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

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Abstract. Project managers often face some challenges resulting from the scarcity of resources in construction management. Levelling the used resources in multiple projects is a frequently encountered problem in construction areas and manufacturing sectors. In this regard, the current study proposes a robust Forensic-Based Investigation (FBI) algorithm for resource leveling in multiple projects, considering different objective functions of the resource graphs. To this end, Fuzzy C-Means (FCM) clustering approach was fused into the main operation of the FBI to enhance the convergence rate using the population information. The proposed scheduling examines different objective functions to efficiently optimize the resource profile selection. Two case studies were taken into account in this research to elaborate on the performance of the improved optimization algorithm while dealing with the resource-leveling problem in multiple projects. The experimental findings and statistical comparisons revealed that the developed Fuzzy clustering Forensic-Based Investigation (FFBI) could acquire solutions of high quality and outperform the compared optimization algorithms.

1. Introduction

Construction management is complicated due to several influencing factors such as high intensity of the interrelationship among project activities, uncertainty in projects, and demands for several parties, to name a few [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 a new technique to resource management is a prerequisite for construction contractors in today's complex construction environment [4]. An appropriate method for resource management can

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ensure high levels of project success and avoid project delay and cost overrun [5,6].

The project managers generate schedules using conventional approaches such critical path method and program evaluation and review the proposed technique, resulting in the earliest start time mode for all activities [7]. However, the above-mentioned methods neglect the overconsumption of resources during project implementation. In addition, incorporation of the resource usage into activities cannot guarantee an appropriate schedule because of resource demanding variations along with the project timeline. Due to the resource fluctuations, contractors often face difficulty hiring and firing the essential workers to control the efficient resource profiles. Accordingly, the project cost will increase and productivity will decrease. Hence, effective resource management is essential to minimize resource expenditures and satisfy the planned schedule.

The method for reducing the resource fluctuations, i.e., resource levelling, plays an essential role in construction project management that has attracted considerable attention in the academic milieu [8,9]. Resource levelling primarily aims to reduce the resource usage fluctuations as much as possible within a specific time span along the project timelines. It also attempts to schedule noncritical activities within their available floats without changing the 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];
4. Leveling multiple resources in different projects [14–16].

However, real construction projects are still subject to some challenges 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 developed and investigated to deal with the problem of resource leveling among the most significant ones including mathematical, heuristics, and metaheuristics methods. Among the abovementioned techniques, Evolutionary Algorithms (EAs), a class of metaheuristics, have attracted considerable attention [17–20]. The EAs use iterative calculations instead of substantial gradient information that help them tackle many optimization issues successfully. Despite their great achievement in many engineering fields, they still have some limitations. Among their major inherent drawbacks are their weak exploited ability and premature convergence when solving complex optimization problems. Therefore, many researchers prefer using hybrid techniques instead to boost the performance of the EAs.

Forensic-Based Investigation (FBI) is a recent metaheuristic algorithm proposed in 2020 by Chou and Nguyen [21]. FBI based on the situation of police officers handles problems through suspect, site, and pursuit. It is easy to use with no demand for predefined controlling parameters while showing great robustness in tackling single optimization problems. Many studies have proved that the FBI outperformed the other well-known algorithms [22–25]. Indeed, it is a novel and powerful algorithm, and the use of its variant to solve the resource leveling problems would be interestingly efficient. The original FBI operates only through two main phases, namely investigation and pursuit. However, independent interaction of each phase and lack of communication between the two teams lead to a decrease in the convergence rate. This study highlights the advantages of the original FBI and fuzzy clustering to establish a robust FBI algorithm for resource leveling in multiple projects.

This research significantly contributes to the available literature. First, a hybrid algorithm is developed to improve the intensification and diversification abilities of the FBI. Second, a scheduling method is proposed considering multiple resources in different projects via real case studies and different evaluation criteria. Third, its outcomes can be a useful tool for project managers that assist them in controlling resource management at project planning and implementation phases.

The rest of the paper is organized as follows: Section 2 presents the related studies on resource levelling. Section 3 describes a mathematical formulation of resource leveling in multiple projects. Section 4 develops a model to solve the resource-levelling problem. Section 5 presents the optimization outcomes, result comparisons, and analysis results. Section 6, concludes the study and suggests some relevant issues for further investigation.

2. Related works on resource leveling

Resource Levelling (RL) problems have drawn considerable attention due to their practical applications [26,27]. Given the involvement of the RL problems in many construction projects, RL have been deeply investigated through many approaches. Derbe et al. [28] presented a scientometric review on Construction Project Scheduling (CPS) studies. The resource-constrained project scheduling problems are the most significant fields in the CPS studies. Other areas such as resource utilization, resource allocation, and resource levelling are included without limitation.

Zhou et al. [29] presented an extensive review on the proposed methodologies for CPS optimization.

A variety of methods have been developed to date to handle the RL problem including the mathematical, heuristic, and meta-heuristic approaches. Mathematical methods such as dynamic programming [30,31], integer programming [32], enumerative search [33], and branch-and-bound methods can offer exact solutions. These methods, however, 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 will lead to computational explosion and impractical calculation.

Several researchers prefer using heuristic methods to address the aforementioned drawback of the mathematical approaches. Efforts have been made to make heuristic rules and improve the quality of the feasible solutions [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. Given the reliance of the proposed methods on the pre-defined rules, their effectiveness highly depends on the specific types of problem-solving manners. Therefore, it can be concluded that both mathematical and heuristic methods are not suitable for handling real-world construction projects [18,39].

Numerous researchers have investigated the application of meta-heuristic algorithms that use intelligent search-based population to solve different 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 that the researchers used for handling RL are the particle swarm optimization [5,16], ant colony optimization [45], and differential evolution [46,47]. Some studies have recently introduced optimization algorithms to deal with the RL problem. For instance, in a study conducted by Khanzadi et al. [48], two new algorithms namely the colliding bodies optimization and charged system search were proposed to simultaneously handle the resource levelling and resource constraint. In another recent study, Prayogo et al. [49] used a modified symbiotic organisms search to deal with the resource leveling problem [50]. The metaheuristic methods have been successfully applied to handle the RL problems at a certain degree; however, 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.

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

3. Description of RL in multiple projects

A construction company will start simultaneously n projects, and every project includes many activities that require M types of resources to be executed. The optimization model aims to minimize the fluctuations in the usage of resources by reducing the peak demand resources and daily resource consumption. The RL in multiple projects can be defined as an optimization problem, as shown below [14,55]:

Minimization of resource intensity

$$= \frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{M}\left[w_m\left(R_m(t)-\overline{R_m}\right)^2\right], \tag{1}$$

subject to:

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

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

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

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

where $R_m(t)$ represents the mth resource demand on the day t of all involving projects, and $R_{mt}(i)$ denotes the mth resource demand on the day t of the ith activity. In addition, T^{ST}, T^{FT}, T^{ES}, and T^{LS} are the start time, finish time, earliest start time, and latest start time of the ith activity, respectively. Moreover, $pset_i$ represents the predecessor set of activity i, and the coefficient w_m determines the importance level of the mth resource. The values of w_m are determined via Analytical Hierarchy Process (AHP) method. The large value of w_m corresponds to the high level of significance of the resource m.

Eq. (1) denotes the general objective function of the resource leveling in multiple projects aimed at minimizing the sum of the square of the deviations between the daily and average resource usage. Eq. (2) represents the first constraint where the start times of non-critical activities must be in the range of the earliest and latest start times. Eq. (3) is the second constraint where the start time of the actual activities must satisfy the dependencies in the project networks. Eqs. (4) and (5) are used to calculate the daily required resource ($R_m(t)$) and average resource usage ($\overline{R_m}$), respectively, of all the implemented projects in an enterprise.

4. Robust optimization for RL

The newly introduced Fuzzy clustering Forensic-Based Investigation (FFBI) is rigorously presented to deal with the resource levelling problems. The FFBI is a new hybrid optimizer that functions based on the recently developed FBI algorithm proposed by Chou and Nguyen [21]. The original FBI mimics the investigation of the criminal 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 newly proposed FFBI mainstream is analogous to those in the original FBI composed of initial population, investigation and pursuit phase, selection, and stopping steps. However, the FFBI differs from the original version since it integrates the Fuzzy C-Means (FCM) clustering approach into the investigation and pursuit phase to improve the convergence speed by efficiently utilizing population information via cluster centers (Figure 1). More details of FFBI for RL problems are given in the following:

4.1. Initialization and decision variables

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

$$Population = \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_i \\ \cdots \\ X_{NP} \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,D} \\ \cdots & \cdots & \cdots & \cdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,D} \\ \cdots & \cdots & \cdots & \cdots \\ x_{NP,1} & x_{NP,2} & \cdots & x_{NP,D} \end{bmatrix}. \qquad (6)$$

The D-element vector in Eq. (7) represents the decision

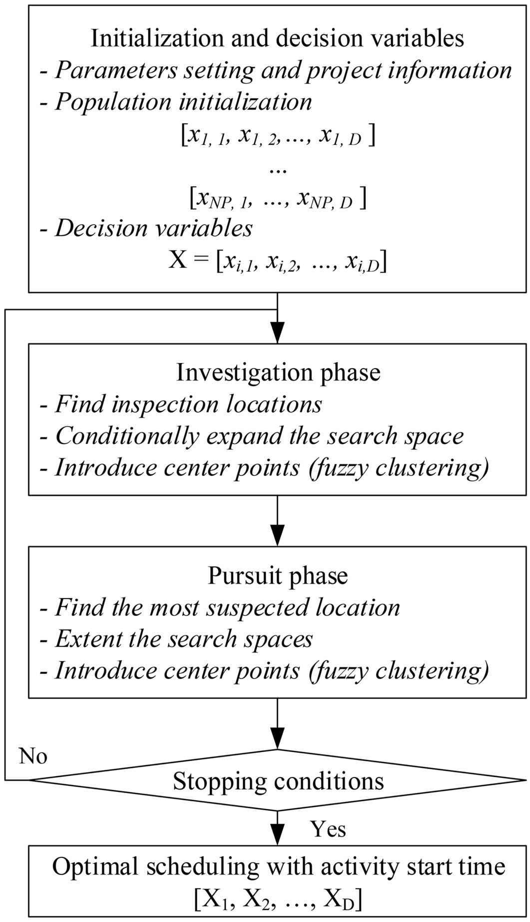

Figure 1. FFBI for RL problem.

variable for resource leveling in multiple projects. D is the total non-critical activities in active projects. The index i denotes the ith 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).

$$X = \left[x_{i,1}, x_{i,2}, \cdots, x_{i,j}, \cdots, x_{i,D}\right]. \qquad (7)$$

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

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

where x_{ij} is an element of the D-element vector in Eq. (7). In addition, LB_j and UB_j are the earliest and latest start times of the jth non-critical activity in the total D non-critical activities after handling the constraints. The actual start time of all activities in the project networks must satisfy two conditions:

1. Being in the range of the earliest and latest start times;

2. Being restricted by the actual start time of any of its predecessor activities.

The first condition can be fixed prior to the calculating process. The second condition, however, must be decided in turn. The actual start time of one activity is confirmed when all activities in its predecessor set are determined.

4.2. Investigation phase

The investigation phase includes two steps:

1. Interpretation of the results,
2. Directions of inquiry.

In the results interpretation step (A1), other individuals affect each individual movement as can be seen in Eq. (9):

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

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

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

$$Prob(X_{A1_i}) = (P_{A1_i} - P_{worst}) / (P_{best} - P_{worst}). \tag{10}$$

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

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

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

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 affects the new individual by the probabilities. In case 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, $\{r, i\} \in \{1, \cdots, NP\}$, and r is set randomly.

4.4. Fuzzy clustering process

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

When the remainder of dividing the maximum generation $G_{\max}$ by the clustering period m equals zero ($mod(G_{\max}, m) = 0$). The FCM produces k individuals involved in the process of updating the population. This process contains four steps namely the selection, generation, substitution, and update [59].

a) *Selection:* Randomly select k individuals from the current population (*set A*). Here, k represents the number of clusters, and $k \in [2, \sqrt{NP}]$;
b) *Generation:* FCM clustering method creates k offspring (*set B*);
c) *Substitution*: Choose k best solutions (*set C*) from the merged set (*set A* + *set B*) for substitution;
d) *Update:* 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 be terminated. The search procedure stopping generates the optimum start time for all activities in the project networks. The final schedule and its corresponding resource graph will be figured out for project implementation.

5. Case studies

This paper analyzes two construction case studies to determine the effectiveness of the proposed FFBI in resource leveling in multiple projects. The first

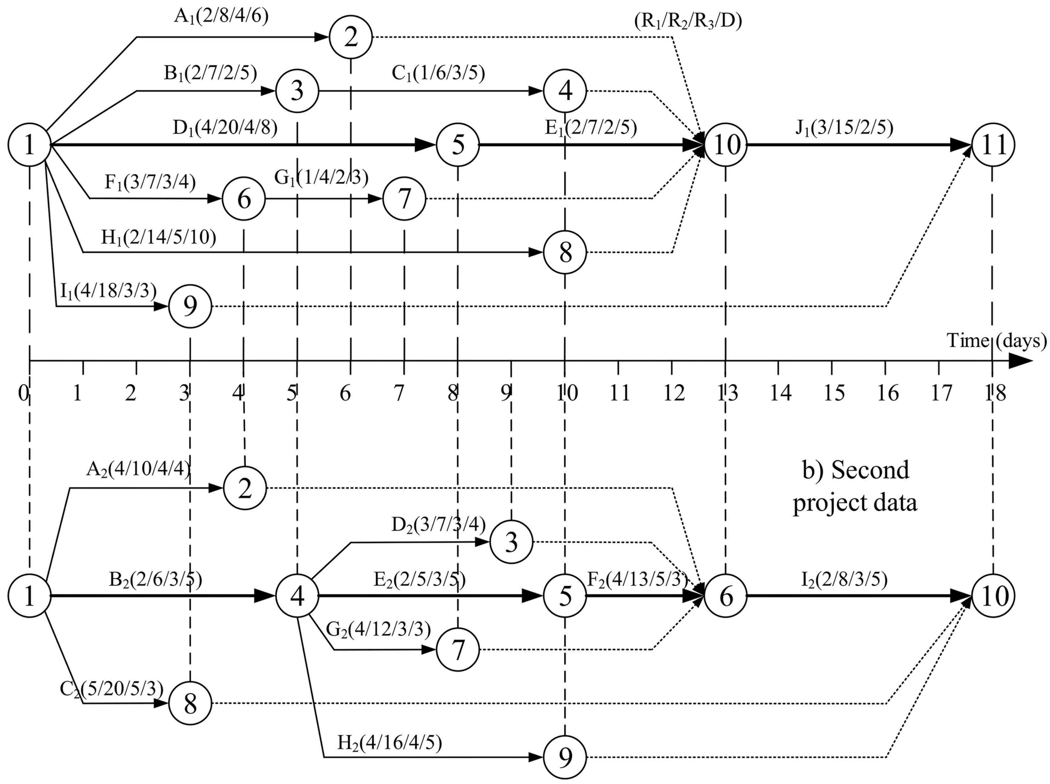

Figure 2. Network diagram of projects in the first case.

construction project case study was examined using data given by Yan et al. [16]. This 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). Figure 2 lists the values of duration, required resource, and dependency for all activities in the project networks.

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. The weights of each resource are computed as: $w_1 = 0.637$, $w_2 = 0.258$, and $w_3 = 0.105$. The general objective of resource leveling in multiple projects is to minimize the sum of the square of the deviations between daily and 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:

$$\begin{cases} 0 \leq T_s(A_1) \leq 7 \\ 0 \leq T_s(B_1) \leq 3 \\ T_s(B_1) + 5 \leq T_s(C_1) \leq 8 \\ 0 \leq T_s(F_1) \leq 6 \\ T_s(B_1) + 4 \leq T_s(G_1) \leq 10 \\ 0 \leq T_s(H_1) \leq 3 \end{cases}$$

and:

$$\begin{cases} 0 \leq T_s(I_1) \leq 15 \\ 0 \leq T_s(A_2) \leq 9 \\ 0 \leq T_s(C_2) \leq 15 \\ 5 \leq T_s(D_2) \leq 9 \\ 5 \leq T_s(G_2) \leq 10 \\ 5 \leq T_s(H_2) \leq 13 \end{cases}$$

The first example was performed on the small-scale construction projects. Hence, the second case on the medium-sized projects was utilized to further evaluate the performance of the evolutionary algorithms. Figure 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

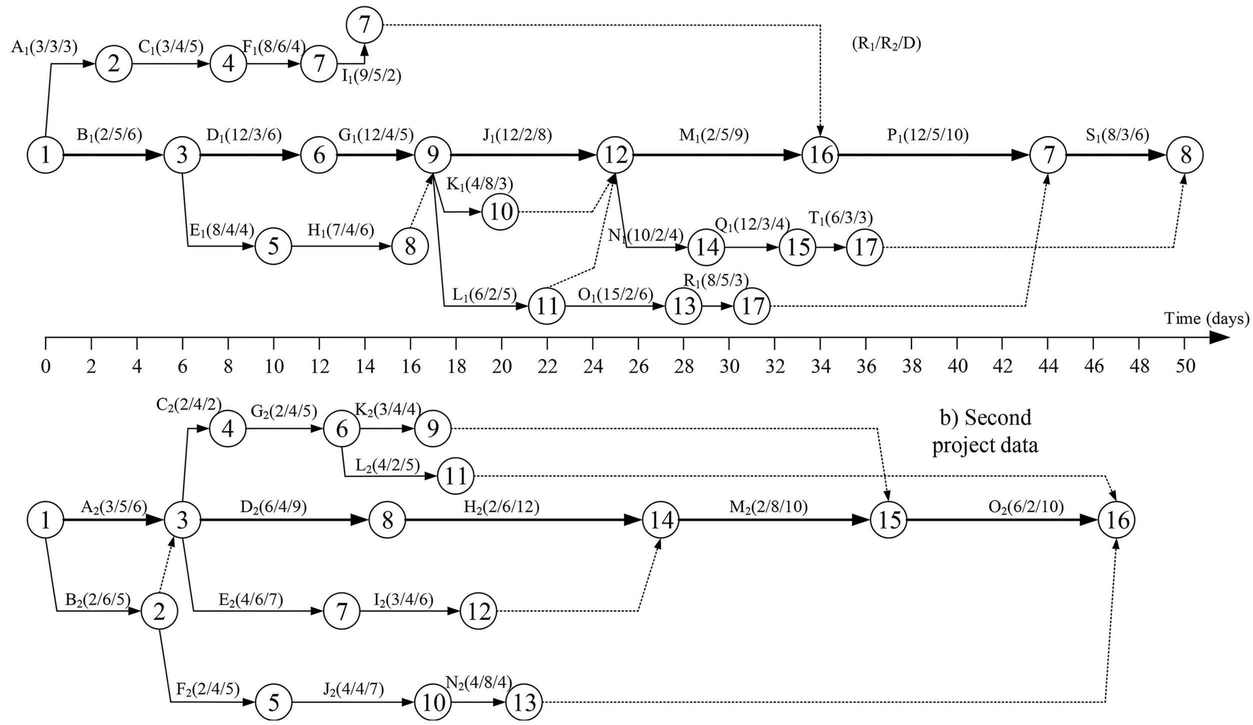

Figure 3. Network diagram of projects in the second case.

a fixed duration D that are shown above the arrow line. The weights of each resource are defined as $\alpha_1 = 0.7$ and $\alpha_2 = 0.3$ based on the importance level. A mathematical model proposed to solve multiple resource leveling in the second case is expressed as follows:

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

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 with the population size NP and maximum number of generations $G_{\max}$ should be defined. The values of NP and $G_{\max}$ were set to 100 and 100 for the first case, and 150 and 200 for the second case. In each case, the experiment was run 30 times in the randomness avoidance. The proposed FFBI significantly reduces fluctuation in resource use of an enterprise in both case studies. Figure 4 displays the resource graph of the initial networks followed by leveling via FFBI algorithm in both cases. As shown in Figure 4, the maximum daily required resource of R_1 in the second case as an example ranges from 48 to 34 workers.

Table 1 shows the findings of the optimal values of the indicators using the proposed FFBI. In addition to the start times of the non-critical activities for both

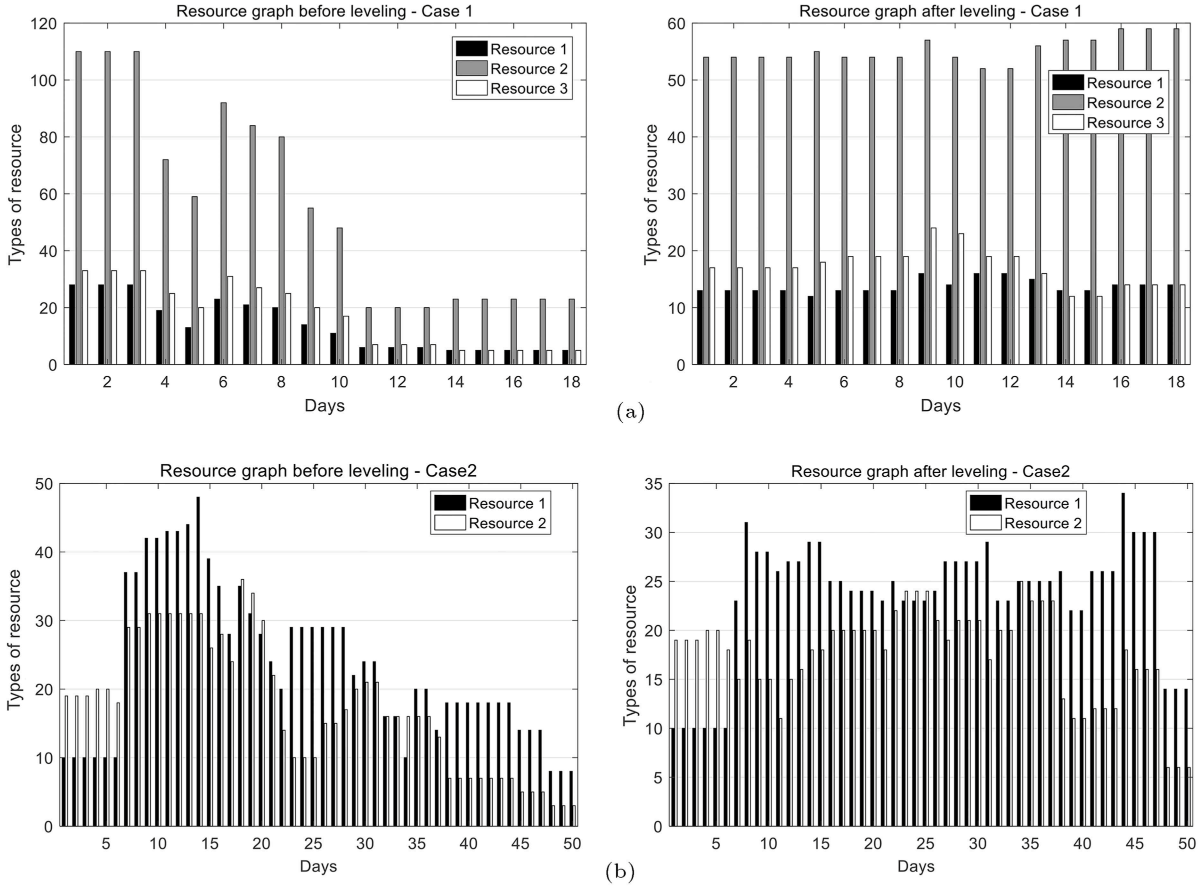

Figure 4. Resource graph before and after levelling by FFBI: (a) first case; (b) second case.

Table 1. Best solutions obtained by FFBI.

Indicators		**RI**	**RI$_1$**	**RI$_2$**	**RI$_3$**	**Actual start time of non-critical activities**
						$\boldsymbol{A_1.B_1.C_1.F_1.G_1.H_1.I_1.A_2.C_2.D_2.G_2.H_2}$
1st 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
2nd 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**	—	0.3.26.31.7.11.22.17.25.40.30.43.47.0.11.21.33.3 3.13.20.5.33.43

cases, $RI_{m(m=1,2,3)}$, given in Table 1, is the Resource Intensity (RI) for the single resource m:

$$RI_m = \frac{1}{\text{Project duration } (D)} \sum_{t=1}^{D} \left[\alpha_m \left(SR_m(t) - \overline{SR_m(t)}\right)^2\right].$$

The single RI acquired by FFBI was significantly reduced in comparison to the initial schedule.

5.2. Result comparisons

The results of the proposed FFBI were compared with those from the well-known algorithms including GA [60], Particle Swarm Optimization (PSO) [61], and Differential Evolution (DE) [62]. The recently developed optimization algorithms include Symbiotic Organisms Search (SOS) [63], Whale Optimization (WO) [64], and FBI [21]. In both cases, the parameters of the comparative algorithms were set as follows: In the GA, the constant mutant and crossover probability factors were set at 0.5 and 0.9, respectively. In addition, PSO sets the values of cognitive (c_1) and social (c_2) factors at two, and the inertia weight parameter w lies between 0.3 and 0.7. Moreover, the DE control parameters are 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. The two parameters NP and $G_{\max}$ are the same as the above settings for all the compared algorithms.

The final results are subject to the fitness function value that is the total RI obtained from the corresponding algorithm. The average value and standard deviation of the RI were utilized to evaluate the performance of the algorithms after 30 runs. Table 2 presents the experimental results where the bold values are indicative of the best acquired solutions. In this table, the FFBI has a competitive performance with regard to the accuracy and stability indicators. The FFBI is able to find the optimal solutions in fitness functions of both cases. Moreover, FFBI outperformed all its counterpart algorithms since it succeeded in finding 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 Figure 4, the resource graph found by the FFBI in the first case has the maximum daily resource usage of R_1, R_2, and R_3 of 16, 59, and 24, respectively. These values were determined to be 15, 62, and 23 previously by Tran et al. [46]. Overall, the value of the total obtained RI of the FFBI is higher than that of the previous findings. Therefore, it can be concluded that the FFBI is comparable to other algorithms in solving multiple resource leveling in multiple projects.

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

5.3. Analytical outcomes with different objective functions

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

Such an improvement highly depends on the project characteristics. In other words, different projects may yield the best improvement on another objective function(s). Therefore, Project Managers (PMs) need to apply the model to different objective functions to determine the objective function and gain the highest improvement. In addition, based on particular demands, the PMs should set coefficients for these objectives to obtain the best fit for their resource graph.

Figure 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 the values of different parameters and yield different solutions.

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 of 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 of resource requirement between required on day t and $t+1$; R_{av} = Average resource use; R_t = Resources required on day t.

5.4. Discussion

A comparison of the results given above indicates that the proposed FFBI outperformed other popular algorithms in terms of solving resource-leveling problems. Further discussion and inferences are drawn in the following.

The FCM clustering approach played an important role in the operation of the FBI mechanism by introducing cluster center as the new potential candidate. This operator facilitates making a balance between the exploration and exploitation at the investigation and pursuit phases of FBI.

The proposed FFBI exhibits simplicity and stable performance, mainly because it does not require any tuning parameter during the optimization process. This characteristic favors the diversified optimization problems.

Investigation of the three case studies confirmed the efficiency and effectiveness of the FFBI. The first two cases are about multiple resource levelling in multiple projects. The third case handles the publicly available data. The FFBI outperformed the considered algorithms in terms of the objective function value.

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

6. Conclusions and further study

This study proposed a robust Forensic-Based Investigation (FBI) algorithm to solve the multiple resources 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 Fuzzy clustering Forensic-Based Investigation (FFBI) outperformed the considered algorithms in terms of resource intensity indicator.

The statistical results proved the superior performance of the FFBI in dealing with the multiple resources in multiple project problems. The FFBI could find the best solution in the two considered case studies with the values of 3.184 and 33.299, respectively. Moreover, the proposed model generated the lowest average fitness functions of 3.450 and 33.502

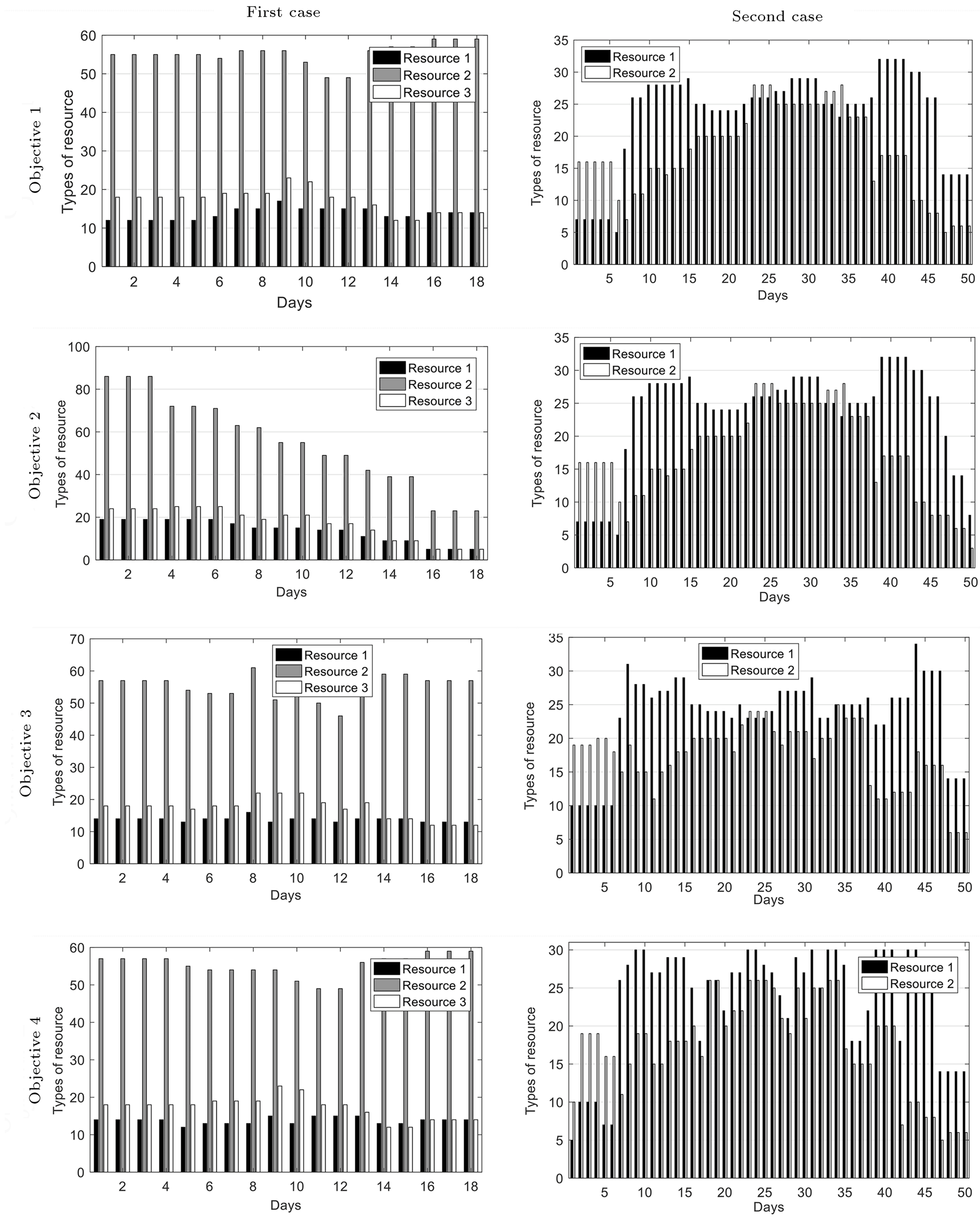

Figure 5. Levelled resource graph by FFBI in different objective functions of both cases.

in both cases. Furthermore, the FFBI exhibited excellent performance on eight different objective functions with a considerable improvement in the 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 constraint and allocation. Furthermore, integration of the leveling resource objective with other project management objectives could be an interesting direction. Therefore, extending the current

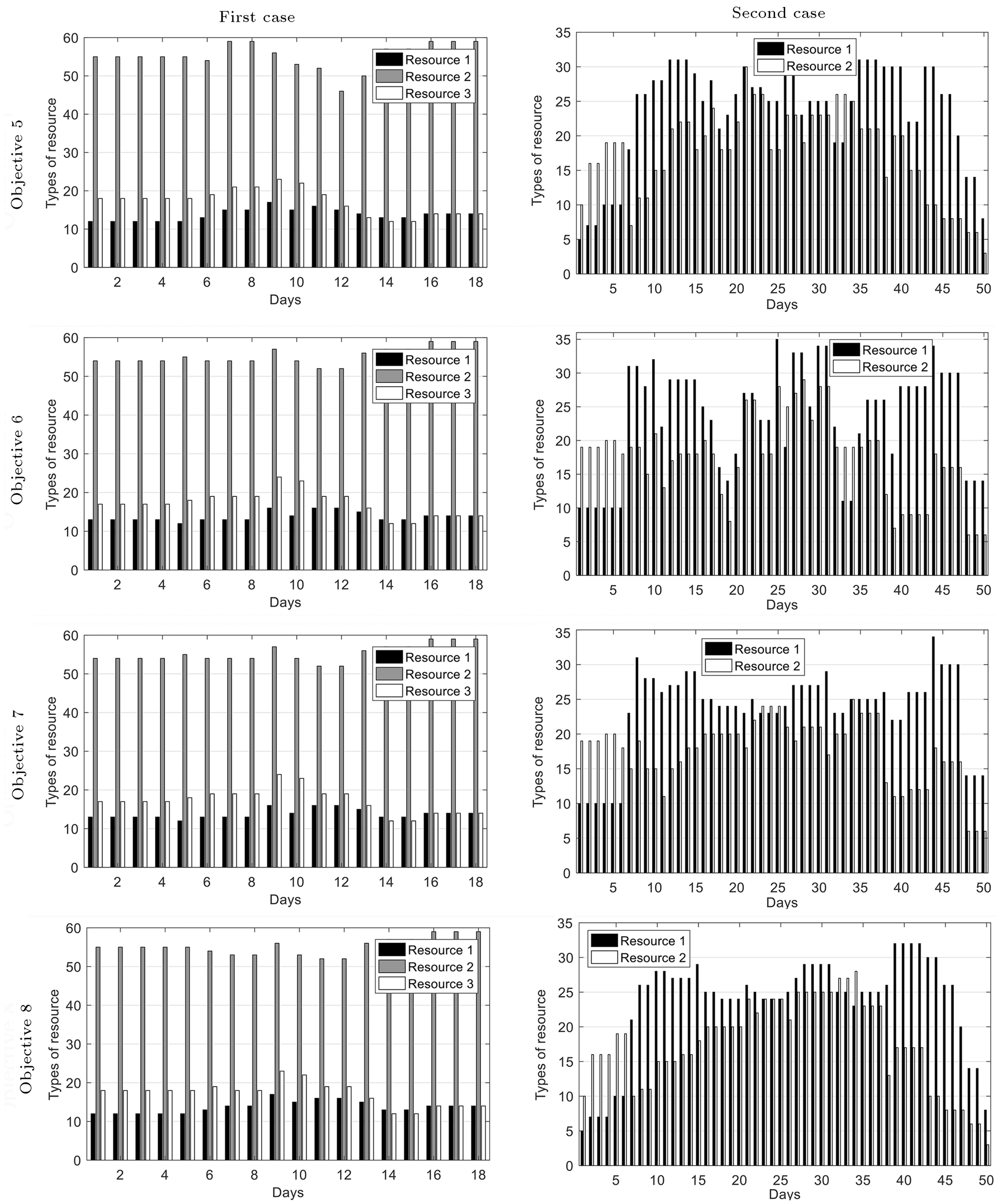

Figure 5. Levelled resource graph by FFBI in different objective functions of both cases (continued).

algorithm to multiple objective versions would be a potential improvement for further research.

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