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ORIGINAL RESEARCH

A hybrid metaheuristic and simulation approach towards green project scheduling

Rahmat Rabet[1] · Seyed Mojtaba Sajadi[2] · Mahshid Tootoonchy[3]

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Abstract

This research tackles the environmental concern of greenhouse gas emissions in the execution of projects, with a focus on multi-site projects where the transportation of resources is a major source of emissions. Despite growing consciousness among consumers and stakeholders about sustainability, the domain of project scheduling has often overlooked the environmental impact. This paper seeks to bridge this oversight by exploring how to reduce greenhouse gas emissions during both project activities and resource transportation. A novel approach is proposed, combining a simulation model with an improved non-dominated sorted genetic algorithm. The simulation model incorporates the stochastic nature of emission rates and costs. This method is further refined with innovative techniques such as magnet-based crossover and mode reassignment. The former is a genetic algorithm operation inspired by magnetic attraction, which allows for a more diverse and effective exploration of solutions by aligning similar 'genes' from parent solutions. The latter is a strategy for reallocating resources during project execution to optimize efficiency and reduce emissions. The efficacy of the proposed method is validated through testing on 2810 scenarios from established benchmark libraries, 100 additional scenarios adhering to the conventional multi-site problems, and a case study. The Best-Worst Method (BWM) is applied for identifying the best solution. The findings indicate substantial enhancements compared to traditional methods with a 12.7% decrease in project duration, 11.4% in costs, and a remarkable 13.6% reduction in greenhouse gas emissions.

Keywords Simulation-based optimization · Green project scheduling · Multi-site · Multi-mode · Resource-constrained

1 Introduction

In project-oriented organizations, project scheduling is a central problem and managers face pressure to deliver projects to meet performance criteria of the investors, such as project

✉ Seyed Mojtaba Sajadi
s.sajadi@aston.ac.uk

1 Islamic Azad Univeristy, Science and Research Branch, Tehran, Iran

2 Operations and Information Management Department, Aston Business School, Aston University, Birmingham, UK

3 The University of Sydney, Faculty of Engineering, School of Project Management, Sydney, NSW 2037, Australia

duration, costs, or quality (Tian et al., 2022; Wei et al., 2023). However, the complexity of project scheduling is further compounded by the stochastic nature of key parameters, including emission rates and costs, which can vary significantly due to uncertainties in resource availability, environmental conditions, and market fluctuations. In the following paragraphs, different variations of the project scheduling problems are briefly introduced, including resource-constrained, multi-mode, and multi-site problems. Subsequently, the environmental aspects together with the stochastic nature of the project scheduling problems are discussed.
The primary concern in Project Scheduling Problem (PSP) is finding an optimal sequence of activities to minimize project makespan. However, the scarcity of resources limits the project managers' options for finding the precedence-feasible optimal allocation of resources. Former studies widely investigated Resource-Constrained Project Scheduling Problem (RCPSP) (Delgoshaei et al., 2017, 2016, 2015). Organizations attempt to control and decrease makespan by dedicating more resources to critical activities to execute them in faster modes. The Multi-Mode Resource-Constrained Project Scheduling Problem (MMRCPSP) considers different activities' durations depending on the availability of resources. Considering multiple modes of activities increases the flexibility and complexity of the RCPSP, as they offer more choices for resource allocation trade-offs and the opportunity to dedicate resources to the most effective activities. However, concentrating on faster modes to reduce the project makespan causes escalations in project expenditures. Thus, many scholars have proposed solutions in the literature considering project costs (Sajadi et al., 2017).
Multi-site multi-mode resource-constrained project scheduling problem (MSMMRCPSP) is a generalization of the classic RCPSP. MSMMRCPSP is a pertinent problem, as it can be applied to various domains, such as construction, manufacturing, logistics, and disaster relief (Cheraghi et al., 2023; Fink & Gerhards, 2021; Laurent et al., 2017). While project duration and costs are common objectives for the PSP, greenhouse gas emissions are a relatively new objective in the literature, reflecting the environmental responsibility and sustainability of project management (Makhova et al., 2023). These objectives are often conflicting or interrelated, as reducing one may increase another. Therefore, it is necessary to consider them simultaneously in solving the RCPSP and to find a balance or a trade-off among them (Zhu et al., 2021). Furthermore, projects' activities may be executed at different locations and the transportation of resources and materials between sites may influence the project duration, costs, and greenhouse gas emissions (Fernandes et al., 2021; Peng et al., 2023; Zhao & Zhe, 2021). Greenhouse gases are mainly emitted during activity implementation or resource transportation (Palander, 2016; Quiros et al., 2017; Sciara et al., 2017; Wu et al., 2018). The United States Environment Protection Agency (EPA) reports that the transportation industry, is responsible for 27% of annual greenhouse gas emissions, releasing 1.8 billion metric tons of equivalent CO_2 per year (Desai & Harvey et al., 2017). Therefore, it is essential to consider the effects of the transportation of resources in the PSP and to find efficient and sustainable solutions. Ozcan-Deniz and Zhu (2017) examined the relationship between projects' time, cost, and environmental impacts and concluded that project time and environmental impacts, positively correlate. Former research reveals that minimizing the transportation time of renewable resources reduces the emission index (Aramesh et al., 2023; Banihashemi & Khalilzadeh, 2023).
In a broader context, the objectives of the problem are inherently influenced by uncertainties. These uncertainties encompass factors such as the fluctuation in emission rates both during activity execution and transportation, as well as the associated costs tied to transportation and the utilization of renewable resources (Song et al., 2021; Lotfi et al., 2022). Despite the notable importance of these uncertainties, the current body of literature has yet to comprehensively delve into their nuanced implications. Our research objective is to develop

a simheuristic approach (a simulation model linked to a metaheuristic algorithm) to minimize greenhouse gas emissions while optimizing makespan and cost in a multi-site project, considering multiple modes and uncertainties in activities' duration.
Although few research investigated the multi-site version of the problem, this paper may be the first to propose a simheuristic approach to incorporate stochastic parameters of real-world situations (Liu et al., 2023b, 2021; Wang et al., 2021; Zhu et al., 2021). The MSMMRCPSP is tackled from both a theoretical and a practical perspective. A novel mathematical model that captures the main characteristics and challenges of MSMMRCPSP is proposed. Moreover, The MSMMRCPSP is a highly combinatorial and nonlinear problem that belongs to the class of Non-deterministic Polynomial-time hard (NP-hard) problems. Kolisch and Drexl (1997) demonstrated that finding a feasible solution for MSMMRCPSP with more than one non-renewable resource is an NP-hard problem. Therefore, the Non-dominated Sorting Genetic Algorithm (NSGA-II) enhanced by a simulation model that incorporates uncertainty that can cope with complexity and diversity is applied as a simheuristic algorithm. Therefore, the main contributions of this study are:

- Minimizing greenhouse gas emissions during transportation and project activities.
- Developing a hybrid approach by coordinating a simulation model, an improved version of the NSGA-II incorporating uncertainties of several parameters, and the BWM to single out the best fitting solution.
- Proposing a new multi-objective mixed-integer linear programming (MILP) model that considers multiple sites for the MMRCPSPs.

The performance of the proposed model and algorithm is evaluated on two single site sets of instances from the literature (PSPLIB by Kolisch and Drexl (1997) and MMLIB by Van Peteghem and Vanhoucke (2014)) and compared with state-of-the-art approaches. Additionally, 100 randomly selected instances are extended to meet multi-site conditions with deterministic parameters and solved by the proposed algorithm. Finally, a real-world case study is solved with uncertain parameters. Multi-objective metaheuristic methods generate a set of non-dominated solutions, not all of which are practical; however, project managers require a specific solution that complies with multiple concerns and predetermined criteria. To address this issue, a Multi-Criteria Decision-Making method namely the Best Worst Method (BWM) developed by Rezaei et al. (2015), is applied to find the best solution from the last Pareto front of the algorithm.

The remainder of this paper unfolds as follows: Sect. 2 conducts a thorough review of relevant literature, contextualizing the research. In Sect. 3, the problem is defined, and a novel model is introduced for the MSMMRCPSP. Section 4 outlines the proposed methodology, including the simulation model, multi-objective meta-heuristic algorithm, and the application of the Best Worst Method. Moving to Sect. 5, an empirical comparison of the solution approach with state-of-the-art algorithms is presented, using instances from well-known libraries, alongside a practical case study demonstrating the algorithm's efficacy. Sections 6 and 7 respectively discuss practical implications and conclude, while also pointing toward potential future research directions. This structured framework guides readers through the study's various facets, fostering a comprehensive grasp of the proposed methodology and its implications.

2 Literature review

Project scheduling is a critical component of project management. Precedence constraints between a project's activities necessitate a predetermined sequence of activities (Chu et al., 2023; Laurent et al., 2017; Nemati-Lafmejani et al., 2019; Shariatmadari et al., 2017). Resource scarcity and sharing are other common issues in project scheduling. The RCPSP aims to schedule a project's activities based on precedence and resource sharing/scarcity to minimize the project's makespan (Hartmann & Briskorn, 2022; Pellerin et al., 2020). Previous research has applied optimization models to address RCPSP's constraints in project management (Chakrabortty et al., 2016; Golab et al., 2023). One of the primary concerns in project scheduling for production systems and manufacturing is the allocation of renewable resources (Wang et al., 2021). The availability of renewable and non-renewable resources affects the time–cost trade-off in projects (Hafezalkotob et al., 2018; Hochbaum, 2016; Hussain & Hussain, 2023; Nemati-Lafmejani et al., 2019). The RCPSP has garnered increasing interest from decision-makers and scholars. Numerous studies have considered single/multi-objective problems from various perspectives. Sánchez et al. (2023) have published a survey regarding multi-project scheduling problems.
Our research endeavor aims to formulate a simheuristic methodology. This intricate approach considers various project types, project modes, and solution approaches. In the forthcoming sections, the array of objectives encompassed by this study have been meticulously examined. Furthermore, this study offers a comprehensive exploration and valuable contribution to the existing project scheduling body of knowledge.

2.1 Project type: multi-site versus multi-project

In a single but multi-site project, mobile resources shall move from one site to the other. When a mobile resource is required for several consecutive activities on various sites, the transportation time of this resource and the precedence relation of activities shall be considered. Modeling the transportation time can minimize the project execution time. In contrast, in a multi-project case, mobile resources are transferred between the locations of several projects (Villafáñez et al., 2019). In general, two components must be considered when applying heuristics for feasible project scheduling: the priority rule and project scheduling.

- Priority rule: determines the order of activities based on processing time, cost, network information, total slack, and activities' earliest start time/latest finish time (Luo et al., 2023).
- Project scheduling: This can be done in three ways: a) Serial scheduling, where the algorithm determines the order of activities once at the beginning; b) Parallel scheduling, where the algorithm dynamically re-determines the orders to reduce the number of delayed activities; and c) Backward scheduling, where the algorithm dynamically re-determines the order from the desired completion date (Lalas et al., 2006). Zhang et al. (2023) combined the parallel and serial scheduling schemes. Tritschler et al. (2017) proposed a parallel scheduling approach and variable neighborhood search to solve the RCPSP with flexible resource profiles. Poppenborg and Knust (2016a) also proposed a flow-based algorithm for RCPSP for resource flows in serial and parallel directions.

A single-project multi-site algorithm combines sub-projects into a mega-project with a single critical path (Browning & Yassine, 2010). Some research addresses the multi-project scheduling problem, where the transfer time between each project has been modeled (Issa et al., 2021; Krüger & Scholl, 2010; Saif et al., 2022; Zhang et al., 2022). Considering different locations is common in a multi-project setting (Rostami & Bagherpour, 2020). Therefore, a single project can be widely expanded to solve the multi-project case. Previous research has been extended by modeling the RCPSP considering the transportation times of a multi-site single project with serial, parallel, and backward scheduling. This model can be extended to a multi-site multi-project (as a mega-project) by considering the critical paths of all included projects (Browning & Yassine, 2010).

2.2 Project mode: single versus multi-mode

The various modes of the resource-constrained scheduling problem explain the different modes in which a single activity can be executed (Elloumi et al., 2017). Krüger and Scholl (2010) first proposed a framework for single/multi-project scheduling problems given resource transfers and developed two linear and mixed-integer programming models. Hessami et al. (2024) studied the MSMMRCPSP with the ability to transport resources among the project sites, aiming to minimize the total project time and cost simultaneously. To this end they developed a bi-objective optimization model. Then, they applied the ϵ-constraint method to solve 24 different-sized instances and performed sensitivity analysis to find the impact of changing parameters on objective values. Rostami et al. (2017) considered a decentralized resource-constrained multi-project scheduling problem with periodic services aiming to minimize associated costs using a mixed-integer linear programming model for small-scale instances and an ant colony bee optimization algorithm for large-scale instances. Stiti and Driss (2019) investigated a multi-site resource-constrained project scheduling problem and adapted a particle swarm optimization algorithm aiming to minimize the project duration. Kadri and Boctor (2018) proposed a genetic algorithm for sequence-dependent transfer times and the single-mode version of the problem using idle resources waiting to be transferred within the schedule. Kadri et al. (2014) solved the project scheduling problem with transfer times considering multiple modes by assigning each activity a mode and then solving it in the single-mode version. They then used improvement techniques to shorten the project timeline. In this research, the multi-site multi-mode resource-constrained project scheduling problem is addressed considering resource transfer times between sites.

2.3 Solution approach

The realm of project scheduling problems has seen notable advancements through various innovative approaches. Former studies contribute collectively to enriching this understanding of project scheduling dynamics. Hessami et al. (2024) investigated MSMMRCPSP and developed a bi-objective model to minimize the total cost and the total completion time of the project. They applied ϵ-constrained method to solve 24 different-sized instances, ranging from 5 to 120 activities. Bigler et al. (2024) delved into the multi-site resource constrained projects and presented a continuous-time model using binary variables to arrange a sequence for activities assigned to a set of resources and compared the performance of the model with a devised matheuristic algorithm. Liu et al. (2023a) studied the project scheduling problem with unit-capacity resources and transfer times. They designed five dominance rules to speed up the exploration of applied branch-and-bound tree by After identifying identical and unpromising nodes. Also, They suggested a heuristic using a series of priority rules to compute two lower bounds and produce an upper bound.

Chen et al. (2022) developed a Genetic Algorithm with a heuristic workforce assignment procedure considering material arrival times. They solved a multi-project case study using their model. Abdzadeh et al. (2022) integrated the PSP with supplier selection and transportation problems and proposed a tabu search algorithm to solve the problem and reduce associated costs. Liu et al. (2023b) have solved the PSP with resource transfer times using an improved serial schedule generation scheme and a tree search heuristic method that prunes unpromising nodes in the search tree. Liu et al. (2021) proposed two methods for a unit-capacity resource-constrained version of the PSP with transfer times based on neighborhood search to minimize project duration. Zhao and Zhe (2021) developed a policy-based approximate dynamic programming algorithm for solving decentralized multi-project scheduling problems with transfer times. They also built and examined the performance of 12 priority rule heuristics. Patoghi and Mousavi (2021) developed a mathematical model for a combination of ordering problems considering discount policy and the multi-site version of the RCPSP to minimize project duration and total costs. Wei et al. (2023) considered a partial RCPSP for the execution of parallel activities in single projects to achieve the minimum makespan. Wang et al. (2021) compared the performance of two metaheuristics namely NSGA-II and Pareto simulated annealing with the ϵ-constraint method and then solved a case study. Ren et al. (2020) scheduled a case study of an aircraft moving assembly line using a branch-and-bound embedded genetic algorithm, presuming that resource transfers and activities are coupled with each other.

Rostami and Bagherpour (2020) investigated a decentralized multi-project scheduling problem and proposed a mixed integer linear programming model and an adapted GA aiming to minimize the costs attributed to facility location and costs related to the project duration. They applied a scenario-based TOPSIS approach (Technique for Order of Preference by Similarity to Ideal Solution) to rank the final solutions. Ma et al. (2019) examined the tradeoff between the number of activities splitting times and resource transfer times in an uncertain environment. They solved the model with a commercial mathematical programming solver and a tabu search algorithm and found out that robustness has a direct relationship with the project due date and has a reversed relationship with transfer times. Poppenborg and Knust (2016b) applied the project scheduling problem with transfer times to a hospital evacuation case study and proposed a decomposition-based tabu search algorithm with priority rules.

Limited research has ventured into the utilization of simulation-based optimization methodologies for tackling this specific project type. Notably, the incorporation and thorough analysis of uncertainties associated with activities' durations and other relevant factors should be underscored. It is imperative to acknowledge that conventional techniques have struggled to offer optimal solutions in the face of these challenges.

2.4 Summary of literature review findings

Table 1 listed the relevant papers on the transportation of resources in the PSP Literature. According to Table 1, distinctive contribution of this paper lies in the simultaneous minimization of greenhouse gas emissions while optimizing for makespan, and cost within a multi-site project by meticulous consideration of various activities' modes and uncertainties inherent in the duration of activities. While prior works have not addressed sequence-independent transfer times, this paper makes a unique contribution by incorporating this factor into the analysis. In addition, a unique mathematical model is presented to describe the model accurately and then a simheuristic approach is developed to solve the problem. By doing so, this paper provides a more comprehensive understanding of the impacts of resource transportation in project scheduling taking environmental aspects into account.

Table 1 Resource transfer scheduling in the PSP literature

Author(s)	Project Type		Activities' Mode		Solution Approach				Scheduling			Objectives		
	Multi-Site	Multi-Project	Single mode	Multi-mode	Exact	Meta/Heuristic	Simheuristic	MCDM	Backward	Serial	Parallel	Makespan	Cost	Gas Emission
Krüger and Scholl (2010)		✓	✓		✓					✓		✓	✓	
Poppenborg and Knust (2016a)	✓		✓			✓				✓	✓	✓		
Kadri et al. (2014)	✓			✓	✓					✓		✓		
Poppenborg and Knust (2016b)	✓		✓			✓				✓	✓	✓		
Suresh et al. (2015)		✓	✓			✓				✓			✓	
Laurent et al. (2017)	✓		✓		✓	✓				✓			✓	
Tritschler et al. (2017)	✓		✓			✓				✓	✓	✓		
Rostami et al. (2017)		✓	✓		✓	✓				✓			✓	
Kadri and Boctor (2018)	✓		✓			✓			✓	✓	✓	✓		
Ma et al. (2019)	✓		✓			✓				✓		✓		
Stiti and Driss (2019)	✓		✓			✓				✓		✓		
Ren et al. (2020)	✓		✓		✓	✓				✓		✓		
Rostami and Bagherpour (2020)	✓		✓		✓	✓		✓		✓	✓		✓	
Zhao and Zhe (2021)		✓	✓			✓				✓		✓		
Patoghi and Mousavi (2021)	✓			✓	✓					✓		✓	✓	
Wang et al. (2021)	✓		✓		✓	✓				✓		✓	✓	
Liu et al. (2021)	✓		✓			✓				✓		✓		
Abdzadeh et al. (2022)		✓	✓			✓				✓			✓	
Chen et al. (2022)		✓	✓			✓				✓			✓	
Liu et al. (2023b)	✓		✓			✓				✓		✓		
Wei et al. (2023)	✓		✓			✓					✓	✓		
Liu et al. (2023a)	✓		✓		✓	✓				✓		✓		
Bigler et al. (2024)	✓		✓		✓	✓				✓		✓		
Hessami et al. (2024)	✓			✓	✓					✓		✓	✓	
This study	✓			✓		✓	✓	✓	✓	✓	✓	✓	✓	✓

3 Problem description and formulation

3.1 Problem description

The MSMMRCPSP consists of J activities whose relationships are described by a graph ($G(U, E)$). In this graph, nodes are sets of activities ($U = \{1, ..., J\}$), and edges (E) are precedence relationships between each activity in a set. These activities have zero-lag and finish-to-start relationships, indicating that an activity can only commence once its predecessors (P_j) are completed and its successors (Z_j) can only begin after its completion. The problem entails allocating renewable and non-renewable resources to activities, which can be executed in various modes with distinct durations, resource requirements, and costs. The total available renewable resources of type k and the total available non-renewable resources of type w for the projects are denoted by R_k and N_w respectively. Each activity can be implemented in a mode ($m_j \in \{1, ..., M\}$). The duration of activities in their modes is denoted by $d_{j,m}$ and required renewable resources of type $k \in K$ and required non-renewable resources of type $w \in W$ which is necessary to fulfill activity j in mode m_j are denoted by ($R'_{j,m,k}$) and $N'_{j,m,w}$) separately. Implementing each activity within a mode imposes its attributed costs (CR_k and CN_w) on the total project costs. Also, the total amount of greenhouse gas emitted (G) is driven by the amount of emitted greenhouse gases during activity implementation and resource transportation.

In the MSMMRCPSP, each activity must be executed in its predefined location ($l_j \in \{1, ..., L\}$) and resources are allocated to each location. After fulfilling each task renewable resources can be allocated to the activities in the same location or be scheduled for any other locations. The transfer times for all renewable resources between the location of the i^{th} activity and the location j^{th} activity is denoted by $\delta_{i,j}$. Transfer times must fulfill the triangular inequality ($\delta_{i,j} < \delta_{i,h} + \delta_{h,j}$ ($\forall i, j, h \in J$)). This inequality constraint makes sure that all routes are the fastest route, and no shortcut is available. Transportation costs, resource consumption costs, emission rate of transportation, and emission rate during activity implementation are considered stochastic. Additionally, since non-renewable resources are assumed to be directly transported to their determined locations at the beginning of the project and will not be transported thereafter, the sum of the transfer times for non-renewable resources is constant and negligible. Table 2 lists the indices, parameters, variables, and objective functions of this study.

Figure 1 illustrates a simple numerical example of a single-mode version of the PSP at three locations with two dummy activities (1 and 10). The first dummy activity distributes renewable resources, while the latter collects them. Equation 1 displays a sample for Delta matrix, which shows the transfer times between activities i, j and h. Transfer times within a location are not significant and are therefore excluded from the model and this study. Figure 2 presents the optimal solution for the numerical example, which includes three locations ($L1$, $L2$, and $L3$). When transfer times are considered, the makespan is 15 days. However, if transfer times were ignored, the project makespan would be 11 days.

Although controlling and monitoring project makespan and costs are highly tied to the availability of resources and logistics concerns, the environmental effects of activity implementation and resource transportation have received minor attention in conventional studies. Hence, this research aims to reduce Greenhouse gas emissions (G) while reducing project duration (D), and total project costs (C). This pursuit of optimizing renewable resource scheduling serves to advance sustainability objectives, augmenting the significance of the

Table 2 Notations of the MSMMRCPSP

Symbols	Description
Indices	
$i, j, h \in U = \{1, ..., J\}$	Activity
$k \in \{1, ..., K\}$	Renewable resource type
$n \in \{1, ..., N\}$	Non-renewable resource type
$m \in \{1, ..., M\}$	Mode of the activity
$t \in \{1, ..., T\}$	Time
$l \in \{1, ..., L\}$	Location
Parameters	
P_j	Predecessors of the j-th activity
π_j	Indirect predecessors of the j-th activity
Z_j	Successors of the j-th activity
Q_j	Indirect successors of the j-th activity
$d_{j,m}$	Duration of the j-th activity in mode m
R_k	Total available renewable resource type k
N_w	Total available non-renewable resource type w
$R'_{j,m,k}$	Required k-th renewable resource for implementing j-th activity in mode m
$N'_{j,m,w}$	Required non-renewable resource from w-th type for j-th activity in mode m
$\Delta_{i,j}$	Transfer time between i-th and j-th activity locations
EST_j	Earliest start time of the j-th activity
LST_j	Latest start time of the j-th activity
τ_j	$[EST_j, LST_j]$
L_j	Location of the j-th activity
CR_k	Costs of utilizing one unit of the k-th renewable resource
CN_w	Cost of consuming the w-th nonrenewable resource type
CT_k	Cost of transporting k-th renewable resource per unit of time
θ	Conversion factor for calculating emitted greenhouse gases during activity implementation
θ'	Conversion factor for calculating emitted greenhouse gases during resource transfer
Decision Variables	
$x_{j,m,t}$	The binary variable takes 1 if j-th activity is scheduled for time t in mode m, otherwise 0
$y_{i,j,k}$	Binary variable takes 1 if at least one unit of k-th renewable resource type is transferred from i-th activity location to j-th one
$f^R_{i,j,k}$	The amount of k-th renewable resource type transferred from i-th activity location to j-th one
Objectives	
D	Duration of the Project
C	Total costs (modes and transportation costs)
G	The amount of greenhouse gas emitted (Ton)

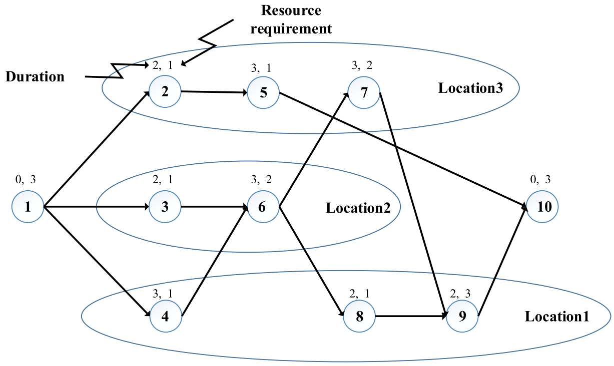

Fig. 1 Activity on the node network of the example

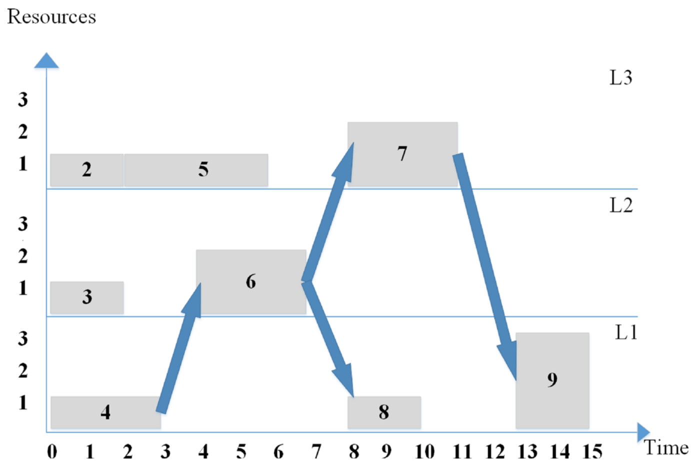

Fig. 2 Resource transfers in the optimum solution of the example

research.

$$\Delta_{i,j,h} = \begin{bmatrix} 0 & 1 & 2 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix} \tag{1}$$

3.2 Problem formulation

A mathematical model of the problem, inspired by Kadri and Boctor (2018) is developed as follows:

$$D = \sum_{m=1}^{M} \sum_{t=1}^{\tau} t x_{f,m,t} \tag{2}$$

$$C = \sum_{i=1}^{J} \sum_{j=1}^{J} \sum_{k=1}^{K} CT_k \Delta_{i,j} f_{i,j,k}^{R} + \sum_{i=1}^{J} \sum_{m=1}^{M} \sum_{t=1}^{\tau} \sum_{k=1}^{K} CR_k R_{i,m,k} x_{i,m,t}$$

$$+\sum_{i=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{\tau}\sum_{w=1}^{W} CN_w N_{i,m,w} x_{i,m,t} \tag{3}$$

$$G = \sum_{i=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{\tau} d_{i,m}\theta x_{i,m,t} + \sum_{i=1}^{J}\sum_{j=1}^{J}\sum_{k=1}^{K} \Delta_{i,j}\theta' f^{R}_{i,j,k} \tag{4}$$

Subject to:

$$\sum_{m=1}^{M}\sum_{t=1}^{\tau} d_{i,m}\theta x_{i,m,t} = 1 \qquad \forall i \in U \tag{5}$$

$$\sum_{m=1}^{M}\sum_{t=1}^{\tau} t x_{j,m,t} - \sum_{m=1}^{M}\sum_{t=1}^{\tau} (t + d_{i,m}) x_{i,m,t} \geq 0 \qquad \forall i, j \in P \tag{6}$$

$$\sum_{m=1}^{M}\sum_{t=1}^{\tau} t x_{j,m,t} - \sum_{m=1}^{M}\sum_{t=1}^{\tau} (t + d_{i,m}) x_{i,m,t} - (T - \Delta_{i,j}) y_{i,j,k} \geq T$$
$$\forall i \in U - \{J\},\ \forall j \in U - \{\pi_i\},\ \forall k \in K \tag{7}$$

$$f^{R}_{i,j,k} \leq min(R_{i,m,k}, R_{j,m,k}) y_{i,j,k} \qquad \forall i \in U - \{J\},\ \forall j \in U - \{\pi_i\},\ \forall k \in K \tag{8}$$

$$\sum_{i \in U - \{Q_i\}} f^{R}_{i,j,k} = \sum_{m=1}^{M} R_{j,m,k} \qquad \forall j \in U - \{1\},\ \forall k \in K \tag{9}$$

$$\sum_{j \in U - \{\pi_i\}} f^{R}_{i,j,k} = \sum_{m=1}^{M} R_{i,m,k} \qquad \forall j \in U - \{J\},\ \forall k \in K \tag{10}$$

$$x_{i,m,t} \in \{0, 1\} \qquad \forall i \in U,\ \forall m \in M,\ \forall t \in \tau_i \tag{11}$$

$$y_{i,j,k} \in \{0, 1\} \qquad \forall i \in U - \{J\},\ \forall j \in U - \{\pi_i\},\ \forall k \in K \tag{12}$$

$$f^{R}_{i,j,k} \geq 0 \qquad \forall i \in U - \{J\},\ \forall j \in U - \{\pi_i\},\ \forall k \in K \tag{13}$$

Equation (2) calculates the total duration of the project (D) based on the finish time of the last activity. The project cost (C) for implementing activities in their respective modes is determined using Eq. (3), which comprises three components that calculate the cost of transporting renewable resources and the costs of consuming both renewable and nonrenewable resources. Equation (4) calculates the amount of CO_2-equivalent greenhouse gas emitted (G) during the implementation of activities in their relevant mode and renewable resource transfers. Constraint (5) ensures that each activity is executed within its designated time window (τ_i) without being split or preempted. Constraint (6) ensures that all activities are scheduled after their predecessors. Constraint (7) stipulates that when transferring some units of resource k from activity i to activity j, the transfer time must be considered. Constraints (8) ensure that the number of transferred resources ($f^{R}_{i,j,k}$) does not exceed the available or required resources. Constraints (9) and (10) are resource-flow conservation constraints, which ensure that the flow of resources into and out of each activity is conserved. Constraints (11), (12), and (13) define the domain of the model's decision variables.

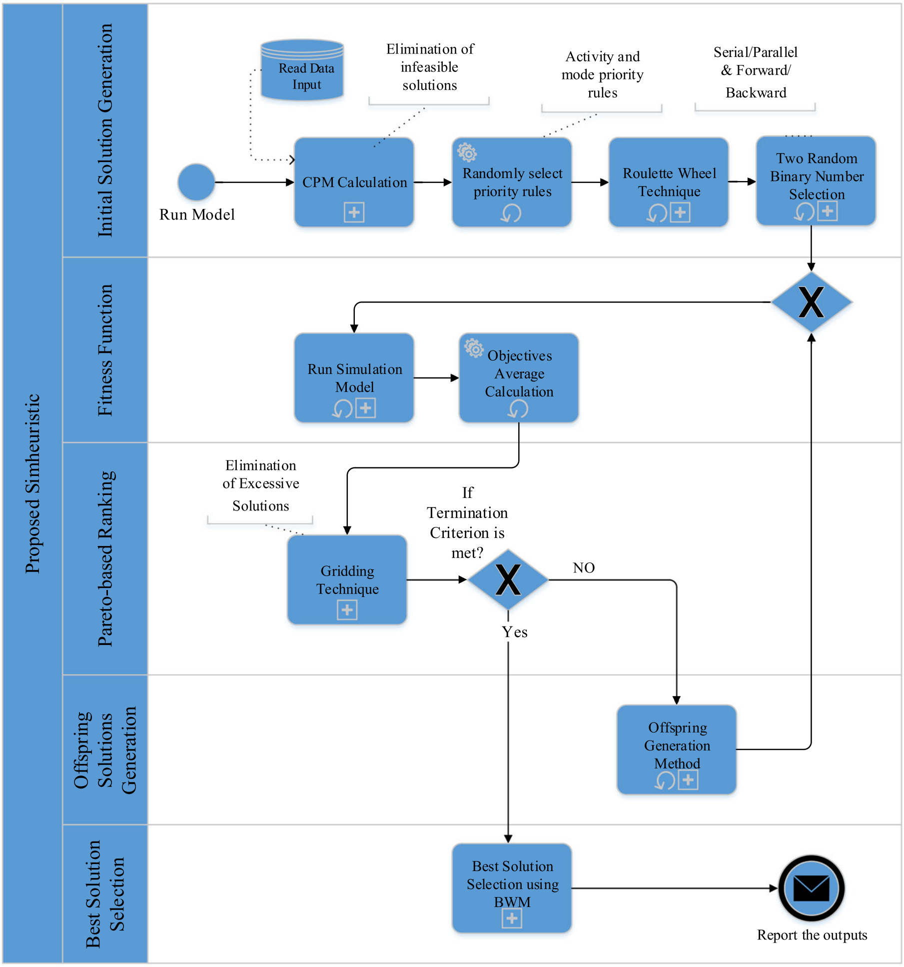

Fig. 3 The proposed Simheuristic approach

4 The simheuristic approach

The paper presents a comprehensive solution methodology comprised of two key elements: a scheduling simulation model and a tailored adaptation of the NSGA-II algorithm, specifically designed to tackle the MSMMRCPSP. Illustrated in Fig. 3, the NSGA-II algorithm yields a set of non-dominated solutions upon execution (Amelian et al., 2019). To identify the optimal solution among these, the BWM technique is employed.

A simheuristic approach is relevant for metaheuristic and simulation problems due to its ability to deal with uncertainty and stochastic elements. This approach enhances solution quality by evaluating solutions under various scenarios, ensuring robustness (Juan et al., 2010). Additionally, it is adaptable across logistics and manufacturing problems and efficiently explore large solution spaces, leading to computational efficiency (Grasas et al., 2016). Finally, the simheuristic approach provides practical, high-quality solutions for real-world problems (Panadero et al., 2017). The choice of NSGA-II in this study is supported by its established success. NSGA-II is one of the most frequently used algorithms in the literature for various aspects of the problem, known for its broad applicability and robustness across different problem settings without requiring extensive parameter tuning (Servranckx et al., 2024; Bredael & Vanhoucke, May 2024; Liu et al., 2024).

4.1 The simulation model

Due to the stochastic nature of real-world situations, estimates for costs and greenhouse gas emissions during activity implementation and resource transportation are inherently uncertain. The costs and the rate of greenhouse gas emissions are dependent on several factors such as market fluctuations, vehicles, and activity machinery. This uncertainty directly affects the total costs (C) and emitted greenhouse gases (G), and as a result, necessitates the design of a simulation model that can effectively account for these stochastic variables. The proposed simulation model, inspired by the work of Kadri and Boctor (2018), is designed to handle both stochastic and deterministic input data types. To ensure the reliability of our results, the model was run 30 times with stochastic input data, and the averages were reported. Additionally, we conducted a sensitivity analysis to evaluate the impact of these parameters on the model's performance. The validation test results for the model outputs, presented in Sect.5, confirm the robustness of our approach. This emphasis on the stochastic nature of real-world situations is crucial for accurately modeling project scheduling problems. In this research, both serial and parallel scheduling schemes are included in the model, along with forward and backward schemes. Sections 4.1.1 and 4.1.2 describe the serial and parallel adaptations of scheduling schemes with transfer times.

4.1.1 Serial forward scheduling scheme

Forward Serial Scheduling Scheme (FSSS) begins and goes forward strictly based on the sequence of the activity list. The FSSS selects the first unscheduled activity in the sequence and each time searches the whole timeline ($\forall t \in \{0, \ldots, T\}$) to find the first suitable time unit. The optimal time unit aligns with the fulfillment of both precedence relationships and resource constraints. While precedence requirements are met by the FSSS through a straightforward scan of the timeline from the conclusion of preceding activities, adept resource constraint management necessitates the recurrent calculation of the subsequent variables each time an activity is under scrutiny for a given time instance, denoted as t:

- $F_{k,t,l}$ expresses the amount of free k^{th} renewable resource type located at l that at time t. The free resources are unscheduled from time t to the end of the scheduling horizon (T).
- $R_{k,t,l}$ represents the amount of reserved renewable resources of type k at time t and location l. The reserved resources must be returned to their location at the reserved time.
- $A_{k,j,t}$ is an $L \times 4$ matrix of the available ($F_{k,t,l}$ and $R_{k,t,l}$) amount of k^{th} resource type from all locations for the j^{th} activity starting at time t.

Equation 14 illustrates an example of $A_{k,j,t}$ matrix containing accessibility information of k^{th} renewable resource type (free and reserved) for the whole duration of the j^{th} activity. The first column corresponds to all locations, the second column represents the distances from locations to l_j. The third column shows the free resources ($F_{k,t,a}$) from all locations at starting time of the activity considering the distances. The last column represents the reserved resources of type k which are ready to arrive from all locations to the location of

```
Initialize D, C, and G with 0
For j in activity list (Chromosome):
  For t ∈ {0, ..., T}:
    If all predecessors of job j are finished:
      Calculate A_kjt(∀k ∈ {0, ..., K}:
        If A_kjt ≥ R'_jmk (∀k ∈ {0, ..., K}):
          Schedule j at time t:
          Update C using Equation (3)
          For w ∈{0, ..., W}:
            N_w = N_w − N'_imw
          For k ∈ {0, ..., K}:
            For l ∈ {0, ..., L}:
              Update F_ktl(∀t ∈ {t − Δ_lj, ..., T})
              Update R_ktj(∀t ∈ {t − Δ_jl, ..., t +d_im+ Δ_lj})
              Update G using Equation (4)
  If all activities are finished:
    Calculate D considering Equation (2)
    Update the ERR
Report the outputs
```

Fig. 4 Pseudo-code for serial forward scheduling scheme

the j^{th} location (l_j) at start time and return to the reserved location on time.

$$A_{k,j,t} = \begin{bmatrix} 1 & \Delta_{1,l} & a_{13} & a_{14} & a_{15} \\ 2 & \Delta_{2,l} & a_{23} & a_{24} & a_{25} \\ 3 & \Delta_{1,l} & a_{33} & a_{34} & a_{35} \\ \dots & \dots & \dots & \dots & \dots \\ L & \Delta_{L,l} & a_{43} & a_{44} & a_{45} \end{bmatrix} \tag{14}$$

$F_{k,t,l}$ is set equal to R_k and $R_{k,t,l}$ equal to 0 ($\forall k \in K, \forall t \in \{0, \dots, Upper-bound\}, l = 0$). Then the next activity-mode combination in the solution sequence will repeatedly be selected until the final dummy activity. At the same time, the algorithm searches the timetable from where all the predecessors of the activity are finished until the upper bound. Then schedules the activity at the earliest opportunity under the condition that a bigger or equal number of resources must be available at its location. For every chosen activity in the sequence list where precedence relationship constraints are met at time t, resource availability must be checked. To this end, the available resources matrix, known as $A_{k,j,t}$, is calculated. It contains the information on the locations, distances, and units of the free resources that can be transferred until implementation time, as well as reserved resources that would arrive in time and will return to their location before their previously assigned activity begins.

If the sum of all free and reserved available resources for set K, which includes all k types, is bigger than or equal to the required resources of the activity-mode combination, the activity can be scheduled at time t. After that, the locations in $A_{k,j,t}$ are sorted based on two priorities: first, the closest locations, and second, the locations containing the most units of free and reserved resources available. Accordingly, providing the resources must begin from the closest location containing the most resources until enough units are provided from the furthest location with the least resources. Moreover, $F_{k,t,l}$ and $R_{k,t,l}$ should be updated to incorporate the latest modifications. Figure 4 presents a pseudo-code for the proposed serial forward scheduling simulation, where T is the maximum scheduling time horizon.

Initialize D, C, and G with 0
For t ∈ {0, …, T}:
  For a_i in activity list (Chromosome):
    Generate an empty list called "Green list"
    If a_i is not scheduled:
      If all predecessors of a_i are finished:
        Append a_i to the green list
  For a_i in the green list:
    Calculate A_{kat}(∀ k ∈ {0, …, K}):
    If all $(A_{kat}) \geq R'_{amk}$ (∀ k ∈ {0, …, K}):
      Schedule a_i at time t:
      Update C using Equation (3)
      For w ∈ {0, …, W}:
        $N_w = N_w - N'_{imw}$
      For k ∈ {0, …, K}:
        For l ∈ {0, …, L}:
          Update F_{ktl}(∀ t ∈ $\{t - \Delta_{la}$, …, T})
          Update R_{kta}(∀ t ∈ {t − Δ_{al}, …, t +d_{im}+ Δ_{la}})
          Update G using Equation (4)
  If all activities finished:
    Calculate D considering Equation (2)
    Calculate ERR
Report the outputs

Fig. 5 Pseudo-code for parallel forward scheduling scheme

4.1.2 Parallel forward scheduling scheme

The parallel forward scheduling scheme (PFSS) begins and continues strictly on the project timeline. It starts from the first time-unit of the project and lists all activities that its predecessors have finished in the "Green list". Then, the PFSS checks the resource availability of activities in the green list at time t consecutively by calculating the $A_{k,j,t}$ matrix for K types of resources. The first activity that its required resources are available would be scheduled at time t. The PFSS continues to schedule activities at time t until all activities in the green list are scheduled or not enough resources are accessible for them at time t. Since the PFSS only moves forward in time, considering the reserved resources are impossible. After scheduling at time t, time moves forward by one unit. Then the same steps are repeated until timetable all activities. Figure 5 shows the pseudo-code of this process.

4.1.3 Backward scheduling schemes

In this paper, serial backward and parallel backward scheduling schemes are incorporated in the simulation model. These schemes start from a predetermined end time for the project and schedule the last activity to finish at that time. Then, they schedule the remaining activities in reverse order, following the precedence relations. The difference between forward and backward scheduling schemes is the direction of scheduling. Backward Scheduling is a classic improvement method for project scheduling and is often more successful than forward scheduling scheme in reducing the makespan (Asadujjaman et al., 2021; Pellerin et al., 2020).

Generate PG initial population
Schedule and **sort** the initial population,
While PG ≤ TC:
  Generate |PG×α| offspring solutions
  Evaluate the offspring using the simulation model
  Append offspring solutions to the population
  Sort population and remove other than G-best chromosomes
  Set PG = PG + |PG×α|
Report Final output

Fig. 6 Pseudo-code of the NSGA-II

4.2 Adapted NSGA-II

The NSGA-II is a simple meta-heuristic that is easy to understand, apply, and modify for project scheduling problems. In this study, it has been adapted to solve the MSMMRCPSP. The NSGA-II is an extended version of the Genetic Algorithm (GA) that optimizes two or more objectives (Ala et al., 2021). Inspired by the theory of evolution, the GA begins by generating an initial set of solutions called the initial population. These solutions are then evaluated using a fitness function to calculate the value of their objectives (in the case of stochastic parameters the simulation technique is applied to evaluate the fitness values). The GA ranks the solutions (known as chromosomes) and selects the best ones to reproduce a better generation by mixing genes from the selected solutions. New chromosomes are reproduced using single or multi-point crossover and mutation operators. The GA evaluates the chromosomes again using the fitness function and reproduces new generations until it reaches its termination limit.

The solution approach in this paper follows a similar structure, starting with generating $|PG|$ initial solutions and sending them to the simulation model to calculate the value of their objectives. Then, the algorithm compares the solutions with each other and ranks them based on the number of solutions that were dominated by other solutions. To search the solution space the NSGA-II selects a portion of the best solutions and reproduces a new set using these solutions.

In this step, the NSGA-II algorithm selects $|PG \times \alpha|$ chromosomes to reproduce new populations using several operators, including Two-Point Crossover (TPX), Magnet-Based Crossover (MBX), Sequence Mutation, Mode Mutation, and Mode Reassignment using the minimum Non-renewable Resource Consumption (NRC) priority rule. In genetic algorithms, crossover operators are crucial as they create new generations of solutions from the existing parental pool. The primary objective of these crossovers is to explore the potential solution space effectively.

The algorithm sends the new population of solutions to the simulation model again. This loop continues until a certain number of generated solutions are scheduled and evaluated. Figure 6 illustrates the pseudo-code of the NSGA-II. The following subsections describe the steps in detail.

4.2.1 Generation of the initial population

In this step, a population of initial precedence-feasible solutions is generated using the structure shown in Fig. 6 . There are several solution encodings used in the PSP, including random key, priority value list, activity list, and extended activity list (Luo et al., 2023). In this research, the extended activity list is used as the chromosome, with two binary integers appended to it.

							1 = Serial 0 = Parallel	1 = Forward 0 = Backward
Activity	J = 3	J = 1	…	J = j	…	J = 12	1/0	1/0
Mode	m_3 ∈ {1, ..., M}	m_1 ∈ {1, ..., M}	…	m_j ∈ {1, ..., M}	…	m_{12} ∈ {1, ..., M}		

Fig. 7 Precedence feasible solution encoding for chromosomes

It contains the activity list without altering its size or structure and eliminates extra computation for translating it into a schedule. Also, it follows the presented model and algorithm by Kadri and Boctor (2018), making it available to address some aspects not considered in their study. If the first binary integer equals 1, it indicates the use of a serial scheduling scheme; otherwise, a parallel scheduling scheme is used. The second binary integer is dedicated to forward or backward scheduling. Another list contains information on modes according to the related activity list. Each solution in the NSGA-II algorithm is called a chromosome. Figure 7 shows an example of an activity list as a chromosome.

To generate initial solutions, a list of activities that their predecessors are finished is created and named “Green list”. The algorithm then selects an activity (gene) and appends it to the activity list (chromosome). To do this, the algorithm calculates the Critical Path Duration (CPD) and applies the following priority rules for each activity:

- Latest Start Time (LST)
- Latest Finish Time (LFT)
- Slack Time (SLK)

The Roulette Wheel Technique (RWT) is then used to select a gene, which is appended to the end of the chromosome. This process is repeated until the chromosome is complete. This approach iteratively selects the activities until the chromosome is completed. The same technique is applied to select modes; however, the priority rules are the minimum shortest feasible mode (SFM) and minimum total work content (TWC) (Peteghem & Vincent and Mario Vanhoucke,, 2011). Finally, the serial/parallel (S/P) and forward/backward (F/B) binaries are selected randomly. The related pseudo-code is displayed in Fig. 8.

4.2.2 The TPX operator

The TPX operator selects two chromosomes, called father and mother, to generate a new chromosome called son. The TPX selects two positions n_1, n_2 (from 2 to $J-1$, and $n_1 < n_2$) from the father’s activity list. The son then inherits the genes from positions 1 to n_1 and from n_2 to J. The empty positions between n_1 and n_2 in the son’s chromosome are filled with genes from the mother in their original order. To create a daughter chromosome, the same procedure can be performed by swapping the mother and father chromosomes in the explained procedure. Operators modify the mode list using the same steps as for activity lists.

4.2.3 The MBX operator

The Magnet-Based Crossover (MBX) operator is as an innovative crossover in genetic algorithms, particularly in the realm of project scheduling optimization. The MBX Operator is distinguished by its unique selection mechanism, where a segment of one parent’s chromosome is transplanted into the other’s, ensuring the inheritance of critical genetic blocks.

Calculate CPM
For s in range | PG×α |:
    Choose a priority rule (LST, LFT, SLK) for the activity list, randomly
    Choose a priority rule (SFM, TWC) for the mode list, randomly
    Create an empty list called "Green-list"
    Ω = set of unselected genes
    While |Ω| > 0:
        For gene in Ω:
            If all predecessors of the gene are in the chromosome:
                Append the gene to the green list
                Calculate the priority rule value for the gene
        Choose a gene from the green list by RWT
        Add the gene to the chromosome and remove it from Ω
        Calculate the selection priority rule value of modes
        Choose a mode by the RWT and **add** it to the chromosome
    Choose a Serial/Parallel binary randomly **add** it to the chromosome
    Choose a Forward/Backward binary randomly **add** it to the chromosome
    Save the chromosome in the population
Send the population to the NSGA-II main function

Fig. 8 Pseudo-code for generation of initial solutions

It meticulously identifies and preserves the relational structure between activities, thereby enhancing the search for optimal scheduling sequences. The MBX operator not only retains essential characteristics from the parent chromosomes but also introduces "free activities" in a strategic manner, augmenting the diversity of the solution pool.
To implement the MBX operator, the chromosomes of two parents (father and mother) are required. The MBX randomly selects two integers, n_1 and n_2 $(1 < n_1 < n_2 < J)$. It then stores the father's genes in positions n_1 to n_2 as a block. The MBX scans inside the mother chromosome to find the minimum and maximum position numbers (indices) of the activities within the block and stores them as n_0 and n_3 respectively (Zamani, 2013).
Offspring in the MBX contain the following main sets of activities:

1. Activities in position 1 to $n_0 - 1$ in the mother chromosome
2. The predecessors of all activities in the block
3. Activities in the block
4. All successors of activities in the block
5. Activities in the position $n_3 + 1$ to J in the mother chromosome

Some activities may exist between positions n_0 and n_3 that are neither predecessors nor successors to any of the activities in the block. These activities are called 'free activities' and q represents the total number of them. Free activities are inserted directly before or after the block in their original order. To determine whether an activity should be inserted before or after the block, a stochastic variable p $(p = 0.5 \mid q = 1, p = 2/(q + 2) \mid q \neq 1)$ and a uniform random number between 0 and 1 is assigned to every free activity. Starting with the first activity, if the assigned number is greater than p, then the free activity is placed before the block. If it is smaller than or equal to p, the rest of the free activities are placed after the block. Figure 9 illustrates the different parts of the offspring's chromosomes.

i = 1 to n0 from Mother	Predecessors of block	Free activities	Block activities	Free activities	Successors of block	I = n3 to |J+2| from Mother

Fig. 9 A representation of finished MBX offspring

4.2.4 Mode reassignment

Mode reassignment is a technique in resource-constrained project scheduling, aiming to optimize the consumption of non-renewable resources. At its core, this method employs the Non-Renewable Resource (NRC) priority rule, which intelligently assigns modes to jobs based on the probability of minimizing resource usage. By calculating the likelihood of each job-mode combination, Mode reassignment technique ensures that the most resource-efficient modes are favored, thereby increasing the chances of achieving feasible solutions. This technique is particularly beneficial in scenarios where resource availability is a limiting factor, and its strategic application can lead to significant improvements in both project efficiency and sustainability.
To reassign the mode lists using NRC priority rule, $P_{i,m}$ which represents the probability of selecting the i^{th} job with mode m, is calculated according to Eq. (15) and (16) (Heilmann, 2001):

$$X_i = (N'_{i,1,w}.N'_{i,2,w}...N'_{i,M,w}) \qquad \forall i \in J, \forall m \in M \tag{15}$$

$$P_{i,m} = (X_i - N'_{i,m,w})/X_i \tag{16}$$

This priority rule can be applied to all or some non-renewable resources and maximizes the probability of generating mode lists with the least possible non-renewable resource consumption. As a result, it maximizes the probability of finding non-renewable resource feasible solutions.

4.2.5 Mutation

To generate new solutions using the mutation operator, three random values x_1, x_2, and x_3 between 0 and 1 are generated for every incoming chromosome. If x_1 is lower than μ = 0.95, mutation is applied on the activity list, if x_2 is lower than μ, it is applied to the F/B integer, and if x_3 is smaller than μ, it is applied to the S/P integer. Mutation on the activity list randomly selects position i in the $(2, J-2)$ range. If the i^{th} activity has no precedence relationship with the $i+1^{th}$ activity their positions on the activity list are switched. This switch is also executed on the mode list. Mutation in F/B or S/P integers changes them from 0 to 1 and vice versa.

4.2.6 Pareto-based ranking

In this study, solutions are ranked based on the Pareto front approach. This approach compares all solutions with each other and ranks them by the number of times they were dominated in all objectives. Solutions that are not dominated, form a set called the first Pareto front. Using the gridding technique, some similar solutions were removed to maintain solution variety and leave room for new solutions. The detailed procedure of the Pareto-based ranking is described by Yue et al. (2021).
During the calculation of objectives, some near-optimum solutions may exceed the prearranged number of non-renewable resources (N_w), but they may still help the algorithm to

Table 3 Tuned Parameters for NSGA-II

Symbol	Parameter	Optimal Value
I	Maximum Iteration	TC
PG	Population of generations	100
α	Rate of eminent parent selection	0.5
RX	Rate of crossovers	0.5
RM	Rate of mutations	0.15
PF	Pareto fronts max population	20

become closer to the optimum solution. To keep such infeasible solutions in the basket, Alcaraz et al. (2003) suggested imposing a penalty on project duration based on Excess of Required Resources (ERR) according to Eq. (17) and (18). The total number of requested non-renewable resources that exceed the predetermined capacity of N_w are stored as ERR as formulated in Eq. (17):

$$P_{i,m} = \sum_{w=1}^{W} max\left(0, \left(\sum_{i=1}^{J}(N'_{i,m,w}) - N_w\right)\right) \tag{17}$$

If, after calculating the objectives, the ERR value is larger than zero, then the solution is infeasible in terms of non-renewable resources. However, such solutions may still help the algorithm find better solutions, especially if they are close to the optimum feasible search area. Therefore, this approach is designed to keep them in the current population by applying a penalty using Eq. (18), where MDU is the maximum duration of feasible solutions in the current population.

$$Rank = \begin{cases} D & \text{If ERR } = 0 \\ D + MDU - CPD + ERR & \text{Otherwise} \end{cases} \tag{18}$$

4.2.7 Parameter setting

The parameters of an algorithm play a key role in its performance. Even a well-customized algorithm may generate weak solutions if its parameters are not set appropriately. There are several methods for parameter setting in the literature, and this study uses the Taguchi method. In the Taguchi method, the Signal-to-Noise (S/N) ratio is defined to minimize variations in results in response to different input scenarios. Four performance metrics were examined to calculate S/N ratios for different levels of input parameters. The considered performance metrics are the Ratio of Non-Dominated Individuals (RNI), Mean Ideal Distance (MID), Maximum Diversity (MD) and the Spacing Metric (SM). Description of these metrics are provided by Ganji et al. (2021), Audet et al. (2021), and Sharifi et al. (2021). Termination Condition (TC) is reaching a total of 1000 visited solutions for the first set of computations, and 5000 for the second set of computations. Both limitation criteria are trending TCs in the literature. The tuned parameters are shown in Table 3.

4.3 The best-worst method

Selecting a single solution from a set of alternatives while considering multiple criteria can be complex and challenging, particularly when priorities conflict. To identify the most fitting solution, the Best-Worst Method (BWM) is applied to the solutions on the final Pareto front obtained from the proposed simheuristic method. The BWM determines the most appropriate weights for evaluating these solutions. The BWM is a renowned method in Multi-Criteria Decision Making (MCDM) literature, with several extensions developed in conjunction with other methods (Dong et al., Feb. 2021; Wu et al., 2024). Due to its unique procedure, the BWM requires fewer pairwise comparisons compared to other MCDM methods such as the Analytic Network Process (ANP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This advantage significantly enhances the efficiency of the BWM (Mi et al., 2019).

The BWM consists of five steps. In the first step, a set of decision criteria is defined, which are the same as the objectives for the simheuristic approach ($O = \{o = 1$ (Duration), $o = 2$ (Costs), $o = 3$ (Greenhouse gases)$\}$). In the second step, the project manager determines the most and least valued criteria. In the third step, the project manager ranks the preference of the best criterion over all other criteria by assigning a number between 1 and 9 and generating the Best-To-Others vector ($A_{BO} = (a_{B1}, a_{B2}, a_{B3})$). Likewise, in the fourth step, a Worst-To-Others vector is created by an expert ranking all criteria over the worst criterion using a number between 1 and 9 ($A_{OW} = (a_{1W}, a_{2W}, a_{3W})$). Finally, in the fifth step, optimum weights (W_1^*, W_2^*, W_3^*) for the criteria are found using Eqs. (19) to (21). The W_B and W_w are weights of the best and worst criteria in the BWM.

$$max_o\{|\frac{W_b}{W_o} - a_{BO}|, |\frac{W_o}{W_w} - a_{OW}|\} \tag{19}$$

Subject to:

$$\sum_{o=1}^{O} W_o = 1 \tag{20}$$

$$W_o \geq 0 \qquad \forall o \in O \tag{21}$$

5 Computational results

This section serves several purposes. Firstly, it provides a detailed comparison of the results obtained by the proposed algorithm and state-of-the-art algorithms under deterministic and single-objective conditions. Secondly, it describes the generated instances, the case study, and provides simulation model validation. In other words, the NSGA-II is tested first, followed by testing the model for deterministic MSMMRCPSP and finally testing the proposed simheuristic using a case study. Subsections 5.5 and 5.6 are dedicated to the convergence of NSGA-II and the optimization results of the algorithm for the studied case. Finally, the results of the BWM for Pareto front solutions are presented. The proposed approach was developed entirely using the Python programming language (CPU: Intel Core i5-9300 H, 2.4GHz).

5.1 Assessment of the algorithm

To assess the performance of the proposed solution approach, instances from two well-known datasets were solved without considering resource transfer times. These datasets are PSPLIB and MMLIB, which includes MMRCPSP with the single objective of minimizing makespan while allowing a maximum number of schedules of 5000. PSPLIB consists of instances with 10, 20, and 30 activities (536, 554, and 640 instances respectively), while MMLIB50 and

Table 4 The comparison of main algorithms in J10 and J20 data sets

ID	Algorithm		J10	J20
			%Dev. BKS	
1	Cooperative co-evolutionary	WLZO	0.28	NR
2	Simulated annealing	JSA	1.16	6.74
3	Artificial bee colony	CLPE	1.06	5.78
4	Ant Colony	CHA	0.32	2.05
5	GA	AGA	0.24	1.91
6	PSO and DE	ZLZH	0.00	1.82
7	Reinforcement learning	TCGLS	0.33	1.69
8	Modified shuffled frog-leaping	RSS	0.18	1.64
9	Ant colony	EFEA	0.14	1.62
10	Estimation of distribution	JRR	0.28	1.55
11	GA	LCSFLA	0.10	1.40
12	Shuffled frog-leaping	LZA	0.09	1.10
13	Discrete PSO	SEEDA	0.09	1.09
14	Cooperative discrete PSO	LCEDA	0.12	1.28
15	Hybrid-GA	CYDP	NR	0.97
16	Multi-agent based learning	SLC	0.05	1.62
17	Controlling search	LHGA	0.06	0.87
18	Artificial immune system	MAN	0.05	0.80
19	GA	CWC	0.01	0.71
20	Local Search	VPVAIS	0.02	0.70
21	GA	VPVGA	0.01	0.57
22	Cooperative co-evolutionary	SAAGA	0.03	0.56
23	Hybrid GA	HGFA	0.02	0.41
24	Path relinking	Albert18	0.01	0.06
25	Modified variable neighbourhood	MVNSH	0.15	0.27
26	Evolutionary hybrid algorithm	HEA	0.00	0.06
27	Hybrid-GA	LOVA09	0.06	0.87
28	Differential evolutions	DAMA09	0.09	0.70
29	GA	VANP10	0.01	0.57
30	Scatter search	VANP11	0.00	0.32
31	This study	GA	0.01	0.92

MMLIB100 from MMLIB each contain 540 instances with 50 and 100 activities respectively. Vanhoucke et al. (2016) published a comprehensive overview and detailed characteristics of these commonly used datasets.

After solving all instances, the results are presented in Tables 4 and 5. The columns labeled J10 and J20 represent the percent deviation of the results from the Best-Known Solutions (BKS), expressed as %Dev. BKS. In Table 5, the columns labeled J30, MMLIB50, and MMLIB100 compare the datasets using the percent deviation from the Lower Bound (LB),

Table 5 The percent deviation from Lower Bound in J30, MMLIB50, and MMLIB100 datasets

ID	Algorithm		J30	MMLIB50	MMLIB100
			%Dev. LB		
1	GA	COEL11	14.44	NF	NF
2	GA	OZDA99	27.38	NF	NF
3	Ant colony optimization	CHIA08	15.18	NF	NF
4	GA	MORE97	24.99	NF	NF
5	GA	ALCA03	21.83	NF	NF
6	Multi-agent learning	WAUT11	13.91	NF	NF
7	Particle swarm optimization	JARB08	18.14	49.98	NF
8	Particle swarm optimization	ZHAN06	18.63	49.25	57.42
9	GA	TSEN09	17.06	65.17	72.95
10	Estimation of distribution	WANG12	15.55	43.17	52.94
11	Scatter search	RANJ09	16.21	38.49	45.16
12	Simulated annealing	JOZE01	18.64	49.06	53.97
13	GA	ELLO10	16.16	43.84	56.21
14	GA	HART01	15.96	35.40	39.96
15	Hybrid-GA	LOVA09	14.58	34.16	36.29
16	Differential evolution	DAMA09	15.43	46.19	52.31
17	GA	VANP10	13.75	34.07	37.58
18	Scatter search	VANP11	13.66	28.17	29.77
19	Path relinking	PR	12.85	NF	NF
20	Mirror-based GA	MGA	19.55	45.00	52.00
21	Modified variable neighborhood	MVNSH	13.63	42.50	73.20
22	Evolutionary hybrid algorithm	HEA	12.55	26.53	27.78
23	This study	GA	15.10	32.31	38.39

expressed as %Dev. LB. In Tables 4 and 5, NR indicates that the authors have not reported the results, while NF means that not all obtained solutions were feasible.

The total number of evaluated solutions are constrained to 1000 and 5000, respectively. As illustrated in Tables 4 and 5, the findings indicate that the proposed algorithm excels in yielding outcomes that closely approach optimality. The abbreviations employed within these tables are elucidated and detailed by Zaman et al. (2020).

Figure 10 depicts the average time required to solve the multimode subsets of the PSPLIB and MMLIB using the proposed algorithm. The results demonstrate the high performance of the algorithm in generating feasible and applicable solutions within a reasonable computational time.

5.2 Generated instances

To further validate the model, a total of 100 instances from the J10, J20, J30, MMLIB50, and MMLIB100 subsets are extended to fit the MSMMRCPSP. This extension, inspired by Laurent et al. (2017), has three main features:

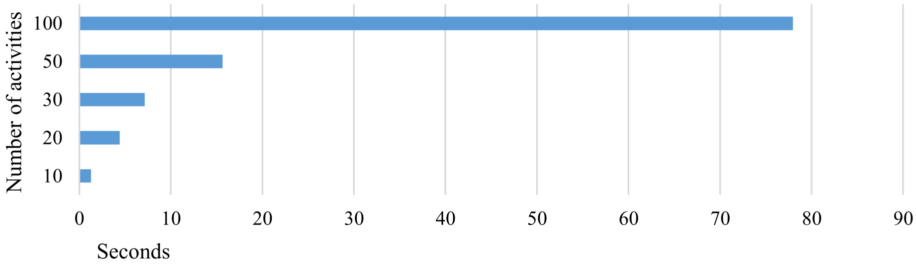

Fig. 10 Average computational time The Real-World Case

Table 6 Pareto front metrics

Subsets	Average of SM	Average of RNI	Average of MID	Average of MD
J10	45354	0.0029	360866	1099948
J20	52292	0.0030	399917	1229396
J30	93177	0.0030	565115	1820606
J50	99865	0.0031	972460	2719752
J100	62209	0.0031	708743	1712142
Grand Total	70579	0.0030	601420	1716369

1. The subsets were randomly grouped into two groups: one with two sites and one with three sites.
2. Direct routes are the fastest routes, while detours are slower than direct ones.
3. All renewable resources are mobile and can be transferred upon managers' decision.

The algorithm's performance is evaluated using four metrics introduced in Sect. 4.2.7 and the results are listed in Table 6. The SM measures the average distance of adjacent solutions in Pareto front and shows the uniformity of the distribution of the solutions. Smaller values of SM indicate a more evenly distributed Pareto front. The RNI measures the proportion of non-dominated solutions in the Pareto front to total number of generated solutions. The MID shows the average distance between each solution and the point with the best objective value for each objective. Larger values of RNI and smaller values of MID indicate better Pareto front approximation. The MD measures the maximum distance between any two solutions along each objective dimension. Larger values of MD indicate more diverse Pareto front approximation. Additionally, Fig. 11 displays the last Pareto front for "$J10016-4$" instance in contour shape.

5.3 Case study

The primary objective of this paper is to propose a solution methodology for a company active in engineering, procurement and construction projects in the petrochemical industry. The project under study involves 235 activities across three sites of a petrochemical plant. These activities must be carried out non-preemptively in three operational modes and require key renewable resources such as heavy machinery and skilled workforce. Non-renewable resources required for most activities include materials such as cement, concrete, bricks, different types of steels and pipes.

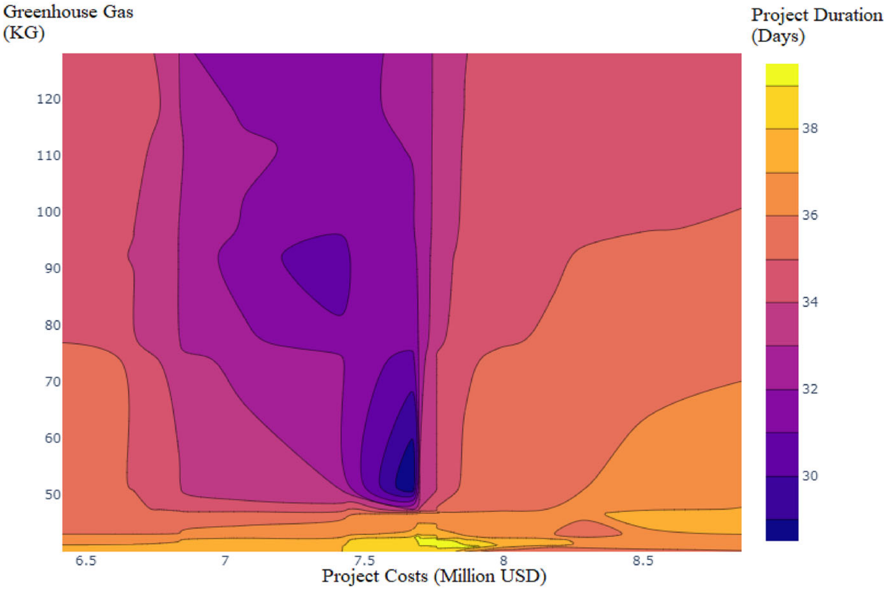

Fig. 11 Contour chart of the last Pareto front for $J10016-4$ instance

Due to the limited availability of resources, it is critically important to coordinate activities within a single timetable while considering resource transportation. This presents a significant challenge for the project's decision-makers. To address this challenge, this paper proposes a solution approach based on case data gathered from the company's records.

Three steps were implemented to fit the data to distribution functions using the maximum likelihood estimation method. Activities were first sorted based on expert consultations and resource consumption. Then, the minimum, maximum, and average values of activity duration, resource costs, and transfer cost for each mode were extracted. Finally, the maximum likelihood estimation method was applied to find the best-fitting distribution. The main parameters of the case study are reported in Table 7 and are in line with results provided by López et al. (2009) regarding greenhouse gas emission. The case study is available on Mendeley Data.

5.4 Simulation model validation

To validate the simulation model, 20 scenarios were extracted from the records of the studied company and solved using the simulation model. The input data for the model included the sequence of activities and related modes, as in Sect. 4.2.1. The average results of 30 times running the model were compared with actual case study values for 20 selected scenarios, as shown in Fig. 12.

The mean and median differences between the actual and calculated durations using the simulation model are -0.25 and -2 days respectively. The same values for costs and emitted greenhouse gases are -0.44, -1.35, 1.28, and 0.42. Based on the closeness of the actual values with simulation results, it can be concluded that the simulation model generates reliable results.

Table 7 Main characteristics of the case study

Symbol	Description	Value
J	Number of the activities	235
M	Number of modes	3
K	Number of key renewable resources	2
W	Number of key non-renewable resources	2
L	Number of activity sites	3
CR_1	Costs of one unit of the 1^{st} renewable resource	Triangular (100, 150, 180)
CR_2	Costs of one unit of the 2^{nd} renewable resource	Triangular (2500, 3200, 5300)
CN_1	Cost of one unit of the 1^{st} nonrenewable resource type	2100
CN_2	Cost of one unit of the 2^{nd} nonrenewable resource type	5000
CT_1	Cost of transporting 1^{st} renewable resource per unit of time	Triangular (1100, 4200, 5000)
CT_2	Cost of transporting 2^{nd} renewable resource per unit of time	Triangular (1000, 3500, 7000)
θ	Emission rate during activity implementation (Ton/ day)	Triangular (0.05, 0.09, 0.1)
θ’	Emission rate during transportation (Ton/ day)	Triangular (1.6, 1.8, 2)
$\Delta_{12} = \Delta_{21}$	Transfer time between first and second sites (days)	7
$\Delta_{13} = \Delta_{31}$	Transfer time between first and third sites (days)	3
$\Delta_{23} = \Delta_{32}$	Transfer time between second and third sites (days)	5

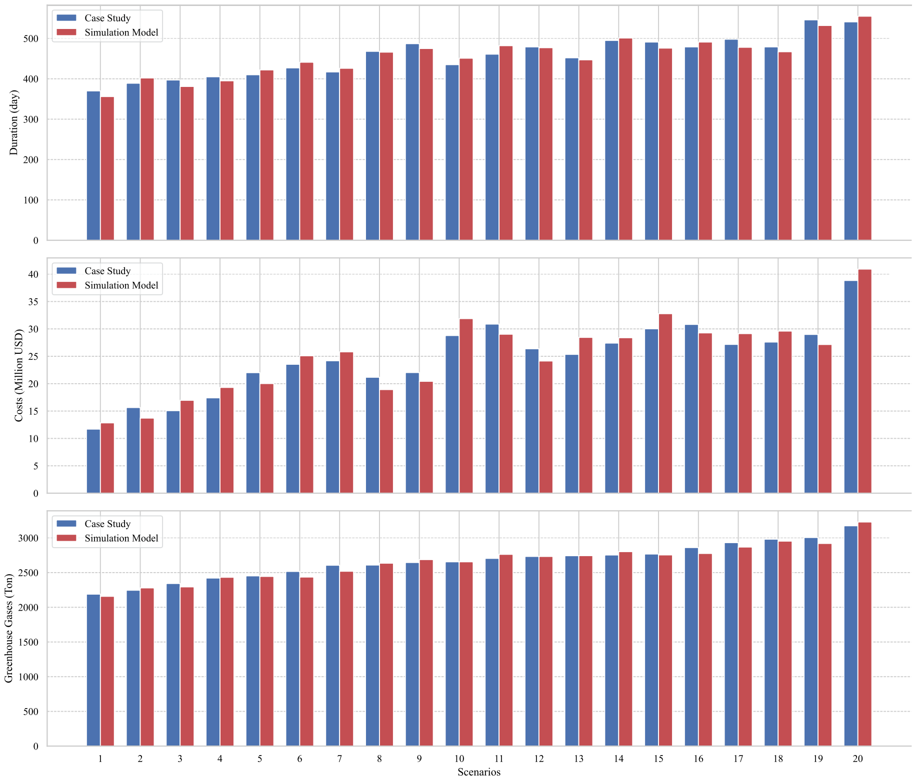

Fig. 12 Comparison of the simulation outputs with sample projects of the company

5.5 Convergence

Convergence in algorithms refers to a stable trend of solutions in several loops of iterative algorithms toward a certain point. To assess the ability of the proposed NSGA-II in producing converging results the value of the objectives through optimization loops was monitored and recorded. Figure 13 illustrates that project duration, cost, and greenhouse gas emitted narrow down toward the minimum objective values found within 25 loops of the NSGA-II.

5.6 Case study optimization

This subsection provides information on optimization results of the case study using the proposed simheuristic with presented parameters in Sect. 4.2.7. The NSGA-II solved the problem in 280 and 1380s respectively with 1000 and 5000 termination condition. The final objective values of the results are listed in Table 8. Each row represents the value of the objectives for each solution in the front. The first column represents the project makespan in days and the other columns report total project cost regarding mode selection and transportation in million United States Dollar (USD) and emitted greenhouse gases in tons.

Based on classic methods of project scheduling, managers plan to transfer resources based on their knowledge and experience. However, these conventional methods are not efficient. The proposed simheuristic approach achieved significant improvements, as follows:

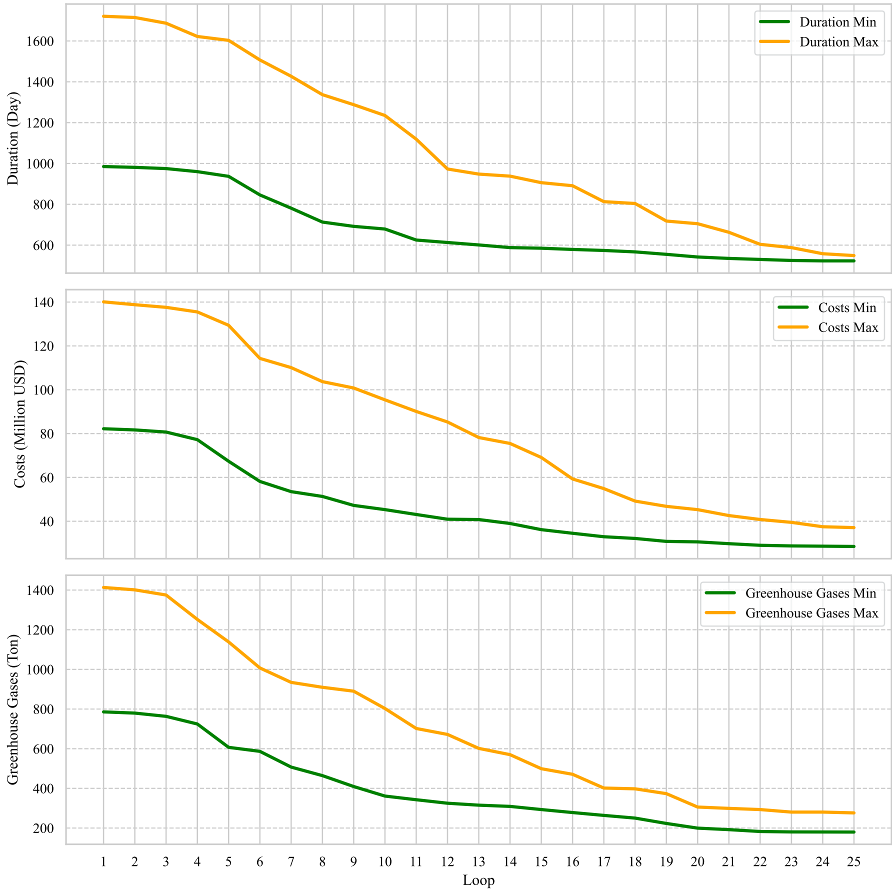

Fig. 13 Converging values of the objectives in NSGA-II iterations

- **Project Duration** (D): Reduced from 599 days to 523 days, a 12.7% decrease.
- **Costs** (C): Reduced from 32.2 million USD to 28.5 million USD, an 11.4% decrease.
- **Greenhouse Gas Emissions** (G): Reduced from 207.9 tons to 179.7 tons CO_2-equivalent, a 13.6% decrease.

These comparisons highlight the effectiveness of the proposed model in optimizing project scheduling, reducing costs, and minimizing environmental impact compared to conventional methods based on the knowledge and experience of project managers.

The last Pareto front for solutions in Table 8 is illustrated in Figs. 14 and 15, which show the surface and contour charts, respectively. Figure 15 represents project duration as depth, with Bold italic indicating shorter durations and yellow indicating longer durations. The chart shows that as total project costs (X-axis) and greenhouse gas emissions (Y-axis) decrease, project duration increases, and vice versa. In other words, scheduling the project with shorter modes results in higher greenhouse gas emissions and expenditures.

Table 8 The objective values of the last Pareto front

Solution	Project Duration (Day)	Project Costs (Million USD)	Greenhouse Gas Emission (Ton)
1	536	36.8	182.0
2	529	37.1 *max*	191.2
3	529	34.1	192.3
4	536	33.4	183.3
5	529	31.7	194.1
6	526	34.2	198.4
7	523	32	276.3 *max*
8	549 *max*	32.8	179.7 *min*
9	526	32.6	199.4
10	523 *min*	32.5	271.2
11	537	32	186.4
12	529	35.3	191.7
13	549	30.3	180.7
14	529	30.4	195.6
15	526	29.9	209.7
16	526	29.6	215.7
17	526	29.1	238.5
18	537	29.1	203.0
19	534	28.8	265.6
20	530	28.5 *min*	265.8

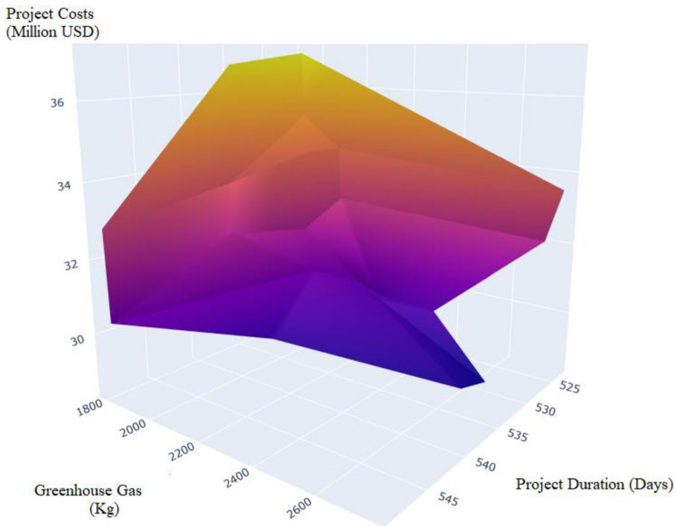

Fig. 14 The surface of the last Pareto front of the NSGA-II

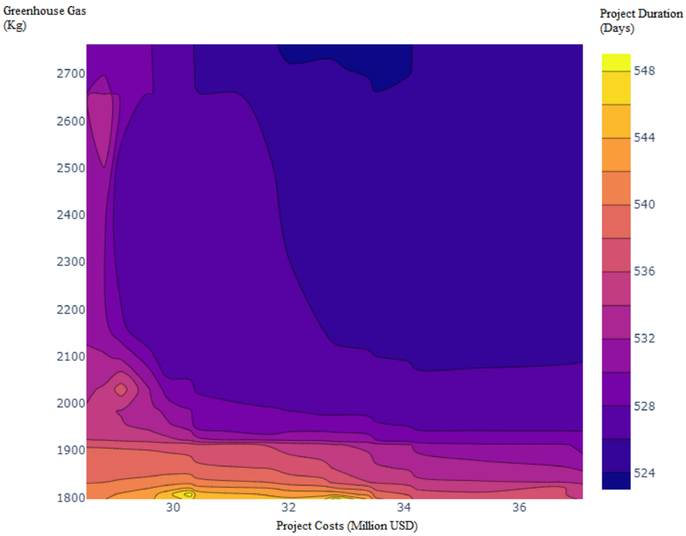

Fig. 15 Contour chart of the last Pareto front of the NSGA-II

Table 9 Input variables and output values of the BWM

	Project duration	Project costs	Greenhouse gas Emission
Project duration	$a_{B1} = 1$	$a_{B2} = 2$	$a_{B3} = a_{1W} = 3$
Project costs	1/2	1	$a_{2W} = 2$
Greenhouse gas emission	1/3	1/2	$a_{3W} = 1$
Weights	0.54	0.29	0.17

5.7 Selecting the best solution

The BWM is applied to select the best solution among 20 solutions of the Pareto front where opposing selection objectives make the decision-making process complicated. The project owner may rather pay for more expensive modes to finish the project earlier than assigning fewer resources and spending more time on the project. This also applies to emitted greenhouse gases. The first part of Table 9 lists the results of a survey conducted to extract the relative preference of the project owner for each objective. Based on the information, the owner has assigned more priority to the project makespan. The final row in Table 9 lists the resulting weights of the problem by solving Eqs. (19) to (21).

After calculating the weights for each criterion using the BWM, solutions of the Pareto front are normalized between the minimum and maximum values of each objective. Then, the sum-product values are computed and listed in Table 10. According to this Table, the 15^{th} solution is ranked as the best solution. Although the BWM is a recognized approach in the literature, the outputs of the simheuristic model were tested using the Analytic Hierarchy Process to verify the results of the BWM. In this experiment, solutions 15 and 16 were ranked as the best-fitting solutions.

Table 10 Comparing Pareto front solutions by BWM

Solution	Project Duration	Project Costs	Greenhouse Gas Emission	Sum product	Rank
1	0.50	0.03	0.98	0.4437	18
2	0.77	0.00	0.88	0.5635	16
3	0.77	0.35	0.87	0.6633	11
4	0.50	0.43	0.96	0.5568	17
5	0.77	0.63	0.85	0.7416	6
6	0.88	0.34	0.81	0.7119	8
7	1.00	0.59	0.00	0.7146	7
8	0.00	0.50	1.00	0.3125	20
9	0.88	0.52	0.80	0.7645	5
10	1.00	0.53	0.05	0.7065	9
11	0.46	0.59	0.93	0.5781	15
12	0.77	0.21	0.88	0.6237	13
13	0.00	0.79	0.99	0.3956	19
14	0.77	0.78	0.84	0.7831	4
15	0.88	0.84	0.69	0.8383	1
16	0.88	0.87	0.63	0.8381	2
17	0.88	0.93	0.39	0.8157	3
18	0.46	0.93	0.76	0.6478	12
19	0.58	0.97	0.11	0.6125	14
20	0.73	1.00	0.11	0.7056	10

Table 11 Parameter levels for sensitivity analysis

Parameter	Low Level	Medium Level	High Level
CT_1	TRI(880, 2800, 5600)	TRI(1100, 3500, 7000)	TRI(1320, 4200, 8400)
θ	TRI(0.04, 0.072, 0.08)	TRI(0.05, 0.09, 0.1)	TRI(0.06, 0.108, 0.12)
θ'	TRI(1.28, 1.44, 1.6)	TRI(1.6, 1.8, 2)	TRI(1.92, 2.16, 2.4)

5.8 Sensitivity analysis

Sensitivity analysis is a crucial step in validating the robustness and reliability of the model. This section aims to evaluate how the variations in stochastic input parameters influence the model's output. In this experiment, CT_1, θ, and θ' were systematically altered by $\pm 20\%$, across 21 scenarios of the case study. The different values considered for these variables are shown in Table 11.

The results of running the model for each scenario are listed in Table 12 (L, M, and H symbolize Low, Medium, and High levels from Table 11). From this table, it is evident that altering the three variables did not affect the project duration (D). However, changes in the transportation cost of the resources (CT_1) had a direct effect on the total project cost (C), with costs ranging from 23.9 to 38.8 Million USD. Similarly, when the greenhouse gas emission conversion factors (θ and θ') are at low levels, the emitted greenhouse gases (G) decrease,

Table 12 Sensitivity analysis

Run	CT_1	θ	θ'	D	C	G
1	L	L	L	518	23.9	147.7
2	L	L	M	519	24.2	146.1
3	L	M	M	517	20.9	243.1
4	L	L	H	517	26.3	174.3
5	L	H	H	522	25.4	309.4
6	L	M	H	517	31.0	296.3
7	L	H	M	517	29.1	308.4
8	M	M	M	526	29.9	209.7
9	M	M	L	522	30.8	201.4
10	M	L	L	533	29.9	144.7
11	M	M	H	533	25.7	206.8
12	M	H	H	512	28.7	253.1
13	M	L	H	524	29.7	158.8
14	M	H	L	509	26.4	174.3
15	H	H	H	510	38.8	304.1
16	H	H	L	529	25.0	271.2
17	H	L	L	539	31.3	140.9
18	H	H	M	519	25.3	230.2
19	H	M	M	517	34.7	293.6
20	H	L	M	544	27.0	143.2
21	H	M	L	507	34.3	196.3

and they increase when the conversion factors are higher, with emissions ranging from 140.9 to 309.4 tons.

6 Discussion

Project scheduling is the backbone of management in project-oriented organizations and plays a fundamental role in the success of such organizations by optimizing the costs and duration of projects. Project-oriented companies repeatedly face the need for transferring scarce resources such as huge machinery between activity locations. Also, companies are under social pressure to cut their harmful impacts on the environment and since logistic operations take a big share of damaging effects through greenhouse gas emissions, it is necessary to implement a reliable and efficient approach to find an optimum or near-optimum solution to minimize project makespan, costs, and greenhouse gas emissions simultaneously.

6.1 Theoretical contribution

A simulation model was developed to incorporate the stochastic nature of greenhouse gas emission rates, costs of resource transportation and costs of using renewable resources. To validate the model outputs, the results of 20 project instances from the studied company were compared with the results of the simulation model. Also, a metaheuristic algorithm (NSGA-II) was adapted with magnet-based crossover, two-point crossover, mode reassignment, and mutation operators for this problem. To assess the algorithm, it was run to optimize the project instances from the PSPLIB and the MMLIB. The proposed approach proved compatibility with the datasets and generated feasible solutions in a reasonable computational time. Then, the suggested algorithm was applied to the studied project. The results indicate that the algorithm successfully reduced three objectives of project duration (D), project costs (C), and Greenhouse gas emission (G). As advised by Wang et al. (2021), transfer times in the proposed model is considered to enable simultaneous scheduling and resource transfers in an uncertain environment.

6.2 Managerial/practical implication

Interesting managerial insights can be received from the results. Resource transfers are ignored mostly while they profoundly affect timetables. Project duration is extremely dependent on the sequence of activities as well as transfer times. Therefore, it is necessary to regard resource transfers accordingly, especially in infrastructure projects such as railways or pipeline establishment. Project managers are responsible for several stakeholders with different priorities and must control numerous parameters and variables while scheduling and implementing projects. The proposed procedure in this study was able to include a diverse range of parameters and variables and can assist managers to schedule projects considering resource transfers and to optimize conflicting objectives in large-sized problems in reasonable computational time. This paper provides managerial and practical implications not only for project managers but also government authorities to help them legislate more sustainable and environmentally friendly policies.

6.3 Limitations

One major limitation of this study refers to the assumption that precedence relations are zero-lag and finish-to-start. Further research shall consider possible lags due to the projects' uncertainties. Second, the main assumptions are a) the sum of the transfer times for non-renewable resources is constant and negligible, b) the transfer times within a location are not significant, and c) the renewable resources require no set-up time in every location. Including these parameters in the algorithm increases the precision level of scheduling. Another limitation applied is considering a single project problem. This limitation can be easily expanded to multi-project problems by considering the transfer times between projects and the critical paths of a set of projects simultaneously.

A comprehensive cost analysis of the proposed approach is not included in this study. Since, the cost of implementation may depend on various factors, such as the quality and availability of the data, the complexity and size of the problem, the maintenance and updating of the models and algorithms, the computational resources, etc. The calculations and in this study had a limited scope to perform an analysis since they were applied a personal computer.

6.4 Future research

The authors would like to point out that future research should focus mainly on more features and aspects from real-world projects. These features may include the effects of routing on the problem, uncertainty, risk management, and robustness maximization. For instance, papers from Rabet et al. (2024), and Ganji et al. (2021) focusing on the applications of scheduling are valuable sources of inspiration.

Future research could expand on this study by creating new algorithms or refining existing ones, like Multi-Objective Evolutionary Algorithms based on Decomposition, or heuristic methods (like NSGA-II and the Q-learning algorithm), to address similar issues. This would allow for comparisons between the proposed methods in this study and newly developed algorithms (Rodríguez-Ballesteros et al., Mar. 2024; Yang et al., 2024). Additionally, the published paper by Torba et al. (2024) inspires evaluating the performance of priority rules for selecting activities in an uncertain environment and investigating the multi-skill multi-project resource-constrained scheduling problem. The proposed models in these papers and current study can be expanded for multi-project contexts considering global and local resource transfers. Furthermore, considering schedule risk analysis during project control while optimizing the RSCPC problem will improve the project outcome (Song et al., 2021). Future research shall include risk parameters in resource allocation to better manage scheduling. Furthermore, logistics managers shall identify competitive performance scores and analyze the performance of their decision-making system based on competitive priorities (Pathak et al., 2021). Finally, the project activities are assumed non-preemptive. Future research shall allow activity splitting or interruption of activities at any time of project execution by considering the relevant costs. The development of an optimal algorithm to solve complex cases and the assessment of the algorithm's performance shall be investigated.

Moreover, addressing the limitations identified in this study could enhance the applicability of the proposed method. This includes performing a comprehensive cost analysis of the proposed approach, conducting a sensitivity analyses on modes and activity durations, and expanding the applicability of the simulation model. These advancements could provide more accurate and holistic view on the MSMMRCPSP.

7 Conclusion

In summary, our research endeavors to pioneer a novel pathway in addressing the intricacies of multi-site multi-mode resource-constrained project scheduling algorithm. By ingeniously amalgamating simheuristic modeling, our approach emerges as a beacon of innovation, steering the optimization process towards the triad of minimizing greenhouse gas emissions, optimizing makespan, and costs during resource transportation. Significantly, the essence of this research lies in its unprecedented integration of environmental considerations and sequence-independent transfer times, effectively breaking new ground in the domain of the MSMMRCPSP. Remarkably versatile, the proposed algorithm holds promise for broader application across a spectrum of resource-constrained scheduling challenges encountered within multi-project setting. In addition, the inclusion of transfer times within our model empowers simultaneous scheduling and resource transfers, even within the unpredictability of the environment. By orchestrating this intricate symphony, our research not only contributes to efficient problem-solving but also showcases its potential to drive sustainable and environmentally conscious project management practices. In the landscape of project scheduling, our study stands as a testament to the capacity of innovation to reshape conventions and align objectives, fostering a future where optimal project outcomes and environmental stewardship go hand in hand.

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Data Availibility The supplementary data files for this study have been published on Mendeley Data.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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