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Research Article

Environmental Pollutions Assessment by a New Project Scheduling Model under a Fuzzy Environment

Alireza Faghih [a], Hossein Safari [a,*], Mostafa Zandieh [b], Hani Arbabi [c]

[a] Department of Industrial Management, Faculty of Management, University of Tehran, Tehran, Iran
[b] Department of Industrial Management, Faculty of Management and Accounting, Shahid Beheshti University, Tehran, Iran
[c] Faculty of Arts, Tarbiat Modares University, Tehran, Iran

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Abstract
Infrastructure projects are generally implemented in less developed areas. These areas usually have a pristine and pollution-free environment. Environmental pollution during project implementation is considered in various countries under strict regulations. Therefore, it has become necessary to consider environmental factors during scheduling a project in recent decades. The project schedule is one of the primary and widely used planning fields. Applying theories in practice and extensive studies in this field indicate its importance more than before. These problems have various kinds regarding the limitations and conditions of the financial aspects of the contract. Resource-constrained project scheduling problems (RCPSP) are non-polynomial problems - hard (NP-Hard), and usually, meta-heuristic methods were used for solving them. This paper developed a new model for RCPSP called fuzzy green multi-objective multi-mode resource-constrained project scheduling problems (GFMMRCPSP). This model considers three objectives: minimum environmental pollution, minimum C_{max}, and maximum NPV. Because of the uncertainty in the real world, all model parameters are assumed fuzzy. The initial feasible solution algorithm was introduced to increase the speed of problem-solving algorithms (NSICA, NSGA-II, and MOPSO), which removed the unfeasible search space. The proposed model and algorithms were tested using standard PSPLIB problems. The test results of different methods for solving the GFMMRCPSP model were compared using eight different criteria: Number of Pareto Solutions (NPS), Mean Ideal Distance (MID), Mean of Coefficient of Closeness (MCC), Mean of Similarity (MS), Quality Metric (QM), Spacing, Diversity, and Running time. The results show that NSICA is the most efficient and effective algorithm, and the NSGA-II algorithm is more suitable than the MOPSO algorithm to solve the research problems.
Keywords: Project management, Green Fuzzy Multi-Objective Multi-Mode Resource-Constrained Project Scheduling Problems, Multi-objective Meta-Heuristic Methods, Initial Feasible Solution

Introduction

Planning is one of the main things affecting human life, especially organizations, production, and project management. Scheduling, resource allocation, budgeting, and financing throughout

* Corresponding author E-mail: hsafari@ut.ac.ir

a project make the project planning. One of the most challenging and significant project management tasks is excellent and effective scheduling due to the limited resources (Khalilzadeh et al., 2017).

In practice, project-scheduling methods suffer from a lack of precision; therefore, creating a realistic and useable project schedule is a big challenge. It is difficult and time-consuming to correctly estimate time, assign resources, determine interdependencies between tasks, and manage changes. That is why it is essential to discover the differences between the theory and practice of scheduling methods (Francis et al., 2013).

Project scheduling is done with resource limitation conditions in these problems, so these problems are known as Resource-Constrained Project Scheduling Problems (RCPSP). Researches use different approaches to solve multiple types of RCPSP, but there is always a gap to find a new way that offers better solutions because RCPSP and its various types are the NP-Hard (Blazewicz et al., 1983).

This paper developed the new RCPSP model with three objectives based on fully fuzzy parameters as Green Fuzzy Multi-Objective Multi-Mode Resource-Constrained Project Scheduling Problems (GFMMRCPSP). Three methods were also used to solve the problems, the non-dominated sorting imperialistic competitive algorithm (NSICA), the non-dominated sorting genetic algorithm II (NSGA II), and the multi-objective particle swarm algorithm (MOPSO). In addition to increasing these algorithms' efficiency, this paper presents the initial feasible solution calculation algorithm (IFSCA).

Usually, environmental factors are not considered in scheduling and carrying out projects, and the general emphasis is placed on cost management and project completion time. These causes show a project to bring many environmental pollutions into the project area constructed. This paper tries to measure ecological factors simultaneously with cost and time in project scheduling. There are alternative ways to do its activities when building a project, so diverse pollution methods were created differently. Besides, based on the standards of the project scope, methods with less pollution were selected.

Project management dates back at least 4,500 years. The creators of Egypt's pyramids and the Maya temples in Central America are often cited as the world's first project managers (Demeulemeester & Herroelen, 2002). However, the emergence of project management in its current form began with World War I. In 1913, Henry L. Gantt presented the Gantt chart (Gantt, 1913). Other techniques such as CPM, PERT, and GERT were later developed.

According to the Project Management Knowledge Range Handbook (PMPOK 6) definition, project scheduling is critical for project planning processes. Also, scheduling methods, scheduling tools, schedule models, and project information (e.g., WBS, activities, resources, durations, dependencies, constraints, calendars, milestones lags, etc.) lead to the project schedule (PMBOK® Guide 6, 2017).

The resource-constrained project-scheduling problem (RCPSP) is one of the most studied project scheduling problems. The RCPSP aims to develop a project schedule with a minimum make-span satisfying the precedence relations of the network and the restricted availability of renewable resources. Due to its NP-hardness status, RCPSP has attracted attention, and different algorithms have been proposed to solve various RCPSP instances to optimality or near-optimality (Coelho & Vanhoucke, 2020).

Therefore, researchers have always sought to provide more effective solutions to these problems, and several articles and books have been published in this field. To review the evolution of project scheduling and research until 2014, books and review articles in this field are referred to (Abdolshah, 2014; Brucker et al., 1999; Demeulemeester & Herroelen, 2002).

This study is a multi-faceted classification of recent seven years of research in this area. On the one hand, this research category model is based on Demeulemeester & Herroelen's classification of project scheduling problems (Demeulemeester & Herroelen, 2002). On the other hand, the solution method is classified into three categories: exact, heuristic, and meta-heuristic. Owing to the high number of studies in this field, it has emphasized the most relevant studies.

Table 1. Classification of research in resource-constrained project-scheduling problem during 2014 to 2020

Classification of solution method	Solution method	Classification of RCPSP model	Researchers and Years
Meta-heuristic method	Multiple justification particle swarm optimization	$m, 1 \mid cpm \mid C_{max}$	Fahmy et al. (2014)
Meta-heuristic method	Developed Imperialist Competitive Algorithm	$m, 1 \mid cpm \mid C_{max}$	Safari & Faghih (201)
Meta-heuristic method	NSGA II / MOPSO	$m, 1 \mid cpm \mid C_{max}, Cost$	Zarei & Hasanpor (2015)
Exact method	Binary linear programming	$m, 1 \mid pmtn-rep, cpm \mid C_{max}$	Kreter et al. (2016)
Exact method	Binary linear programming	$0 \mid cpm \ , \tilde{d}_j \mid C_{max}, cost$	Morovatdar et al. (2016)
Exact method	DICOPT in GAMS	$m, 1T \mid cpm, mu \mid NPV$	Mahdavian Attar et al. (2016)
Meta-heuristic method	Electromagnetism (EM) and NSGA-II, SPEA2, and MOEA/D	$m, 1 \mid cpm \mid C_{max}, TWT$	Xiao et al. (2016)
Meta-heuristic method	Multi-Objective Bees Metaheuristic Algorithm	$m, 1 \mid cpm, mu \mid C_{max}, Cost, Quality$	Sadeghi et al. (2016)
Heuristic method	Coin-Branch & Cut (CBC)	$m, 1 \mid cpm, \tilde{d}_j \mid C_{max}$	Chakrabortty et al. (2017)
Exact method	Zero–one linear programming	$m, 1 \mid cpm \mid C_{max}$	Artigues (2017)
Exact method	Shortest path algorithm	$m, 1 \mid cpm \mid C_{max}$	Lacomme et al. (2017)
Meta-heuristic method	Frog leaping algorithm combination (SFLA)	$m, 1 \mid cpm \mid C_{max}$	Haji akhondi et al. (2017)
Exact method	specific decomposition algorithm	$m, 1, \tilde{a} \mid cpm \mid C_{max}$, Robustness	Bruni et al. (2017)
Exact method	One-Point Decomposition-Based Approach (OPDA)	$m, 1 \mid cpm \mid C_{max}$	Liu et al. (2017)
Meta-heuristic method	MOPSO/MOFA	$0 \mid gpr \mid Cost,\ C_{max}, EI$	Taghizade yazdi & Sabori (2017)
Heuristic method	Ant Colony Optimization	$m, 1 \mid cpm \mid C_{max}$	Gonzalez-Pardo et al. (2017)

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Classification of solution method	Solution method	Classification of RCPSP model	Researchers and Years
Heuristic method	Heuristic algorithm base on parallel Scheduling Scheme	$m\,,1 \mid cpm\,, \tilde{d}_j \mid C_{max}$	Khalilzadeh et al. (2017)
Meta-heuristic method	LS / SA / ILS|BW / ILS|SA	$m\,,1 \mid cpm \mid C_{max}$	Laurent et al. (2017)
Exact method	Branch and bound algorithm	$m\,,1 \mid cpm \mid C_{max}$	Coelho & Vanhoucke (2018)
Exact method	Benders decomposition	$m\,,1 \mid cpm \mid C_{max}$, Robustness	Bruni et al. (2018)
Meta-heuristic method	NSGA II	$m\,,1T \mid cpm, mu \mid C_{max}, NPV$	Gholizade & Afsharnajafi (2018)
Exact method	Hybrid Benders Decomposition and Lagrangian Relaxation	$m\,,1 \mid cpm, mu \mid C_{max}$	Changchun et al. (2018)
Exact method	Fuzzy goal	$0 \mid gpr \mid C_{max}, Cost, Quality$	Sholl & Keshavarz (2018)
Meta-heuristic method	Path-Relinking (PR) algorithm	$m\,,1T \mid cpm, mu \mid C_{max}$	Fernandes Muritiba et al. (2018)
Meta-heuristic method	Genetic programming based hyper-heuristic (GPHH)	$m\,,1 \mid cpm \mid C_{max}$	Chand et al. (2018)
Meta-heuristic method	NSGA II / NSGA III / MODA	$m\,,1 \mid cpm, mu \mid C_{max}, Cost, Risk, Reliability$	Faroghi et al. (2019)
Meta-heuristic method	PRCPSP-ST	$m\,,1 \mid pmtn-rep, \rho_j, cpm \mid C_{max}$	Vanhoucke & Coelho (2019)
Exact method	ε-Constraint	$m\,,1 \mid cpm, mu \mid Cost, C_{max}, Quality, Plloution$	Heydari et al. (2019)
Heuristic method	self-adaptive DE hyper-heuristic algorithm	$m\,,1 \mid cpm\,, \tilde{d}_j \mid C_{max}$	Alipouri et al. (2019)
Meta-heuristic method	Particle Swarm Optimization (PSO) and Genetic Algorithm (GA)	$m\,,1 \mid cpm, mu, \tilde{d}_j, Multiple\ Routes \mid Cost$	Birjandi & Mousavi (2019)
Meta-heuristic method	four-part non-distinct (FPND) approach	$m\,,1 \mid cpm, mu, \tilde{d}_j, Multiple\ Routes \mid Cost$	Birjandi et al. (2019)
Exact method	approximate dynamic programming (ADP) algorithm	$m\,,1 \mid cpm, mu, overlapping \mid C_{max}$	Chu et al. (2019)

Table 1. Classification of research in resource-constrained project-scheduling problem during 2014 to 2020

Classification of solution method	Solution method	Classification of RCPSP model	Researchers and Years
Meta-heuristic method	Particle Swarm Optimization (PSO) and Genetic Algorithm (GA)	$m\ ,1 \mid cpm, mu, Multiple\ Routes\ \vert Cost$	Birjandi et al. (2020)
Meta-heuristic method	Satisfiability Modulo Theories	$m\ ,1 \mid cpm, mu\ \vert C_{max}$	Bofill et al. (2020)
Meta-heuristic method	extended genetic algorithm (GA-NND)	$m\ ,1 \mid cpm, CPRs - cal\ \vert C_{max}$	Kong & Dou (2020)
Heuristic method	CP-based methods	$m\ ,1 \mid cpm, generalised\ precedence\ constraints \vert C_{max}$	Edwards et al. (2021)
Meta-heuristic method	NSGA-II and Pareto simulated annealing (PSA) algorithm	$m\ ,1 \mid cpm \vert resource\ transfer\ cost,$ Robustness	Wang et al. (2021)

A review of the research literature during the last seven years in the model's section emphasizes the models primarily in line with the real-world and project managers' demands, such as considering different activities and several goals.

Recently research more emphasized multi-objective models. However, none of the reviewed research has addressed the impact of scheduling on their model's environment. Generally, objective functions emphasize C_{max} and costs or increase project financial revenue. Therefore, this paper has sought to cover this research gap and minimize environmental pollution.

Uncertainty in the project has also been answered in two ways, using the possible PERT method or fuzzy logic. The use of probabilistic methods requires a previous background in the project. The activities are generally non-repetitive and make it very difficult to estimate the probability function for each activity. Therefore, in this study, fuzzy logic has been used to overcome uncertainty. In addition, articles based on fuzzy logic generally assume only the activities' duration to be fuzzy. Sometimes, their model does not consider resources or assume them definitive. However, in the present paper, all the model parameters include each activity's environmental pollution level, the total acceptable level of environmental pollution, duration of activities, latency, cash flows of activities, discount rate, activity needs, and total available resources. Usually, Triangular or trapezoidal fuzzy numbers are used for fuzzy numerical calculations. This paper uses fuzzy triangular numbers because of the convenience of working with them. Therefore, the study's model is green fuzzy multi-objective multi-mode resource-constrained project scheduling problems (GFMMRCPSP).

The literature review shows exact methods used in problems with a small size or project schedules without resource constraints in solution methods. Most research in this area has been limited to providing a numerical example, and some of them are based on only minor standard RCPSP issues up to 30 activities. The heuristic methods are generally prepared for specific RCPSP problems with particular assumptions, and their generalizability is limited. Meta-heuristic methods have been the most attractive approaches for solving RCPSP because, on the one hand, they do not have a project size limit, and on the other hand, they can be generalized to different types of RCPSP problems.

Material and Methods

Problem Definition

The resource constraint project-scheduling problem has different types, and various categories have been provided. Based on Demeulemeester and Herroelen (2002), the classification of project scheduling problems is formed on three factors: resource characteristics, activity characteristics, and performance measures (objectives). The study's model can be presented as:

$$m\ ,1T,\tilde{a}\ \big|\ fuzzy,\tilde{d_j},fuzzy,mu,\tilde{c_j},fuzzy\ \big|multi(Pollution,C_{max},npv) \tag{1}$$

GFMMRCPSP abbreviates the green fuzzy multi-objective multi-mode resource-constrained project scheduling problems for short. Briefly, the characteristics of this paper model are shown in Table 2.

Table 2. The model's characteristics

Factors	The study's model
Resource characteristics $\{\alpha_1,\alpha_2,\alpha_3,\alpha_4\}$	$\{0$, M, 1T, $\tilde{a}\}$
Activity characteristics $\{\beta_1,\beta_2, \dots, \beta_{10}\}$	$\{0$, fuzzy, 0, $\tilde{d_j}$, 0, fuzzy, mu, $\tilde{c_j}$, 0, fuzzy$\}$
Performance measures (objectives) $\{\boldsymbol{\gamma_i}\}$	{Pollution, C_{max}, NPV }

* Zero in the table means no assumption in the model.

Based on Table 2, the most critical assumptions of the model are:

- α_2=M: The project has more than two resources
- α_3=1T: The use of both renewable and non-renewable resources in the project
- $\alpha_4= \tilde{a}$: The initial resources inventory and the amount of resource usage of each activity are fuzzy triangular numbers.
- β_2=fuzzy: The precedence relations of activities are finished to start, and their delay is fuzzy.
- $\beta_4=\tilde{d_j}$: Brake is not possible in activities, and the duration of each one in each mode is fuzzy triangular numbers.
- β_6=fuzzy: The source's need for each activity in each mode is fuzzy triangular numbers.
- β_7=mu: Each activity can be done in different modes.
- $\beta_8=\tilde{c_j}$: The cash flows of activities are fuzzy triangular numbers.
- β_{10}=fuzzy: The environmental pollution of each activity is fuzzy triangular numbers.
- γ_i= Pollution, C_{max}, NPV: Triple model goals.

Problem formulation

The mathematical model of the GMMRCPSP is as follow:

$$x_{im_it} = \begin{cases} 1, & if\ Activity\ i\ start\ in\ time\ t\ in\ mode\ m_i \\ 0, & others \end{cases} \tag{2}$$

$$Z_1 = Minimize \quad \sum_{i=1}^{n+1} \sum_{m_i=1}^{M_i} \sum_{t=es_i}^{ls_i} \tilde{P}_{im_i}.x_{im_it} \tag{I}$$

$$Z_2 = Minimize \quad \sum_{t=es_n}^{ls_n} \tilde{t}x_{n1t} \tag{II}$$

$$Z_3 = Maximize \quad \sum_{i=1}^{n+1} \sum_{m_i=1}^{M_i} \sum_{t=es_i}^{ls_i} \frac{\widetilde{CF}_{im_i}.x_{im_it}}{\left(1+\widetilde{AIR}\right)^t} \tag{III}$$

$Subject\ to$:

$$\sum_{m_i=1}^{M_i} \sum_{t=es_i}^{ls_i} x_{im_it} = 1, \quad i = 1, \cdots, n \tag{IV}$$

$$\sum_{m_i=1}^{M_i} \sum_{t=es_i}^{ls_i} (\tilde{t} + \tilde{d}_{im_i})x_{im_it} \le \sum_{m_j=1}^{M_j} \sum_{t=es_j}^{ls_j} \tilde{t}.x_{jm_jt} \quad < i,j > \in E_{fs^{min}(0)} \tag{V}$$

$$\sum_{i=2}^{n-1} \sum_{m_i=1}^{M_i} \tilde{r}_{imk} \sum_{s=max\{t-d_{im},es_i\}}^{min\{t,ls_i\}} x_{im_is} \le \tilde{R}_k \quad k = 1, \cdots, K\ ,\ t = 1, \cdots, \bar{T} \tag{VI}$$

$$\sum_{i=2}^{n-1} \sum_{m_i=1}^{M_i} \tilde{r}_{imp} \sum_{t=es_i}^{ls_i} x_{im_it} \le \tilde{R}_p \quad p = 1, \cdots, P\ ,\ t = 1, \cdots, \bar{T} \tag{VII}$$

$$\sum_{m_i=1}^{M_i} \sum_{t=es_i}^{ls_i} \tilde{P}_{m_i}.x_{im_it} \le \widetilde{MAP}_i, \quad i = 1, \cdots, n \tag{VIII}$$

$$x_{im_it} \in \{0,1\} \qquad i = 1,2, \cdots, n+1,\ \ m_i = 1, \cdots, M_i, \qquad t = 1, \cdots, \bar{T} \tag{IX}$$

The objective function (I) minimizes the total project environmental pollution; the objective function (II) minimizes the completion time of the dummy end activity and the project duration; and the objective function (III) maximizes the project's net present value (NPV), including the NPV of positive and negative cash flows. Equation (IV) assures that each activity can be done precisely in one mode and one start time. Constraint (V) represents precedence relations. Constraint (VI) guarantees renewable resource availability, and Constraint (VII) guarantees non-renewable resources. Constraint (VIII) represents the maximum acceptable environmental pollution of each activity. Constraint (IX) states binary values on the decision variables, equal to 1 if activity i starts in time t in mode mi, and otherwise, it is 0.

Fuzzy logic and fuzzy numbers

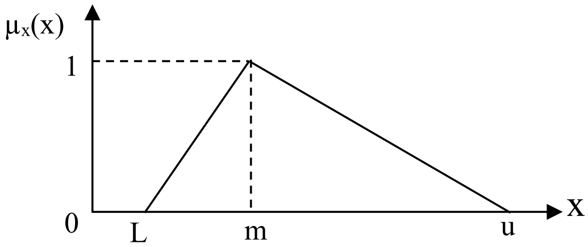
The fuzzy sets theory was first proposed in 1965 by Professor Lotfi A. Zadeh (Zadeh, 1965). Fuzzy theory is to act under uncertainties. The theory can mathematically formulate many imprecise and ambiguous concepts, variables, and systems and provide the basis for reasoning, inference, control, and decision-making under uncertainty.

According to this theory, a fuzzy number is a particular fuzzy set in the form of $\tilde{A} = x \in R|\mu_{\tilde{A}}(x)$, where x is the member value of the real number sets, and its membership function is as $\mu_{\tilde{A}}(x)$. In research, fuzzy numbers are generally used in fuzzy triangular numbers or trapezoidal fuzzy numbers. In this study, fuzzy triangular numbers have been used due to the simplicity of calculations. In the following, the membership function of a triangular fuzzy number is shown (Wu & Li, 2007):

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \leq x < m \\ \frac{u-x}{u-m}, & m \leq x < u \\ 0, & x \geq u \end{cases} \tag{3}$$

Which can be summarized as $\tilde{A} = (l, m, u)$. The above membership function is shown in Figure 1.

Figure 1. A triangular fuzzy number



If $\tilde{A} = (a_l, a_m, a_u)$ and $\tilde{B} = (b_l, b_m, b_u)$ are two fuzzy triangular numbers, the algebra of fuzzy triangular numbers are defined in Table 1 (Safari & Khanmohammadi, 2017).

Table 3. Algebra of fuzzy triangular numbers

Fuzzy equivalent	Algebraic operation
$\tilde{A} \oplus \tilde{B} = (a_l + b_l, a_m + b_m, a_u + b_u)$	Addition of two fuzzy numbers
$\tilde{A} \ominus \tilde{B} = (a_l - b_l, a_m - b_m, a_u - b_u)$	Subtraction of two fuzzy numbers
$\tilde{A} \otimes \tilde{B} = (a_l \times b_l, a_m \times b_m, a_u \times b_u)$	Multiplication of two fuzzy numbers
$k \times \tilde{A} = (k \times a_l, k \times a_m, k \times a_u)$	Multiplication of a number in a fuzzy number
$\frac{\tilde{A}}{\tilde{B}} = (\frac{a_l}{b_u}, \frac{a_m}{b_m}, \frac{a_u}{b_l})$	Division of two fuzzy numbers
$\tilde{A}^{-1} = (\frac{1}{a_u}, \frac{1}{a_m}, \frac{1}{a_l})$	Inverse fuzzy number
$\tilde{A}^{\tilde{B}} = \left({a_u}^{b_u}, {a_m}^{b_m}, {a_l}^{b_l}\right), \quad 0 \leq a_i < 1$ $\tilde{A}^{\tilde{B}} = \left({a_l}^{b_l}, {a_m}^{b_m}, {a_u}^{b_u}\right), \quad a_i \geq 1$	Power of two fuzzy numbers*

*Researchers have considered this item, and it is not listed in the source.

Since different research steps require a comparison of fuzzy numbers, the area approach has been used among the different methods of comparing two fuzzy triangular numbers (Amiri et al., 2018). The difference between two fuzzy triangular numbers is obtained in the area method, a triangular fuzzy number. For calculating the difference between two fuzzy triangular numbers:

First, subtract the first fuzzy number's lower limit from the second fuzzy number; then, subtract the middle of the first fuzzy number from the middle of the second one. Finally, subtract the upper limit of the first fuzzy number from the lower limit of the second fuzzy number. Then, the area of the positive and negative parts of the difference between the two fuzzy numbers is

calculated. If the positive part was more significant than the negative part, the first fuzzy number was more significant than the second, and vice versa.
Also, in this study, for the defuzzification of fuzzy triangular numbers $\tilde{A} = (l, m, u)$, the center of gravity method is used, which is calculated as follows:

$$Diffuzzy(\tilde{A}) = \frac{l+4m+u}{6} \quad (4)$$

Solution Methods

Multi-objective optimization seeks to optimize conflicting goals that compete with each other, so it provides one solution as the optimal solution and provides a set of optimal solutions. This optimal solution set is called Pareto Optimal. These solutions consider all objectives at the same time, none of them is superior to the other, and there is a kind of balance between these objectives.
Optimum schedules will not necessarily minimize environmental pollution, minimize C_{max}, and maximize NPV. Therefore, in most cases, the simultaneous use of these three objective functions causes a conflict between the objectives. So using multi-objective solution methods, the solution will be in the form of a three-dimensional Pareto front.

Solution representation

Solution representation affects the solution quality obtained by the solution algorithms. This paper uses a two-row matrix to represent the solution: the first row is a permutation vector showing the order of activities, and the second row of the matrix shows the mode of that activity. For example, a solution is shown below in a project with ten activities.

2	1	4	5	6	3	8	9	7	10
2	1	1	3	2	2	1	3	2	3

In this solution, the first row of the matrix shows the order of activities. Activity 1 is executed after Activity 2, and Activity 10 is implemented as the last activity. The second row shows that Activity 1 is performed in its first mode, Activity 2 in its second mode, and Activity 10 in its third mode.

This solution representation can quickly determine the activities' sequence, execution mode, and each activity's start and end time. It is also easy to get the amount of activity resource requirement at any time, the amount of environmental pollution of that activity, and the cash flow. From these cases, the values of all three objective functions can be easily obtained.

Initial feasible solution calculation algorithm (IFSCA)

This algorithm is a heuristic method that removes part of the infeasible area from the search area of meta-heuristic algorithms. This action increases the quality and speed of meta-heuristic algorithms. The flowchart and steps of this algorithm are:

1. Create a random initial solution that gives priority to activities. So, among N!, priorities of activities without constraints of the problem. If the unexpected results are obtained in precedence constraints, it is correct, and it will be an initial feasible solution; otherwise, go to step 2.
2. Select the first activity in the list of non-checked activities. If all precedence relations are passed, go to step 4; otherwise, go to step 3.

3. Skip the activity that is not passed the precedence relation and return to step 2. Among other activities in the list of checkable activities, select the subsequent activities.
4. The activity checked in Step 2 can be deleted from the list of checkable activities. Transfer to the evaluated activities. If still unevaluated activities remain, return to the second step. Otherwise, activities stored in the assessed activities show as an initial feasible solution.

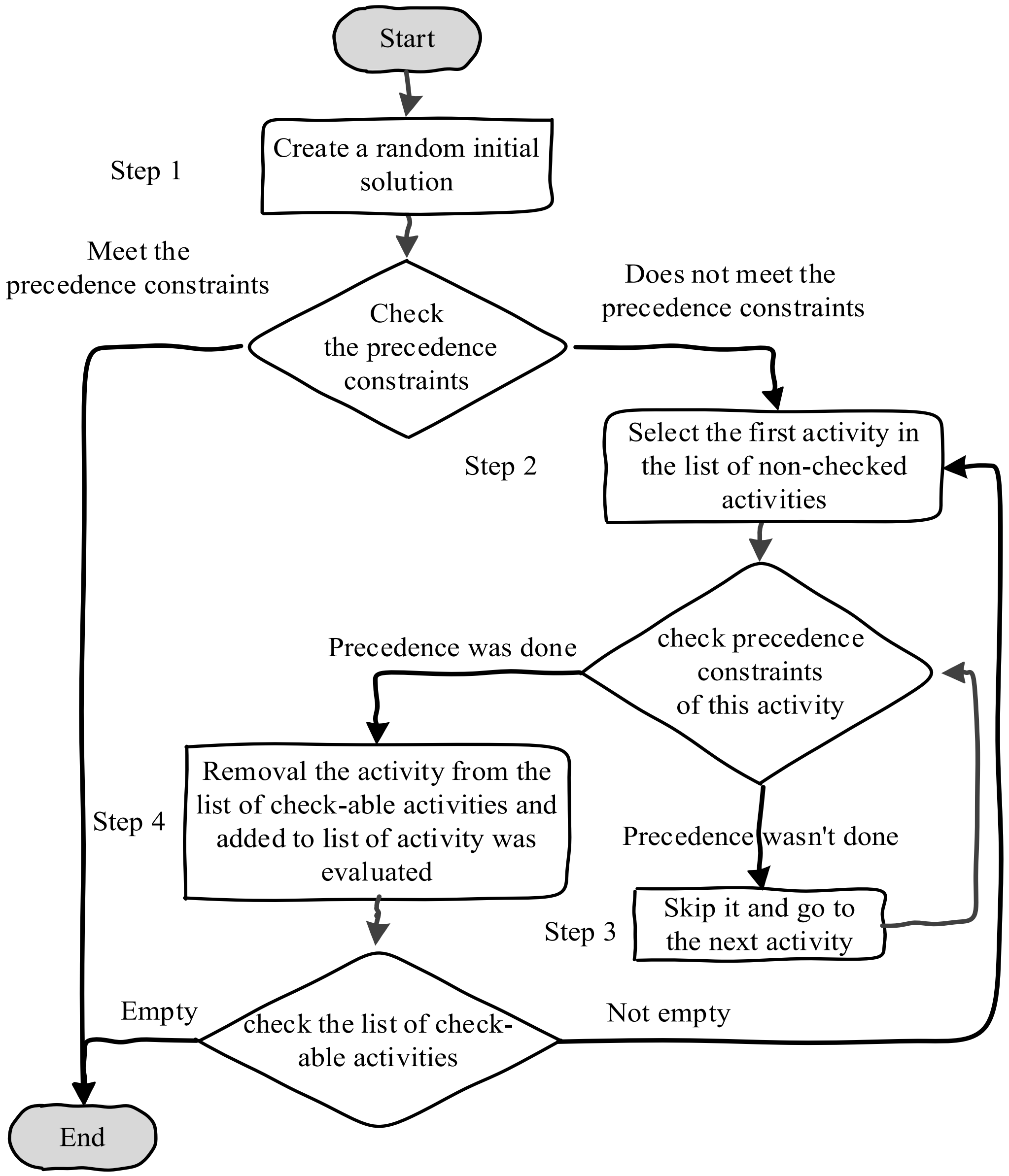


Figure 2. Flowchart of the initial feasible solution calculation algorithm

Solution process

The initial population of each meta-heuristic algorithm is created using the initial feasible solution calculation algorithm based on solution representation in the problem-solving process. Then three multi-objective meta-heuristic algorithms solved the problem. The schematic process of these steps is as follows.

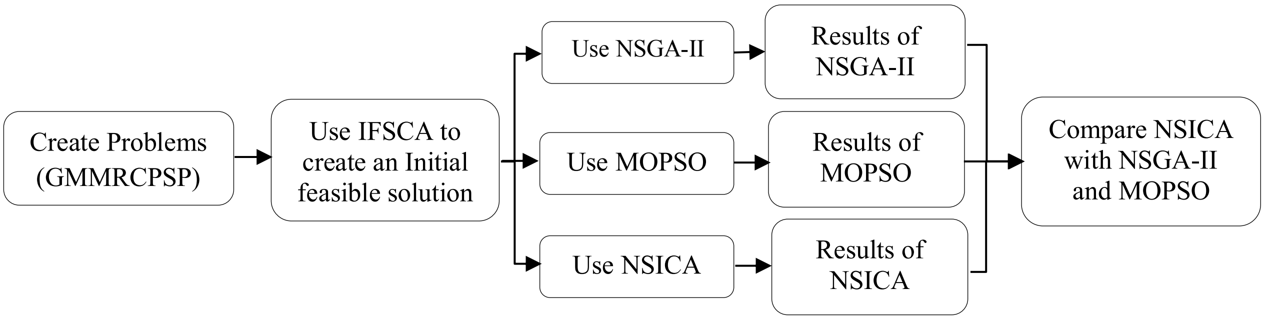


Figure 3. Flowchart of the solution process

One of the meta-heuristic algorithms used in this paper is NSGA II (Deb et al., 2002). Deb et al. (2002) developed a non-dominated sorting genetic algorithm II (NSGA-II) by introducing the elitism strategy, density estimation strategy, and fast non-dominated sorting approach to NSGA to find a much better solutions' spread and better convergence near the Pareto-optimal front.

The second meta-heuristic algorithm used in this study is MOPSO (Coello et al., 2004). The multi-objective particle swarm optimization (MOPSO) uses the concept of Pareto dominance to find solutions for multi-objective problems. It also employs a secondary population or external archive to store non-dominated solutions and guide future generations. This unique feature helps this algorithm's solutions be more accurate and faster than other algorithms in some problems.

The Third meta-heuristic algorithm used in this study is NSIat developed by this paper. This algorithm utilizes the capabilities and strengths of multi-objective algorithms, including non-dominated sorting genetic algorithm II (NSGA II), multi-objective particle swarm algorithm (MOPSO), and imperialist competitive algorithm (ICA) simultaneously. Section 4.4 describes this algorithm.

Non-dominated Sorting Imperialistic Competitive Algorithm (NSICA)

NSICA is the product of the Imperialistic Competitive Algorithm (ICA) evolution, one of the recent evolutionary algorithms (Atashpaz-Gargari & Lucas, 2007). NSICA is a meta-heuristic algorithm for solving multi-objective problems, just like the single-objective imperialist competitive algorithm (ICA), originated from the development of human society and the simulation of the imperialist competitive process.

Phase I: *Establishment of Early Empires*

In this algorithm, countries are first created as the primary solution. In this paper, this section is performed using the initial feasible solution calculation algorithm (IFSCA). Then, countries are divided into several ranks for ranking through a non-dominated sorting approach (Deb et al., 2002). (This section is taken from the NSGA-II algorithm).

Each country's power is calculated using the following equation to compare countries of the same rank. This method, known as the Sigma approach, is evident in the following equation with a slight change from the reference version (Kheirkhah et al., 2016):

$$Power_n = \frac{1}{\sum_{j=1}^{D}[Fj(n)/\sum_{i=1}^{Nrank(c)} Fj(i)]Rank(c)*D} \tag{5}$$

Where $Power_n$ indicates the power of each country, D is the number of objective functions (here three functions), $Fj(n)$ is the amount of jth cost function from the nth country, $rank\ (c)$ is the value of the country rank, and $Nrank(c)$ is the number of countries with rank c.

After gaining rank and power for each country, countries are first sorted by rank and power. Of all the countries, the first Pareto front countries are stored in the best archive/repository (like the MOPSO algorithm). The number of empires (N_{emp}) is then removed from the set sorted as imperialists, and the rest of the countries are divided as colonies among the imperialists through Roulette Wheel Selection's logic with the following probability:

$$P_{emp} = e^{\frac{-\alpha\left(Rank*\frac{1}{power}\right)}{max(Rank)*max\left(\frac{1}{power}\right)}} \tag{6}$$

The above formula, known as the Boltzmann relation, makes any more powerful empire more likely to occupy the colonies. In single-objective ICA, objective function values were used to determine this probability. Nevertheless, due to the multi-objective nature of the problem, it is impossible to compare empires' superiority through the objective function. Therefore, each imperialist's rank and power are used to calculate this probability with a slight change in the calculation.

Finally, after all the empires are established, and the colonies are assigned to them through the following formula, each empire's total cost is calculated to compete with the imperialists.

$$TP\ of\ Emp_n = TotalCost\ (Imperialist_n) + \xi * mean\{TotalCost(Colonies\ of\ Empire_n)\} \tag{7}$$

Where ξ is a value between 0 and 1, the above equation states that for obtaining the total cost of each empire, the value of the colonial cost function must be added to a percentage of its colonies' average cost function (for example, ξ = 0.1). Due to several objective functions, each empire's total cost is multivalued like the cost functions. Finally, the values of the total cost functions of each empire are summed to normalize it.

Phase II: *Main Cycle of Algorithm*

In the second phase, like the single-objective ICA, assimilation policy is first implemented through the colonies' movement towards the imperialist. Then, each empire's internal power is examined. If the power of one colony of that empire increases after assimilating, the imperialist in that empire changes; otherwise, those imperialists remain. A percentage of the colonies are also chosen to carry out the revolution. Once again, if one revolutionary has more power, it will be replaced by the previous imperialist.

In the multi-objective ICA, rankings and powers must be recalculated to update countries. Thus, the countries are decolonized, the desired changes are made (ranking and recalculation of power), and the same empires are rebuilt with the same colonies. (Here, there is no need to sort again). The total cost of each empire is then recalculated.

During the imperialist competitive process, strong empires' power gradually increases, and weak empires' power decreases. The powerful empires conquer the colonies of weak empires. If the defeated empire in the imperialist competitive process became so weak that it no longer had a colony, the empire itself would be considered a colony of a more powerful empire, and it would be eliminated. This competition continues until only one empire remains.

At the end of the imperialist competitive process, first-ranked countries (those that have not been defeated) are stored in a temporary repository and compared with previous values stored in the best repository. In other words, all the values in this repository are ranked and compared by power; those ranked first remain in the best repository, and the rest are eliminated. Thus, the best solutions will be stored in the best repository over time. Finally, the cycle continues until the stop conditions (number of iterations or remaining only one empire) are met.

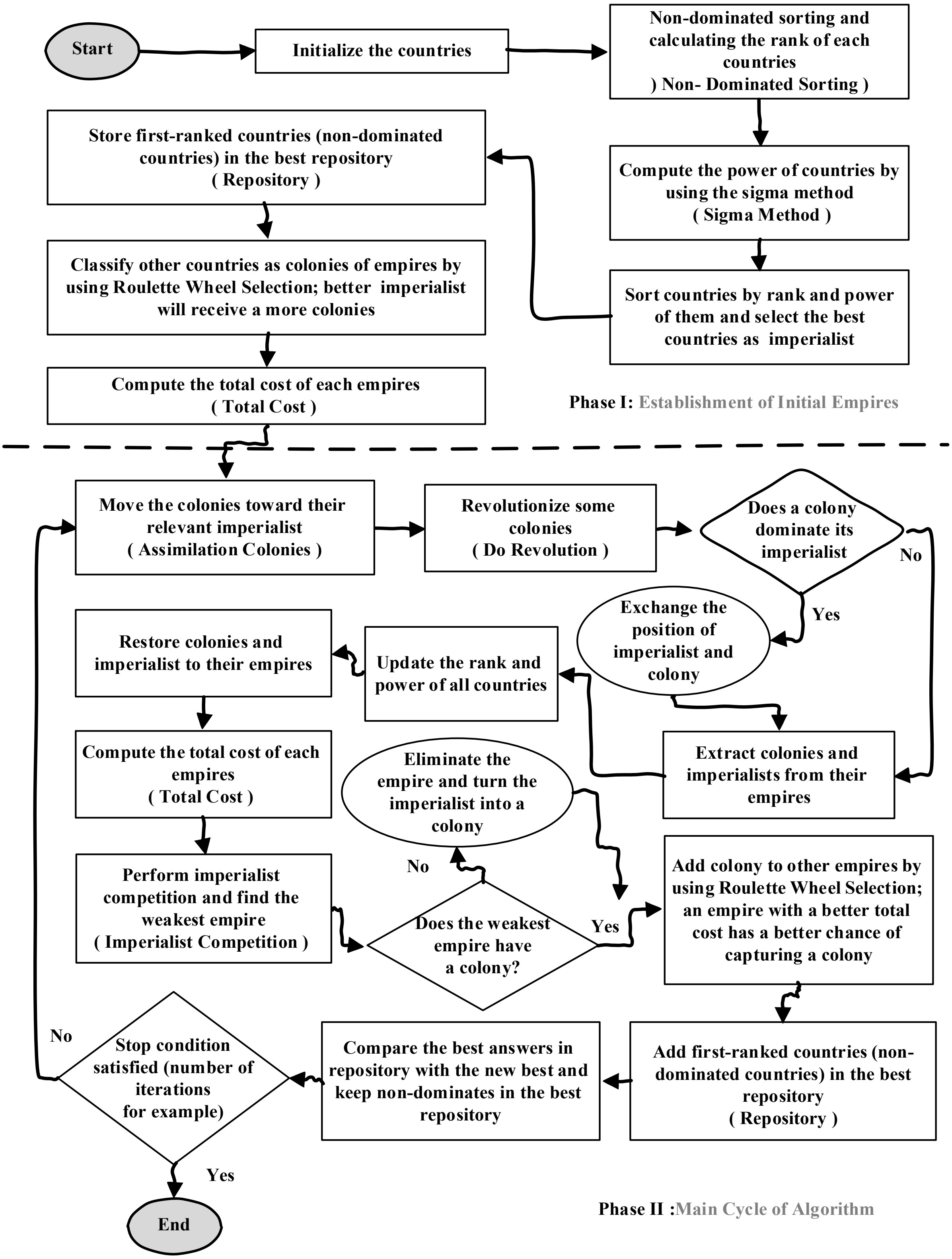


Figure 4. Flowchart of Non-dominated Sorting Imperialistic Competitive Algorithm

Results

For testing the research problem, the first three categories of problems were created using the PSPLAB database problems format for MRCPSP problems. A series of random triangular fuzzy numbers were generated for other objective functions and their related parameters. The structure of the created problems is as follows.

Table 4. Structure of the created problems

Number of Problems	Number of Activity	Number of renewable & Non-renewable resources	Number of Activity Modes	Description
10	10	3 & 3	4	All parameters are
10	20	3 & 3	4	fuzzy triangular
10	30	3 & 3	4	numbers

The parameter adjustment of meta-heuristic algorithms is made using response surface methodology (RSM) and Design Expert 12 software. The results are as follows.

Table 5. Parameters adjustment by RSM

Algorithms	Parameters
NSICA	Max Iteration=100, Number of Population=80, Number of Empires=30, beta=2, Probability of Revolution=0.3, zeta=0.1, alpha=2
NSGA II	Max Iteration=100, Number of Population=80, Probability of crossover=0.8, Probability of mutation=0.3
MOPSO	Max Iteration=105, Number of Population=42, number of repository=50, w=0.5, w_{damp}=0.99, c1=1, c2=1, nGrid=5, alpha=0.2, beta=2, gamma=2

Problems and algorithms were coded in MATLAB software and run by a Core i7 CPU and eight gigs RAM. All problems run four times, and the best Pareto front was extracted from each run. Finally, these Pareto Fronts are integrated by the non-dominated sorting approach, and the best Pareto front was developed.

Table 6. Example result of each problem and quality criteria of solutions

number of all solution creation in each run	8880	Quality criteria of solutions							
		number of Pareto solutions	MID	Mean of Coefficient of Closeness	Mean of Similarity	Quality Metric	Spacing	Diversity	Running time
Problem: j104-3 NSICA Run	run 1	52	13.801	0.626	0.066	0.247	0.003	29.056	98.484
	run 2	49	11.727	0.645	0.060	0.286	0.042	33.039	99.344
	run 3	48	12.020	0.638	0.061	0.286	0.033	33.067	98.125
	run 4	46	11.658	0.694	0.063	0.382	0.048	30.060	100.031
Problem: j104-3 NSGA-II Run	run 1	48	11.270	0.585	0.061	0.180	0.037	27.060	104.578
	run 2	50	9.903	0.692	0.059	0.300	0.006	32.062	104.234
	run 3	54	10.461	0.684	0.055	0.320	0.072	33.067	105.578
	run 4	68	12.324	0.639	0.043	0.200	0.035	34.065	124.125
Problem: j104-3 MOPSO Run	run 1	28	12.946	0.621	0.105	0.195	0.127	34.059	100.652
	run 2	26	11.119	0.591	0.114	0.390	0.014	27.067	101.681
	run 3	27	6.675	0.531	0.110	0.220	0.095	14.103	103.709
	run 4	27	10.513	0.545	0.110	0.195	0.025	23.049	104.942

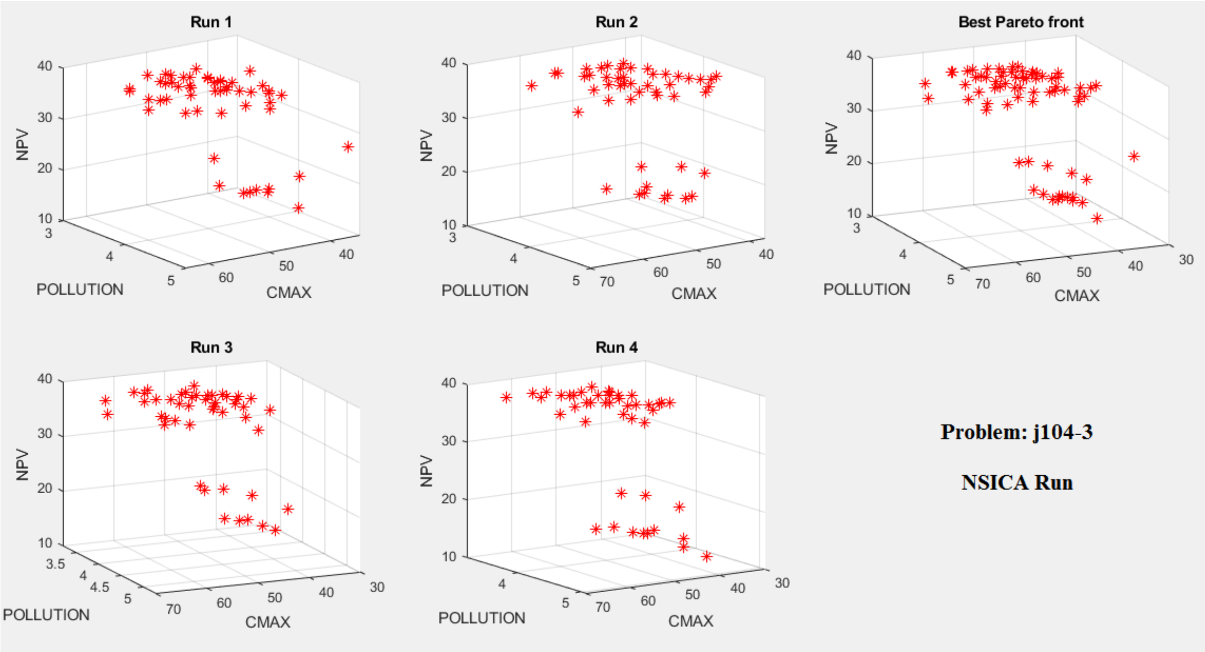


Figure 5. Example Pareto front of four runs of one problem and Integrated Best Pareto front

The particular criteria are used to compare multi-objective algorithms. These criteria help compare one algorithm's Pareto Front with another or one run's Pareto Front. These criteria are classified into two general categories: quality measurement criteria and coverage criteria. The criteria of the primary category are the Number of Pareto Solutions (NPS), Mean Ideal Distance (MID), Mean of Coefficient of Closeness (MCC), Mean of Similarity (MS), and Quality Metric (QM). The criteria of the second category are spacing and diversity. Typically, the running time is calculated as a criterion of the performance of algorithms.

Comparing NSICA with NSGAII and MOPSO algorithms in solving 10, 20, and 30 activities problems is as follows.

Table 7. Comparing the results of NSICA with NSGA-II and MOPSO

Algorithms	Number of Activity	Quality criteria of solutions							
		Number of Pareto solutions	MID	Mean of Coefficient of Closeness	Mean of Similarity	Quality Metric	Spacing	Diversity	Running time
NSICA Average of 10 problems and four runs	10	34.3	11.27	0.621	0.184	0.178	0.040	23.821	224.517
	20	38.325	10.3	0.613	0.156	0.194	0.044	21.833	273.487
	30	29.4	11.05	0.610	0.132	0.244	0.035	25.810	382.236
NSGA-II Average of 10 problems and four runs	10	37.975	9.307	0.600	0.084	0.178	0.040	23.821	342.914
	20	41.2	8.550	0.594	0.076	0.194	0.044	21.833	290.557
	30	34.75	10.06	0.605	0.092	0.244	0.035	25.810	395.272
MOPSO Average of 10 problems and four runs	10	23.75	9.232	0.576	0.138	0.088	0.048	22.020	394.180
	20	24.6	8.394	0.573	0.126	0.138	0.049	20.233	327.111
	30	22.9	10.07	0.578	0.150	0.205	0.047	23.807	461.248

Research innovation

The research innovations can be divided into the following two categories:

- Innovation in modeling: This study presents new modeling of the project-scheduling problem, and the proposed model has new and exclusive capabilities that previous models lacked. The first feature of the model shown in this study is its application under uncertainty, emphasizing fuzzy logic and estimation of all model parameters as a triangular fuzzy number. The second feature of the model presented in this study is the simultaneous use of several objectives with time, cost, and environmental optimization approaches. The minimization of environmental pollutants is one of the goals that has not been considered in any previous models studied in the literature.
- Innovation in optimization method: In this section, the first research innovation is to provide a heuristic algorithm to increase the speed (efficiency) of the solution method. This algorithm improves the speed of meta-heuristic algorithms when solving the model by removing a large part of the unjustified search space. The study's second innovation introduces a new multi-objective meta-heuristic algorithm (non-dominated sorting imperialist competitive algorithm-NSICA). This algorithm utilizes the capabilities and strengths of multi-objective algorithms, including non-dominated sorting genetic algorithm II (NSGA-II), multi-objective particle swarm algorithm (MOPSO), and imperialist competitive algorithm (ICA) simultaneously. It offers far better results than these algorithms in solving the extended scheduling problem.

Conclusion

This study presents a new project-scheduling model. This model has three objectives: minimizing environmental pollutions, minimizing project completion time (Cmax), and maximizing NPV. Besides, in this paper, uncertainty in estimating the model parameters is obtained by fuzzy logic. Thus, all model parameters were considered fuzzy triangular numbers for the first time. Therefore, the final model of this paper was GMMRCPSP.

This new model allows the three main criteria of environmental pollution, profitability, and scheduling to be combined simultaneously.

The model solution results show that the NSGA-II algorithm finds more solutions than NSICA and MOPSO. However, NSICA offers a better approximation of optimum Pareto Front than NSGA-II and MOPSO algorithm. In addition, almost all solutions with MOPSO are covered by NSICA and NSGA-II algorithms. In addition, the running time of the NSICA shows that the speed of this algorithm is more than NSGA-II and MOPSO algorithms. Therefore, the NSICA is the best algorithm, and the NSGA-II algorithm is more suitable than the MOPSO algorithm to solve the research problems.

The current study hopes to open a new way to measure and enter environmental variables in modeling and scheduling projects to emphasize ecological variables in the future.

Future research suggests that other multi-objective meta-heuristic methods are used to solve this problem. The results are compared with the present study to achieve efficient solution algorithms.

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