project contained 8 activities (Fig. 6).

Agents and project environment were evaluated with following parameters:

Activities contained these attributes:

1 Agent part

(a) Complexity level
(b) Repetition level
(c) Severity level
(d) Activity volume

2 Environment part

(a) Level of the accessibility to the activity materials

All activities used four types of agents (R1, R2, R3, and R4). Each labor is an individual agent with its following personal attribute:

1 Average level of labor's skill.

The project environment was described with the following parameters:

1 Management condition of the project

A 5-point Likert scale was used to evaluate the parameters of the activity. Moreover, a 3-point Likert scale was used for the evaluation of labor agents. (Table 2).

The numerical details and the description of these sample activities of the project, based on 5-point Likert scale, are tabulated in Table 3.

To accomplish any activity, four types of labors must be assigned to it, subjected to the following constrains:

$$1 \leq nR1_i \leq 3 \tag{15}$$

$$nR1_i \leq nR2_i \leq 3nR1_i \tag{16}$$

$$2nR1_i \leq nR3_i \leq 5nR1_i, 3nR2_i \tag{17}$$

$$2nR1_i \leq nR3_i \leq 6nR1_i, 2nR2_i, 4nR3_i \tag{18}$$

where $nR1_i$ to $nR4_i$ are the number of R1 to R4 labors of activity$i$, respectively.

The price of each type of labors, based on his/her skill level, is shown in Table 4. The project overhead cost was 300 monetary units per day. This project was managed in a normal manner (Scale 3).

Duration of activity $i(d_i)$ was calculated based on the interaction among resources (R1, R2, R3, & R4), activity, and project management conditions. This interaction was calculated through Eq. (19), where f approximated with SVR as follows

$$\begin{aligned}
&D_i = f\Big((nR1_i, SLR1_i), (nR2_i, SLR2_i), (nR3_i, SLR3_i), \\
&(nR4_i, SLR4_i), AA_i, AV_i, PMC\Big) \\
&SLR1_i = \frac{\sum_{j=1}^{nR1_i} SLr1_j}{nR1_i}, SLR2_i = \frac{\sum_{1}^{nR2_i} SLr2_j}{nR2_i}, \\
&SLR3_i = \frac{\sum_{1}^{nR3_i} SLr3_j}{nR3_i}, SLR4_i = \frac{\sum_{1}^{nR4_i} SLr4_j}{nR4_i}
\end{aligned} \tag{19}$$

where $SLr1_j$ to $SLr4_j$are the skill levels of $j-th$, R1 to R4 are labors of activity i, respectively,$SLR1_i$ and $SLR4_i$ are the average skill rates of expert and common labors of activity i, respectively, AA_i is the properties of activity i, AV_i is the volume of activity i, and PMC is the project management condition.

To train SVR, 220 hypothetical data were generated for each activity. These data contain some nonlinear function that calculate the results of agents' interactions in different situations and SVR tries to find this function in the training phase. Out of the 220 data, 150 data were used for training, 35 for validating and 35 for testing the AI core.

The duration and cost of each activity were calculated based on the quality and quantity of the assigned work crew. Project duration and cost were calculated in accordance with project network and predecessor relations among activities, calculated duration, and cost through Eq. (8)-(10)

7 Results and discussion

This example case was solved in both single and multi-objective optimizations as follows:

1 Project duration minimization

2 Project cost minimization

3 Project Time-Cost optimization

In the duration minimization, the objective function is minimizing the project duration subjected to project network constrains (Eq. (11)-(14)), the results of this optimization is shown in Fig. 7. The best work crew subjected to duration minimization is presented in Table 5.

Total project time after minimization is 67 days and project cost is 239440 monetary unit. The duration, early start, free float, and direct cost of each activity are presented in Table 6. If every activities' work crews have 3 R1, 9 R2, 15 R3, and 18 R4, the project duration will be 66 days and project cost will be 263478 monetary unit; it means, 1 day project duration reduction (1.4%) can cause 10% increase in project cost. So, sometimes, in some activities, it is better to change some fully skilled resources with cheaper lower skill ones. Table 7 shows the result of this resource allocation. Since minimizing the noncritical activities' duration did not affect total project duration, in the optimized case, the free floats were smaller.

Project total cost is the sum of the direct and indirect costs. The result of cost minimization is presented in Fig. 8. The optimum resource allocation is presented in Table 8.

Based on resource allocation results, in the cost optimization, the model reduced the total cost through reducing direct cost by using the cheaper resource with lower skills. The project duration in minimum cost is 99 days and in optimum cost is 214234 monetary unit. Table 9 shows the duration, early start, free float, and direct cost of each activity after cost minimization. In this situation, project duration increased up to33 days (50%) in comparison with minimum project long span, and project cost decreased about 20%. It shows that in this case study the decision about choosing optimum project time or cost is highly depended on the criticality of time. In the cost optimization, the model reduced the total cost through reducing direct cost by using the cheaper resource with lower skills.

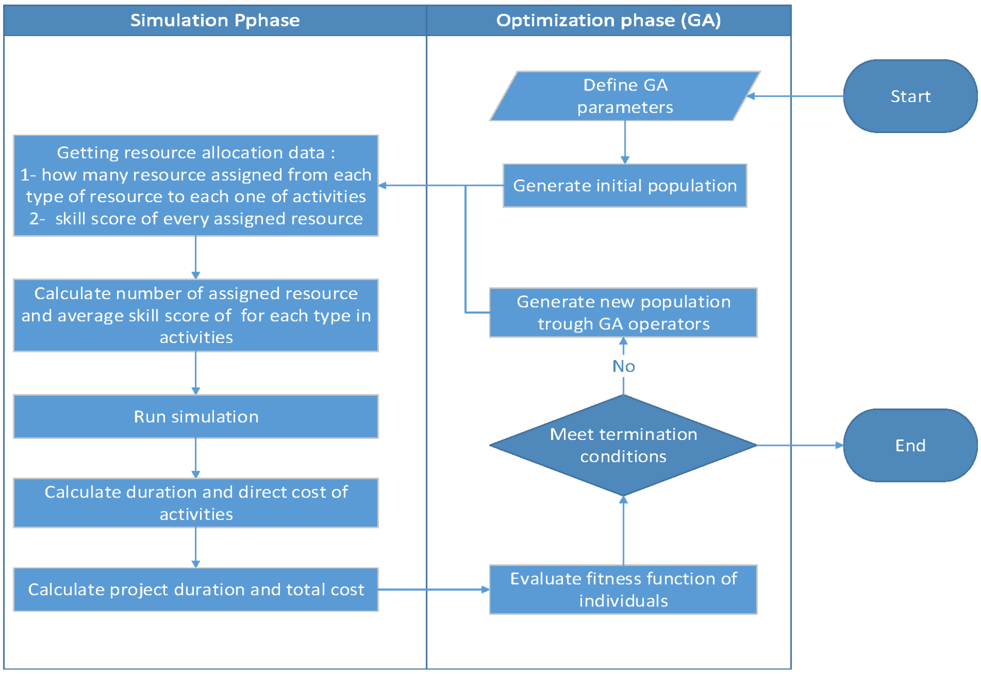

Fig. 5. The view of the modeling procedure

Tab. 2. The likert scales of proposed model

LIKERT SCALE POINT		*1*	*2*	*3*	*4*	*5*
ACTIVITIES PARAMETERS	Severity	Very easy work	Easy work	Moderate	Hard work	Very Hard Work in stressful condition
	Complexity	Very routine	Simple	Moderate	Somedeal complex	Very complex
	Repetition Level	Without any repetition	Very low repetitive	Normal repetitive	More than normal repetitive	completely repetitive
	accessibility to material	Very hard	Hard	Normal	Easy	Trouble-free
LABORS PARAMETERS	Skill level	very weak experience	Normal knowledge	Professional labor	N/A	N/A
ENVIRONMENTAL PARAMETER	Management Condition	Very weak project management	weak project management	Normal project management	Good project management	professional project management

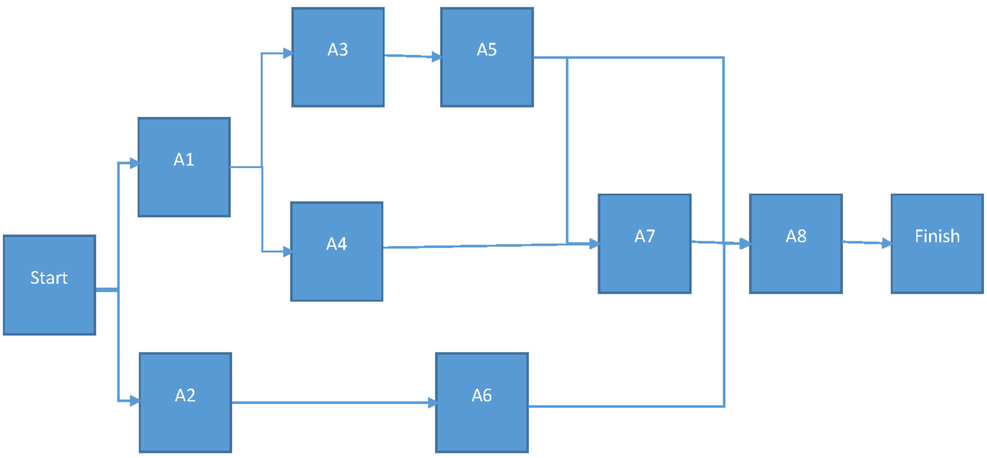

Fig. 6. The example project network

Tab. 3. Activities details

ACTIVITY NAME	A1	A2	A3	A4	A5	A6	A7	A8
VOLUME(UNIT)	296	734	1695	783	2950	2000	936	853
SEVERITY	5	3	3	1	4	3	1	4
COMPLEXITY	4	2	4	5	1	2	1	3
REPETITION LEVEL	1	1	1	1	3	1	5	2
MATERIAL AVAILABILITY	5	3	5	3	1	3	5	5

Tab. 4. Labors cost (monetary unit per date)

SKILL LEVEL	1	2	3
TYPE 1	23	30	41
TYPE 2	42	54	72
TYPE 3	35	45	65
TYPE 4	15	25	33

Tab. 5. The best work crew subjected to duration minimization

RESOURCE TYPE	R1			R2			R3			R4		
SKILL SCORE	1	2	3	1	2	3	1	2	3	1	2	3
A1	0	0	3	0	6	3	3	12	0	0	8	10
A2	0	0	3	0	9	0	15	0	0	18	0	0
A3	0	0	3	0	2	7	0	3	12	1	4	13
A4	2	0	0	5	1	0	6	0	0	4	0	0
A5	0	0	3	0	2	7	0	0	15	0	0	18
A6	0	0	3	0	0	9	0	15	0	3	0	15
A7	0	1	2	0	9	0	0	15	0	5	5	8
A8	0	0	3	0	4	5	0	0	15	1	4	13

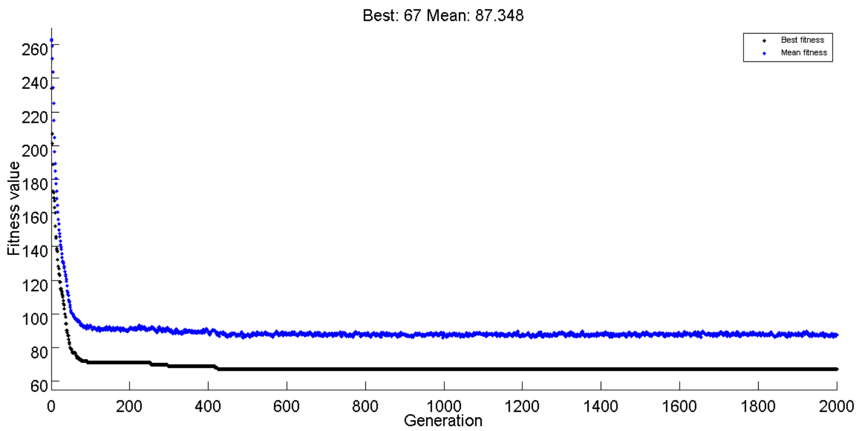

Fig. 7. Results of duration optimization

Tab. 6. The duration, early start, free float and direct cost of activities of optimized work crew (duration)

	A1	A2	A3	A4	A5	A6	A7	A8
Duration	13	13	21	21	19	27	8	6
Early Start	0	0	13	13	34	34	53	61
Direct Cost	22022	16653	42462	10479	40508	48600	12856	12360
Free Float	0	0	0	19	0	21	0	0

Tab. 7. The duration, early start, free float and direct cost of activities of professional work crew

	A1	A2	A3	A4	A5	A6	A7	A8
Duration	13	9	21	7	19	25	7	6
Early Start	0	0	13	13	34	20	53	60
Cost	28002	19386	45234	15078	40926	53850	15078	12924
Free float	0	0	0	33	0	26	0	0

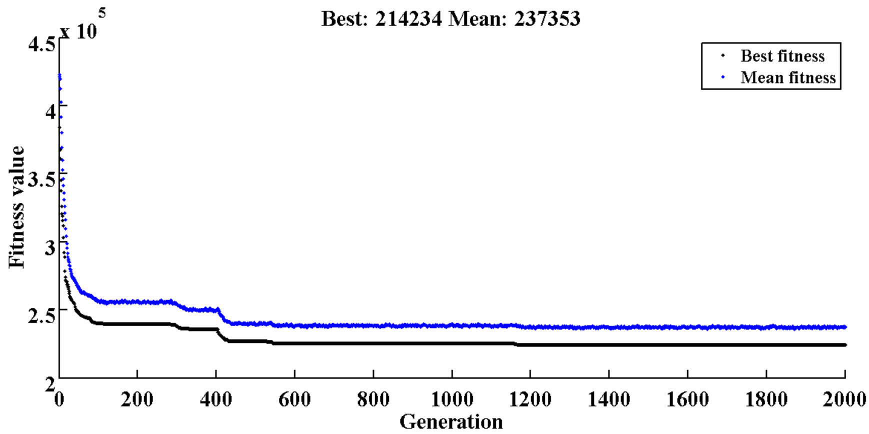

Fig. 8. Results of cost optimization

Tab. 8. The best work crew subjected to cost minimization

RESOURCE TYPE	R1			R2			R3			R4		
SKILL SCORE	1	2	3	1	2	3	1	2	3	1	2	3
A1	3	0	0	9	0	0	6	0	0	17	0	0
A2	1	0	0	1	0	0	2	0	0	2	0	0
A3	0	1	2	0	9	0	15	0	0	17	0	0
A4	1	0	0	1	0	0	2	0	0	2	0	0
A5	0	0	3	0	0	9	0	13	2	10	0	8
A6	0	0	3	0	2	7	13	2	0	16	0	2
A7	0	1	0	1	1	0	4	0	0	4	0	0
A8	0	0	3	0	9	0	0	15	0	8	10	0

Tab. 9. The duration, early start, free float and direct cost of activities of optimized work crew (cost)

	A1	A2	A3	A4	A5	A6	A7	A8
Duration	19	57	26	30	21	34	26	7
Early Start	0	0	19	19	45	57	66	92
Cost	15162	9405	32448	4950	35994	48076	7982	10717
Free float	0	0	0	17	0	1	0	0

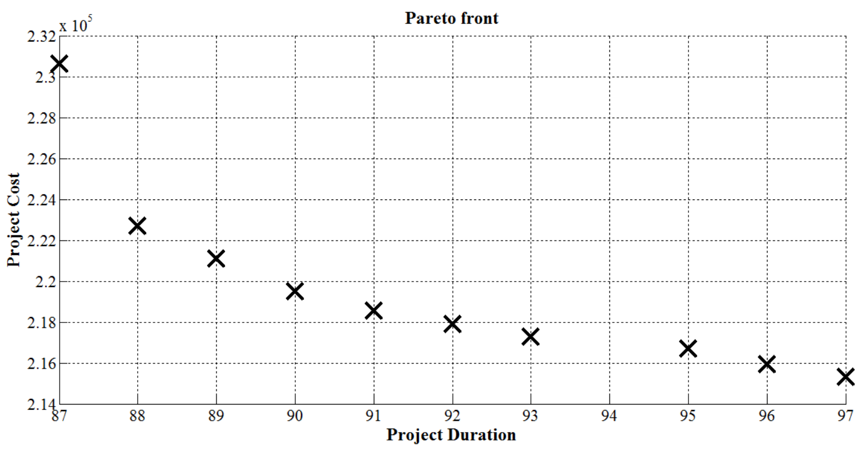

Fig. 9. Pareto front of time-cost optimization

Tab. 10. Numerical results of Time-Cost trade off

PROJECT DURATION	*PROJECT COST*	*DIRECT COST*	*INDIRECT COST*
87	230636	187136	43500
88	222718	178718	44000
89	221091	176591	44500
90	219523	174523	45000
91	218548	173048	45500
92	217922	171922	46000
93	217301	170801	46500
95	216705	169205	47500
96	215955	167955	48000
97	215334	166834	48500

Fig. 9 shows the Pareto front of time-cost optimization. The numerical results, also, are presented in Table 10.

With Pareto front of time-cost trade off of project, the manager could choose different scenarios to accomplish the project based on project time and cost objectives.

8 Conclusions

Simulation techniques usually are used to model project operations. Project planner has to choose the resource allocation scheme among existing options for each activity. Generally, there is more than one scheme available for running each activity. So, for finding the best known resource arrangement, regarding to the total project life span or cost minimization, all feasible combinations must be modeled through simulation study. When there are a large numbers of resource combinations, examining every combination through this process is uneconomical. Therefore, this study proposed a hybrid model which allowed the project planner to find out the best or near optimal resource combination regarding the project's primary goals (time, cost, or time-cost). According to the conducted case study, this new hybrid model, showing proper results, could optimize resource allocation in both single and multi-objective optimizations. In future research, the abilities of this hybrid model can be evaluated to possibly solve the resource constrain project scheduling problem (RCPSP).

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