Vol. 10, No. 2, 2023, Pages 42-58

JIEMS
Journal of Industrial Engineering and Management Studies

journal homepage: www.jiems.icms.ac.ir

A stochastic chance constraint-based model for a project supply management (A metaheuristic method)

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Received: Oct 2023-02/ Revised: Dec 2023-08/ Accepted: Dec 2023-15

Abstract

In today's era, organizations recognize the challenges of meeting the evolving needs and preferences of customers. Simply improving products and individual performance is insufficient to satisfy customer requirements. Instead, organizations have embraced a collaborative strategy, utilized efficient supply chains and leveraged each other's expertise and resources to enhance customer satisfaction. This approach has been made possible by technological advancements. The literature review identifies two research gaps: insufficient consideration of inherent uncertainty in construction projects and inadequate attention to the multi-objective and multimodal nature of construction project models. To address uncertainties in construction projects, this study employed the Chance-Constrained Programming approach. Uncertainty-related parameters were identified and integrated into an optimization model. The primary objective of this study is to minimize project implementation delays. To achieve this, we employ exact algorithms for small and medium-scale problems and utilize NSGAII for large-scale scenarios. Our research emphasizes the critical importance of efficient project timing, cost optimization, and proactive delay management for achieving successful project outcomes. The study reveals critical insights into the impact of resource allocation on the first objective function. The findings show 20% increase in resources for the first activity (i) raises the objective function to 310 units, while a 30% reduction in activity i's completion time lowers it to 188 units. These findings offer valuable benchmarks for decision-making and project optimization. Managers can use these insights to enhance decision-making, optimize resource allocation, and ensure timely project completion while maintaining quality and cost control.

Keywords: Chance constraint programming, minimizing delay, stochastic uncertainty, resource allocation

Paper Type: Original Research

1. Introduction

In order for corporations and industries to compete effectively in the global arena, it is essential for them to possess the necessary expertise and experience on a large scale (Grabs and Garrett, 2023). To succeed in this competitive landscape, they need to learn from and benchmark themselves against leading companies, organizations, and industries to identify areas for improvement (Danladi et al., 2023, Ahmadi and Peivandizadeh, 2022; Abolghasemian et al. 2021). The rapid progress and evolution in economic, social, and technological aspects, both nationally and internationally, have brought about instability for many renowned organizations. Failure to adapt to these rapid changes puts them at risk of disappearing (Wang et al., 2023; Ahmadi and Ghasemi, 2023; Chobar et al. 2023). Significant strides have been made in the realm of knowledge development and project management tools aimed at mitigating project delays. These advancements encompass a multifaceted approach to addressing delays by leveraging cutting-edge methodologies and technologies. Knowledge development has yielded a deeper understanding of the intricate causes and dynamics behind project delays, encompassing factors such as resource constraints, scope changes, and external dependencies. Concurrently, the advent of sophisticated project management software tools and platforms has revolutionized the field (Ahmadi et al. 2021). These tools employ data-driven

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approaches and predictive analytics to identify potential delays early in the project lifecycle, facilitating timely interventions (Balstrous et al., 2019, Shafipour-Omrani et al. 2021). The identified research gaps in the literature review highlight key shortcomings in the current state of construction project management research. First, there is insufficient consideration of the inherent uncertainty associated with construction projects, indicating a need for studies that address and incorporate uncertainties in project dynamics. Second, the literature lacks adequate attention to the multi-objective and multimodal nature of construction project models, signaling a gap in understanding and managing the complex interactions among diverse project objectives and modes. Lastly, the absence of focus on new methods for converting and verifying stochastic models into deterministic ones at a specified level of certainty (alpha) reveals a need for research to explore and develop robust techniques for handling stochastic elements in construction project models. Addressing these gaps could significantly contribute to the advancement of effective and comprehensive approaches in construction project management.In construction project management, the necessity arises from the challenge of balancing the simultaneous minimization of project delays and total costs while working within resource constraints. This is crucial to achieve timely project completion and financial efficiency. Project delays not only incur additional costs but also risk disruptions in subsequent project phases. The constraint of limited resources, including labor, equipment, and materials, underscores the need for careful allocation and scheduling. The integration of real-world data further enhances the practicality and accuracy of the optimization model, aligning it with the complexities of actual construction projects.

So, the research questions are as follows:

- Research Question 1: How can the proposed mathematical model be further refined or augmented to enhance its efficiency in minimizing both project delays and total costs simultaneously, with a specific focus on optimizing the allocation and scheduling of key resources in the context of construction project management?
- Research Question 2: What is the sensitivity of the developed optimization model to variations in input parameters, and how can insights gained from this sensitivity analysis be leveraged to provide practical managerial guidance for construction project managers facing resource constraints, with the aim of achieving a balance between minimizing delays and total project costs?

The primary goal is to develop a robust mathematical model for construction project management, focusing on minimizing project delays and total costs within resource constraints. The specific objectives include reducing delays to mitigate cost consequences and disruptions and minimizing overall project costs, covering labor, materials, and equipment expenses for financial efficiency. Mathematical modeling techniques, specifically GAMS for smaller problems and NSGA-II for case studies, are employed. The chosen methodologies aim to explore potential Pareto-optimal solutions, providing valuable insights and decision support for construction project managers. The research seeks to contribute a practical and effective solution to optimize project outcomes in the complex construction project management environment.The remainder of this manuscript is organized as follows. Section 2 provides a literature review and relevant research in the project supply management. Sections 3 and 4 present the problem description and implementation mathematical model. The solution approach and computational results are given in Sections 5 and 6. Section 7 introduces our case study. Finally, the main findings, managerial insights, and work extensions are explained in Section 8.

2. Literature review

Donyavi et al. (2023) concentrate on the procurement process from the standpoint of these companies, aiming to explore the influence of efficient materials management on the construction site. The contribution of the paper is to shape construction supply management and is grounded in the identification of five primary stages, spanning from material specification to data management and feedback. Nigar et al. (2023) utilized a Genetic Optimization Algorithm to address the problem of resource allocation. They presented mechanisms to design and regulate parameters, resulting in high-quality algorithmic solutions. Their study introduced a cooperative timing approach that considers optimized constrained resources. The findings indicated improved performance with the implementation of their proposed model. Ghoroqi et al. (2023) presented a supplier selection model with optimal scheduling for multi-mode resource-constrained projects. The model was solved using a multi-objective whale optimization algorithm based on the Pareto archive and (NSGA-II). The paper's contribution lies in incorporating diverse implementation modes and considering the time value of money. Peiris et al. (2023) introduced a production scheduling model tailored for modular construction. They offer an in-depth analysis of genetic algorithm (GA) applications in scheduling, alongside newer techniques such as particle swarm optimization (PSO), simulated annealing (SA), and ant colony optimization (ACO). Their paper contributes by considering the responsiveness of the scheduling system to new tenders or work and integrating production scheduling with Manufacturing Execution and Control Systems (MECS).

Hafezi Zadeh et al. (2022) introduced a human resource scheduling model in project management, focusing on the context of an oil extraction project. The study addresses the challenge of scheduling human resources in the specific context of an oil exploration project. The contributions of the paper encompass the allocation of three human resource groups across four task types in oil exploration operations, covering geology, geophysics, petrophysics, and oil engineering. In Myszkowski and Laszczyk, (2022), a new model was introduced to minimize project completion time. The approach considered a project deadline and aimed to minimize costs associated with delays and rushed completion. The results demonstrated the effectiveness of their proposed model.

Khalilzadeh et al. (2020) presented a mathematical modeling and an Exact Solution Approach for minimizing delays and resource allocation in construction projects. The study aimed to minimize project timing and delays, and introduced the innovation of considering uncertainty in demands. The results showed favorable outcomes with proposed solution.

Pellerin et al. (2020) presented a Particle Swarm Optimization algorithm for mimizing delays. Strategies such as efficient project scheduling, proactive risk management, and clear communication among stakeholders can help mitigate delays. Employing technology like construction management software and employing experienced project managers can further enhance delay reduction efforts.

Altinats et al. (2020) proposed criteria for minimizing activity costs in project timing. The cost structure included two parts: constant activity costs and time-dependent maintenance costs. The study aimed to minimize maintenance costs until the actual project completion time.

Chen et al. (2020) presented two algorithms cooperatively searched the solution space, and local search was applied when they converged on the same answer. Reducing delays in information technology projects involves meticulous planning and communication. Employing agile methodologies, setting realistic timelines, and conducting regular progress assessments can help identify and address potential bottlenecks swiftly. Utilizing skilled IT professionals and robust project management tools also contribute to minimizing delays and ensuring successful project outcomes.

Habibi et al. (2019) employed a second Genetic ordering Approach to solve the model, with a case study conducted in Iran. Sensitivity analysis indicated that the developed model supported better decision-making for contractors. Tirkola'ee et al. (2019) investigated project timing problems with reduced cash flows in both unimodal and multimodal forms. They introduced a cash flow-based timing technique to improve the net value of the project. The results demonstrated the efficiency of the recommended model after implementation.

- **Inherent Uncertainty in Construction Projects**: Existing literature lacks sufficient consideration of the inherent uncertainty present in construction projects. This suggests a need for research that addresses and incorporates the uncertainties associated with various aspects of construction activities.
- **Multi-objective and Multimodal Nature of Construction Project Models**: Current research does not adequately account for the multi-objective and multimodal nature of construction project models. There is a gap in understanding and addressing the complex interplay of multiple objectives and diverse modes within the context of construction project management.
- **Conversion and Verification Methods for Stochastic Models**: The literature review highlights a gap in attention towards new methods for converting and verifying stochastic models into deterministic models, particularly at a specified level of certainty (alpha). This points to a need for research that explores and develops effective methods for handling stochastic aspects in construction project models and ensuring a reliable transition to deterministic frameworks.

3. Statement of the problem

In the domain of construction project management, a challenging task is to simultaneously minimize project delays and total costs while adhering to resource constraints. This multi-objective optimization problem arises from the necessity to strike a balance between ensuring the timely delivery of projects and achieving financial efficiency. In response to this challenge, we propose a mathematical model that leverages real-world data to inform decision-making. The primary objectives of this study encompass:

Minimize Project Delay: The first objective entails the reduction of delays in the completion of construction projects. Project delays can result in increased costs and potential disruptions in subsequent phases.

Minimize Total Cost: The second objective focuses on minimizing the overall cost associated with the construction project. This encompasses expenses related to labor, materials, equipment, and any other relevant cost factors.

A pivotal aspect of the problem revolves around resource limitation. The availability of key resources, including labor, equipment, and materials, is restricted. This constraint necessitates careful allocation and scheduling of resources to avoid bottlenecks and delays. Furthermore, our approach is enriched by the utilization of real-world data. We have collected data pertaining to project parameters, resource availability, and historical performance to enhance the practicality and accuracy of our optimization model.To address this multi-objective optimization problem, we employ mathematical modeling techniques. Specifically, the General Algebraic Modeling System (GAMS) is utilized for small and medium-sized problems, while the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is employed for case studies. These methodologies enable us to explore potential Pareto-optimal solutions, offering valuable insights and decision support for construction project managers striving to balance the competing goals of minimizing delays and total project costs within the constraints of available resources.

4. Mathematical Modelling

In this part of the research, the findings of the research in Farzan Fan Andish Farda Company, which is among the top knowledge-based companies in Iran and a subset of the knowledge-based institutions of the Amirkabir University of Technology, which is located in Tehran. This company operates in the field of producing electronic components and is considered a case study in this research. Farzan Fan Andish Farda Company (FFAFC) was established in 2014 and is engaged in conducting research studies, production, and commercial engineering design in the field of new energy, electronics and mechatronics and industrial parts, material handling systems and feeding production lines, and export and import of permitted commercial goods and obtains domestic and foreign representation. All research results have been implemented in the deterministic part using GAMS software and in the parametric part using MATLAB software in a system with Intel Core i3 1.8 GHz, 4GB RAM specifications. Tables 4 to 8 show the numerical solution of the problem using the BARON tool in the GAMS software. Before running the model, it is necessary to define the parameters related to the sets considered to solve the model. In this article, according to Table 3, the number of main components related to the supply chain is considered in the FFAFC. In addition, we must first check the feasibility of the problem in a solution space. Table 4 also shows the feasibility of the problem. In this research, to solve the model according to the supply chain components of Company FFAFC shown in Table 3, we assume that two suppliers are used to provide two types of products. The two distributors that exist in Company FFAFC provide different products to customers, which are classified into two categories, internal and external. Waste or defective products are sent to two recycling centers for preparation for reuse, which are located in Tehran and Karaj. In general, we examine the supply chain process of company FFAFC in two scenarios of recession and market boom during two time periods.

Indices

j	Kind of resources
I	activity

Model Parameters

p_i	Duration of activity i
b_j	Amount of resource j
su_i	Number of activities after activity i
q_{ij}	Available resource j for activity i

Variables

$\boldsymbol{h_{it}}$	Binary variable that shows completion time of activity I in period t between the proposed time windows

$\boldsymbol{us_i}$	Upper-limit of activity i
$\boldsymbol{y_{it}}$	Binary variable that shows if activity i started in period t
$\boldsymbol{a_{it}}$	Binary variable that shows if activity i finished in period t
$\boldsymbol{z_{it}}$	Completed percentage of activity i in period t
$\boldsymbol{Q_{it}}$	Binary variable that shows activity i's floating
$\boldsymbol{g_{jit}}$	Binary variable that shows if sufficient number of resource j is available i activity I in period t
$\boldsymbol{v_{it}}$	Binary variable that shows activity i will be available period t
$\boldsymbol{d_{it}}$	Binary variable that shows that activity i started at the end of period t

$$\min\{max_{i\epsilon A} f_i\} = \min\{max_{i\epsilon A}(T - \sum_{t=1}^{T} a_{it} + 1)\} \quad 1$$

$$max \sum_{t=1}^{T} \sum_{i=1}^{A} Q_{it} \quad 2$$

$$\sum_{t=1}^{T} d_{it} \geq \sum_{t=1}^{T} d_{jt} + l_{ij} \qquad \forall (i,j)\epsilon E \quad 3$$

$$z_{i,t+1} - z_{i,t} = \frac{1}{p_i}(d_{it} - a_{it}) \qquad \forall i\epsilon A \quad 4$$

$$t = 1, \dots, T-1$$

$$d_{it} \leq d_{it+1} \qquad \forall i\epsilon A \quad 5$$

$$t = 1, \dots, T-1$$

$$a_{it} \leq a_{it+1} \qquad \forall i\epsilon A \quad 6$$

$$t = 1, \dots, T-1$$

$$d_{iT} = a_{iT} = z_{iT} = 1 \qquad \forall i\epsilon A, t\epsilon T-1 \quad 7$$

$$d_{i0} = a_{i0} = z_{i0} = 1 \qquad \forall i\epsilon A \quad 8$$

$$a_{it} \leq z_{it} \leq d_{it} \qquad \forall i\epsilon A \quad 9$$

$$t = 1, \dots, T$$

$$\sum_{i=1}^{A} q_{ij}\,(z_{it} - z_{it-1}).\,p_i \leq b_j \qquad j = 1, \dots, J \quad t = 1, \dots, T \qquad 10$$

$$b_j - \left(\sum_{i=1}^{A} q_{ij}\,(z_{it} - z_{it-1}).\,p_i\right) - Q_{ij} \leq M.\,g_{jit} \qquad \forall i \epsilon A \quad t = 1, \dots, T \qquad 11$$

$$b_j - \left(\sum_{i=1}^{A} q_{ij}\,(z_{it} - z_{it-1}).\,p_i\right) - Q_{ij} \geq M.\,(g_{jit} - 1) \qquad \forall j \epsilon J \quad t = 1, \dots, T \qquad 12$$

$$v_{it} = \prod_{j=1}^{K} g_{jit} \qquad \forall i \epsilon A \quad t = 1, \dots, T \qquad 13$$

$$US_i = min_{j \epsilon su_i}\{\sum\nolimits_{t=1}^{T} d_{it} - l_{ij} - \sum_{t=1}^{T} d_{jt}\} \qquad \forall i \epsilon A \qquad 14$$

$$\left(T - \sum\nolimits_{t=1}^{T} a_{it} + 2\right).\,h_{it} \leq t \leq \left(\left(T - \sum\nolimits_{t=1}^{T} a_{it} + 2\right) + us_i\right).\,N_{it} \qquad \forall i \epsilon A \quad t = 1, \dots, T \qquad 15$$

$$Q_{it} = h_{it} * v_{it} \qquad \forall i \epsilon A \quad t = 1, \dots, T \qquad 16$$

$$d_{it}, f_{it}, g_{jit}, v_{it}, Q_{it} \in \{0,1\} \qquad 17$$

This mathematical model has two primary objectives: Objective 1 minimizes project completion time, and Objective 2 maximizes total activity free floating. Constraints (3) and (4) relate to scheduling and activity continuity, Constraint (4) ensuring uninterrupted activity once it starts. Constraints (5) and (6) enforce specific conditions on activity start and completion times. Constraints (7) and (8) ensure all activities align with the project timeline and meet prerequisites. Constraint (9) links variables z_{it} and d_{it}. Constraints (10-12) and (13) handle resource availability and utilization. Constraint (14) defines free floating limits without considering resource constraints. Constraints (15) and (16) relate to resource allocation during specific time periods, and Constraint (17) defines decision variables for the optimization problem.

5. Solution approaches

a. Selected approach for dealing with uncertainty

The stochastic chance constraint method is a powerful mathematical and computational approach employed in various fields, such as operations research, finance, and engineering, to address decision-making problems under uncertainty. Unlike traditional deterministic optimization, this method accounts for probabilistic uncertainties in the input parameters of a problem by introducing constraints that specify acceptable levels of risk or failure probabilities. By leveraging probability distributions and statistical tools, the stochastic chance constraint method allows decision-makers to make robust and reliable decisions that balance the trade-off between achieving desired objectives and managing the inherent uncertainty in real-world scenarios, making it an indispensable tool for tackling complex problems in an uncertain world. (Fazli et al., 2019). Assume the minimization model through. d_{ij} 'a_{kj} , and f_i parameters. ~ resembles uncertainty of any parameter:

$$p(\sum_{j=1}^{n} d_{ij} y_j \geq e_i^{\sim}) \geq \alpha_i \qquad i = 1, 2, \ldots, m \tag{18}$$

$$\min\ f_k = E\left(\sum_{j=1}^{n} a_{kj}^{\sim} y_j \geq e_i^{\sim}\right) \qquad k = 1, \ldots, K \quad i = 1, 2, \ldots, m \tag{19}$$

$$p\left(\sum_{j=1}^{n} d_{ij}^{\sim} y_j \geq e_i^{\sim}\right) \geq \alpha_i \qquad i = 1, 2, \ldots, m \tag{20}$$

$$y = (y_1, \ldots, y_n) \tag{21}$$

$$y \geq 0 \tag{22}$$

$$b_k - \left(\sum_i \sum_k E(q_{ik}) + \varphi^{-1}(1 - \alpha_i).\sqrt{\mathrm{var}(q_{ik})})(x_{it} - x_{it-1}).p_i\right) - Q_{it} \leq M.E_{kit} \qquad \forall i \epsilon A \quad t = 1, \ldots, T \tag{23}$$

Constraint (18) indicates that the mentioned constraint must be meaningful at the alpha level of certainty. Constraint (19) represents the stochastic objective function to be minimized. The term $\tilde{e}$ resembles the uncertainty in any parameter. Constraint 20 is replaced by constraint (18) in the mathematical model Constraints (21) and (22) show the types of decision variables Finally, the customization of constraint (23) represents the chance constraint for our proposed model.

b. Epsilon Constraint method

The epsilon constraint method is a powerful technique in multi-objective optimization that allows decision-makers to explicitly prioritize one objective while treating the others as constraints (Fan et al., 2019). In this method, an "epsilon" value is introduced to specify the acceptable trade-off between the primary objective, which is to be minimized, and the secondary objectives, which are to be constrained. By iteratively adjusting this epsilon value, a set of Pareto-optimal solutions is generated, providing a range of solutions that balance the primary objective against the constraints (Agha'ee et al., 2011). This approach aids in exploring a spectrum of trade-offs, enabling decision-makers to make informed choices based on their preferences and requirements in complex decision-making scenarios as follows.

$\mathbf{min\ f_1(x)}$

$\mathbf{x \in X}$

$\mathbf{f_2(x) \leq \varepsilon_2}$

$\vdots$

$\mathbf{f_n(x) \leq \varepsilon_n}$

a. Designing NSGA-II algorithm to solve problem

The NSGA-II (Non-dominated Sorting Genetic Algorithm II) is a widely recognized and influential evolutionary optimization algorithm used to solve multi-objective optimization problems. Developed as an extension of the original NSGA algorithm, NSGA-II is renowned for its ability to efficiently generate a diverse and high-quality set of solutions along the Pareto front, representing the trade-offs between conflicting objectives. NSGA-II employs a combination of techniques, including non-dominated sorting, crowding distance measurement, and genetic operators such as crossover and mutation, to evolve a population of candidate solutions over successive generations.With its capability to handle multiple objectives and produce a well-distributed set of Pareto-optimal solutions, NSGA-II has found applications in various domains, including engineering design, finance, and resource allocation. This makes it a valuable tool for decision-makers seeking optimal solutions in complex, multi-objective optimization scenarios. The algorithm's ability to balance exploration and exploitation, along with its efficiency in maintaining diversity within the solution set, contributes to its widespread use and success in tackling real-world problems where conflicting objectives need to be considered simultaneously.

i. Chromosome representation

Chromosome representation is a crucial concept in genetic algorithms and evolutionary computing. It defines how potential solutions to a problem are encoded into a form that can be manipulated and evolved. Common representations include binary strings, real-valued vectors, permutations, and tree structures. The choice of representation significantly impacts the algorithm's performance and its ability to explore the search space effectively. A well-designed chromosome representation should balance the need for accuracy and computational efficiency while capturing the essential characteristics of the problem domain. The chromosome is composed of four parts: N_{it}, y_{it}, z_{it} and v_{it} as follows:

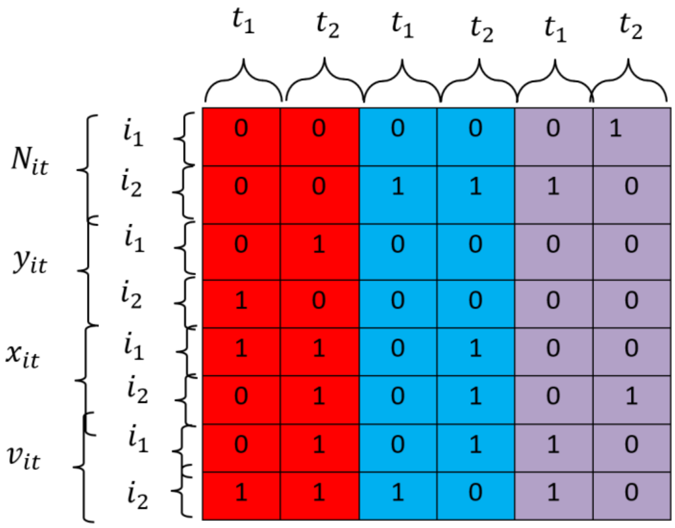

Figure 1: An illustration of the chromosome

i. Search mechanism (crossover-mutation)

Double-point crossover is a NSGA-II operator commonly employed in binary genetic algorithms and similar evolutionary optimization techniques. In this method, two random crossover points are selected along the parent chromosomes, dividing them into three segments. The genetic material between the two crossover points in both parents is swapped to produce two offspring, each inheriting genetic information from both parents. Double-point crossover introduces greater diversity into the offspring compared to single-point crossover, as it allows for the recombination of segments from the middle of the parent chromosomes. This increased diversity can enhance the exploration of the solution space, potentially leading to the discovery of novel and better solutions

ii. Ranking mechanism

By combining non-dominated sorting, crowding distance assignment, elitism, and selective reproduction, NSGA-II effectively balances the exploration of diverse Pareto-optimal solutions with the exploitation of promising regions in the multi-objective optimization problem's solution space. This ranking mechanism contributes to the algorithm's ability to provide a well-distributed and high-quality set of trade-off solutions to decision-makers facing complex optimization problems with multiple conflicting objectives. After sorting the solutions into fronts, NSGA-II assigns a crowding distance to each solution within each front. The crowding distance measures how crowded a solution is within its front. Solutions with a higher crowding distance are preferred because they are located in less dense areas of the Pareto front and provide better coverage of the trade-off space. Then, d would be calculated form the following equation:

$$d_i^1 = \frac{f_1(x_{i+1}) - f_1(x_{i-1})}{f_1^{max} - f_1^{min}}$$

$$d_i^2 = \frac{f_2(x_{i+1}) - f_2(x_{i-1})}{f_2^{max} - f_2^{min}}$$

$$d_i = d_i^1 + d_i^2$$

Figure 2 displays the crossover operator.

Parent1

1	0	1	1	0	1
1	1	0	0	0	0
0	0	1	1	1	1
1	1	0	1	1	0

Parent2

0	1	1	0	0	1
0	1	0	0	1	1
0	1	1	1	1	0
1	0	0	1	0	0

Offspring1

1	0	1	0	0	1
1	1	0	0	0	0
0	0	1	1	1	1
1	1	0	1	1	0

Offspring2

0	1	1	1	0	1
0	1	0	0	1	1
0	1	1	1	1	0
1	0	0	1	0	0

Figure 2: Two-point crossover operator

Figure 3 displays the mutation operator. To this end, a row is optionally selected and it would be inversed.

Parent

1	0	0	0	1	0
1	1	0	0	1	0
0	0	1	0	1	1
0	1	0	1	0	1

Offspring

1	0	0	0	1	0
0	1	0	0	1	1
0	0	1	0	1	1
0	1	0	1	0	1

Figure 3: Inverse mutation operator

The recommended parameters are as follows:

Table 1: The NSGA-II algorithm parameters

Mutation	Crossover	nPop	maxIt
0.03	0.04	100	100

iv. Constraint handling

The suggested model ensures that Constraints (1)– (10) and (13)– (17) are met through the proposed solution algorithms, while the remaining constraints are fulfilled using a penalty strategy. To illustrate, the penalty strategy for constraints (12), (13), and (14) is defined in the following manner. It is important to observe that the index p indicates the count of objective functions. The e_o, $e'_o$and e''_o are auxiliary variables that indicate the value of the violation of the o th constraint.

$$e_o = Max_k\{\sum_{i=1}^{A} q_{ik}\,(x_{it} - x_{it-1}).\,p_i - b_k\} \qquad o = 1,2 \qquad (24)$$

$$e'_o = b_k - \left(\sum_{i=1}^{A} q_{ik}\,(x_{it} - x_{it-1}).\,p_i\right) - Q_{ik} - M.\,E_{kit} \qquad o = 1,2 \qquad (25)$$

$$e''_o = b_k - \left(\sum_{i=1}^{A} q_{ik}\,(x_{it} - x_{it-1}).\,p_i\right) - Q_{ik} + M.\,(E_{kit} - 1) \qquad o = 1,2 \qquad (26)$$

Please take note that the degree of violation is dynamic and changes depending on the number of iterations based on equation (27).

$$(e_o + e'_o + e''_o) * iteration \qquad o = 1,2 \qquad (27)$$

6. Computational results

The analysis of 20 samples using the Epsilon Constraint Method in Table 2 emphasizes a noteworthy trend: the increase in problem-solving time as problem dimensions and size grow. This insight alerts managers to potential computational challenges associated with larger-scale projects, prompting a need for efficient algorithms or parallel processing to maintain timely decision-making.

Table 2: Computational results in different scales

No.	Number of activities	OBJ functions		Time(s)	No.	Number of activities	OBJ functions		Time(s)
		timing	floating				timing	floating	
1	16	96	132	116	2	64	1592	308	3514
2	18	116	160	122	4	66	454	350	3616
3	20	126	170	130	6	68	474	366	3580
4	22	136	186	148	8	70	502	402	3432
5	24	174	204	152	10	72	542	432	3420
6	26	192	216	166	12	74	590	472	3500
7	28	210	234	190	14	76	616	502	3570
8	30	244	262	208	16	78	636	506	3648
9	32	276	268	216	18	80	668	554	3712
10	34	284	282	228	20	82	700	578	3922

Table 3 displays the model's solutions for small and medium scales using a second non-dominated sorting genetic method. Table 3 further extends the managerial insights by showcasing the model's solutions for small and medium scales using a second non-dominated sorting genetic method. These results offer a valuable comparative perspective, aiding managers in selecting appropriate optimization approaches based on project size and complexity, thereby facilitating effective decision-making in project management.

Table 3: Model solution in small and medium scales through second non-dominated sorting genetic approach

No.	Number of activities	OBJ function		Time (s)	No.	Number of activities	OBJ functions		Time (S)
		Project timing	Total floating				Project timing	Total floating	
1	5	37	53	25	1	2	189	140	425
2	6	48	66	36	2	21	221	161	445
3	7	53	70	41	3	22	230	167	451
4	8	57	80	43	4	23	241	185	488
5	9	78	86	46	5	24	300	198	496
6	10	87	95	51	6	25	308	210	516
7	11	98	102	54	7	26	325	234	537
8	12	112	112	59	8	27	343	240	551
9	13	128	119	204	9	28	271	262	568
10	14	136	122	217	10	29	289	274	578

7. Case study

The ongoing project in Tehran City, specifically in Valiasr Street, holds great significance. However, it has faced delays caused by various uncertainties. These delays have had adverse effects on the city's finances, culture, and aesthetics. Consequently, the contractor has prioritized investigating the underlying causes of these delays. The project consists of 10 activities, and the interdependencies between these activities are depicted in Figure 4.

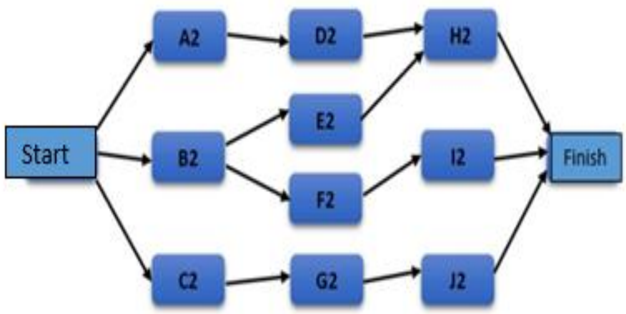

Figure 4: Pre-requisite network of the case study

As shown in Figure 5, this project includes 10 floors of commercial building and 5 floors of parking. The project area is located on a land of 36,400 square meters. This project is equipped with 58 advanced earthquake energy damping systems (triangular metal). In the domain of construction project management, a challenging task is to simultaneously minimize project delays and total costs while adhering to resource constraints. This multi-objective optimization problem arises from the necessity to strike a balance between ensuring the timely delivery of projects and achieving financial efficiency.

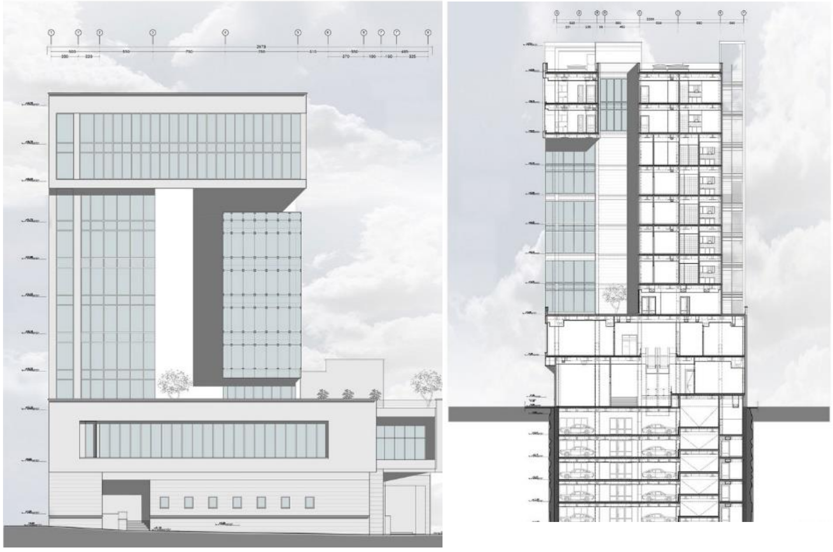

Figure 5. Schematic plan of proposed project

Table 4 displays the case study's parameters. The comprehensive overview of case study parameters in Table 4 provides vital insights for managers. Particularly, it highlights the distinct resource requirements, activity timings, and potential bottlenecks, empowering decision-makers to strategically allocate resources, identify critical paths, and optimize project efficiency in accordance with the specific characteristics of each activity.

Table 4: Case study's parameters

Activity	Activity timing	Resources					
		K1	K2	K3	K4	$k'1$	$k'2$
1	24	17	15	19	16	55	55
2	21	17	19	17	15	95	95
3	26	16	15	20	19	45	95
4	22	19	21	15	16	85	35
5	23	17	21	16	15	105	95
6	20	15	18	20	15	75	25
7	23	16	18	21	20	105	55
8	22	15	18	18	18	45	95
9	21	16	16	16	21	115	105
10	22	18	16	18	16	25	95

7.1 Case study results

Table 5 presents a comprehensive overview of 20 Pareto-optimal solutions obtained through multi-objective optimization. These solutions represent a diverse set of trade-offs between multiple conflicting objectives, highlighting assessments for MID and SM metrics.

Table 5: Assessment metrics

Pareto No	MID	SM	Pareto No	MID	SM
1	5.42	0.052	11	5.46	0.142
2	5.45	0.027	12	5.34	0.174
3	5.4	0.058	13	5.41	0.17
4	5.46	0.036	14	5.49	0.129

5	5.43	0.043	15	5.26	0.131
6	5.51	0.023	16	5.38	0.135
7	5.25	0.061	17	5.49	0.149
8	5.36	0.017	18	5.43	0.219
9	5.35	0.081	19	5.5	0.176
10	5.26	0.056	20	5.36	0.205

Therefore, considering the metric results, one can argue that the model performed efficiently in solving problems in small and medium scales and the provided algorithm can be used to solve problem in large scale as well. Therefore, the model will be solved for one of the Pareto points. **Figure 6** presents the Pareto points extracted from the proposed real case.

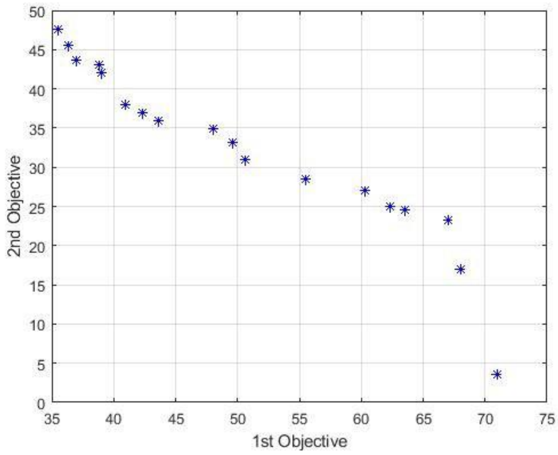

Figure 6: Two-dimensional illustration of Pareto points obtained from the case study

Table 6 shows how the decision variable N_{it} is determined based on the timing of activity i, indicating that i2's second activity duration matches its floating upper limit.

Table 6: Finishing time of activity

Activity	First term	Second term
1	1	0
2	0	1
3	1	0
4	1	0
5	0	0
6	1	0
7	1	0
8	1	0
9	1	1
10	0	0

The insights from Table 7, with a value of 1 for the decision variable y indicating the in-progress status of E2 activity in the initial period, provide a real-time snapshot for managers. This information aids in monitoring project timelines, enabling proactive adjustments to resource allocation and schedules to ensure smooth progression and adherence to project timelines.

Table 7: Results activity progress

Activity	First term	Second term
1	1	0
2	0	1
3	1	0
4	1	1
5	0	0
6	1	0
7	1	0
8	0	1
9	0	1
10	1	0

Table 8 shows the results of the decision variable, where a value of 1 indicates that all the required resources for activity i in period t were available, while 0 means they were not. Consequently, according to this table, it can be concluded that there were inadequate resources in the initial period to finish J2.

Table 8: Output of v_{it}

Activity	First term	Second term
1	0	1
2	0	1
3	1	0
4	0	1
5	1	1
6	0	1
7	0	1
8	0	1
9	0	0
10	1	1

Table 9 shows the outcomes for the g_{jit} in the initial term. g_{jit} equals one if enough k resources are accessible for activity i at time t in the first term; otherwise, it's zero. This table suggests, for example, that there's an ample supply of k4 resources for C2 activity. The insights gleaned from Table 9 underscore the critical role of the g_{jit} variable in assessing resource availability. Specifically, the presence of "1" for g_{jit} indicates a robust supply of k4 resources, offering managers a valuable signal to confidently proceed with the C2 activity in the initial term, facilitating effective resource management and timely project execution.

Table 9: Output of G_{jit} in the first term

Activity	Resources					
	K1	K2	K3	K4	k′1	k′2
1	0	1	1	0	0	1
2	0	1	0	1	1	1
3	1	0	1	1	1	1
4	0	1	0	0	1	0
5	0	0	0	1	0	0
6	1	0	1	1	0	0
7	0	1	0	0	1	1
8	1	0	0	0	0	1
9	0	1	0	0	0	0
10	0	1	0	0	0	1

Table 10 shows the outcomes for the g_{kjt} decision variable in the second term. g_{kjt}equals 1 when there are enough k resources for activity i at time t; otherwise, it's zero. This table suggests, for example, that there are ample k3 resources for completing C2 activity in the second term. The insights from Table 10 highlight the strategic importance of the g_{kjt} decision variable in resource allocation. Specifically, the presence of "1" for g_{kjt} signifies resource adequacy, exemplified by the ample availability of k3 resources for completing the C2 activity in the second term. This understanding aids managers in efficiently deploying resources, ensuring optimal task execution and overall project success.

Table 10: Output of G_{jit} in the second term

Activity	Resources					
	K1	K2	K3	K4	k′1	k′2
1	0	1	1	0	0	0
2	1	0	1	1	1	0
3	1	1	1	1	0	1
4	0	0	1	1	0	0
5	0	1	1	0	1	0
6	0	1	0	0	1	1
7	1	0	1	1	0	0
8	1	0	0	1	1	1
9	0	0	1	0	1	1
10	0	1	1	1	0	1

Sensitivity analysis evaluates model accuracy by studying parameter changes in sensitive variables or objectives. In Figure 7, a 20% longer activity completion time increases the objective function by 24 units, while a 30% resource reduction decreases it by two units. This underscores the importance of conducting sensitivity analyses, revealing that fine-tuning activity completion times is crucial, as even a modest 20% increase can lead to a substantial impact on the objective function. Furthermore, the marginal influence of a 30% resource reduction suggests the need for judicious resource management to optimize performance and achieve desired project outcomes.Top of Form

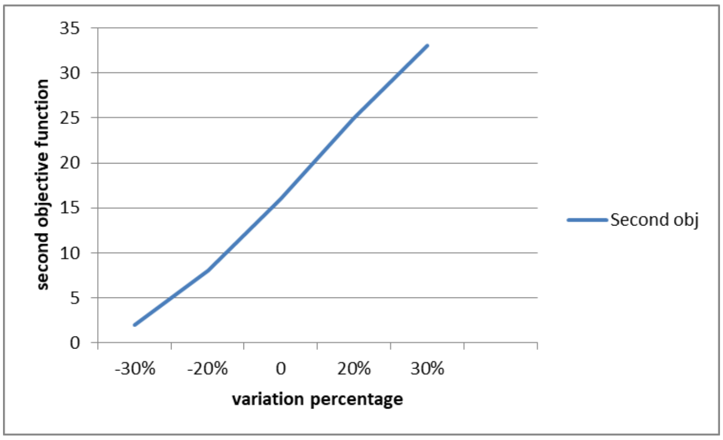

Figure 7: Second OBJ variations

Figure 8 illustrates how the number of resources needed for activity i in each time period impacts the first objective function. A 20% resource increase raises the objective function to 310 units, while a 30% reduction in activity i's completion time lowers it to 188 units. These findings underscore the critical role of resource allocation in optimizing project performance, highlighting that a strategic 20% resource boost can significantly enhance overall outcomes, while a 30% reduction in completion time for specific activities yields notable efficiency gains, providing valuable managerial insights for project optimization.

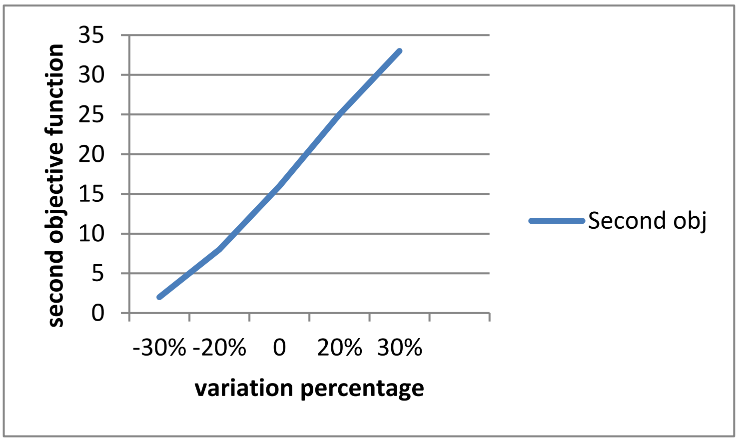

Figure 8: Effect of resources on second OBJ

8. Conclusion

Minimizing project timing is particularly important, as it is closely related to cost optimization. The total cost of a project depends on its timing, and reducing the project duration leads to cost savings. Delays in project completion can result in various issues related to time, cost, and quality. Effective supervision plays a crucial role in identifying and addressing potential delays in a timely manner. To handle uncertain mathematical models, it is necessary to make them deterministic. Various methods can be employed to convert probabilistic models into deterministic ones. In summary, the research underscores the significance of effective project timing, cost optimization, and proactive delay management in achieving successful project outcomes. Managers can leverage the insights provided to enhance their decision-making processes, improve resource allocation, and ensure timely project completion while controlling costs and maintaining quality. Therefore, the managerial insights are as follows:

1. Cost Optimization and Project scheduling: The research identifies two critical objective functions for project management: project timing and maximizing the floating time of activities. Minimizing project timing is particularly crucial as it directly impacts cost optimization. By reducing the duration of a project, cost savings can be achieved. Therefore, managers should focus on efficient project scheduling and timely completion to control costs effectively.
2. Impact of Delays on Time, Cost, and Quality: Delays in project completion can lead to various issues related to time, cost, and quality. Managers need to pay close attention to effective supervision and monitoring to identify and address potential delays promptly. Timely intervention and proactive management can help mitigate the negative consequences of delays, ensuring project success.
3. Deterministic Models for Uncertainty Handling: Uncertain mathematical models need to be converted into deterministic ones to facilitate decision-making. Various methods, such as Stochastic Chance Constraint Programming (SCCP), can be utilized to achieve this. Managers should explore and adopt suitable techniques to handle uncertainty in project management, enabling more accurate planning and risk assessment.
4. Sensitivity Analysis: The study's sensitivity analysis provides valuable insights into the impact of changes in resources and activity timing on the objective function. Managers can use this information to make informed decisions. For example, increasing resources by 20% resulted in a significant increase in the objective function, indicating the importance of resource allocation. Similarly, adjusting activity timing showed notable effects on the objective function, highlighting the need for careful scheduling and optimization.
5. Future Research Recommendations: The research suggests potential areas for future exploration in project management. Managers can consider conducting further studies in these areas to enhance their understanding and improve decision-making. These areas might include investigating alternative optimization techniques, exploring additional factors affecting project performance, or examining the applicability of different modeling approaches in different project contexts.

Considering additional objectives, such as minimizing human resource costs.

- Exploring alternative multi-objective optimization approaches like Particle Swarm Optimization or Tabu Search.
- Investigating other uncertainty approaches, such as fuzzy logic.
- Incorporating different quality levels, including construction materials quality and project supervision quality, into the analysis.

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