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Presenting and Solving the Resilient Project Scheduling Model with Limited Resources by Considering Human Skills in Conditions of Uncertainty using Meta-Heuristic Algorithms

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ABSTRACT

In this article, it was presented and solved the resource-constrained project scheduling model, taking into account human skills and resilience considerations under uncertainty conditions, using whale optimization algorithm (WOA) based on Pareto archive and NSGA-II. Due to research goal, a multi-objective mathematical fuzzy model is presented with the objectives of minimizing the total tardiness penalty of activities and minimizing the total fines for assigning employees to lower skill levels. To solve the model, the multi-objective WOA and NSGA-II algorithms are used, and the solution results of the two algorithms are compared based on the comparative indicators named quality, spacing and diversity. The results showed that, in all cases, the whale optimization algorithm has a higher ability to produce higher quality solutions than the NSGA-II algorithm. Moreover, the WOA is able to produce solutions with higher diversity compared to NSGA-II algorithm, or in other words, the proposed algorithm has a greater ability to explore and extract the more feasible solutions, whereas, the NSGA-II algorithm produces solutions with higher spacing.

Keywords: project scheduling; resource constraints; Resilience; uncertainty; Metaheuristic algorithms.

1. Introduction

Project scheduling is one of the most important issues in project management. Therefore, many researchers tried to create different models to solve this problem and by adding new restrictions, they could make it closer to real problems (Chen et al, 2010). The scheduling problem generally includes n activities, each activity in the project needs resources to complete. In the project, the prerequisite relationships between the activities are shown by the graph and are clear from the beginning (Neron and Boptista, 2002).

Growing studies in the field of project scheduling have led to a wide range of different types of problems. This diversity is caused by the characteristics of the used resources (number, type and limitation), the characteristics of the project activities (possibility of interruption, prerequisite limitations, preparation time, completion time, due date, need for resources, type and number of execution situations, financial concepts and transfer times between them) and the objectives. In general, organizations face resource limitations (renewable and non-renewable) and capital to carry out their projects. Therefore, in order to get more income, it is necessary to pay attention to the allocation of resources to the activities in addition to scheduling the activities (Eshraghi, 2016).

In this research, the problem of multi-objective project scheduling with limited resources is addressed by considering resilience criteria and human skills under conditions of uncertainty. The model studied in this research is designed with two objectives: the first objective function is to minimize the sum of lateness penalties of the project activities and the second objective function is to minimize the sum of fines that are considered for allocating employees to lower skill levels.

In this model, we want the employees to be assigned to a level closer to their skill, and for this purpose, an amount will be considered as a penalty, which will be entered into the model in case of deviation from the actual level. It should be noted that the minimization of the first goal does not mean the minimization of the second goal and vice versa, because the first goal seeks to minimize the delay, the minimization of the delay depends on the timely allocation of resources. While optimizing the first objective, some forces may be allocated to skills lower than their actual level, because otherwise the activity interruptions and delays will increase. Therefore, we want the tardiness to be minimized while the workforce is not assigned to lower levels (as far as possible). Therefore, we are able to claim that the goals are contradictory and the model can be called a multi-objective one. In this article, the multi-objective whale optimization algorithm based on the Pareto archive is used to solve the model, and its results are compared with the results of the NSGA-II algorithm (multi-objective version of the genetic algorithm) based on quality, diversity and spacing metrics.

This article is organized in 6 parts, in the first part called the introduction, the importance of the subject and an introduction to the problem under investigation are presented. The literature review section reviews previous research to explain the research gap. In the third part, problem definition and mathematical modeling were assigned. In the fourth section, the structure of multi-objective WOA based on Pareto archive is described. Finally, in the fifth part, the results of solving the model are presented, and in the sixth part, the summary and suggestions are presented.

2. Literature review

The resource-constrained project scheduling problem (RCPSP) is one of the most important issues in the field of project scheduling, which has repeatedly attracted the attention of researchers in the last decade, and a lot of research has been done in this field. For example, Li and Womer (2009) presented a combined algorithm based on mixed integer modeling and constraint programming to solve the project scheduling problem with multi-skilled personnel considering the limited workload capacity for each worker. In their model, workers are able to provide several skills, but they have to provide one skill at a time. In 2010, Elif studied a bi-objective project scheduling problem with multi-skilled workforce and hierarchical skills. In order to solve the problem, a mathematical model was presented and to solve the model, a two-objective genetic algorithm was applied, which minimizes the maximum completion time and minimizes the wastage of labor. In 2011, Wang and Fang designed and presented a new algorithm obtained from the simulation of the frog's leaping behavior (SFLA) to solve the multi-mode project scheduling problem.

Karam et al. (2017) investigated the problem of project scheduling considering multi-skilled workforce and flexible working hours. For this problem, they presented a mixed integer mathematical model considering resource limitations. In the model presented by them, the workforce had multiple skills and the workload of people was considered different weekly and monthly in different periods. The main problem of the research was the limited project schedule based on the need of each project activity for each skill. Tabrizi (2017) investigated the project planning and scheduling problem and provided an overview and theoretical summary of the rescheduling of project activities along with the issue of raw material procurement. Habibi et al. (2017) investigated the problem of project scheduling with limited resources. They considered the amount of resources required for each activity and the amount of resources available at different times, and for this problem, they presented a multi-objective mathematical model with the objectives of minimizing project time and cost, maximizing NPV and project robustness. Also, they used multi-objective particle swarm algorithms and NSGA-II to solve the mentioned model.

Wang and Zheng (2018) presented a knowledge-based multi-objective optimization algorithm to solve the project scheduling problem with resource constraints. One of the resources that they considered in the problem under investigation was human skills, which were assumed to be limited in number. They presented a multi-objective mathematical model for this problem and used the multi-objective fruit flight optimization algorithm to solve the model. Uysal et al. (2018) presented and solved the project scheduling model with possible resources in which resources may be interrupted. In their model, they defined a probability constraint for resource outages that could be used to construct baselines with a predetermined confidence interval. Habibi et al. (2019) investigated the project scheduling problem and ordering raw materials, taking into account sustainability considerations for construction projects. They presented an integrated framework for project scheduling and material ordering with environmental considerations and the benefits of potential suppliers of project resources in the form of a mathematical model. They used multi-objective particle swarm meta-heuristic algorithms and NSGA-II to solve the model. Vanhoucke and Coelho (2019) investigated the project scheduling problem with limited resources, considering the division of work and preparation time. In their paper, they divided the activities into smaller parts and also considered the sequence-dependent preparation time to perform the activities. They presented a single-objective mathematical model for this problem, the objective of which is to minimize C_{max} (the maximum project completion time) and they also used an innovative algorithm to solve the model.

Torabi Yeganeh and Zegordi (2020) presented a multi-objective model of resilient project scheduling under conditions of uncertainty. In this article, the concept of resilient project scheduling was investigated to measure the ability of rescheduling to deal with disruption in time. They presented a multi-objective mathematical model for this problem by considering resilience factors such as risk and the model was solved using the NSGA-II algorithm. Bocewicz et al. (2020) dealt with multi-project scheduling considering the allocation of labor force according to their qualification and competence. Tian et al. (2021) studied the multi-objective project scheduling problem with limited resources with skill switches. They developed a mixed integer programming model with the aim of minimizing the project completion time and total cost, and then used an evolutionary algorithm to effectively solve this problem. Ghamginzadeh et al. (2021) also investigated the problem of project scheduling considering multiple skills under conditions of uncertainty. In their paper, a multi-objective multi-skill project scheduling problem was considered in terms of fuzzy time with two main objectives: 1) minimizing the project completion time and 2) minimizing the total labor allocation cost. In addition, a multi-objective imperialistic competitive algorithm was adopted to solve the model. Also, in order to evaluate the performance of the algorithm, the proposed algorithm was compared with the NSGA-II based on three indicators. Snauwaert and Vanhoucke (2022) studied and analyzed the project scheduling problem with multi-skilled resources. They proposed a new classification scheme based on an existing classification plan for the project scheduling problem. This scheme allows researchers to categorize all multi-skill project planning issues and their developments. They also proposed a new data generation method for mentioned problem and introduced several synthetic datasets for different research purposes.

Chen et al. (2022) addressed the multi-project scheduling problem with limited resources and multi-skilled labor allocation for the large-scale equipment manufacturing industry under uncertainty. In their article, the processing time is non-deterministic and the actual processing time is calculated based on the skill efficiency and the duration of the random process. Foreign labor is hired when domestic labor cannot meet the processing demand. The objective of the model in their paper is to minimize the expected integrated cost, which is the sum of the delay penalty and the external labor cost. Haroune et al. (2022) have also dealt with the problem of multi-project scheduling and the allocation of multi-skilled employees with hard and soft constraints. In their paper, the goal is to assign employees to project tasks in such a way that the total weighted tardiness and undesired goal deviations are minimized. They presented a mathematical model for the problem and used the forbidden search algorithm to solve the model. Yu et al. (2022) addressed the multi-project scheduling problem with the assumption of sharing multi-skilled workers. In their problem, it is assumed that each project is independently planned by project managers and that multiple projects compete for limited employees with multiple skills. They presented a two-stage decomposition model and then proposed a two-stage approach with a software scoring mechanism to minimize the project completion time and minimize the total delay cost.

Table 1- Summary of previous research

References	single-project	multi-project	resilience	workforce	uncertainty	Multi-objective	Solving algorithm
Li and Womer (2009)	√			√			Genrtic Algorithm
Elif (2010)	√			√		√	Genrtic Algorithm
Wang and Fang (2011)	√					√	Frog Algorithm
Karam et al. (2017)	√			√		√	Genrtic Algorithm
Habibi et al. (2017)	√			√	√	√	PSO and NSGA-II
Wang and Zheng (2018)	√			√		√	Fruit Flight Optimization Algorithm
Uysal et al. (2018)	√		√				-
Habibi et al. (2019)	√					√	PSO and NSGA-II
Torabi Yeganeh and Zegordi (2020)	√		√		√	√	NSGA-II
Bocewicz et al. (2020)		√		√			Genrtic Algorithm
Tian et al. (2021)		√		√		√	Evolutionary Algorithm
Ghamginzadeh et al. (2021)	√			√	√	√	NSGA-II
Snauwaert and Vanhoucke (2022)	√			√			Literature review
Chen et al. (2022)		√		√	√	√	Evolutionary Algorithm
Haroune et al. (2022)		√		√		√	Goal programing
Yu et al. (2022)		√		√		√	-
Our research	√		√	√	√	√	Whale Optimization Algorithm and NSGA-II

Table (1) summarizes the previous researches and compares the present research with them. As seen in the research background section, a lot of research has been done in the field of project scheduling problem optimization. But so far, in the field of project scheduling, considering the resilience factors in the conditions of uncertainty, only research by Torabi Yeganeh and Zegordi (2020) has been done. The present research was developed in line with the development of Torabi Yeganeh and Zegordi (2020) and in order to develop the mentioned research model, multiple human skills were added to the model of the article of Torabi Yeganeh and Zegordi (2020) and the present research is innovative in this respect.

3. Mathematical model

The purpose of this article is to present a project scheduling model with non-deterministic processing time and risk-related factors considering multi-skilled workforce as renewable resources. In the current research model, the project has n activities that are ready to be performed at different times, and this parameter is indicated by $ready_i$. Each activity requires p_i time for processing (which is uncertain in this research) and also each activity requires a certain number of workers with required skills to complete.

In the case of skilled workforce, three skill levels are considered: senior, standard and worker (low level). Every person has a skill and it is necessary to mention that every person has the ability to perform a skill lower than his own. For example, a person with senior skills also has standard and worker skills. In the project, each activity needs a certain amount of man-hours to complete some skills (one or more skills), which is considered definite.

Several assumptions or limitations have been considered for mathematical modeling, which are as follows:

• Every workforce can be assigned only at their skill level or levels lower than their real skill.

• The number of manpower required for each skill to complete each activity is determined.

• The processing time of the project activities are definitely assumed.

• The penalty considered for assigning employees to skills lower than their actual skills is definitely stated.

• The penalty for the lateness of the activities is definitively stated.

• The date of completion of the activities is definitely stated.

• Resources (workforce) can be transferred between activities and transfer time is considered 0.

• The problem has several goals.

In this research, a mathematical model is presented based on the model in the article of Torabi Yeganeh and Zegordi (2020). In this section, the indices, parameters, and variables of the model are described first, and then the mathematical model, which includes the objective functions and constraints, is described.

Table 2- the indexes and parameters of the model

Symbol	Description	Symbol	Description
G (V, P)	Network graph of activities and relationships between them	ls_i	The latest time to start the activity i
P	Set of prerequisite relationships between project activities	w_i	Weight of activities to allocate resources
V	Set of activities	B_{max}	Total time buffer to allocate among project activities
K	Set of renewable resources	C_{max}	Maximum project completion time
Q	Set of risk factors	v_{ij}	The amount assigned to each activity, according to the level of criticality
L	Set of Staff (work force)	T	Upper limit of maximum completion time
S	The set of skills available and needed for project activities	r_{ik}	The amount of consumption of type K resource to perform activity i
i	Activity index	R_{kt}	The available capacity of the K-type source in the period
t	Period index	π	Budget available
K	Renewable resource index	c_i	The cost of completing activity i
q	Risk factor index	$N_{pre,i}$	Number of prerequisite activities of activity i

S, s'	skill index	$N_{suc,i}$	The number of post-requirement activities of activity i
l	Labor index	AC_l	Complexity of activity i
D	Project due date	RSL_l	The actual skill level of the workforce
DD_i	The due date of activity i	Rk_{ls}	It is equal to 1 if the actual skill level of the labor force l is higher than the skill level of s or equal to s, and otherwise it is equal to 0.
l_{ij}	The time difference between the start of activity i and j	pen	Penalty considered for assigning employees to skills lower than their actual skill.
$\tilde{d}_{is}$	Fuzzy processing time of activity i by skill s	$ready_{i,s}$	The presence time of skill s from activity i to perform.
es_i	The earliest time to start the activity i	WT_i	Penalty for late project activities

Table 3-variables of the model

Symbol	Description
x_{ilst}	It is a binary variable and it is equal to 1 if the activity i is started at time t by the workforce to perform skill s, and otherwise it is equal to 0.
S_i	Time to start the activity i
F_i	Finish time of activity i
b_i	Buffer time allocated to activity i
EFF_i	The earliest free float time
LFF_i	The latest free float time
CT_i	The time to complete activity i.
y_{il}^{s}	The start time of activity i by workforce l in skill s

Before explaining the structure of the mathematical model, the following points are presented:

$$\boldsymbol{RU_i = \sum_{k=1}^{m} r_{ik} \sum_{j=1}^{n}\sum_{k=1}^{m} r_{ik}, \forall_i} \qquad (1)$$

The density of precedence relations defines the complexity index of the network. Activities that have more priority have a greater risk of delay in successors. The more the number of successors of the activity, in case of any disruption, the possibility of transferring it to future activities will be greater. In addition, the effect of disrupting the activity is directly related to the number of precedence. Therefore, the complexity of the activities is calculated with the average number of pre-requirement and post-requirement activities as equation (2).

$$\boldsymbol{AC_i = \frac{(N_{suc\,i} + N_{pre\,i})}{n}} \qquad (2)$$

The concept of time overlap is related to the disruption of resources during the activity. The longer the activity, the higher the probability of disruption during execution. Based on this, the duration percentage index is defined as equation (3):

$$\boldsymbol{DP_i = \max(\tilde{d}_{is} / \sum_{i=1}^{n} \tilde{d}_{is}\ )} \qquad (3)$$

Equation (4) also calculates the weight or priority of the activity for resource allocation.

$$W_i = \frac{(AC_i + RI_i + DP_i)}{3} \quad (4)$$

Table 4- Calculation of prerequisite relationships of activities

PREREQUISITE RELATIONSHIP TYPE	FORMULA
$FS_{ij}(x)$	$l_{ij} = d_i + x$
$FF_{ij}(x)$	$l_{ij} = d_i - d_j + x$
$SF_{ij}(x)$	$l_{ij} = x - d_j$

$$EFF_i = S_i - \max(S_i + l_{ij}) \quad (j,i) \in P \quad (5)$$

Expression (5) calculates the earliest free float time of the activity.

$$LFF_i = \min(S_i - l_{ij}) - S_i \quad (i,j) \in P \quad (6)$$

Expression (6) calculates the latest free float time of the activity.

According to the indices, parameters, variables and calculations mentioned above, the structure of the mathematical model is as follows:

$$\min z1 = \sum WT_i T_i \quad (7)$$

$$\min z2 = \sum\sum\sum\sum pen(RSL_l - s)x_{ilst} \quad (8)$$

Subject to:

$$\sum_{t=es_i}^{l_{si}} x_{ilst} = 1 \qquad \forall i, l, s \quad (9)$$

$$\sum_{i=1}^{n} x_{ikst} = 1 \qquad \forall l, s, t \quad (10)$$

$$y_{\mathrm{il}}^{\mathrm{s}} = \sum_{i=es_i}^{ls_i} t\, x_{ilst} \qquad \forall i, l, s \quad (11)$$

$$\sum_{i=es_i}^{ls_i} (t + l_{ij}) x_{ilst} + b_{is} \leq \sum_{t=es_i}^{ls_i} tx_{jl's't} \qquad (i,j) \in P, \forall l, s \quad (12)$$

$$CT_i \geq y_{\mathrm{il}}^{\mathrm{s}} + b_{is} \qquad \forall i, l, s \quad (13)$$

$$\sum_{i=1}^{n} b_{is} \leq D - C_{max} = B_{max} \qquad i = 1, 2, \dots, n, \forall s \quad (14)$$

$$EFF_1 \leq \sum_{t=es_1}^{ls_i} tx_{ilst} - \sum_{t=es_i}^{ls_i} tx_{jl's't} + l_{ij} \qquad (j,i) \in P, \forall l, l', s, s' \quad (15)$$

$$LFF_1 \leq \left[\sum_{t=es_j}^{ls_j} tx_{jlst} - l_{ij}\right] - \sum_{i=es_i}^{ls_i} tx_{il's't} \qquad (i,j) \in P, \forall l, l', s, s' \quad (16)$$

$$\sum_{i=1}^{n} \sum_{t'=max\{t-d_{i,esi}\}}^{min\{t-1,ls_i\}} r_{ik} \cdot x_{ilst'} \leq R_{kt} \qquad t = 1,2,\dots,t \quad k = 1,\dots,m \tag{17}$$

$$\sum_{s=1}^{S} \sum_{i=1}^{n} c_i\, b_{is} \leq \pi \qquad i = 1,2,\dots,n \tag{18}$$

$$b_{is} \leq \left[\frac{\sum_{q=1}^{s} v_{iq}}{\max_{q=1,2,\dots,s} v_{iq}}\right] \tilde{d}_{is} \qquad \forall s, i = 1,2,\dots,n \tag{19}$$

$$x_{ilst} \leq RK_{ls} \qquad \forall i, \forall s, \forall k \tag{20}$$

$$y_{il}^{s} \geq ready_{i,s} x_{ilst} \qquad \forall i, \forall s, \forall l \tag{21}$$

$$T_i = \max\{0, CT_i - DD_i\} \qquad \forall i \tag{22}$$

$$x_{ilst} \in \{0,1\} \qquad i = 1,2 \dots, n \quad t = es_i, \dots. ls_i \tag{23}$$

$$y_{il}^{s}, T_i, CT_i, b_{is} \geq 0 \qquad \forall i, l, s \tag{24}$$

Equation (7) shows the first objective function, which is the minimization of the total late payment penalty. Equation (8) represents the second objective function, which is the minimization of the total fines that are considered for allocating employees to lower skill levels.

Constraint (9) guarantees that each activity starts once for each skill and each workforce. Constraint (10) guarantees that each force is assigned to one skill in only one activity at a time and no interference occurs. Constraint (11) calculates the start time of an activity for a skill by the workforce. Constraint (12) guarantees that if i is a prerequisite of j, then activity i must be completed before starting activity j. Constraint (13) calculates the time to complete the activities. Constraint (14) guarantees that the buffer time does not exceed a certain time, B_{max}. The maximum buffer time or $B_{max}$is equal to the difference between the delivery time and the maximum completion time. Constraints (15) and (16) are introduced to linearize the equations related to EFF and LFF.

Constraint (17) guarantees that the consumption of resources to complete the project activities in each period does not exceed the available amount. Constraint (18) guarantees that the budget spent to complete the activities does not exceed the available budget. Constraint (19) Define an upper bound for the buffer time of each activity. Equation (20) ensures that each workforce is assigned only to skills equal to or less than their own skill level. Equation (21) guarantees that the processing start time of an activity is greater than the activity's presence time. Equation (22) is used to calculate the amount of delay of activity i. Constraints (23) and (24) represent the permissible and feasible values of the model variables.

As seen, in the current research model, the $\tilde{d}_{is}$ is parameter is fuzzy. It needs to be diffused. In this research, the ranking method provided by Jimenez et al. (2007) has been used. Jimenez proposed a method of ranking fuzzy numbers based on the comparison of their expectation intervals. And by using the mentioned method, we convert the provided fuzzy programming model to its deterministic model by replacing the following expression in the model:

$$\tilde{d}_{is} = \gamma \frac{d_{id}^{1} + d_{is}^{2}}{2} + (1-\gamma) \frac{d_{is}^{2} + d_{is}^{3}}{2} \qquad \forall i, s \tag{25}$$

4. The solution approach

Since researchers have shown that the whale optimization algorithm is effective in solving the project scheduling problem (Ghoroqi, et al, 2024), in this article we use this algorithm to solve the presented model. In this study, a multi-objective whale optimization algorithm (WOA) based on the Pareto archive is employed to solve the proposed model. The algorithm begins with a set of random solutions. The search elements update their position according to a search element randomly or within the best-obtained solution in each iteration. To provide exploration and exploitation, parameter a is reduced from 2 to 0. Two modes are considered to update the position of search elements. If |A|>1, the random search element is selected. On the other hand, if |A|<1, then the best solution is selected. According to the value of p, the whale can switch between spiral and rotational movements. Finally, the algorithm terminates after reaching the satisfaction criterion. In the following, the pseudo-code of the algorithm is presented. In this study, the algorithm is designed based on the Pareto archive. The Pareto archive is updated at the end of each iteration of the algorithm. Also, an improvement procedure is used in each iteration of the algorithm. The structure of the proposed algorithm is shown in Fig. 1.

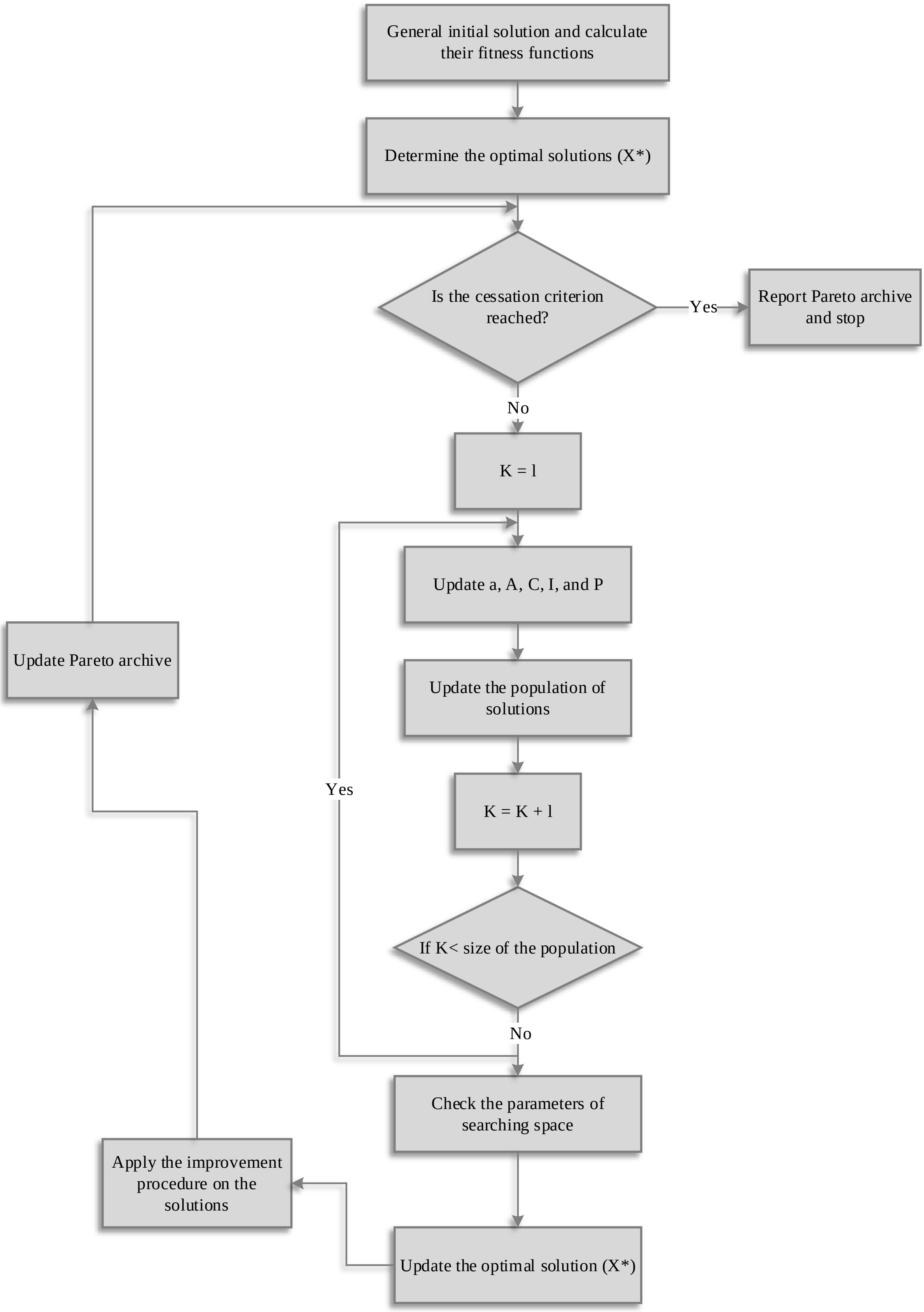

Fig. 1. The structure of the whale optimization algorithm (Azarkish & Aghaeipour, 2022)

4.1 Solution representation

In all meta-heuristic algorithms, due to the need for a feasible solution at the beginning of the work, it is necessary to store the solution according to a specific structure, which is called the way of displaying the answer. In this article, the display of the solution includes two structures, the first structure is a one-dimensional matrix whose number of elements is equal to the number of project activities. This matrix includes the schedule of project activities. In fact, in this structure, the order of performing the project activities are shown, observing the required restrictions. The way to display the first matrix of the answer structure is described in the example below. Suppose the project has 8 activities.

1	2	3	6	4	5	7	8

Fig 2. The first matrix

As seen in the figure above, the matrix has 8 houses that show a sequence of project activities.

The second structure is a two-dimensional matrix in which it is determined who or those are assigned to each skill of each project activity. The number of rows of this matrix is equal to the number of skills needed for all activities. The second dimension or columns, which is equal to the number of activities, represents the number of employees assigned to each skill.

1	3	0	0	4	1	0	3
5	0	4	2	0	0	2	0
1	0	5	1	5	3	4	0

Figure 3- The second matrix

As you can see, the number of lines is 3, which indicates the number of available skills. Also, the number of columns is 8, which is equal to the number of activities. For example, according to the second matrix of the first skill, the first activity is performed by workforce number 1. The second skill of activity 3 is performed by workforce number 4.

4.2 Solution initialization method

In this research, a parallel neighborhood search method is used to generate initial solutions.

Most evolutionary meta-heuristic methods use a random approach to generate initial solutions. But since the quality of the final solutions obtained from these methods is directly dependent on the quality of the initial produced solutions, in this article, a method of two-way serial scheduling and serial scheduling (Kolisch, 1996) are used to generate feasible sequences of activities.

In this article, each of these methods separately produce N solutions which N of them are selected as the initial population. For choosing the solutions, the whole 2N obtained solutions of two methods are considered as a set and ranked using the rule of Deb (2002). The crowding distance is calculated for each rank. Then c_s criteria is calculated foe each solution. Finally, N solutions that have less c_s criteria are selected.

$$c_s = \frac{rank}{crowding\ distance} \quad (26)$$

Since this operator requires both the rank and crowded distance of each solution in the population, we calculate these quantities according Deb (2002). The lower the value of c_s for a solution, the higher the quality and diversity of that solution.

4.3 Improvement procedure

In the proposed WOA, an improvement procedure is designed to improve the previous step's selected solutions. Spiritual output solutions are selected as the collection of iterations after the algorithm. The improved solutions are considered as the population of the next iteration of the algorithm. The proposed improvement procedure is based on the variable neighborhood search (VNS). VNS uses two neighborhood search structures.

The employed neighborhood search structures are described in the following.

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

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

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

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

These structures are applied in the form of VNS, and its general structure is as follows (Tavakoli-Moghaddam et al, 2010):

```
The pseudo-code of our VNS is as follows:

{For each input solution
K=1
While stopping criterion is meet do
        New solution=Apply NSS type k

        If new solution is better  then
            K=1
        Else
            K=k+1
            If k=4 then
                K=1
            Endif
        Endif
Endwhile
}
```

Each solution of the population enters the VNS algorithm, a solution obtained as an output, and the correction procedure, then applied to the rest of the solution matrices, and they replaced by the input solutions.

The general structure of the improvement procedure is as follow:

```
Improvement method
{For each si in input population
Si=apply VNS procedure on si.
Si=check feasibility method.
}
```

4.4 Updating solutions and searching parameters

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

$$\vec{D} = |\vec{C}.\vec{X}^*(t) - \vec{X}(t)| \tag{27}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A}.\vec{D} \tag{28}$$

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

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

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad (29)$$

$$\vec{C} = 2\vec{r} \quad (30)$$

In the formulas as mentioned (29) and (30), $\vec{a}$ is initialized with a value of 2 and decreases linearly in each iteration; also, $\vec{r}$ is a random value in the interval [0,1].

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

4.5 Updating Pareto archive

In this research, the proposed solution method is based on the Pareto archive. The proposed algorithm provides a set called the Pareto archive, which contains the non-dominated solutions generated by the algorithm. This set is updated in each iteration of the algorithm. The generated solutions of the last iteration and the Pareto archive solutions are poured into a pool and ranked to update the set. Then, the first-ranked (non-dominated) solutions are selected and considered as a new Pareto archive.

4.6 Selecting the next-generation solutions

In each iteration, the algorithm requires a set of solutions. Therefore, to select the next iteration population, solutions of the last iteration and the newly generated solutions by the algorithm are poured into a solution pool. After ranking and calculating the crowding distance of solutions, N solutions with the highest quality and diversity are selected according to the rule of Deb (2002) as the population of the next iteration.

5. Computational results

As mentioned, in order to solve the mathematical model, the Whale Optimization Algorithm (WOA) and Non-dominate Sorting Genetic Algorithm (NSGA-II) have been proposed. In this article, first of all in order to check the validity of the model and algorithm, the model is solved for a sample problem with a small size by the whale algorithm and the results are presented. After validating the model and algorithm, the whale and NSGA-II algorithms were implemented in the MATLAB software environment and the results of the two mentioned algorithms have been compared with each other using comparative metrics.

5.1 Comparative metrics

For evaluating the proposed algorithms' efficiency, some criteria such as Quality Metric (QM), Spacing Metric (SM), and Diversity Metric (DM) are used (Tavakoli-Moghaddam et al, 2010).

Quality Metric: This criterion is equal to the number of Pareto (non-dominated) solutions.

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

$$\boldsymbol{s} = \frac{\sum_{i=1}^{N-1} |\boldsymbol{d}_{mean} - \boldsymbol{d}_i|}{(\boldsymbol{N}-\boldsymbol{1}) \times \boldsymbol{d}_{mean}} \quad (31)$$

Where $\boldsymbol{d}_i$ represents the Euclidean distance between two adjacent non-dominated solutions and $\boldsymbol{d}_{mean}$ represents the mean value of $\boldsymbol{d}_i$.

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

$$\mathbf{D} = \sqrt{\sum_{i=1}^{N} \max(\|x_t^i - y_t^i\|)} \quad (32)$$

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

5.2 Test problems

In this article, several experimental problems are randomly designed to be solved by algorithms. The designed sample problems are classified into two groups with small and large size. The following tables (tables 4 and 5) show the characteristics of the designed sample problems.

Table 4- Sample problems with small size

Row	Number of project activities	Number of skills	Number of employees	Number of renewable resources
1	8	3	4	2
2	10	3	5	2
3	12	3	5	3
4	14	3	5	3
5	16	3	5	3
6	20	3	6	3

Table 5 - Sample problems with large size

Row	Number of project activities	Number of skills	Number of employees	Number of renewable resources
1	25	3	6	2
2	40	3	7	4
3	50	3	8	2
4	60	3	8	4
5	70	3	10	2
6	80	3	10	4
7	90	3	15	2
8	100	3	15	4

5.3 Setting algorithms and model parameters

In order to implement the solution algorithms, the required parameters were set as follows:

- In the whale optimization algorithm, the population size is equal to 150; the number of iterations in the variable neighborhood search algorithm is equal to 5 and the number of iterations of the algorithm is considered equal to 300.

- The rate of 0.75 for crossover and 0.01 for mutation are considered in the implementation of NSGA-II algorithm.

- Also, to run NSGA-II, the number of iterations of the algorithm and the size of the population are set to 500 and 300, respectively.

Also, the model parameters are set as follows:

In order to generate triangular numbers related to each of the fuzzy parameters $(m1, m2, m3)$, first $m2$ is generated, then a random number r is generated in the interval (0,1), $m1$ using the relationship $m2 \times (1 - r)$ and $m3$ will also be produced using the relationship $m2 \times (r + 1)$. The direction of fuzzy parameters $m2$ is determined and two values $m1$ and $m3$ are determined using MATLAB software. For this reason, in the setting of these parameters, we only mention the value of $m2$.

- The number of labor required for skill s to complete activity i is considered in the uniform interval $[2..4]$.
- The actual skill level of employees is randomly generated in the interval $[1..S]$ (S is the number of skills).
- The processing time of activities are considered in the uniform interval $[10..40]$.
- The completion date of the activities are produced in the uniform interval $[p1..p2]$, where $p2$ is equal to 1.5 times the total processing times of prerequisite activities and $p1$ is equal to 1.2 times the total processing times of prerequisite activities.
- The penalty considered for allocating employees to skills lower than their actual skill is produced in the uniform interval $[10..20]$.
- The lateness penalty for each activity is considered in a uniform interval $[10..20]$.
- The presence time of the skills is generated in the interval $[0..3]$.

5.4 Model validation results

In order to evaluate the validity of the model, a sample problem with a small size has been designed, which is solved by the whale optimization algorithm. The investigated problem has 6 activities, two workforce and two skill levels. It should be noted that this project has two dummy activities 0 and 5 and only activities 1, 2, 3 and 4 are main.

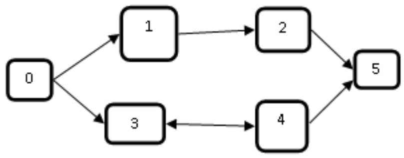

Fig 4. The graph related to the relationships between activities

Table 6- Sample problem parameters

Activity	Skill	p_{is}	b_{is}	$ready_{is}$	D_i	w_i
1	1	3	1	1	5	3
	2	4	1	1		
2	2			1	6	2
		4	1			
3	1	2	1	2	11	4
	2	5	1	2		
4	1	4	1	3	14	4
	2	3	1	3		

Moreover, in the table below, the amount of consumption of renewable resources, which are two sources, is presented:

Table 7- Amount of resource consumption

Activity	Resource 1	Resource 2
1	3	3
2	2	2
3	2	5
4	4	1

The described problem is solved by the whale optimization algorithm. The results of problem solving are shown in table (8), figure (5) and figure (6). It should be mentioned that nw indicates the workforce number, x indicates the time of starting to perform the relevant skill by that workforce and c indicates the time of completion of the relevant skill by that workforce.

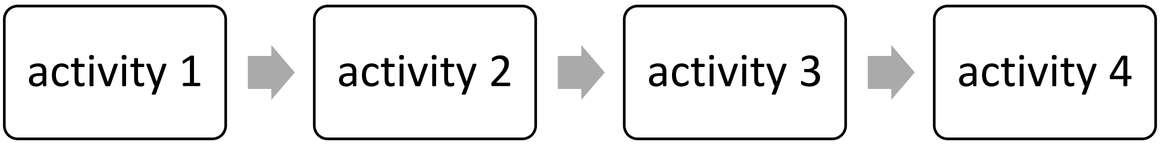

Fig 5. Optimal scheduling

Table 8. the result of assigning labor's skill to activities, start and finish time of activities

Activity	Skill 1	Skill 2
0	0	0
1	$Nw = 1, x = 3, c = 5$	$Nw = 1, x = 1, c = 6$
2	0	$Nw = 2, x = 1, c = 4$
3	$Nw = 1, x = 8, c = 10$	$Nw = 2, x = 5, c = 9$
4	$Nw = 1, x = 11, c = 15$	$Nw = 2, x = 11, c = 14$
5	0	0

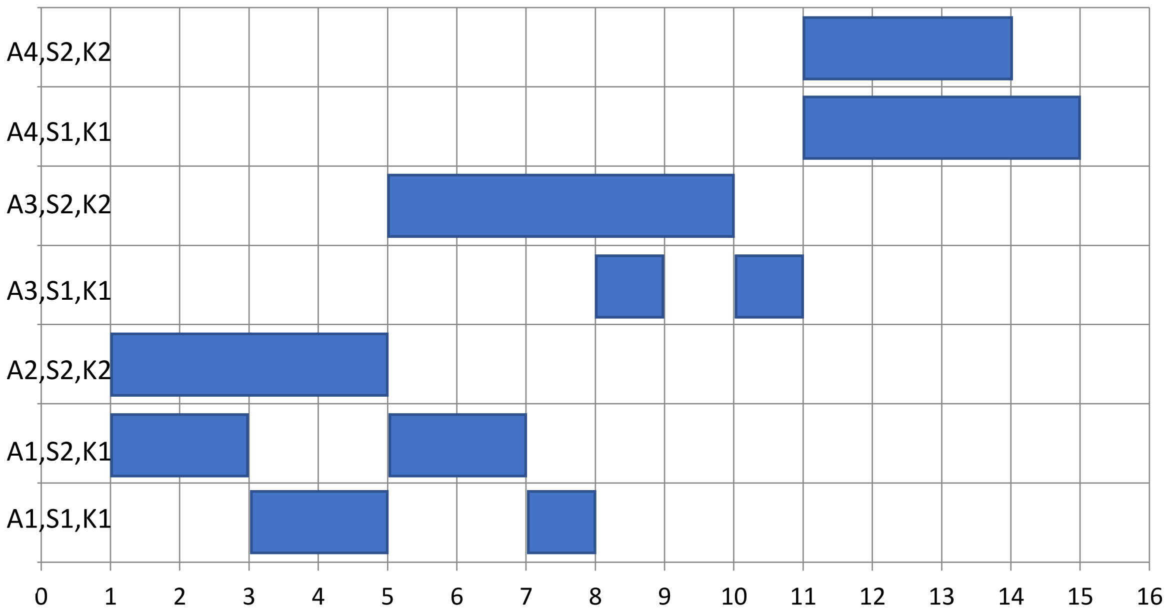

Fig 6. Scheduling activities and assigning skills

5.5 Results of solving sample problems

In this research, as it has been mentioned, sample problems are designed in two groups, small and large size, whose are solved by whale optimization algorithm and NSGA-II. Tables (9) and (10) show the results of solving these problems with different size.

Table 9- The results of solving the small size problems

Prob.	WOA			NSGA-II		
	Quality metric	Spacing metric	Diversity metric	Quality metric	Spacing metric	Diversity metric
1	85.3712	0.8694	633.2	14.6288	0.6601	333.01
2	99.011	1.003	790.6	0.989	0.8649	415.5
3	100	0.7634	919.5	0	0.99	777.1
4	100	0.9911	1092.3	0	0.4562	879.3
5	79.5204	1.3482	1213.7	20.4796	0.7941	906.6
6	89.7846	0.889	1609.4	10.2154	0.7054	992.4

Table 10- The results of solving the large size problems

Prob.	WOA			NSGA-II		
	Quality metric	Spacing metric	Diversity metric	Quality metric	Spacing metric	Diversity metric
1	69.13	0.88	1599.5	30.87	0.73	1302.6
2	77.65	0.69	1694.8	22.35	0.45	1399.4
3	100	1.23	2834.7	0	0.93	1549.2
4	94.76	0.98	11009.3	5.24	0.74	1666.5
5	84.49	0.99	11517.2	15.51	0.44	2709.3
6	90	1.07	11859.1	10	0.68	3016.2
7	81.5	0.89	13763.2	18.5	0.71	4405.1
8	100	0.91	16783.7	0	0.82	6901.6

The comparative results in Tables (9) and (10) show that WOA has a higher ability to generate high-quality solutions compared to NSGA-II. Moreover, the proposed WOA is able to generate solutions with higher diversity, which means it has more efficient to explore and extract the solution feasibility area than the NSGA-II. On the other hand, NSGA-II generates more uniform solutions according to spacing metric.

Also, in order to compare the execution time of two algorithms, all problems were executed in all two groups, and the execution time of one iteration of each algorithm was calculated when solving these problems, the values can be seen in Table (11). This table shows that the computational time of the multi-objective WOA is higher than the NSGA-II algorithm. The execute time of the proposed whale algorithm in solving the presented model can be justified by the different structures of neighborhood search and improvement procedure.

Table 11- Computational times (in second)

Prob.	Run time	
	WOA	NSGA-II
1	0.34	0.12
2	0.37	0.15
3	0.42	0.21
4	0.62	0.30
5	0.75	0.47
6	1.74	0.89
7	2.86	0.77
8	4.11	1.023
9	6.76	2.32
10	7.5	4.60
11	10.37	6.023
12	15.49	7.72
13	22.70	10.53
14	30.16	14.67

6. Conclusion

In this research, a developed model of the MSPSP application problem, titled MOMSPSP (Project Scheduling Problem with Multi-Skilled Multi-Objective Workforce) is investigated and we present a mathematical model for it. Since the discussed problem is NP-Hard, efficient methods based on whale optimization algorithm and NSGA-II are used to solve it. The mentioned model is designed with two objectives, the first objective function is minimization of fines for lateness of activities and the second objective function is to minimize the sum of penalties that are considered for allocating employees to lower skill levels. With considering the second objective, we try to assign the employees to closest level to their actual skills. Due to deal with, an amount is considered as a penalty, which is entered into the model in case of deviation from the actual level.

As it can be seen, a bi-objective mathematical model is developed considering the multi-skilled workforce in fuzzy conditions. Since the project scheduling problem considering multi-skilled workforce is an NP-HARD problem, it is impossible to be solved via exact methods and for this reason, in this article, the whale optimization algorithm is presented to solve the model. Also, the results of solving the problems by the proposed algorithm have been compared with the results of solving by the NSGA-II algorithm based on the important comparative indicators of multi-objective problems (quality, diversity and spacing metrics).

The proposed WOA is combined with the neighborhood search structure to achieve high quality solutions. Since the model has two conflicting goals, the WOA algorithm is designed based on the Pareto archive. In other words, the proposed algorithm uses non-dominated relations in each step to select the solutions close to the optimal boundary. Also, this algorithm uses the dispersion criterion to guarantee the search of all points of the solution space and to avoid getting stuck in a local optimum. The features of the designed algorithm guarantee that the algorithm is successful in reaching the global optimal points and is convergent.

The results of the comparison of two algorithms in solving sample problems indicate that the proposed whale algorithm has a higher ability to produce diverse and scattered Pareto solutions in all problems. Also, since based on the designed structure of the proposed method, this method intelligently searches many points of the solution space in each iteration. Obviously, this method consumes more computing time than the NSGA-II method.

References

1. Azarkish M, Aghaeipour Y (2022) A fuzzy bi-objective mathematical model for multi-depot electric vehicle location routing problem with time windows and simultaneous delivery and pick-up. Asian J Basic Sci Res 4(2):01–03.

2. Bocewicz, Grzegorz & Wikarek, Jarosław & Sitek, Paweł & Banaszak, Zbigniew. (2020). Robust Competence Allocation for Multi-project Scheduling. In book: Information Systems Architecture and Technology: Proceedings of 40th Anniversary International Conference on Information Systems Architecture and Technology – ISAT 2019 (pp.16-30)

3. Chen, James & Chen, Yin-Yann & Chen, Tzu-Li & Lin, Yi-Hsuan. (2022). Multi-Project Scheduling with Multi-Skilled Workforce Assignment Considering Uncertainty and Learning Effect for Large-Scale Equipment Manufacturer. Computers & Industrial Engineering. 169. 108240. 10.1016/j.cie.2022.108240.
4. Chen, R., Wu, CH-L., Wang, CH-M., Lo, SH-T. (2010). 'Using novel particle swarm optimization scheme to solve resource-constrained scheduling problem in PSPLIB', Expert systems with applications, Vol. 37, pp. 1899-1910.
5. Deb, Kalyan & Pratap, Amrit & Agarwal, Sameer & Meyarivan, T.. (2002). A fast and elitist multi-objective genetic algorithm: NSGAII. IEEE Transactions on Evolutionary Computation. 6.
6. Elif, G. (2010). A genetic algorithm for bi-objective multi-skill project scheduling with hierarchical levels of skills, A thesis submitted to the graduate school of NATURAL AND APPLIED SCIENCES OF MIDDLE EAST TECHNICAL UNIVERSITY.
7. Eshraghi, A. (2016). A new approach for solving resource constrained project scheduling problems using differential evolution algorithm. International Journal of Industrial Engineering Computations 7, 205–216.
8. Ghamginzadeh, Arman & Najafi, Amir & Khalilzadeh, Mohammad. (2021). Multi-Objective Multi-Skill Resource-Constrained Project Scheduling Problem Under Time Uncertainty. International Journal of Fuzzy Systems. 23. 10.1007/s40815-020-00984-w.
9. Ghoroqi, M., Ghoddousi, P., Makui, A., Shirzadi Javid, A.A., Talebi, S.(2024). Integration of resource supply management and scheduling of construction projects using multi-objective whale optimization algorithm and NSGA-II. Soft Comput (2024). https://doi.org/10.1007/s00500-023-09467-0
10. H. Li and K. Womer. (2009). Scheduling projects with multi-skilled personnel by a hybrid milp/cp benders decomposition algorithm. Journal of Scheduling, 12(3):281–298.
11. Habibi, F., Barzinpour, F., Sadjadi, S.J. (2017). A Multi-objective optimization model for project scheduling with time-varying resource requirements and capacities. Journal of Industrial and Systems Engineering, Vol. 10, Special Issue on Scheduling, pp. 92-118.
12. Habibi, F., Barzinpour, F., Sadjadi, S.J. (2019). A mathematical model for project scheduling and material ordering problem with sustainability considerations: A case study in Iran. Computers & Industrial Engineering, Vol. 128, pp. 690-710.
13. Haroune, Meya & Dhib, Cheikh & Néron, Emmanuel & Soukhal, Ameur & Babou, Hafed & Nanne, Mohamedade. (2022). Multi-project scheduling problem under shared multi-skill resource constraints. TOP. 10.1007/s11750-022-00633-5.
14. Jimenez, M., Arenas, M., & Bilbao, A. (2007). "Linear programming with fuzzy parameters: an interactive method manufacturer". Applied Mathematical Modelling, 36(6), 2762-2776.
15. Karam, A., Attia, E-A., Duquenne, PH. (2017). A MILP model for an integrated project scheduling and multi-skilled workforce allocation with flexible working hours. IFAC-PapersOnLine, Volume 50, Issue 1, July 2017, Pages 13964-13969.
16. Kolisch, R.(1996). "Serial and parallel resource-constrained project scheduling methods revisited: Theory and computation", European Journal of Operational Research, Vol. 43, pp. 23–40.
17. Neron, E. and Boptista, D.(2002). 'Heuristics for the multi-skill project scheduling problem', International Symposium on Combinatorial Optimization (CO'2002), Paris, France.
18. Shadrokh, Shahram & Kianfar, Fereydoon. (2007). A genetic algorithm for resource investment project scheduling problem, tardiness permitted with penalty. European Journal of Operational Research. 181. 86-101. 10.1016/j.ejor.2006.03.056.
19. Snauwaert, Jakob & Vanhoucke, Mario. (2022). A classification and new benchmark instances for the multi-skilled resource-constrained project scheduling problem. European Journal of Operational Research. 10.1016/j.ejor.2022.05.049.
20. Tabriz, B. (2017). A Brief Review on Integrated Planning of the Project Scheduling and Material Procurement Problem. Adv Automob Eng 6: 162. doi: 10.4172/2167-7670.1000162.
21. Tavakkoli-Moghaddam R, Azarkish M, Sadeghnejad A (2010) A new hybrid multi-objective Pareto archive PSO algorithm for a classic job shop scheduling problem with ready times. Adv Intell Comput Theor Appl Commun Comput Inf Sci 93:61–68.
22. Tian, Yuan & Xiong, Tifan & Liu, Zhenyuan & Mei, Yi & Wan, Li. (2021). Multi-Objective Multi-Skill Resource-Constrained Project Scheduling Problem with skill switches: Model and Evolutionary Approaches. Computers & Industrial Engineering. 167. 107897. 10.1016/j.cie.2021.107897.
23. Torabi Yeganeh, F., Zegordi, S.H. (2020). A multi-objective optimization approach to project scheduling with resiliency criteria under uncertain activity duration. Annals of Operations Research (2020) 285:161–196.
24. Uysal, F., İşleyen, S.K., Çetinkaya, C. (2018). Resource Constrained Project Scheduling with Stochastic Resources. Journal of Applied Research on Industrial Engineering. Vol. 5, No. 1, PP: 39–49.

25. Vanhoucke, M., Coelho, J.(2019). Resource-constrained project scheduling with activity splitting and setup times. Computers and Operations Research 109 (2019) 230–249
26. Wang, L., Fang, C. (2011). An effective shuffled frog-leaping algorithm for multi-mode resource-constrained project scheduling problem. Inform Sciences 181:4804– 4822.
27. Wang, L., Zheng, X-L.(2018). A knowledge-guided multi-objective fruit fly optimization algorithm for the multi-skill resource constrained project scheduling problem. Swarm and Evolutionary Computation 38 (2018) 54–63.
28. Yu, Yining & Xu, Zhe & Liu, Dongning & Zhao, Song. (2022). A two-stage approach with softmax scoring mechanism for a multi-project scheduling problem sharing multi-skilled staff. Expert Systems with Applications. 203. 117385. 10.1016/j.eswa.2022.117385.