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A comprehensive framework for multi-aspectual project portfolio resource allocation and evaluation

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ABSTRACT

Efficient resource allocation is a vital aspect of project portfolio management (PPM) and is critical for organizations managing multiple complex projects with interdependencies. This study presents a comprehensive resource allocation framework for multifaceted project portfolios by integrating project performance metrics with expediting methods, such as fast-tracking and crashing, and considering a detailed analysis of interproject interdependencies. A mixed-integer linear programming (MILP) model optimizes resource utilization and minimizes total portfolio costs. The proposed framework explicitly considers human, fixed, and consumable resource types while incorporating mechanisms to balance time–cost quality trade-offs. Nuanced interdependency classifications and time-dependent effects further distinguish the proposed framework. Evaluation through a real-world case study reveals significant reductions in project duration and costs, while maintaining overall portfolio quality. Multi-criteria decision-making (MCDM) techniques, including the fuzzy best-worst method (BWM) and WASPAS, are employed to validate the improvements. The proposed project portfolio resource allocation and evaluation framework lays the groundwork for new, practical applications in organizations managing complex project portfolios.

1. Introduction

Project management enables organizations to achieve their strategic objectives by driving innovation, fostering growth, and enhancing efficiency. Projects transform ideas into tangible outcomes and deliver value across organizations [1,2]. Traditionally, projects are temporary initiatives designed to drive positive transformations, such as delivering specific products or services. Project management represents the structured process for achieving these transformations [3]. Projects contributed to over 20 % of global economic activity, exceeding 30 % in some emerging economies [4].They are valuable for instigating organizational change and implementing specific policies and standards. Successful project execution often increases organizational efficiency and productivity [5]. As modern societies increasingly depend on projects, organizations face persistent challenges in managing them [6]. Projects constitute a substantial share of organizational budgets and strategic development. Organizations must carefully select projects to remain competitive while considering resource constraints and potential benefits [7,8].

A project portfolio is a group of projects managed to achieve organizational objectives and optimize resource utilization. Due to resource constraints such as personnel, finances, and time, not all proposed projects can align with the organizational strategy and be executed simultaneously [9,7]. Therefore, it is essential to consider organizational strategy, project interdependencies, resource demands, and shared resources during project selection [10]. Project portfolio management (PPM) is a dynamic decision-making framework for evaluating, selecting, prioritizing, and balancing projects within an existing portfolio [11]. The main objectives of PPM are ensuring the implementation of the right projects, aligning them with the organization's strategies, and maintaining a balanced portfolio [12]. PPM typically involves project evaluation, selection, prioritization, and resource allocation [13]. In this

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context, individual projects compete for limited resources [3]. Existing research predominantly focuses on specific PPM components, including project evaluation, selection, resource allocation, scheduling, strategic alignment, risk management, and portfolio monitoring [14].

Resource allocation under various constraints and conditions is a crucial aspect in many fields and domains, e.g., supply chain management [15], healthcare [16], energy systems [17,18], cloud manufacturing systems [19], port operations [20], 2024), air traffic [21], and telecommunication [22]. In project management, resource allocation is a foundational practice and plays a vital role in enhancing the performance of organizations managing multiple projects [23]. A rational allocation of limited resources can optimize organizational performance and profitability [24]. Cost and time play a critical role in project portfolios. Numerous studies have proposed methods for balancing cost and time, enabling organizations to optimize the interplay between these factors to achieve desired outcomes [25,26]. Quality is another critical factor in project management, but it is rarely considered when modelling portfolio resource allocation. Some studies have examined specific quality aspects, such as the quality of human resources or team building, within project portfolios [27,28].

Resource constraint is often the primary consideration when evaluating potential constraints for a resource allocation programming model. This is especially important when examining the resource usage of individual projects, particularly in cases where multiple projects within the portfolio overlap. It is also essential to distinguish between different types of resources: human resources, which refers to individuals whose job directly contributes to the task or project; fixed resources (i.e., facilities, machinery, and equipment), which are considered a company's long-term or reusable resources; and consumable resources (i.e., supplies, energy, and raw materials), which are expended during use and require replenishment and periodic restocking.

Another core aspect to consider is project expediting (leveraging resources to meet the deadline constraints, usually as a time–cost trade-off). These processes are generally performed via project fast-tracking and crashing. [3]). Fast-tracking involves reducing the time of project activities (and, in turn, the overall project duration) by ignoring project precedence relationships amongst activities and executing activities that should be performed sequentially in parallel. This action decreases the duration (if the activities are on the critical path). In turn, the overall quality of the project may decline due to the disregard for standard sequencing. There is also a chance of rework risk (the need to restart the activity from scratch) [29]. Similar to the previous method, crashing also involves reducing the project duration; however, in crashing, the trade-off is between time and cost, rather than quality and cost. This involves spending money to enhance workflow, increase resources, or outsource certain activities to save time. Although it is considered that the projects selected for the portfolio are chosen to be delivered by the deadline, finishing within the scheduled time might provide benefits and monetary value, which can be weighed against the quality and cost spent.

Interdependencies amongst the projects in a portfolio are another essential consideration. Interdependencies among projects refer to the effects that occur when projects are executed simultaneously. This effect could be synergetic (positive) or cannibalistic (negative) [30]. It is typically caused by cooperation in human resources, concurrent procurement of items from the same vendor, or simultaneous equipment allocation [31]. Project interdependencies are often overlooked during portfolio selection to avoid unmanageable complexities [32]. This is particularly true when interdependent relationships exist among resources, costs, technology, and value [33]. When modelling interdependencies in PPM selection or allocation problems, the effect is considered by defining a coefficient or parameter [34,28]. While differentiating between various types of interdependencies, these studies have not considered the time required for the interdependencies to trigger and take effect. For example, a minimum of five time periods may be needed for the impact to be significant when two projects share equipment. A key consideration is whether the effect is time-dependent, specifically whether the project has a long-term or one-time impact. To our knowledge, this distinction has not been mentioned in the literature.

This study presents a comprehensive project portfolio resource allocation model using multi-integer linear programming, incorporating the previously mentioned constraints. Table 1 provides a comparison between our study and previous research.

The remainder of the paper is organized as follows: Section 2 presents a comprehensive literature review of recent PPM studies. Section 3 introduces the resource allocation framework. Section 4 evaluates the new portfolio in light of the changes. Section 5 tests and assesses the proposed framework in a case study. Sections 5 and 6 present the discussion and conclusion.

2. Literature review

PPM has been the subject of research and discussion for decades, with studies dating back to the 1960s that aimed to address optimization using linear programming [43]. Later, with the increasing complexity of PPM problems, new studies added new layers of constraints for scheduling [44,45], resource allocation [46,35], risk and uncertainty [47,48], interdependency, and synergy [49,50,51] to contextualize the problem for specific situations and environments. When discussing project portfolios, studies typically aim to address two key problems: the project portfolio selection problem (PPSP) and the project portfolio resource allocation problem. While both problems are equally important, the PPSP has garnered more attention and has been seen more frequently in the literature, in contrast to the resource allocation problem. Although some PSPP studies also incorporate the scheduling and allocation of resources within their models [52,39], the primary focus is on selecting projects that fit the portfolio constraints rather than allocating the different resources in detail. Table 2 presents the findings of the literature review.

When analysing the literature regarding resource allocation, the majority utilize mathematical algorithms and optimization methods to find the best solution, each study differentiated itself from the rest by the specific aspects and conditions it assumed, generally; the goal is the optimization of the leading indicators (e.g. cost, schedule, quality or value) while satisfying the problems constraints (e.g. budget, due date, resource constraints) and considering a specific condition or factor (e.g. risks, project types or interdependencies).

As mentioned before, studies focusing on project portfolio resource allocation are in the minority when compared to the PPSP. Existing resource allocation studies have certain limitations and gaps. While all the studies assume the resource constraint, many studies do not differentiate between differing resources and refrain from classifying them to resemble real-world problems (e.g., fixed resources and consumable ones as seen in [36]. Project expedition is another uncommon theme in the studies even though it is practiced in nearly most construction or medium sized projects, the studies that do consider project expediting only consider project crashing (i.e. a time and cost trade-off), project fast-tracking which is another commonly used expediting method (in some projects even prioritized above crashing) is rarely seen in any studies and to the best of the authors knowledge has not been considered in any resource allocation model. While the assumption of project interdependencies has been explored in several studies, the dynamic nature of project interdependencies remains a topic that is still under development, with variations across different case studies. This study aims to address the gaps mentioned above by proposing a model to allocate resources within a project portfolio and testing it on a real-world problem.

3. Proposed model

The proposed resource allocation model is tailored to PPM and addresses the critical gaps in the existing methodologies. The model

Table 1
Properties of similar studies.

Studies	Performance			Resources			Other considerations			
	Schedule	Cost	Quality	Human resources	Fixed resources	Consumable resource	Risk & uncertainty	Project expediting	Project inter-dependencies	Multi-phase projects
Oliveira et al. [35]	✓			✓						
Zhong et al. [36]	✓	✓			✓	✓				
Tavana et al. [28]	✓	✓	✓	✓				✓	✓	✓
Chen et al. [37]		✓		✓						✓
Hashemizadeh & Ju [38]	✓	✓		✓			✓			
Zolfaghari & Mousavi [39]	✓	✓		✓	✓	✓	✓	✓	✓	
Ramedani et al. [40]		✓		✓			✓			✓
Mohagheghi et al. [34]	✓	✓	✓	✓					✓	✓
Şahin Zorluoğlu & Kabak [27]	✓	✓	✓	✓						✓
Tian et al. [41]	✓	✓			✓	✓				✓
Habibi et al. [42]	✓	✓		✓	✓	✓	✓			✓
This study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

integrates project performance metrics, resources, expediting strategies, and project interdependencies. It optimizes diverse resource allocation and leverages a mixed-integer linear programming (MILP) approach to optimize resource utilization and minimize total portfolio costs. The proposed approach also incorporates advanced mechanisms for handling project interdependencies, both synergetic and cannibalistic, and accounts for the temporal effects of these interdependencies. This section presents a detailed step-by-step explanation of the model, including its sets, decision variables, and parameters, as summarized in Table 3.

3.1. Basic model

The proposed model is an MILP problem, with the portfolio's total cost (TC) being the primary driver. The total cost itself is a summation of the cost of each project in the portfolio, followed by the optimization function represented by Eq. (1).

$$Min(z) = TC = \sum_i c_i^p \forall i \in I, p \in P(i) \tag{1}$$

The two basic constraints in the proposed model are time and cost. Project time constraints typically require the completion of the project (or, in this case, the portfolio) by the specified due date. Additionally, projects that depend on another project (or a specific phase of a different project) cannot start until the preceding project is finished $\left[\max\left(d_j^p\right), D\right]$, as outlined in Eqs. (2) and (3).

$$\sum_t x_{i,t}^p = d_i^p \forall i \in I, p \in P(i), t \in T, a \in A \tag{2}$$

$$x_{i,t}^p \le x_{j,t}^q \forall i \in I, p \in P(i), j \in U(i,p), q \in P(j), t \in T \tag{3}$$

3.2. Resource constraints

The next set of constraints relates to the resource usage in each project. These resources include human, fixed, and consumable resource types. The goal is to ensure that the maximum capacity of each resource is not exceeded during the project portfolio periods. Human and fixed resources are similar (do not require periodic replenishment) and represented by Eqs. (4) and (5). On the other hand, the consumable resources (which require periodic replenishment) are represented by Eqs. (6) and (7).

$$\sum_i x_{i,t}^p h_i^{h,p} \le H^h \forall i \in I, p \in P(i), t \in T, h \in H \tag{4}$$

$$\sum_i x_{i,t}^p k_i^{m,p} \le K^m \forall i \in I, p \in P(i), t \in T, m \in M \tag{5}$$

$$F_t^n \ge 0 \tag{6}$$

$$F_t^n = F_{t-1}^n - \sum_i x_{i,t}^p g_i^{n,p} + S_t^n \forall i \in I, p \in P(i), t \in T, n \in N \tag{7}$$

3.3. Project expediting

Various methods are available to account for the time–cost-quality trade-off. Since changes in these parameters are continuous, it is imperative to accurately incorporate them into the model and avoid transforming the problem into a non-linear one. Zolfaghari & Mousavi [39] proposed a mode-based system in which each project is split into modes with different quantities to counter this concern by transforming the continuous nature into a discrete one. We adopt a similar approach by introducing binary variables to represent different project modes and their impact on quality, time, and cost. This approach establishes a discrete environment and avoids a non-linear problem. This adoption requires rediscovering the previous cost and duration parameters and accounting for the loss of quality, as seen in Eqs. (8)–(11). Fast-tracking disregards the precedence relation between two projects, shown in Eq. (12). Lastly, there should be an incentive to use project expediting techniques, namely opportunity cost, the opportunity cost (*OPC* is measured by the amount of time remaining before the due date, thus; by finding the maximum time where the portfolio finishes its last project, and subtracting that time from the due date, the remining time can be multiplied by the opportunity cost coefficient to measure the opportunity cost. as seen in Eqs. (13) and (14).

$$Q = \sum_i y_i^p q_i^{a,p} \forall i \in I, p \in P(i), a \in A \tag{8}$$

$$Q \le AQ \tag{9}$$

$$c_i^p = c_i^{p'} + z_i^p w_i^{a,p} \forall i \in I, p \in P(i), t \in T, a \in A \tag{10}$$

$$d_i^p = d_i^{p'} - z_i^p v_i^{a,p} \forall i \in I, p \in P(i), t \in T, a \in A \tag{11}$$

$$x_{i,t}^p + y_i^p \le x_{j,t}^q \forall i \in I, p \in P(i), j \in U(i,p), q \in P(j), t \in T \tag{12}$$

$$OPC = (D - \max(t)\ )O \tag{13}$$

$$c_i^p = c_i^{p'} - OPC \forall i \in I, p \in P(i) \tag{14}$$

Table 2
Literature review findings.

Author (year)	Central theme	Method	Project context
Carazo et al. [44]	A multi-objective binary programming model for project portfolio selection and scheduling with resource constraints and interdependencies.	Scatter search-based metaheuristic	Organizational
Solak et al. [53]	A dynamic selection and resource allocation model for R&D projects under uncertainty.	Multi-stage stochastic integer programming	R&D
Oliveira et al. [35]	An integrated model for classifying projects and managers and allocating resources effectively.	MCDM and mathematical programming.	Energy sector
Momeni & Martinsuo [54]	A resource allocation model for hybrid and bottom-up approaches for service units handling projects and non-project activities in dynamic environments.	Qualitative comparative case study	Organizational
Song et al. [55]	A study on managing multi-criteria project portfolio selection and scheduling under uncertainty.	Stochastic multi-criteria acceptability analysis	–
Chen et al. [37]	A multi-objective optimization model for project portfolio scheduling and staff assignment in IT product development.	Multi-objective Pareto ant colony optimization algorithm	IT & software
Özpeynirci et al. [56]	An interactive resource allocation model for generating balanced and high-return project portfolios.	Pairwise comparisons and quasiconcave value function	–
Şahin Zorluoğlu & Kabak [27]	A multi-objective programming model for integrating project selection and scheduling processes.	Multi-objective programming	IT & software
Lotfi et al. [57]	Sustainable project scheduling under uncertainty considering cost, quality, energy, and environmental factors	Robust non-linear programming	Construction
He et al. [58]	A multi-agent resource planning and scheduling approach in multi-project environments with shared and non-regular resources.	Multi-agent system with genetic and ant colony optimization algorithms	Organizational
Tian et al. [41]	An optimization model for storage space allocation, activity scheduling, and material ordering in projects with limited storage space.	Integrated genetic and exact algorithms	–
Habibi et al. [42]	A robust integration model for project portfolio selection, scheduling, and material ordering under material supply uncertainty.	Modified genetic algorithm	Construction
Taghaddos et al. [59]	A data-driven framework for efficient scheduling and resource allocation in large-scale industrial projects.	Simulation and graph-based optimization	Construction
Goli [60]	A four-objective optimization model for resource-constrained project scheduling under uncertainty in Industry 4.0.	Red deer–genetic algorithm and machine learning clustering	Production
Yousefzadeh et al. [61]	Enhancing multi-project scheduling through resource complexity measures and integration strategy.	Integrated project approach	Organizational
Bai et al. [62]	A dynamic risk management and resource allocation model for construction project portfolios	System dynamics and optimization	Construction
Soleymani et al. [63]	An autonomous resource allocation model for construction projects using deep reinforcement learning.	Simulation and deep reinforcement learning	Construction
Liu et al. [64]	Multi-project scheduling with global resource transfers and multiple transfer modes	Rule-based heuristics, genetic algorithms, and machine learning-based	Organizational
Karsu et al. [65]	Equitable resource allocation under uncertainty, balancing efficiency and fairness	Robust programming	Organizational
Han et al. [52]	Project portfolio selection considering risk propagation delays in dynamic environments.	Complex network theory and diffusion dynamics modeling	Organizational (Enterprise)

3.4. Interdependencies

Simultaneously executing certain phases of a project can affect its parameters, either positively or negatively. This effect could require a certain amount of time for the concurrent execution of both phases. The impact could also intensify depending on the length of the simultaneous execution. Some utility variables and parameters are introduced in the following equations to consider these effects.

$$b_{i,j}^{p,q} \leq x_{i,t}^{p}\ ,\ b_{i,j}^{p,q} \leq x_{j,t}^{q}\ ,\ b_{i,j}^{p,q} \geq x_{i,t}^{p} + x_{j,t}^{q} - 1\ \ \forall i\&j \in I, p \in P(i)\ , q \in P(j)\ , t \in T \tag{15}$$

$$\begin{cases} c_i^p = c''^p_i \alpha_{i,j}^{p,q} if \sum_t b_{i,j}^{p,q} \geq \gamma_{i,j}^{p,q}, \theta_{i,j}^{p,q} \leq 0 \\ c_i^p = c''^p_i \beta_{i,j}^{p,q} \sum_t b_{i,j}^{p,q} if \sum_t b_{i,j}^{p,q} \geq \gamma_{i,j}^{p,q}, \theta_{i,j}^{p,q} > 0 \forall i,j \in I, p \in P(i), q \in P(j), t \in T \\ c_i^p = c''^p_i if \sum_t b_{i,j}^{p,q} < \gamma_{i,j}^{p,q} \end{cases} \tag{16}$$

To avoid a non-linear scenario, $b_{i,j}^{p,q}$ is defined as the determinant of the simultaneous execution of both events, as seen in Eq. (15). Eq. (16) illustrates the alteration to the redefined cost parameter based on the condition of the interdependencies. The interdependency threshold ($\gamma_{i,j}^{p,q}$) depicts the required duration for the coefficient to take effect. No change will occur if the number does not meet the threshold. The first term represents a condition where the interdependency effect does not rely on the number of periods. In contrast, the second term depends on the number of standard periods executed between project phases. Both of these terms, of course, have their coefficients. If there is no

Table 3
Model guide (sets, parameters, and variables).

Sets	
I	Set of projects
$P(i)$	Set of phases of the project i
T	Set of time periods
$U(i, p)$	Set of phases of projects that are dependent on i in phase p
M	Set of fixed resource types
N	Set of consumable resource types
H	Set of human resource types
A	Set of actions/ conditions that affect the Project
Decision variables	
$x_{i,t}^p$	Binary variable: whether phase p of Project i is executed in time t or not
y_i^p	Binary variable: whether phase p of Project i is subject to fast-tracking or not
z_i^p	Binary variable: whether phase p of Project i is subject to crashing or not
Parameters	
c_i^p	The standard cost of Project i within Phase p
d_i^p	The standard duration of Project i within Phase p
$h_i^{h,p}$	Required number of human resources type h for Project i within Phase p
$k_i^{m,p}$	Required number of fixed resources m for Project i within Phase p
$g_i^{n,p}$	Required number of consumable resources n for Project i within Phase p
S_t^n	Restock the amount of consumable resource n provided in Period t
F_t^n	Amount of consumable resources n available in period t
Q	The total change to portfolio quality
AQ	Acceptable level for portfolio quality
$q_i^{a,p}$	The effect of action/ condition a on the quality of phase p of Project i
$v_i^{a,p}$	The effect of action/ condition a on the duration of phase p of Project i
$w_i^{a,p}$	The effect of action/ condition a on the cost of phase p of Project i
$b_{i,j}^{p,q}$	Binary value depicting if phase p of project i and phase q of j are executed in the same period
$\theta_{i,j}^{p,q}$	Binary value depicting if the interdependency of phase p of project i and phase q of j increases with time or not
$\gamma_{i,j}^{p,q}$	The required amount of shared execution period between phase p of project i and phase q of j for interdependencies to take effect
$\alpha_{i,j}^{p,q}$	Interdependency coefficient for phase p of project i and phase q of j if it is not affected by time
$\beta_{i,j}^{p,q}$	Interdependency coefficient for phase p of project i and phase q of j, if it is affected by time
OPC	Opportunity cost resulting from finishing before the deadline.
O	Opportunity cost coefficient
D	Due date
H^h	Max available human resources of type h
K^m	Max available fixed resource of type m

interdependency involved, then $\gamma_{i,j}^{p,q}$ is given a significantly large number. Although this case focuses on cost interdependency, it can be expanded to include interdependencies related to quality, time, or human resources. The values of $\beta_{i,j}^{p,q}$, $\alpha_{i,j}^{p,q}$ and $\gamma_{i,j}^{p,q}$ are to be determined through expert judgments, based on prior experience with similar project portfolios. Given the subjective nature of these data, it is advisable to use a structured data elicitation technique such as the Delphi method [66]. This iterative approach facilitates the development of expert consensus while minimizing individual bias, making it especially suitable for complex decision-making contexts where quantitative data are limited or uncertain.

The final form of the model is presented in Eqs. (17) to (27) using the parameters in Table 3 and the explanations done in the prior:

$$Min(z) = \sum\nolimits_i c_i^p + z_i^p w_i^{a,p} - OPC \forall i \in I, p \in P(i), a \in A \tag{17}$$

s.t.

$$\sum\nolimits_t x_{i,t}^p = d_i^p - z_i^p v_i^{a,p} \forall i \in I, p \in P(i), t \in T, a \in A \tag{18}$$

$$x_{i,t}^p \le x_{j,t}^q \forall i \in I, p \in P(i), j \in U(i,p), q \in P(j), t \in T \tag{19}$$

$$\sum_i x_{i,t}^p h_i^{h,p} \le H^h \forall i \in I, p \in P(i), t \in T, h \in H \tag{20}$$

$$\sum_i x_{i,t}^p k_i^{m,p} \le K^m \forall i \in I, p \in P(i), t \in T, m \in M \tag{21}$$

$$F_t^n = F_{t-1}^n - \sum_i x_{i,t}^p g_i^{n,p} + S_t^n \forall i \in I, p \in P(i), t \in T, n \in N \tag{22}$$

$$\sum_i y_i^p q_i^{a,p} \le AQ \forall i \in I, p \in P(i), a \in A \tag{23}$$

$$OPC = (D - \max(t))Ot \in T \tag{24}$$

$$x_{i,t}^p + y_i^p \le x_{j,t}^q \forall i \in I, p \in P(i), j \in U(i,p), q \in P(j), t \in T \tag{25}$$

$$b_{i,j}^{p,q} \le x_{i,t}^p \ , \ b_{i,j}^{p,q} \le x_{j,t}^q \ , \ b_{i,j}^{p,q} \ge x_{i,t}^p + x_{j,t}^q - 1 \ \forall i\&j \in I, p \in P(i)\ , q \in P(j)\ , t \in T \tag{26}$$

$$\begin{cases} \partial_i^p = \partial''^p_i \alpha_{i,j}^{p,q} if \sum\nolimits_t b_{i,j}^{p,q} \ge \gamma_{i,j}^{p,q}, \theta_{i,j}^{p,q} \le 0 \\ \partial_i^p = \partial''^p_i \beta_{i,j}^{p,q} \sum\nolimits_t b_{i,j}^{p,q} if \sum\nolimits_t b_{i,j}^{p,q} \ge \gamma_{i,j}^{p,q}, \theta_{i,j}^{p,q} > 0 \ \forall \partial \in \{C, Q, D, H, K\}, i\&j \\ \partial_i^p = \partial''^p_i if \sum\nolimits_t b_{i,j}^{p,q} < \gamma_{i,j}^{p,q} \end{cases}$$
$$\in I, p \in P(i), q \in P(j), t \in T \tag{27}$$

4. Model evaluation

Two data sets will be generated following the execution of the model: one corresponding to the original portfolio and the other to the modified portfolio. Both portfolio forms are compared based on the modified parameters of cost, duration, quality, rework risk, and resource consumption to evaluate the modified portfolio and the model. We use multi-criteria decision-making (MCDM) to compare the two forms and alternatives. In addition, a fuzzy approach is used to represent the linguistic terms since the collected data will be primarily qualitative [67]. The best-worst method (BWM) [68] is used as the weighting method, and the weighted aggregated sum product assessment (WASPAS) [69] is used as the alternative scoring method.

4.1. Fuzzy BWM

The BWM is a relatively new method widely used for subjective weighting in MCDM. A distinguishing feature of the BWM is that it significantly requires fewer pairwise comparisons with consistent results when compared to other weighting methods [70]. We use a fuzzy BWM method suggested by Guo & Zhao [71] to capture the ambiguity associated with linguistic terms and judgments in the evaluation process. The linguistic terms and their associated membership function are presented in Table 4, and a summary of the steps required for the fuzzy BWM used in this study is presented in Table 5.

Table 4
Linguistic terms for fuzzy conversion [71].

Linguistic terms	Membership function
Equally important	(1,1,1)
Weakly important	(2/3,1,3/2)
Fairly important	(3/2,2,5/2)
Very important	(5/2,3,7/2)
Absolutely important	(7/2,4,9/2)

Table 5
Fuzzy BWM procedure.

Steps	Descriptions
1	Ask a set of decision-makers to choose the best and worst criteria.
2	Determine fuzzy vectors to represent the preference of the most important (best) criterion towards all other criteria, and vice versa, the least important (worst) criterion. $\widetilde{A}_B = (\widetilde{a}_{B1}, \widetilde{a}_{B2}, \cdots, \widetilde{a}_{Bn})$ $\widetilde{A}_W = \left(\widetilde{a}_{1W}, \widetilde{a}_{2W}, \cdots, \widetilde{a}_{nW}\right)$
3	Determine the optimal fuzzy values for the criteria's weights $\left(\widetilde{W}_1^*, \widetilde{W}_2^*, \cdots, \widetilde{W}_n^*\right)$ using: $\min max_j \left\{ \left\| \frac{\widetilde{W}_B}{\widetilde{W}_j} - \widetilde{a}_{Bj} \right\|, \left\| \frac{\widetilde{W}_j}{\widetilde{W}_W} - \widetilde{a}_{jW} \right\| \right\} s.t. \begin{cases} \sum_{j=1}^{n} R\left(\widetilde{W}_j\right) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \cdots, \mathrm{n} \end{cases}$ where $\widetilde{W}_B = (l_B^w, m_B^w, u_B^w)$, $\widetilde{W}_j = \left(l_j^w, m_j^w, u_j^w\right)$, $\widetilde{W}_W = (l_W^w, m_W^w, u_W^w)$, $\widetilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$, $\widetilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW})$. The optimization problem can be expressed as follows: where $\widetilde{\xi} = \left(l^{\xi}, m^{\xi}, u^{\xi}\right)$. Considering $l^{\xi} \le m^{\xi} \le u^{\xi}$, and $\widetilde{\xi}^* = (k^*, k^*, k^*)$, $k^* \le l^{\xi}$, is expressed as follows: $\min \widetilde{\xi} \min \widetilde{\xi}^*$ $s.t. \begin{cases} \left\| \frac{\widetilde{W}_B}{\widetilde{W}_j} - \widetilde{a}_{Bj} \right\| \le \widetilde{\xi} \\ \left\| \frac{\widetilde{W}_j}{\widetilde{W}_W} - \widetilde{a}_{jW} \right\| \le \widetilde{\xi} \\ \sum_{j=1}^{n} R\left(\widetilde{W}_j\right) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \cdots, n \end{cases} s.t. \begin{cases} \left\| \frac{(l_B^w, m_B^w, u_B^w)}{\left(l_j^w, m_j^w, u_j^w\right)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right\| \le (k^*, k^*, k^*) \\ \left\| \frac{\left(l_j^w, m_j^w, u_j^w\right)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW}) \right\| \le (k^*, k^*, k^*) \\ \sum_{j=1}^{n} R\left(\widetilde{W}_j\right) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \cdots, n \end{cases}$
4	Finally, the crisp weights for each criterion are obtained using $crisp\left(\widetilde{N}\right) = \frac{l_i + 4m_i + u_i}{6}$

Table 6
Fuzzy-WASPAS procedure.

Steps	Descriptions
1	Establish the decision matrix with the triangular fuzzy numbers: $\widetilde{X} = \begin{bmatrix} \widetilde{x}_{11} & \widetilde{x}_{12} & \cdots & \widetilde{x}_{12} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & \cdots & \widetilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{x}_{m1} & \widetilde{x}_{m2} & \cdots & \widetilde{x}_{mn} \end{bmatrix}; 1 \le i \le m; 1 \le j \le n$
2	Normalize the matrix using: $\widetilde{x}_{ij} = \begin{cases} \frac{\widetilde{x}_{ij}}{\max \widetilde{x}_{ij}} if \max \widetilde{x}_{ij} is preferable \\ \frac{min \widetilde{x}_{ij}}{\widetilde{x}_{ij}} if \min \widetilde{x}_{ij} is preferable \end{cases}$ both min and max function on index i
3	Calculating the weighted matrix component of WSM and WPM using: $\widetilde{x}_{ij} = \widetilde{\overline{x}}_{ij}\widetilde{w}_j$ for WSM $\widetilde{x}_{ij} = \widehat{\widetilde{x}_{ij}}^{\widetilde{w}_j}$ for WPM
4	Calculate the function values of WSM and WPM via: $\widetilde{Q}_i = \sum_j^n \widetilde{x}_{ij}, i = [1, m]$ $\widetilde{P}_i = \prod_j^n \widehat{\widetilde{x}}_{ij}, i = [1, m]$
5	Defuzzification: $Q_i = \frac{1}{3}(Q_{i\alpha} + Q_{i\beta} + Q_{i\gamma})$ $P_i = \frac{1}{3}(P_{i\alpha} + P_{i\beta} + P_{i\gamma})$
6	Finally, each alternative is scored by: $K_i = \lambda \sum_i^m Q_i + (1 - \lambda) \sum_i^m P_i, \lambda \& K_i \in [0, 1]$ where λ is usually determined by expert opinion (default value is $\lambda = 0.5$)

4.2. Fuzzy WASPAS

The WASPAS method is an aggregation of the weighted sum method (WSM) and the weighted product model (WPM) [69]. WASPAS was selected for its simplicity, flexibility, and versatility (handling cost and benefit criteria) [72]. The method also produces similar results when compared to other more complex MCDM methods [73]. We use the fuzzy-WASPAS method in Table 6, developed by Keshavarz Ghorabaee et al. [74].

5. Case study

The proposed model was tested at the Thermal Energy System (TES),[1] an innovative energy company located in the Persian Gulf region. TES specializes in sustainable heating, cooling, and energy storage solutions, utilizing advanced technologies to enhance efficiency and reduce environmental impact. This study examined a diverse portfolio of TES projects, ranging from those in the construction phase to others encompassing multiple stages, including engineering, procurement, and other related activities. The primary portfolio information was collected by accessing the company project documentations, and other data, such as interdependency coefficients and quality loss due to fast-tracking, were determined using expert opinions. Three experts, two senior project managers, and an operational manager, were included in the study. The data was collected through a semi-structured interview

[1] The name is changed to protect the anonymity of the company.

Table 7
Case portfolio data.

Project-phase	Cost	Duration	Precedence relation	Human Resource		Fixed Resource		Consumable Resources
				HR A	HR B	FR C	FR L	
1 – 1	10	1	–	20	–	–	–	–
1 – 2	60	3	1 – 1	10	10	–	–	–
1 – 3	30	5	1 – 2	–	60	5	10	100
2	35	4	1 – 1	–	50	3	8	80
3 – 1	40	4	–	15	–	–	–	–
3 – 2	15	3	3 – 1	–	30	–	10	50
4 – 1	10	2	–	15	–	–	–	–
4 – 2	25	3	4 – 1	–	15	2	–	–
5	40	4	4 – 1	–	45	2	5	65
Capacity	–	DD = 12	–	55	200	10	35	Initial = 600 Restock = 450

Table 8
Project expediting data.

Projects	Fast-tracking			Crashing	
	Relation	Quality	Risk	Cost	Duration
1–2	1 – 1*	1 ↓	3 ↑		
1–3				10 ↑	2 ↓
2				20 ↑	2 ↓
3–2	3 – 1*	3 ↓	6 ↑		
4–2				10 ↑	1 ↓
5	4 – 1*	4 ↓	4 ↑	10 ↑	1 ↓

Note: *indicates the precedence relationship can be disregarded while ↑ representing an increase and ↓ a decrease.

following three iterations of the Delphi method (A. [66]. The collected data are displayed in Tables 7 and 8.

This table presents a detailed overview of the portfolio's projects and their phases, including key metrics and constraints. Column 1 displays the projects and their associated phases, while Column 2 provides the estimated costs for each phase in normal conditions, with units representing 10 million Tomans. Column 3 shows the normal duration of each phase, measured in months. Column 4 presents the precedence relationships, such as dependencies, where one phase or project cannot start until a preceding phase or project is completed. Columns 5 and 6 detail human resource requirements per unit of time. They further distinguish managers (HR Type A) and staff (HR Type B)—columns 7 and 8 present fixed resources needed per unit of time. Column 9 shows consumable resources, including batch requirements, initial stock, and restock amounts. The final row describes resource capacity constraints to ensure alignment with the available resources.

Furthermore, any delay beyond the due date incurs a penalty of five cost units for each unit of time. Conversely, shortening the overall portfolio completion date provides a benefit of five cost units as an opportunity cost, encouraging project acceleration. Only scheduling and resource constraints were considered in the following case, while factors such as project expediting and interdependencies were excluded. This represents the initial state of the portfolio, which is visualized in Fig. 1 as a Gantt chart.

The model proposed in this study will generate additional data on project expediting and interdependencies, as well as their subsequent effects on other parameters. Expert opinions are used to estimate the possible impact. These estimated projects, expediting, and interdependency data are presented in Tables 8 and 9. Project expediting using fast-tracking was considered in some projects to break the precedence relation and, in turn, lower the quality and increase rework risk by a certain

Table 9
Project interdependency data.

Interdependent projects	Required periods and dependency type	Effect
1 – 1 and 4 – 1	1 and Type 2 (Synergy)	Human Resources (HR) ↓ by 5
1 – 3 and 2	3 and Type 1 (Dual)	Cost ↑ by 5 and Fixed Resources (FR) ↓ by 20 %
3 – 2 and 4 – 2	2 and Type 1 (Synergy)	Cost ↓ by 4 and Shared Resources ↓ by 30 %
2 and 5	2 and Type 1 (Dual)	Cost ↓ by 3 and Shared Resources ↑ by 10 %

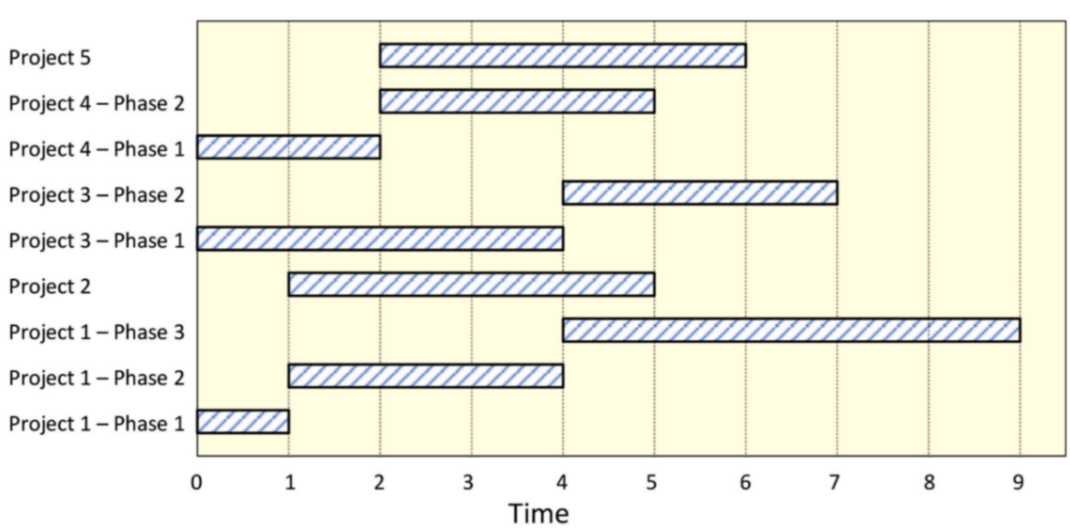


Fig. 1. Portfolio execution schedule (initial state).

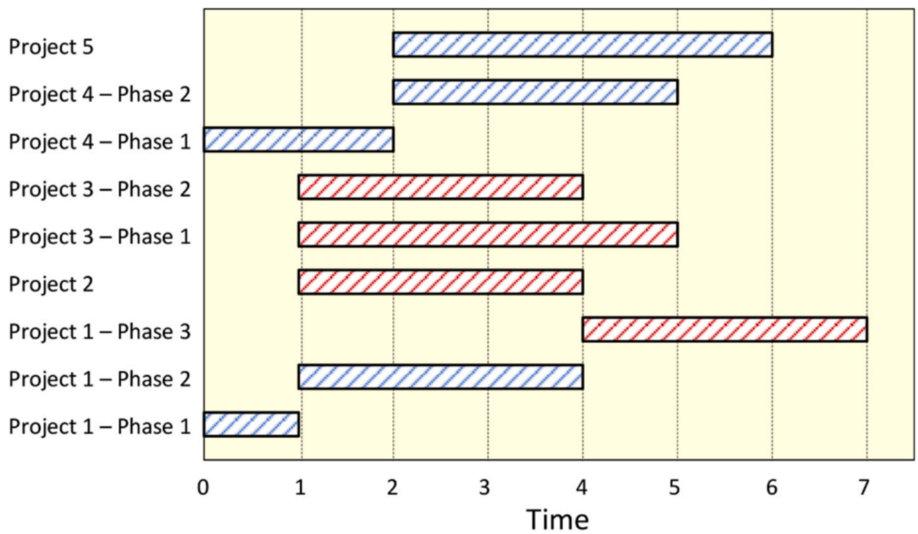


Fig. 2. Portfolio execution schedule (modified state).

degree (on a qualitative scale of 1 to 10). Table 8 shows the potential for expediting projects through fast-tracking and crashing methods.

Fast-tracking involves breaking precedence relationships to enable the simultaneous execution of projects, reducing duration at the expense of quality and increased rework risk. Column 1 identifies the projects, while the three fast-tracking columns indicate which precedence relationships can be ignored and the associated impacts on portfolio quality and risk. Crashing represents a trade-off between time and cost, specifying fixed values for reducing project phase durations by incurring additional costs. For example, in phase 3 of project 1, spending 10 cost units reduces the duration by 2 units. Similarly, disregarding the precedence relationship between Project 5 and Phase 1 of Project 4 allows Project 5 to start immediately (Time 0) but increases rework risk and decreases overall portfolio quality by 4 units.

The interdependencies are categorized as synergetic or cannibalistic, based on the shared period duration between projects, and whether the impact increased with the shared periods (Type 1) or remained unaffected (Type 2), as presented in Table 9.

The first column shows the projects and phases involved. The second column specifies the duration of shared execution required for the effect and the type of interdependency. The interdependencies are classified as Type 1 (increasing effect) or Type 2 (no effect) and are further categorized as positive (synergy) or negative (cannibalism). For instance, if Phase 1 of Project 1 and Phase 1 of Project 4 overlap during a single period, a Type 2 synergistic effect reduces their total HR cost by 5 units, regardless of the duration. On the other hand, if projects 2 and 5 overlap during two time periods, a Type 1 dual effect occurs where 3 units reduce the cost for each shared unit, but resource consumption increases by 10 %. In the updated portfolio, where these projects share two time periods, the effect results in a 10 % increase in total resource consumption per unit of time and a cost reduction of 6 units.

Although these newly added considerations benefit the project, they come with setbacks. Therefore, these advantages and disadvantages must be carefully evaluated to determine the optimal solution. The new parameter values are added to the model to find the exact scheduling and resource allocation sequence under these new conditions. The model is run using Python code under the CPLEX linear solver. The optimum produced a cost of $ 220 over a 7-unit duration, in contrast to the initial state, which had a cost of $ 260 over 9 units. The solution involved fast-tracking the second phase of Project 3 and crashing the third phase of Projects 1 and 2. The change to the overall portfolio scheduling is illustrated in Fig. 2.

Interdependencies and outsourcing parts of the projects also modified the resource flow of the portfolio, resulting in a reduction of overall resources. These changes are illustrated in Figs. 3, 4, and 5 for human resources, fixed resources, and consumable resources, respectively. Outsourcing projects would appear to reduce overall resource consumption. At the same time, the interdependencies also reduced the number of resources needed in one period, causing the peaks of consumption to be shortened.

The final step involves comparing the initial and modified portfolios to evaluate the effectiveness of the changes to the portfolio. The first step consists of weighing the following criteria:

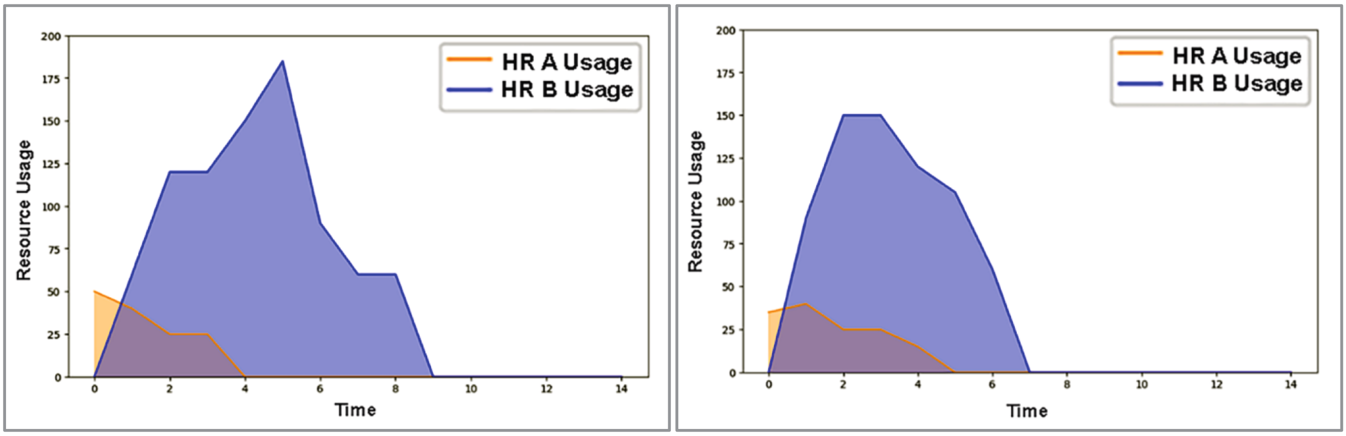
- Cost: the total cost of the portfolio.
- Duration: the period during which the final project of the portfolio concludes.
- Quality: the overall quality of the portfolio's projects (being affected by fast-tracking).
- Reword risk: risk of having to start over the project from the beginning (being affected by fast-tracking).
- Resource consumption: the overall consumption rate of all resources.

The experts were instructed to compare the criteria using the BWM method procedure. The linguistic terms used were translated into fuzzy logic using Table 5, resulting in the calculation of both the fuzzy and crisp weights for each criterion, as presented in Table 10 and illustrated in Fig. 6.

The next step after determining the weight of the criteria is to establish the decision matrix. The procedure of establishing and processing the decision matrix follows the instructions in Table 6, starting with the generation and normalization of the fuzzy decision matrix presented in Table 11.

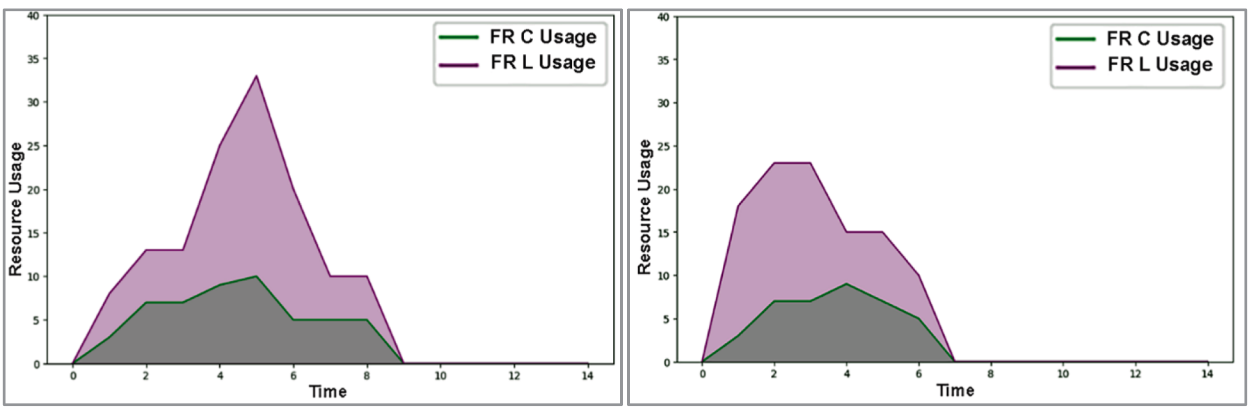
Subsequently, the weighted sum and product values are calculated before defuzzification and scoring both portfolio states. The mathematical equations of WSM and WPM are executed using fuzzy numbers, and the results are shown in Table 12.

The next step involves determining the Q and P values. While still in



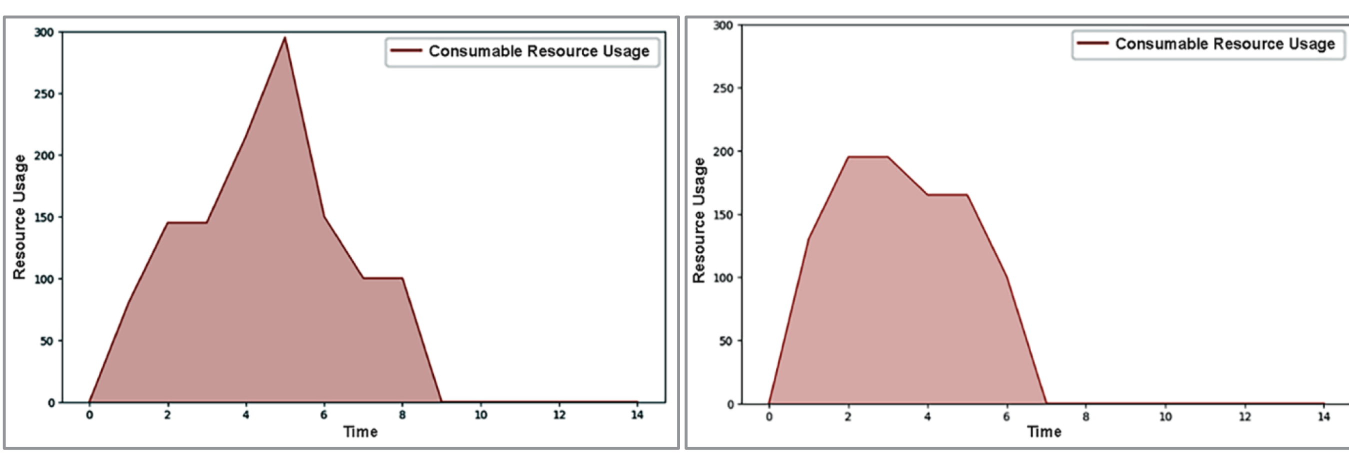
a(Initial state) b(Modified state)

Fig. 3. Human resource utilization over time.



a(Initial state) b(Modified state)

Fig. 4. Fixed resource utilization over time.



a(Initial state) b(Modified state)

Fig. 5. Consumable resource utilization over time.

a fuzzy state, these values are transformed into crisp numbers, which are depicted in Table 13.

Finally, with the calculated values of Q and P, it is possible to compare the portfolio's initial and modified states. The only remaining variable is the λ in the WASPAS method. λ is a number between 0 and 1, typically determined by the decision maker and traditionally considered to be 0.5. The initial state score (0.789) and the modified state score (0.808) for $\lambda = 0.5$ and all other λ values between 0 and 1 are presented in Fig. 7.

The above WASPAS results suggest that the portfolio's modified state is valued higher than its initial state, as changes implemented through expediting and rescheduling the projects positively impact the

Table 10
Fuzzy and crisp weights of the criteria.

Cost	Duration	Quality	Rework risk	Resource
0.276	0.266	0.077	0.137	0.243
(0.21, 0.281, 0.323)	(0.151, 0.268, 0.375)	(0.074, 0.075, 0.086)	(0.114, 0.134, 0.175)	(0.232, 0.24, 0.268)

portfolio's performance and should be considered for adoption.

5.1. Secondary case

To further demonstrate the model's capability, a similar project portfolio case from the same company was selected, and the model was utilized again to test its robustness. The new case, identical to the previous one, is a TES project portfolio with projects that use the same resources as before, which can be subject to project expediting and exhibit dynamic interdependency relations. The portfolio comprises six projects, including two small-scale, two medium-scale, and two large-scale projects. The medium and larger projects are construction-type and have multiple phases with precedence relations similar to the previous case; other smaller research and development, and engineering projects are also involved. The initial portfolio Gantt chart structure is presented in Fig. 8.

The due date and other resource constraints are the same as the initial case; the resource requirements and detailed project information are presented in the Appendix section. The initial total cost of the portfolio is 398 units, and the portfolio finishes at time 12. The goal again is to optimize the portfolio's resources while utilizing the project-expediting and assuming the interdependencies amongst projects, the information on project crashing, fast-tracking, and interdependencies is added to the Appendix section. The post-model execution portfolio is depicted in Fig. 9.

As shown in Fig. 9, by fast-tracking two of the projects and crashing a project, and also aligning the interdependent project phases, the optimum portfolio can be achieved, resulting in a 310 cost within 11 units of time, reducing the total cost by 22.11 % and shortening the portfolio by a single unit of time. The changes in resource consumption between the initial portfolio state and the modified portfolio state are illustrated in Figs. 10–12.

Unlike the previous case, the interdependencies mostly did not affect the resources; thus, the changes in resource consumption are due to changes in the schedule.

The next step involved measuring the change in the portfolio after the modification. Following the proposed MCDM structure. Since the same experts were asked for the secondary case, their opinions on the

Table 11
Initial and normalized matrix.

	Cost	Duration	Quality	Risk	Resource
Initial					
Initial	(240, 258, 258)	(7, 8, 8)	(3.5, 4, 4.5)	(3.5, 4, 4.5)	(150, 200, 240)
Modified	(150, 200, 240)	(6, 6, 7)	(1.5, 2, 2.5)	(0.3, 1, 1.5)	(100, 100, 140)
Normalized					
Initial	(0.625, 0.775, 0.93)	(0.857, 0.75, 0.875)	(1, 1, 1)	(1, 1, 1)	(0.667, 0.5, 0.583)
Modified	(1, 1, 1)	(1, 1, 1)	(0.428, 0.5, 0.556)	(0.0857, 0.25, 0.333)	(1, 1, 1)

Table 12
WSM and WPM values.

	Cost	Duration	Quality	Risk	Resource
WSM					
Initial	(0.131, 0.217, 0.3)	(0.129, 0.2, 0.328)	(0.074, 0.075, 0.086)	(0.114, 0.134, 0.175)	(0.154, 0.12, 0.156)
Modified	(0.21, 0.281, 0.323)	(0.151, 0.286, 0.375)	(0.031, 0.037, 0.047)	(0.009, 0.033, 0.058)	(0.232, 0.24, 0.268)
WPM					
Initial	(0.906, 0.93, 0.976)	(0.976, 0.925, 0.951)	(1, 1, 1)	(1, 1, 1)	(0.91, 0.846, 0.865)
Modified	(1, 1, 1)	(1, 1, 1)	(0.939, 0.949, 0.95)	(0.755, 0.83, 0.825)	(1, 1, 1)

Table 13
WASPAS's values of Q and P in fuzzy and crisp forms.

Fuzzy form		
State	Q	P
Initial	(0.603, 0.747, 1.045)	(0.805, 0.729, 0.804)
Modified	(0.634, 0.86, 1.072)	(0.709, 0.788, 0.784)
Crisp form		
Initial	0.799	0.780
Modified	0.855	0.760

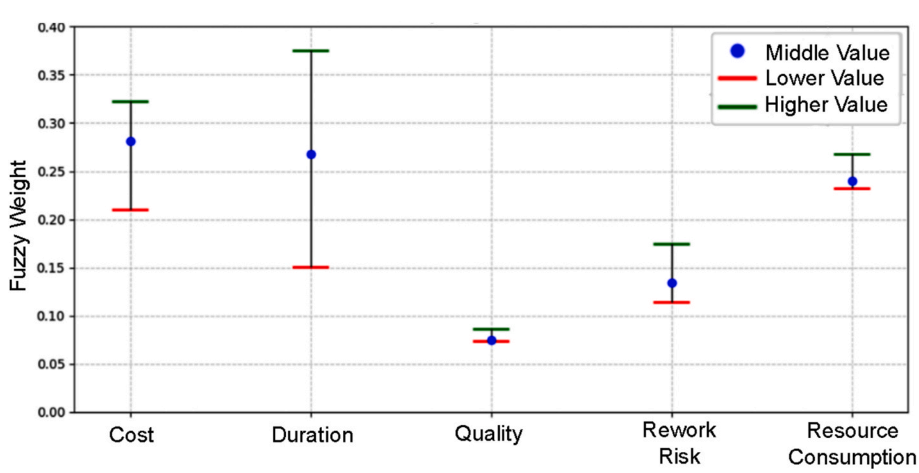


Fig. 6. Fuzzy weight of the criteria.

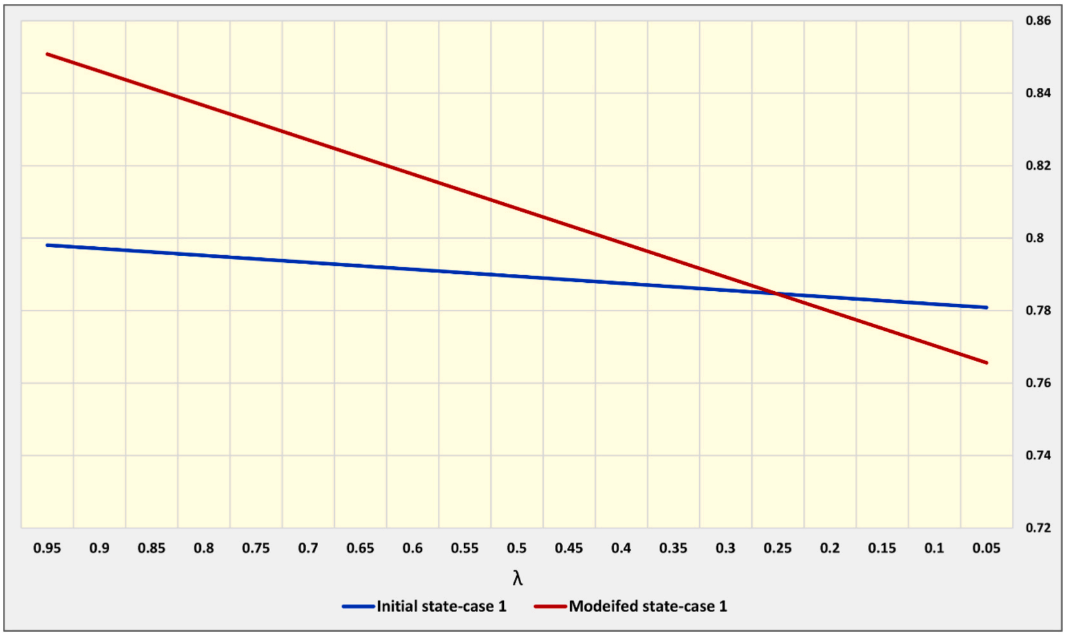


Fig. 7. The WASPAS results for different coefficient values.

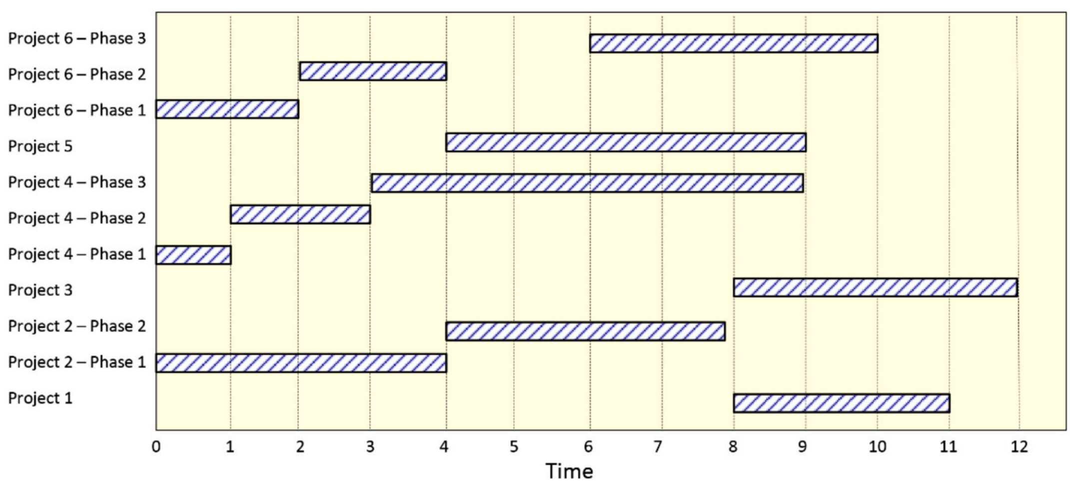


Fig. 8. Initial project portfolio execution schedule for case 2.

criteria weights remain the same, as measured by the fuzzy BWM. However, the decision matrix is changed and reorganized based on the values of the new portfolio, and the normalized decision matrix is inserted in the Appendix section. The result of the fuzzy WASPAS is illustrated in Fig. 13.

Similar to the first case, here, the modified version of the portfolio outweighs the initial state based on the opinions of the experts.

5.2. Model testing

In this section, several tests are designed and conducted to test the robustness and scalability of the model.

5.2.1. Synthetic test

A synthetic test is conducted to validate the model's accuracy and robustness. Since the case revolves around the portfolio of engineering and construction projects, real-world data is scarce or difficult to obtain, and such portfolios typically have a limited number of projects. In these cases, synthetic tests are typically conducted using simulated data rather than historical or generated data. To conduct this specific test, the simulated data of a similar case related to a PPSP was used [75]. The synthetic test is employed for a simulated portfolio with 10, 15, 20, 30, 40, and 50 projects. The findings related to the total cost, portfolio duration, number of projects fast-tracked and crashed, number of constraints and variables, and solution time are shown in Table 14.

As the number of projects increases, so does the number of variables, constraints, and the time required for solution. Interestingly, the portfolio duration increase isn't just affected by the number of projects, but also by the number of projects that were fast-tracked and crashed, which aim to reduce the portfolio duration.

5.2.2. Sensitivity analysis

Next, to test the sensitivity and impact of the input parameters, a sensitivity analysis was conducted on the main parameters that affect the model. The project cost (i.e., the individual cost of each project) was held as the primary parameter, followed by project duration, resource capacity, interdependency, and opportunity costs. A total of 49 scenarios were considered (the base scenario was excluded), each scenario varying

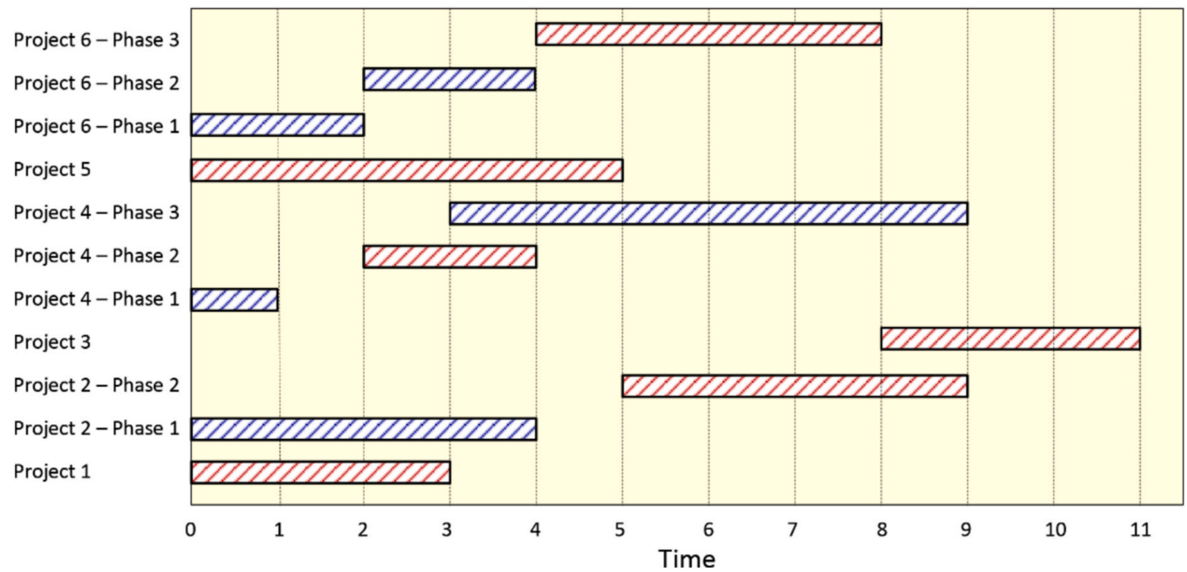


Fig. 9. The post-model execution portfolio for case 2.

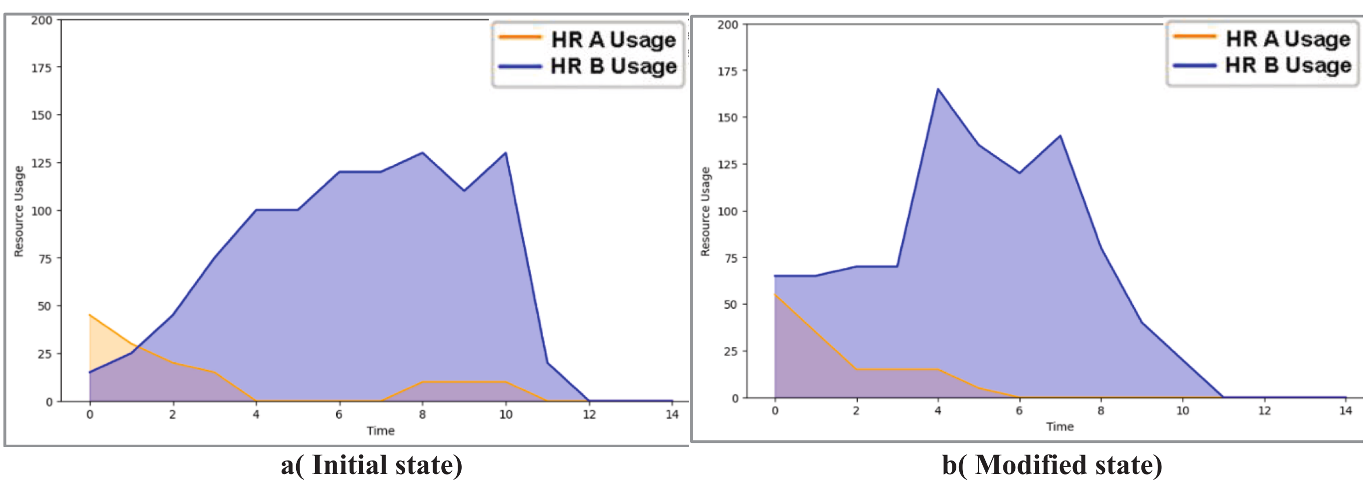


Fig. 10. Human resource utilization over time (secondary case)

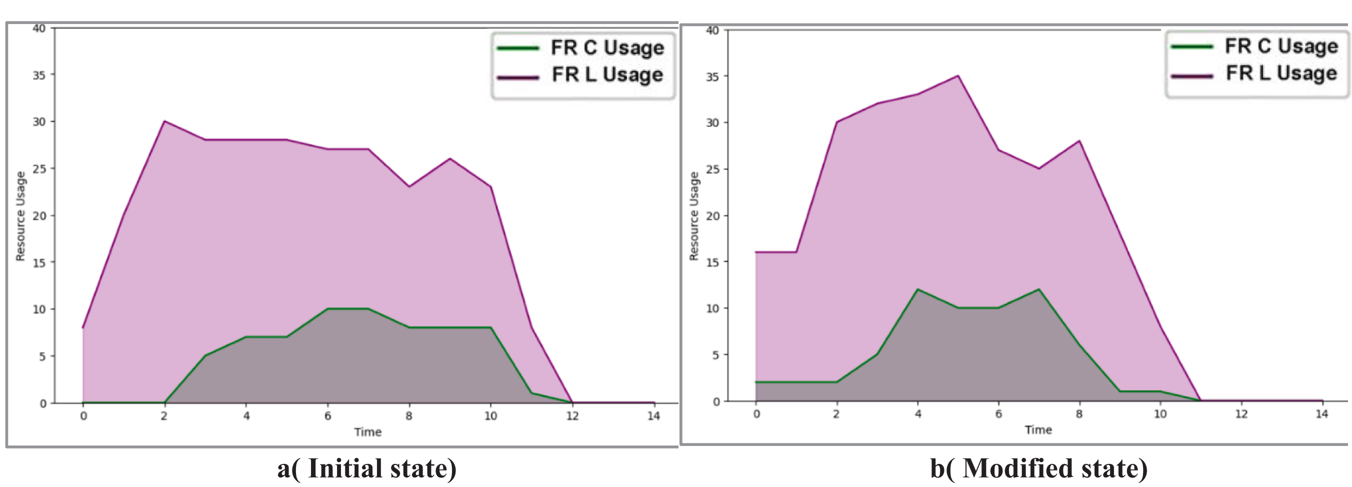
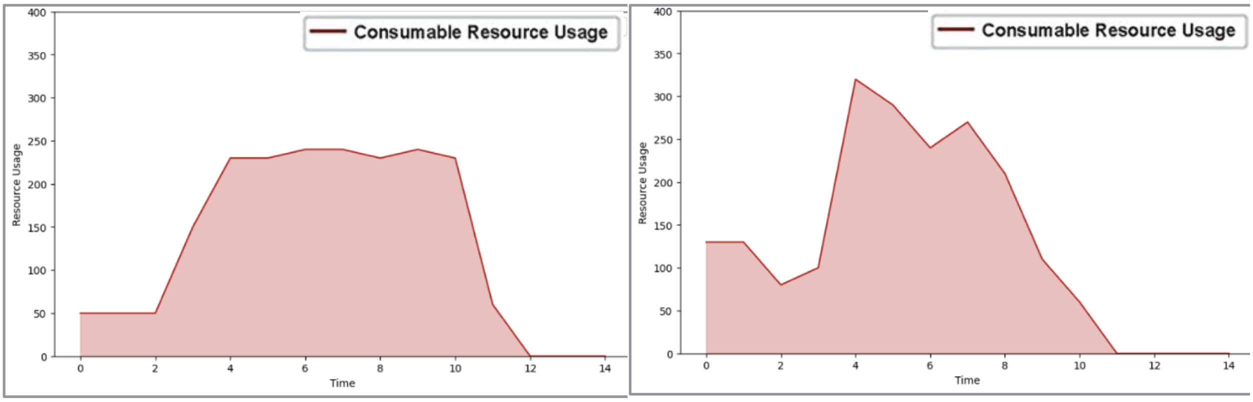


Fig. 11. Fixed resource utilization over time (secondary case).



a(Initial state) b(Modified state)

Fig. 12. Consumable resource utilization over time (secondary case).

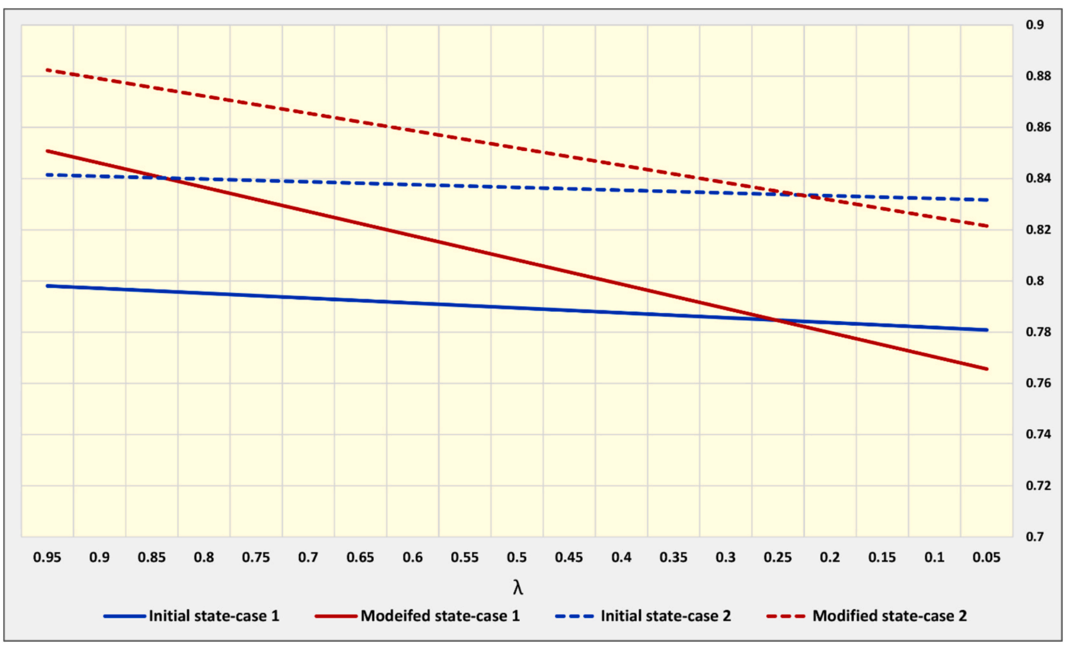


Fig. 13. The WASPAS results for different coefficient values (secondary case).

Table 14
Synthetic test findings.

Number of projects	Total cost	Portfolio duration	Fast-tracked	Crashed	Model variable	Model constraints	Solve time
10	192	13	0	3	175	89	0.28
15	310	14	4	4	271	99	3.57
20	640	26	8	6	650	178	2.94
30	847	31	5	4	1177	224	2.19
40	1138	34	14	8	1967	299	7.29
50	2528	55	12	9	2957	360	48.57

the value of a specific parameter on a scale of 1 % to 200 %. The findings are shown in Fig. 14.

The figure presents the objective value of the model based on the change in the scenario for a specific parameter. As expected, the parameter with the most significant influence on the objective value is the cost of each project, followed by interdependency costs and project duration. When analysing the constraint values, it appears that the capacity of human resources (types A and B) and fixed resource L act as the primary constraints and thresholds for the model.

5.2.3. *Stress test*

Stress tests are typically conducted to assess the robustness and reliability of models under extreme or adverse conditions. In this case, four stress tests are considered. Two of the stress tests considered scenarios with resource shortages. In this case, considering the findings of the sensitivity analysis, human resources and fixed resource L were prioritized as they are more critical. The other two test scenarios related to an increase in the effectiveness of the interdependency effect and a change in the due date. The findings of the stress tests are presented in Table 15.

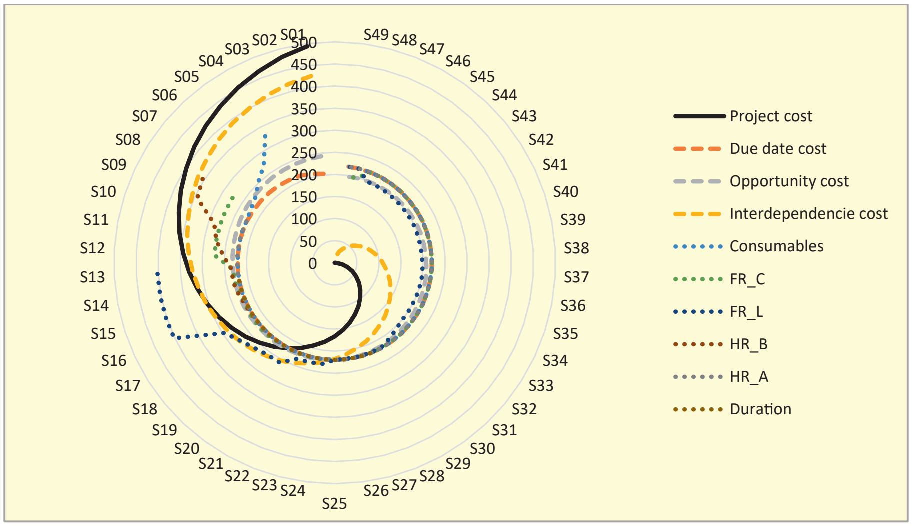


Fig. 14. Result of the sensitivity analysis.

Table 15
Stress test results.

Scenario	Total cost	Duration	Feasible	Changes
Base model	220	7	yes	non
Human resource shortage – moderate (50 %)	238	10	yes	Increase in duration and cost to leverage the shortcomings
Human resource shortage – intense (37.5 %)	268	14	yes	Went over the due date and incurred penalty costs to address shortcomings
FR_L shortage – moderate (50 %)	250	9	yes	Increase in duration and cost to leverage the shortcomings
FR_L shortage – intense (37.5 %)	–	–	no	The feasibility threshold (14 units) was passed.
Longer due date – 25 % increase	210	10	yes	Duration increases, and the optimum solution involves no more crashing
Shorter due date – 25 % decrease	274	8	yes	Fast-tracking and crashing were utilized to minimize the due date penalty
Interdependencies – doubled efficiency	183	7	yes	No change in schedule occurred, and the existing interdependencies reduced the total cost.
Interdependencies – halve efficiency	237	7	yes	A slight schedule change occurred, resulting in an increase in total cost due to existing interdependencies.

Four scenarios were designed to simulate a resource shortage, including both human resources and fixed-type L resources, in two stress scenarios: one for a moderate shortage and one for an intense shortage. In cases of shortage, there was an increase in cost and portfolio duration to compensate for the scarcity of resources. Two scenarios were designed for the due date, and one scenario for a short due date, which resulted in more instances of project expediting techniques being utilized, which in turn increased the cost. A scenario with a longer due date was also considered, as expected, as a longer due date negated the need for the project to be expedited, which in turn reduced the cost. Finally, two other stress scenarios involving the intensity of the interdependency effect of the projects were considered (both synergetic and cannibalistic effects); one scenario doubled the efficiency, and the other halved it. However, there were no effects on duration; a subtle change was observed in the portfolio's cost.

6. Discussion

This study proposed a model to solve the resource allocation problem in project portfolios containing multi-phased projects, considering resource, scheduling, project expediting, and interdependency aspects and constraints. The scheduling and resource constraints are an integral part of this and other studies (found in the literature) that proposed similar models; however, a distinction has been made for different resources and different resource types (e.g., human resource A or fixed resource C). Project expediting involves reducing the overall duration by allocating resources more efficiently. Previous studies only considered Project crashing, where the trade-off is between cost and time. Fast-tracking, which changes the project precedence relations to reduce duration (i.e., the trade-off between time and quality), is rarely seen in previous studies, much less in resource allocation models. Finally, project interdependencies were assumed in the model, the effect stemming from the simultaneous execution of related projects. In previous studies, this concept was grouped into either synergetic or cannibalistic effects. In this study, interdependency effects were classified in more detail:

- Effect type: synergetic or cannibalistic.
- Effect requirement: the number of shared periods for significant change.
- Effect based on duration: whether the effect scales with the number of shared periods or not.

The model also accounted for other areas not seen in every study, such as overdue or opportunity costs. After the model was executed, changes were made to the portfolio. A comparison would need to happen to measure whether this new portfolio has been modified for the better or the worse. Both states (alternatives) must be evaluated based on the changes (criteria) to compare both states of the portfolio. For this reason, an evaluation framework based on the MCDM concept was established. The evaluation was conducted in a fuzzy space using fuzzy BWM to weigh the criteria, and the fuzzy WASPAS method was employed to score the alternatives. Executing this model on data collected from a private construction company resulted in a new state for the portfolio with a reduced total cost. After the evaluation, it was measured to be better than its initial state.

6.1. Theoretical implications and managerial insight

The sensitivity analysis depicted the most important parameters, with cost being the most influential. This highlighted the crucial factors that managers should focus on when planning to improve portfolio performance. It also depicted some of the parameters that could act as bottlenecks for the optimization model, giving insight into which aspects of the portfolio should be considered mainly to avoid a non-feasible scenario, i.e., which resources are limiting and what are their critical thresholds.

As mentioned, the sensitivity analysis provided insight into the parameters that could act as bottlenecks. Using this information, several stress tests were designed to test the model in extreme and adverse scenarios. The findings from the stress tests could provide insight into how the model would handle the problem and what the results for the cost and duration of the portfolio would be. From the test, it can be inferred that in this specific case, the project expediting techniques introduce the most variation in the model. These techniques are typically employed more frequently in highly adverse scenarios to achieve feasibility. In less constrained scenarios, they are avoided to preserve cost efficiency and maintain quality. Another observation is that the interdependencies do not significantly influence the results. Finally, the test reveals which extreme scenarios may lead to infeasible solutions, thereby requiring countermeasures and contingency planning. For example, under extreme conditions, resource FR_L creates a bottleneck in the portfolio and may lead to an infeasible solution. This underscores the importance of proactive contingency strategies, such as strategic outsourcing or buffer planning. Addressing such risks would require a comprehensive planning framework and a robust risk response structure within the organization. This study contributes to the theoretical body of project portfolio optimization by integrating several features that are often underrepresented in academic literature. First, the model accounts for a set of industry-standard resource types, including human, fixed, and consumable resources. These distinctions mirror the realities of engineering and construction projects. Second, the inclusion of project expediting mechanisms, especially fast-tracking, represents a meaningful theoretical advancement. While crashing is occasionally addressed in academic models, fast-tracking, where precedence relationships are deliberately relaxed at the expense of quality and rework risk, is rarely formalized in portfolio-level optimization. Third, the model incorporates dynamic project interdependencies, which are categorized both by their effect type (synergetic or cannibalistic) and their temporal behaviour (duration-sensitive vs. duration-insensitive). This two-dimensional view allows for a more realistic representation of how concurrent project execution can influence costs and resource usage. Taken together, these features offer a framework that researchers can extend to other domains (e.g., manufacturing, infrastructure, or logistics) where interdependencies, realistic resources, and expediting decisions play a critical role in portfolio outcomes.

6.2. Limitations and future research

This research also faced some limitations, which could provide opportunities for future research. Although real-life data from two project portfolios were used to test the model, the number of projects in the industry's construction projects is typically relatively low, consisting of three to six projects. To address this issue, the model was tested on two separate portfolios. However, further testing could shed light on further findings. As mentioned prior, the model was explicitly designed with construction and engineering projects in mind, meaning that the resource structure, project expediting techniques used or the dynamics of the interdependencies are designed intricately with that context in mind, hence; the model can be modified and changed to suit different types of projects (e.g., software development projects, agile projects, etc.). Another limitation involves the objective value based on the total cost. These limitations, however, do not diminish the contributions and practical utility of the proposed framework but rather highlight opportunities for further refinement. The current study already offers a robust foundation that blends theoretical rigor with industry-relevant considerations, paving the way for more advanced and context-specific extensions in future work.

Future research could consider implementing a cash flow system or a budget constraint and modifying the objective function to optimize quality, schedule, or value instead of minimizing costs. It could also be translated into a multi-objective problem. Another topic for future study relates to risk management. As seen in the literature, a common theme in project portfolio-related studies is the theme of risk, where studies primarily focus on solving the PPSP or resource allocation problem while also addressing risks. However, this model does take into account the risk of rework. Other relevant risks could also be considered based on the context of the projects, adding another layer to the optimization of the portfolio, for instance, risk analysis for optimum risk response selection and contingency planning.

7. Conclusion

PPM is an important field that gains more importance based on the gravity of the projects; resource allocation, a key process in PPM, also shares this importance. This research proposed a novel resource allocation model tailored to PPM, addressing critical gaps in existing methodologies. The model integrates four key dimensions: project performance metrics, resources, expediting strategies, and interdependencies among projects. The model optimizes the allocation of diverse resources, leveraging an MILP approach, including human, fixed, and consumable types. Furthermore, it incorporates advanced mechanisms for handling project interdependencies, both synergetic and cannibalistic, and accounts for the temporal effects of these interdependencies. One of the standout contributions is the explicit inclusion of Project expediting strategies. The model considers fast-tracking and crashing tools for reducing project durations, offering nuanced trade-offs between time, cost, and quality. Fast-tracking challenges traditional task sequencing by allowing tasks to be executed in parallel, which can accelerate project timelines but often comes at the cost of reduced quality and heightened rework risks. Crashing, on the other hand, accelerates tasks by increasing resource inputs, thereby raising costs. These strategies, integrated into the model, enable portfolio managers to make informed decisions that align with strategic objectives. The study also highlights the importance of addressing project interdependencies. Unlike previous models that treat interdependencies as a binary factor, this model introduces detailed classifications. It differentiates between effects that require a minimum overlap period to manifest and those that scale with extended overlaps. This granular approach allows for more accurate modelling of real-world scenarios, such as shared resources or vendor discounts, and their impact on portfolio outcomes.

The evaluation of the model employed data from a real-world TES firm, showcasing its practical applicability. By comparing the initial and optimized portfolio states, the model achieved a 15 % reduction in total costs and a 22 % decrease in project duration. These improvements were achieved without compromising overall quality, as validated through an MCDM framework combining fuzzy BWM and WASPAS methods. The evaluation criteria—cost, duration, quality, rework risk, and resource consumption—were carefully weighted and scored, confirming the superiority of the optimized portfolio. The practical implications of this study are significant for organizations managing complex project portfolios. By offering a structured framework for resource allocation, the model enables decision-makers to navigate the intricate trade-offs between competing priorities. Expediting strategies provide a valuable tool for addressing time-sensitive projects, while the detailed treatment of interdependencies ensures a holistic perspective on portfolio optimization.

This research makes a significant contribution to PPM by proposing a novel resource allocation model and a portfolio evaluation framework. For academic purposes, this study presents a new perspective on modelling resource allocation, taking into account the aspects mentioned earlier. The model's integration of quality considerations, expediting strategies, and detailed interdependencies represents a substantial advancement over existing frameworks.

CRediT authorship contribution statement

Madjid Tavana: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Mohammad Senisel Bachari:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Ali Solouki:** Writing – original draft, Methodology, Investigation. **AmirMohammad Larni-Fooeik:** Writing – original draft, Methodology, Investigation. **Hossein Ghanbari:** Writing – original draft, Validation, Methodology.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

In the following section, information regarding the second project portfolio case is displayed. Tables A-1 to A-3 present the overall information of the second portfolio.

Table A-1
Project portfolio data (second case).

Project-phase	Cost	Duration	Precedence relation	Human Resource		Fixed Resource		Consumable Resources
				HR A	HR B	FR C	FR L	
1	20	3	2 – 2	10	10	–	–	–
2 – 1	25	4	–	5	15	–	10	50
2 – 2	35	4	2 – 1	–	20	–	15	50
3	30	4	2 – 2 & 4 – 2	–	20	1	10	60
4 – 1	10	1	–	20	–	–	–	–
4 – 2	45	2	4 – 1	5	10	–	15	–
4 – 3	50	6	4 – 2	–	40	5	15	100
5	35	5	6 – 2	–	40	2	10	80
6 – 1	15	2	–	20	–	–	–	–
6 – 2	40	2	6 – 1	10	20	–	10	–
6 – 3	45	4	6 – 2	–	60	5	10	90
Capacity	–	DD = 12	–	55	200	10	35	Initial = 600 Restock = 450

Table A-2
Project expediting data (second case).

Projects	Fast-tracking			Crashing	
	Relation	Quality	Risk	Cost	Duration
1–1	2 – 2*	3 ↓	6 ↑		
3	2 – 2*	4 ↓	4 ↑	10 ↑	1 ↓
4–3				20 ↑	2 ↓
4–2				10 ↑	1 ↓
5	6 – 2*	3 ↓	3 ↑	20 ↑	1 ↓
6–1				5 ↑	1 ↓

Table A-3
Project interdependency data (second case).

Interdependent projects	Required periods and dependency type	Effect
1 and 4	2 and Type 1 (Cannibal)	Cost ↑ by 10
2–2 and 5	1 and Type 1 (Cannibal)	Cost ↑ by 8 and Human Resources ↑ by 15 %
4 – 3 and 6 – 3	2 and Type 1 (Synergy)	Cost ↓ by 5
2 – 1 and 6 – 1	1 and Type 2 (Synergy)	Cost ↓ by 6 and Consumable Resources ↓ by 10 %

Table A-4De
picts the decision matrix that determines the change in preference of the post-modification portfolio, visualized in Fig. 13. Table A-4 Project portfolio decision matrix values (second case).

Cost			Duration			Quality			Risk			Resources		
Normalized														
0.743	0.779	0.800	0.909	0.917	0.923	1.000	1.000	1.000	1.000	1.000	1.000	0.640	0.700	0.706
1.000	1.000	1.000	1.000	1.000	1.000	0.714	0.750	0.778	0.120	0.333	0.429	1.000	1.000	1.000
WSM														
0.156	0.218	0.2584	0.137	0.245	0.346	0.074	0.075	0.086	0.114	0.134	0.175	0.148	0.168	0.1891
0.21	0.281	0.323	0.151	0.268	0.375	0.052	0.056	0.066	0.013	0.044	0.075	0.232	0.24	0.268
WPM														
0.939	0.932	0.930	0.985	0.976	0.970	1	1	1	1	1	1	0.901	0.917	0.910
1	1	1	1	1	1	0.975	0.978	0.978	0.785	0.863	0.862	1	1	1

Data availability

Data will be made available on request.

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