Robust forensic-based investigation algorithm for resource leveling in multiple projects

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Abstract

The project managers often face challenging due to a scarcity of resources in construction management. Levelling the used resources in multiple projects is a frequently encountered problem in construction areas and manufacturing sectors. This study proposes a robust forensic-based investigation (FBI) algorithm for resource leveling in multiple projects with considerations of different objective functions of resource graphs. The fuzzy c-means clustering approach is fused into the main operation of the FBI to enhance the rate of convergence by utilizing population information. The scheduling examines different objective functions for optimizing resource profile selection. Two application case studies are used to demonstrate the performance of the improved optimization algorithm in dealing with the resource-leveling problem in multiple projects. Experimental findings and statistical comparisons demonstrated that the developed FFBI could acquire high quality solutions and surpass those of compared optimization algorithms.

Key Words: Resource levelling; project management; fuzzy clustering; Forensic-based investigation algorithm; optimization.

1 Introduction

Construction management is complicated due to several influencing factors such as high intensity of interrelationship among project activities, nature of uncertainty in projects, requiring several parties, and so on [1, 2]. To overcome the aforementioned difficulties and achieve successful project outcomes, advanced scheduling technologies should be used instead of traditional techniques such as critical path analysis, program evaluation and review technique, and linear scheduling [3]. Applying the new technique to resource management is a prerequisite for construction contractors in today's complex construction environment [4]. An appropriate method for resource management could determine the high level of project success to avoid project delay and cost overrun [5, 6].

The project managers generate schedule using conventional approaches such critical path method and program evaluation and review technique, which results in the earliest start time mode for all activities [7]. Nevertheless, the abovementioned methods neglect the overconsumption of resources during project implementation. In addition, the incorporation the resource usage into activities cannot guarantee an appropriate schedule because of the variation of resource demanding along a project timeline. Resource fluctuations cause difficulty for contractors to hire and fire the essential workers to control the efficient resource profiles. Accordingly, the project cost will be increased and productivity will be decreased. Hence, effective resource management is obligatory to minimize resource expenditures and satisfy the planned schedule.

The method of reducing the resource fluctuations called resource-levelling plays an imperative role and attracts a lot of attention in construction project management [8, 9]. The purpose of resource levelling is to reduce resource usage fluctuations as much as possible in time span along the project timelines. Resource levelling attempts to schedule noncritical activities within their available floats without changing total project time to attain a good resource histogram [10]. The problems of resource leveling can be classified into four categories: (1) considering a single resource in a project [11], (2) handling multiple types of resources in a project [12], (3) dealing with a single resource in many projects [13], and (4) leveling multiple resources in different projects [14-16]. However, real construction projects are still facing challenging when dealing with sharing resources, and multiple mode activities due to the lack of a regular guiding process. In this regard, project planners should pay more attention to reducing resources fluctuations in many projects during the planning stage of project management.

Numerous methods have been investigated to deal with the resource-leveling problem including mathematical, heuristics, and metaheuristics. Among the abovementioned techniques, the evolutionary algorithms (EAs), a class of metaheuristics, have attracted considerable attention from researchers [17-20]. The EAs use iterative calculations instead of using substantial gradient information that has been successfully used to tackle many optimization issues. Due to the great achievement in many engineering fields, they still have some limitations. The major inherent drawbacks such as weak exploited ability and converging too early when solve the complex optimization problems. Therefore, many researchers have used hybrid techniques to boost the EAs performance.

Forensic-based investigation (FBI) is a recent metaheuristic algorithm proposed in 2020 by Chou and Nguyen [21]. The FBI based on the situation of police officers handles problems through suspect, site, and pursuit. FBI is easy to use and does not require predefined controlling parameters while showing great robustness in tackling single optimization problems. Many studies have proved that the FBI has superior performance compared to well-known algorithms [22-25]. The FBI is a novel and powerful algorithm, application of its variant to solve the resource leveling problems would be very interested. The original FBI only operates through two main phases including investigation and pursuit. However, the independently interact of each phase and lack of communication between the two teams lead to a decrease in convergence rate. This work utilizes the advantages of the original FBI and fuzzy clustering to establish a robust forensic-based investigation algorithm for resource leveling in multiple projects.

This research contributes to extant literature as follows. First, a hybrid algorithm is developed to improve the intensification and diversification abilities of the FBI. Second, this study proposes a scheduling method by considering multiple resource in different projects via real case studies and various evaluation criteria. Third, the research outcomes give a useful tool for project managers in controlling resource management during project planning and implementation phases.

The rest of the paper is organized as in the following: Section 2 presents the related works on resource levelling. Section 3 describes a mathematical formulation of resource leveling in multiple projects. Section 4 presents proposed model for solving the resource-levelling problem. Section 5 discusses the optimization outcomes, result comparisons and analysis. The final section draws conclusions and offers recommendations for further work.

2 Related works on resource leveling

The resource levelling (RL) problems gain a lot of attention due to their practical application [26, 27]. Since the RL problems involved in construction projects, many studies of RL have been considered in depth with many approaches. Derbe, G., et al. [28] conducted scientometric review on construction project scheduling (CPS) studies. The resource-constrained project scheduling problems are the most concerned filed in CPS. Other areas such as resource utilization, resource allocation, resource levelling are included without limitation to. Zhou, J., et al. [29] performed an extensively review on methodologies for optimizing construction project schedule.

Various methods to handle the RL problem include the mathematical, heuristics, and meta-heuristic approaches. Mathematical methods such as dynamic programming [30, 31], integer programming [32], enumerative search [33], and branch-and-bound methods could provide the exact solutions. Nevertheless, these methods face many drawbacks when dealing with large-scale and complex problems. As a construction project becomes complicated, expanding the number of activities and decision variables leads to computational explosion and impractical calculation.

Several researchers prefer to use heuristic methods to address the above-mentioned weaknesses of mathematical approaches. Many efforts of proposing heuristic rules have been made to improve feasible solution quality [34, 35]. The heuristic approaches have been successfully applied to handle large and complex problems [36-38]. However, the project managers are not satisfied with using heuristic methods in practical applications. Because the methods rely on pre-defined rules, their effectiveness highly depends on specific types of solving problem. Therefore, both mathematical and heuristic methods are not suitable for handling real-world construction projects [18, 39].

Numerous researchers have investigated the use of meta-heuristic algorithms, which utilize intelligent search based population to solve various resource leveling problems in construction projects [40]. Genetic algorithm (GA) is the most popular method for solving RL problems [1, 41-44]. Other well-known algorithms are still active for researchers in handling RL such as particle swarm optimization [5, 16], ant colony optimization [45], and differential evolution [46, 47]. Some studies have used recently introduced optimization algorithms for tackling the RL problem. Khanzadi, M., et al. [48] proposed two new algorithms named colliding bodies optimization and charged system search to handle the resource levelling and resource constrained simultaneously. Recently, Prayogo, D., et al. [49] used a modified symbiotic organisms search to cope with the resource leveling problem [50]. The metaheuristic methods have been successfully applied to handle the RL problems at a certain degree. They still have some limitations such as easy trapping in local optima and poor exploitation when facing problems that are more complicated. Therefore, more advanced methods are required for further improvement of the quality and efficiency of the resource leveling solution.

Various advanced techniques have been proposed for other variants of resource levelling problems [51]. Masmoudi, M. and Haït, A. [52] proposed a fuzzy model to deal with project scheduling problems. Kyriklidis, C., et al. [53] studied the RL problem using hybridization strategy of two intelligent metaheuristics. Khalilzadeh, M. [10] considered multi-mode activities and allowed splitting in RL modelling. Damci, A., et al. [54] examined the influence of many objective functions in RL problems [11]. Damci, A., et al. [2] introduced a new method that considers the available float of activities in RL. The novelty of this study lies in the proposal of a robust hybrid optimization algorithm to handle complex multiple resource levelling in multiple projects.

3 Description of resource leveling in multiple projects

A construction company will start simultaneously n projects. Every project includes many activities that required M types of resources to execute. The optimization model aims at minimizing the fluctuation in using resources by reducing the peak demand resources and daily resource consumption. The definition of resource leveling in multiple projects can be expressed as an optimization problem as follows [14, 55]:

$$\text{Minimization of resource intensity} = \frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{M}\left[\mathrm{w}_m \left(R_m(t) - \overline{R_m} \right)^2 \right] \tag{1}$$

subject to:

$$T_i^{ES} \le T_i^{ST} \le T_i^{LS} \tag{2}$$

$$\max\left(T_{pset_i}^{ST} + T_{pset_i} \right) \le T_i^{ST} \le T_i^{LS} \tag{3}$$

$$R_m(t) = \sum_{k=1}^{n} \sum_{i} R_{mt}(i); \quad \overline{R_m} = \frac{1}{T} \sum_{t=1}^{T} R_m(t) \tag{4}$$

$$R_m(t) = \begin{cases} R_m(t) \ if \ T_i^{ST} < t \leq T_i^{FT} \\ 0 \ if \ t \leq T_i^{ST} \ or \ t > T_i^{FT} \end{cases} \tag{5}$$

where $R_m(t)$ represents the m^{th} resource demand on day t of all involving projects. $R_{mt}(i)$ denotes the m^{th} resource demand on day t of the i^{th} activity. T^{ST}, T^{FT},T^{ES}, T^{LS} are the start time, finish time, earliest start time, and latest start time of the i^{th} activity, respectively. The predecessor set of activity i is $pset_i$. The coefficient w_m specifies the level of importance of the m^{th} resource. The values of w_m are determined via the analytical hierarchy process (AHP) method. The large value of w_m corresponds to high level of significance of resource m.

Equation (1) denotes the general objective function of resource leveling in multiple projects, which aims at minimizing sum of the square of the deviations between daily resource usage and the average resource usage. Equation (2) represents the first constraint that the start times of non-critical activities must be in the range of the earliest and latest start times. Equation (3) is the second constraint that the actual activities' start time must be satisfied the dependencies in project networks. Equation (4) and (5) are used to calculate the daily required resource ($R_m(t)$) of all implementing projects in an enterprise and average resource usage ($\overline{R_m}$).

4 Robust optimization for resource leveling

The newly introduced fuzzy clustering forensic-based investigation (FFBI) is rigorously presented to resource levelling problems. The FFBI is a new hybrid optimizer that based on the recent developed FBI algorithm by Chou and Nguyen [21]. The original FBI mimics the criminal investigation behavior of police officers [56, 57]. The forensic investigation process is composed of five stages: investigation start, explanation of detection, inquired direction, actions, and prosecution. The new proposed FFBI mainstream is analogous to those in the original FBI composing of initial population, investigation and pursuit phase, selection, and stopping steps. However, the FFBI differs from the original version by integrating the fuzzy c-means clustering approach into the investigation and pursuit phase to improve the convergence speed by utilizing population information efficiently via cluster centers (Fig 1). The details of FFBI for RL problems are further illustrated as follows:

<Insert Fig 1 here>

4.1 Initialization and decision variables

The FFBI-RL requires the inputs including precedence relations between activities, activity duration, and requested resources. The user also needs to set the two common optimizer parameters including the maximum generation G_{max} and the population size (NP). The total project duration and resource requirements for all activities are calculated via critical path method and project data information. A random generator creates the initial population as in Eq. (6). x_{ij} denotes random numbers in the interval (0,1) and will be improved during optimization process of FFBI.

$$\text{Population} = \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_i \\ \cdots \\ X_{NP} \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,D} \\ \cdots & \cdots & \cdots & \cdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,D} \\ \cdots & \cdots & \cdots & \cdots \\ x_{NP,1} & x_{NP,2} & \cdots & x_{NP,D} \end{bmatrix} \tag{6}$$

The D-element vector in Eq. (7) represents the decision variable for resource leveling in multiple projects. D is total non-critical activities in active projects. The index i denotes the i^{th} individual in the current population. The vector in Eq. (7) is a row vector of the matrix that contains NP rows and D columns as shown in Eq. (6).

$$X = \left[x_{i,1}, x_{i,2}, ..., x_{i,j}, ..., x_{i,D} \right] \tag{7}$$

The original FBI operates the optimization mechanism via real numbers. Hence, the ceil function in Eq. (8) is applied to convert the real numbers in the decision vector into start time ($X_{i,j}$) values of all non-critical activities.

$$X_{i,j} = LB_j + ceil\left(x_{i,j} * (UB_j - LB_j)\right) \quad (8)$$

where x_{ij} in Eq. (8) is an element of the D-element vector in Eq. (7). LB_j and LB_j are earliest and latest start times of the j^{th} non-critical activity in total D non-critical activities after handling the constraints. The actual start time of all activities in project networks must satisfy two conditions: (1) be in the range of the earliest and latest start times, and (2) be restricted by the actual start time of any of its predecessor activities. The first condition can be fixed before the calculating process. Nevertheless, the second condition must be decided in turn. The actual start time of one activity can confirm when all activities in its predecessor set are determined.

4.2 Investigation phase

The investigation phase includes the steps of (1) interpreting results; and (2) directions of inquiry. In the interpreting results step (A1), other individuals affect each individual movement as Eq. (9).

$$X_{A1_{ij}} = X_{A1_{ij}} + \left(2*(rand() - 0.5)\right) * \left(X_{A_{ij}} - (X_{A_{kj}} + X_{A_{hj}})/2\right) \quad (9)$$

where (2*rand()-0.5) denotes a random number in range of [-1;1]; $j=1,\ldots,D$; D is the dimensional number; *k*, *h*, and *i* represent three random indices, $\{k, h, i\} \in \{1, \ldots, NP\}$.

In the second step (A2), each individual operation depends on the probability value of each individual in Eq. (10). P_{worst} and P_{best} denote the worst and the best objective values, respectively. P_{A1_i} is the fitness value of individual X_{A1_i}.

$$\text{Prob}(X_{A1_i}) = \left(P_{A1_i} - P_{worst}\right) / \left(P_{best} - P_{worst}\right) \quad (10)$$

The new movement location of the individual $X_{A2_{ij}}$ is updated using Eq. (11).

$$X_{A2_{ij}} = X_{best} + X_{A_{dj}} + rand() * \left(X_{A_{ej}} + X_{A_{fj}}\right) \quad (11)$$

where X_{best} is the best individual in the current population. *d*, *e*, *f* and *i* are four arbitrarily indexes, $\{d, e, f, i\} \in \{1, ..., NP\}$.

4.3 Pursuit phase

The pursuit phase also consists of two steps. The updated movement of each individual in the first step (B1) can be formulated in Eq. (12).

$$X_{B1_{ij}} = rand()*X_{B_{ij}} + rand()*(X_{best} - X_{B_{ij}}) \tag{12}$$

In the second step (B2), the other member influences the new individual by the probabilities. In case of P_{B_r} is better than P_{B_i}, the new movement of B_i can be expressed as Eq. (13)

$$X_{B2_{ij}} = X_{B_{rj}} + rand()*\left(X_{B_{rj}} - X_{B_{ij}}\right) + rand()*\left(X_{best} - X_{B_{rj}}\right) \tag{13}$$

Otherwise, the Eq. (14) is applied.

$$X_{B2_{ij}} = X_{B_{ij}} + rand()*\left(X_{B_{ij}} - X_{B_{rj}}\right) + rand()*\left(X_{best} - X_{B_{ij}}\right) \tag{14}$$

where X_{best} denotes the best individual; r and i are two indices, $\{r, i\} \in \{1, ..., NP\}$, and r is set randomly.

4.4 Fuzzy clustering process

The fuzzy c-means (FCM) clustering approach was integrated with FBI to enhance the convergence rate in optimization process. The FCM is involved in population evolution by introducing cluster centers as candidate individuals. The role of FCM in the FFBI provides high quality starting point in the searching procedure via its cluster centers. Therefore, the clustering technique will enhance the exploitation effectively during the optimization process. The clustering method used in this study is analogous to those in [58]. Early operating clustering may fail in establishing good clusters. Therefore, the clustering period needs to perform adequately to allow the optimization algorithm appropriate timeframe to create complete and steady clusters. This study uses a parameter called clustering period *m* to control the process of clustering. The value of *m* is set to 20.

When the remainder after division of the maximum generation G_{max} and clustering period m equal to zero (mod (G_{max},m) = 0). The FCM produces k individuals, which involve in process of updating the population. This process contains four steps: selection, generation, substitution, and update step [59].

a) Selection step: Randomly select k individuals from the current population (set A). k represents the number of clusters, $k \in \left[2, \sqrt{NP}\right]$.

b) Generation step: Fuzzy c-means clustering method creates k offspring (set B).

c) Substitution step: Choose k best solutions (set C) from the merged set (set A + set B) for substitution.

d) Update step: Update the population as P=P-Set A+Set C.

4.5 Stopping Condition

When the predetermined maximum generation G_{max} is reached, the optimization process will terminate. The search procedure stopping generates the optimum start time for all activities in project networks. The final schedule and its corresponding resource graph will be figured out for project implementation.

5 Case Studies

This paper analyzed two construction case studies to demonstrate the effectiveness of the proposed FFBI for the resource leveling in multiple projects. The first construction project case study is examined using data given in Yan, G., et al. [16]. The case consists of two projects with similar total project duration and uses three kinds of resource including human (R_1), fund (R_2), and equipment (R_3). Fig. 2 displays the values of duration, required resource, and dependency of all activities in project networks

<Insert Fig. 2 here>

The AHP determines the importance level of each resource via a pairwise comparison matrix, which is generated by the experts as follows:

$$\begin{array}{c} R_1 \\ R_2 \\ R_3 \end{array} \begin{bmatrix} 1 & 3 & 5 \\ 1/3 & 1 & 3 \\ 1/5 & 1/3 & 1 \end{bmatrix}$$

The consistency checking is acceptable since the value of the consistency ratio is less than 0.1. Weights for each resource are computed as: w_1 = 0.637; w_2 = 0.258; w_3 = 0.105. The general objective of resource leveling in multiple projects is to minimize the sum of the square of the deviations between daily resource usage and the average resource usage. The mathematical programming model for the first case is formulated as follows:

$$Min\,RI = \frac{1}{18}\sum_{t=1}^{18}\left[0.637\left(SR_1(t)-\overline{SR_1(t)}\right)^2 + 0.258\left(SR_2(t)-\overline{SR_2(t)}\right)^2 + 0.105\left(SR_3(t)-\overline{SR_3(t)}\right)^2\right]$$

subject to: $\begin{cases} 0 \le T_s(\mathrm{A}_1) \le 7 \\ 0 \le T_s(B_1) \le 3 \\ T_s(B_1)+5 \le T_s(C_1) \le 8 \\ 0 \le T_s(F_1) \le 6 \\ T_s(B_1)+4 \le T_s(G_1) \le 10 \\ 0 \le T_s(H_1) \le 3 \end{cases}$ and $\begin{cases} 0 \le T_s(I_1) \le 15 \\ 0 \le T_s(A_2) \le 9 \\ 0 \le T_s(C_2) \le 15 \\ 5 \le T_s(D_2) \le 9 \\ 5 \le T_s(G_2) \le 10 \\ 5 \le T_s(H_2) \le 13 \end{cases}$

The first example was performed on small-scale construction projects. Hence, the second case on the medium sized projects is utilized to further measure the performance of the evolutionary algorithms. Fig. 3 illustrates the network diagram of both projects. Each activity in both projects uses two types of resources (R_1 human, R_2 equipment) and a fixed duration D that are shown above the arrow line. Weights for each resource are defined as: α_1=0.7; α_2=0.3 that based on the importance level. The mathematical model proposed to solve multiple resource leveling in the second case is expressed as follows.

<Insert Fig. 3 here>

$$Min\,RI = \frac{1}{50}\sum_{t=1}^{50}\left[0.7\left(SR_1(t)-\overline{SR_1(t)}\right)^2 + 0.3\left(SR_2(t)-\overline{SR_2(t)}\right)^2\right]$$

subject to: $\begin{cases} 0 \le T_s(A_1) \le 20 \\ T_s(A_1)+3 \le T_s(C_1) \le 23 \\ T_s(C_1)+5 \le T_s(F_1) \le 28 \\ T_s(F_1)+4 \le T_s(I_1) \le 32 \\ 6 \le T_s(E_1) \le 7 \\ T_s(E_1)+4 \le T_s(H_1) \le 11 \\ 17 \le T_s(K_1) \le 22 \\ 17 \le T_s(L_1) \le 20 \\ T_s(L_1)+5 \le T_s(O_1) \le 35 \\ T_s(O_1)+6 \le T_s(R_1) \le 41 \\ 25 \le T_s(N_1) \le 39 \\ T_s(N_1)+4 \le T_s(Q_1) \le 43 \\ T_s(Q_1)+4 \le T_s(T_1) \le 47 \end{cases}$ and $\begin{cases} 0 \le T_s(B_2) \le 1 \\ 6 \le T_s(C_2) \le 26 \\ T_s(C_2)+2 \le T_s(G_2) \le 28 \\ T_s(G_2)+5 \le T_s(K_2) \le 33 \\ T_s(G_2)+5 \le T_s(L_2) \le 42 \\ 6 \le T_s(E_2) \le 14 \\ T_s(E_2)+7 \le T_s(I_2) \le 21 \\ T_s(B_2)+5 \le T_s(F_2) \le 31 \\ T_s(F_2)+7 \le T_s(J_2) \le 36 \\ T_s(J_2)+7 \le T_s(N_2) \le 43 \end{cases}$

5.1 Optimization results

The FFBI is a parameter-free algorithm. Two common control parameters that are population size *NP* and maximum number of generations G_{max} needed to define. The values of *NP* and G_{max} were set to 100 and 100 for the first case, 150 and 200 for the second case respectively. For each case, we run the experiment 30 times in the randomness avoidance. The proposed FFBI significantly reduces fluctuation in resource use of an enterprise in both case studies. Fig. 4 displays the resource graph of initial networks and after leveling by FFBI algorithm in both cases. As shown in Fig. 4, the maximum daily-required resource of R1 of the second case as an example lower from 48 to 34 workers.

<Insert Fig. 4 here>

Table 1 shows the findings of the optimal values of indicators using the proposed FFBI. In addition to the start times of non-critical activities for both cases. $RI_{m(m=1,2,3)}$ in Table 1 is the resource intensity for single resource *m*:

$RI_m = \dfrac{1}{\text{Project duration (D)}} \sum_{t=1}^{D} \left[\alpha_m \left(SR_m(t) - \overline{SR_m(t)} \right)^2 \right]$. The single RI acquired by FFBI was significantly reduced compared to the initial schedule.

<Insert Table 1 here>

5.2 Result Comparisons

The results of the proposed FFBI are compared with the well-known algorithms including Genetic algorithm (GA) [60], Particle swarm optimization (PSO) [61], and differential evolution (DE) [62]. The recently developed optimization algorithms such as Symbiotic organisms search (SOS) [63], Whale optimization (WO) [64], and forensic-based investigation (FBI) [21]. In both cases, the parameters of the comparative algorithms were set as follows: In GA, the constant mutant and crossover probability factors were set at 0.5 and 0.9, respectively. PSO sets the cognitive (c1) and social (c2) factors equal to two, and the inertia weight parameter w lies between 0.3 and 0.7. DE control parameters were set as 0.5 and 0.7 for mutant factor F and crossover probability Cr, respectively. Other algorithms retain the recommended settings in the original works. Two parameters (NP, G_{max}) are the same as the above settings for all comparative algorithms.

The results are described subject to the fitness function value that is total resource intensity (RI) obtained by the corresponding algorithm. The average value and standard deviation of RI were utilized to evaluate the performance of the algorithms after thirty runs. Table 2 shows the experimental results, in which the bold values indicate the best acquired solutions. As demonstrated in Table 2, the FFBI has a competitive performance with regard to accuracy and stability indicators. The FFBI is able to find optimal solutions in fitness functions of both cases. Moreover, FFBI outperformed all compared algorithms since it found solutions with the lowest average fitness values of 3.45 in the first case and of 33.502 in the second case.

As the curves shown in Fig. 4, the resource graph found by FFBI in the first case has the maximum daily resource usage of R1, R2, and R3 of 16, 59, and 24, respectively. These values found by previous research by Tran, D.-H., et al. [46] are 15, 62, and 23. Overall, the value of total resource intensity obtained FFBI is better than previous findings. Therefore, the

FFBI is competitive with other algorithms for solving multiple resource leveling in multiple projects.

<Insert Table 2 here>

The performance of the proposed FFBI on two case studies is very promising to the reader. The third case verifies the robustness of the proposed algorithm on available case in research works of Prayogo, D., et al. [49] and Cheng, M.-Y., et al. [47]. The project case has 44 activities with total duration of 70 days. The FFBI yielded lower values of fitness function of 9486 compared to those found by fuzzy clustering chaotic based differential evolution of 9522 and modified symbiotic organisms search of 9518.

5.3 Analytical outcomes with different objective functions

The proposed FFBI performance is further investigated on eight different objective functions on the resource graphs. The eight objective functions formula is present in the second column in Table 3 [54]. The notes at the bottom of Table 3 explain the notations in objective functions and the third column describes the optimization criteria of those objective functions. Table 3 displays the initial values using the earliest start times of all non-critical activities and the optimal values of eight objective functions obtained by FFBI in both case studies. As shown in all values of eight considered objective functions have significant improvement compared to their initial values. The percentage of improvement on each objective function is computed to analyze the improvement levels. As demonstrated in Table 3, FFBI yielded the best improvement percentage (100% and 67.08%) in the second objective function of the first case and the eighth objective function of the second case, respectively.

The improvement is depended on the project characteristics. Different projects may yield the best improvement on another objective function(s). Therefore, the project managers (PM) need to perform the model on different objective functions to determine the objective function gained the highest improvement. In addition, the PM should base on their particular demands to set the coefficient for these objectives to obtain the best fit for their resource graph.

Fig. 5 displays the optimized project resource graph by FFBI on eight different objective functions of both cases. The proposal model generated distinct resource graphs on each objective function. Eight different objective functions attempt to minimize different parameters, therefore they yield different solutions.

<Insert Table 3 here>

<Insert Fig. 5 here>

5.4 Discussion

The above result comparisons proved that the proposed FFBI surpassed other popular algorithms in solving resource-leveling problems. Further discussion and inferences can be drawn as follows:

The fuzzy c-means clustering approach played an important role in operating mechanism of the FBI by introducing cluster center as new potential candidate. This operator helps in balancing exploration and exploitation in investigation and pursuit phases of FBI.

The proposal FFBI has simplicity and stability performance because it does not required any tuning parameter during optimization process. This characteristic favors to diversified optimization problems.

Three case studies have demonstrated the efficiency and effectiveness of FFBI. The first two case are about multiple resource levelling in multiple projects. The third case handles the publicly available data. The FFBI outperformed the considered algorithms in term of objective function value.

The analytical results on eight different objective functions of the resource graphs have proved the feasibility and robustness of FFBI in dealing with the resource-levelling problem. The outcomes provides helpful information for project managers in planning project schedule in early phase.

6 Conclusions and further study

This study proposes a robust forensic-based investigation (FBI) algorithm to solve the multiple resource in multiple projects on different objective functions. The FBI was integrated with the fuzzy c-means clustering technique to enhance the performance of the original algorithm. Two case studies were utilized to validate the effectiveness and efficiency of the proposed model in finding the solutions that level the resource fluctuations. The obtained solutions were compared with those of well-known and recently developed optimization algorithms. The FBBI surpassed the considered algorithms in terms of resource intensity indicator.

The statistical results prove a superior performance of the FFBI in dealing with the multiple resources in multiple project problems. FFBI was able to find the best solution in two considered case studies with the values of 3.184 and 33.299, respectively. Moreover, the proposed model generated the lowest average fitness function of 3.450 and 33.502 in both cases. Furthermore, the FFBI has an excellent performance on eight different objective functions with considerable improvement in fitness value compared to their initial values.

The FFBI algorithm can be easily modified to solve other real-world engineering optimization problems such as resource constrained and allocation. Furthermore, the integration of the leveling resource objective with other project management objectives could be an interesting direction. Therefore, extending the current algorithm to multiple objective versions would be a potential improvement for further research.

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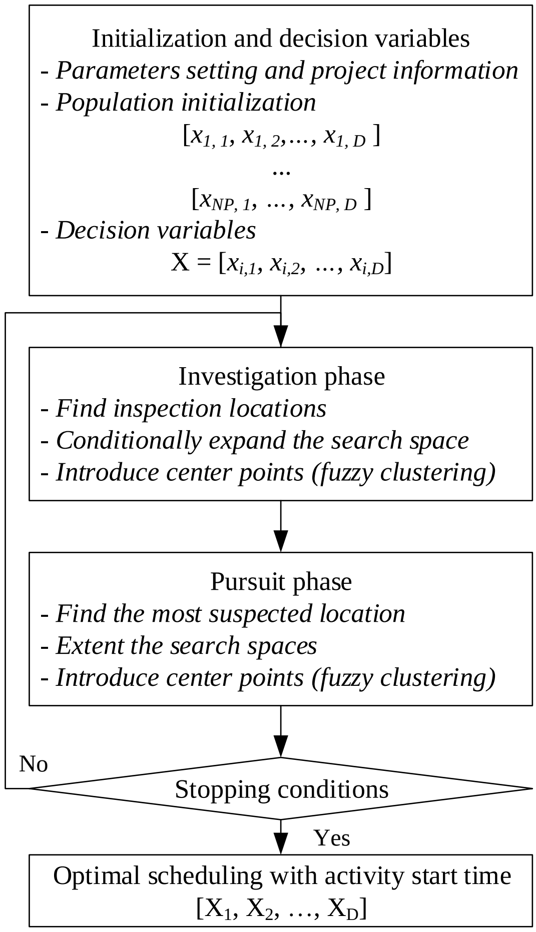


Fig. 1 FFBI for RL problem

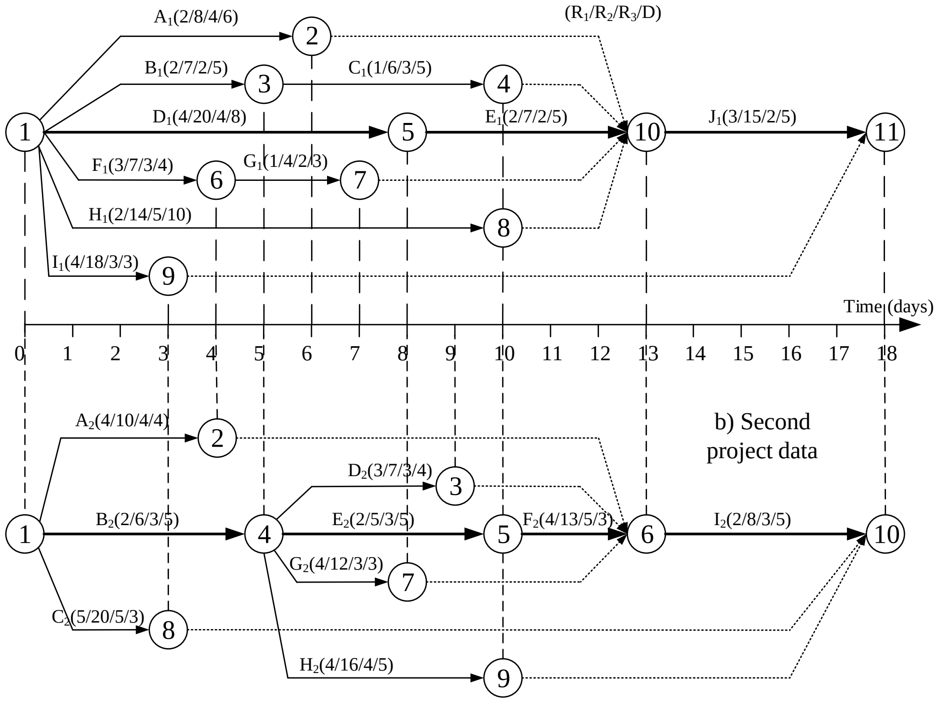


Fig. 2 Network diagram of projects in first case

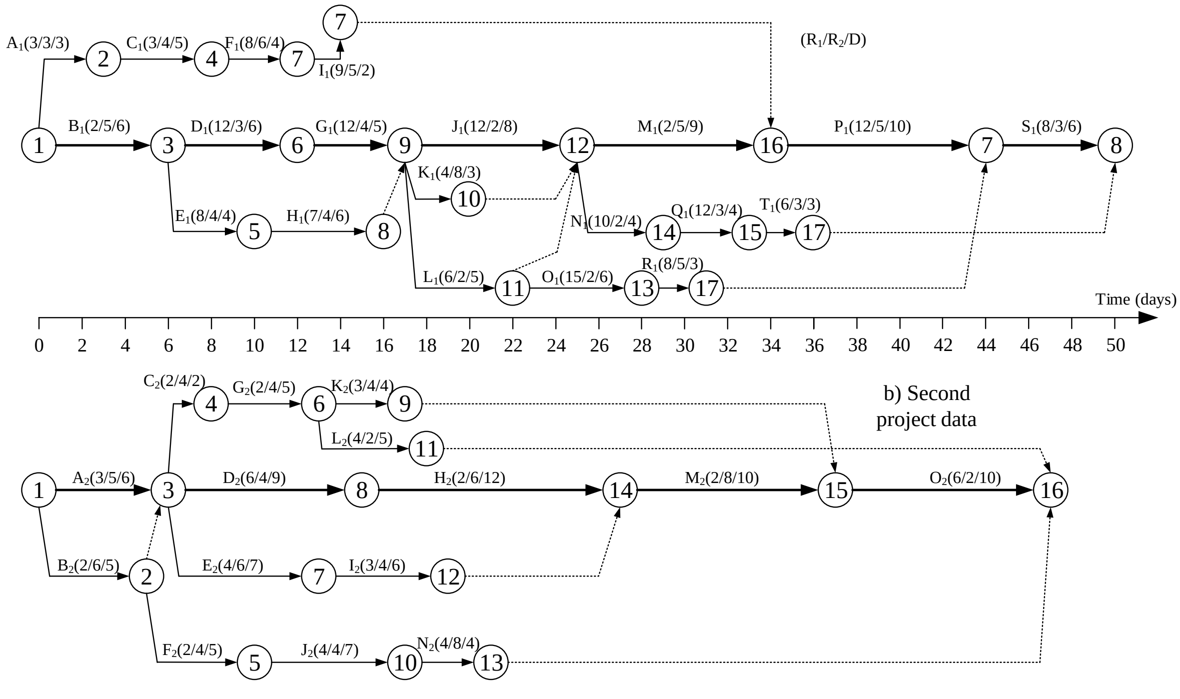


Fig. 3 Network diagram of projects in second case

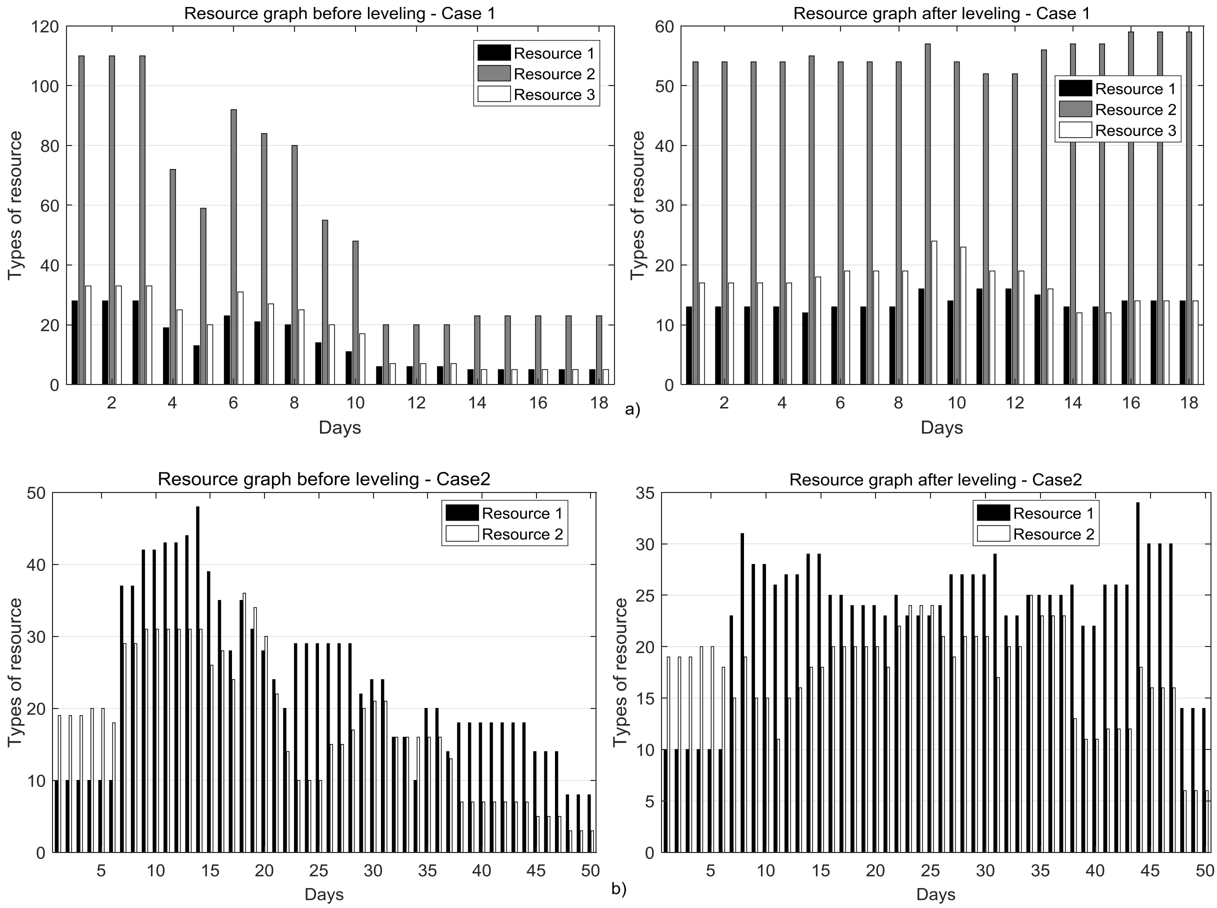
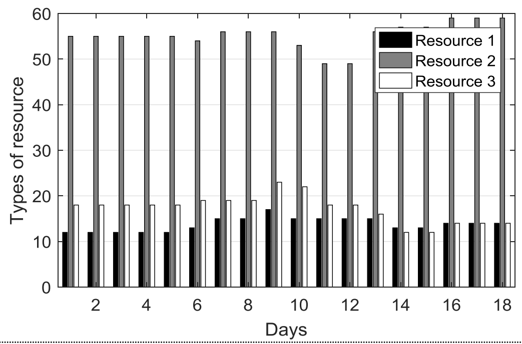
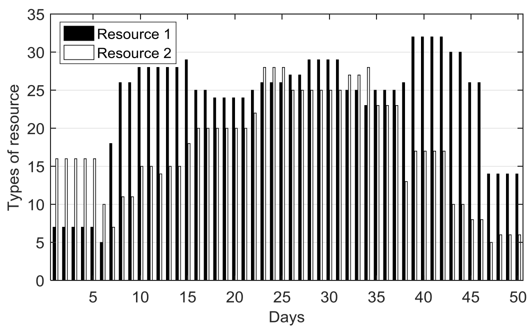
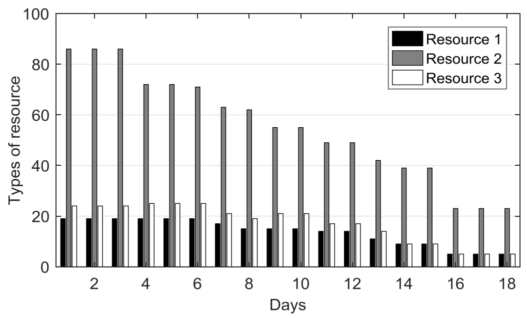
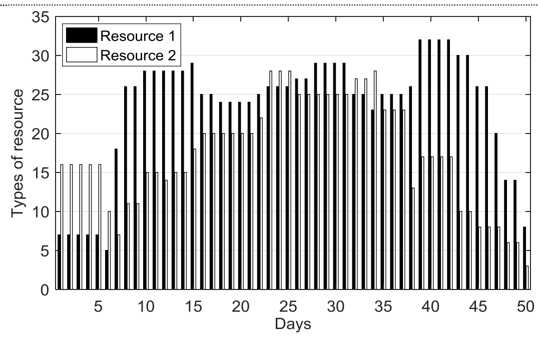
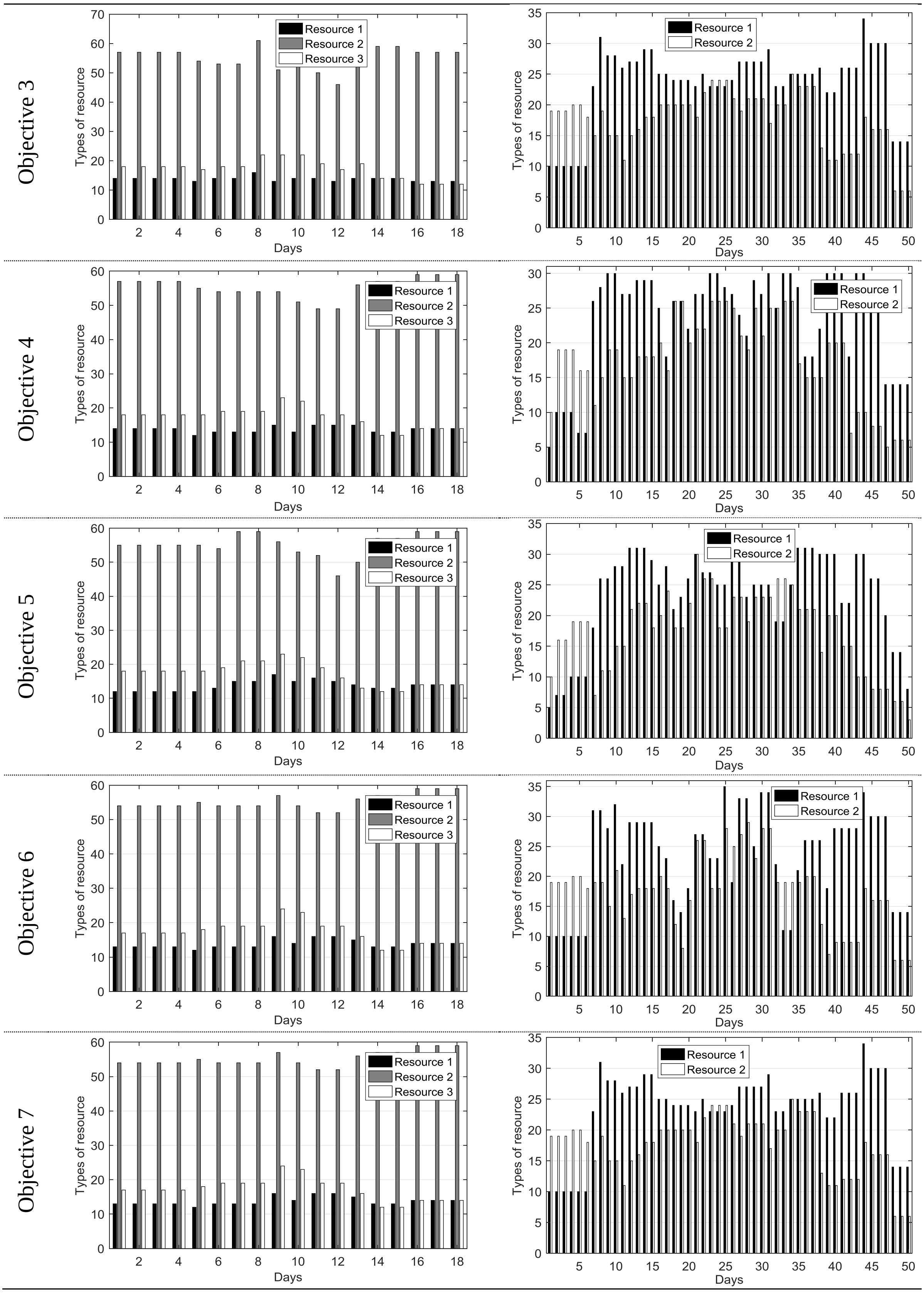


Fig. 4 Resource graph before and after levelling by FFBI: a) first case; b) second case

	First case	Second case
Objective 1		
Objective 2		



Objective 3
Objective 4
Objective 5
Objective 6
Objective 7
Types of resource
Days
Resource 1
Resource 2
Resource 3

Objective 8

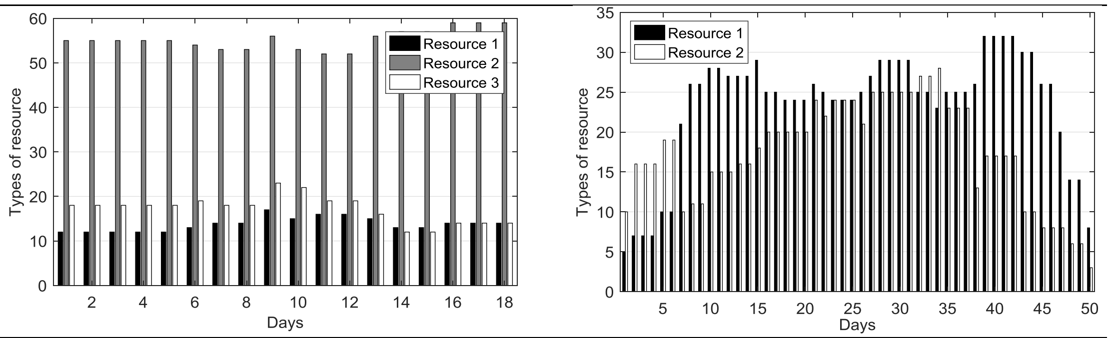


Fig. 5 Levelled resource graph by FFBI in different objective functions of both cases

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Table 1. Best solutions obtained by FFBI

Indicators		RI	RI_1	RI_2	RI_3	Actual start time of non-critical activities
						$A_1.B_1.C_1.F_1.G_1.H_1.I_1.A_2.C_2.D_2.G_2.H_2$
First case	Initial	363.85	76.95	1169.87	123.84	0.0.5.0.4.0.0.0.0.5.5.5
	FFBI	**3.184**	**1.39**	**4.76**	**10.17**	4.0.8.0.9.0.12.8.15.5.10.13
Second case	Initial	115.79	126.67	90.41	115.79	$A_1.C_1.F_1.I_1.E_1.H_1.K_1.L_1.O_1.R_1.N_1.Q_1.T_1.B_2.C_2.G_2.K_2.L_2.E_2.I_2.F_2.J_2.N_2$
						0.3.8.12.6.10.17.17.22.28.25.29.33.0.6.8.13.13.6.13.5.10.17
	FFBI	**33.299**	**38.31**	**21.61**	**---**	0.3.26.31.7.11.22.17.25.40.30.43.47.0.11.21.33.33.13.20.5.33.43

Table 2. Comparison of obtained results for both cases

Performance Measurement			GA	PSO	DE	WO	SOS	FBI	FFBI
Resource intensity (RI)	Case 1	Best	3.627	**3.184**	**3.184**	**3.184**	**3.184**	**3.184**	**3.184**
		Avg.	3.705	3.702	3.682	3.626	3.614	3.599	**3.450**
		Std.	0.062	0.115	0.146	0.183	0.203	0.181	0.221
		Worst	3.903	3.903	3.903	3.805	3.805	3.726	3.627
	Case 2	Best	33.983	33.651	33.323	**33.299**	**33.299**	**33.299**	**33.299**
		Avg.	35.006	34.886	34.435	34.422	34.390	34.055	**33.502**
		Std.	1.411	1.279	0.563	0.596	0.559	0.729	0.249
		Worst	38.355	38.355	35.347	35.471	35.471	35.347	34.159

Table 3. Results on different objectives obtained by FFBI

No	Objective function formulas	Optimization criteria	Initial schedule		Optimized by FFBI		Improvement percentage	
			Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
1	$w * \sum_{t=1}^{T} \lvert Rdev_t \rvert$	Sum of the absolute deviations in daily resource usage	73.663	127.60	13.42	69.30	81.78%	45.69%
2	$w * \sum_{t=1}^{T} \lvert Rinc_t \rvert$	Sum of only the increases in daily resource usage from one day to the next	15.658	60.70	0	35.30	100.00%	41.85%
3	$w * \sum_{t=1}^{T} \lvert R_t - R_{av} \rvert$	Sum of the absolute deviations between daily resource usage and the average resource usage	251.276	456.744	24.069	214.456	90.42%	53.05%
4	w*max(R_t)	Maximum daily resource usage	49.681	44.40	27.1920	28.80	45.27%	35.14%
5	w*max($Rdev_t$)	Maximum deviation in daily resource usage	17.329	22.50	3.395	9.20	80.41%	59.11%
6	w*max($\lvert R_t$-$R_{av}\rvert$)	Maximum absolute deviation between daily resource usage and the average resource usage	24.835	22.78	3.0875	12.82	87.57%	43.72%
7	w*$\sum_{t=1}^{T}(R_t)^2$	Sum of the square of daily resource usage	23476.74	29514.0	16984.81	25389.4	27.65%	13.98%
8	$w * \sum_{t=1}^{T} (Rdev_t)^2$	Sum of the square of the deviations in daily resource usage	1321.52	1203.4	31.78	396.2	97.60%	67.08%

Note: t = day under consideration; T = total project duration; $Rdev_t$ = deviation between resources required on day t and t+1; $Rinc_t$ increase in between resources required on day t and $t+1$; R_{av} average resource use; R_t resources required on day t.

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