A multi-purpose model for optimising project selection and activities scheduling by balancing resource allocation

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Abstract: This research aims to analyse and solve the problems of project portfolio selection and project scheduling simultaneously based on the resource constraints and specific modelling parameters. The first objective function is to maximise the current value of a particular profit (income) and the second function is levelling the resources. Therefore, a model was presented based on linear programming that had the capacity of expressing different possible situations in this problem. Small problems were solved by the Epsilon constraint method in GAMS whose results are accurate in small scale, and then two platform-independent meta-algorithms were used to check the quality of the proposed answers. Of course, these results show that NSGA-II is more accurate than MOPSO. Big-scale problems were solved by using two platform-independent meta-algorithms in MATLAB software. By testing the results, the quality of the solutions in the two objective functions and the low-level solving time of NSGA-II algorithm were compared with the MOPSO algorithm which had better performance than NSGS-II algorithm. Regarding the C-index, the NSGA-II method provided better answers than the MOPSO method. Also, in the dispersion index, the uniform Pareto border was obtained based on the results of the MOPSO method.

Keywords: project portfolio selection; scheduling project; net present value; MOPOS; NSGA-II.

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1 Introduction

Today, with globalisation of trade, the best use of resources for survival in global scenes is the imperative method. Concepts such as project, project control, and project scheduling with resource constraint have been raised in this regard. 'Project selection' is an evaluation and analysis process for selecting the best project and as a result, achieving the organisational goals. In project selection, various factors are involved such as project risk, organisational goals, organisational resource constraints, etc. (Wey and Wu, 2007). The permanent challenge is how to select some projects out of a large number of competitive projects, considering budget constraints, resource availability, and other technical constraints in the real world. So far, different approaches have been used to decide on project choices. Various mathematical programming models have been designed for making such decisions. Perhaps, each aspect of this problem (i.e., selecting a projects portfolio, planning the activities of the selected projects, balancing the use of different resources by activities in different periods, simultaneous mathematical modelling of these aspects, providing an accurate solution for the proposed model, and finally proposing multifunctional models to solve this large-scale model) have been separately investigated in previous studies. However, no study was observed to consider all the mentioned problems simultaneously to overcome the complexity of computations in an easy manner for the researchers' decision-making. Badri and Davise (2001) proposed a model based on ideal programming for selecting information system projects in hospitals. Chen and Cheng (2002) proposed a multi-criteria decision-making model (MCDM) by using fuzzy tools to select IT projects and then tested this model with a numerical example in the test case. Maravelias and Grossmann (2004) have considered a problem in which there is a possibility of serving renewable resources. Also, the type and amount of consumable resources can be chosen to reduce the time of activities. The cost reduction problem is modelled as a complex integer programming problem and solved with a large meta-bundle algorithm due to the large dimensions of the problem. Huang (2007) has achieved the optimal project selection model by using fuzzy parameters. The two fuzzy variables were the investment amount and annual the net fiscal flows. In this research, the net worth method was used with two zero and one integer programming models and the combined genetic algorithm and randomised fuzzy simulation. Through several numerical examples were also used presented to prove the efficiency of the model. Bozorgi-Amiri et al. (2013) showed that the facility location and resources allocation can be properly done by designing a potentially sustainable multi-purpose model to eliminate the possibility of disasters in non-deterministic logistics with study of earthquake cases in Iran. Liu et al. (2013) used NSGAII to optimise the multi-purpose topological structure (cognitive form) of the telescope shell with several constraints. Mazzuto et al. (2017) identified a multi-criteria priority indicator integrating the principles of critical chain project management (CCPM) which observes human factors task completion delay, and the fuzzy logic (FL) which models human reasoning. The defined priority indicator provides a different distribution of the activities' weights based on their position in project scheduling. In particular, the fuzzy scheduling approach has been adopted to fill the gap in the literature. The results have shown the efficiency of the method improving the project makespan with a 40% reduction compared to traditional approaches. According to Masuin et al. (2020), the implementation of integrated management system (quality, health and safety, environment management systems) began in manufacturing industry its application is being studied in the construction industry. If the risk is recognised and managed well, it will provide a strategy for improving the organisational performance. Therefore, this study aims to discuss the risks that can occur in the integrated management system process and consequently, improve the organisational performance. This research uses the relative important index to identify the most serious risk. The results explain that the variables/clauses to improve the organisational performance include the scope of organisation and leadership. Construction companies must be able to motivate their worker by leadership in the integrated management process and define the scope of organisation, especially the integrated work breakdown structure in the integrated management system. In the proposed algorithm, each chromosome was represented by a single bits matrix. Finite factor analysis was done by ANSYS and optimising the basic matrix of the problem. Yang et al. (2009) used the MOPSO algorithm to solve a set of problems and compared the results with sigma method. Then they solved the problem of setting cascade tanks. The study also investigated the optimal allocation of multi-purpose resources by using the particle clustering algorithm, Pareto optimisation, and particle pool algorithm in which a pseudo-algorithm is also included (for optimisation of the multi-objective functions) to evaluate problems related to mastery and scoring function (Yin and Wang, 2006).

Ogulata and Erol (2003) set of hierarchical multiple criteria mathematical programming models are developed to generate weekly operating room schedules. The goals considered in these models are maximum utilisation of operating room capacity, balanced distribution of operations among surgeon groups in terms of operation days, lengths of operation times, and minimisation of patient waiting times. Developed models are tested on the data collected in College of Medicine Research Hospital at Cukurova University as well as on simulated datasets using MPL optimisation package (Rajendran et al., 2019). Since the objectives of minimising lawsuit cost and potential customer loss are conflicting in nature, and therefore, it is necessary to determine the side effects to report on the label such that the best compromise is achieved between the two. A stochastic multiple criteria mathematical programming (SMCMP) model is developed to serve as a decision support system in assisting pharmaceutical companies with labelling decisions. A non-preemptive stochastic goal programming technique is used to solve the SMCMP model to attain a tradeoff solution between the two objectives. Finally verify the model with sample datasets and conduct sensitivity analysis by varying the lawsuit costs and number of customers lost. The results indicate that when the target value for lawsuit cost increases, fewer drug-related reactions are declared, while more side effects are labelled with an increase in target customer loss. Korhonen et al. (1992) provide a problem oriented review of multiple criteria decision research and focus on classifying multiple criteria decision-making problems, and discussing how decision makers can be assisted (supported) in structuring and solving such problems. We do not review existing multiple criteria procedures, but do provide references to relevant software systems implementing such procedures for the computer. Both discrete alternative and continuous mathematical programming multiple objective problems are discussed. Conclude the paper by identifying exciting directions and promising areas for continued and future research in multiple criteria decision support. Habibi et al. (2017) propose a multi-objective project scheduling optimisation model with time-varying resource requirements and capacities. This model, with the objectives of minimising the project makespan, maximising the schedule robustness, and maximising the net present value, considers the interests of both project owner and contractor simultaneously. Two multi-objective solution algorithms, NSGA-II and MOPSO, are modified and adjusted with Taguchi method to be used for determination of the set of Pareto optimal solutions for the proposed problem. The proposed solution methods are evaluated by the use of 15 problems of different sizes derived from project scheduling problem library (PSPLIB). Finally, solutions of the algorithms are evaluated in terms of five evaluation criteria. The comparisons show that NSGA-II yields better results than MOPSO algorithm. Also, we show that ignoring the time-based variations in consumption and availability of resources may lead to underestimation of project makespan and significant deviation from the optimal activity sequence.

Although there is a wide range of studies investigating project selection and evaluation, most of them have been focused on single projects with a single period of time and less attention has been to multiple projects. Each of these projects has activities with preconditions in different periods of time. In this research, the conditions are considered in which, various projects are to be implemented in a few time periods. Also, the model was designed to optimise the selection with setting the goal of levelling resources besides the main objective function (maximising the net present value) by using two meta-algorithms.

2 Research methodology

Doing a research always requires a theoretical framework. This theoretical framework depends on the research nature, the type of data, the analysis method, the research goal, and the motives for selecting the topic. This paper is based on library studies and it was started by composing a mathematical model of the problem and solving that by linear programming software (GAMS is used in this study). Regarding the hybrid problem of selecting and scheduling the project portfolio out of the NP-hard category (Demeulemeester and Herroelen, 2002), two powerful meta-algorithms were selected for large-scale problems and some of their examples were solved by MATLAB software.

2.1 Mathematical model

The problem parameters are defined as follows: first we define the model decision variable to select or not to select the project at a specific time (types zero and one). Suppose T is the total time frame for projects. In this case, T' the time period after the completion of the projects and the profitability period of the projects are defined and the portfolio of the desired projects consists of J projects, each of which also includes I activities. It is also assumed that each project needs h resources to carry out the project. Other model variables are also defined as follows:

Variables

x_{ijt} Equal to selecting/not selecting activity i from the j project at time t. If this activity starts at time t, the value of this variable is equal to one, otherwise its value will be zero.

y_j Equal to select or not j project. If the j project is selected, its value is equal to one, otherwise its value will be zero.

u_{ijt} Equal to one from start to end and indicates that x_{ijt} is using resources in time interval $[es_{ij}, ls_{ij}]$ and returning resources when the activity is complete.

Parameters

d_{ij} Duration required to run as activity i from project j.

es_{ij} The earliest starting time as activity i from project j.

ls_{ij} The best starting time as activity i from project j.

r_{ijh} The amount of resource as activity i required from source h to run project i.

R_h Available capacity of resource h.

$\overline{R}$ The average required resource.

θ_t Positive variable.

$b_{t'j}$ The amount of profit or revenue obtained from the completion of the project j at t *priority*(i, i', j): The set of post-activities of activity i from the project j.

a Interest rate or return of investment.

The parameters used in the model, except the discount rate, are defined as integers. The objective functions of this problem include the profit or revenue expected from doing the project and resource levelling. The formulation of these two objective functions is described in the following:

The first objective function (maximising the earnings or revenue expected from the project implementation):

$$\max \sum_{j=1}^{J} y_j \sum_{t=1}^{T} \sum_{t'=1}^{T'} \sum_{i \in end\ activity\ of\ project\ j}^{I} x_{ijt} \frac{b_{it'}}{(1+\alpha)^{(t+d_{ij}+t'-1)}} \tag{1}$$

The second objective function (minimising the fluctuations in resource consumption levels):

$$\min \sum_{i}^{I} \sum_{j}^{J} \left(u_{ijt} r_{ij} - \overline{R}\right)^2 \tag{2}$$

Which is a nonlinear objective function and of course it cannot be solved by linear programming, but this Function turns to a linear one in the following mathematical operations.

Which is a nonlinear objective function and becomes linear by performing the following mathematical operations.

$$\min \sum_i^I \sum_j^J \left(u_{ijt} r_{ij} - \bar{R}\right)^2 \Rightarrow \sum_i^I \sum_j^J \left(u_{ijt} r_{ij}\right)^2 + \sum_i^I \sum_j^J (\bar{R})^2 - \sum_i^I \sum_j^J u_{ijt} r_{ij} \times \bar{R} \tag{3}$$

So because $\bar{R}$ is constant value $\sum_i^I \sum_j^J 2u_{ijt} r_{ij} \times \bar{R}, \sum_i^I \sum_j^J (\bar{R})^2$ will eliminate from equation (3).

$$\Rightarrow \min \sum_i^I \sum_j^J \left(u_{ijt} r_{ij} - \bar{R}\right)^2 + \sum_i^I \sum_j^J \left(u_{ijt} r_{ij}\right)^2 \tag{4}$$

It should be noted that the second power in the objective function is because negative fluctuations do not neutralise positive fluctuations. Therefore we will have:

$$\left(u_{ijt} r_{ij} - \bar{R}\right)^2 = \left|u_{ijt} r_{ij} - \bar{R}\right| \tag{5}$$

On the other hand, as in many papers such as Bozorgi-Amiri et al. (2013), for linearisation of magnitude, it is possible to replace the objective function with an expression in the magnitude of the variable, and it can be assumed that expression is limited to the row of the negative problem:

$$\left|u_{ijt} r_{ij} - \bar{R}\right| = u_{ijt} r_{ij} - \bar{R} + 2\theta_t \tag{6}$$

where θ is positive. As a result, the second objective function is as follows: it has a completely linear form and will not have problem for solving through linear programming.

$$\min \sum_i^I \sum_j^J u_{ijt} r_{ij} - \bar{R} + 2\theta_t \tag{7}$$

The constraints of this problem are:

Each activity in the project can only be selected once:

$$\sum_{t=es_{ij}}^{ls_{ij}} x_{ijt} = y_j \quad \forall i, j \tag{8}$$

Each activity is only selected at $[es_{ij}, ls_{ij}]$:

$$\sum_{t=1}^{es_{ij}-1} x_{ijt} = 0 \quad \forall i, j \tag{9}$$

$$\sum_{t=ls_{ij}+1}^{T} x_{ijt} = 0 \quad \forall i, j \tag{10}$$

To initiate an activity, it is necessary to complete the precondition of the previous activity. So we will have:

$$\sum_{t=1}^{T} \left(t + d_{ij}\right) x_{ijt} \le \sum_{t=1}^{T} t x_{i'jt} \quad \forall (i, i', j) \in priority \tag{11}$$

x_{ijt} activity is using resources at $[es_{ij}, ls_{ij}]$ period, upon completion of activity, it restores resources.

$$u_{ijt} = \sum_{t''"=t-d_{ij}+1}^{t} x_{ijt''} \quad \forall i, j, t \tag{12}$$

Each resource has a specific capacity at a certain period:

$$\sum_{i}^{I}\sum_{j}^{J} u_{ijt} r_{ij} \le R_h \quad t = 1 \ldots T, h = 1 \ldots H \tag{13}$$

The limitation of the linearisation of absolute magnitudes is as follows:

$$u_{ijt} r_{ij} - \overline{R} + \theta_t \ge 0 \quad \theta_t \ge 0 \tag{14}$$

Finally, the mathematical model is presented as follows:

$$\max \sum_{j=1}^{J} y_j \sum_{t=1}^{T}\sum_{t'}^{T'} \sum_{i \in end\ activity\ of\ projrct\ j}^{I} \left(b_{t'j}\right) x_{ijt} - \left(t + d_{ij} + t' - 1\right) x_{ijt} (1 + a) \tag{15}$$

$$\min \sum_{i}^{I}\sum_{j}^{J} u_{ijt} r_{ij} - \overline{R} + 2\theta_t$$

$$\textit{Subject to}:$$

$$\sum\nolimits_{t=es_{ij}}^{ls_{ij}} x_{ijt} \le 1 \quad \forall i, j$$

$$\sum\nolimits_{t=1}^{es_{ij}-1} x_{ijt} = 0 \quad \forall i, j$$

$$\sum_{t=ls_{ij}+1}^{T} x_{ijt} = 0 \quad \forall i, j$$

$$\sum_{t=1}^{T} \left(t + d_{ij}\right) x_{ijt} \le \sum_{t=1}^{T} t x_{i'jt} \quad \forall (i, i', j)\, priority$$

$$u_{ijt} = \sum\nolimits_{t''"=t-d_{ij}+1}^{t} x_{ijt''} \quad \forall i, j$$

$$\sum_{i}^{I}\sum_{j}^{J} u_{ijt} r_{ij} \le R_h \quad t = 1 \ldots T, h1 \ldots H$$

$$\sum_{t=1}^{T} \left(x_{ijt} + x_{i'jt}\right) = 2 y_j \quad \forall (i, i', j)\, priority$$

$$u_{ijt} r_{ij} - \overline{R} + \theta_t \ge 0 \quad \theta_t \ge 0$$

2.2 Problem solving approaches

The *ε*_constraint method is one of the well-known approaches for dealing with multi-objective problems that can be solved by transferring all the objective functions except one at any level of limitation (Ehrgott and Gandibleux, 2002). Pareto's border can be created by the *ε* constraint method (Bérubé et al., 2009). The NSGA method is a common method for solving problems with multiple objective functions based on a genetic algorithm (Srinivas and Deb, 1994). This algorithm is known as one of the multi-objective genetic algorithms (MOGAs). It is an efficient method for solving multiple problems. The objective function is to select the dominant particles and overcome computational complexity. For this purpose, a modified method called NSGA-II has been developed. The MOPSO algorithm was proposed by Coello Coello and Lechuga (2002). This generalisation algorithm is a PSO algorithm used to solve continuous and single-dimensional optimisation problems. PSO can be extended to MOPSO by making a set of changes, i.e., replacing a number of operators. It is done because of the multi-objective nature of the problem. In fact, the MOPSO principle is a state of PESA-II algorithm. There is a concept in this algorithm called Repository or Archive, which is added to the PSO algorithm. Actually, this repository is a collection of defective responses that look like an archive of the best answers ever found. It has limited the capacity and is stored outside the algorithm.

Table 1 Sample issues

Small-scale			*Large-scale*		
Issue	*Number of project*	*Number of activity*	*Issue*	*Number of project*	*Number of activity*
A1	3	22	B1	7	87
A2	4	33	B2	9	127
A3	5	41	B3	11	165
A4	4	30	B4	12	174
A5	4	33	B5	13	185
A6	4	38	B6	14	195
A7	3	42	B7	15	212
A8	5	40	B8	16	234
A9	4	37	B9	17	241
A10	3	33	B10	18	254

2.3 Producing generate sample and standard problems

Standard projects must be designed for evaluating the performance of a model. The production method of a problem should be routine and corresponding to other researchers' works in the world. In this study, the PSPLIB site was used to produce 20 projects. Due to lack of the second objective function or some of the constraints that have been added to the problem as innovations in the research, the selected problems have several changes. These problems are solved and reviewed after applying the necessary changes, and editing with the software that are used in this research like GAMS and MATLAB. The network view used in this paper to represent for AOA vector images. The problems include two categories consisting of ten problems. These are small and large-scale problems. Table 1 presents the typical problems encountered in this research.

3 Results and discussion

3.1 Solving the problem by GAMS and ε_constraint method

In ε_constraint method, four fractures were considered for each objective function, and totally, up to five points were generated for each problem. The results of solving ten small-size problems have been reported in Table 2.

Table 2 Pareto points by *ε_constraint* method

ε_constraint					*Issue number*
Pareto 5	*Pareto 4*	*Pareto 3*	*Pareto 2*	*Pareto 1*	
(132, 110)	(122, 82)	(120, 55)	(115, 27)	(0, 0)	A1
(211, 84)	(198, 63)	(205, 42)	(198, 21)	(0, 0)	A2
(278, 104)	(276, 78)	(271, 52)	(252, 26)	(0, 0)	A3
(192, 118)	(186, 88)	(172, 59)	(166, 30)	(0, 0)	A4
(255, 96)	(239, 72)	(246, 48)	(221, 24)	(0, 0)	A5
(303, 95)	(213, 71)	(155, 47)	(86, 24)	(0, 0)	A6
(204, 158)	(199, 118)	(194, 79)	(143, 40)	(0, 0)	A7
(262, 123)	(259, 92)	(241, 61)	(225, 31)	(0, 0)	A8
(315, 162)	(286, 121)	(298, 81)	(267, 40)	(0, 0)	A9
(255, 159)	(246, 119)	(236, 79)	(234, 40)	(0,0)	A10

The results of the Epsilon constraint method show the efficiency of this method in small-scale problems and accuracy of the ε_constraint method in reaching optimal solutions. For example, the Pareto chart obtained by solving the example of A6 has five target points using the GAMS software as shown in Figure 1. The goals of the presented problem in this study are in the two horizontal and vertical axes of this diagram. As presented in the chart, the two objective functions between points (0, 0) and (95 and 303) are changing and optimised, and (95 and 303) is the best point for the optimal objective function.

3.2 Solving the model through the (MOPSO) and (NSGA-II) algorithm

Since hyper-operator algorithms are usually sensitive to their parameters, and the presented solutions greatly depend on their parameters, to set out the parameters of the proposed algorithms, a problem is randomly selected and repeatedly solved by the conscious changing parameters of the method. The values of the MOPSO and NSGA-II parameters are shown in Table 3. $_1$ and $_2$ are the acceleration factors and *W* is determined for particle convergence.

Figure 1 Pareto chart resulting from solving problem in GAMS software (see online version for colours)

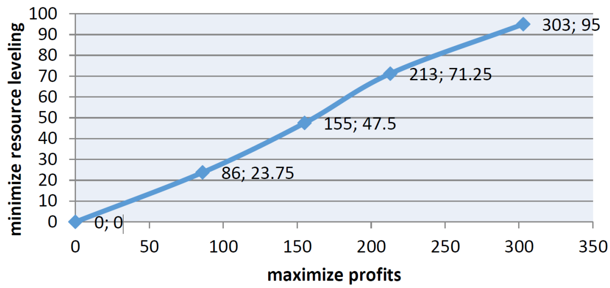


Table 3 The parameters of the metaphysical methods

NSGA-II algorithm parameters	*MOPSO algorithm parameters*
Number of particles 50	Number of particles 50
Number of reps 200	Number of reps 200
Intersection operator 0.6	C_1 parameter 2
Leakage operator 0.4	C_2 parameter 2
	W parameter 0.4
	β parameter 0.99
	n parameter 5

As can be seen, these parameters are obtained after solving a problem repeatedly and then used for other parameters. The *g* error test method mentioned above means that after examining different values for modifying each parameter while maintaining other parameters, the researcher led the subsequent changes of the parameters to lower or increase the value of that parameter until the answers inclined toward the optimum. The process was continued similarly for the other parameters. To solve the model of the MOPSO algorithm, the problem is coded in MATLAB software. In this section, we describe the massive multi-objective particle algorithm to solve the problem of scheduling and selecting a project in resource levelling. The computational results of the solution model will be shown in small and large-scales. To show the effectiveness of NSGA-II and MOPSO algorithms, ten problems were produced in small scale and the results were compared with the results of the ε_constraint method. In ε_constraint method, four fractures were considered for each objective function, and totally, up to five Pareto points were generated for each problem. Due to the NP-hardness of the problem, the exact solution of ε_constraint method does not have the capacity to solve the model in large-scale. Table 4 shows the results of solving small problems. First the best result of the error of the algorithms in each objective function (RG) is evaluated, and then the best obtained answer is compared with the response of each algorithms (RA) response [equation (16)].

$$RG = \frac{BR - RA}{BR} \tag{16}$$

The evaluation of the presented solutions quality in the NSGA-II method is acceptable in terms of the best Answer for each objective functions, and the mean error for the target functions. The average error levels obtained for the objective function are respectively: 0% and 0.01%; these extreme amounts are higher than a researcher's expectation from the meta-heuristic method. Also, the quality of the solutions for the MOPSO algorithm is acceptable and the average errors for the target functions are respectively 0.03% and 0.1%.

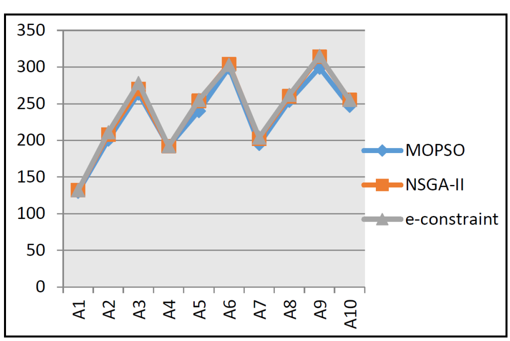
Table 4 The results of solving small problems

Issue	*ε_constraint*		*NSGA-II*				*MOPSP*			
	FOF	*SOF*	*FOF*	*SOF*	*FEOF*	*SEOF*	*FOF*	*SOF*	*FEOF*	*SEOF*
A1	132	110	132	110	0	0	130	115	0	0
A2	211	84	208	89	0	0.1	201	100	0	0.2
A3	278	104	270	114	0	0.1	264	120	0.1	0.1
A4	192	118	192	116	0	0	192	140	0	0.2
A5	255	96	254	102	0	0.1	240	138	0.1	0.3
A6	303	95	304	99	0	0	299	149	0	0.4
A7	204	158	202	149	0	–0.1	195	143	0	–0.1
A8	262	123	260	119	0	0	254	140	0	0.1
A9	315	162	314	156	0	0	299	165	0.1	0
A10	255	159	255	160	0	0	247	162	0	0
Average	240.7	121	239.1	121.4	0	0.01	232.1	137.2	0.03	0.1

Notes: FOF = the first objective function, SOF = the second objective function, FEOF = first error of objective function, SEOF = second error of objective function.

These results show the more accurate performance of the NSGA-II algorithm than the MOPSO. In Figure 2, the comparison diagram of the three solutions of the first objective function verifies the results clearly. However, both algorithms have an extraordinary level of accuracy compared to other applications of meta-heuristic algorithms.

Figure 2 Comparative graph of three solving method for the profit function (see online version for colours)



To evaluate the quality of the solutions in terms of the solving time, the two proposed algorithms have been compared for large-dimensional problems in Table 5. In Table 5, the first column is the problem, and the next three columns present the solving time and the values of the first and second objective functions of the NSGS-II algorithm. The fifth to seventh columns also present the results of the MOPSO algorithm. By examining the results of this table, we will find the quality of the solutions in the two target functions maximising the first objective function and minimising the second objective function and the low solving time of the NSGA-II algorithm compared to MOPSO algorithm. The results show the better performance of the NSGS-II algorithm. In Figure 3, Pareto's responses of the two objective functions can be seen in terms of NSGAII and MOPSO algorithms.

Table 5 Compare two algorithms for solving large-scale problems

Issue	*NSGA-II*			*MOPSP*		
	Solving time	*Second purpose*	*First purpose*	*Solving time*	*Second purpose*	*First purpose*
B1	168	119	200	836	150	245
B2	307	140	300	1,245	110	260
B3	339	83	280	2,196	120	295
B4	214	131	347	1,460	118	319
B5	599	113	410	1,614	99	290
B6	244	112	415	1,780	130	328
B7	257	107	400	2,011	140	370
B8	315	76	410	2,446	137	313
B9	532	118	468	2,341	132	377
B10	289	70	462	2,474	168	372
Average	326.4	106.9	369.2	1,840.3	130.4	316.9

3.3 Comparison of the quality of solutions in the two meta-algorithms in terms of the two indicators

The performance of multi-objective algorithms is much more complex than the performance of single-objective algorithms. Based on the presented criteria, a single evaluation index cannot be sufficient to examine the solutions of the proposed algorithms. Therefore, in this section, two major large-scale indicators are used to evaluate the quality of the solutions obtained from the two proposed algorithms.

3.3.1 Indicator C

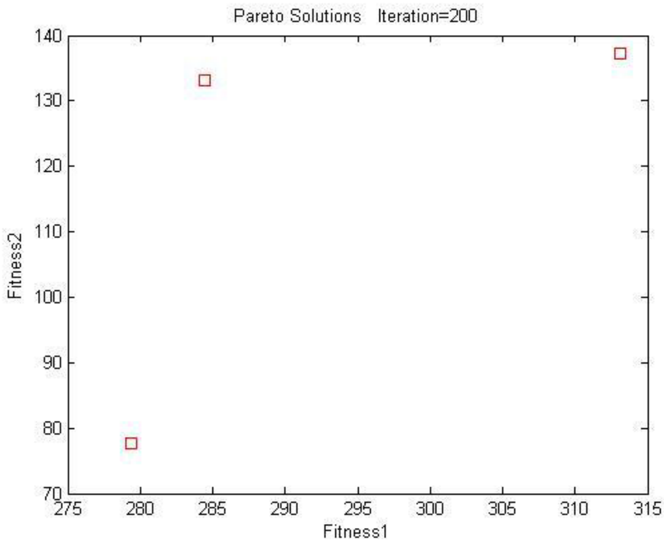
The index C is used to determine the coverage of the two sets. To calculate this index, equation (17) is used:

$$C(A, B) = \frac{\left|\{b \in B \mid \exists a \in Aa > b\}\right|}{|B|} \tag{17}$$

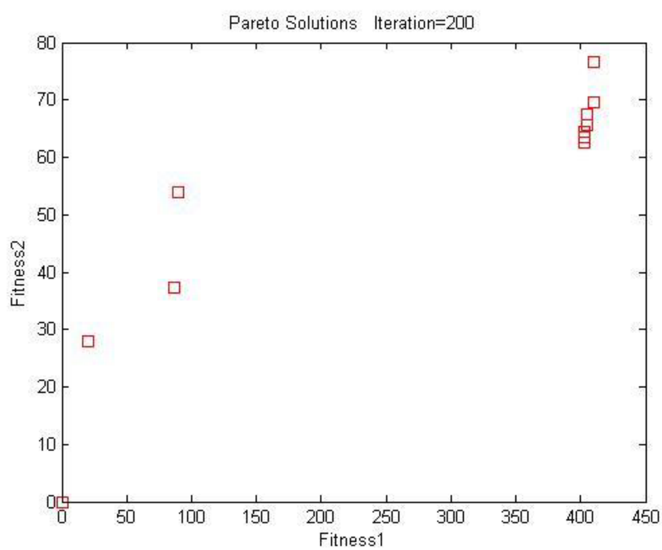
In this equation, A and B are respectively the dominant sets obtained from the first and second algorithms, and the $|X|$ is the number of spaces existing in X. When we have $1 = C$

(*A*, *B*), it means that all members of the set *B* are defeated by the set *A*. It should be noted that the amount of *C* (*A*, *B*) is not necessarily equal to 1 *C* (*A*, *B*).

Figure 3 Pareto comparative responses of target functions compared to B8 (a) NSGA-II algorithm and (b) MOPSO algorithm (see online version for colours)



(a)



(b)

3.3.2 Dispersion index

This is a benchmark for evaluating the distribution of the set of answers found by the algorithm. Equations (18) and (19) describe how this index is calculated. This index, in contrast to the C index which is considered as the centred state, shows the dispersion of the two criteria.

$$E = \sqrt{\frac{\sum_{i=1}^{n}\left(\bar{d} - d_i\right)^2}{N-1}} \tag{18}$$

$$d_i = \min,\ j \neq i\left(\sum_{m=1}^{M} |\, f_i^m - \right) f_j^m \,| \tag{19}$$

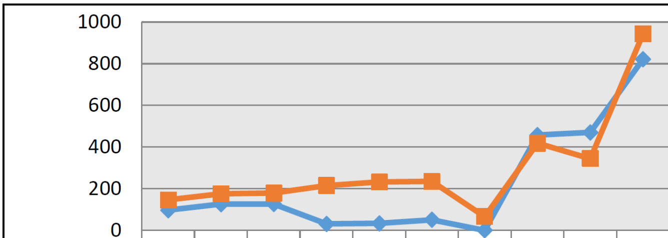
In these equations, *m* is the counter of the objective functions, and is the shortest distance of point *i* from the remaining points in the Pareto-part of the algorithm in the objective function space.

In Table 6, the responses provided by MOPSO and NSGA-II are presented for Category A problems. Regarding the C-index, the NSGA-II method provides better answers than MOPSO method. In this group of problems, the average value of C for the NSGA-II method is 0.4, which means that approximately 0.4% of the Pareto solutions obtained from the MOPSO method are dominated by the solutions of this method. In the dispersion index, the MOPSO gained an average of 221. In Figure 4, the results of the two algorithms are compared with each other. According to these results, the MOPSO method has obtained a higher unit than the Paretos border.

Table 6 Solution for solving bits of problems with NSGA-II and MOPSP methods

Issue	*NSGA-II*			*MOPSP*		
	Solving time	*Index C*	*Dispersion index*	*Solving time*	*Index C*	*Dispersion index*
B1	198	0.2	1,460.4	789	0	96.65
B2	252	0	175.61	1,334	0	125.99
B3	256	0.2	178.59	1,335	0	126.05
B4	306	0.2	215.2	548	0	30.84
B5	329	0.5	231.88	2,794	0	23.18
B6	333	0.4	234.65	720	0	50.59
B7	103	0.5	65.33	3,276	0	0
B8	567	1	418	3,776	0	457
B9	466	0	344	3,888	0	470
B10	1,280	0	944	6,794	0	822
Average	409	0.4	295.33	2,526.3	0	221.23

Figure 4 Comparing the results of the algorithm with the dispersion index (see online version for colours)



	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
MOPSO	97	126	126	31	33	51	0	457	470	822
NSGA-II	146	176	179	215	232	235	65	418	344	944

4 Conclusions

In this research, a model was proposed for project portfolio selection and activity schedule in resource levelling to obtain the maximum benefit from the projects. The results of the studies showed that using GAMS and MATLAB, this model provides accurate and desired results at an optimal time. The average error of MOPSO method in obtaining the two objective functions is respectively 0.03 and 0.1, and respectively 0 and 0.01 for the NSGA-II algorithm. The accuracy of these results is in contrast with the application of meta-algorithms for solving other extraordinary problems. It should be noted that the C indices and the MOPSO method were respectively 0 and 221/23, and 0.4 and 295/33 for the NSGA-II algorithm. These results indicate the approximate advantage of the NSGA-II method, taking into account the C index, the superiority of the MOPSO method, and the dispersion index compared to their counterparts. However, the average time of solving the presented problems by MOPSO and NSGAII methods respectively was 2,526.3 and 409 seconds. The comparison of the two values shows the absolute advantage of the NSGA-II method over its competitor.

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