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Efficient Model with an Intelligent Approach for Powerful Construction Projects Scheduling

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Abstract: The multi-project resources scheduling in construction engineering application has received much attention in recent years due to it is an important issue to achieve the best performance for any organization. In this paper, a multi-objective multi-resources (MOMR) mathematical model is proposed to handle the multi-project scheduling problem. In this model, the local objectives and the global objective of construction organizations are considered. Although the multi-project multi-resource scheduling (MPMRS) problem is one of the important issues that is increasingly considered by researchers, most of the reported projects scheduling approaches are applicable by the scheduling of multi-project as a single project. This due to a MPMRS problem is more difficult than a single project in case of multi-resource scheduling. Consequently, the MOMR model in terms of improved solutions to generate the best resource scheduling in the multi-project environment is needed. The modified genetic approach (MGA) is adopted to solve the proposed model. Finally, the experimental results showed that the total penalty cost of projects and customers' satisfaction are improved by using the proposed approach compared with the previous approaches.

Keywords: Multi-project scheduling, Multi-resource, Multi-objective, Genetic approach, Construction engineering, Penalty cost.

1. Introduction

The MPMRS problem is one of the challenges in most applications. In the multi-project environment, each project includes a set of activities. Each activity has a demand for different resources. These resources can be shared between a multi-project. Also, the due date and the penalty cost are varying from project to another project. The MPMRS problem is marked by the large size of the solution space and the nonlinear relationships among the objective functions. Consequently, meta-heuristic approaches are very suitable for this case [1]. In particular, the genetic algorithms used in such problems have yielded good results in this context. Most researches solved the multi-project resource scheduling problem as a single super project [2]. This super project includes all single projects. Also, most researches relied on the total make-span (TMS) of a super project with ignoring a set of individuals make-span [3, 4]. This methodology ignored important facts, in most cases of multi-project scheduling problems; the relationship between the make-span function of the super project and the penalty cost function of the supper project is a linear relationship because the penalty cost/unit varies from one project to another project. Also, the target time of the project varies from project to another project. In contrast, in a single project scheduling case, the relationship between the make-span function and the penalty cost function is a linear relationship because the penalty cost/unit is fixed in a single project scheduling case.

In an attempt to improve the scheduling in the multi-project environment, the researchers relied on other objectives besides minimizing make-span such as minimizing an average project delay (APD) and minimizing a deviation for average project delay

(DPD) [5, 6]. Also, some researchers solved the MPMRS problem as a multi-objective includes the TMS objective and the APD objective [7].

Many exact optimization approaches have been developed in the literature to solve the resource scheduling problem such as a branch and bound [8]. The execution time of any exact algorithm increases according to the number of activities [1]. Furthermore, the MPMRS problem is more complex when a variety of resources is considered. In this context, no feasible scheduling can be achieved by using the exact optimization algorithms [9]. So, to find feasible scheduling for all problems, many heuristic priority rules are proposed in this context.

Most of the efficient heuristic priority-rules to achieve a feasible resource scheduling can be found in [10]. [9] presented a performance analysis of different heuristic rules for resource constraints scheduling in multi project environment. The heuristic approaches solve the resource scheduling problems in a reasonable amount of time, but these approaches cannot adapt dynamically to the constraints. So, the scheduling by these approaches cannot be guarantees optimum scheduling or good quality schedule.

It is well known that MPMRS problem belongs to NP-hard optimization problems, many researchers showed that the intelligent approaches outperform the heuristic approaches for solving the NP-hard optimization problems. Thus, intelligent approaches are best approaches for solving the MPMRS problem [11].

Intelligent approaches are recently proposed to improve the multi-project and single project scheduling. The intelligent approaches use to generate near optimal resource scheduling. An intelligent approach of resource scheduling problems uses to generate the activities order list which, can produce better than solutions based on an experience gained in the previous generation. Various intelligent optimization search approaches were adopted in this context. such as the particle swarm optimization (PSO), a tabu search (TS), a simulated annealing (SA) [12-14], and a genetic approach (GA) [15, 16].

The genetic approach is one of the most well-known intelligent approaches that are widely used in a single objective optimization scheduling and a multi-objective optimization scheduling. Since 2012, the genetic approach developed to deal with a multi-objective scheduling problem.

[17] developed strength Pareto evolutionary approach-II (SPEA-II) to solve the resource constraints of the project scheduling problem whose objective functions are to minimize the resource cost and the total project duration. [18] modified the niched Pareto genetic algorithm (NPGA) for an optimal construction project scheduling in terms of three objectives, minimization of construction time, cost, and resource fluctuation. [19] developed the non-dominated sorting genetic algorithm II (NSGA II) for the time/cost trade-offs project scheduling problem. [20] developed two metaheuristic approaches to solve the resources constrained scheduling (RCPS) problem, the non-dominated sorting genetic algorithm II (NSGA-II) and the multi-objective simulated annealing (MOSA) algorithm to maximize the net present value and minimize the completion time concurrently. NSGA-II approach is shown to outperforms developed strength Pareto evolutionary approach (SPEA) in certain test problems. In an attempt to eliminate the potential weaknesses of evolutionary multi-objective optimization (EMO) approaches, the SPEA-II approach is developed. In the proposed approach, we base the strength of Pareto in the phase of population sorting according to the SPEA-II approach with different crossover and mutation.

The proposed model includes a set of objective functions. We assign objective function for every customer to minimize the time of its project. Also, a single function is assigned to minimize the total penalty cost of all projects. In the previous models, the set of objectives of all customer are collected in a single objective in an attempt to simplify the problem and total penalty cost is ignored like the single project resource scheduling models. The relationship between the time and the penalty cost in a single project resource scheduling case is a linear relationship, but the relationship between the time and the penalty cost in MPMRS case is a non-linear relationship. So, we take into consideration this objective in the proposed model. Furthermore, the complexity of this problem is increased when the number of objectives is increased. So, we proposed an efficient intelligent approach to solve this problem.

This paper is organized as follows: Section 2 introduces the problem description. The problem formulation is introduced in section 3. In section 4 the details of the proposed approach are described. The experiment and results are discussed in section 5. Finally, conclusion and future work are presented in section 6.

2. Problem description

The MPMRS is a general case from the single project resource scheduling. In the case of the single project scheduling, each decision maker has a local objective to minimize the cost of his project. There is no conflict between the time and the cost. So, the decision maker depends on minimizing make-span as a means of minimizing the project cost in this case. While in the MPMRS case, the make-span for all projects cannot be minimized simultaneously with the cost. Therefore, additional criteria are added to compare alternative solutions in the multi project scheduling. Most researches, when converting the multi-project to a single project ignore the conflict between the time and the cost objectives of multi-project. The relationship between the total make-span and the total penalty cost is a nonlinear relationship in a multi-project. This is due to the difference in the penalty cost according to each project. So, the reduction of the total make-span or average project delay does not necessarily mean reducing the total penalty cost.

In this section, we introduce an analysis of MPMRS problem to find the best scheduling to improve the performance of any company. The main objective of any owner is maximizing the profit of the company. The profit of the company improves in two directions, reducing the penalty cost and increasing the sales of the company.

According to the proposed analysis, any company includes a set of customers; each customer has a single project in the company. Every single project has two local objectives function minimizing the make-span of the project and minimizing the penalty cost of the project.

The minimizing of the individuals' make-span of projects tends to satisfy the customer. The satisfaction of the customer improves the performance of company and achieves the increase in sales. The satisfaction of the customer means completes the project of this customer without any delay. So, the minimization of individuals' make-span has an indirect effect on the success of the company. On the other hand, the minimization of the total penalty cost of all projects has a direct effect on the performance of the company. Fig. 1 illustrates the relationships of the proposed MOMR model for the MPMRS problem.

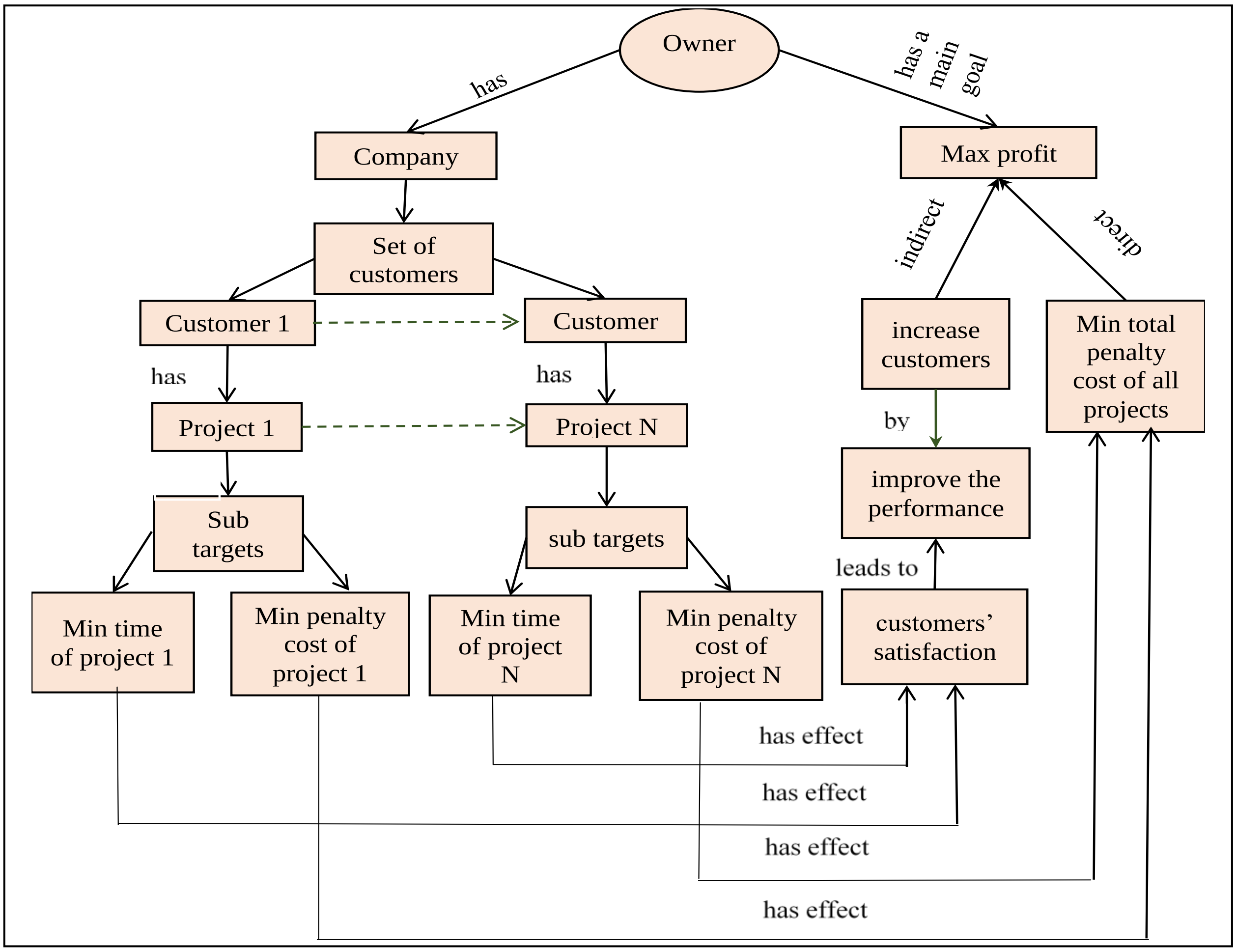

Figure. 1 The relationship between the objectives of the proposed MOMR model

3. Problem formulation

In this section, the MOMR model for the MPMRS problem to achieve a set of objectives is proposed. A set of the objectives represents the minimization of make-span for every project (i.e. the benefit of the customers) and the minimization for a total penalty cost of all projects (i.e. the benefit of the owners). The MOMR model of the MPMRS has two types of objective functions the local objective function and the global objective function can be formulated as follows:

Each project has a local objective function to minimize the make-span of this project. The make-span for every project is expressed by Eq. (1).

$$Min\ MS_i = max_{j=1}^{n_i}\{ft_{ij}\} - AD_i \quad (1)$$

Where $i \in (1, 2, \dots, N), N$ represents the number of projects. Each i^{th} project includes set of n_i activities, MS_i is make-span of the i^{th}project, ft_{ij} represents the finishing time for j^{th} activity in i^{th} project, and AD_i represents the arrival date of i^{th}project. There is only global objective function represents the total penalty cost for all projects as formulated in Eq. (2).

$$Min\ TPC = \sum_{i=1}^{N} PC_i \quad (2)$$

Where PC_i is the penalty cost for i^{th} project, the PC_i is defined by Eq. (3) as follows:

$$PC_i = \begin{cases} 0 & IF\ Max_{j=1}^{n_i}\{ft_{ij}\} \le t_i \\ \left(t_i - Max_{j=1}^{n_i}\{ft_{ij}\}\right) p_i & otherwise \end{cases} \quad (3)$$

Where $t_i$is the target time of the i^{th} project, p_i is the penalty cost of one unit delay for i^{th} project. The proposed MOMR model includes four main sets of constraints. A set of constraints for MPMRS problem are known as precedence constraints set, a set of local resource constraints, a set of global resource constraints, and a set of arrival date constraints. Eq. (4) shows the precedence constraints between the activities for every project. Eq. (5) and Eq. (7) show the local resource constraints and the global resource constraints respectively.

$$st_{ij} \le st_{ik} - d_{ij} \quad , \forall i \in N;\ \forall\ j \in M_{ik} \quad (4)$$

Where M_{ik} presents a set of preceding activities of the k^{th} activity in the i^{th} project, and s_{ik} is the finish time of k^{th} activity of i^{th} project.

$$\sum_{j=1}^{n_i} x_{ijt} qA_{ijr_{i_l}} \le r_{i_l} \quad , \forall (l \in r_i), \forall (i \in N), \forall (t \in T) \quad (5)$$

Where r_i represents a number of local resources types for the i^{th} project, and r_{il} presents the limitation of l^{th} local resources in i^{th} project, $qA_{ijr_{i_l}}$ presents the demand of the j^{th} activity in the i^{th} project from the local resource l^{th} type for the i^{th} project. x_{ijt} describes the state of the j^{th} activity in i^{th} project at time t by Eq. (6) , and T denote by $\max\{MS_i\}$.

$$x_{ijt} = \begin{cases} 1, & \text{if } j^{th} \text{ activity of } i^{th} \text{ project} \\ & \text{in an execution phase at time t}. \\ 0, & \text{Otherwise} \end{cases} \quad (6)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{n_i} x_{ijt} qA_{ijR_g} \le R_g \quad , \forall (g \in R), \forall (t \in T) \quad (7)$$

Where g is the number of global resources types, and R_g represents the limitation of the g^{th} global resources, and qA_{ijR_g} presents the demand of the j^{th} activity in the i^{th} project from global resource of g^{th} type.

In the static project phase, the arrival dates of all project equal to zero, but the execution phase of the projects includes different arrival dates constraints as well as previous precedence and resource constraints. Eq. (8) shows the arrival date constraints for each project and Eq. (9) indicates the non-negative constraints as follows.

$$st_{ij} \ge AD_i, \forall (j \in n_i), \forall (i \in N) \quad (8)$$

Eq. (8) means each j^{th} activity in i^{th} project does not begin after the arrival date of i^{th} project.

$$st_{ij} \ge 0 \forall i \in N, j \in n_i \quad (9)$$

Eq. (9) represents the non-negative constraints for all j^{th} activity in i^{th} project.

4. Proposed approach

In this section, the modified genetic approach to generate the best scheduling of construction projects under a set of above constraints and the above objectives is developed. The genetic approach has received increased interest in projects scheduling area due to an ability to provide acceptable solutions in a reasonable amount of time for solving large and complex scheduling problems. A multi-objective genetic algorithms (MOGAs) are adaptive intelligent search algorithms based on the evolutionary ideas of natural selection and genetics. In MOGA, the chromosome representation and the genetic operators play an important role, as it must be suitable to the problem.

MOGA operates execute through a cycle of three phases. The first phase begins with an initial population of a randomly generated individuals. Each individual represents a feasible solution for the problem. These individuals are evaluated according to a set of time objective functions and a penalty cost objective function. In the second phase, the genetic operators are applied to improve these individuals. The genetic approach adopts three different genetic operators such as selection parents, crossover and mutation. Firstly, select a set of parents from the old population to construct a new population. Secondly, apply the crossover with a specified probability on the selected parents for generating new offspring. Finally, apply the mutation with a specified probability on the new offspring to make a non-inherit change. This cycle is repeated until stopping criteria are met.

The proposed approach multi-objective multi-resource-modified genetic approach (MOMR-MGA) includes the same phases of MOGA and bases on the modified serial scheduling generation scheme (SSGS). [21] used SSGS to construct the feasible solutions in a single project case. The schematic diagram of the proposed approach is illustrated in Fig. 2. Also, the modified procedure of SSGS to construct and evaluate a feasible solution for any chromosome in the population as follows.

Modified Procedure of SSGS

0: Begin
1: $E_K \leftarrow$ Sort A_{ij} according to the value of current chromosome
2: For $K = 1 : \sum_{i=1}^{N} n_i$
4: IF $A_{ij} \notin E_K$ go to step 13
5: Cheek the PCA_{ij} by Eq. (4); IF invalid Then update j, go to step 3.
6: For $l = 1 : r_i$
7: IF $qA_{ijr_{i_l}} \geq qr_{i_l}^t$; Then update j , go to step 3
8: For $g = 1 : R$
9: IF $qA_{ijR_g} \geq qR_g^t$; Then update j , go to step 3
10: $st_{ij} \leftarrow t$, delete A_{ij} from E_K
11: Update $qr_{i_l}^t\ \forall (l \in r_i)$
12: $qR_g^t\ \forall\ (g \in R)$
13: END For
14: IF (met stopping criteria); Then go to step 16
15: Update t, go to step 2.
16: END

In the following, we will discuss in more detail the different components of the proposed MOMR-MGA approach. These components include the chromosome representation as well as parent selection, crossover and mutation operators.

4.1 Chromosome representation

in the proposed MOMR-MGA approach, the chromosomes are represented as depicted in Fig. 3. In this process, the chromosome consists of a set of genes. The value of each gene indicates the execution priority of the activity. The position of each gene represents by two dimensions. The first dimension indicates the i^{th} project. The second dimension indicates the j^{th} activity in project i^{th} .

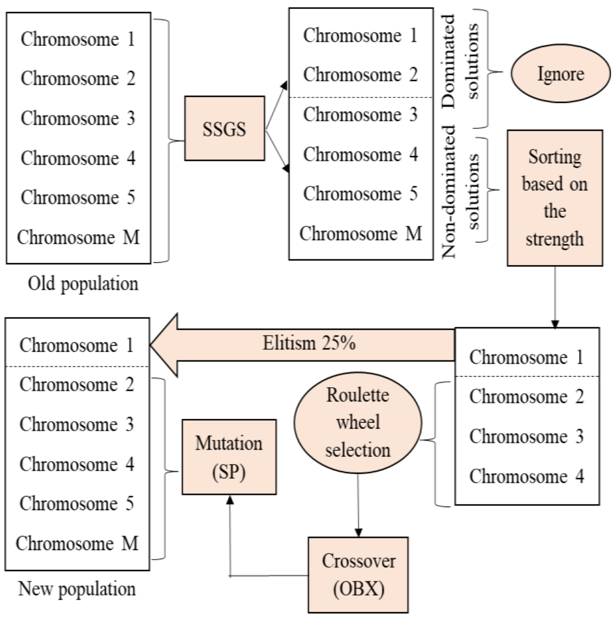

Figure. 2 Schematic diagram of the proposed MOMP-MGA approach

Project1			Project i			Project N		
A_{11}	A_{1j}	A_{1n_1}	A_{i1}	A_{ij}	A_{in_i}	A_{N1}	A_{Nj}	A_{Nn_N}
1	3	8	5	7	9	6	4	2
Sub-chromosome 1			Sub-chromosome i			Sub-chromosome N		

Chromosome

Figure. 3 Representation of chromosome

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4.2 Parent selection

In parent selection, a pool of individuals is constructed by the roulette wheel selection method based on the strength of dominators. also, elitism 25% is used to increase the performance of the proposed approach. Because it does not miss the best solutions from the old population.

4.3 Crossover operator

Crossover is applied to parents' chromosomes selected by roulette wheel selection with probability 0.95. the process is performed on the parents' individuals by order-based crossover (OBX). Then, the new offspring are produced by exchanging the shaded sections between the parent chromosomes as showed in Fig. 4. the OBX crossover operator is applied by a binary mask. The OBX converts a subset of genes from the first parent to offspring. this subset of genes equals to one in the random binary mask. The subset genes are copied in the same order into the offspring at the same positions of these genes. Then the empty positions in the offspring are filled by the genes from the second parent at these positions. The OBX crossover is described in Fig. 4.

The OBX crossover has the ability to generate a huge number of the offspring for each pair of parents (e.g. The presented experiment in this paper includes 20 projects, each project includes 30 activities, and each activity is represented in the binary mask 0 or 1; this means that the number of available masks for each pair of parents = 2600 masks for each of them has the ability to generate a different child for the same pair of parents).

Parent 1

A_{11}	A_{1j}	A_{1n_1}	A_{i1}	A_{ij}	A_{in_i}	A_{N1}	A_{Nj}	A_{Nn_N}
1	2	3	4	5	6	7	8	9

Parent 2

A_{11}	A_{1j}	A_{1n_1}	A_{i1}	A_{ij}	A_{in_i}	A_{N1}	A_{Nj}	A_{Nn_N}
7	5	8	4	2	9	3	1	6

Binary Crossover

A_{11}	A_{1j}	A_{1n_1}	A_{i1}	A_{ij}	A_{in_i}	A_{N1}	A_{Nj}	A_{Nn_N}
0	1	0	1	1	0	0	0	0

Offspring 1

A_{11}	A_{1j}	A_{1n_1}	A_{i1}	A_{ij}	A_{in_i}	A_{N1}	A_{Nj}	A_{Nn_N}
7	2	8	4	5	9	3	1	6

Offspring 2

A_{11}	A_{1j}	A_{1n_1}	A_{i1}	A_{ij}	A_{in_i}	A_{N1}	A_{Nj}	A_{Nn_N}
1	5	3	4	2	6	7	8	9

Figure. 4 OBX crossover in MOMR-MGA approach

Before mutation

A_{11}	A_{1j}	A_{1n_1}	A_{i1}	A_{ij}	A_{in_i}	A_{N1}	A_{Nj}	A_{Nn_N}
7	2	8	4	5	9	3	1	6

After mutation

A_{11}	A_{1j}	A_{1n_1}	A_{i1}	A_{ij}	A_{in_i}	A_{N1}	A_{Nj}	A_{Nn_N}
7	2	8	3	5	9	4	1	6

Figure. 5 Mutation by swapping priority

4.4 Mutation operator

After the crossover process, the mutation operator is applied on the offspring with probability 0.3 In this problem, swapping is very suitable to perform mutation process. The swapped genes are randomly selected. Fig. 5 describes the mutation process by swapping priority.

The notation of pseudocode and the pseudocode of the proposed MOMR-MGA approach is detailed as follows.

Notation of pseudocode:

N:Number of projects
i: Project index, $i = (1, 2, \ldots, N)$
AD_i: Arrival date of project i
MS_i: Make-span of project i $MS_i = Max_{j=1}^{n_i}\{ft_{ij}\}$
p_i: Penalty cost/unit of project i
n_i: Number of activities j of project i
j: Activity index of project i ($j = 1, 2, \ldots, n_i$)
d_{ij}: Duration of activity j of project i.
PM_{iK} Precedence matrix, represent the precedence of every activity k^{th} for every project i^{th}.
r_i: Number types of local resources l of project i
l: Index pointers to types of local resources, $l = (1, 2, \ldots, r_i), i \in N$
r_{i_l}: Fixed capacity of local resource l of project i
qA_{ijR_g}: Demand from global resource type g to start work in activity j of project i
$qA_{ijr_{il}}$:Demand from local resource type l for activity j of project i.
R: Number types of global resources g
g: Index pointers to type of global resources, $g = (1, 2, \ldots, R)$.
ft_{ij}: Finish time of activity j of project i.
st_{ij}: Start time of activity j of project i.

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NI: Number of iterations.
SA: Size of population.
ER: elitism rate.
CR: Crossover rate.
MR: Mutation rate.
P: Old population.
$\bar{P}$: New population.

Pseudocode of proposed MOMR-MGA

Start
Initiation: $\mathrm{N}, \mathrm{AD_i}, \mathrm{MS_i}, \mathrm{p_i}, \mathrm{n_i}, \mathrm{d_{ij}}, \mathrm{PM_{ik}}, \mathrm{r_i}, \mathrm{r_{i_l}}, \mathrm{qA_{ijr_{i_l}}}, \mathrm{R_g}, \mathrm{qA_{ijR_g}}, \mathrm{NI}, \mathrm{SP}, \mathrm{SA}, \mathrm{CR}, \mathrm{MR}, \mathrm{TPC}$
Deceleration: $\mathrm{st_{ij}}, \mathrm{TPC}, \mathrm{valid}, \mathrm{P}, \overline{\mathrm{SP}}, \overline{\mathrm{P}}$
1: $\mathrm{st_{ij}} \leftarrow$ Initial_scheduling$(\mathrm{N}, \mathrm{n_i}, \mathrm{PM_{ik}}, \mathrm{d_{ij}}, \mathrm{AD_i})$
2: Valid $\leftarrow$ Constraints$\left(\mathrm{st_{ij}}, \mathrm{r_i}, \mathrm{r_{i_l}}, \mathrm{qA_{ijr_{i_l}}}, \mathrm{g}, \mathrm{R_g}, \mathrm{qA_{ijR_g}}\right)$
3: IF (Valid = True) then go to step 17
4: $\mathrm{P} \leftarrow$ Initial_population$(\mathrm{N}, \mathrm{n_i}, \mathrm{sp})$
5: $l \leftarrow 1$
6: While $(\mathrm{I} \leq \mathrm{NI})$
7: Construct _scheduling$(\mathrm{P}, \mathrm{sp}, \mathrm{N}, \mathrm{n_i}, \mathrm{d_{ij}}, \mathrm{PM_{ik}}, \mathrm{r_i}, \mathrm{r_{i_l}}, \mathrm{qA_{ijr_{i_l}}}, \mathrm{g}, \mathrm{R_g}, \mathrm{qA_{ijR_g}})$
8: Fitness-p $\leftarrow$ Fitness$(\mathrm{t_i}, \mathrm{PC_i}, \mathrm{P})$
9: $\mathrm{p} \leftarrow$ Non-dominated $(\mathrm{P}, \mathrm{SP})$
10: Strength-p ← strength (Fitness-p, SP)
11: P ←Sort (strength-p)
12: $\overline{\mathrm{P}} \leftarrow \mathrm{P}$
13: $\mathrm{P} \leftarrow$ Elitism $(\overline{\mathrm{P}}, \mathrm{ER})$
14: genetic _operators $(\overline{\mathrm{P}})$
15: $\mathrm{I} \leftarrow \mathrm{I} + 1$
16: End While
17: Print outputs
Outputs: $\mathrm{TPC}, \mathrm{st_{ij}}, \mathrm{MS_i}, \mathrm{pc_i} \quad \forall(\mathrm{i} \in \mathrm{N}), (\mathrm{j} \in \mathrm{n_i})$

The details of the pseudocode of the proposed MOMR-MGA approach are expressed as follows:
Step 1: Find initial scheduling based on only the precedence constraints.
Step 2: Cheek the feasibility of the local and the global resource constraints by Eqs. (6) and (7) respectively; if all resource constraints are valid in this case the initial scheduling is an optimal solution then go to step 12.
Step 3: Generate the initial population of MOMR-MGA.
Step 4: Construct the feasible scheduling for every chromosome in the current population by SSGS.
Step 5: Evaluate the fitness of a set of the local objective functions (1) and the fitness of the global objective function (2) respectively.
Step 6: Cheek the non-dominated solutions for the current population.
Step 7: Sort the non-dominated solutions based on the strength.
Step 8: Check the number of iterations; if valid go to step 12.
Step 9: Select the parents by the roulette wheel selection method based on the strength of dominator solutions
Step 10: Apply the order-based crossover and the swapping priority mutation.
Step 11: Go to step 4
Step 12: Print the outputs

5. Experiment and results

In this section, the experimentation designed to verify the performance of the proposed MOMR-MGA approach for the MPMRS problem is introduced. In this experiment, the presented MOMR model is verified against three of the state-of-the-art models such as TMS, APD, and DPD models. This benchmark problem called 30a20nr4 is available on MPSP library. This problem includes 20 projects. Each project consists of 30 activities, only one local resource, and three global resources. The arrival dates for the 20 projects are 0, 3, 6, 12, 14, 16, 16, 19, 22, 23, 29, 32, 33, 37, 39, 40, 45, 46, 50, 55 respectively. The penalty costs of projects are 1, 22, 17, 5, 26, 4, 9, 9, 5, 25, 6, 6, 13, 2, 11, 18, 4, 10, 27, 19 respectively. The due dates of projects are 60, 57, 68, 44, 65, 26, 53, 42, 76, 43, 42, 64, 59, 51, 54, 60, 48, 60 respectively.

Table 1, includes the project's make-span for the 20 projects by the proposed MOMR-MGA approach. Also, the delay time and the penalty cost for every project are illustrated in Tables 2 and 3. The number of satisfied customers (NSC), the total penalty cost (TPC), and the value of utility for every non-dominated solution for the problem by the presented MOMR-MGA approach are illustrated in Table 4.

Notation of tables:
M: Make-span
D: Project delay
C: Delay cost
S: Solution number
P: priority
U: Utility

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Table 1. Make-span of projects by MOMR-MGA approach

MOMR-MGA		Make-span of projects																			
		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20
Non-dominated solution	S1	117	166	176	142	176	**29**	**58**	**45**	**76**	53	**42**	90	63	**51**	17	**60**	72	92	76	85
	S2	141	174	202	130	196	32	61	**45**	**76**	48	45	**69**	83	**51**	**54**	78	60	**60**	56	66
	S3	170	209	140	132	191	40	61	84	**76**	**43**	49	72	99	**51**	**54**	76	64	62	**48**	80
	S4	62	206	181	220	**126**	208	176	101	260	186	82	69	**59**	**51**	179	237	64	232	100	201
	S5	282	185	236	226	163	91	86	93	121	110	73	109	171	68	62	92	**53**	**60**	48	**60**
	S6	**60**	**62**	**114**	95	156	97	139	138	180	151	136	155	173	158	141	174	175	186	181	188
	S7	242	218	195	141	156	72	104	99	86	72	73	82	84	70	57	60	62	60	51	66
	S8	203	244	296	198	170	100	134	46	81	109	73	103	68	97	117	71	57	60	**48**	94
	S9	148	151	197	**56**	193	127	88	46	160	62	49	111	97	56	63	94	65	126	58	80
	S10	180	194	179	173	182	48	115	129	120	168	86	107	103	92	117	124	84	60	89	97

Table 2. Delay of projects by MOMR-MGA approach

MOMR-MGA		Project Delay																				NSC
		D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	D16	D17	D18	D19	D20	
Non-dominated solution	S1	57	109	108	98	111	**3**	**5**	**3**	**0**	10	**0**	26	4	**0**	17	**0**	19	32	82	25	4
	S2	81	117	134	86	131	6	8	**3**	**0**	5	3	**5**	24	**0**	**0**	18	7	**0**	8	6	4
	S3	110	152	72	88	126	14	8	6	**0**	**0**	7	8	40	**0**	**0**	16	11	2	**0**	20	5
	S4	2	149	113	176	**61**	182	123	59	184	146	40	**5**	**0**	**0**	125	177	11	172	52	141	2
	S5	222	128	186	182	98	65	15	51	45	67	31	45	112	17	8	32	**0**	**0**	**0**	**0**	4
	S6	**0**	**5**	**46**	51	91	71	86	96	104	108	94	91	114	107	87	114	122	129	133	128	1
	S7	182	161	127	97	91	46	51	57	10	29	31	18	25	19	3	**0**	9	**0**	3	6	2
	S8	143	187	228	154	105	74	81	4	5	66	31	39	9	46	63	11	4	**0**	**0**	34	2
	S9	88	94	129	**12**	128	101	35	4	84	19	7	47	38	5	9	34	12	66	10	20	0
	S10	120	137	111	129	117	22	62	87	44	125	44	43	44	41	63	64	31	**0**	41	37	1

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Table 3. Penalty cost of projects by MOMR-MGA approach.

MOMR-MGA		Penalty cost of projects																				TPC
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	
Non-dominated solution	S1	57	2398	1836	490	2886	**12**	**45**	**27**	**0**	250	**0**	156	52	**0**	187	**0**	76	320	756	475	10023
	S2	81	2574	2278	430	3406	24	72	**27**	**0**	125	18	**30**	312	**0**	**0**	324	28	**0**	216	114	10059
	S3	110	3344	1224	440	3276	56	72	45	**0**	**0**	42	48	520	**0**	**0**	288	44	20	**0**	380	9918
	S4	2	3278	1921	880	**1586**	728	1107	53	920	3650	240	**30**	**0**	**0**	1375	3186	44	1720	1404	2679	25281
	S5	222	2816	2856	910	2548	260	135	459	225	1675	186	270	1456	34	88	576	**0**	**0**	**0**	**0**	14716
	S6	**0**	**110**	**782**	225	2366	284	774	864	520	2700	564	546	1482	214	957	2052	488	1290	3591	2432	22271
	S7	182	3542	2159	485	2366	184	459	513	50	725	186	108	325	38	33	**0**	36	**0**	81	114	11586
	S8	143	414	3876	770	2730	296	729	36	25	1650	186	234	117	92	693	198	16	**0**	**0**	646	16551
	S9	88	2068	2193	**60**	3328	404	315	36	420	475	42	282	494	10	99	612	48	660	270	380	12284
	S10	120	3014	1887	645	3042	88	558	783	220	3125	264	258	572	82	693	1152	124	**0**	1107	703	18437

Table 4. Best scheduling based on the balance utility NSC & TPS

MOMR-MGA		NSC	TPC	P(NSC) = NSC/Max (NSC)	U(NSC) = P(NSC)/sum(P(NSC))	P(TPC) = TPC/Min(TPC)	U(TPC)=P(TPC) /Sum P(TPC)	U (NSC, TPC) =U(NSC) + U(TPC)/Sum(U(NSC)+U(TPC))
Non-dominated solution	S1	4	10023	0.8	0.16	0.989524095	0.135779772	0.147889886
	S2	4	10059	0.8	0.16	0.985982702	0.135293832	0.147646916
	S3	**5**	**9918**	**1**	**0.2**	**1**	**0.137217247**	**0.168608623 (Best scheduling)**
	S4	2	25281	0.4	0.08	0.392310431	0.053831757	0.066915879
	S5	4	14716	0.8	0.16	0.673960315	0.092478979	0.126239489
	S6	1	22271	0.2	0.04	0.445332495	0.061107299	0.050553649
	S7	2	11586	0.4	0.08	0.856033143	0.117462511	0.098731255
	S8	2	16551	0.4	0.08	0.599238717	0.082225887	0.081112943
	S9	0	12284	0	0	0.807391729	0.11078807	0.055394035
	S10	1	18437	0.2	0.04	0.537940012	0.073814647	0.056907324

Table 5. Make-span, project delay, and penalty cost of projects for TMS, APD, and DPD models

	TMS			APD			DPD		
	Make-span	Project delay	Penalty cost	Make-span	Project delay	Penalty cost	Make-span	Project delay	Penalty cost
Project 1	172	112	112	141	81	81	186	126	126
Project 2	180	123	2706	174	117	2574	188	131	2882
Project 3	176	108	1836	202	134	2278	181	113	1921
Project 4	166	122	610	130	86	430	176	135	675
Project 5	186	103	2678	196	131	3406	178	113	2938
Project 6	77	15	60	32	6	24	135	109	436
Project 7	73	20	180	61	8	72	162	109	981
Project 8	113	71	639	45	3	27	153	111	999
Project 9	111	35	175	76	<u>0</u>	0	164	88	440
Project 10	143	100	2500	48	5	125	167	124	3100
Project 11	106	64	384	45	3	18	144	102	612
Project 12	145	39	234	69	5	30	220	76	456
Project 13	110	51	663	83	24	312	159	100	1300
Project 14	91	40	80	51	<u>0</u>	0	156	105	210
Project 15	107	53	583	54	<u>0</u>	0	128	74	814
Project 16	72	12	216	78	18	324	153	93	1674
Project 17	92	39	156	60	7	28	146	93	372
Project 18	110	50	500	60	<u>0</u>	0	121	61	610
Project 19	83	53	945	56	8	216	126	78	2106
Project 20	112	52	988	66	6	114	123	63	1197
NSC		0			4			0	
TPC			16245			10059			23849

Table 6. Number of satisfied customers and total penalty cost by several approaches

Models	Best solution approach	NSC, TPS according the best solution approach	
		NSC	TPS
<u>MOMR</u>	**<u>MOMR-MGA</u>**	**<u>5</u>**	**<u>9918</u>**
TMS	PSGSMINSLK	0	16245
APD	PEREZ/POZADA	4	10059
DPD	GMAS/ES	0	23849

The purpose of the MOMR-MGA approach is to minimize the make-span of projects that are requested by the customers of projects and minimize the total cost of all projects that are requested by the owners of the construction company. These objectives are conflicting because each customer has its own project and the penalty cost. Also, the due dates of projects are varied from project to another. Thus, the decision maker would like to find the best scheduling that balances the benefit of customers and owners. The best scheduling for MPMRS problem is selected by the balance utility function that tries to balance customers' benefit and owners' benefit. In this research, customer's satisfaction is defined as the number of customers whose projects are completed on the specified due date in the contract of the project without any delay. S_3 is selected from the non-dominated solutions as a best solution for MOMR-MGA approach based on the balance utility function of the NSC and TPC.

The MPMRS problem is formulated by three models TMS, APD, and DPD. The benchmark 30a20nr4 problem is solved according to these models by several approaches. The best scheduling for this problem for every model is 183, 32.1, and 21.71 respectively. Also, the values of make-span and project delay for the 20 projects that is used to calculate the penalty cost of these projects are available by author [3, 5, 6] in MPSP library (http://www.mpsplib.com, last check of address: 31 DES 2019). The solutions of these authors are ranked in MPSP library as a best solution to solve the three existing models for this problem. The make-span, delay time, and the penalty cost of projects for TMS, APD, and DPD models are illustrated in Table 5. The performance of the presented MOMR-MGA approach is measured by two components. The number of satisfied customers and the value of the total penalty cost for all projects is compared with previous approach in Table 6.

From the above results in Table 6 clear that the NSC by TMS and APD model = 0. These models do not guarantee the satisfaction for any customer; this means not any customer can be received your project at the determined time in the contract of project. Also, the proposed approach reduced the total penalty cost to 9918 compared with the previous approach 16245, 10059, 23849 respectively. Consequently, the best solution by the proposed MOMR-MGA approach is shown to outperform TMS, DPD, and APD approaches. (i.e. the best scheduling multi-project resource by the proposed MOMR-MGA approach achieves the best benefit for the customers and the owners together). When the problem of construction scheduling tends to more reality such as the presented experiment in this section (i.e. the company has a variety of projects, different resources, different penalty cost, and different arrival dates and due dates). In this case, the presented approach achieves the best scheduling as an alternative than other approaches.

6. Conclusion and future work

The contributions of this paper are: formulate a novel multi-objective mathematical model for MPMRS problem of construction projects and propose an intelligent approach to solve this model. The proposed model takes into account when allocating the resources in construction projects the interests of the customers and the owners together. MPMRS problem is one of the most difficult decision-making problems and this problem becomes more difficult when the goals of the problem are increased. The presented MOMR-MGA approach has a set of advantages to deal with this problem. firstly, it overcomes the redundancy in the solutions by the OBX crossover that has the ability to explore a huge search space. Secondly, knowing that the MPMRS problem has a huge search space for this reason the proposed approach relied on the modified SSGS to construct and evaluate only the feasible solutions from the search space in order to accelerate the research and discover the non-dominated solutions. Finally, the proposed MOMR-MGA approach offers two distinct advantages over the previous approaches of solving the MPMRS problem: The ability to find the best scheduling for any important customer or project easily from the non-dominated solutions and it provides several alternatives for the customers' satisfaction and the total penalty cost. We have compared the proposed MOMR-MGA approach with existing approaches and observed the average 75 % and 32 % improvement in terms of NSC and TPC respectively.

Future research could be developing other intelligent approaches to solve the presented MOMR model of MPMRS problem. Also, adopt the presented mathematical model to solve the multi-mode resource scheduling problem in multi-project environment.

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