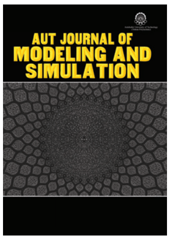

AUT Journal of Modeling and Simulation

AUT J. Model. Simul., 50(2) (2018) 129-140
DOI: 10.22060/miscj.2018.13848.5084

Optimization of an energy based bi-objective multi-skilled resource investment project scheduling problem

Sh. Javanmard[1], B. Afshar-Nadjafi[1*], S. T. Akhavan-Niaki[2]

[1] Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran
[2] Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran

ABSTRACT: Growing concern in management of energy due to the increasing energy costs, has forced managers to optimize the amount of energy required to provide products and services. This research integrates an energy-based resource investment project-scheduling problem (RIP) under a multi-skilled structure of the resources. The proposed energy-based multi-skilled resource investment problem (EB-MSRIP) consists of a single project with a set of tasks that require several skills to be competed. Each skill could be applied in several levels of efficiency, each including significant energy and implementation costs. Similar to RIPs, in the EB-MSRIP the required levels of skills are considered as decision variables and a bi-objective formulation is proposed for the problem. The first objective of the model minimizes total cost with regards to energy consumption cost and implementation cost of required multi-skilled resources, and the second one minimizes the project's makespan. The epsilon constraint method has been used to validate the developed formulation on several small-size instances. For larger problem instances, as epsilon constraint method fails to obtain a solution, the multi-objective ant colony optimization (MOACO) algorithm has been implemented to tackle the problems. The key control parameters of the proposed MOACO are tuned by Taguchi method. Computational results in terms of several measures, including MID, DM, NPS and SNS, determine notable advantages of proposed MOACO.

Review History:

Received: 18 December 2017
Revised: 5 September 2018
Accepted: 22 September 2018
Available Online:30September 2018

Keywords:

Multi-skilled project scheduling
resource investment problem
Energy usage
Ant colony optimization

1- Introduction

Wise consumption of energy resources has gained increasing attention in many fields of engineering as a necessity for sustainable development. In addition, many researchers have found energy-oriented solutions to help decision makers with efficient management of their energy usage. Contriving energy-based frameworks within scheduling problems has been one of the most attractive ideas, which result in several real-life solutions for different applications. The reference [1] developed a mathematical formulation for the single machine scheduling problem with variable energy tariffs. The paper [2] presented a novel scheduling model which integrates the economic and ecological issues under a time-of-use energy tariff. In [3], a multi-objective framework for scheduling of a micro-grid was developed to minimize the total operation cost and the emission caused by generating utilities. [4] proposed an evolutionary algorithm for better consumption energy use in agriculture system. Recently, [5] developed a multi-objective particle swarm optimization algorithm for managing Energy and greenhouse gas (GHG) emissions for agricultural systems. Due to the growing attraction of energy optimization methods, in this research we aim to introduce an energy-based extension of resource investment problem (RIP) in project-scheduling problem under a multi-skilled structure of the resources.

The resource investment problem (RIP) which is sometimes called as resource availability cost problem (RAC) is an attractive version of resource constraint project scheduling problem (RCPSP) which was initially proposed by [6]. This reference introduced the RIP problem and proved its NP-hardness proof. Afterwards, many researchers studied different extensions of RIPs. RIP has been recently focused to be implemented in different fields of optimization problems. Production design [7], software engineering [8], military capability planning [9], research and development project management [10], and project scheduling [11, 12] are just a few practical cases of RIP implementations. Looking at the literature available on resource availability cost problem (RAC), one could refer to [13] that implemented the path relinking and genetic algorithm for RACP. Their experimental results confirm the supremacy of the algorithm. [14] represented a time-dependent resource cost and tardiness penalty model to tackle the resource investment problem which aims to minimize the sum of resource cost and the tardiness cost. Besides RIP, the other concentration aspect of this research is on the multi-skilled project scheduling problem (MSPSP). Generally defined, in multi-skilled project scheduling problem (MSPSP), each of the project's tasks is considered to require several skills to be accomplished wherein the candidate skills are represented in different levels of efficiency associated with significant implementation costs and completion time.

Likewise RIPs, the software development, research and development projects, chemical industry and maintenance projects are just a few potentials of this field of study. Many researchers have focused on multi-skill project scheduling problem within which we can refer to [15] that considered a model for MSPSP that is being solved by two complementary and efficient lower bounds, adapted from known lower bounds for the classic RCPSP. [16] studies the project scheduling problem considering multiple skills that cannot be mastered by all workforces involved. He proposes several methods to solve the problem that include heuristics, meta-heuristics and a branch-and-bound algorithm. [17, 18] consider multi-

Corresponding author, E-mail: behrouz.afshar@gmail.com

project version of multi-skilled project scheduling problem. [19] considered the MSPSP in emergency departments to optimize the scheduling of candidate medical staff system.
Consider the two mentioned topics of project scheduling problems. To the best of our knowledge, although many researchers have focused on RIP and MSPSP separately, integration of the two mentioned problems have rarely been studied. In another words, considering the required levels of multi-skilled renewable resources of projects as a decision variable and focusing on the optimization of resource implementation costs introduces a new RIP-MSPSP oriented problem. Recently, [20] has considered the preemptive multi-skilled resource investment project scheduling problem for chemical processes where flexible workplace requiring multi-skilled workers is an undeniable fact.
According to the best of the authors' knowledge, no research has ever been conducted on the integration of energy-efficiency within the MSPSP or RIP. This was the main motivation of this paper. We call this problem as energy-based multi-skilled resource investment problem, EB-MSRIP thereafter. In the EB-MSRIP, one faces the problem of finding the best availability for different levels of the multi-skilled resources which have time-dependent energy usage costs. Similar to RIPs, in the EB-MSRIP the required levels of the skills are considered as decision variables and the main objective is to minimize the total energy usage and implementation costs of multi-skilled resources of project. On the other hand, similar to MSPSPs, assignment of multi-skilled resources to the activities and the best start time of all the activities are to be determined in EB-MSRIP. Therefore, the main contribution of the current work includes proposing a new bi-objective model for the integrated multi-skilled project scheduling and resource investment project scheduling problem under time-dependent tariff for energy usage. Then the proposed mathematical formulation of EB-MSRIP is validated using the epsilon-constraint method applied by GAMS software in small-scale instances and implementation of a bi-objective ant colony optimization algorithm to solve large-scaled instances. Furthermore, the performance of the proposed bi-objective ant colony optimization (MOACO) will be evaluated by comparing it to the one achieved by the epsilon-constraint method.
The rest of the paper is structured as it follows. Section 2 describes the EB-MSRIP and its bi-objective mathematical model. Section 3 represents the solving approach including the bi-objective ant colony algorithm. Section 4 provides comprehensive experiments to validate the proposed approach. Finally, Section 5 concludes the paper and suggests some directions for future work.

2- Theoretical modeling

A bi-objective energy-based multi-skilled resource investment problem (EB-MSRIP) that is an integration of RCPSP and RIP considering energy consumption, is defined in this section. This problem consists of a single project with a set of activities, each requiring several skills for execution. Each skill can be applied in several levels of efficiency with different implementation costs. Each level of efficiency introduced for the skills includes significant energy cost. Inherited from its RIP features, the EB-MSRIP assumes that availability of all levels of multi-skilled resources are decision variables to be determined in order to minimize total cost of multi skilled implementation and energy consumption costs. On the other hand, inherited from its MSPSP features, all the required skills are to be available at the start of any activity and the second objective is to determine the best schedule of the activities with minimum makespan. The following assumptions are considered throughout the paper.

- There is a single project represented as an activity on node (AON) network.
- Precedence relations are 'Finish to Start' with zero time-lags.
- Preemption of activities are not allowed.
- All resources are renewable and multi-skilled.
- All the required resources are available at the start of each activity.
- Each skill can be applied in several levels with different rates of energy tariff.
- Each activity may require more than one skill to be executed.
- A single level of each required skill would be assigned to each activity.
- Higher levels of skills lead to lower execution time and higher implementation cost.
- Higher levels of skills lead to lower or at least equal energy consumption cost.
- Each multi-skilled resource has a time-dependent cost of energy consumption.

The following notations are used to formulate the bi-objective energy-based multi-skilled resource investment problem (EB-MSRIP).

2- 1- Mathematical modeling

Based on the notations defined above, the mathematical formulation of EB-MSRIP is as it follows,

$$Min\, Z_2 = \sum_t \sum_{k\in S_i} \sum_l (IC_{kl}^t + EC_{kl}^t)\times R_{kl}^t, \tag{1}$$

$$Min\, Z_1 = C_n, \tag{2}$$

$$\sum_l y_{ikl} = N_{ik}, \quad \forall i,k\in S_i \tag{3}$$

$$\sum_{t=es_i}^{lf_i} y_{ikl}^t = p_{ikl}\times y_{ikl}, \quad i,k\in S_i\ ,l, \tag{4}$$

$$\sum_k \sum_l y_{ikl}^t \le 1, \quad \forall i,t\in\left[es_i,lf_i\right], \tag{5}$$

$$p_{ikl}\left(y_{ikl}^t - y_{ikl}^{t+1}\right) - \sum_{u=\max\left(es_i+1,\ t-p_{ikl}+1\right)}^{t-1} y_{ikl}^u \le 1, \quad \forall i,k,l\ ,t\in\left[es_i+1, lf_i-1\right], \tag{6}$$

$$\sum_{i=1}^n r_{ikl}\times y_{ikl}^t \le R_{kl}^t\ ,\ \forall k\in S_i,l,t\in\left[es_i,lf_i\right], \tag{7}$$

$$S_{ik} - M \times (1 - \sum_{l} y_{ikl}^{t}) \leq \sum_{l} y_{ikl}^{t} \times t, \quad \forall i,k \in S_i, t \in [es_i, lf_i] \ , \tag{8}$$

$$\sum_{l} y_{ikl}^{t} \times t - M(1 - \sum_{l} y_{ikl}^{t}) \leq C_{ik}, \quad \forall i,k \in S_i \ , t \in [es_i, lf_i], \tag{9}$$

$$S_{ik} = S_{iv}, \ \forall i, k \neq v \in S_i, \tag{10}$$

$$S_i = S_{ik}, \ \forall i, k \in S_i, \tag{11}$$

$$C_i \leq S_j, \ \forall (i,j) \in E, \tag{12}$$

$$C_n \geq C_i, \ \forall i \tag{13}$$

The first objective function in (1) aims to minimize the total cost of applying multi-skilled resources including the application cost of multi-skilled resources and the total energy consumption cost for the multi-skilled resources over the length of the project. Eq. (2) minimizes the project's makespan. Eq. (3) assigns a single level of each required skill to the activities. Eq. (4) calculates the time within which any required skill is in process after its earliest start and before latest finish times. Eq. (5) declares that each level of a single skill can be assigned to at most one activity within a time frame. Eq. (6) guarantees that the activities must be in progress without preemption. Eq. (7) computes the required amount of candidate skill levels with regard to the resource assignments. Eqs. (8) and (9) compute the start and the completion times of applying skill k to perform activity i by satisfying the logical relations between the variables y_{ikl}^{t}, S_{ik} and C_{ik}. Eq. (10) guarantees the necessity of concurrent application of all the required skills for any single task. Eq. (11) determines the start time of the activities. Eq. (12) satisfies the finish to start precedence relations between the activities. Eq. (13) calculates the project makespan.

2- 2- Implementation platforms

One of the potentials of the proposed model is in implementation of gas or oil transmission pipelines where different skills with multiple levels of proficiencies must stay together to perform the tasks. Various skills like, gas engineering, mechanical engineering, electrical engineering, project managing, computer engineering and many other skills shall be applied to perform these projects well. Besides, optimization of the energy consumption costs associated with the supplementary machinery required to apply the multi skilled resources is another challenging issue in this kind of projects. For instance, optimization of energy consumption to launch the suction pumps and the compressors in the gas transmission pipelines or the fuel needed to apply the diesel engines in the oil rigs that are mostly prepared by helicopters could be taken into consideration to optimize the project costs. Furthermore, special effects projects, many construction projects and setting up the telecommunications masts are just a few of existing real cases of the proposed model.

3- Solution methodology

The EB-MSRIP is an NP-hard optimization problem, as it is the integration of two NP-hard problems including the multi-skilled project scheduling problem and the resource investment one. To solve this problem, we have applied a meta-heuristic approach to provide acceptable solutions in a reasonable computational time. Since implementation of ant colony optimization (ACO) among meta-heuristic approaches has been successfully applied into project scheduling problems specially for MSPSPs [21, 22], the application of ACO has been considered to deal with the problem of this research.

3- 1- Construction of the solutions

A multi-objective ant colony optimization (MOACO) has been presented in the current paper that begins with generation of feasible solutions among the solution space. Each solution consists of two parts, i.e. determination of *tasks' sequences* and assignment of *required levels of skills*. Each part consists of two matrices including matrix of heuristic function (η_{ih}) and matrix of pheromone value (τ_{ih}).

3- 1- 1- Heuristic function

The heuristic function matrix of the first part of solution, i.e. *tasks' sequences,* is a matrix of n rows and T columns where n is the number of tasks and T represents the summation of execution times while the tasks are accomplished by the slowest available levels of skills (to avoid infeasible solutions). Heuristic function of first part of solution (η_{ih}^{1}) is being calculated according to Eq. (14),

$$\eta_{ih}^{1} = \frac{1}{sub_{ih}} \tag{14}$$

in which sub_{ih} shows the number of subsequent activities for task i located at position h. This allows tasks with more number of subsequent activities to be selected earlier.

For second part of solution, assignment of *required levels of skills*, η_{ih}^{2}, is calculated through Eq. (15),

$$\eta_{ih}^{2} = \frac{1}{Nc_{ih} + Nt_{ih}} \tag{15}$$

where Nc_{ih} and Nt_{ih} represent the cost and the execution time associated with level of required skills. Eq. (16) guarantees that the candidate levels of skills with lower energy costs and lower execution times will have higher priority to be selected.

3- 1- 2- pheromone value matrix

The pheromone value matrix (τ_{ih}) is a matrix of k rows and l columns where k and l are number of required skills and maximum efficiency levels of skills. In the proposed MOACO, the pheromone value matrix is updated through three updating pheromone rules, namely, local pheromone updating, global pheromone updating and pheromone evaporation procedures. In this paper, the initial value for elements of pheromone matrix (τ_0) are considered as 1 and then updated by two pheromone updating rules.

local pheromone-updating rule:

The local pheromone is updated during the construction of solution and whenever a new task is sequenced and, subsequently, the required efficiency levels of skills are allocated. The local pheromone updating is done using Eq. (16), through which, $\xi \in [0,1]$ corresponds to the control parameter of pheromone as in Eq. (16). Eq. (17) guarantees $\tau_{ih} \geq \tau_0$ during the algorithm.

$$\tau_0 \le (1-\xi)\tau_{ih} + \xi\tau_0 \le \tau_{ih}, \tag{16}$$

$$\tau_{ih} = (1-\xi)\tau_{ih} + \xi\tau_0. \tag{17}$$

The global pheromone-updating rule:

This procedure provides pheromone updating at the end of each iteration by allowing participation of all ants. The procedure is designed to accelerate the exploration of new paths or solutions in the solution region. In our proposed approach for global pheromone updating, every ant can leave the pheromone procedure, however, the better the solution is, the more pheromone could be left by the ant [23]. In this stage, first, the dominant rank and crowding distance of each constructed solution is computed. Then, the value of pheromone is updated using Eq. (18) at the end of each iteration.

$$\tau_{ih}^{new} = \tau_{ih}^{old} + \frac{Q}{D_x}. \tag{18}$$

In Eq. (18), Q is the pheromone-updating factor considered as a parameter and D_x is the non-dominant rank of the x^{th} solution.

Pheromone evaporation:

Pheromone evaporates iteratively which guaranties the exploration of new areas in the search space. Pheromone evaporation is done by decreasing the value of pheromone in every iteration (see Eq. (19)).

$$\tau_{ih} = (1-\rho)\tau_{ih}. \tag{19}$$

By determining the heuristic function and pheromone updating rules, the solutions are constructed according to Eq. (20). In order to avoid generating infeasible solutions, the following points are taken into consideration when the tasks and skills are selected: (1) precedence relations shall be met, (2) all the required skills shall be allocated to each associated task.

$$p_{ih}^{a} = \frac{[\tau_{ih}]^{\alpha}[\eta_{ih}]^{\beta}}{\sum_{l\delta S_j}[\tau_{ih}]^{\alpha}[\eta_{ih}]^{\beta}}, \qquad \forall l, \forall i \in \vartheta_h. \tag{20}$$

In Eq. (20), p_{ih}^{a} denotes the probability of locating activity *i* /skill *k* at position *h* by ant *a*. Position *h* denotes a part of sequence in which activity *i* is selected there and the efficiency level in which the required skill is applied. In addition, the pheromone value (τ_{ih}) and heuristic function (η_{ih}) are embedded in p_{ih}^{a} with regards to the control parameters α and β. It is noticeable that ϑ_h is the set of activities that could be located at position h.

3- 1- 3- Decoding procedure

Having specified the tasks' sequences and skill assignments, the next step is to schedule the tasks within the planning horizon according to the announced earliest and latest start times. With regard to the sequences defined in the previous section, the tasks are then scheduled at time *t* considering Eq. (21),

$$\mathrm{t} = \max\left(F_{pr_i} + 1,\ es_i\right), \tag{21}$$

where F_{pr_i} and es_i denote the completion time of preceding activities of task *i* and the earliest start time of task *I*, respectively. This procedure ensures that activities do not start before their earliest start time. Besides by considering the precedence relations in the solution construction mechanism, the value of F_{pr_i} will be automatically resulted less than latest start time (ls_i).

3- 2- Comparison measures

Four measures are introduced in this section to evaluate the performance of the developed MOACO.

Mean ideal distance (MID): defines the distance between the ideal solution (the best solution) and the Pareto solutions calculated by:

$$MID = \sqrt{\frac{\left(\frac{\sum_i (f_{1i} - f_1^{best})}{f_{1,total}^{\max} - f_{1,total}^{\min}}\right)^2 + \left(\frac{\sum_i (f_{2i} - f_2^{best})}{f_{2,total}^{\max} - f_{2,total}^{\min}}\right)^2}{n}} \tag{22}$$

where $f_{i,total}^{\max}$, $f_{i,total}^{\min}$ are the minimum and maximum values of the objective functions via all the applied algorithms, and (f_1^{best}, f_2^{best}) are the coordinates of the ideal point. Lower value of this criterion is preferable.

Diversification Metric (DM): finds the spread of a Pareto solution set. The higher the value of DM is, the more efficient the algorithm would be. DM is computed as below:

$$DM = \sqrt{\sum_{i=1}^{I}(\min f_i - maxf_i)^2}, \tag{23}$$

where $\min f_i$ and $\max f_i$ are the minimum and the maximum value of each fitness function among all non-dominated solutions achieved by the algorithms.

Number of Pareto solutions (NPS): exhibits the number of the Pareto solutions that each algorithm have found. Although NPS does not include comprehensive information about the quality of the solutions, higher values of SNS is preferable.

Spread of non-dominance solution (SNS): This criterion comtes the diversity of the Pareto archive solution. Higher values of SNS represent superiority of the algorithm. The value of this criterion is computed as:

$$SNS = \sqrt{\frac{\sum_{i=1}^{n}(MID - D_i)^2}{n-1}}, \tag{24}$$

where

$$D_i = \sqrt{f_1^2 + f_2^2} \tag{25}$$

3- 3- Parameter tuning

We adopt the Taguchi method to tune the 9 affecting parameters (factors) of the proposed MOACO. Herein, the signal to noise ratio, i.e. S/N, is used to evaluate the performance of the algorithm as:

$$S/N = 10 \times \log\left(\frac{s(y^2)}{nr}\right), \tag{26}$$

where *nr* defines the number of orthogonal arrays and *y* represents the response values. If a parameter's level has the highest S/N, then it will become the most beneficial level of the parameter. To do so, we have considered the *MID* factor as the response value.

Table 1 demonstrates the nine affecting factors of the proposed MOACO and shows the three levels of the corresponding factors. In Table 1, $iter_{max}$ denotes the maximum number of iterations, n^{ant} represents the number of ants, Q and τ_0 stand for the pheromone updating factor and initial pheromone, respectively, and α and β are associated by the pheromone

Table 1. Levels of key factors of MOACOs

	Key parameters								
Parameter levels	$iter_{max}$	n^{ant}	Q	τ_0	α	β	ρ	ξ	NPF
Level 1	$3\times N$	10	0.8	1	1	1	0.001	0.1	100
Level 2	$4\times N$	15	0.9	1.2	1.5	1.2	0.005	0.15	150
Level 3	$5\times N$	20	1	1.5	2	1.5	0.05	0.2	200

exponential weight and the heuristic exponential weight, respectively. Besides, ρ and ξ represent the evaporation rate and the control parameter of pheromone while NPF defines the maximum number of Pareto members. It is notable that an instance including 25 activities, 4 skills and 3 levels is considered to set the parameters of proposed MOACO through the L^{27} orthogonal array design, implemented on the MINITAB software.

In Tables 2 and Fig. 1 the responses for signal to noise ratios of proposed MOACO are represented. Besides, the best value of signal to noise ratios associated with each parameter level is high-lighted in Table 2.

3- 4- Instance generation

With considering the number of activities (n), number of candidate skills (K), and the maximum number of skill levels (L), the problem instances are classified into two different sizes of small and large. Moreover, it should be noted that the precedence relations are taken from the PSPLIB. The execution times of applying the candidate levels of the skills to perform activities (p_{ikl}) follow a uniform distribution in the interval [15, 20] while the number of the resources required to perform activity i for each level of the skills (r_{ikl}) are generated uniformly from the interval [1, 6]. For each task, the required number of skills is generated randomly between 1 and the maximum number of skills (K). It is considered that the skill levels with higher indices will lead to lower executing times and less number of the required resources but with higher implementation costs (IC^t_{kl}) and lower energy consumption cost (EC^t_{kl}). Finally, IC^t_{kl} and EC^t_{kl} follow the uniform distribution in the intervals [100, 500] and [6, 15], respectively.

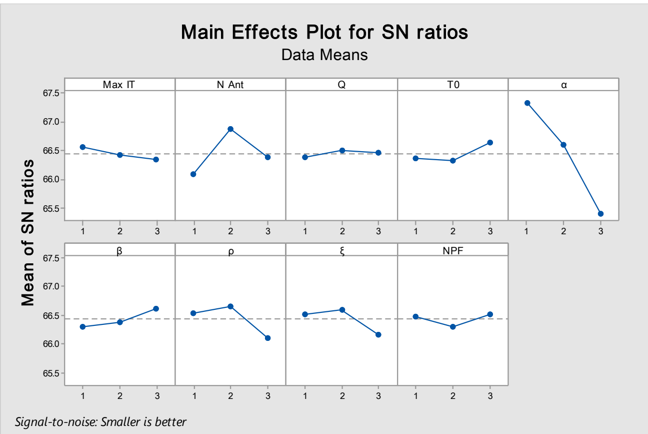

Fig. 1. Taguchi results for MOACO

4- Computational results

All the designed test problems were solved by the proposed MOACO coded in MATLAB R2013b, with a core i5 CPU and 4 GB memory. Each problem instance has been solved three times and the average results are considered to evaluate the algorithms. The quantitative results have been compared with the optimal solutions obtained by epsilon-constraint method on GAMS 22.9. It should be noted that as GAMS software is unable to solve problems with larger sizes than 30 activities, large-sized problems (problem number 31 and larger) are solved by the proposed MOACO. Computational results of the proposed MOACO and epsilon-constraint method based on four comparison criteria are demonstrated in Tables 3 and Table 4. The first four columns of Tables 3 and Table 4 reflect the characteristics of each problem instance according to which Pr_N and N_{task} represent the problem number and the number of activities while N_s and N_l represent the number of skills and the maximum number of the candidate levels of proficiency for each skill, respectively. As it is clear from Table 3, epsilon-constraint method achieved the best *MID* in comparison with the proposed MOACO wherein on the basis of *DM* criterion, MOACO with the average value of 619368 outperforms epsilon-constraint method with the value of 216379. Computational results obtained by the proposed MOACO in case of *NPS* determine the supremacy of MOACO in comparison with epsilon-constraint method

Table 2. Response for S/N ratios of MOACO-ALL parameters

Parameter levels	$iter_{max}$	n^{ant}	Q	τ_0	α	β	ρ	î	NPF
Level 1	**66.56**	66.09	66.38	66.35	**67.32**	66.31	66.55	66.54	66.49
Level 2	66.42	**66.87**	**66.49**	66.33	66.60	66.39	**66.67**	**66.61**	66.31
Level 3	66.34	66.37	66.45	**66.64**	65.40	**66.62**	66.11	66.18	**66.52**
Delta	0.22	0.78	0.11	0.31	1.92	0.30	0.56	0.43	0.21
Rank	7	2	9	5	1	6	3	4	8

Table3. Computational results obtained by the proposed MOACO and epsilon-constraint method for small-size problems based on MID and DM

Small sized problems							
				MID		DM	
Pr.N	N_{task}	N_s	N_l	MOACO	Epsilon- constraint	MOACO	Epsilon- constraint
1	5	2	2	111.8525	105.852	367325	46077
2	5	2	3	113.1171	107.617	622669	52418
3	10	2	2	86.92738	80.927	530257	38514
4	10	2	3	186.1505	182.65	703388	42518
5	10	3	2	137.6298	121.13	511600	85517
6	10	3	3	206.2158	202.216	582870	27001
7	15	2	2	109.1855	102.686	556489	83986
8	15	2	3	206.3811	193.881	600110	99758
9	15	3	2	123.3991	119.399	503891	90176
10	15	3	3	195.1995	179.7	582515	82457
11	15	4	2	179.8422	160.842	553867	97059
12	15	4	3	261.056	251.556	507727	130259
13	20	2	2	128.8272	123.827	650942	130711
14	20	2	3	289.401	286.401	696739	170398
15	20	3	2	123.4329	145.433	321045	161282
16	20	3	3	269.3247	262.825	731107	287447
17	20	4	2	183.3332	183.833	663928	225327
18	20	4	3	258.0679	240.068	594514	383514
19	25	2	2	188.0846	191.085	567354	103449
20	25	2	3	224.542	214.042	602514	322528
21	25	3	2	173.4966	175.497	748824	239614
22	25	3	3	208.8058	191.806	687856	734345
23	25	4	2	184.9479	172.948	826017	303214
24	25	4	3	278.6913	258.191	857230	420058
25	30	2	2	160.3933	150.893	805875	240252
26	30	2	3	226.9243	211.424	535256	129874
27	30	3	2	237.9200	218.92	634696	303159
28	30	3	3	251.0515	251.551	896798	398745
29	30	4	2	198.0849	189.585	690568	264359
30	30	4	3	275.8161	272.316	447065	797348
average				193.270	184.636	619368	216379

Table 4. Computational results obtained by proposed MOACO and epsilon constraint method for small-size problems based on NPS and SNS.

Small sized problems							
Pr.N	N_{task}	N_s	N_l	NPS		SNS	
				MOACO	*Epsilon constraint*	MOACO	*Epsilon constraint*
1	5	2	2	9	6	555772.3	79472.689
2	5	2	3	8	9	644172.5	91089.704
3	10	2	2	7	4	588467.0	188453.25
4	10	2	3	20	15	739437.2	202127.47
5	10	3	2	5	6	666931.1	162683.78
6	10	3	3	15	12	649995.7	322581.19
7	15	2	2	10	8	704973.3	185546.38
8	15	2	3	17	12	741238.6	353325.92
9	15	3	2	10	10	704900.9	299637.58
10	15	3	3	13	13	708612.6	447917.43
11	15	4	2	12	11	688574.7	361803.10
12	15	4	3	6	6	660998.0	565954.34
13	20	2	2	7	7	781160	320836.60
14	20	2	3	15	14	765879.8	584770.62
15	20	3	2	9	6	782040.4	306170.82
16	20	3	3	18	10	799064.6	649824.25
17	20	4	2	9	9	754416.2	530094.72
18	20	4	3	22	17	762284.1	781503.06
19	25	2	2	8	8	661413.5	419569.86
20	25	2	3	25	16	745980.2	402055.55
21	25	3	2	12	8	709208.1	483952.5
22	25	3	3	23	17	737845.9	696265.09
23	25	4	2	9	7	828466.5	646693.75
24	25	4	3	18	17	771834.3	1016250.4
25	30	2	2	15	13	738285.9	349092.46
26	30	2	3	21	17	639672.0	604667.90
27	30	3	2	12	7	701382.8	685388.78
28	30	3	3	15	14	741485.9	886819.39
29	30	4	2	14	10	660531.2	558800.43
30	30	4	3	20	16	564022.9	952888.20
average				13.466	10.833	706634.98	471207.91

Table 5. Computational results obtained by the proposed MOACO for large-sized problems

Large-sized problems							
Pr.N	N_{task}	N_s	N_l	MOACO			
				MID	DM	NPS	SNS
31	50	3	2	219.983	428608	12.000	1033521
32	50	3	3	261.859	1186682	20.000	1447225
33	50	3	4	388.193	2250153	18.000	1655024
34	50	4	2	252.48	512263	14.000	1123168
35	50	4	3	355.069	1208360	13.000	1911604
36	50	4	4	398.388	2796026	17.000	3191041
37	50	5	2	311.802	751482	10.000	1729456
38	50	5	3	436.202	1954957	15.000	2030673
39	50	5	4	476.99	1339372	15.000	3884731
40	50	6	2	358.476	851606	14.000	1612785
41	50	6	3	393.119	2341547	17.000	3048884
42	50	6	4	727.285	4421114	13.000	4350098
43	50	6	5	691.353	7871687	18.000	6429073
44	60	3	2	258.97	777606	16.000	1202844
45	60	3	3	379.991	1873402	16.000	1978346
46	60	3	4	348.204	2444159	15.000	2449458
47	60	4	2	287.045	797650	19.000	1352465
48	60	4	3	443.203	1935927	20.000	2319340
49	60	4	4	446.914	2184827	15.000	3358087
50	60	5	2	325.697	710863	15.000	1685462
51	60	5	3	456.882	2567311	22.000	2700971
52	60	5	4	506.751	4033916	21.000	4109297
53	60	6	2	348.61	1045599	17.000	2055279
54	60	6	3	290.267	1894112	22.000	2795617
55	60	6	4	491.004	4389356	21.000	4405311
56	60	6	5	453.199	3051385	14.000	6990081
57	60	7	2	513.167	1311770	22.000	2654193
58	60	7	3	514.812	3197033	21.000	3311974
59	60	7	4	565.966	6422731	19.000	5984801
60	60	7	5	1145.078	8714693	20.000	7102748
average				434.8986	2508873	17.033	2996785

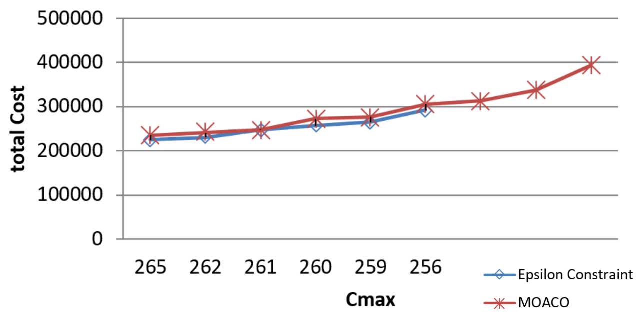

Fig. 2. Obtained Pareto fronts of MOACO and epsilon-constraint method on problem number 15

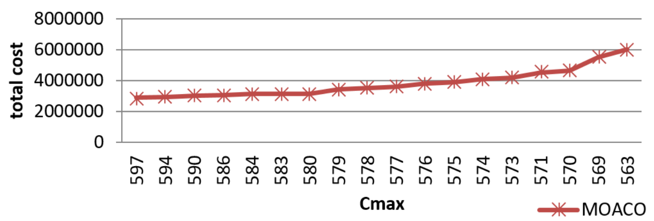

Fig. 3. Obtained Pareto fronts of MOACO-ALL and MOACO-ELITE on problem number 52

by achieving 13.466 versus 10.833. Furthermore, in terms of *SNS*, the proposed MOACO achieved better performance by obtaining the value 706634.98 versus the value of 471207.91 gained by epsilon-constraint method for small problem sizes. As epsilon-constraint method was unable to solve the large-sized problems in a reasonable computational time, MOACO has been applied to tackle the problem of larger sizes. According to Table 5, the average value of *MID*, *DM*, *NPS* and *SNS* are achieved as 434.8986, 2508873, 20.333 and 2996785, respectively.

The Pareto fronts obtained by MOACO and epsilon constraint method on problem number 15 and the Pareto fronts obtained by MOACO on problem number of 52 are depicted in Fig. 2 and Fig. 3.

4- 1- Sensitivity analysis

In this section, a sensitivity analysis is done to investigate the effect of energy consumption cost on final scheduling of activities. To this end, an illustration consisted of *4* activities and *4* skills, each of which introduces three levels of efficiency, is taken into consideration. Execution times and implementation cost of efficiency levels of candidate skills are represented in Tables 6 and 7. As an example, Task 1 requires concurrent application of skills a, b, c and d that could be implemented in *3* levels of efficiency, each of which resulted in a specific execution time and cost. Besides, time-based energy consumption cost regarding efficiency levels of candidate skills is represented in Table 8.

To accomplish the sensitivity analysis, energy consumption cost is shifted within -20% to +300% and the changes made to the scheduling of activities has been reported in Table 9. As can be seen, by increasing energy consumption cost, total energy cost and total application cost of multi-skilled resources are increased while makespan is decreased. In other words, by increasing the energy consumption cost, the activities will be scheduled as soon as possible.

5- Summary and conclusion

In this paper, a bi-objective energy-based integration of the multi-skilled project scheduling problem and resource investment problem, named EB-MSRIP, was formulated and solved. Indeed, this was the first work that considers minimizing the total cost including the implementation of multi-skilled resources as well as the energy consumption cost of multi-skilled resources as an objective in the project scheduling. The second objective minimizes project's makespan. Application of the proposed model enables decision makers to obtain the best availability for efficiency levels of multi-skilled resources along with the best schedule of the activities while energy costs are considered. A mixed-integer programming formulation was proposed for EB-MSRIP, where its validity is established based on 30 small scales within application of epsilon-constraint method by GAMS software. Afterwards, the ant colony optimization (ACO) was developed to overcome the computational complexities of large-sized problems. The performance of the proposed ACO was evaluated by means of four performance measures within 60 test instances. Results achieved by epsilon-constraint method in terms of MID, DM, NPS and SNS were compared with MOACO. Therefore, regarding the advantages of proposed MOACO, the larger scales of problems were solved through the proposed MOACO and the computational results were depicted in terms of comparison measures. As it was shown, the *MOACO* algorithm obtained the best results in terms of *DM*, *NPS* and *SNS* but worst results based on *MID*.

As this paper considers the cost of energy consumption in the field of multi-skilled project scheduling, several extensions could be noted for future researches. One can extend the

Table 6. Execution times and resource requirements of tasks

	Skill a			Skill b			Skill c			Skill d		
Level	1	2	3	1	2	3	1	2	3	1	2	3
Task 1	4	3	1	4	2	1	4	3	2	4	3	1
Task 2	4	3	1	-	-	-	-	-	-	-	-	-
Task 3	4	3	2	3	2	1	4	3	2	-	-	-
Task 4	3	2	1	-	-	-	6	4	2	3	2	1

Table 7. Implementation cost of multi-skilled resources

Levels of efficiency	1	2	3
Skill a	128	299	322
Skill b	116	280	352
Skill c	137	284	390
Skill d	114	285	389

Table 8. Energy consumption cost according to time and efficiency levels of candidate skills

Time	1 to 5	6 to 9	10 to 24
Level 1	20	16	13
Level 2	15	13	12
Level 3	10	8	5

Table 9. Sensitivity analysis of energy consumption cost on final scheduling of activities

Change in Energy cost	Start Time				Makespan	Total Energy cost	Multi-skilled resources' cost
	Task 1	Task 2	Task 3	Task 4			
-20%	1	11	18	25	29	381	31204
-50%	1	11	15	21	25	995	31256
100%	1	6	10	19	23	1981	31264
+150%	1	7	11	15	19	2998	34120
+200%	1	5	9	11	15	3440	36206
+300%	1	5	9	11	15	36683	36206

current work to develop a sustainable model when there is a dynamic policy for energy tariffs. Another extension can be consideration of bonus and penalty strategies for low and high energy consumptions as well as extending the problem to multiple project scheduling problems.

Parameters

E	Set of prerequisite relations between activities
S_i	Set of required skills to execute activity i
p_{ikl}	Execution time of activity i using the l th level of skill k
r_{ikl}	Number of workforces needed to perform activity i using l th level of skill k
EC_{kl}^t	Energy consumption cost for the l th level of skill k at time t
IC_{kl}^t	Implementation cost of applying l th level of skill k at time t
$[es_i, ls_i]$	Earliest and latest start times of activity i
$[ef_i, lf_i]$	Earliest and latest finish times of activity i
N_{ik}	1 , if activity i needs skill k ; 0 , otherwise
n	Number of activities

Decision variables:

S_{ik}	Start time of applying skill k to perform activity i
S_i	Start time of activity i
C_{ik}	Completion time of applying skill k to perform activity i
C_i	Completion time of activity i
R_{kl}^t	Availability of the l th level of skill k at time t
y_{ikl}	1 , if activity i is performed by the l th level of skill k; 0 , otherwise
y_{ikl}^t	1 , if activity i is in progress by the l th level of skill k between [t-1, t]; 0 , otherwise

References

[1] F. Shrouf, J. Ordieres-Meré, A. García-Sánchez, M. Ortega-Mier, Optimizing the production scheduling of a single machine to minimize total energy consumption costs, Journal of Cleaner Production, 67 (2014) 197-207.

[2] A. Sharma, F. Zhao, J.W. Sutherland, Econological scheduling of a manufacturing enterprise operating under a time-of-use electricity tariff, Journal of Cleaner

Production, 108 (2015) 256-270.

[3] A. Rezvani, M. Gandomkar, M. Izadbakhsh, A. Ahmadi, Environmental/economic scheduling of a micro-grid with renewable energy resources, Journal of cleaner production, 87 (2015) 216-226.

[4] B. Khoshnevisan, E. Bolandnazar, S. Barak, S. Shamshirband, H. Maghsoudlou, T.A. Altameem, A. Gani, A clustering model based on an evolutionary algorithm for better energy use in crop production, Stochastic environmental research and risk assessment, 29(8) (2015) 1921-1935.

[5] S. Barak, M. Yousefi, H. Maghsoudlou, S. Jahangiri, Energy and GHG emissions management of agricultural systems using multi objective particle swarm optimization algorithm: a case study, Stochastic environmental research and risk assessment, 30(4) (2016) 1167-1187.

[6] R.H. Möhring, Minimizing costs of resource requirements in project networks subject to a fixed completion time, Operations Research, 32(1) (1984) 89-120.

[7] S.-H. Cho, S.D. Eppinger, A simulation-based process model for managing complex design projects, IEEE Transactions on engineering management, 52(3) (2005) 316-328.

[8] L.L. Minku, D. Sudholt, X. Yao, Evolutionary algorithms for the project scheduling problem: runtime analysis and improved design, in: Proceedings of the 14th annual conference on Genetic and evolutionary computation, ACM, 2012, pp. 1221-1228.

[9] L.T. Bui, M. Barlow, H.A. Abbass, A multi-objective risk-based framework for mission capability planning, New Mathematics and Natural Computation, 5(02) (2009) 459-485.

[10] B. De Reyck, R. Leus, R&D project scheduling when activities may fail, IIE transactions, 40(4) (2008) 367-384.

[11] M. Sabzehparvar, S. Seyed-Hosseini, S. Nouri, A mathematical model for the multi-mode resource investment problem, Journal of Industrial Engineering International, 4(7) (2008) 25-32.

[12] A.A. Najafi, F. Azimi, A priority rule-based heuristic for resource investment project scheduling problem with discounted cash flows and tardiness penalties, Mathematical Problems in Engineering, 2009 (2009).

[13] M. Ranjbar, F. Kianfar, S. Shadrokh, Solving the resource availability cost problem in project scheduling by path relinking and genetic algorithm, Applied Mathematics and Computation, 196(2) (2008) 879-888.

[14] A. Hattab, M. Haouari, Robust resource investment problem with time-dependent resource cost and tardiness penalty, in: Industrial Engineering and Engineering Management (IEEM), 2016 IEEE International Conference on, IEEE, 2016, pp. 1693-1698.

[15] O. Bellenguez, E. Néron, Lower bounds for the multi-skill project scheduling problem with hierarchical levels of skills, in: International Conference on the Practice and Theory of Automated Timetabling, Springer, 2004, pp. 229-243.

[16] O. Bellenguez-Morineau, Methods to solve multi-skill project scheduling problem, 4OR: A Quarterly Journal of Operations Research, 6(1) (2008) 85-88.

[17] C. Heimerl, R. Kolisch, Work assignment to and qualification of multi-skilled human resources under knowledge depreciation and company skill level targets, International Journal of Production Research, 48(13) (2010) 3759-3781.

[18] M. Walter, J. Zimmermann, Minimizing average project team size given multi-skilled workers with heterogeneous skill levels, Computers & Operations Research, 70 (2016) 163-179.

19] S.B. Othman, S. Hammadi, A. Quilliot, Multi-objective evolutionary for multi-skill health care tasks scheduling, IFAC-PapersOnLine, 48(3) (2015) 704-709.

[20] S. Javanmard, B. Afshar-Nadjafi, S.T.A. Niaki, Preemptive multi-skilled resource investment project scheduling problem: Mathematical modelling and solution approaches, Computers & Chemical Engineering, 96 (2017) 55-68.

[21] J. Xiao, X.-T. Ao, Y. Tang, Solving software project scheduling problems with ant colony optimization, Computers & Operations Research, 40(1) (2013) 33-46.

[22] G. Campos Ciro, F. Dugardin, F. Yalaoui, R. Kelly, Open shop scheduling problem with a multi-skills resource constraint: a genetic algorithm and an ant colony optimisation approach, International Journal of Production Research, 54(16) (2016) 4854-4881.

[23] Y.-C. Liang, A. Chen, W.-C. Kao, C.-C. Chyu, An ant colony approach to resource-constrained project scheduling problems, in: Proceedings of the fifth Asia Pacific industrial engineering and management systems conference, 2004, pp. 31.35.

Please cite this article using:

Sh. Javanmard, B. Afshar-Nadjafi, S. T. Akhavan-Niaki, Optimization of an energy based bi-objective multi-skilled resource investment project scheduling problem, *AUT J. Model. Simul.*, 50(2) (2018) 129-140.

DOI: 10.22060/miscj.2018.13848.5084