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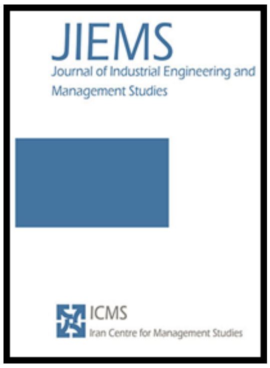

A multi-objective optimization model for multiple project scheduling and multi-skill human resource assignment problem based on learning and forgetting effect and activities' quality level

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Abstract

One of the most important aspects of human resource management is the allocation of the workforce to activities. Human resource assignment to project activities for its scheduling is one of the most real and common issues in project management and scheduling. This becomes even more significant when human resource assignment to multiple projects simultaneously is considered. On the one hand, workforces can have multi skills due to technological and scientific development so that they can be assigned to project activities based on their skill level. On the other hand, the learning effect is also taken into account to make the model more realistic. These factors can affect completion time, total cost and execution quality of projects. In this study, a multi-objective optimization model for multi-project scheduling and multi-skilled human resource assignment problem based on the learning effect and activities' quality is presented. A mixed-integer linear programming model (MILP) is developed for the proposed problem and solved by the ε-constraint method in GAMS software. Managers can select a solution based on their priority. Finally, a sensitivity analysis is done on the learning and forgetting effect to investigate their impacts on each objective function.

Keywords: multi-objective optimization; multi-project scheduling; multi-skilled human resources; learning and forgetting effect; activity's quality level.

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1. Introduction

Project scheduling is an optimization problem, in which a set of activities must be scheduled such that a predefined objective is optimized (Chakrabortty et al., 2016). This problem is mainly concerned with determining the feasible start time of activities with respect to precedence relationship such that the completion time of project is minimized (Hartmann and Briskorn, 2010). A remarkable variant of the classical project scheduling problem (PSP) is the

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multi-skilled project scheduling problem (MSPSP). It contains project scheduling and human resource assignment problem simultaneously. The aim of the MSPSP is to identify the start time of activities subject to precedence relationship and resource constraint that only includes human resources with different skills. Moreover, this problem seeks to find the most appropriate combination of multi-skilled workforces assigned to each activity (Schwindt and Zimmermann, 2015).

In the MSPSP assumes that each activity may need one or several skills to be executed. Since workers are capable to perform one or more skills, there are many possible combinations of workers which can be assigned to each skill of an activity. Each worker is allowed to use only one of his/her skills in each period to accomplish an activity. It is possible to assign workforces to several activities without overlapping in their processing time. Results show that multi-skilled human resources cause to increase productivity, quality and work continuity. It makes manager to allocate work to labor with more flexibility. In this problem, each activity can be assigned to workers with number of varied mode due to activity necessity to different skill, thus problem complexity is remarkably increased. As a result, the MSPSP is a kind of NP-hard problem (Bellenguez, 2008).

In real world, human resources have different efficiencies in each skill. In this case, their efficiencies can improve by learning (Maghsoudlou et al., 2017). Learning phenomenon occurs when workforces spend more time on performing a skill. Since the make span of the project depends on the efficiency of workers, the learning effect plays a remarkable role in decreasing the required time to accomplish the project. On the other hand, workers skill can be reduced when it has not been used for a long time that causes to reduce workers' efficiency. This phenomenon is named forgetting effect. It also makes completion time of project increase.

In this study, several objective functions have been considered. One the most applicable ones is completion time of project. Most MSPSPs aim to minimize make span of the project as the main objective function. In some kind of project such as construction one, execution cost is also considered. Thus a second objective function is considered total cost of project execution in this research. As be mentioned, human resources have different skill level so that it can be affected execution quality of project. Employees' work experiences not only promote productivity, but also improve project quality Therefore, maximizing the total quality of project is considered as well.

Hence, the contributions of this study can be stated as follows. A multi-objective multi-skilled multi-project scheduling problem and human resource assignment is considered simultaneously. Activity's quality level is considered as the objective function as well as completion time and execution cost of projects. Learning and forgetting effect are defined simultaneously for multi-project scheduling problem for a first time.

The rest of the paper is organized as follows: Section 2 presents a literature review for the project scheduling and human resource assignment problem. Problem definition as well as proposed mathematical model is described in Section 3. The proposed solution approach is discussed in Section 4. Section 5 is devoted to computational experimentations. Finally, Section 6 provides concluding remarks and discusses further research opportunities.

2. Literature Review

Many research have been done in project scheduling and human resource assignment area because of their importance in executing project to reduce various factors such as completion time and total cost. In this section, the most related studies to the current research is reported.

Human resource assignment as an important phase in decision-making has investigated, recently. Markoulli et al. (2017) presented a review research on human resource management problem. Kianto et al. (2017) studied knowledge-based human resource management problem. To do this end, a data set consisting 180 company is collected and analyzed by structural equation modelling and Partial least squares approaches. Results show that suitable management of human resources causes to increase rate of return. Batarlienė et al. (2017) analyzed the human resource management effect on the competitiveness of transportation organizations. Furthermore, competitive advantages and human resource management models are discussed. Berk et al. (2018) studied a human resource planning problem in the services industry in which a high level of uncertainty is considered in a revenue forecast. A robust optimization approach is applied to maximize profit. Lian et al. (2018) studied a multi-skilled human resource assignment problem in seru production firm. They proposed a linear programming model considering different skills and proficiency levels for workers. A non-dominated sorting genetic algorithm is also developed to solve problem in large size.

Some research consider project scheduling problem and human resource assignment simultaneously while worker have just one skill (Alfares and Baile 1997; Wu and Sun 2006). Firat and Hurkens (2012) developed an improved mixed integer programming model for multi-skill workforce scheduling problem. Nie and Liu (2013) presented a mixed integer linear programming model for an integrated project scheduling and multi skilled human resource assignment problem. They also developed a memetic algorithm for large size problem. Fernandez-Viagas and Framinan (2014) developed an integrated project scheduling and workforce assignment problem considering controllable processing time. A greedy randomized adaptive search procedure (GRASP) is developed to achieve a near-optimal solution for large scale problem. Maenhout and Vanhoucke (2015) evaluated various scheduling policies in an integrated project scheduling and personnel staffing plan that leads to minimum costs. Karam et al. (2017) studied an integrated project scheduling and multi-skill workforce allocation problem considering flexible time for manpower working. They presented a mixed integer linear programming model to solve proposed problem. Till now, there is not a lot of research in project scheduling problem and human resource assignment that is considered learning effect to raise productivity and efficiency. Heimerl and Kolisch (2010) presented an optimization model for work assignment to multi-skilled human resources considering learning effect, knowledge depreciation, and company skill level. Van Peteghem and Vanhoucke (2015) assessed the learning effect on multi-mode resource constrained project scheduling problem so that each activity has different execution modes with different duration and cost. In order to solve the proposed problem a genetic algorithm is developed. Shen et al. (2018) studied a multi-objective software project scheduling problem. The proposed model considered that skill proficiency can be improved by the employees' learning ability. They developed a Q-learning based memetic algorithm to solve problem. Zabihi et al (2019) developed a multi-objective teaching-learning-based meta-heuristic algorithms to solve MSPSP.

As well, few studies have considered learning and forgetting in the MSPSP, simultaneously. Wu and Sun (2006) used only the concept of learning (not forgetting) for employee’s efficiency. They merely have developed a genetic algorithm without solving the problem with exact methods. Mehmanchi and Shadrokh (2013) studied a human resource scheduling problem in which activities need some skill to perform. They developed a mathematical model considering the learning and forgetting effect on worker efficiency.

Moreover, multi-skill resource constrained project scheduling problem (MSRCPSP) is investigated in this filed. Myszkowski et al. (2019) studied MSRCPSP in a software library. They developed two meta-heuristic algorithm consist of Greedy and Genetic algorithm. Laszczyk and Myszkowski (2019) a multi-objective model for MSRCPSP. The developed a non-dominated sorting genetic algorithm (NSGA-II) to solve problem in large scale.

Quality of project execution is other significant factor of project scheduling problem as well as completion time and costs. Whereas, only little work has considered the minimum quality limit of tasks and the quality learning effect in this filed. Tiwari et al. (2009) studied project quality and cost trade-off in multi-mode resource constrained project scheduling problem. Certa et al. (2009) studied a human resource allocation in R&D projects scheduling. They proposed a quality-based model considering different skill level and learning ability for workers. The lexicographic goal programming method is used to determine best solution. Qin et al. (2016) studied a multi-skilled manpower scheduling problem considering learning effect and project quality. A piecewise linear programming model is developed to minimize the total cost of workforces. Chen et al. (2020) studied a competence-time-quality scheduling model of multi-skilled staff for IT project. They developed a multi-objective ant colony optimization algorithm to find Pareto solution set.

Multi-objective solving approach has been considered in the most research that developed multi-objective models. There are various method to solve multi-objective problems. One of the most popular methods is ε-constraint method (Babaee Tirkolaee et al., 2019; Goli et al., 2019; Babaee Tirkolaee et al., 2019; Taheri Amiri et al., 2018; Taheri Amiri et al 2017; Taheri Amiri et al., 2017). Table 1 reported a summary of related research.

Table 1. Summary of related papers

Author(s)	Project scheduling	Staff assignment	Multi-skill	Learning effect	Forgetting effect	Quality	Solution method
Wu and Sun (2006)	*	*	*	*			GA
Tiwari (2009)	*		*			*	MILP
Certa et al (2009)	*	*	*	*		*	LGP
Heimerl and Kolisch (2010)		*	*	*			MILP Heuristic
Firat and Hurkens (2012)	*		*				MIP
Mehmanchi and Shadrokh (2013)	*		*	*	*		MINLP
Nie and Liu (2013)	*	*	*				MA
Fernandez-Viagas and Framinan (2014)	*	*		*			ILP GRASP
Maenhout and Vanhouke (2015)	*	*					Heuristic
Van Peteghem and Vanhoucke (2015)	*			*			MIP
Qin et al (2016)	*		*	*		*	MILP
Karam et al (2017)	*	*	*				MINLP
Berk et al (2018)		*					Robust Optimizatio n
Lian et al (2018)		*	*				ILP NSGA-II
Shen et al (2018)	*		*	*			MIP MA
Tirkolaee et al (2019)	*						ε-constraint NSGA-II MOSA
Zabihi et al (2019)	*		*	*			MOPSO MOIWO
Chen et al. (2020)	*	*	*			*	MOACO
Current Study	*****	*****	*****	*****	*****	*****	**MIP** **ε-constraint**

According to Table 1, just few work studied multi-project scheduling and multi-skill workforce assignment while consider the learning and forgetting effect simultaneously. Furthermore, there is not a lot of research that considers project quality as well as completion time and execution cost. Therefore, a multi-objective model for an integrated multi-project scheduling and multi skilled workforce assignment considering learning and forgetting effect has been developed.

3. Problem Description

In this study an integrated project scheduling and workforce assignment problem considering the learning and forgetting effect is presented. Despite a great number of researches investigated the learning effects in machine scheduling settings, It has been rarely used in the integrated problem. There are *m* projects that each project has *j* activity. Each activity may require one or more skills. A given number of workers are needed to execute each required skill. In this paper, the impact of forgetting as well as learning is assessed on project completion time, total cost, and project quality that are considered as main objective functions. Some of the most important features of the real-world projects have been considered in this research. The learning effect causes to reduce the required durations for activities, while it imposes more costs on the project. However, it improves activity's execution quality. On the opposite side, forgetting effect increase the execution time of activity if the worker cannot work for a long time. The learning and forgetting process is formulated based on related research (Wu and Sun 2006; Mehmanchi and Shadrokh 2013; Van Peteghem and Vanhoucke 2015). Some assumptions are considered as follows that make the proposed model close to real-world situations.

3. 1. Assumptions

- The activities are numbered in topological order labeled as $j = 0,1,2,...,N+1.$ The activities 0 and $N+1$ are dummy activities that represent the start and the finish of the project, respectively. Dummy activities $j=0$ and $j = N+1$ have zero standard duration and they require no resources.
- Activity preemption is not allowed
- Precedence relationships between activities are finish-to-start with zero lag
- A single mode is available for activities to be performed.
- Human resources are multi-skilled
- Resource requirements are deterministic and known in advance.
- Each worker is able to execute one or several specific skills.
- Only workforces can be assigned to an activity that has required skill to do it
- Each worker has to be assigned to only one skill of an activity at each period.

3.2. Notation

3.2.1. Indices

m	Index for project	$(m=1,...,M)$
j	Index for activity	$(j=1,...,J)$
s	Index for skill level	$(s=1,...,S)$
e	Index for employee	$(e=1,...,E)$
t	Index for time	$(t=1,...,T)$

3.2.2. Parameters

r_{mj} Release time of activity j in project m

pd_{mjes}	Processing time of activity j in project m which is done by optimal number workforce e with skill level s
q_{es1}	The primary quality level of worker e in performing skill s
c_{mjes}	Execution cost of worker e with skill level s for processing activity j in project m per day
α_{es}	Learning effect
β_{es}	Forgetting effect
b_{mjes}	1 if the workforce e with skill level s can perform activity j in project m ; 0 otherwise
pr_{mij}	1 if activity i precedes activity j in project m ; 0 otherwise
N	A large number

3.2.3. Decision Variables

p_{mj}	Processing time of activity j in project m
st_{mj}	Start time of activity j in project m
ct_{mj}	Completion time of activity j in project m
$C_{\max}$	Maximum completion time of projects' last activity
q_{est}	The quality level of worker e in performing skill s at period t
γ_{est}	The efficiency of worker e in skill s at period t
x_{mjt}	1 if activity j in project m starts at period t ; 0 otherwise
y_{mjest}	1 if workforce e with skill level s performs activity j in project m at period t
z_{mjes}	1 if activity j in project m is done by workforce e with skill level s ; 0 otherwise

3.3. Mathematical model

The proposed mathematical model is formulated as follows:

$$Min\ Z_1 = C_{\max} \tag{1}$$

$$Min\ Z_2 = \sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{e=1}^{E}\sum_{s=1}^{S}\sum_{t=1}^{T} y_{mjest} \times c_{mjes} \tag{2}$$

$$Max\ Z_3 = \sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{e=1}^{E}\sum_{s=1}^{S}\sum_{t=1}^{T} y_{mjest} \times q_{est} \tag{3}$$

$$\sum_{t=1}^{T} x_{mjt} = 1 \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{4}$$

$$\sum_{e=1}^{E}\sum_{s=1}^{S} Z_{mjes} = 1 \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{5}$$

$$\sum_{m=1}^{M}\sum_{j=1}^{J} y_{jmest} \le 1 \quad \forall e = 1,\dots,E, \quad \forall s = 1,\dots,S, \quad \forall t = 1,\dots,T \tag{6}$$

$$st_{mj} = \sum_{t=1}^{T} x_{mjt} \times t \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{7}$$

$$ct_{mj} = st_{mj} + p_{mj} - 1 \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{8}$$

$$st_{mj} \ge r_{mj} \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{9}$$

$$C_{\max} \ge ct_{mj} \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{10}$$

$$y_{mjest} \le b_{mjes} \times z_{mjes} \quad \forall e = 1,\dots,E, \quad \forall s = 1,\dots,S, \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M, \quad \forall t = 1,\dots,T \tag{11}$$

$$st_{mj} - st_{mi} \ge p_{mi} \times pr_{mij} - N \times \left(1 - pr_{mij}\right) \quad \forall i, j, \quad \forall m = 1,\dots,M \tag{12}$$

$$p_{mj} \le \sum_{e=1}^{E}\sum_{s=1}^{S} pd_{mjes} \times e^{-(\sum_{t=1}^{T} x_{mjt} \times \gamma_{est} \times pd_{mjes})} \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{13}$$

$$p_{mj} \ge \sum_{e=1}^{E}\sum_{s=1}^{S} pd_{mjes} \times e^{-(\sum_{t=1}^{T} x_{mjt} \times \gamma_{est} \times pd_{mjes})} \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{14}$$

$$\gamma_{es(t+1)} = \left[\gamma_{est}^{(1-\alpha_{es})} \times \sum_{m=1}^{M}\sum_{j=1}^{J} y_{mjest} \right] + \left[\gamma_{est}^{(1-\alpha_{es}+\beta_{es})} \times (1 - \sum_{m=1}^{M}\sum_{j=1}^{J} y_{mjest}) \right] \quad \forall e = 1,\dots,E, \forall s = 1,\dots,S, \forall t = 1,\dots,T-1 \tag{15}$$

$$q_{es(t+1)} = \left[q_{est}^{(1-\alpha_{es})} \times \sum_{m=1}^{M}\sum_{j=1}^{J} y_{mjest} \right] \quad \forall e = 1,\dots,E, \quad \forall s = 1,\dots,S, \quad \forall t = 1,\dots,T-1 \tag{16}$$

$$1 - x_{mjt} \ge \frac{t - ct_{mj}}{T} \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M, \quad \forall t = 1,\dots,T \tag{17}$$

$$1 - x_{mjt} \ge \frac{st_{mj} - t}{T} \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M, \quad \forall t = 1,\dots,T \tag{18}$$

$$q_{est} \le 1 \quad \forall e = 1,\dots,E, \quad \forall s = 1,\dots,S, \quad \forall t = 1,\dots,T \tag{19}$$

$$C_{\max} \ge 0 \tag{20}$$

$$x_{mjt} \in \{0,1\} \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M, \quad \forall t = 1,\dots,T \tag{21}$$

$$Z_{mjes} \in \{0,1\} \quad \forall e = 1,\dots,E, \quad \forall s = 1,\dots,S, \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M \tag{22}$$

$$y_{mjest} \in \{0,1\} \quad \forall e = 1,\dots,E, \quad \forall s = 1,\dots,S, \quad \forall j = 1,\dots,J, \quad \forall m = 1,\dots,M, \quad \forall t = 1,\dots,T \tag{23}$$

$$ct_{mj}, st_{mj}, p_{mj} \geq 0 \quad \forall j = 1,...,J, \quad \forall m = 1,...,M \tag{24}$$

$$q_{est} \geq 0 \quad \forall e = 1,...,E, \quad \forall s = 1,...,S, \quad \forall t = 1,...,T \tag{25}$$

The first objective function in Equation (1) is minimizing completion time of the project. The second one in Equation (2) aims to minimize total execution cost. Equation (3) presents the third objective function which is maximized total activities' quality level. The first constraint (Eq. (4)) ensure that each activity is started just once in each project. Equation (5) enforces that activity j in project m is processed by only one workforce with specific skill. Constraint (6) implies that a human resource can work at most in one activity at each period. Equations (7) and (8) show start and completion time of each activity, respectively. Constraint (9) secures that activity cannot be started before its release time. Completion time of last activity in each project is calculated by constraint (10). Constraint (11) guarantees that workforce can perform activity only if he/she can do it. Precedence relationships are considered in constraint (12). Processing time of each activity according to the learning and forgetting effect is calculated by constraint (13) and (14). The learning and forgetting rate is computed by equation (15). The quality level of workforce is calculated by equation (16). Equations (17) and (18) state that activities is non-preemptive. Equation (19) assures that maximum value of quality is 1. Finally, equation (20) to (25) denote the type of decision variables.

4. Solution Procedure

In this study, the ε-constraint method is applied to solve a proposed multi-objective project scheduling and workforce assignment problem exactly. The ε-constraint approach is used as one of the well-known approaches for modifying the multi-objective problems that transfers all objective functions except one to the constraints in each step to solve such problem (Ehrgott and Gandibleux 2003). Recently, many research have used this method to solve multi-objective problems exactly (Vafaeenezhad et al. 2019; Bula et al. 2019; Balaman et al. 2018). A set of non-dominated solution is created by this method that is set on Pareto frontier which is formed by ε constraint (Bérubé et al. 2009).

$$\begin{aligned} &Min\ f_1(X) \\ &x \in X \\ &f_2(X) \leq \varepsilon_2 \\ &\dots \\ &f_n(X) \leq \varepsilon_n \end{aligned} \tag{26}$$

The steps of the ε-constraint method are as follows:

- One of the objective function is selected as main target.
- Problem is solved based on one of the sub-objective function each time and its optimal value is obtained.
- The interval between two values of the sub-objective functions is divided by a predefined number and created a table of values for $\varepsilon_2, ..., \varepsilon_n$.
- Main problem is solved by values $\varepsilon_2, ..., \varepsilon_n$.
- Pareto solution obtained is reported.

In the proposed model, completion time of project is considered as main objective. Then, 8 breakpoints for the objective functions are generated. The formulation associated with the proposed problem is shown as follows:

$$Min\ Z_1 = C_{\max}$$

S.t.

Constraint (4) to (25)

$$Z_2 \le \varepsilon_1 \quad (27)$$

$$Z_3 \ge \varepsilon_2 \quad (28)$$

5. Computational Results

In this section, the validity of the proposed model is assessed by generating three instance problems. The input parameters are randomly generated using a uniform distribution. All of the computations were carried out by CPLEX solver of GAMS software running on a computer with the following specifications: 4 GB RAM, 2.40 GHz, Intel Core i5-2430M CPU.

5.1. Instance problems generation

The instance problems presented in the study were derived from the studies by Hematian et al. (2019). Table 2 shows the instance problem dimension. Moreover, the value of the model's parameters is reported in Table 3.

Table 2. Instance problems dimension

Prob. No.	Project	Activity	Employee	Skill
1	2	5	3	2
2	2	6	4	3
3	2	7	5	3

Table 3. Parameters' value for instance problems

Parameter	Value
r_{mj}	Uniform(1,20)
pd_{mjes}	Uniform(2,10)
q_{es1}	Uniform(0.75,0.85)
c_{mjes}	Uniform(120000,300000)
α_{es}	Uniform(0.03,0.06)
β_{es}	Uniform(0.06,0.09)
b_{mjes}	[0,1]
N	1000000

5.2. Experimental results

To implement the proposed solution technique, the single-objective problems are solved considering the three objectives, respectively. The model complexity is high, for example, the instance problem number 3 has 6988 variables and 10414 equations. The objective functions value for each instances are reported in Table 4.

Table 4. Objective function value for single objective problems

Prob. No.	Min Z_1			Min Z_2			Max Z_3			Time Avg. (s)
	C_{max}	Cost	Quality	C_{max}	Cost	Quality	C_{max}	Cost	Quality	
1	**40**	5618500	8.25	47	**5440000**	8.16	43	5721500	**8.31**	197.41
2	**49**	6021800	8.04	57	**5769500**	7.97	52	6202400	**8.12**	444.84
3	**54**	6865400	8.38	72	**6322000**	8.19	65	7010500	**8.46**	808.32

As shown in Table 4, the instance problem number is represented in first column. The minimum value of project completion time as well as two other objective functions value is reported in the next three columns. This procedure is repeated for two more objective functions. Then, the breakpoints can be calculated using the obtained values for total execution costs and project quality objectives because completion time of projects is considered as main goal. Table 5 indicates the value of ε_1 (cost) and ε_2 (quality) value for each breakpoints.

Table 5. Breakpoint value

Prob. No.	Objective	Breakpoints							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	ε_1	5440000	5480000	5520000	5560000	5600000	5640000	5680000	5721500
	ε_2	8.16	8.28	8.2	8.22	8.24	8.26	8.28	8.31
2	ε_1	5769500	5831500	5893500	5955500	6017500	6079500	6141500	6202400
	ε_2	7.97	7.99	8.01	8.03	8.05	8.07	8.09	8.12
3	ε_1	6322000	6420000	6518000	6610000	6702000	6800000	6892000	7010500
	ε_2	8.19	8.23	8.27	8.31	8.35	8.39	8.43	8.46

Finally, the main proposed problem are solved for each breakpoint. The best possible value of project completion time are reported in Table 6. Moreover, the Pareto frontier obtained for the three instance problems is depicted in Figure 1 to 3, respectively. As can be seen, there is not a direct relation between three objectives, and the Pareto fronts show a strong contradiction between time and cost objectives, thus decision-makers should choose only one point among the existing Pareto points.

Table 6. Objective functions value for different breakpoint

Prob. No.	**1**			**2**			**3**		
Pareto solution No.	Z_1	ε_1	ε_2	Z_1	ε_1	ε_2	Z_1	ε_1	ε_2
1	**47**	5440000	8.16	**57**	5769500	7.97	**72**	6322000	8.19
2	**46**	5480000	8.18	**56**	5831500	7.99	**69**	6420000	8.23
3	**45**	5520000	8.20	**54**	5893500	8.01	**66**	6518000	8.27
4	**44**	5560000	8.22	**53**	5955500	8.03	**62**	6610000	8.31
5	**42**	5600000	8.24	**51**	6017500	8.05	**60**	6702000	8.35
6	**40**	5640000	8.26	**49**	6079500	8.07	**57**	6800000	8.39
7	**41**	5680000	8.28	**50**	6141500	8.09	**54**	6892000	8.43
8	**43**	5721500	8.31	**52**	6202400	8.12	**65**	7010500	8.46

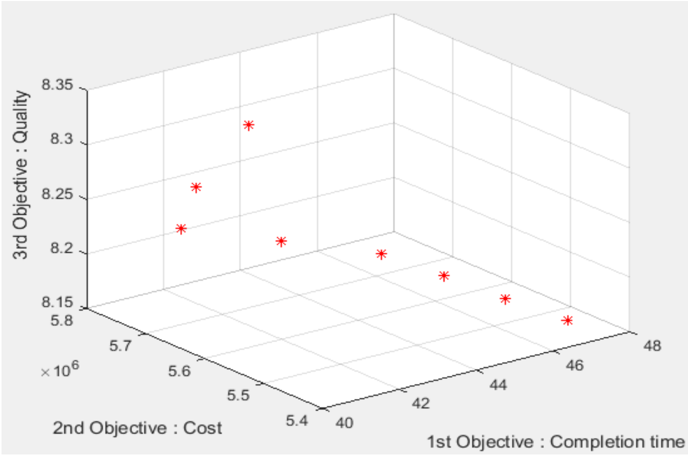

Figure 1. Pareto frontier for instance problem No. 1

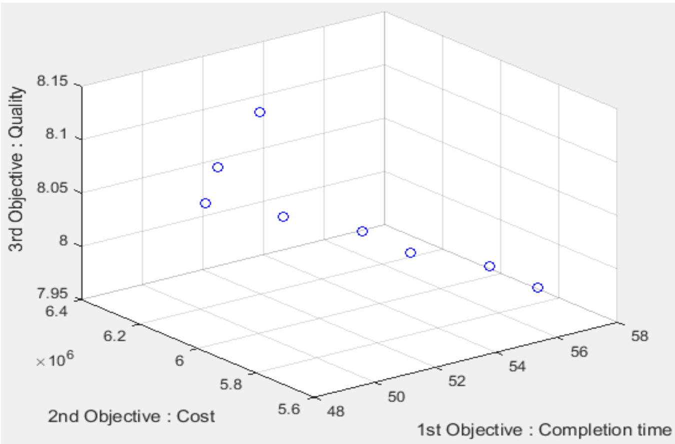

Figure 2. Pareto frontier for instance problem No. 2

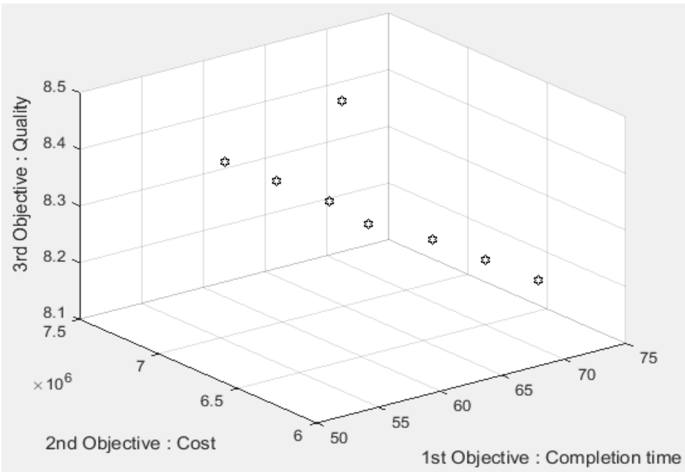

Figure 3. Pareto frontier for instance problem No. 3

Furthermore, the computational time average of the problems demonstrate that the problem has a high complexity such that the average time is increased by raising instance problem size (Figure 4).

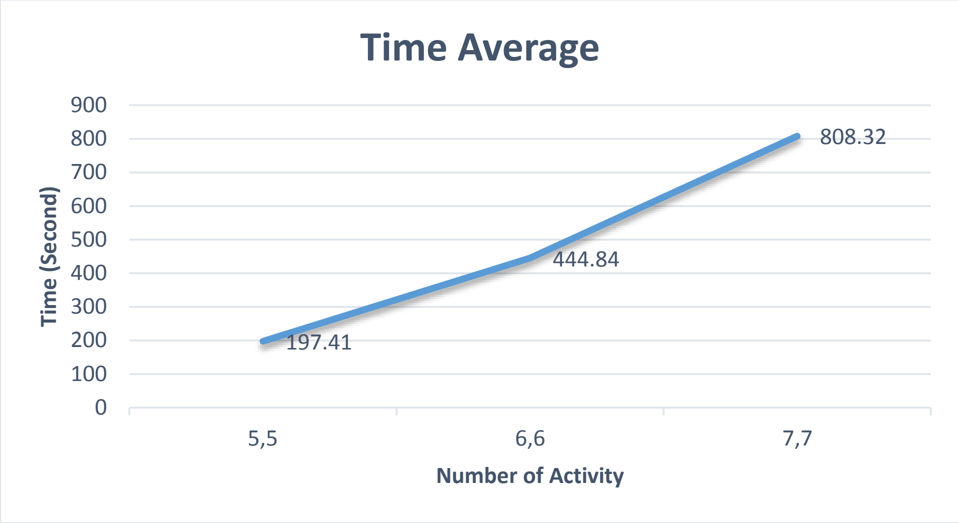

Figure 4. Computational time comparison

In order to evaluate Pareto solution and select best one, reference point approach (RPA) method is applied in this study. Deb and Sundar (2006) introduced RPA to determine the best point in a multi-objective problem. The main idea is to identify the solutions which are close to the reference point. The normalized Euclidean distance (dev_p) between each non-dominated solutions is calculated by Eq. (29) so that each solution with the lowest value of dev_p has the highest priority for the decision-maker.

$$dev_p = \sqrt{\sum_{o=1}^{O} \left(\frac{f_o - z_o}{f_o^{\max} - f_o^{\min}}\right)^2} \qquad \forall p = 1, 2, \ldots, 8. \tag{29}$$

Where f_o present the value of objective *o*, z_0 denotes the value of the reference objective or reference point, $f_o^{\max}$ and $f_o^{\min}$ are the maximum and minimum values for objective *o*, respectively. The value of reference point is tuned based on the objective function significance (Table 7).

Table 7. Parameters' value in RPA

Parameters	Values
z_1	$\frac{f_1^{\min}}{1.05}$
z_2	$\frac{f_2^{\min}}{1.05}$
z_3	$\frac{f_3^{\max}}{0.99}$

As can be seen in Table 7, completion time and total execution costs of project have the same importance. Their value is greater than one because they should be minimized whereas the third objective is maximized, then its value is considered lower than one. Now, the values obtained, dev_p for each instance problem are represented in Table 8.

Table 8. The dev_p value for each problem

Pareto solution No. \ Prob. No.	1	2	3
1	2.213	4.433	6.461
2	2.107	4.374	6.329
3	2.024	4.257	6.256
4	1.967	4.242	**6.144**
5	1.892	4.182	6.251
6	**1.879**	**4.157**	6.354
7	1.973	4.318	6.494
8	2.119	4.522	7.564

According to Table 8, the best Pareto solution is obtained based the minimum value of the dev_p . As can be seen in Table 9, the best Pareto solution for two first instances contains minimum value of completion time that indicates the significance of this goal in project scheduling problem.

Table 9. Best Pareto solution for each problem.

Problem No.	Minimum dev_b	Best Pareto Solution		
		Z_1	Z_2	Z_3
1	1.879	40	5640000	8.26
2	4.157	49	6079500	8.07
3	6.144	62	6610000	8.31

5.2. Sensitivity Analysis

Furthermore, sensitivity analysis of important parameters affected on objective function is done. Firstly, the impact of learning effect on each objective function is investigated, separately. Its amount varies from 0.03 to 0.06. Figure 5 shows the objective functions variation according to the learning effect parameter.

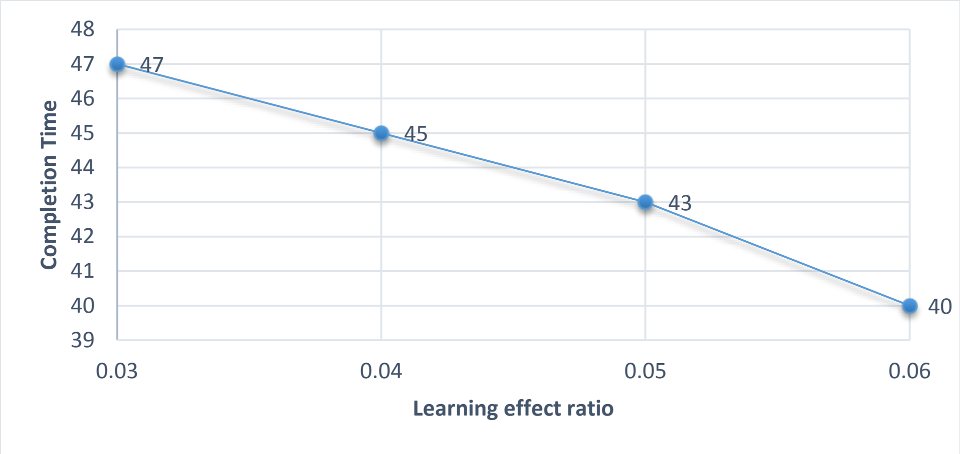

Figure 5-a. Project completion time variation according to learning effect ratio

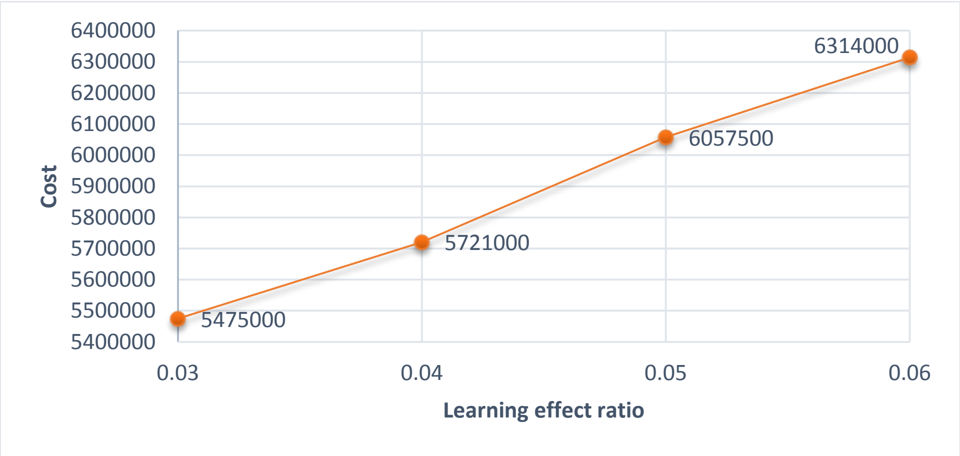

Figure 5-b. Cost variation according to learning effect ratio

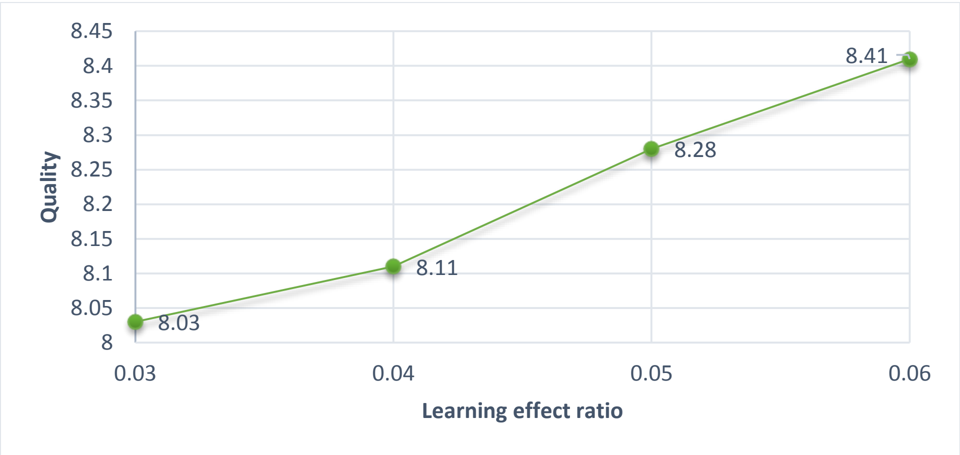

Figure 5-c. Quality variation according to learning effect ratio

As shown in Figure 5, the learning effect changing has different impact on objective functions. It indicates that increasing learning effect coefficient cause to decrease completion time of projects while the amount of cost is increased. As well, increasing the learning effect makes human resource skill improved, as a result quality of activity during processing is increased. The forgetting effect is also analyzed to investigate its effect on each objective functions. To do this end, its amount is changed from 0.06 to 0.09. Figure 6 depicts the trend of objective function variation according to forgetting effect.

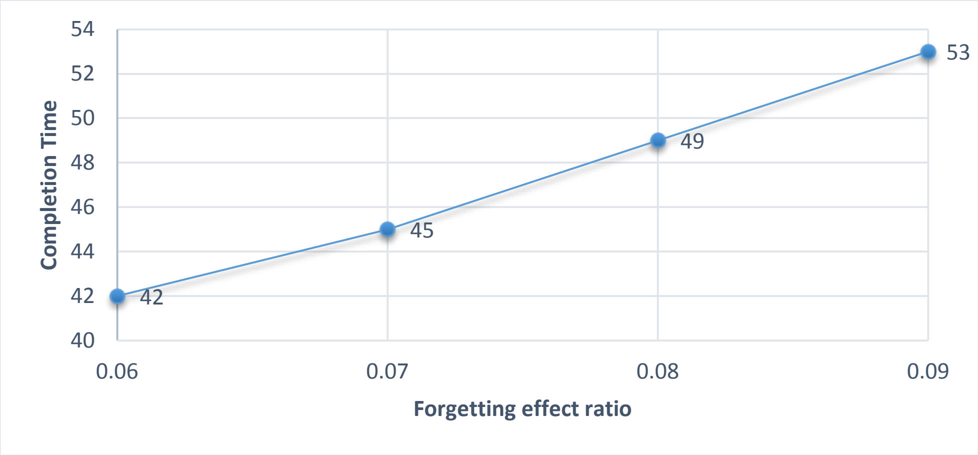

Figure 6-a. Project completion time variation according to forgetting effect ratio

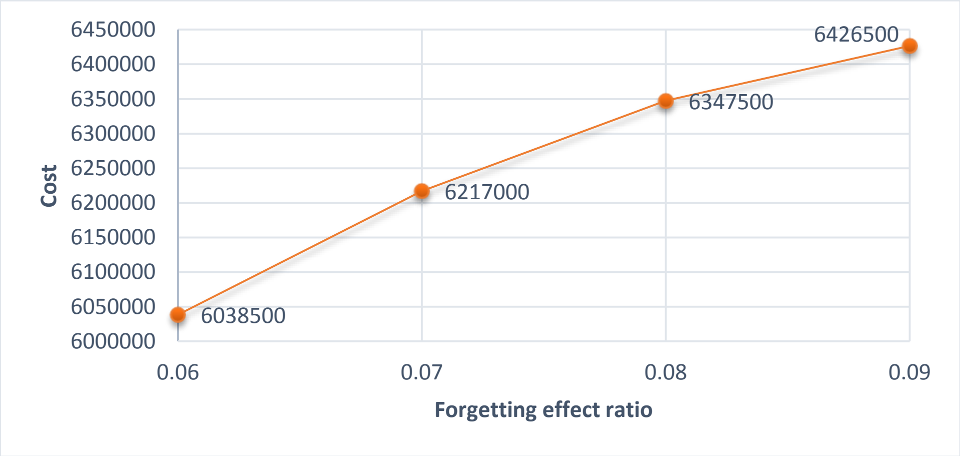

Figure 6-b. Cost variation according to forgetting effect ratio

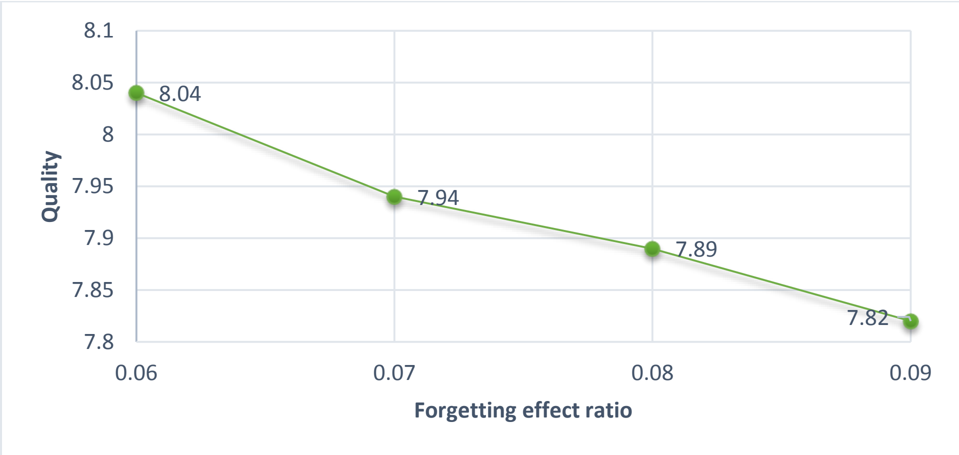

Figure 6-c. Quality variation according to forgetting effect ratio

As shown in Figure 6, increasing the forgetting effect ration has a negative impact on all objective function due to decreasing workforce skill level. When workforces have not work for a couple of day, its skill level is somewhat reduced. Furthermore, comparison between the learning and forgetting effect stated that forgetting one has more negative impact on objective functions. Thus, managers should concentrate on workforces' selection based on their ability to learn more quickly and skill level.

6. Conclusions and Future Directions

In this paper, a novel multi-objective mixed integer linear programming model is proposed for an integrated multi-project scheduling and multi-skill workforce assignment model. The learning and forgetting effect is considered for human resource that causes to change processing time of activity during planning period. The objectives are to minimize completion time and total cost of projects as well as maximize project quality. In order to evaluate the proposed mathematical model, some instance problems are generated randomly and solved using CPLEX solver of GAMS software. Moreover, the ε-constraint approach is applied to solve multi-objective problem. Furthermore, a reference point approach (RPA) is then implemented to help the decision-maker for finding the best Pareto solution in each problem. Then a sensitivity analysis is performed on the two important parameters consist the learning and forgetting effect. Results show that the forgetting effect has more significant role on each objective function.

As projects consist lots of activities it is impossible solve such problems exactly, thus meta-heuristic and artificial intelligence-based algorithms can be employed to solve the large-sized problems in reasonable run times (Goli et al. 2019; Davoodi and Goli 2019; Goli and Davoodi 2018). In the real world, none of the data in such problems is immune to uncertain factors. It is recommended that proposed problem is considered under uncertainty. Then, several approach such as fuzzy theory, robust and stochastic optimization can be used to model uncertainty (Tirkolaee et al. 2020; Tirkolaee et al. 2020). Furthermore, the goal programming model can be used to solve multi-objective problems (Tirkolaee et al. 2019; Tirkolaee et al. 2019).

References

Alfares, H.K., and Bailey, J.E., (1997). "Integrated project task and manpower scheduling" *IIE transactions*, Vol. 29, pp. 711-717.

Babaee Tirkolaee, E., Goli, A., Pahlevan, M., and Malekalipour Kordestanizadeh, R., (2019). "A robust bi-objective multi-trip periodic capacitated arc routing problem for urban waste collection using a multi-objective invasive weed optimization", *Waste Management & Research*, Vol. 37, No. 11, pp. 1089-1101.

Babaee Tirkolaee, E., Hadian, S., and Golpira, H., (2019). "A novel multi-objective model for two-echelon green routing problem of perishable products with intermediate depots", *Journal of Industrial Engineering and Management Studies*, Vol. 6, No. 2, pp. 101-110.

Balaman, Ş. Y., Matopoulos, A., Wright, D. G., and Scott, J., (2018). "Integrated optimization of sustainable supply chains and transportation networks for multi technology bio-based production: A decision support system based on fuzzy ε-constraint method", *Journal of cleaner production*, Vol. 172, pp. 2594-2617.

Batarlienė, N., Čižiūnienė, K., Vaičiūtė, K., Šapalaitė, I., and Jarašūnienė, A., (2017). "The impact of human resource management on the competitiveness of transport companies", *procedia Engineering*, Vol. 187, pp. 110-116.

Bellenguez-Morineau, O., (2008). "Methods to solve multi-skill project scheduling problem", *4OR: A Quarterly Journal of Operations Research*, Vol. 6, No. 1, PP. 85-88.

Berk, L., Bertsimas, D., Weinstein, A. M., and Yan, J., (2019). "Prescriptive analytics for human resource planning in the professional services industry" *European Journal of Operational Research*, Vol. 272, No. 2, pp. 636-641.

Bérubé, Jean-François, Michel Gendreau, and Jean-Yves Potvin., (2009). "An exact ε-constraint method for bi-objective combinatorial optimization problems: Application to the Traveling Salesman Problem with Profits", *European Journal of Operational Research*, Vol. 194, No. 1, pp. 39-50.

Bula, G.A., Afsar, H. M., González, F.A., Prodhon, C., and Velasco, N. (2019). Bi-objective vehicle routing problem for hazardous materials transportation", *Journal of cleaner production, 206*, 976-986.

Chakrabortty, R.K., Sarker, R.A., and Essam, D.L., (2016). "Multi-mode resource-constrained project scheduling under resource disruptions", *Computers & Chemical Engineering*, Vol. 88, pp. 13-29.

Certa, A., Enea, M., Galante, G., and Manuela La Fata, C., (2009). "Multi-objective human resources allocation in R&D projects planning", *International Journal of Production Research*, Vol. 47, No. 13, pp. 3503-3523.

Davoodi, S.M.R., and Goli, A. (2019). "An integrated disaster relief model based on covering tour using hybrid Benders decomposition and variable neighborhood search: Application in the Iranian context", *Computers & Industrial Engineering*, *130*, 370-380.

Deb, K., and Sundar, J., (2006). "Reference point based multi-objective optimization using evolutionary algorithms", *Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation*, Vol. 12, pp. 635-642.

Ehrgott, M., and Xavier G., (2003). "Multi objective combinatorial optimization theory, methodology, and applications, multiple criteria optimization: State of the art annotated bibliographic surveys" Springer US, pp. 369-444.

Fırat, M., and Hurkens, C.A.J., (2012). "An improved MIP-based approach for a multi-skill workforce scheduling problem", *Journal of Scheduling*, Vol. 15, No. 3, pp. 363-380.

Fernandez-Viagas, V., and Framinan, J. M., (2014). "Integrated project scheduling and staff assignment with controllable processing times" *The Scientific World Journal*, Vol. 2014.

Goli, A., and Davoodi, S.M.R., (2018). "Coordination policy for production and delivery scheduling in the closed loop supply chain", *Production Engineering*, *12*(5), 621-631.

Goli, A., Zare, H.K., Tavakkoli-Moghaddam, R., and Sadegheih, A., (2019). "Multiobjective fuzzy mathematical model for a financially constrained closed-loop supply chain with labor employment", *Computational Intelligence*.

Goli, A., Zare, H.K., Tavakkoli-Moghaddam, R., and Sadeghieh, A. (2019). "Hybrid artificial intelligence and robust optimization for a multi-objective product portfolio problem Case study: The dairy products industry", *Computers & Industrial Engineering*, Vol. 137, 106090.

Hartmann, S. and Briskorn, D., (2010). "A survey of variants and extensions of the resource-constrained project scheduling problem", *European Journal of Operational Research*, Vol. 207, No. 3, pp. 1-14.

Heimerl, C., and Kolisch, R., (2010). "Work assignment to and qualification of multi-skilled human resources under knowledge depreciation and company skill level targets", *International Journal of Production Research*, Vol. 48, No. 13, pp. 3759-3781.

Hematian M., Seyyed Esfahani M.M., Mahdavi I, Mahdavi-Amiri N, Rezaeian J., (2019). "A multi-objective integrated multi-project scheduling and multi-skilled workforce assignment model considering learning effect under uncertainty", *Computational Intelligence*, pp. 1–21.

Karam, A., Attia, E. A., and Duquenne, P., (2017). "A MILP model for an integrated project scheduling and multi-skilled workforce allocation with flexible working hours", *IFAC-Papers Online*, Vol. 50, No. 1, pp. 13964-13969.

Kianto, A., Sáenz, J., and Aramburu, N., (2017). "Knowledge-based human resource management practices, intellectual capital and innovation", *Journal of Business Research*, Vol. 81, pp. 11-20.

Lian, J., Liu, C., Li, W., and Yin, Y., (2018). "A multi-skilled worker assignment problem in seru production systems considering the worker heterogeneity", *Computers & Industrial Engineering*, Vol. 118, pp. 366-382.

Maenhout, B., and Vanhoucke, M., (2017). "A resource type analysis of the integrated project scheduling and personnel staffing problem", *Annals of Operations Research*, Vol. 252, No. 2, pp. 407-433.

Maghsoudlou, H.M., Afshar-Nadjafi, B., and Niaki S.T.A., (2017). “Multi-skilled project scheduling with level-dependent rework risk; three multi-objective mechanisms based on cuckoo search”, *Applied Soft Computing*, Vol. 54, pp. 46-61.

Markoulli, M.P., Lee, C.I., Byington, E., and Felps, W.A., (2017). "Mapping Human Resource Management: Reviewing the field and charting future directions", *Human Resource Management Review*, Vol. 27, No. 3, pp. 367-396.

Mehmanchi, E., and Shadrokh, S., (2013). "Solving a new mixed integer non-linear programming model of the multi-skilled project scheduling problem considering learning and forgetting effect on the employee efficiency", *IEEE International Conference on Industrial Engineering and Engineering Management*, pp. 400-404.

Nie, H., and Liu, B., (2013). "Combining MILP with Memetic Algorithm for Scheduling and Staffing Construction Project with a Multi-skilled Workforce", *International Conference on Computational and Information Sciences*, pp. 1150-1153.

Qin, S., Liu, S., and Kuang, H., (2016). "Piecewise linear model for multi-skilled workforce scheduling problems considering learning effect and project quality", *Mathematical Problems in Engineering*, Vol. 2016.

Tirkolaee, E.B., Goli, A., and Weber, G.W. (2019). Multi-objective Aggregate Production Planning Model Considering Overtime and Outsourcing Options Under Fuzzy Seasonal Demand, In *Advances in Manufacturing II* (pp. 81-96). Springer, Cham.

Tirkolaee, E.B., Goli, A., Hematian, M., Sangaiah, A.K., and Han, T. (2019). "Multi-objective multi-mode resource constrained project scheduling problem using Pareto-based algorithms", *Computing*, Vol. 101, No. 6, pp. 547-570.

Tirkolaee, E.B., Hadian, S., Weber, G. W., and Mahdavi, I. (2019). "A robust green traffic-based routing problem for perishable products distribution", *Computational Intelligence*.

Tirkolaee, E. B., Mahdavi, I., Esfahani, M.M.S., and Weber, G. W. (2020). "A robust green location-allocation-inventory problem to design an urban waste management system under uncertainty", *Waste Management*, Vol. 102, pp. 340-350.

Tirkolaee, E.B., Mardani, A., Dashtian, Z., Soltani, M., and Weber, G. W. (2019). "A novel hybrid method using fuzzy decision making and multi-objective programming for sustainable-reliable supplier selection in two-echelon supply chain design. *Journal of Cleaner Production*, 119517.

Tiwari, V., Patterson, J. H., and Mabert, V.A., (2009). "Scheduling projects with heterogeneous resources to meet time and quality objectives", *European Journal of Operational Research*, Vol. 193, No. 3, pp. 780-790.

Schwindt, C., and Zimmermann, J., (2015). "Handbook on Project Management and Scheduling" Springer International Publishing Switzerland, Vol. 1.

Shen, X. N., Minku, L. L., Marturi, N., Guo, Y. N., and Han, Y., (2018). "A Q-learning-based memetic algorithm for multi-objective dynamic software project scheduling", *Information Sciences*, Vol. 428, pp. 1-29.

Vafaeenezhad, T., Tavakkoli-Moghaddam, R., and Cheikhrouhou, N., (2019). "Multi-objective mathematical modeling for sustainable supply chain management in the paper industry", *Computers & Industrial Engineering*, Vol. 135, pp. 1092-1102.

Van Peteghem, V., and Vanhoucke, M., (2015). "Influence of learning in resource-constrained project scheduling", *Computers & Industrial Engineering*, Vol. 87, pp. 569-579.

Wu, M.C. and Sun, S.H., (2006). "A project scheduling and staff assignment model considering learning effect", *The International Journal of Advanced Manufacturing Technology*, Vol. 28, No. 11, pp. 1190-1195.

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