Soft Computing

Integration of resource supply management and scheduling of construction projects using multi-objective whale optimization algorithm and NSGA-II

--Manuscript Draft--

Manuscript Number:	SOCO-D-22-01231R1
Full Title:	Integration of resource supply management and scheduling of construction projects using multi-objective whale optimization algorithm and NSGA-II
Article Type:	Original Research
Keywords:	Multi-project scheduling; Supply management; Mathematical modeling; Optimization algorithms; Construction industry
Corresponding Author:	Parviz Ghoddousi, Ph.D. Iran University of Science and Technology IRAN, ISLAMIC REPUBLIC OF
Corresponding Author Secondary Information:	
Corresponding Author's Institution:	Iran University of Science and Technology
First Author:	Mahyar Ghoroqi
First Author Secondary Information:	
Order of Authors:	Mahyar Ghoroqi
	Parviz Ghoddousi
	Ahmad Makui
	Ali Akbar Shirzadi Javid
	Saeed Talebi
Funding Information:	
Abstract:	This study explores the intricate integration and synchronization of supplier selection with the optimal scheduling of multi-mode resource-constrained projects, which is a genuine and complex challenge prevalent in the construction industry, by proposing new multi-objective mathematical modeling considering various items. Within this context, a multifaceted network of concurrent projects (multi-project) is examined with different suppliers' resources (multi-supplier) to minimize the overall projects' delay times and associated costs. The mathematical model formulation also incorporates diverse implementation modes (multi-mode) and the time value of money (TVM). In order to use and unravel the complexities of the proposed model, two distinct algorithms, including a multi-objective whale optimization algorithm (WOA) based on the Pareto archive and the well-known non-dominated sorting genetic algorithm II (NSGA-II), are employed. The algorithms were subjected to a comparative analysis of several sample problems and evaluated against multi-objective criteria, including quality metric (QM), diversity metric (DM), spacing metric (SM), number of solutions (NOS), mean ideal distance (MID), and computational time. The evaluation reveals that the tailored multi-objective WOA outperforms NSGA-II, exhibiting greater solution precision and diversity. The WOA demonstrates an enhanced ability to efficiently explore the problem's feasible solution space, albeit at the increased computational time to pinpoint optimal solutions. Notably, the validity and practicality of the proposed model and method were field-tested within the context of construction projects in Iran, with the obtained results juxtaposed against the real-world data. The comparative analysis indicates that implementing the scheduling approach and solution methodology espoused by the multi-objective WOA led to significant improvements, with financial gains of up to 6% and time savings reaching 16%. Overall, this research substantiates the proposed model and algorithms' benefits in reducing project costs and delays, offering valuable insights for construction industry practitioners.
Section/Category:	Optimization

Integration of resource supply management and scheduling of construction projects using multi-objective whale optimization algorithm and NSGA-II

Mahyar Ghoroqi[1], Parviz Ghoddousi [1,*], Ahmad Makui[2], Ali Akbar Shirzadi Javid[1] and Saeed Talebi[3]

[1] School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran

[2] School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran

[3] School of Engineering and the Built Environment, Birmingham City University, Birmingham, UK

Abstract

This study explores the intricate integration and synchronization of supplier selection with the optimal scheduling of multi-mode resource-constrained projects, which is a genuine and complex challenge prevalent in the construction industry, by proposing new multi-objective mathematical modeling considering various items. Within this context, a multifaceted network of concurrent projects (multi-project) is examined with different suppliers' resources (multi-supplier) to minimize the overall projects' delay times and associated costs. The mathematical model formulation also incorporates diverse implementation modes (multi-mode) and the time value of money (TVM). In order to use and unravel the complexities of the proposed model, two distinct algorithms, including a multi-objective whale optimization algorithm (WOA) based on the Pareto archive and the well-known non-dominated sorting genetic algorithm II (NSGA-II), are employed. The algorithms were subjected to a comparative analysis of several sample problems and evaluated against multi-objective criteria, including quality metric (QM), diversity metric (DM), spacing metric (SM), number of solutions (NOS), mean Ideal distance (MID), and computational time. The evaluation reveals that the tailored multi-objective WOA outperforms NSGA-II, exhibiting greater solution precision and diversity. The WOA demonstrates an enhanced ability to efficiently explore the problem's feasible solution space, albeit at the increased computational time to pinpoint optimal solutions. Notably, the validity and practicality of the proposed model and method were field-tested within the context of construction projects in Iran, with the obtained results juxtaposed against the real-world data. The comparative analysis indicates that implementing the scheduling approach and solution methodology espoused by the multi-objective WOA led to significant improvements, with financial gains of up to 6% and time savings reaching 16%. Overall, this research substantiates the proposed model and algorithms' benefits in reducing project costs and delays, offering valuable insights for construction industry practitioners.

Keywords: Multi-project scheduling; Supply management; Mathematical modeling; Optimization algorithms; Construction industry.

1. Introduction

Project management is a decision-making process governed by cost and time, comprising three phases: planning, scheduling, and controlling the project. The planning phase encompasses the needs and required activities for initiating the project and estimating the time needed. The scheduling phase determines the start and finish times and the activities' implementation method. Finally, the controlling phase investigates the deviation between the developed and actual work progress (Cheng et al. 2015). Project scheduling is a critical aspect of project management, prompting numerous researchers to create diverse models for this problem, aiming to align it more closely with real-world complexities through innovative assumptions (Chen et al. 2010; Ghoroqi et al. 2023). The project scheduling problem typically involves multiple activities requiring resources for completion. These activities' precedence relationships, defined initially, can be represented as a network (Néron and Baptista 2002).

The burgeoning number of project scheduling studies has spawned many problem types. This diversity stems from resource features (such as number, type, and limitations), project activity characteristics (such as work interruption possibilities, precedence constraints, readiness and executive time, completion time, resource requirements, implementation methods, financial concepts, and time of transitions), and optimality criteria (Vanhoucke and Coelho 2019). Generally, organizations grapple with renewable and non-renewable resource constraints and capital limitations in implementing their projects. Hence, attention to resource allocation and scheduling is vital to augment revenue (Eshraghi 2016).

The construction industry, a prominent beneficiary of project scheduling, plays an essential role in a country's economic growth and significantly boosts employment. In 2015, the United States construction industry contributed approximately 717 billion dollars to the gross domestic product (GDP), creating over 6 million jobs (Chen et al. 2018). The construction industry's importance makes competition challenging and intricate. Effective supply management coupled with optimal project scheduling can notably influence the success of construction projects. Integrating supply management with project scheduling is key to achieving cost reduction, shorter implementation duration, higher quality facilities, more reliable work plans, and responsive processes in construction. Compared to other industrial sectors like production, the construction industry has a slower adaptation of supply chain management (SCM) concepts and calls for SCM deployment to enhance competitive advantages for construction companies (Chen et al. 2018; Love et al. 2004).

Therefore, it is clear that providing resources from appropriate suppliers is a vital concern in optimal project scheduling and planning, significantly impacting profitability and revenue. In a project-based supply chain, project scheduling and material supply are interrelated. Improved decision-making between project managers and suppliers can heighten supply chain flexibility and competitiveness (Fu and Xing 2021). Although, in recent years, soft computing approaches have facilitated modeling multi-objective optimization of high-dimensional issues in various engineering fields, project management is no exception (Khandelwal et al. 2018; Shahnazar et al. 2017; Gao et al. 2018; Tonnizam et al. 2017; Azarkish and Aghaeipour 2022; Mojtahedi et al. 2019; Ghoroqi et al. 2023). Over the past three decades, integrating project scheduling with material ordering has emerged as a method to ensure profitability, focusing on aspects such as scheduling, selecting the proper supplier, and timing orders to minimize ordering, purchasing, and storage costs, thus maximizing profitability (Asadujjaman et al. 2021). Early works in this area, such as the study by Smith and Aquilano (1984) and subsequent research by others, including Shtub (1988), Dodin and Elimam (2001; 2008), Tabrizi and Ghaderi (2015), and Zorghi et al. (2017), have variously addressed this integration, but often within simple, single-project contexts and outside the construction industry.

In light of the existing research gaps and implementation needs, this study presents an integrated model of resource supply management and multi-project scheduling in the construction industry, considering multiple criteria and diverse implementation modes for activities. It simultaneously aims at minimizing total penalty for project delays and activity times, as well as the overall cost of purchasing resources from suppliers and executing project activities. The selection of resource suppliers sets this work apart, significantly influencing time and cost management in construction projects. Utilizing a multi-objective whale optimization algorithm (WOA) based on the Pareto archive, coupled with a non-dominated sorting genetic algorithm II (NSGA-II), further distinguishes this research, providing an innovative approach to obtaining an optimal solution for construction project implementation. Regarding the mentioned cases and to further clarify the contents, in Figure 1, the conceptual view of the generalities of the current research is presented.

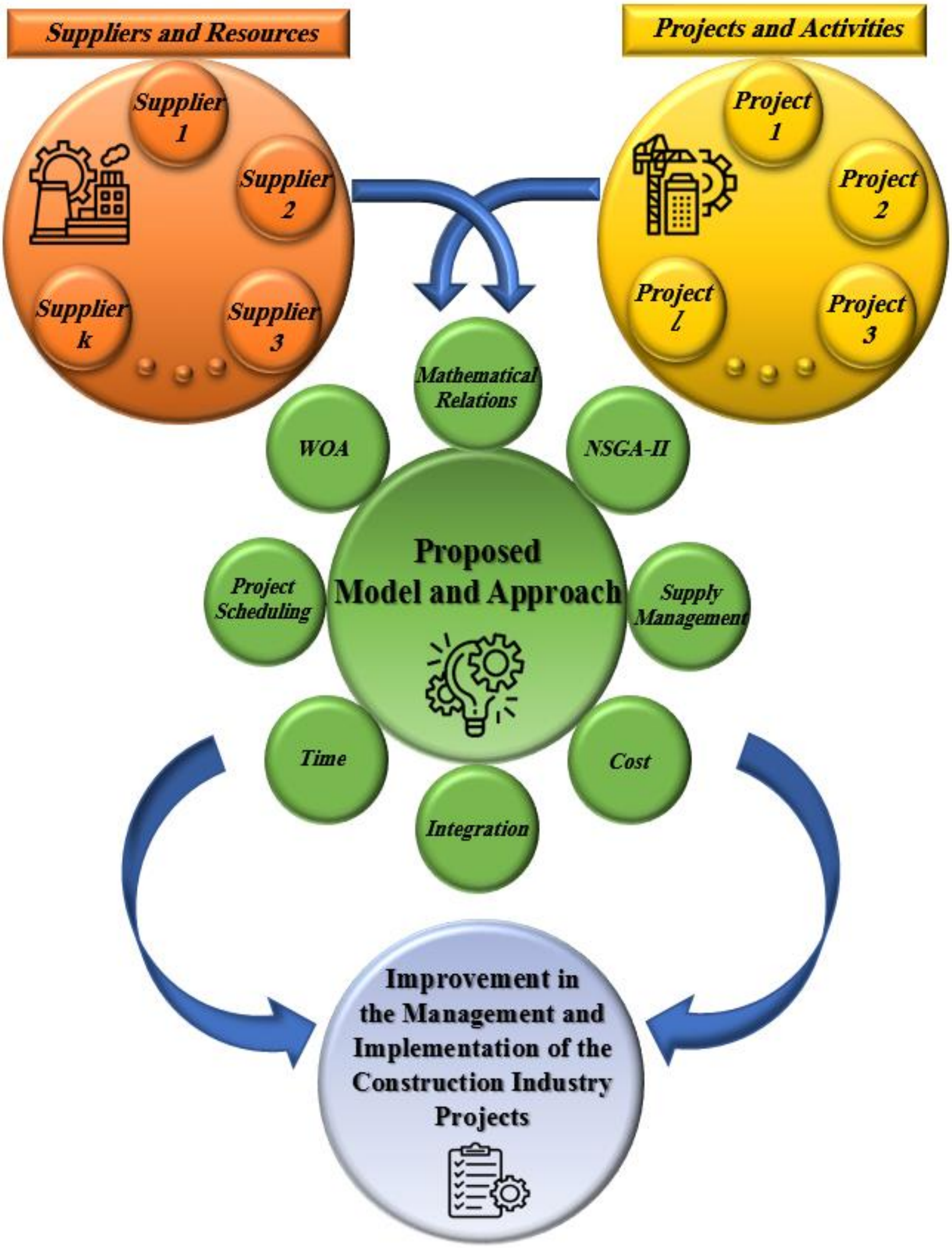

Figure 1. The conceptual view of the generalities of the current research

2. Literature review

A project is characterized as a collection of temporary efforts to realize a specific goal, such as a product or service (Cheng et al. 2015). Project management applies knowledge, skills, tools, and techniques to orchestrate the project's activities to fulfill its requirements (Artigues et al. 2013). Project scheduling involves the formulation of a timeline for carrying out a sequence of activities that constitute a part of the project. The implementation of an activity might hinge on the completion of one or several preceding activities. Under such circumstances, the project is subject to precedence constraints. The schedule is crafted concerning a particular objective or a compilation of goals (Herroelen 2005).

So far, many researchers have studied project scheduling problems in different modes and conditions. Van Peteghem and Vanhoucke (2010) delved into multi-mode project scheduling, utilizing a genetic algorithm (GA). They tackled problems by contemplating both the allowance and prohibition of splitting activities. Their tailor-made genetic algorithm consisted of two distinct populations, and they scrutinized how the permissible division of activities influenced the caliber of the solutions. Wang and Fang (2011) introduced a shuffled frog-leaping algorithm (SFLA), an innovative method that mimics the leaping behavior of frogs, to address the multi-mode project scheduling dilemma. This algorithm engages with a group of solutions and features a crossover operator, amalgamating two varieties of neighborhood search, thereby ensuring an exhaustive exploration of the solution landscape. Liu and Chen (2012) probed into a multi-mode project scheduling conundrum within the construction sector, with various resource allocation schemes in consideration. They deliberated on the resource distribution framework pertinent to multi-mode scheduling challenges and subsequently devised an optimization-centered model to handle resource allocation predicaments.

Rao and Chaitanya (2015) examined the resource-constrained project scheduling problem (RCPSP), exploring the varieties of resources required to carry out project activities and the methodologies for allocating them. Singh (2014) delved into the multi-mode resource-constrained project scheduling problem (MMRCPSP) using rule-based approaches and the analytical hierarchy process (AHP), assuming a prioritization of projects. A hybrid heuristic algorithm, combining the rule-based method and AHP, was introduced to schedule project activities with restricted resource allocation. Suresh et al. (2015) studied the MMRCPSP and considered the transfer time of resources between activities. They proposed an innovative genetic algorithm to tackle the problem, maximizing the net present value (NPV) of all projects within the constraints of renewable resources. Eshraghi (2016) studied the RCPSP, where scheduling was predicated on the minimum time for executing activities and limited resource availability.

Pinha et al. (2016) analyzed the MMRCPSP, formulating a mathematical model to plan a multi-project challenge with multiple resource constraints, specifically in ship repair. Song et al. (2016) looked at decentralized MMRCPSP, contemplating multi-purpose combined auctions. They devised a resource allocation strategy without infringing on information privacy and using fixed costs, a mathematical model built on the combined auction approach, and different periods (seasons) solved by a heuristic algorithm. Habibi et al. (2017) explored the RCPSP, where the required resources for each activity and the available resources at various times fluctuated. They presented a multi-objective mathematical model aiming to minimize the project's time and cost and maximize its NPV and robustness, employing multi-objective particle swarm optimization (PSO) and NSGA-II algorithms.

Joo and Chua (2017) researched the MMRCPSP, considering special divisions of activities within civil engineering firms. They crafted a mathematical model and applied a simulated annealing algorithm (SAA) to solve it. Kannimuthu et al. (2018) focused on the multi-project scheduling problem, taking into account the limited and unlimited resources of construction companies. They evaluated the implementation modes, challenges, and obstacles to the execution of simultaneous projects within the construction field. Forcael et al. (2018) looked into construction project scheduling, utilizing the discrete simulation method, considering uncertain and stochastic parameters. They asserted that their model could be universally applied to all construction project activities. Sharma and Bansal (2018) investigated highway construction project scheduling using location-based techniques and the geographic information system (GIS). Chen et al. (2018) delivered an integrated supplier coordination and project scheduling model, developing a mathematical model solved through a heuristic algorithm. Nabipoor Afruzi et al. (2020) offered a robust optimization mathematical model for the RCMPSP, considering the uncertainty of activity implementation times, examining the multi-project scheduling problem with varying significance weights of projects, and incorporating a resource-sharing policy to allocate resources between the projects.

In a research, Abbasi et al. (2023) examined and designed the context of the supply chain in the healthcare field during the crisis and presented an integrated model for the allocation, location, and routing processes for decision-making. Also, Shirzadi Javid et al. (2017) have investigated the related issues in managing and maintaining hospital facilities using statistical analysis and AHP and have addressed the associated indices in this field through case studies in their research. Furthermore, in the systematic study and review conducted by Abbasi and Ahmadi (2023) regarding the green supply chain network, it has been determined that research in this field has increased in recent years due to environmental concerns, and various stakeholders pay attention to it in the projects for reducing costs and pollution. In this regard, in the research performed by Abbasi and Erdebilli (2023) regarding the response of green supply chain networks to relevant policies. A model was presented in which both costs and emissions are examined to evaluate managers in executive decisions related to the supply chain. In another research, Abbasi et al. (2021) presented a mathematical model for applying a sustainable closed-loop supply chain network and discussed various aspects such as economic, social, and environmental. The Lingo software for mixed integer programming (MIP) is used to solve it.

Habibi et al. (2019) explored the scheduling of project activities and ordering raw materials, focusing on the sustainability aspects of construction projects. They formulated a mathematical model that integrated project scheduling and material ordering while taking into account environmental considerations and the advantages of potential suppliers of project resources. This model could establish the scheduling of activities and timing for material orders to maximize the net present value (NPV), supplier benefits, and social and environmental indicators. They resolved the model using multi-objective particle swarm optimization (PSO) and NSGA-II. García-Nieves et al. (2019) constructed a multi-purpose linear mathematical optimization model for planning repetitive activities in construction projects. Rahman et al. (2020) designed and solved the RCPSP model with a Memetic algorithm, targeting the minimization of the project's maximum completion time. Wang et al. (2020) examined the MMRCPSP within the construction sector, addressing the issue via building information modeling (BIM).

In a study, Asadujjaman et al. (2021) investigated the challenge of single-project scheduling with constrained resources and material ordering aligned with discounted cash flows. They proposed a mathematical model and solution strategy for the project, considering decisions around material ordering, supplier selection, transportation, and raw material inventory. Elmughrabi et al. (2020) also delved into collaborative supply chain planning and scheduling for construction projects. They presented an integrated model for collaborative supply chain planning, multi-project scheduling, and material ordering decisions. The supply chain depicted in their research encompassed a builder, a warehouse, and several construction sites where various independent construction projects were planned. These projects necessitated diverse materials supplied by a manufacturer with finite production capacity; the commencement of each activity was contingent on material availability at construction sites. A complex integer linear programming model was crafted to curtail total costs, enabling cooperation between contractors. Reza Hosseini et al. (2021) introduced a mathematical model for amalgamating multi-project scheduling with the green supply chain of construction projects, contemplating purchases, ordering and transportation costs, and vehicular pollution levels. They outlined a multi-objective model that assessed the environmental impact of vehicles concerning distance, pollution, and road gradient. In another study, Fu and Xing (2021) recommended an agent-based approach to the project-driven supply chain under information asymmetry and decentralized decision-making. They proposed a framework that merges an agent-based technique with an evolutionary algorithm, whereby agents negotiate to refine a solution and collaboratively evaluate the solutions spawned by the evolutionary algorithm. Regarding the noted cases, in the following and the form of Table 1, for easier comprehending and identifying the previous related studies and research gaps, a comparison and overview of some significant associated studies and articles in this field have been made with the current research.

Table 1. An Overview of some previous related research

Works	Multi-Objective	Single-Objective	Multi-Mode	Supplier Selection	Multi-Project	Single-Project	Method / Algorithm
Chen et al. (2018)		✓		✓	✓		Heuristic Algorithm
Van Peteghem and Vanhoucke (2010)		✓	✓			✓	Genetic Algorithm
Wang and Fang (2011)		✓	✓			✓	SFLA
Liu and Chen (2012)	✓				✓		LINGO
Singh (2014)		✓			✓		Rule-Based Methods and AHP
Suresh et al. (2015)		✓			✓		Genetic Algorithm
Pinha et al. (2016)		✓			✓		Simulation Method
Song et al. (2016)		✓			✓		Heuristic Algorithm
Habibi et al. (2017)	✓		✓			✓	PSO and NSGA-II
Forcael et al. (2018)		✓			✓		Discrete Simulation Method
Nabipoor Afruzi et al. (2020)		✓			✓		Robust Optimization
Habibi et al. (2019)	✓		✓			✓	Multi-objective PSO and NSGA-II
García-Nieves et al. (2019)		✓				✓	GAMS
Rahman et al. (2020)		✓				✓	Memetic Algorithm
Wang et al. (2020)		✓	✓			✓	Building Information Modeling
Current Research	✓		✓	✓	✓		Multi-Objective WOA and NSGA-II

Although supply chain management is a well-established concept in various industries, integrating it with construction project scheduling problems is a novel issue that has received limited attention. A review of the research literature reveals that only a few studies have offered an integrated supplier selection model and project scheduling, whether single-project or multi-project. Therefore, this paper contributes to the literature by creating an integrated model of supplier selection and multi-project scheduling. It considers the potential for executing activities with multi-mode and different intensities, aiming to optimize the project's cost and time. Moreover, most researchers have employed a genetic algorithm to solve the model. In this study, the WOA is introduced as a solution method, and the obtained results for assessing its performance are compared to NSGA-II. It is worth noting that considering the concurrent cost and time optimization for multi-mode multi-project scheduling and appropriate allocation of resource-constrained, taking into account the time value of money (TVM) can be practical and helpful for construction companies with several projects simultaneously in the real world to increase the productivity while reducing costs and time.

3. Mathematical Modeling

This study presents a bi-objective mathematical model for multi-mode multi-project scheduling by considering the construction industry suppliers, including several independent projects. The required resources to complete the activities in the projects are provided by different suppliers. In this model, the contractor simultaneously works on several projects to benefit the collaboration of their operations. Traditionally, each project is separately managed, but this paper proposes a coordinated design and planning for implementing simultaneous projects. The activities of each project are independent of the other projects, and their completion needs a set of resources (such as equipment and materials). This coordination can be obtained by investigating the two aspects of selecting the appropriate supplier and determining the sequence of activities in the projects. Accessibility of the resources due to the dependency of the project activities on the raw materials, equipment, and working force considerably affects the project's duration. Sharing the suppliers can eliminate repetitive operations, reduce additional costs, lead to lower prices, and increase communication. Therefore, integrity in the selection of suppliers among the projects can eventually reduce the costs and duration of projects. For this purpose, the integration operation of the construction supply chain management has been presented as a mathematical model, where the network is made of a set of simultaneous projects (l projects), and each project has its activities (A^l).

The assumptions of the proposed problem are as follows:

- The projects are independent of each other, and each project has its own activities.
- The suppliers of resources and the purchasing cost of resources are known.
- The required amount of resources for completing activities is known and certain.
- A resource may be purchased from several suppliers.
- Activities have several execution modes (different intensities), but each activity can be implemented by only one mode.
- The processing time of project activities is deterministic.
- The problem is multi-objective.

The introduced model in this study considers n activities in each project, all of which require a predetermined time (p_i) for processing. The proposed mathematical model has two objectives. The first objective function is to minimize the total penalties of projects time delay. The second objective function is to minimize the total cost of purchasing resources and implementing projects activities.

Subsequently, the indices, parameters, and variables of the research problem are delineated in Tables 2, 3, and 4. Based on these items, the proposed mathematical model is then presented.

Table 2. Indices of the mathematical model

Symbol	Description	Symbol	Description
$A^{\mathrm{l}} = \{\mathrm{a}_1^{\mathrm{l}}, \mathrm{a}_2^{\mathrm{l}}, \dots, \mathrm{a}_{\mathrm{nl}}^{\mathrm{l}}\}$	Set of activities for project l	$G_{\mathrm{l}} = (\mathrm{V}_{\mathrm{l}}, \mathrm{E}_{\mathrm{l}})$	Set of precedence relations of the activities of project l
S	Set of required resources for project activities S={1,2,3}	H	Set of suppliers for resources H={1,2,…, h}
i, j	Set of activities	l, l’	Set of projects
n_l	Number of activities for project l	k	Set of suppliers
s, s’	Set of resources	M	Set of execution modes

Table 3. Parameters of the mathematical model

Symbol	Description	Symbol	Description
b_{ims}^{l}	The number of resource s required to complete activity i of the project l in the execution mode m	p_{ilms}	The processing time of activity i of project l by resource s in execution mode m
D_l	Due date of project l	r_θ	Discount rate
$cost_{ks}$	The purchasing cost of resource s from supplier k	$costm_{ilm}$	Implementing cost of activity i of project l in mode m

Table 4. Variables of the mathematical model

Symbol	Description	Symbol	Description
RK_{ks}	The number of resource s that are purchased from supplier k	x_{ilk}^{s}	The start time of activity i of project l by purchased resource s from supplier k
u_{il}^{m}	If activity i of project l is processed in implementing mode m, it is equal to 1; otherwise 0.	$y_{\mathrm{ilk}}^{\mathrm{s}}$	If a unit of resource s purchased from supplier k is assigned to activity i of project l, the value of this variable is equal to 1; otherwise 0 **.**
c_{il}	Completion time of activity i of project l	c_l	Completion time of project l
$f_{\mathrm{ijkss'}}^{\mathrm{ll'}} = \begin{cases} 0 \ \ if\ x_{iks}^{l} > x_{jks'}^{l'} \\ 1 \ \ \mathrm{if}\ x_{iks}^{l} \leq x_{jks'}^{l'} \end{cases} \forall i,j,s,s',l,l',k$	This variable is used in the constraints of allocating the resources at a time.	T_l	Delay of project l

Finally, the proposed mathematical model for the project scheduling problem is presented, considering the interruption of activities and purchasing of the suppliers' resources. According to the description of the problem, assumptions, indices, parameters, and variables, the proposed model is as follows.

Objective functions of the model:

$$\min Z_1 = \sum_{l=1}^{L} T_l \qquad (1)$$

Eq. 1 shows the first objective function to minimize the total penalty of projects' time delays.

$$\min Z_2 = \sum_{k=1}^{K}\sum_{s=1}^{S}(1+r_\theta)cost_{ks}RK_{ks} + \sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{i=1}^{N_l}(1+r_\theta)costm_{ilm}u_{il}^{m} \qquad (2)$$

Eq. 2 represents the second objective function to minimize the purchasing cost from the suppliers and the cost of project activities.

Model constraints:

$$c_{il} = \max\{(x_{ilk}^{s} + p_{ilms})\, u_{il}^{m}\} \quad \forall k, s, m, l \qquad (3)$$

Constraint (3) determines the completion time of activities for each project.

$$c_{jl} \le x_{ilk}^{s} \ \text{(j must complete before i in the project)} \qquad (4)$$

Constraint (4) ensures that the predecessor activities are completed first.

$$\mathrm{C_l} \ge c_{il} \qquad \forall l\,, i \in l \qquad (5)$$

Constraint (5) calculates the completion time of project l.

$$x_{ilk}^{s} - x_{jl'k}^{s} \ge (y_{ilk}^{s})\left(y_{jl'k}^{s'}\right)(p_{jl'ms'}u_{jl'}^{m}) - bigM\left(f_{ijkss'}^{ll'}\right) \ \ \forall i,k,s,m,i \ne j \qquad (6)$$

$$x_{\mathrm{il'k}}^{\mathrm{s'}} - \mathrm{x_{jlk}^{s}} \ge (y_{ilk}^{s})\left(y_{jl'k}^{s'}\right)(p_{il'ms'}u_{il'}^{m}) - bigM\left(1 - f_{\mathrm{ijkss'}}^{\mathrm{ll'}}\right) \ \ \forall i,k,s,m,i \ne j \qquad (7)$$

Constraint (6) and constraint (7) guarantee that a resource purchased from supplier k cannot simultaneously be allocated to two activities. When a resource is assigned to a specific activity, it can be designated for another activity when that activity is completed.

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} y_{ilk}^{s} = \mathrm{b}_{ilms} \times u_{il}^{m} \quad \forall \mathrm{i,l,s,m} \qquad (8)$$

Constraint (8) ensures that all activities receive the required resources to complete, and each resource can be allocated if purchased.

$$\sum_{l=1}^{L}\sum_{i=1}^{n_l} y_{ilk}^{s} \le RK_{ks} \qquad \forall k, s \qquad (9)$$

Constraint (9) ensures that the allocated resources to the activities do not exceed the purchased number.

$$\min\left\{x_{jlk'}^{s'}u_{jl}^{m}\middle|\mathrm{y}_{\mathrm{jlk'}}^{\mathrm{s'}}=1\right\}-\max\ \{x_{ilk}^{s}u_{il}^{m}|\mathrm{y}_{\mathrm{ilk}}^{\mathrm{s}}=1\}\geq \mathrm{p}_{ilms}\quad \forall m,k,k',s,s'\quad \forall i\geq j \tag{10}$$

Constraint (10) presents the precedence relationships of project activities. For example, if activity i is the precedence of activity j, the minimum start time of activity j must be longer than the completion time of activity i (maximum start time of activity i plus the processing time of activity i).

$$x_{\mathrm{ilk}}^{\mathrm{s}}\leq My_{ilk}^{s}\quad \forall i,k,s \tag{11}$$

Constraint (11) expresses that if a resource is allocated to activity i, this activity can start with this allocation.

$$\sum_{m=1}^{M}u_{il}^{m}=1\qquad \forall l \tag{12}$$

Constraint (12) guarantees that each activity is implemented in only one mode.

$$T_{l}=\max\{0,\mathrm{C_l}-\mathrm{D_l}\}\quad \forall l \tag{13}$$

Constraint (13) determines the delay of project l.

$$x_{\mathrm{ilk}}^{\mathrm{s}}\geq 0\quad \forall i,l,k,s \tag{14}$$

$$T_{\mathrm{l}}\geq 0\quad \forall i,l \tag{15}$$

$$y_{\mathrm{ilk}}^{\mathrm{s}},u_{il}^{m},RK_{k,s}=\{0,1\}\quad \forall i,l,k,s \tag{16}$$

Constraints (14), (15), and (16) show the domain of the decision variables.

4. Solution method

The preceding section presented a multi-objective mathematical model for the multi-mode resource-constrained multi-project scheduling, considering various items such as ordering resources from suppliers and discount rates. In this regard, Sheykh et al. (2009) showed that the nature of this type of problem is NP-HARD, and meta-heuristic methods should be applied in order to solve it. Also, the research of Mirjalili and Lewis (2016) indicated that the whale optimization algorithm is better than other meta-heuristic algorithms, such as PSO, GA, and DE, for solving several optimization problems. The WOA is a newly developed swarm-based meta-heuristic algorithm inspired by humpback whales' bubble-net hunting maneuver technique to solve complex optimization problems. Due to its simple structure, fast convergence rate, less required operator, and better balancing capability between exploration and exploitation phases, it has gained widespread acceptance as a swarm intelligence method in a variety of engineering fields. The algorithm's applications have recently been extensively used in multidisciplinary fields due to its optimal performance and efficiency. The optimization results of the studies demonstrate that the WOA algorithm is highly competitive with advanced meta-heuristic algorithms and conventional methods (Rana et al. 2020; Mohammed et al. 2019). Therefore, based on the mentioned contents, the WOA has been implemented and examined as a new method in this research.

It is worth noting that the review of previous research in this field indicated that most researchers had used the genetic algorithm as a well-known and common algorithm to solve the problems in this scope and related models. Therefore, in this research, although the WOA was proposed to solve the mathematical model, and the main research activities were focused on it as a new method; however, for evaluating its performance and comparing it with other research, the results of this algorithm have been compared with the obtained results through solving the model by the non-dominated sorting genetic algorithm II. NSGA-II is an evolutionary multi-objective optimization algorithm applied to various search and optimization problems (Rahimi et al. 2022). Indeed, NSGA-II is an evolutionary algorithm developed to answer the shortcomings of early evolutionary algorithms, which lacked elitism and used a sharing parameter to support a diverse set of Pareto. NSGA-II uses a fast non-dominated sorting algorithm, elitism, sharing, and crowded comparison. Elitism means that the best solutions from the previous iteration remain unchanged in the current iteration and significantly increase the algorithm's rate of convergence. Additionally, using a fast non-dominated sorting algorithm significantly reduces its computational complexity (Deb et al. 2000; De Buck et al. 2019; Deb 2014).

According to the mentioned points, a multi-objective WOA based on the Pareto archive is employed for solving the proposed model. The algorithm begins with a set of random solutions. The search elements update their position according to a search element randomly or within the best-obtained solution in each iteration. Parameter a is reduced from 2 to 0 to provide exploration and exploitation. Two modes are considered to update the position of search elements. The random search element is selected if $|A|>1$. On the other hand, if $|A|<1$, then the best solution is selected. The whale can switch between spiral and rotational movements according to the value. Finally, the algorithm terminates after reaching the satisfaction criterion. In this study, the algorithm is designed based on the Pareto archive. The Pareto archive is updated at the end of each algorithm iteration. Also, an improvement procedure is used in each iteration of the algorithm. The structure of the proposed algorithm is shown in Figure 2, and the related descriptions are provided in the following sections.

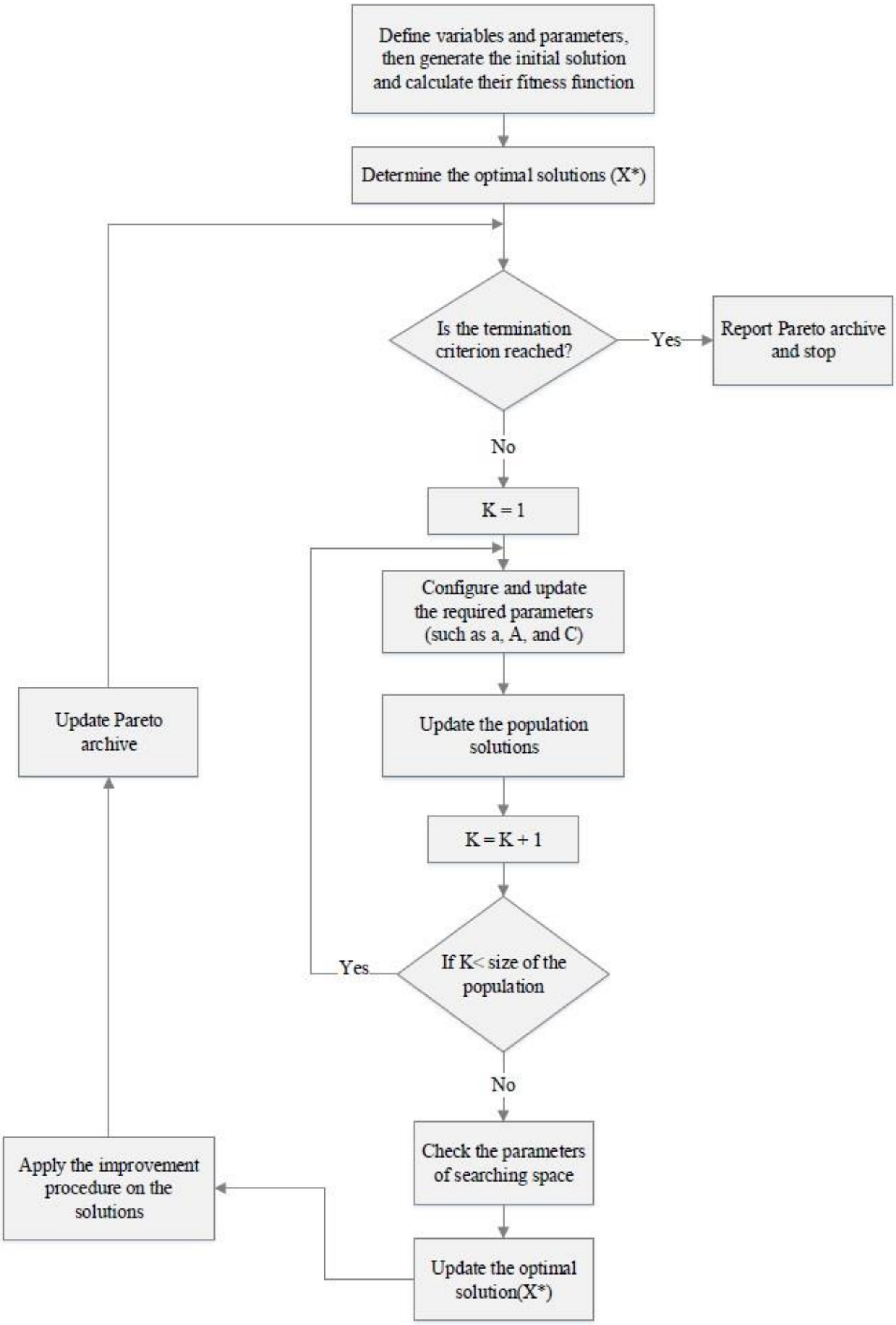

Figure 2. The structure of the whale optimization algorithm (WOA)

4.1. Solution representation

The solution representation method in this paper is built upon two distinct structures. The primary structure is a two-dimensional matrix in which the number of rows corresponds to the number of projects. Specifically, each row encapsulates a schedule for the project activities within the respective row, portraying the implementation order according to their precedence relationships. This mechanism for the first structure is visually represented in Figure 3, based on the assumption that the problem involves two projects comprising six and eight activities, respectively.

1	2	4	3	5	6	0	0
1	2	3	6	4	5	7	8

Figure 3. The first matrix of the solution structure

In Figure 3, the matrix consists of two rows, each delineating the viable sequencing of activities for the first and second projects, respectively.

The secondary structure, a three-dimensional matrix, focuses on allocating suppliers to each project's resources. The rows within this matrix equate to the total resources required across all projects. The second dimension, denoted by the columns, signifies the number of suppliers designated to each specific resource, while the third dimension, or height, corresponds to the number of activities. In the context of two projects and three resources allocated to suppliers, the distribution of suppliers to the essential resources of activity i is conveyed through a two-dimensional matrix, as illustrated in Figure 4.

1	3	0	0
5	0	4	0
1	0	5	4
0	0	0	0
3	1	0	0
4	8	0	0

Figure 4. The structure of solution representation

In Figure 4, the matrix is delineated by six rows; the first three rows specify the resources allocated to the first project, while the subsequent three rows characterize the resources designated for the second project.

4.2. Solution initialization method

Evolutionary meta-heuristic techniques typically employ a stochastic approach to generate initial solutions. Recognizing that the quality of the concluding solutions is intrinsically linked to the integrity of the initial solutions, this study utilizes a series-based method to establish the feasible sequencing of activities for each project. Subsequently, corresponding to the necessary quantity of resources and any overlaps in resources, a secondary matrix is generated for each matrix that pertains to the sequence of activities (first matrix). The methodologies for creating the first matrix of each solution (the feasible sequencing of activities within a project) are described in the following sections.

4.2.1. Series scheduling method

The series method makes a feasible scheduling plan over n iterations, where n corresponds to the total number of project activities. The partial schedule (*PS*) plan is developed by adding and scheduling an activity in each iteration. After determining the set of scheduling activities, one of them is selected and scheduled in the earliest possible time $E \leq ES_j(PS)$, and in the periods of $t+1,\ldots,t+d_{jm}$ that do not violate the constraints. For the obtained partial scheduling called PS', in which $J(PS')=J(PS)\cup\{j\}$, the amount of remaining resources is determined, and the earliest start and finish time ($ES_j\,(PS')$ and $EF_j\,(PS')$) of all unscheduled activities are recalculated. The next iteration of PS' is developed and continues until all activities are scheduled. This iterative method ensures the compliance of each scheduling step with project constraints, providing a systematic approach to generating a feasible solution.

4.2.2. Termination criterion and initial population

In this research, each method produces N feasible sequences for each project independently and subsequently constructs the second matrix for every matrix associated with the sequences of the projects' activities. Afterward, N solutions are selected from these two sets of solutions as the initial population. For choosing the solutions, the whole 2N obtained solutions of two methods are considered as a set and ranked using the rule of Deb et al. (2002). The crowding distance is calculated for each rank, and N solutions are selected based on their higher quality and diversity. This process ensures a balanced initiation, fostering a strong convergence towards an optimal solution while maintaining diversity to explore various regions of the solution space.

4.3. Improvement procedure

In the proposed WOA, an improvement procedure is designed to improve the previous step's selected solutions. The output solutions are chosen as the collection of iterations after the algorithm. The improved solutions are considered for the population of the next iteration of the algorithm.

The proposed improvement procedure is based on the variable neighborhood search (VNS). Variable neighborhood search (VNS) is a meta-heuristic method to solve combinatorial and global optimization problems (Hansen et al. 2010). In this regard, it explores distant neighborhoods of the existing incumbent solution and moves from there to a new one if and only if an improvement has been made. The local search method is repeatedly applied to get from solutions in the neighborhood to local optima.

VNS uses two neighborhood search structures. The employed neighborhood search structures are described in the following.

First neighborhood search structure: This operator was selected based on the research of Shadrokh and Kianfar (2007). The index of a project is generated randomly and uniformly. Then, the operator is applied to the sequence of that project. The second matrix is updated according to the model constraints and the changes of the first matrix. The mechanism of this operator for the sequence of project activities is as follows:

Assume the row related to the selected project in the first matrix as a solution ($j_1,j_2,\dots j_n$). First, an index such as a is randomly generated in the interval [2, n-1]. Suppose j_b and j_c are the last predecessors and the first successor of activity j_a.

Generate random number d in the interval [b+1, c-1]. If d<a, the obtained solutions is ($j_1,j_2,\dots,j_{d-1},j_d,j_{d+1},\dots,j_{a-1},j_a,j_{a+1},\dots,j_n$) and if d>a, the solution is ($j_1,j_2,\dots,j_{a-1},j_a,j_{a+1},\dots,j_{d-1},j_d,j_{d+1},\dots,j_n$).

Second neighborhood search structure: This operator and the previous operator are applied to the sequence of activities for one of the randomly selected projects. This operator randomly selects and swaps the activities scheduled in the sequential cells in the interval [1, n-1].

Each solution within the population is processed through the VNS algorithm, resulting in an output solution. Following this, a correction procedure is applied to the remaining solution matrices, and they are replaced with the input solutions (Tavakkoli-Moghaddam et al. 2011).

4.4. Updating solutions and searching parameters

In the whale optimization algorithm (WOA), the solutions and searching parameters are updated based on the following formulas (Mirjalili and Lewis 2016):

$$\vec{D} = \left|\vec{C}.\vec{X}^{*}(t) - \vec{X}(t)\right| \qquad (17)$$

$$\vec{X}(t+1) = \vec{X}^{*}(t) - \vec{A}.\vec{D} \qquad (18)$$

Where $\vec{D}$ is searching in space, $\vec{C}$ and $\vec{A}$ are the coefficients, $\vec{X}^{*}(t)$ is the optimal solution in iteration t, $\vec{X}(t)$ is the solution for iteration t, and $\vec{X}(t+1)$ is the solution for iteration t+1.

The following relations are also used to update $\vec{A}$ and $\vec{C}$:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \qquad (19)$$

$$\vec{C} = 2\vec{r} \qquad (20)$$

In formulas (19) and (20), $\vec{a}$ is initialized with a value of 2 and decreases linearly in each iteration; also, $\vec{r}$ is a random value in the interval [0, 1].

Moreover, to update the optimal solution, if there is a better solution than $\vec{X}^*$ among all the obtained solutions, it is replaced with $\vec{X}^*$. Otherwise, it remains unchanged.

4.5. Updating Pareto archive

In this study, the suggested solution method relies on the Pareto archive. The proposed algorithm produces a collection referred to as the Pareto archive, encompassing the non-dominated solutions generated throughout the algorithm's implementation. This collection undergoes an update during each iteration of the algorithm. The solutions created in the last iteration and those in the existing Pareto archive are pooled together and ranked to refresh the set. Subsequently, the top-ranked (non-dominated) solutions are chosen and established as the updated Pareto archive.

4.6. Selecting the next-generation solutions

In every iteration, the algorithm necessitates a collection of solutions. Hence, to choose the population for the subsequent iteration, the solutions from the previous iteration and those freshly generated by the algorithm are amalgamated into a solution pool. Following the ranking process and calculation of the crowding distance for the solutions, N solutions demonstrating the highest quality and diversity are selected. This selection is made in accordance with the rule proposed by Deb et al. (2002) and forms the population for the upcoming iteration.

5. Results and evaluations

As delineated in the preceding sections, the WOA based on the Pareto archive and the NSGA-II have been employed to address the proposed model. The outcomes of applying these algorithms to solve the model are detailed in this section and subsequent ones. Consistent with this approach, the proposed algorithms have been implemented using MATLAB software. Several sample problems were crafted. Upon setting the parameters of the model and algorithms, these problems were resolved using the proposed model and methodologies, and the resulting solutions were assessed and juxtaposed. Also, the results of a small-sized sample problem are analyzed, and the values of the variables obtained by WOA and LINGO software are explained in detail. Furthermore, the construction projects contracting company in Iran, active in the residential, commercial, and hotel building sectors, was chosen as a case study to solve the model. After examining the completed projects' documents, two projects constructed concurrently were selected. The model was tackled based on these projects' information using both WOA and NSGA-II, and the derived values and results were contrasted with the real-world data obtained from the company. It is worth noting that the evaluations and comparisons were executed according to various criteria and metrics, to be expounded in the following sections.

5.1. Evaluation metrics

For evaluating the efficacy of the proposed algorithms, several criteria are utilized, including the number of Pareto solutions (NOS), mean ideal distance (MID), quality metric (QM), spacing metric (SM), and diversity metric (DM). The details of some of these criteria are as follows based on the previous research (Azarkish and Aghaeipour 2022; Ghoroqi et al. 2023):

Number of Pareto Solutions (NOS): Since the algorithms operate based on the Pareto archive, the set of solutions acquired corresponds to the final Pareto archive. The number of these final solutions is one of the comparative benchmarks employed.

Mean Ideal Distance (MID): This metric represents the aggregate of the Euclidean distances between the solutions and an ideal point. In this study, the ideal point is a matrix including two cells, in which the first cell's value is equal to the minimum value of the first objective function of all solutions. The second cell's value is equal to the minimum value of the second objective function of all solutions.

Quality Metric (QM): This criterion is equivalent to the count of Pareto (non-dominated) solutions, providing insight into the quality of the obtained solutions in terms of optimization.

Spacing Metric (SM): This criterion calculates the uniformity of the distribution of the obtained Pareto solutions at the Pareto fronts, and it is defined as follows:

$$S = \frac{\sum_{i=1}^{N-1} \left| d_{mean} - d_i \right|}{(N-1) \times d_{mean}} \tag{21}$$

Where $\boldsymbol{d_i}$ represents the Euclidean distance between two adjacent non-dominated solutions, and d_{mean} represents the mean value of d_i.

Diversity Metric (DM): This criterion is used to determine the number of non-dominated solutions of the optimal front. The definition of diversity metric is as follows:

$$D = \sqrt{\sum_{i=1}^{N} \max(\left\| x_t^i - y_t^i \right\|)} \tag{22}$$

Where $\left\| x_t^i - y_t^i \right\|$ represents the Euclidean distance between two adjacent solutions of x_t^i and y_t^i on the optimal front.

5.2. Sample problems

Several sample problems are crafted within this paper and categorized into two groups based on their sizes: small and large. Since there is no specific library for the project scheduling problem that considers suppliers, and given that using existing samples from the project scheduling problem library would not be applicable due to the unique nature of the proposed problem, a variety of sample problems were randomly generated.

Furthermore, the problems in this study consist of a real problem involving two construction projects chosen from the construction undertakings of a contracting company in Iran. Specifically, this scenario includes two construction projects comprising their activities. Also, the required resources to complete these projects are sourced from four different suppliers.

It is worth noting that the random sample problems are created in both small and large sizes to be tested by the algorithms. The characteristics of these generated sample problems are detailed in Tables 5 and 6, allowing for a diverse and comprehensive evaluation of the proposed model.

Table 5. Small-sized sample problems

Problem (Prob. No.)	Number of projects	Number of project activities	Number of resources	Number of suppliers
1	2	8	3	4
2	2	10	3	5
3	2	12	3	5
4	2	14	3	5
5	2	16	3	5
6	2	20	3	6

Table 6. Large-sized sample problems

Problem (Prob. No.)	Number of projects	Number of project activities	Number of resources	Number of suppliers
7	4	25	3	6
8	6	40	3	7
9	8	60	3	8
10	10	80	3	8
11	12	100	3	10

5.3. Parameter setting

In order to apply and implement the algorithms based on previous research and studies (Amirian et al. 2014; Montgomery 2017; Sheykh et al. 2009; Mirjalili and Lewis 2016; Shen et al. 2023; Mohammed et al. 2019; Rana et al. 2020) as well as the execution needs of the projects, the following items have been set in the proposed model solution algorithms.

- In WOA, the population size, the number of iterations in the variable neighborhood search algorithm, and the number of iterations of the algorithm are 200, 10, and 300, respectively.
- In NSGA-II, the rate of crossover and mutation are 0.8 and 0.1, respectively.
- In NSGA-II, the number of iterations and population size are 300 and 200, respectively.

Likewise, setting the parameters of the model are as follows:

- The required number of resources to complete each mode's project activities is considered in a uniform interval [2..4].
- The processing time of project activities in each mode is considered in a uniform interval [10..40].
- The due date of projects is considered in a uniform interval [m_1..m_2] where m_1 and m_2 are respectively 1.2 and 1.5 fold the total processing time of all projects' activities.
- The purchasing cost of resources is generated in a uniform interval [10..20], and the implementing costs of activities are considered in a uniform interval [5..15].
- The time value of money is 0.18.

5.4. Computational results of the model and algorithms

This section describes the outcomes of solving random problems of small and large scales and construction projects for the contracting company under examination. Initially, the results of a small-sized problem by LINGO software and the proposed algorithm are described for model validation. Then, the computational results of addressing the company's specific problem with the WOA and NSGA-II are delineated. Subsequently, the findings from solving randomly generated small-sized and large-sized sample problems are presented using both meta-heuristic algorithms, with a comparison of their performance according to the designated evaluation metrics.

5.4.1. Results and discussion of the model validation

For model validation, a small-sized sample problem is solved by Lingo software. The sample consists of a project with six activities, two suppliers, and two resources. Notably, besides the main activities of 1, 2, 3, and 4, this project has two dummy activities of 0 and 5. Since LINGO software can only solve single-objective problems, the only purpose is to minimize the total delay. The parameters of the sample are presented in Table 7.

Table 1. Parameters of the sample problem

Activity	Resource	P_{is}	b_{is}	D_i
1	1	3	1	5
	2	4	1	
2	2	-	-	6
		4	1	
3	1	2	1	11
	2	5	1	
4	1	4	1	14
		-	-	
	2	3	1	

In the current problem, it is assumed that two resources are required, which are purchased from two suppliers. In other words, the two resources can be supplied by each of the suppliers. The results obtained by LINGO are shown in Table 8, where sup is the number of suppliers, xi is the start time of activity i using the resource purchased from the supplier sup, and ci is the completion time of the activity by the proposed resource.

Table 2. Results obtained by LINGO

Activity	Resource 1	Resource 2
0	0	0
1	sup=1, x1=3, c1=8	sup=1, x1=1, c1=7
2	0	sup=2, x2=1, c2=5
3	sup=1, x3=8, c3=10	sup=2, x3=5, c3=10
4	sup=1, x4=10, c4=14	sup=2, x4=10, c4=13
5	0	0

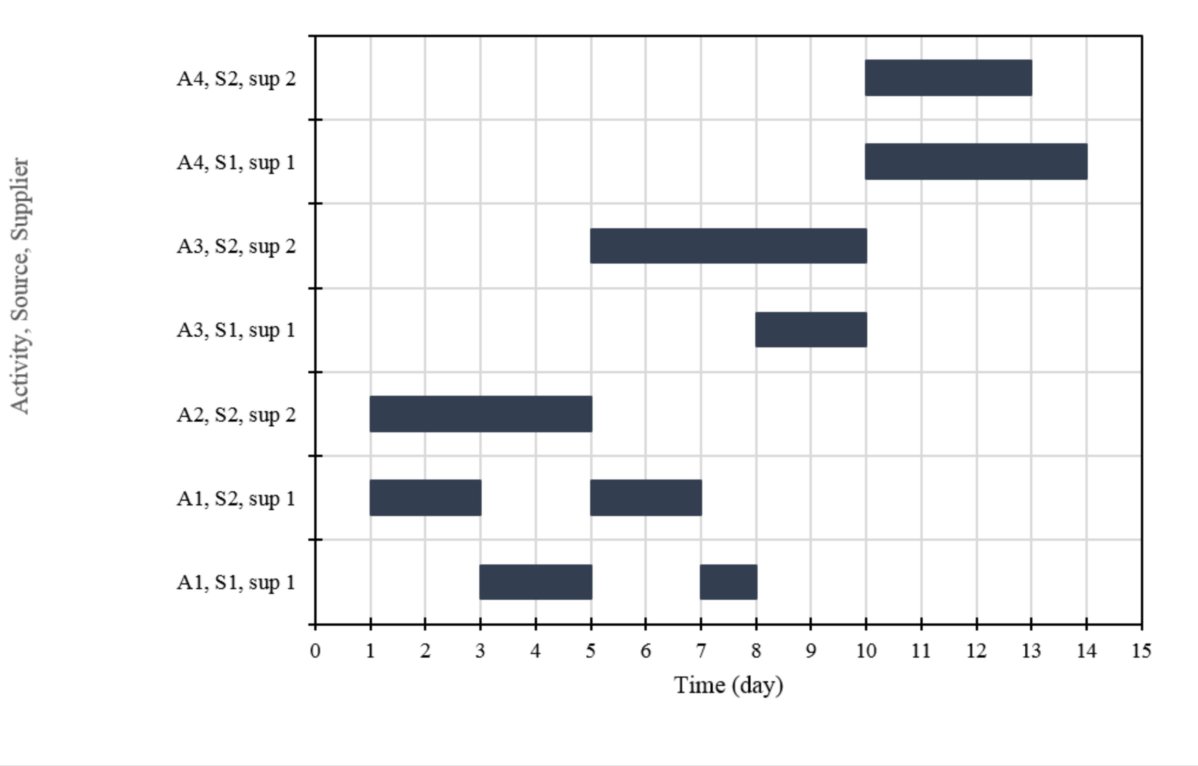

Figure 5. The optimal scheduling diagram resulted from the LINGO

As shown in Figure 5, activity 1 has resource number 2, which is provided by supplier 1 and is started. This resource implements this activity for up to 2 units of time. Then, the implementation of activity 1 is continued up to 2 more time units by resource number 1 (provided by supplier 1). During the time period 5 to 7, resource number 2 (provided by supplier 1) is again assigned to this activity. Finally, activity 1 is completed during the time period 7 to 8 by allocating resource number 1 (provided by supplier 1).

Activity 2 is also started by allocating resource number 2 (provided by supplier 2) and is completed after 4 units of the time period. Similarly, resources 1 and 2 are allocated to activities 3 and 4, and the mentioned activities are also completed.

It is worth noting that the WOA solved the aforementioned sample, and the results are presented in Figure 6. According to the results of WOA, the value of the first objective function is 3, Which is the same as the output of LINGO software.

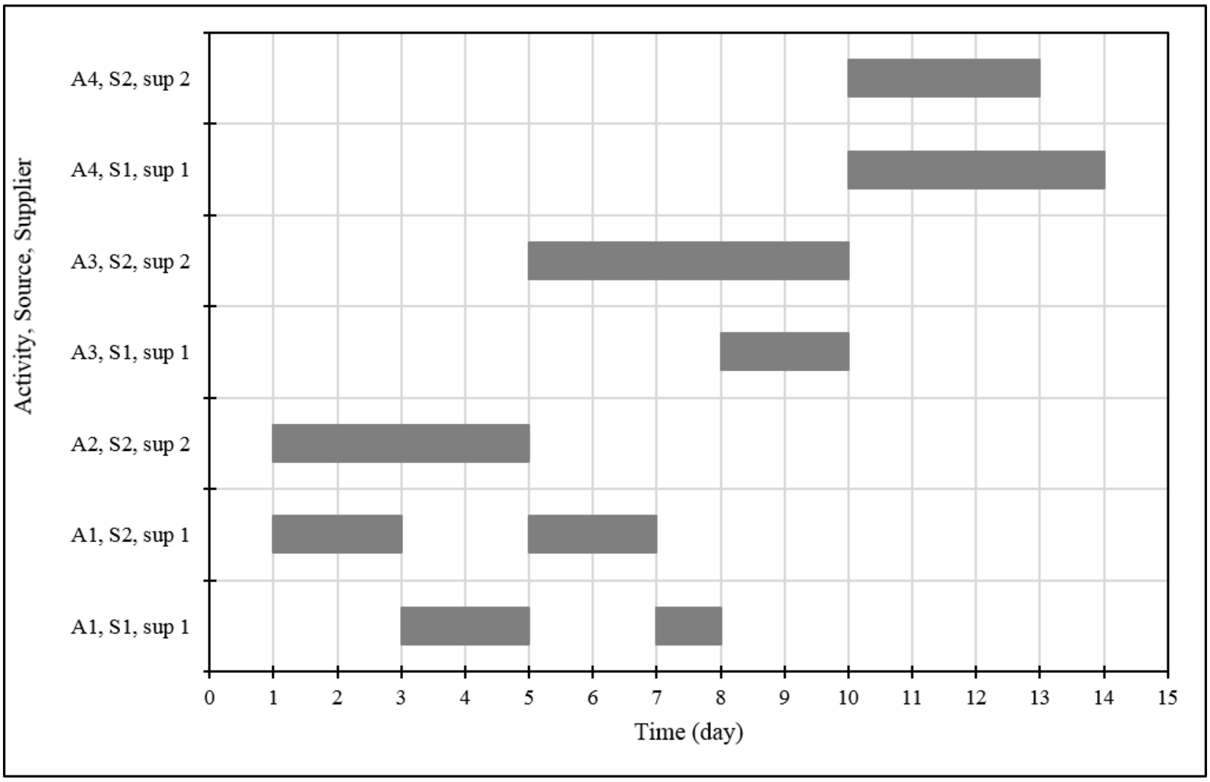

Figure 6. The optimal scheduling diagram resulted from the WOA

5.4.2. Results and discussion of the case study problem

In this article, a multi-objective mathematical model is introduced for the multi-project scheduling problem, taking into account various factors such as resource ordering from suitable suppliers. The model's primary goal is to simultaneously optimize the cost and time of projects. After conceptualizing and creating the model and proposed method, it becomes crucial to verify and validate its efficacy and potential benefits in real-world applications. For this purpose, two construction projects carried out concurrently by a contractor company were chosen as a case study. The existing data for these projects were analyzed using the WOA and NSGA-II. The data required for model parameters were gathered from the company's records and other available sources. The studied company's construction projects comprised 780 and 803 activities, respectively, utilizing various resources for completion. Both WOA and NSGA-II were employed to solve the case study problem, and the results for time and cost were compared to the values achieved through the company's actual project scheduling. These comparisons are detailed in Table 9. It should be noted that among the Pareto solutions obtained from the WOA, the one with the highest diversity was selected for comparison with the company's real values.

Table 9. Results of solving the problem of construction projects in the case study company

Objective	Type	Construction Project 1	Construction Project 2
Time (months)	Company	37	40
	WOA	31	35
	NSGA-II	34	38
Time Improvement (%)	WOA	16.2%	12.5%
	NSGA-II	8.1%	5%
Cost (million dollars)	Company	25	26.5
	WOA	23.5	24.7
	NSGA-II	24.2	25.6
Cost Improvement (%)	WOA	6%	6.7%
	NSGA-II	3.2%	3.3%

As illustrated in Table 9, employing the mathematical model described in this article to manage the scheduling of the company's construction projects leads to a reduction in both the time and cost required for project completion. Using the schedule derived from the model solved by the WOA results in more substantial improvements in construction time and cost compared to the NSGA-II. Specifically, the WOA's time improvement rate is 16.2% for project 1 and 12.5% for project 2. The corresponding cost reductions for the two projects are 6% and 6.7%, respectively. In contrast, the NSGA-II has achieved time improvements of up to 8.1% and 5% and cost reductions of 3.2% and 3.3% for the respective construction projects. These results demonstrate that utilizing the proposed model to manage scheduling across several construction projects and the associated supply of materials can be highly beneficial, leading to substantial decreases in completion time and overall cost.

The Pareto archive of the model solutions, as obtained by the WOA and NSGA-II for this problem, contains 121 and 87 solutions, respectively. The Pareto front of these two multi-objective meta-heuristic algorithms is visually represented in Figure 7.

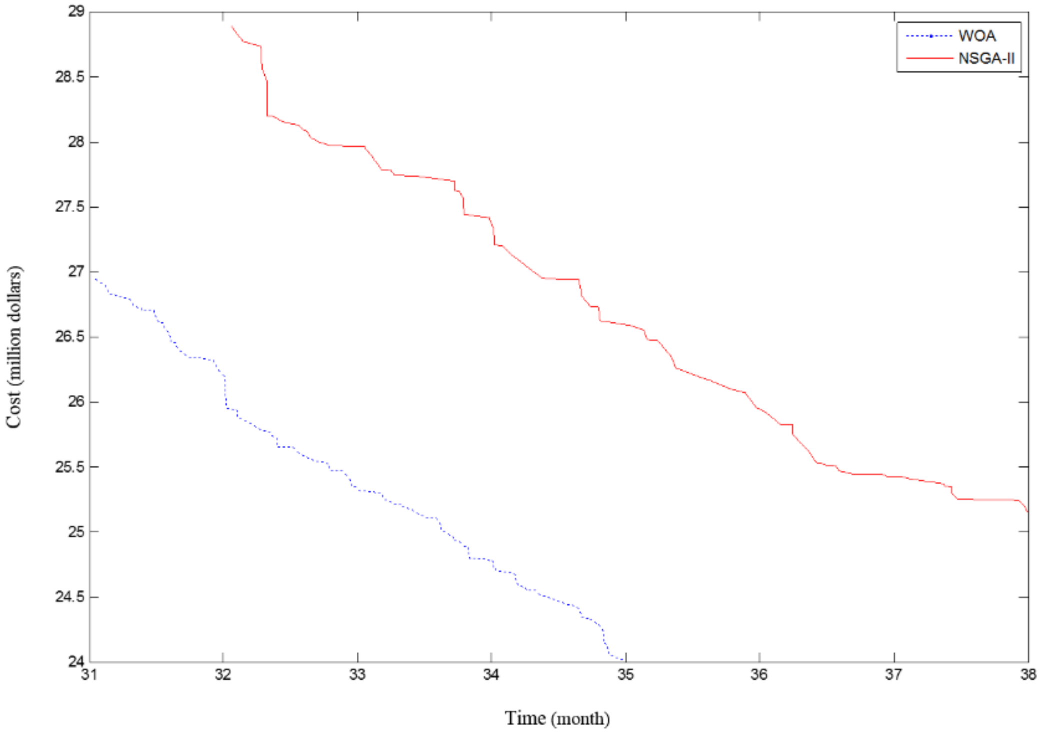

Figure 7. The Pareto front of WOA and NSGA-II in the case study problem

Figure 7 demonstrates that both algorithms reveal a trade-off at the Pareto front between the cost of projects and the completion time; as one decreases, the other increases. This behavior confirms that the two objective functions considered for the model are in conflict with each other and are not aligned. Furthermore, the visual representation shows that the Pareto front of the WOA lies below the boundary of the NSGA-II. This positioning indicates that the quality of the Pareto archive produced by the WOA is superior to that of the NSGA-II.

5.4.3. Results and discussion of the sample problems

In this section, the results derived from the proposed meta-heuristic algorithms are detailed and juxtaposed in Tables 10 and 11. Specifically, Table 10 exhibits the outcomes of small-sized sample problems, evaluated in accordance with specific metrics, while Table 11 highlights the results of the large-sized sample problems.

Table 10. Results of the small-sized sample problems

Prob.	WOA					NSGA-II				
	Quality Metric	Spacing Metric	Diversity Metric	NOS	MID	Quality Metric	Spacing Metric	Diversity Metric	NOS	MID
1	85.37	0.869	633.2	65	1085.56	14.62	0.660	333.0	71	1265.40
2	99.01	1.003	790.6	49	1183.52	0.98	0.864	415.5	33	1842.54
3	100	0.763	919.5	91	863.93	0	0.990	777.1	69	1536.65
4	100	0.991	1092.3	78	689.36	0	0.456	879.3	84	1003.67
5	79.52	1.348	1213.7	53	1153.55	20.47	0.794	906.6	63	1807.62
6	89.78	0.889	1609.4	86	794.09	10.21	0.705	992.4	46	1659.43

Table 11. Results of the large-sized sample problems

Prob.	WOA					NSGA-II				
	Quality Metric	Spacing Metric	Diversity Metric	NOS	MID	Quality Metric	Spacing Metric	Diversity Metric	NOS	MID
7	69.13	0.88	1599.5	118	1997.40	30.87	0.73	1302.6	89	2231.40
8	77.65	0.69	1694.8	125	2017.54	22.35	0.45	1399.4	103	2427.54
9	100	1.23	2834.7	86	1743.40	0	0.93	1549.2	95	2291.33
10	94.76	0.98	11009.3	107	1802.35	5.24	0.74	1666.5	78	2958.45
11	84.49	0.99	11517.2	132	2093.50	15.51	0.44	2709.3	115	2630.26

According to Tables 10 and 11, the WOA has a higher ability to generate high-quality solutions compared to the NSGA-II. Moreover, the MID criterion indicates that the solutions obtained by WOA are closer to the ideal point than NSGA-II. The proposed WOA is able to generate solutions with higher diversity, which means it is more efficient to explore and exploit the solution feasibility space than NSGA-II. On the other hand, NSGA-II generates more uniform solutions.

For comparing the run time of algorithms under the same conditions, each problem is executed in both groups. The computational time of one iteration of each algorithm is determined while solving the problems. The computational times are presented in Table 12. This item shows that the computational time of the multi-objective WOA is higher than NSGA-II. According to Tables 10 and 11, WOA demonstrates a superior capability in generating high-quality solutions in comparison to NSGA-II.

Table 12. Computational times

Prob.	Run time (second)	
	WOA	NSGA-II
1	0.34	0.12
2	0.37	0.15
3	0.42	0.21
4	0.62	0.30
5	0.75	0.47
6	1.74	0.89
7	2.86	0.77
8	4.11	1.02
9	6.76	2.32
10	7.50	4.60
11	10.37	6.02

5.5. Sensitivity analysis

To investigate the behavior and sensitivity of the model, the parameters such as $costm_{ilm}$ (Implementing cost of activity i of project l in mode m) and r_θ (Discount rate) are changed. Then, the results of the objective functions of the model are evaluated, and the sensitivity analysis is performed. In this regard, problem number 7 has been selected among the large-sized problems. In the following the behavior and sensitivity of the objective functions are demonstrated in Tables 13, 14, and 15, as well as Figures 8, 9, and 10.

Table 13. The behavior of the second objective function (*Costs*) of the model versus the changes in the $costm_{ilm}$

Row	$costm_{ilm}$	r_θ	The second objective function (*Costs*)
1	0.5	0.18	1741.3
2	1	0.18	1799.4
3	1.5	0.18	1865.2
4	2	0.18	1945.1
5	2.5	0.18	1986.3

Table 14. The behavior of the second objective function (*Costs*) of the model versus the changes in the r_θ

Row	$costm_{ilm}$	r_θ	The second objective function (*Costs*)
1	1	0.15	1791.1
2	1	0.18	1799.4
3	1	0.20	1806.7
4	1	0.22	1809.5
5	1	0.25	1902.1

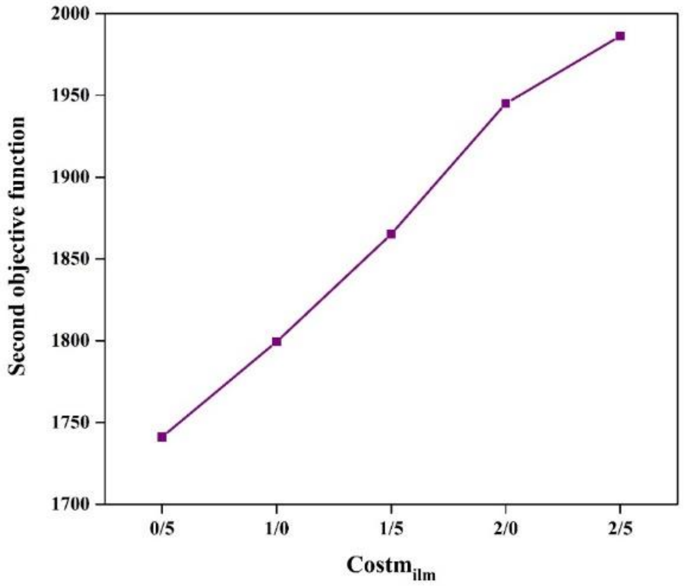

Figure 8. The behavior of the second objective function (*Costs*) of the model versus the changes in the $costm_{ilm}$

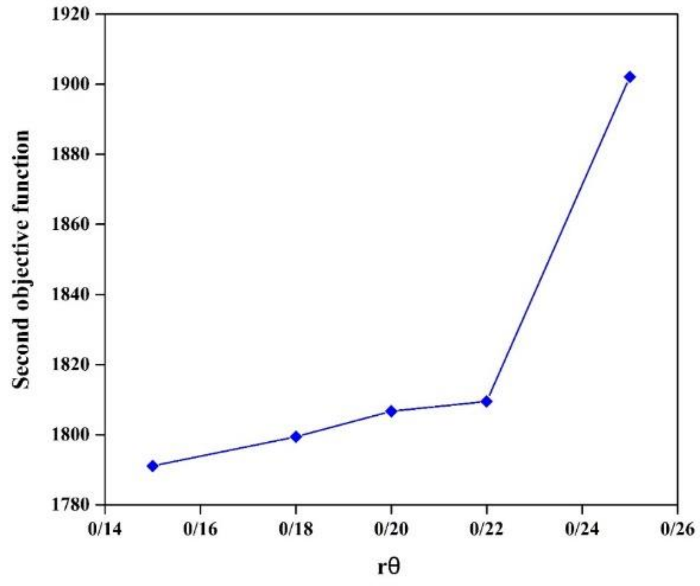

Figure 9. The behavior of the second objective function (*Costs*) of the model versus the changes in the r_θ

As evidenced by Tables 13 and 14, along with Figures 8 and 9, an augmentation in the parameters $costm_{ilm}$ (the implementation cost of activity i of project l in mode m) and r_θ (the factor responsible for increasing the purchasing cost of resources and implementing the activities due to the time value of money) escalates the value of the second objective function. This function pertains to various costs, including the purchasing cost from suppliers and the cost of project activities. Notably, within this context, the model's objective function exhibited a heightened sensitivity to fluctuations in the parameter $costm_{ilm}$.

Moreover, problem number 7, one of the large-sized problems, has been solved with varying numbers of suppliers. Subsequently, the behavior and sensitivity of the model have been explored through an evaluation of changes in the first objective function.

Table 15. The behavior of the first objective function (*Delays*) of the model versus the changes in the number of suppliers

Row	Number of suppliers	The first objective function (*Delays*)
1	3	43
2	4	37
3	5	26
4	6	21
5	7	16

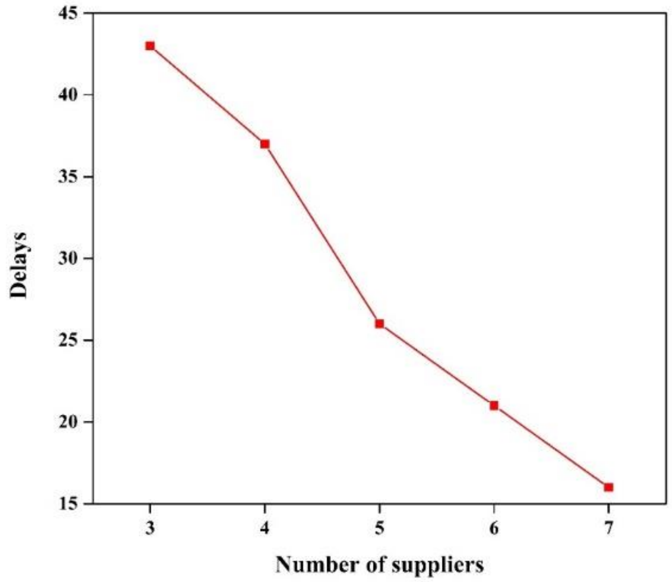

Figure 10. The behavior of the first objective function (*Delays*) of the model versus the changes in the number of suppliers

As illustrated in Figure 10, the total value of delays in the projects diminishes with an increase in the number of suppliers, leading to an overall enhancement in performance. It is significant to recognize, as seen in Figures 8, 9, and 10 that the parameters associated with resource supply management substantially influence the model's objective functions and, by extension, on project planning and management. Indeed, these findings underscore the importance and indispensability of amalgamating resource supply management with project scheduling.

6. Conclusions

This investigation explored the complex terrain of multi-mode resource-constrained multi-project scheduling within the construction industry. An integrated multi-objective mathematical model was formulated, focusing on resource supply management and the scheduling of multi-project activities. The model included various considerations, such as procuring resources from suitable suppliers and accounting for the time value of money, with the ultimate goal of concurrent minimizing total time delays and costs. Two meta-heuristic algorithms, the multi-objective whale optimization algorithm and the non-dominated sorting genetic algorithm II, were employed to resolve the proposed model.

The simultaneous construction projects conducted by a contractor in Iran were selected for analysis to assess the model's efficacy. The improvements offered by the presented model were scrutinized by applying both algorithms to this real-world scenario. Notably, the WOA outperformed NSGA-II, revealing a more effective approach. In financial terms, the implementation of projects in alignment with the proposed scheduling, combined with the multi-objective WOA, yielded a notable enhancement of up to 6%. Meanwhile, time-related improvements reached as high as 16%. These results reflect a significant benefit in minimizing simultaneously costs and delays within construction projects.

Furthermore, small and large sample problems were evaluated using WOA and NSGA-II. Through a meticulous comparison utilizing multi-objective metrics, the WOA was found to have superior quality and diversity metrics across all samples, highlighting its capacity to generate varied and well-dispersed Pareto solutions. The mean ideal distance criterion for WOA was consistently lower than NSGA-II, affirming WOA's potential to attain higher-quality solutions. In an examination of over 90% of the problems, NSGA-II exhibited greater uniformity in generated solutions, while in terms of the number of Pareto solutions, WOA surpassed NSGA-II in 60% of cases. Given WOA's intelligent solution space exploration, it necessitated more computational time compared to NSGA-II.

In conclusion, synthesizing the findings emphasizes the pivotal role of integrating resource supply management with project scheduling. Such an integration has proven to be both indispensable and potent in enhancing project performance within the construction industry. Through the use of the proposed multi-objective model and cutting-edge algorithms like WOA, optimal and tailored solutions can be derived to navigate the intricate challenges that characterize this field.

References

Abbasi S, Choukolaei HA. (2023) A systematic review of green supply chain network design literature focusing on carbon policy. Decision Analytics Journal;6:100189.

Abbasi S, Daneshmand-Mehr M, Ghane Kanafi A. (2021) The sustainable supply chain of CO2 emissions during the coronavirus disease (COVID-19) pandemic. Journal of Industrial Engineering International;17(4):83-108.

Abbasi S, Erdebilli B. (2023) Green closed-loop supply chain networks' response to various carbon policies during COVID-19. Sustainability;15(4):3677.

Abbasi S, Sıcakyüz Ç, Erdebilli B. (2023) Designing the home healthcare supply chain during a health crisis. Journal of Engineering Research;100098.

Amirian H, Bashiri M, Sahraeian R. (2014) A novel DOE-based selection operator for NSGA-II algorithm. 2nd National Conference on Industrial Engineering & Systems, Iran.

Artigues C, Demassey S, Neron E. (2013) Resource-constrained project scheduling: models, algorithms, extensions and applications: John Wiley & Sons.

Asadujjaman M, Rahman HF, Chakrabortty RK, Ryan MJ. (2021) Resource Constrained Project Scheduling and Material Ordering Problem with Discounted Cash Flows. Computers & Industrial Engineering:107427.

Azarkish M, Aghaeipour Y. (2022) A fuzzy bi-objective mathematical model for multi-depot electric vehicle location routing problem with time windows and simultaneous delivery and pick-up. Asian J Basic Sci Res;4(2):01-3.

Chen R-M, Wu C-L, Wang C-M, Lo S-T. (2010) Using novel particle swarm optimization scheme to solve resource-constrained scheduling problem in PSPLIB. Expert systems with applications;37(3):1899-910.

Chen W, Lei L, Wang Z, Teng M, Liu J. (2018) Coordinating supplier selection and project scheduling in resource-constrained construction supply chains. International Journal of Production Research;56(19):6512-26.

Cheng J, Fowler J, Kempf K, Mason S. (2015) Multi-mode resource-constrained project scheduling problems with non-preemptive activity splitting. Computers & Operations Research;53:275-87.

De Buck V, López CA, Nimmegeers P, Hashem I, Van Impe J. (2019) Multi-objective optimisation of chemical processes via improved genetic algorithms: A novel trade-off and termination criterion. InComputer Aided Chemical Engineering;46:613-618.

Deb K, Agrawal S, Pratap A, Meyarivan T. (2000) A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. InParallel Problem Solving from Nature PPSN VI: 6th International Conference Paris, France;849-858.

Deb K. (2014) Multi-objective optimization. Search methodologies. Search Methodol;403-49.

Deb K, Pratap A, Agarwal S, Meyarivan T. (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE transactions on evolutionary computation;6(2):182-97.

Dodin B, Elimam A. (2001) Integrated project scheduling and material planning with variable activity duration and rewards. Iie Transactions;33(11):1005-18.

Dodin B, Elimam AA. (2008) Integration of equipment planning and project scheduling. European Journal of Operational Research;184(3):962-80.

Elmughrabi W, Sassi OB, Dao T-M, Chabaane A. (2020) Collaborative supply chain planning and scheduling of construction projects. IFAC-PapersOnLine;53(2):10761-6.

Eshraghi A. (2016) A new approach for solving resource constrained project scheduling problems using differential evolution algorithm. International journal of industrial engineering computations;7(2):205-16.

Forcael E, González M, Soto J, Ramis F, Rodríguez C, editors. (2018) Simplified Scheduling of a Building Construction Process using Discrete Event Simulation. 16th LACCEI International Multi-Conference for Engineering, Education, and Technology:"Innovation in Education and Inclusion.

Fu F, Xing W. (2021) An Agent-based Approach for Project-driven Supply Chain under Information Asymmetry. Computers & Industrial Engineering:107410.

Gao W, Abdi-khanghah M, Ghoroqi M, Daryasafar A, Lavasani M. (2018) Flow reversal of laminar mixed convection for supercritical CO2 flowing vertically upward in the entry region of asymmetrically heated annular channel. The Journal of Supercritical Fluids;131:87-98.

García-Nieves JD, Ponz-Tienda JL, Ospina-Alvarado A, Bonilla-Palacios M. (2019) Multipurpose linear programming optimization model for repetitive activities scheduling in construction projects. Automation in construction;105:102799.

Ghoroqi M, Ghoddousi P, Makui A, Shirzadi Javid AA, Talebi S. (2023) An Integrated Model for Multi-Mode Resource-Constrained Multi-Project Scheduling Problems Considering Supply Management with Sustainable Approach in the Construction Industry under Uncertainty Using Evidence Theory and Optimization Algorithms. Buildings;13(8).

Habibi F, Barzinpour F, Sadjadi SJ. (2017) A multi-objective optimization model for project scheduling with time-varying resource requirements and capacities. Journal of industrial and systems engineering;10(special issue on scheduling):92-118.

Habibi F, Barzinpour F, Sadjadi SJ. (2019) A mathematical model for project scheduling and material ordering problem with sustainability considerations: A case study in Iran. Computers & industrial engineering;128:690-710.

Hansen P, Mladenović N, Moreno Perez JA. (2010) Variable neighbourhood search: methods and applications. Annals of Operations Research;175:367-407.

Herroelen W. (2005) Project scheduling—Theory and practice. Production and operations management;14(4):413-32.

Joo B, Chua P, editors. (2017) Multimode resource-constrained multi-project scheduling with ad hoc activity splitting. 2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM).

Kannimuthu M, Ekambaram P, Raphael B, Kuppuswamy A. (2018) Resource unconstrained and constrained project scheduling problems and practices in a multiproject environment. Advances in Civil Engineering.

Khandelwal M, Marto A, Fatemi SA, Ghoroqi M, Armaghani DJ, Singh TN, Tabrizi O. (2018) Implementing an ANN model optimized by genetic algorithm for estimating cohesion of limestone samples. Engineering with Computers;34:307-317.

Liu SS, Chen WT, editors. (2012) Construction multi-project scheduling model considering different resource allocation behavior. Applied Mechanics and Materials: Trans Tech Publ.

Love PE, Irani Z, Edwards DJ. (2004) A seamless supply chain management model for construction. Supply chain management: an international journal.

Mirjalili S, Lewis A. (2016) The whale optimization algorithm. Advances in engineering software;95:51-67.

Mohammed HM, Umar SU, Rashid TA. (2019) A systematic and meta-analysis survey of whale optimization algorithm. Computational intelligence and neuroscience.

Mojtahedi SF, Tabatabaee S, Ghoroqi M, Soltani Tehrani M, Gordan B, Ghoroqi M. (2019) A novel probabilistic simulation approach for forecasting the safety factor of slopes: a case study. Engineering with Computers;35:637-46.

Montgomery DC. (2017) Design and analysis of experiments. John wiley & sons.

Nabipoor Afruzi E, Aghaie A, Najafi AA. (2020) Robust optimization for the resource-constrained multi-project scheduling problem with uncertain activity durations. Scientia Iranica;27(1):361-76.

Néron E, Baptista D, editors. (2002) Heuristics for the multi-skill project scheduling problem. International Symposium on Combinatorial Optimization (CO'2002).

Pinha D, Ahluwalia R, Senna P. (2016) The combinatorial multi-mode resource constrained multi-project scheduling problem. International Journal of Supply and Operations Management;3(3):1391-412.

Rahimi I, Gandomi AH, Deb K, Chen F, Nikoo MR. (2022) Scheduling by NSGA-II: Review and bibliometric analysis. Processes;10(1):98.

Rahman HF, Chakrabortty RK, Ryan MJ. (2020) Memetic algorithm for solving resource constrained project scheduling problems. Automation in Construction;111:103052.

Rana N, Latiff MS, Abdulhamid SI, Chiroma H. (2020) Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments. Neural Computing and Applications;32:16245-77.

Rao PB, Chaitanya K. (2015) Resource constrained project scheduling problems-a review article. International Journal of Science and Research;4(3):1509-12.

Reza Hoseini A, Noori S, Ghannadpour SF. (2021) Integrated scheduling of suppliers and multi-project activities for green construction supply chains under uncertainty. Automation in Construction;122:103485.

Shadrokh S, Kianfar F. (2007) A genetic algorithm for resource investment project scheduling problem, tardiness permitted with penalty. European Journal of Operational Research;181(1):86-101.

Shahnazar A, Nikafshan Rad H, Hasanipanah M, Tahir MM, Jahed Armaghani D, Ghoroqi M. (2017) A new developed approach for the prediction of ground vibration using a hybrid PSO-optimized ANFIS-based model. Environmental earth sciences;76:1-7.

Sharma S, Bansal V. (2018) Location-based planning and scheduling of highway construction projects in hilly terrain using GIS. Canadian Journal of Civil Engineering;45(7):570-82.

Shen Y, Zhang C, Gharehchopogh FS, Mirjalili S. (2023) An improved whale optimization algorithm based on multi-population evolution for global optimization and engineering design problems. Expert Systems with Applications;215:119269.

Sheykh SM, Shadrokh S, Hasanzadeh F. (2009) Concurrent project scheduling and material planning: A genetic algorithm approach.

Shirzadi Javid AA, Abolghasemi MS, Ghoroqi M. (2017) The investigation of the effective factors on the maintenance and repair of installations in hospitals. 1st National Conference on Repair and Maintenance of Concrete Structures.

Shtub A. (1988) The integration of CPM and material management in project management. Construction Management and Economics;6(4):261-72.

Singh A. (2014) Resource constrained multi-project scheduling with priority rules & analytic hierarchy process. Procedia engineering;69:725-34.

Smith-Daniels DE, Aquilano NJ. (1984) Constrained resource project scheduling subject to material constraints. Journal of Operations Management;4(4):369-87.

Song W, Kang D, Zhang J, Xi H. (2016) Decentralized multi-project scheduling via multi-unit combinatorial auction. Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems;836-844.

Suresh M, Dutta P, Jain K. (2015) Resource constrained multi-project scheduling problem with resource transfer times. Asia-Pacific Journal of Operational Research;32(06):1550048.

Tabrizi BH, Ghaderi SF. (2015) An integrated mixed-integer programming model to address concurrent project scheduling and material ordering. International Journal of Industrial and Manufacturing Engineering;9(11):1960-3.

Tavakkoli-Moghaddam R, Azarkish M, Sadeghnejad-Barkousaraie A. (2011) A new hybrid multi-objective Pareto archive PSO algorithm for a bi-objective job shop scheduling problem. Expert Systems with Applications;38(9):10812-21.

Tonnizam Mohamad E, Jahed Armaghani D, Ghoroqi M, Yazdani Bejarbaneh B, Ghahremanians T, Abd Majid MZ, Tabrizi O. (2017) Ripping production prediction in different weathering zones according to field data. Geotechnical and Geological Engineering;35:2381-99.

Van Peteghem V, Vanhoucke M. (2010) A genetic algorithm for the preemptive and non-preemptive multi-mode resource-constrained project scheduling problem. European Journal of Operational Research;201(2):409-18.

Vanhoucke M, Coelho J. (2019) Resource-constrained project scheduling with activity splitting and setup times. Computers & Operations Research;109:230-49.

Wang H-W, Lin J-R, Zhang J-P. (2020) Work package-based information modeling for resource-constrained scheduling of construction projects. Automation in construction;109:102958.

Wang L, Fang C. (2011) An effective shuffled frog-leaping algorithm for multi-mode resource-constrained project scheduling problem. Information Sciences;181(20):4804-22.

Zoraghi N, Shahsavar A, Abbasi B, Van Peteghem V. (2017) Multi-mode resource-constrained project scheduling problem with material ordering under bonus–penalty policies. Top;25(1):49-79.