

Optimizing and Solving Project Scheduling Problem for Flexible Networks with Multiple Routes in Production Environments

Alireza Birjandi¹, Seyed Meysam Mousavi*², Mahdi Hajirezaie³ and Behnam Vahdani⁴

1. Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran (alireza.birjandi_67@yahoo.com)

2. Department of Industrial Engineering, Faculty of Engineering, Shahed University, Tehran, Iran.

3. Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran (m_hajirezaie@azad.ac.ir)

4. Department of Industrial Engineering, Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran (b.vahdani@gmail.com)

**Corresponding Author: S. M. Mousavi (E-mail: sm.mousavi@shahed.ac.ir)*

Abstract– In production environments, multi-route Resource-Constrained Project Scheduling Problem (RCPS) is more complex and consists of two types of flexible and fixed parts. The flexible parts comprise the semi-finished products and each part has multiple routes denoted independently with activities and predictive relationships. This research develops a new Mixed-Integer Nonlinear Programming (MINLP) model to minimize the makespan. The proposed mathematical model identifies the optimal routes and, consequently, determines the optimal project network. Also, it allocates renewable resources to each production activity. Production sequencing of activities is optimized by the proposed model. A new hybrid approach by regarding GA and PSO in a binary solving space is introduced to handle two main sub-problems of RCPS-MR in production environments, namely route selection and production scheduling. To evaluate the presented optimization model and algorithm, 60 test problems in various sizes are reported in detail.

Keywords– Flexible production networks, RCPS, Production projects, Production scheduling problem, Mathematical model, Meta-heuristic algorithm, Multiple routes.

I. INTRODUCTION

Production Scheduling Problem (PSP) in production environments with different scales can be defined as overtime allocation of renewable and non-renewable resources (such as raw material, machine, tools, energy, and skill of manpower) to fixed production activities and operations (such as drilling, boring, milling, and treading) with one or more different objectives (Dorfeshan and Mousavi, 2019; Moradi et al., 2018; Bhargav et al. 2017). In today's competitive world, production scheduling is a crucial issue for companies and industrial factories (Mohagheghi et al., 2016, 2017). Production scheduling in different environments (e.g., job shop, flow shop, open shop) can be properly optimized by performance measures that are based on production costs and times, efficiency and effectiveness, delivery, etc. (Birjandi et al., 2019). Fuchigami and Rangel (2018) analyzed 46 different papers published in the field of production scheduling during 1992–2016. They observed that most studies were related to the classification of hybrid flow shop problems. Marichelvam and Mariappan (2018) presented a hybrid genetic scatter search algorithm to minimize makespan and flow time, simultaneously, in a flexible job shop environment. Zhang and Wong (2018) proposed a metaheuristic via ant colony optimization aimed at makespan in a job shop environment. Zareei (2018) scheduled constructing a biogas plant in Iran by the critical phase method. Altaf et al. (2018) applied Radio Frequency Identification (RFID) technology, data mining, and simulation-based optimization to handling a planning and control system for panelized home production facilities.

Achieving an optimal model for the PSP without considering resource constraints is far from reality. Therefore, Resource-Constrained Project Scheduling Problem (RCPSP) has been introduced as an extension of the PSP. RCPSP in production environments is used to optimize objectives intended by production managers, e.g., minimizing the makespan of final products by production scheduling methods. Different conventional methods have been presented to deal with the complexity of PSP (Merchan et al., 2016; Baumung and Fomin, 2018; Le Hesran et al., 2019). Qinming et al. (2018) proposed a trade-off model to coordinate Predictive Maintenance (PM) decisions with production scheduling, simultaneously, for minimizing the total expected cost.

Considering multiple execution modes for production activities is an extension of RCPSP in production environments, named MRCPSPP, in which each mode allocates different processing and resource requirements to the production activities. Therefore, MRCPSPP works in production environments as it does in project environments and different methods and assumptions can be used for the MRCPSPP in production environments (Hartmann and Briskorn, 2010). Some conventional methods are presented to deal with the complexity of MRCPSPP in project and production environments (e.g., Deblaere et al., 2011; Messelis and Causmaecker, 2014; Kopanos et al., 2014; Peteghem and Vanhoucke, 2014; Besikci et al., 2015; Chakraborty et al., 2016; Szeredi and Schutt, 2016; Fernandes et al., 2018). Merkle et al. (2002) proposed an Ant Colony Optimization (ACO) solving approach; Zhang et al. (2006) utilized a Particle Swarm Optimization (PSO) solving approach; and Debels and Vanhoucke (2007) provided a decomposition-based Genetic Algorithm (GA) to handle RCPSP. Paraskevopoulos et al. (2012) considered a Hybrid Evolutionary Algorithm (HEA) with an iterated local search for the problem. Paraskevopoulos et al. (2016) regarded Adaptive Memory Programming (AMP) for the RCPSP. Chand et al. (2018) focused on genetic programming to handle priority rules for RCPSPs. Chiang and Torng (2016) proposed an Iterated Greedy (IG) algorithm to optimize multi-mode job shop scheduling problem with the aim of minimizing total weighted tardiness. Biondi et al. (2017) proposed an MILP model to integrate multi-time scale maintenance and production scheduling of process plants.

This study investigates a problem which can be regarded as an extension of MRCPSPP in production environments. In this extension, product manufacturing process is considered, which includes some flexible parts with several routes to choose. Such problems are defined as RCPSP-MR. In the RCPSP-MR, two main decisions must be taken: how the production manager can select flexible production activities, and how they can choose the appropriate scheduling. Table I summarizes some studies conducted by researchers in recent years in production environments.

Table I. Studies conducted by researchers in recent years

<i>Research</i>	<i>Field</i>	<i>Production route</i>	<i>Renewable resources</i>	<i>Objective function</i>	<i>Solution method</i>
Golmakani & Birjandi (2013)	Production scheduling	Flexible	Multi-skill	Time-based	Heuristic
Golmakani & Birjandi (2014)	Production scheduling	Flexible	Multi-skill	Time-based	Meta-heuristic
Tao & Dong (2018)	Production scheduling	Flexible	Multi-skill	Time-based & cost-based	Meta-heuristic
Nikolakis et al. (2018)	Production scheduling	Fixed	Multi-skill	Time-based	Heuristic
Berger et al. (2018)	Production scheduling	Fixed	Multi-skill	Time-based	Heuristic
Liu et al. (2019)	Production scheduling	Fixed	Single skill	Time-based	Meta-heuristic
Qin et al. (2019)	Production scheduling	Fixed	Single skill	Time-based & cost-based	Heuristic
This research	Production scheduling and project scheduling	Flexible	Multi-skill	Time-based	New hybrid meta-heuristic

The differences between multi-mode RCPSP (MRCPSPP) and RCPSP-MR in production environments are given in Table II. The RCPSP-MR described in this research can be applied to robotic assemblies for reconfiguration and reprogramming of robots in order to handle a variety of designs (Nikolakis et al., 2018), pipeline construction industry

(Duffy et al., 2012), overhaul of complex capital goods such as aircraft engine and passenger aircraft turnaround process at an airport (Kellenbrink and Helber, 2015), different job shop environments (Golmakani and Namazi, 2012; Golmakani and Birjandi, 2013, 2014), and Flexible Manufacturing Systems (FMSs) (Golmakani et al., 2006, 2007; Ozguven et al., 2010; Rajabinasab and Mansour, 2011; Nonaka et al. 2012). Nikolakis et al. (2018) focused on dynamic scheduling of shared human-robot activities in FMSs and presented a hybrid hierarchical model and a multi-criteria decision-making framework based on intelligent search. Berger et al. (2018) proposed an event-based approach to Cyber-Physical Production Systems (CPPSs) in production systems. The aim of this research was to develop a machine model for fast simulations to improve scheduling in production environments by the potential of CPPSs.

Table II. Differences between multi-mode RCPSP (MRCPSP) and RCPSP-MR in production environments

No.	<i>MRCPSP in production environments</i>	<i>RCPSP-MR in production environments</i>
1	Production process is fixed	Production process is flexible
2	Total production activities and operations are fixed	Project network has both flexible and fixed sections simultaneously
3	Some production activities and operations have multiple modes	Flexible parts have multiple routes
4	Each mode of activity is allocated different resources, which change only the processing of activities	The route for each flexible activity can be seen as an independent smaller production process for the semi-finished products
5	Production process for a final product is fixed	Production process for the final product is flexible
6	Number of production activities is fixed	Number of production activities is variable with the routes assigned to flexible sections

In this research, a new generalization of RCPSP is presented. The key contributions of this research are: 1) flexibility in operation network of products, 2) a combination of multiple routes for the parts of the operation network and multiple skills for renewable resources in RCPSP, 3) new modeling for this type of problems through determining the sequencing operations by renewable resources, 4) dealing with both production and project fields in the proposed model, and 5) a new hybrid meta-heuristic approach to solving this type of problems in various scales.

The rest of this research is organized as follows: in Section II, a mathematical model is presented to solve the RCPSP-MR problem in production environments. A meta-heuristic algorithm is presented in Section III to deal with the complexity of computations. The proposed algorithm consists of two non-distinct phases for each flexible activity. The presented solving approach is discussed in Section IV by a number of 60 test problems in different sizes. Also, the solving approach is given and the results are compared. In section V, the conclusions are elaborated on and the possibilities for further studies reported.

II. PROBLEM DESCRIPTION AND MATHEMATICAL MODELING

In the following, the presented RCPSP-MR in production environments will be discussed. The RCPSP-MR activity network in production environments is an Activity on Node (AON) network, which is divided into two main sections of flexible and fixed activities. For flexible activities, multiple routes are considered. Route selection creates new activity sub-networks in the main network of the production process, leading to a more extensive production process network. As a simple instance, as shown in *Fig. (1)*, consider a production process with 12 fixed and 5 flexible activities. Flexible activities 1, 4, and 5 have 3 routes and flexible activities 2 and 3 have 2 routes for an execution (*Fig. 1(A)*). If route 3 is allocated to parts 1, 4, and 5, and route 2 is allocated to parts 2 and 3, the production network for the final product is shown *Fig. 1(B)*.

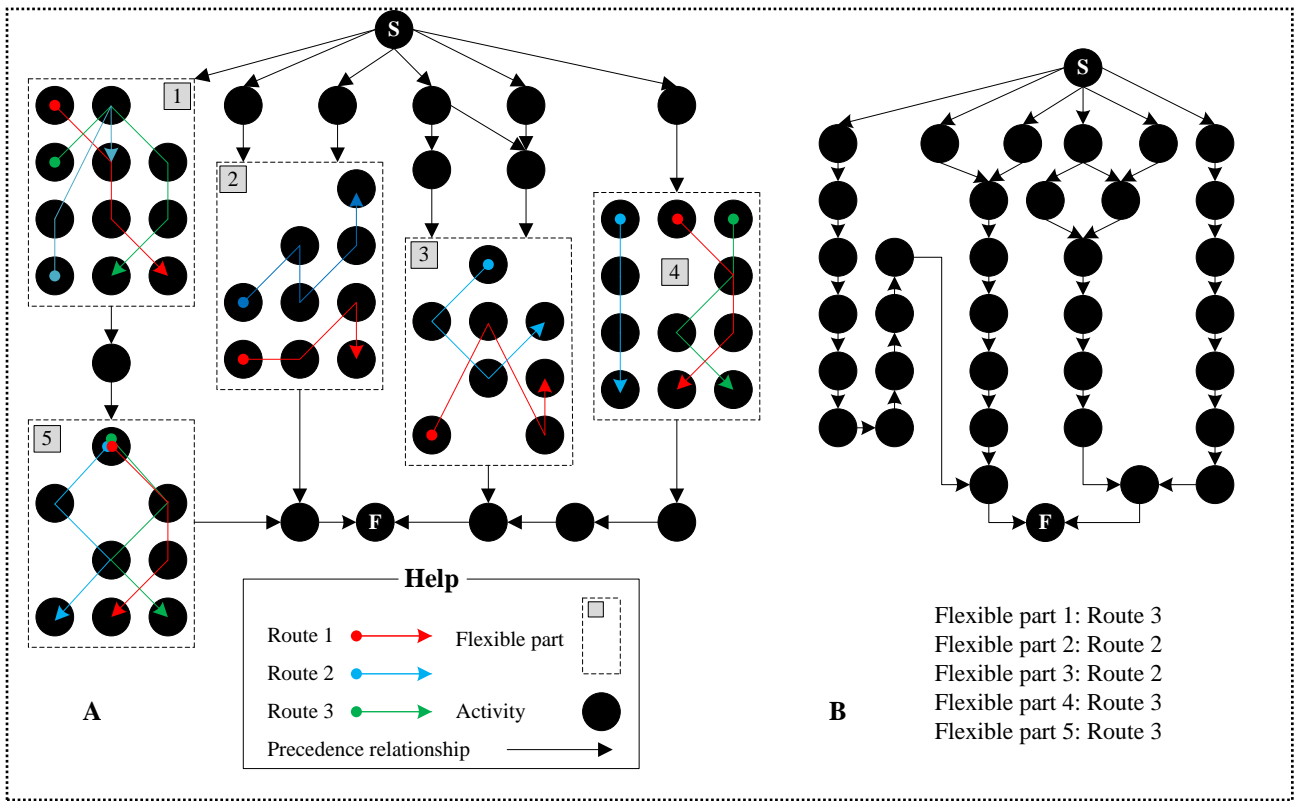


Figure 1. A simple sample of RCPSP-MR in a production environment

A. Definition and notations

The mathematical model presented in this section is primarily based on a mathematical model introduced by Golmakani and Birjandi (2013, 2014) in job shop environments to minimize makespan.

In the model, a production project with N activities is considered and represented by a graph $G=(J, A_J)$. In this graph, the nodes represent activities and arcs represent the precedence relationships. If the arc $(i, j) \in A_J$ can be found in the network, then the activity i should be finished before activity j . The production activity network is the Critical Path Method (CPM). The set of activities is defined as $J = \{1(start), 2, \dots, N+1(end)\}$ and processing times of start and end activities are zero. The sets $J_1 \subseteq J$ and $J_2 = J - J_1$ are respectively related to the fixed and flexible activities. The set of selectable routes for any flexible activity $\rho \in J_2$ is shown by λ_ρ . Any flexible activity ρ , in terms of the route $h \in \lambda_\rho$ selected for it, adds an activity sub-network $G_{\rho_h} = (\rho_h, A_{\rho_h})$ to the main activity network with the set of activities $\rho_h = \{1, 2, \dots, N_{\rho_h}\}$. The problem contains renewable resources (multifunctional machines) and thus, has a resource capacity. R is the set of renewable resources. We assume that the activities require only one renewable resource to be executed. In the model proposed in this research, processing time is only dependent on renewable resources. Therefore, processing time can differ from one to another renewable resource. For each activity $j \in J_1$, the processing time vector $D_R^j = (d_{j1}, \dots, d_{jr}, \dots, d_{jR})$ is considered. For example, $D_2^5 = (4, 6)$ indicates that activity 5 can be run by renewable resource 1 or 2 in processing time 4 or 6. Also, for each vector $j \in \rho_h$, $D_R^{j\rho_h} = (d_{j1\rho_h}, \dots, d_{jr\rho_h}, \dots, d_{jR\rho_h})$ is considered. In this research, we assume that the processing time of an activity is not preemptive.

Sets and indices:

J	Total production activities
J_1	Total fixed production activities
J_2	Total flexible production activities
λ_ρ	Routes for flexible activity $\rho \in J_2$
ρ_h	Activities related to the sub-network created by route $h \in \lambda_\rho$
A_J	Precedence relationships for J
A_{J_1}	Precedence relationships for J_1
A_{ρ_h}	Precedence relationships for ρ_h
R	Renewable resources
i, j	Index of activity
ρ, ρ'	Index of flexible activity
h, h'	Index of route

Parameters:

d_{jr}	Processing time of using renewable resources for activity $j \in J_1$
$d_{jr\rho_h}$	Processing time of using renewable resources for activity $j \in \rho_h$

Binary variables:

$Y_{jr} = \{0,1\}$	Decision-making variable to assign renewable resource $r \in R$ to activity $j \in J_1$
$Y_{jr\rho_h} = \{0,1\}$	Decision-making variable to assign renewable resource $r \in R$ to activity $j \in \rho_h$
$W_{\rho_h} = \{0,1\}$	Decision-making variable to assign selection route $h \in \lambda_\rho$ to flexible activity $\rho \in J_2$
$\alpha_{jji} = \{0,1\}$	Decision-making variable for sequencing $i \in J_1$ and $j \in J_1$ allocated to resource $r \in R$
$\eta_{jji\rho_h} = \{0,1\}$	Decision-making variable for sequencing $i \in \rho_h$ and $j \in \rho_h$ allocated to resource $r \in R$
$\psi_{rj\rho_h i\rho'_h} = \{0,1\}$	Decision-making variable for sequencing $j \in \rho_h$ and $i \in \rho'_h$ allocated to resource $r \in R$

Positive variables:

$F_{jr}(S_{jr})$	Finish (start) time $j \in J_1$ allocated to resource $r \in R$
$F_{jr\rho_h}(S_{jr\rho_h})$	Finish (start) time $j \in \rho_h$ allocated to resource $r \in R$
C_{\max}	Makespan

B. Presented mathematical formulation

The proposed optimization model is presented below:

$$\text{Minimize } C_{\max} = \sum_{r \in R} F_{(N+1)r} \cdot Y_{(N+1)r} \tag{1}$$

subject to:

$$\sum_{r \in R} (F_{jr} \cdot Y_{jr}) \geq \left(\sum_{r \in R} (F_{ir} \cdot Y_{ir}) + \sum_{r \in R} (d_{jr} \cdot Y_{jr}) \right), \forall (i, j) \in A_{J_1} \tag{2}$$

$$\sum_{r \in R} (F_{jr\rho_h} \cdot Y_{jr\rho_h}) \cdot W_{\rho_h} \geq \left(\sum_{r \in R} (F_{ir\rho_h} \cdot Y_{ir\rho_h}) + \sum_{r \in R} (d_{jr\rho_h} \cdot Y_{jr\rho_h}) \right) \cdot W_{\rho_h}, \tag{3}$$

$$\forall \rho \in J_2, \forall h \in \lambda_\rho, \forall (i, j) \in A_{\rho_h}$$

$$\sum_{r \in R} (F_{jr} \cdot Y_{jr}) \geq \left(\sum_{r \in R} (F_{ir\rho_h} \cdot Y_{ir\rho_h} \cdot W_{\rho_h}) + \sum_{r \in R} (d_{jr} \cdot Y_{jr}) \right),$$

$$\forall \rho \in J_2, \forall (\rho, j) \in A_j, \forall h \in \lambda_\rho, \forall i \in \rho_h \quad (4)$$

$$\sum_{r \in R} (Y_{jr} \cdot (F_{jr} - S_{jr} - d_{jr})) = 0, \forall j \in J_1 \quad (5)$$

$$W_{\rho_h} \cdot \sum_{r \in R} (Y_{jr\rho_h} \cdot (F_{jr\rho_h} - S_{jr\rho_h} - d_{jr\rho_h})) = 0,$$

$$\forall \rho \in J_2, \forall h \in \lambda_\rho, \forall j \in \rho_h \quad (6)$$

$$(F_{jr} - F_{ir} - d_{jr}) Y_{jr} \cdot \alpha_{rji} + (F_{ir} - F_{jr} - d_{ir}) Y_{jr} \cdot \alpha_{rij} > 0$$

$$\alpha_{rij} + \alpha_{rji} = Y_{jr} \cdot Y_{ir}, \forall j \neq i \in J_1, \forall r \in R \quad (7)$$

$$(F_{jr\rho_h} - F_{ir\rho_h} - d_{jr\rho_h}) Y_{jr\rho_h} \cdot \eta_{rij\rho_h} + (F_{ir\rho_h} - F_{jr\rho_h} - d_{ir\rho_h}) Y_{ir\rho_h} \cdot \eta_{rji\rho_h} > 0$$

$$\eta_{rji\rho_h} + \eta_{rij\rho_h} = Y_{jr\rho_h} \cdot Y_{ir\rho_h}, \forall r \in R, \forall j \neq i \in \rho_h, \forall h \in \lambda_\rho, \forall \rho \in J_2 \quad (8)$$

$$(F_{jr\rho_h} - F_{ir\rho'_h} - d_{jr\rho_h}) Y_{jr\rho_h} \cdot \psi_{ri\rho'_h j\rho_h} + (F_{ir\rho'_h} - F_{jr\rho_h} - d_{ir\rho'_h}) Y_{ir\rho'_h} \cdot \psi_{rj\rho_h i\rho'_h} > 0$$

$$\psi_{ri\rho'_h j\rho_h} + \psi_{rj\rho_h i\rho'_h} = Y_{jr\rho_h} \cdot Y_{ir\rho'_h}$$

$$\forall r \in R, \forall j \in \rho_h, \forall i \in \rho'_h, \forall h \in \lambda_\rho, \forall h' \in \lambda_{\rho'}, \forall (\rho \neq \rho') \in J_2 \quad (9)$$

$$\sum_{r \in R} Y_{jr} = 1, \forall j \in J_1 \quad (10)$$

$$\sum_{r \in R} Y_{jr\rho_h} = W_{\rho_h}, \forall \rho \in J_2, \forall j \in \rho_h, \forall h \in \lambda_\rho \quad (11)$$

$$\sum_{h \in \lambda_\rho} W_{\rho_h} = 1, \forall \rho \in J_2 \quad (12)$$

$$F_{jr} \geq 0, S_{jr} \geq 0, \forall j \in J_1, \forall r \in R$$

$$F_{jr\rho_h} \geq 0, S_{jr\rho_h} \geq 0, \forall \rho \in J_2, \forall h \in \lambda_\rho, \forall j \in \rho_h, \forall r \in R \quad (13)$$

In Eq. (1), makespan is minimized. Constraints (2-4) ensure that the completion time of each activity is greater than (or equal to) the completion time of its predecessor activities. Constraints (2) is related to activities of set J_1 . Constraints (3) is related to activities of set ρ_h . Constraints (4) is related to the activities of sets J_1 and J_2 . Constraints (5) and (6) determine that each activity should be implemented without interruption. Constraints (7-9) consider the relation between the completion times of each pair of activities by each renewable resource. This set of constraints brings new considerations to the field of project and production scheduling of multiple-route RCPSP. Eqs. (10) and (11) determine that all activities should be carried out by a renewable resource. Eq. (12) guarantees that only one route out of the possible routes is selected for each flexible activity $\rho \in J_2$. This constraint also provides the field of project and production scheduling of multiple-route RCPSP with a new consideration.

It should be noted that the proposed mathematical model is designed in such a way that by selecting a route for any flexible activity, a significant part of the constraints becomes obvious. This is one of the aspects of novelty of this model, which reduces volume and complexity of the problem and increases the speed of problem-solving by reducing the number of practical constraints.

III. PROPOSED META-HEURISTIC ALGORITHM

The proposed meta-heuristic algorithm, namely BPSO-GA, considers two non-distinct parts for the RCPSP-MR in production environments. The first section refers to the problem of route selection for any flexible activity and the second section refers to production scheduling to find the near optimal solution in a short time using a certain mechanism. The general trend of the proposed algorithm is in such a way that, at first, using binary PSO, a route among the allowed routes is assigned to any flexible activity. The initial route is selected and the related activity network is added to the production process network. Then, the algorithm enters the second section. As the routes are assigned to the flexible activities, the RCPSP-MR can be reduced to conventional RCPSP. Hence, any dispatching rule, heuristic or meta-heuristic, applicable to RCPSP is utilized in the second phase. As part of BPSO-GA, an approach can be presented based on GA for the sequencing of activities.

Binary Particle Swarm Optimization (BPSO): BPSO is a discrete version of PSO (Kennedy and Eberhart, 1997). Velocity equation of particle I in the m^{th} iteration, the function *sigmoid* to handle velocity and state of the d^{th} bit of particle I in iteration m , and $dx_{I(m)d}$ are given in the following (Eberhart et al., 2001):

$$\vec{dv}_{I(m)} = \vec{dv}_{I(m-1)} + \vec{\varphi}_1 \cdot \left(\vec{dp}_{I(m-1)} - \vec{dx}_{I(m-1)} \right) + \vec{\varphi}_2 \cdot \left(\vec{dp}_{G(m-1)} - \vec{dx}_{I(m-1)} \right) \quad (14)$$

$$\vec{DV}_{I(m)} = \text{sigmoid}(\vec{dv}_{I(m)}) = \frac{1}{1 + \exp\left(-\vec{dv}_{I(m)}\right)} \quad (15)$$

$$dx_{I(m)d} = \begin{cases} 1 & \rho_{ld} < \vec{DV}_{I(m)d} \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

where $\vec{dx}_{I(m-1)}$ and $\vec{dv}_{I(m-1)}$ are the position and velocity of particle I in iteration $m-1$, respectively. $\vec{dp}_{I(m-1)}$ and $\vec{dp}_{G(m-1)}$ are the personal best and the global best of the particle up to iteration $m-1$, respectively. $\vec{\varphi}_1$ and $\vec{\varphi}_2$ are randomly generated numbers in the interval $[0, 1]$. The vector $\vec{DV}_{I(m)}$ denotes velocity (Tasgetiren and Liang, 2004). $\vec{DV}_{I(m)d}$ is an element of vector $\vec{DV}_{I(m)}$ regarded as the velocity of the d^{th} bit of particle I . ρ_{ld} is a random number with uniform distribution in the interval $[0, 1]$.

The mechanism of this phase in the presented approach is explained with an example. In the sample operation network depicted in Fig. (2), we have 4 flexible parts with alternative routes 3, 2, 5, and 4. Since the numbers are in real space, the routes are transferred into a binary space via velocity vector (14). The new positions are obtained based on Eq. (15) and transferred to the real space.

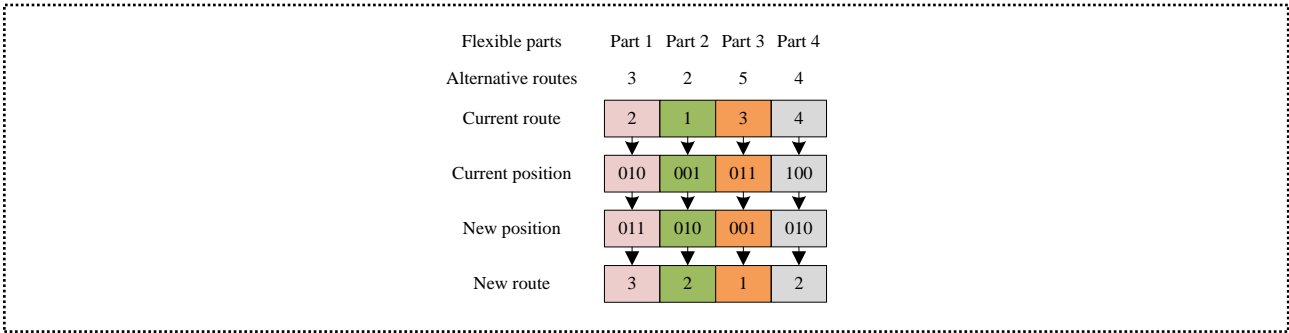


Figure 2. Method of route assignment for flexible parts

Genetic Algorithm (GA): The second part of the presented approach is based on GA, which simulates the process of evolution with a population of solutions and applies genetic operators to each reproduction (Sharma et al., 2011). In Fig. (3), parts of each solution (chromosome) are shown.

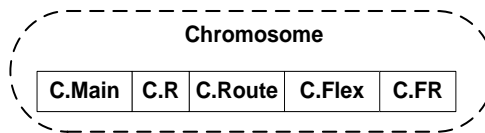


Figure 3. Parts of each solution (chromosome)

(C.Main) determines the order of fixed activities. (C.R) allocates resource to fixed activities. (C.Route) assigns a route to flexible parts. (C.Flex) determines the order of activities in any flexible part. (C.FR) allocates resources to any flexible part. The fitness value or generation solution value is calculated by Eq. (17).

$$P_i = 1 - \frac{TC_i}{\sum_{j=1}^N TC_j} \tag{17}$$

where TC_i is objective function (makespan) in solution i . As shown in Eq. (17), higher ratios increase the chance of chromosome selection for the next solution production. The number of new solutions from each parent by the crossover operation is calculated by Eq. (18). It is also illustrated in Fig. (4).

$$CH = (2 + J_2) \times 2 \tag{18}$$

In Eq. (18), CH indicates the number of new solutions and J_2 indicates the number of flexible activities.

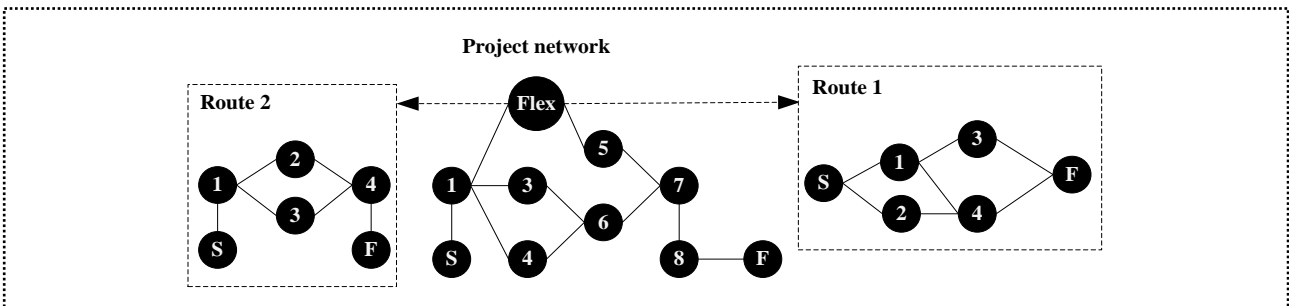


Figure 4. Production activity network

The crossover operations are performed on $C.R$ and $C.FR$ in one solution and presented in Fig. (5).

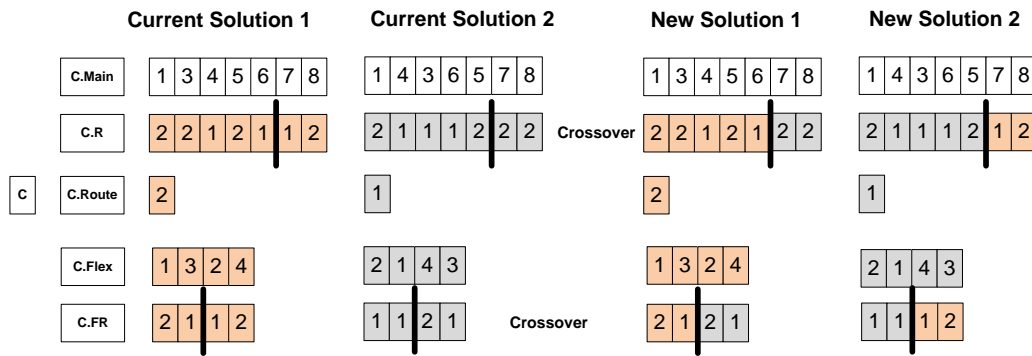


Figure 5. Crossover operation on a solution

Also, the number of new solutions with mutation operations is calculated by Eq. (19), as shown in Fig. (6).

$$CH = 1 + 4J_2 \tag{19}$$

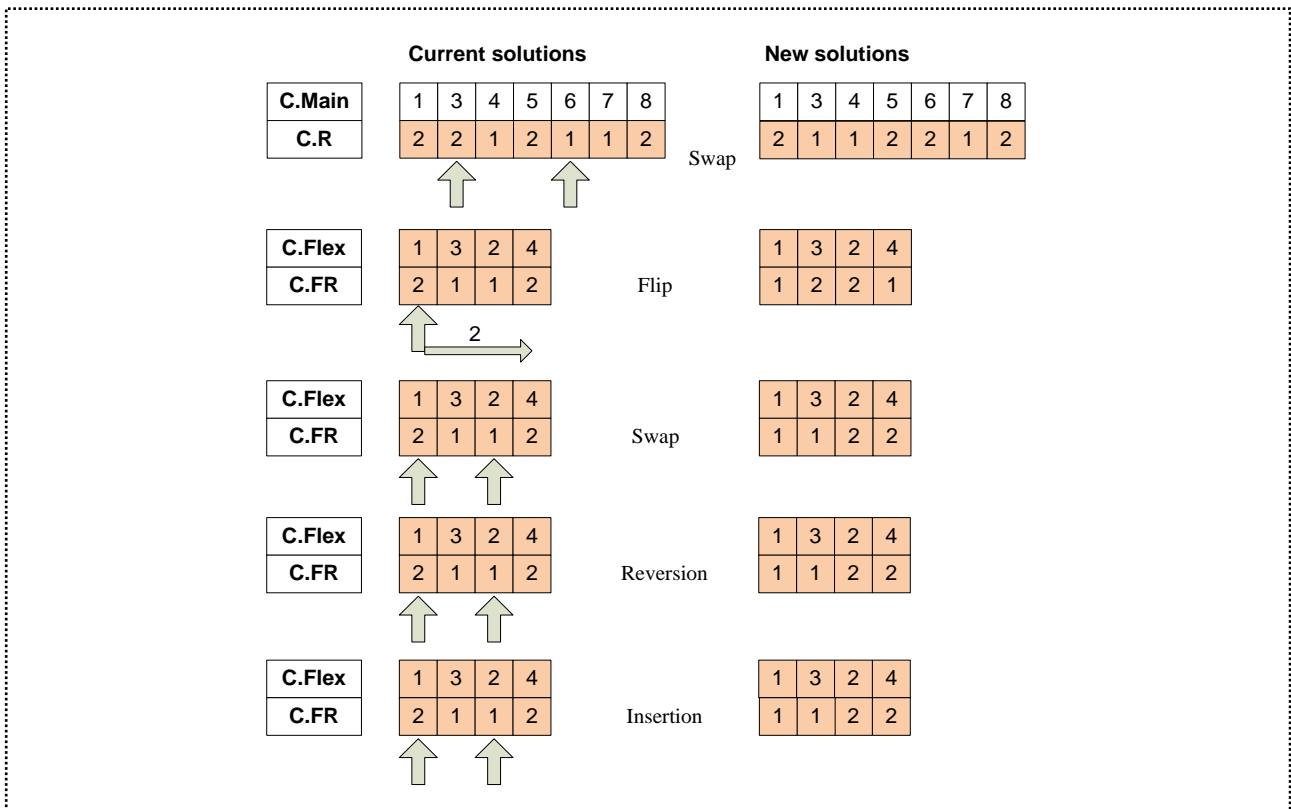


Figure 6. Types of mutation operations

IV. COMPUTATIONAL RESULTS

The flowchart of the presented approach is given in Fig. (7).

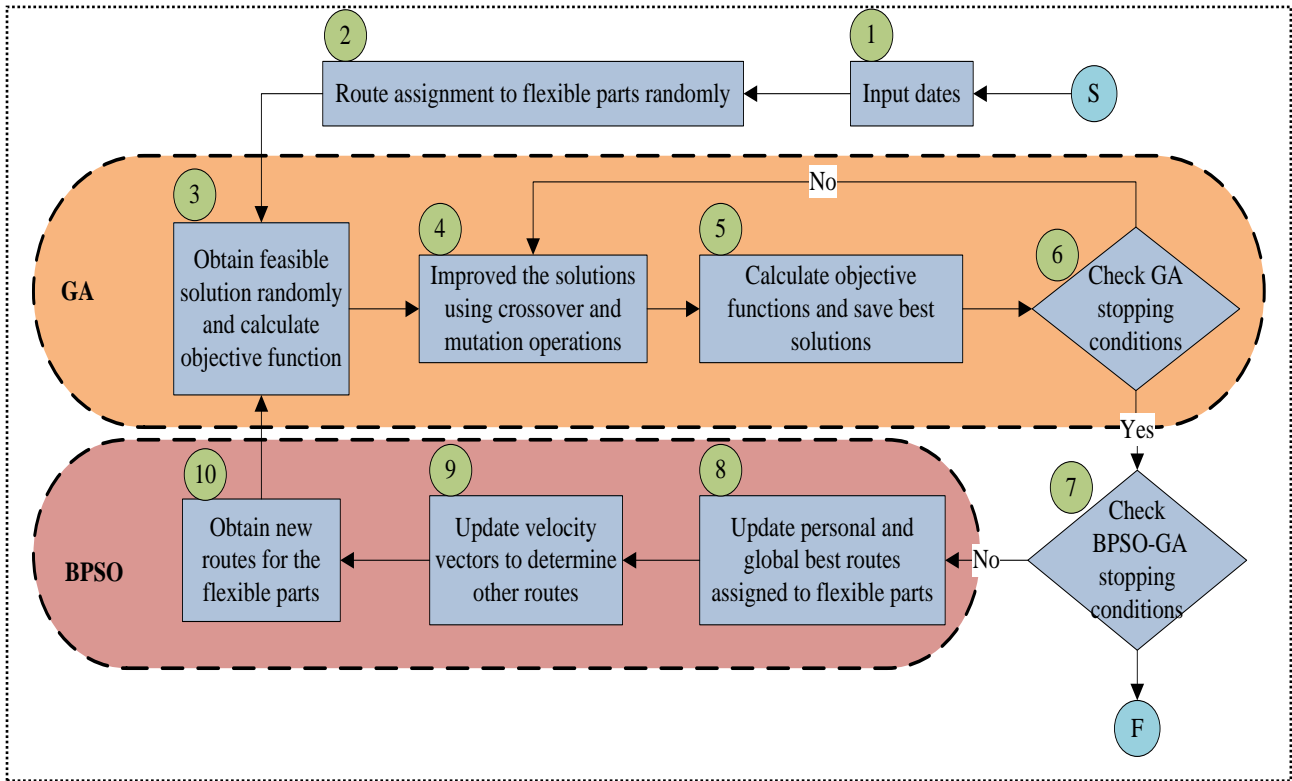


Figure 7. Flowchart of BPSO-GA

A. A simple example

In this section, an example is designed and then, solved by the proposed model and BPSO-GA. In this example, an AON network with 6 main activities is considered, $J = \{1, 2, 3, 4, 5, 6, 7, 8\}$, where activity 2 is flexible, $J_2 = \{2\}$, and other activities are fixed, $J_1 = \{1, 3, 4, 5, 6, 7, 8\}$. There are three different routes for flexible part 2, i.e., $\lambda_2 = \{1, 2, 3\}$. The problem is shown in detail in Fig. (8). For implementation of all activities of the project, two renewable sources $R = \{1, 2\}$ are considered.

The problem is formulated using Eqs. (1-12) and solved by the GAMS optimization software. The numbers of equations and variables used to solve the problem are 2500 and 1386, respectively. Route 1 for flexible activity 2 was selected and optimal solution 90 was obtained in the time limit of 3h (10,800 s). In Fig. 9 (A), details of problem-solving are presented. Also, the problem was solved by BPSO-GA, as presented in Fig. 9 (B). Algorithm route 1 was assigned to flexible activity 2 and the value of 90 was obtained as the best final solution in 22 seconds. It can be stated that the solution obtained by the BPSO-GA algorithm is almost similar to that by the mathematical model, but in a time much less than 10800s. The improvement in the time spent is 99.80%.

B. Another example

Consider an AON network with 5 main activities, $J = \{1, 2, 3, 4, 5, 6, 7\}$, where activity 2 is flexible, $J_2 = \{2\}$, and other activities are fixed, $J_1 = \{1, 3, 4, 5, 6, 7\}$. There are 2 different routes for flexible part 2, $\lambda_2 = \{1, 2\}$. Details of the problem are shown in Fig. 10 (A). For the implementation of all activities of the project, 3 renewable sources, $R = \{1, 2, 3\}$, are considered. The problem was formulated using Eqs. (1-12) and solved by GAMS optimization software. The numbers of equations and variables used to solve the problem were 2248 and 1349, respectively. Route 2 for flexible activity 2 was selected and the optimal solution of 60 was obtained in 4509 s. In Fig. 10 (B), details of problem-solving are

presented. Also, the problem was solved by BPSO-GA the details of which are given in Fig. 10 (C). This algorithm selected route 2 for flexible activity 2 and the value of 60 was obtained as the best final solution in 26 seconds. It can be stated that the solution obtained by the BPSO-GA algorithm is almost similar to that by the mathematical model, but with 99.42% improvement in time with much less than 4509s.

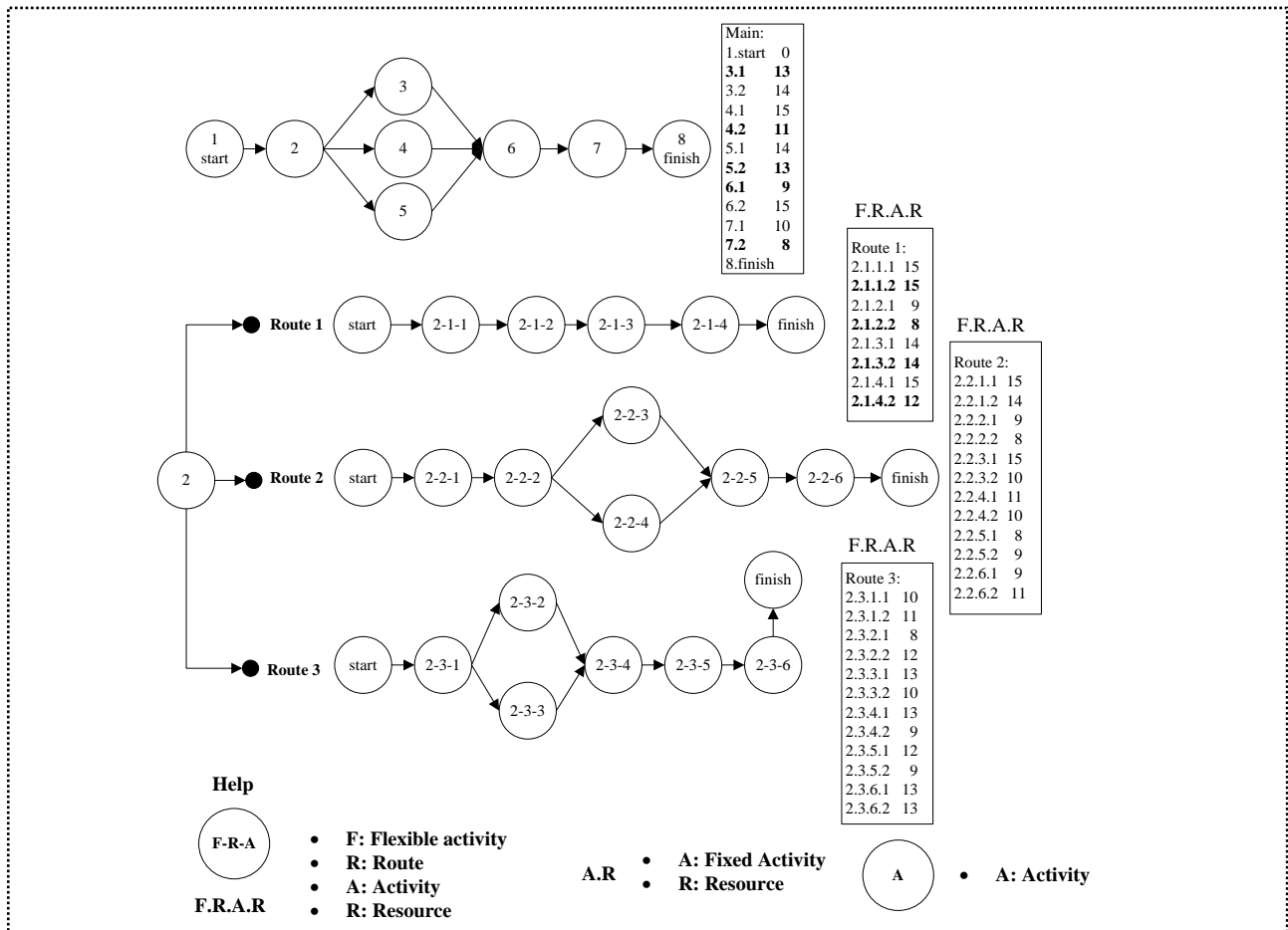


Figure 8. Activity network and selectable routes of the simple example

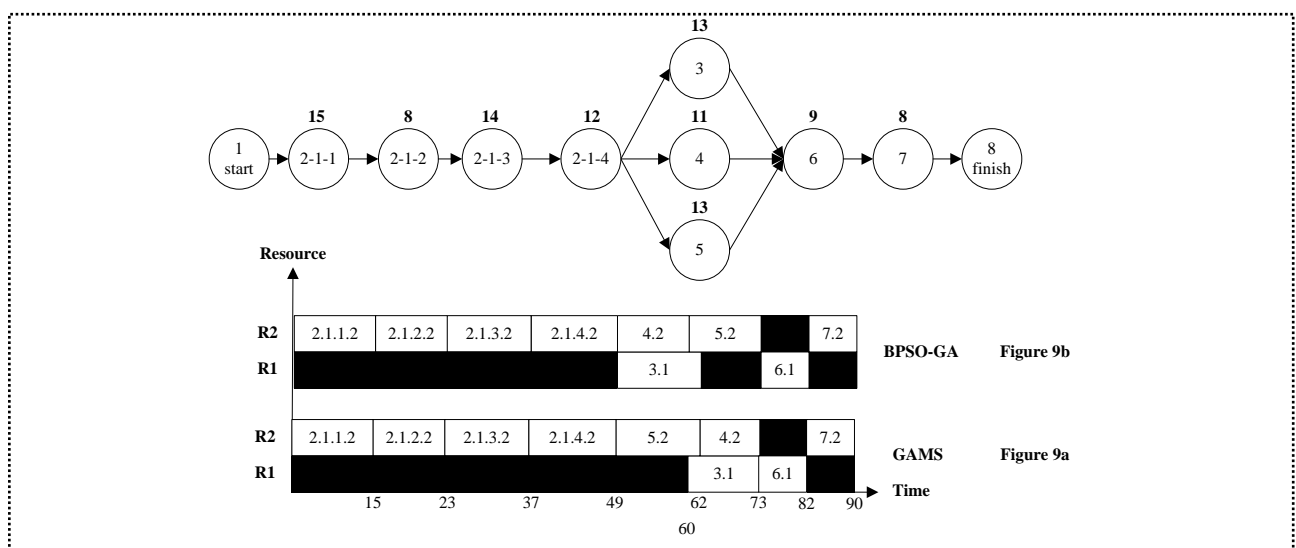


Figure 9. Details of problem-solving

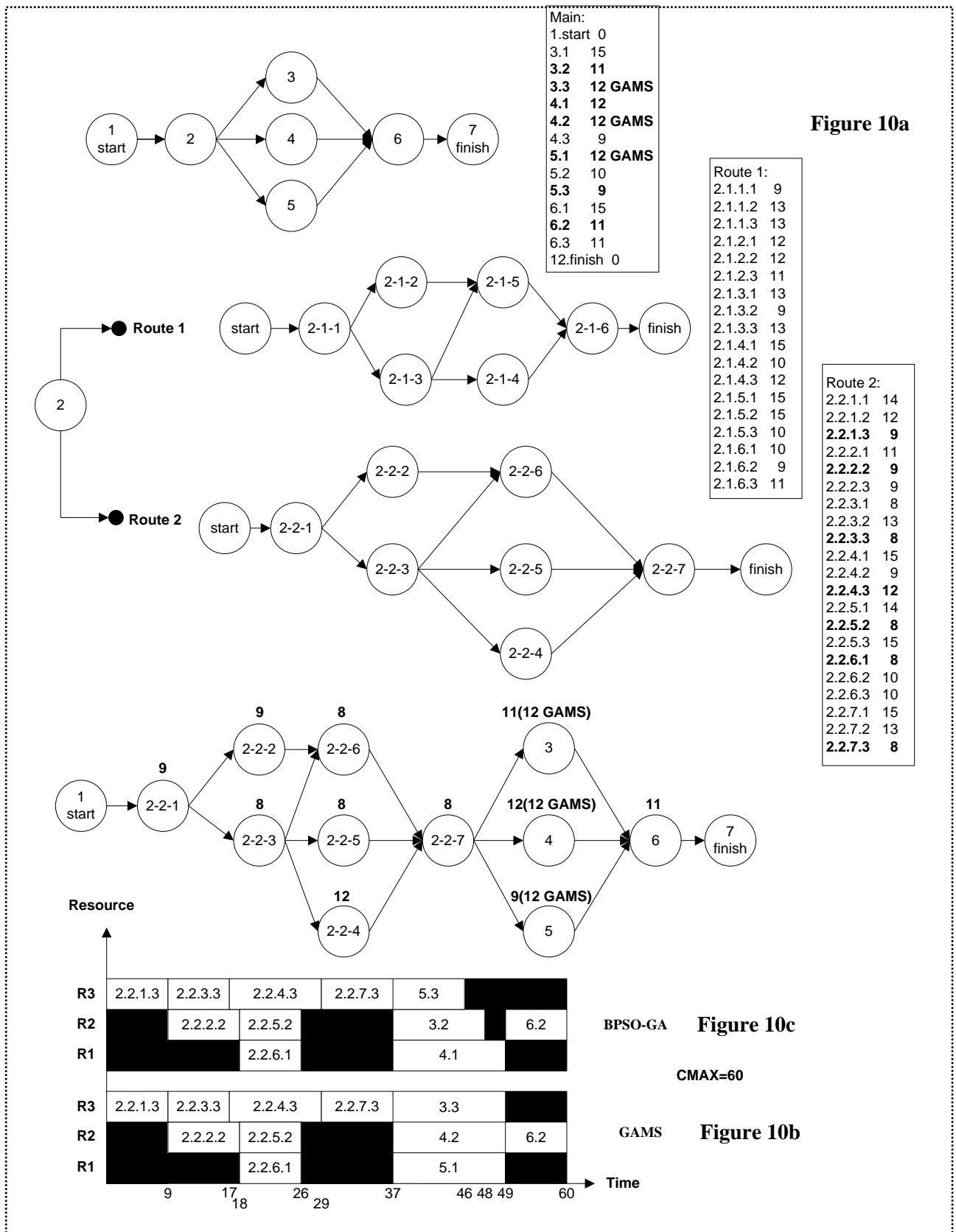


Figure 10. Activity network and selectable routes for the second example

C. Computational analysis

Since no well-known examples were found for the new defined RCPSP-MR problems in production environments, in this research, to test the performance of the proposed model and the solving approach, 60 test problems in various sizes were designed and solved. As shown in Table III, all the designed problems are marked with a Certain Identification (ID) from 01 to 60. To show the designed problems, the ID of each problem is described in Table III.

Table III. Specifications of the proposed problems

ID	J	J1	J2	SPN	R	TAPN		Precedence		Duration	
						Min	Max	Min	Max	Min	Max
01	4	3	1	2	1	10	10	12	13	8	15
02	4	3	1	2	2	9	10	10	11	8	15
03	5	4	1	2	3	9	9	11	12	8	15
04	4	3	1	3	2	8	9	9	11	8	15
05	4	3	1	2	2	8	9	9	9	8	15
06	5	4	1	2	3	9	11	11	13	8	15
07	4	3	1	2	2	8	9	10	12	8	15
08	4	3	1	3	2	9	10	11	12	8	15
09	5	4	1	2	2	9	11	9	13	8	15
10	5	4	1	2	3	10	11	12	13	8	15
11	5	4	1	2	3	11	12	14	16	8	15
12	5	4	1	2	3	10	11	12	14	8	15
13	5	4	1	2	2	10	11	12	13	8	15
14	8	7	1	2	2	12	13	16	17	8	15
15	5	4	1	2	3	11	13	15	21	8	15
16	5	4	1	2	3	14	16	18	25	8	15
17	6	5	1	3	2	10	12	11	14	8	15
18	5	4	1	2	2	13	13	18	18	8	15
19	5	4	1	2	3	12	13	15	21	8	15
20	5	4	1	2	3	11	12	15	16	8	15
21	6	4	2	4	2	23	24	29	35	8	15
22	6	4	2	4	2	21	22	27	30	8	15
23	5	3	2	4	2	16	17	20	21	8	15
24	7	6	1	3	2	10	12	13	16	8	15
25	9	7	2	9	2	16	18	25	30	8	15
26	9	7	2	4	3	17	19	21	26	8	15
27	10	8	2	4	2	16	18	24	28	8	15
28	10	8	2	4	3	17	20	23	29	8	15
29	11	9	2	4	2	17	20	25	32	8	15
30	11	9	2	4	3	21	23	35	38	8	15
31	12	10	2	4	2	20	22	34	39	8	15
32	12	10	2	4	3	19	22	31	36	8	15
33	12	9	3	8	2	25	26	37	41	8	15
34	12	9	3	8	3	21	27	28	39	8	15
35	13	10	3	8	2	23	25	33	37	8	15
36	13	10	3	8	3	24	26	34	38	8	15
37	14	12	2	4	2	20	23	34	39	8	15
38	14	12	2	4	3	22	22	49	49	8	15
39	14	11	3	8	2	25	28	38	42	8	15
40	14	11	3	8	3	25	27	42	46	8	15
41	14	12	2	4	4	20	33	31	36	8	15
42	16	14	2	4	4	23	26	41	46	8	15
43	18	16	2	4	5	27	27	55	55	8	15
44	21	19	2	4	5	33	33	53	54	8	15
45	23	21	2	4	6	39	40	116	120	8	15

Table III. Specifications of the proposed problems

ID	J	J1	J2	SPN	R	TAPN		Precedence		Duration	
						Min	Max	Min	Max	Min	Max
46	25	23	2	4	6	46	47	102	115	8	15
47	28	25	3	8	7	53	57	123	132	8	15
48	30	28	2	4	7	52	52	92	96	8	15
49	4	3	1	2	2	8	9	9	11	8	15
50	4	3	1	2	2	9	10	11	13	8	15
51	11	9	2	6	2	23	25	40	45	8	15
52	11	9	2	6	3	23	26	34	38	8	15
53	5	4	1	2	2	9	11	12	14	8	15
54	5	4	1	3	2	10	11	12	15	8	15
55	5	4	1	3	3	10	11	15	15	8	15
56	5	3	2	4	2	14	15	10	14	8	15
57	5	4	1	2	2	12	13	21	21	8	15
58	5	4	1	2	3	12	13	17	19	8	15
59	5	4	1	2	2	11	12	14	15	8	15
60	5	4	1	2	2	11	13	15	20	8	15

As shown in Table III, J is the set of main operations, J1 is the set of fixed operations, J2 is the set of flexible parts, SPN denotes the final production process network where different routes are assigned to flexible parts, R is total renewable resources, and TAPN is total activities that should be executed when determining the final production process network. Maximum and minimum numbers of precedence relationships in the network are in the precedence column, and the maximum and minimum durations of implementing each activity by the renewable resources are in the duration column. As seen in Table III, the designed test problems contain a discrete uniform distribution such that J is in the range of 4-30. J1 is 3-28 and J2 is 1-3 for the total test problems. SPN is 2-9 and R is 1-7. TAPN is 8-57 and precedence is 9-132 for the total test problems. Durations are in the fixed range of 8-15.

To assess the performance of the proposed mathematical model and BPSO-GA algorithm, 60 test problems were considered and the results obtained by solving the problems were registered in terms of the time and quality. The results obtained by problem-solving using the mathematical model and BPSO-GA are given in Table IV.

Table IV. Results obtained by problem-solving using the mathematical model (GAMS) and BPSO-GA

ID	Cmax			Time (s)		
	Model (GAMS)	BPSO-GA	Improvement%	Model (GAMS)	BPSO-GA	Improvement%
01	118	118	0	64	3	95.31
02	64	64	0	751	15	98.00
03	58	58	0	1395	6	99.57
04	60	60	0	1879	12	99.36
05	65	65	0	2046	8	99.61
06	67	67	0	2301	6	99.74
07	67	67	0	2342	5	99.79
08	71	71	0	2437	6	99.75
09	76	76	0	2536	20	99.21
10	73	73	0	3504	18	99.49
11	60	60	0	4509	26	99.42
12	74	75	-1.35	4960	12	99.76
13	72	72	0	5370	17	99.68
14	93	93	0	5654	14	99.75
15	73	73	0	10425	22	99.79
AVE	72.73	72.80	-0.09	3344.87	12.67	99.22
16	70	70	0.00	10800	28	99.74
17	90	90	0.00	10800	22	99.80
18	95	95	0.00	10800	14	99.87

Table IV. Results obtained by problem-solving using the mathematical model (GAMS) and BPSO-GA

ID	Cmax			Time (s)		
	Model (GAMS)	BPSO-GA	Improvement%	Model (GAMS)	BPSO-GA	Improvement%
19	77	76	1.30	10800	44	99.59
20	81	80	1.23	10800	19	99.82
21	144	140	2.78	10800	104	99.04
22	129	128	0.78	10800	81	99.25
23	112	97	13.39	10800	39	99.64
24	63	58	7.94	10800	34	99.69
25	95	91	4.21	10800	122	98.87
26	92	79	14.13	10800	95	99.12
27	109	105	3.67	10800	122	98.87
28	81	76	6.17	10800	139	98.71
29	114	104	8.77	10800	144	98.67
30	101	92	8.91	10800	160	98.52
31	131	118	9.92	10800	243	97.75
32	108	99	8.33	10800	80	99.26
33	156	143	8.33	10800	399	96.31
34	111	102	8.11	10800	435	95.97
35	146	145	0.68	10800	386	96.43
36	125	113	9.60	10800	349	96.77
37	121	115	4.96	10800	165	98.47
38	98	86	12.24	10800	134	98.76
39	166	158	4.82	10800	438	95.94
40	115	98	14.78	10800	419	96.12
41	114	101	11.40	10800	132	98.78
42	103	89	13.59	10800	366	96.61
43	101	95	5.94	10800	323	97.01
44	127	105	17.32	10800	467	95.68
45	115	107	6.96	10800	253	97.66
46	160	144	10.00	10800	585	94.58
47	180	143	20.56	10800	1054	90.24
48	168	135	19.64	10800	789	92.69
49	78	72	7.69	10800	13	99.88
50	82	74	9.76	10800	21	99.81
51	139	135	2.88	10800	221	97.95
52	124	113	8.87	10800	223	97.94
53	63	62	1.59	10800	3	99.97
54	86	84	2.33	10800	9	99.92
55	62	60	3.23	10800	31	99.71
56	93	90	3.23	10800	38	99.65
57	103	101	1.94	10800	14	99.87
58	81	74	8.64	10800	29	99.73
59	96	88	8.33	10800	18	99.83
60	87	74	14.94	10800	7	99.94
AVE	108.71	100.09	7.42	10800	195.8	98.19
TOTAL AVE	90.72	86.44	3.67	7072.43	104.23	98.70

To verify the convergence of the proposed algorithm, 5 problems from 44 to 48 were solved by BPSO-GA and the details for each iteration are shown in Fig. (11). The maximum iteration intended for stopping the BPSO-GA was 50. As shown in Fig. (11), problems 44 to 48 in iterations 36, 29, 32, 37, and 32, respectively, succeed to obtain the best solutions. The calculated results are 105, 107, 144, 143, and 135, respectively.

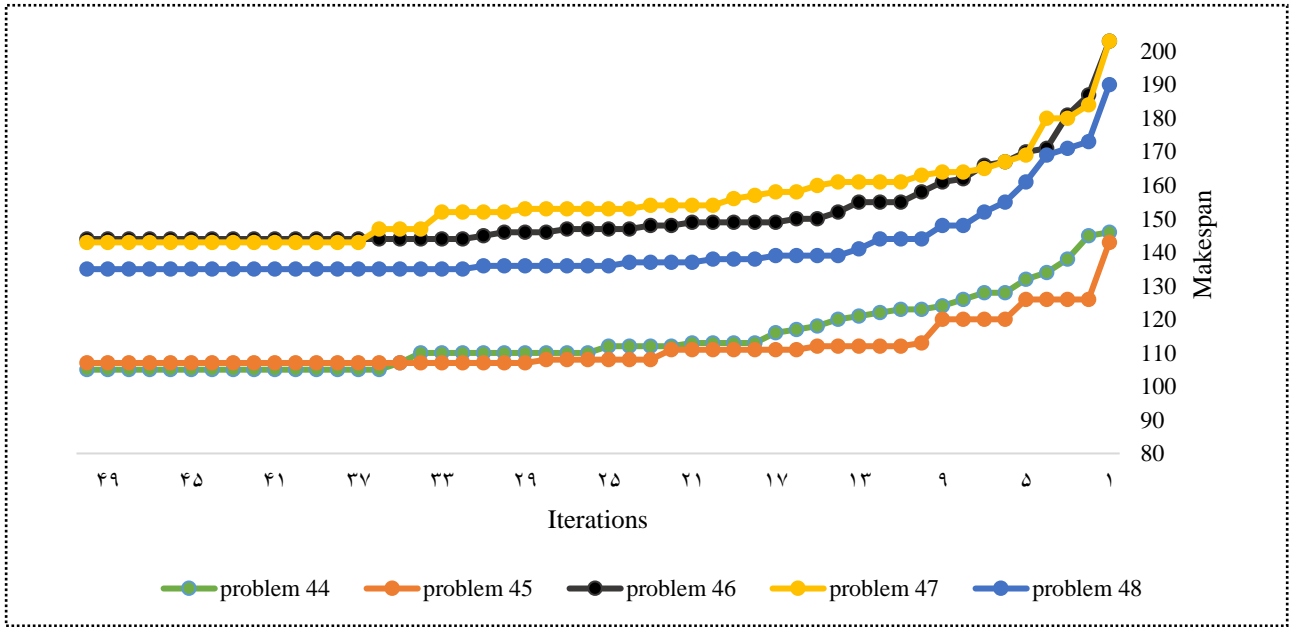


Figure 11. Results obtained by the proposed algorithm in each iteration

Regarding these problems, the reports by GAMS optimization software are provided. We set a time limit of 3h (10,800 s) to handle the best possible solution within the defined time interval.

As shown in Table IV (IDs 01 to 15), all the first 15 problems were solved using BPSO-GA and a mathematical model (GAMS). The average solution obtained by modeling and solving using GAMS software is equal to 72.73 in average time of 3344.87s, while the BPSO-GA in time average of 12.67 s achieves the optimal solutions with a difference of 0.09%. Therefore, the BPSO-GA algorithm, by 99.22% time saving compared to the average time consumed by GAMS software, can generate optimal solutions with the same quality. Accordingly, relatively good performance of BPSO-GA in terms of time and quality of the finalized solutions in comparison with modeling and solving by GAMS is proven, as shown in Fig. (12).

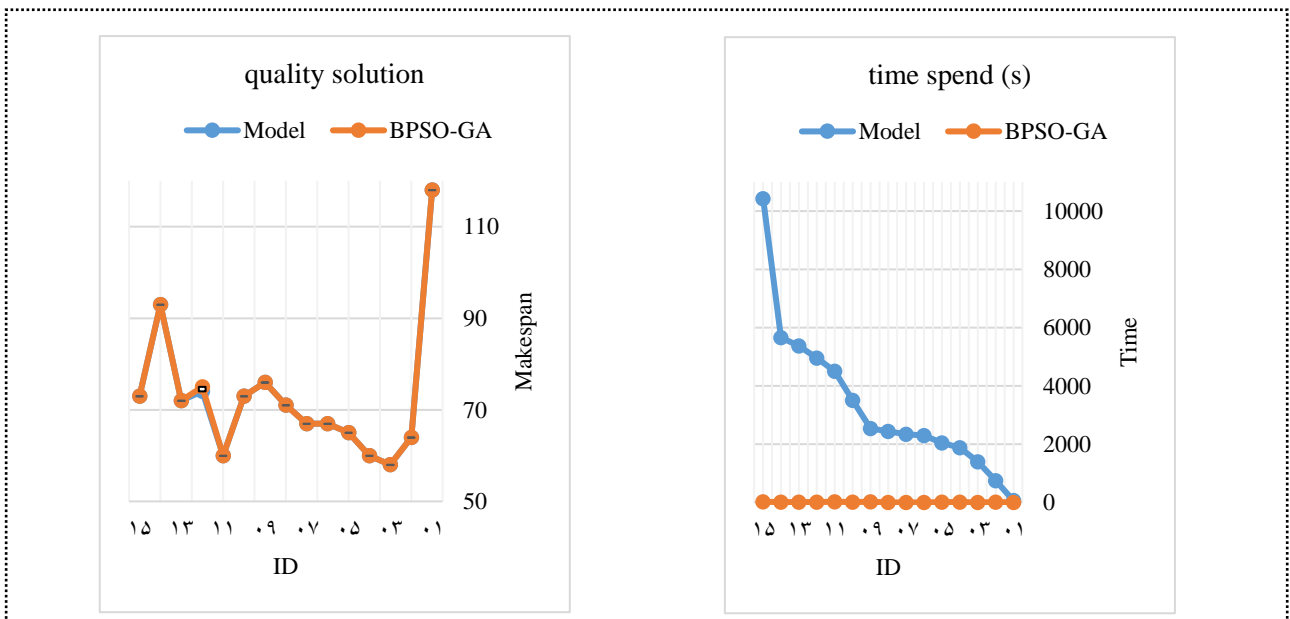


Figure 12. Comparison of the mathematical model and the proposed algorithm (IDs 01 to 15)

For other problems (IDs 16 to 60), the result obtained by the mathematical model proposed in this research is 108.71 on average in 3 hours (10,800s). The result obtained by BPSO-GA is 7.42% better than the outcome of the mathematical model with time saving of 98.19%. Therefore, for IDs 01 to 60, the result obtained by BPSO-GA is 3.67% better than that by the mathematical model. Also, the time spent by BPSO-GA is 98.70% lower than that by the mathematical model, as shown in Figs. (13) and (14).

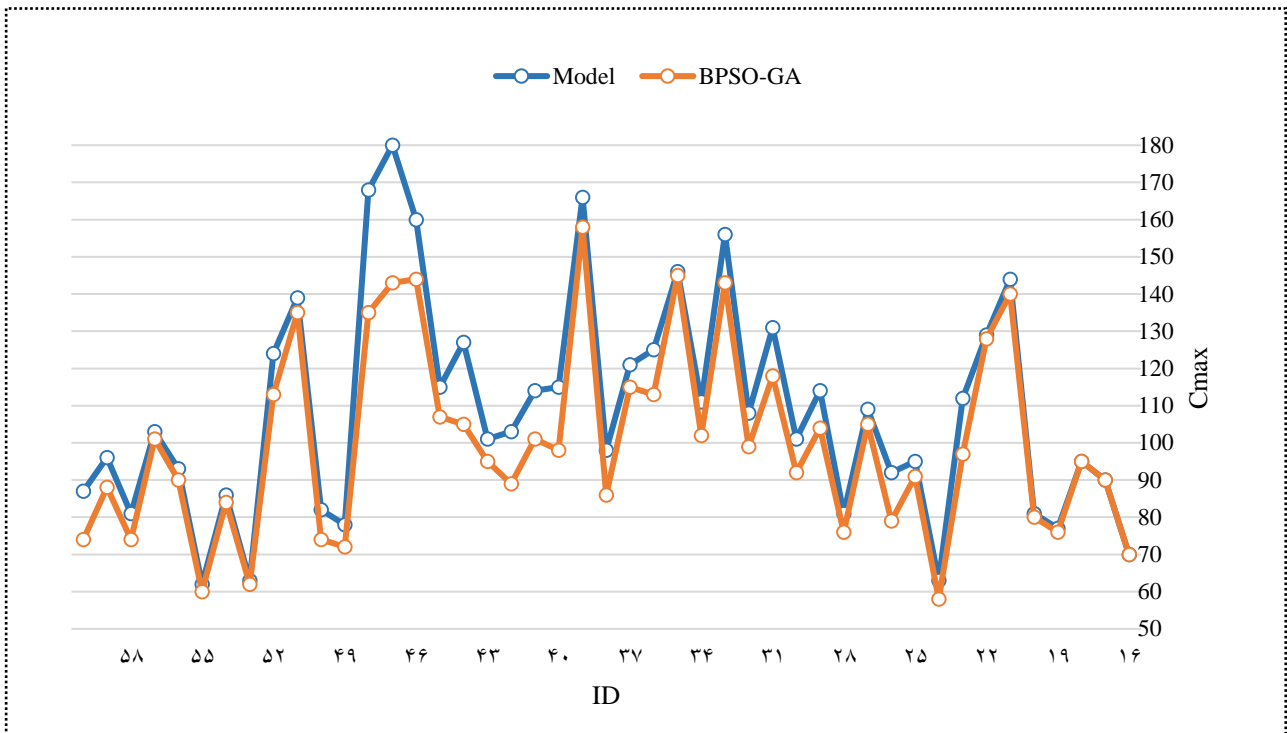


Figure 13. Comparison of the mathematical model and the proposed algorithm (IDs 16 to 60)

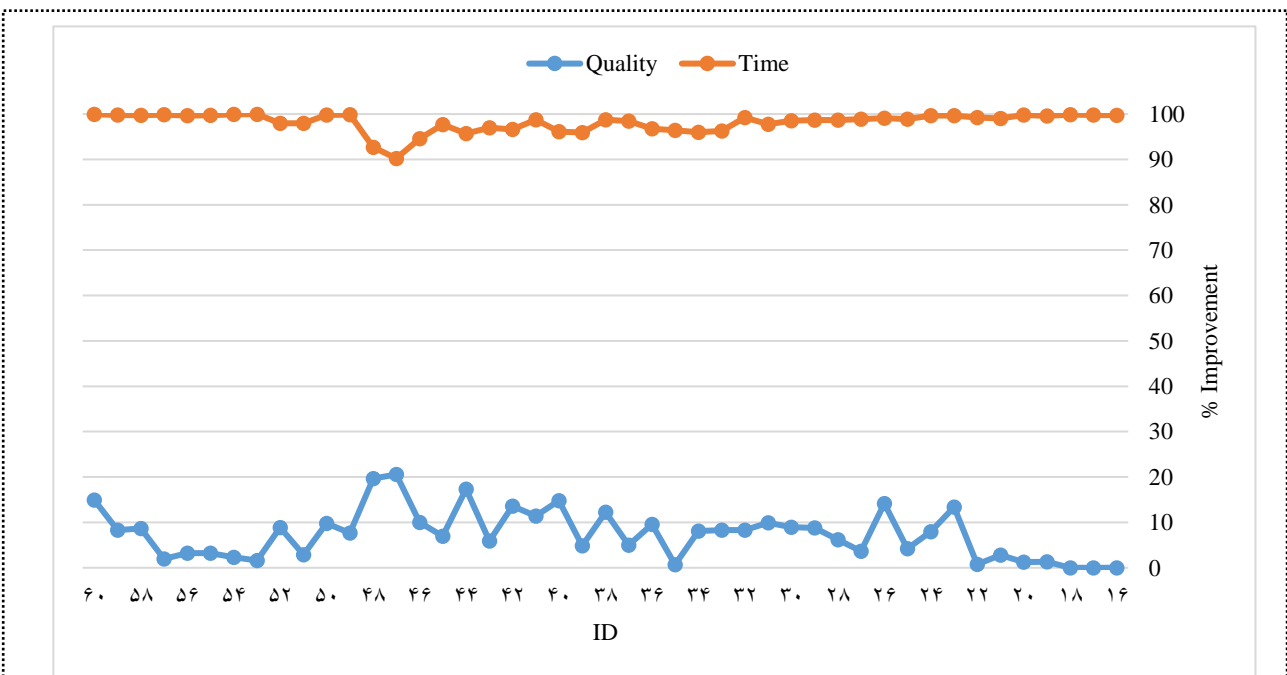


Figure 14. Improvements by BPSO-GA in comparison with the mathematical model (IDs 16 to 60)

V. CONCLUSION

We investigated a problem as an extension of the multi-mode resource-constrained production scheduling problems, in which the production process network had a number of flexible activities. Each flexible activity had multiple routes for its execution. A route could be seen as a smaller production process network with its activities and precedence relations while requiring the same resources in the overall problem. The production scheduling problem was examined by taking into account the resource constraints and multiple routes for implementing different sections. To solve the problem, known as RCPSP-MR in production environments, a new mathematical model of Mixed-Integer Non-Linear Programming (MINLP) was provided. Solving the mathematical model by the optimization software (e.g., GAMS) was very time consuming for large-size problems. Therefore, to achieve near-optimal solutions, an algorithm known as BPSO-GA was proposed to acquire high-quality solutions in an acceptable amount of time. The presented BPSO-GA for problem solving consisted of two general sections and successive repetitions of these two sections led to near-optimal and appropriate solutions. The novelties of this research were: 1) considering flexibility in operation network of products, 2) combining multiple routes for parts of the operation network and multiple skills for renewable resources in RCPSPs, 3) new modeling for the aforementioned type of problems by determining the sequencing operations by renewable resources, 4) handling both production and project fields, and 5) presenting a new hybrid meta-heuristic approach to solving problems in various scales. To study the quality of the proposed mathematical modeling for the RCPSP-MR problem and the performance of the proposed solving algorithm, 60 test problems were provided. The problems were designed by the presented mathematical model and solved by GAMS optimization software as well as the proposed solving algorithm. The results indicated that the presented solving approach had a good performance in terms of the quality of the solutions and the required time.

Since it is possible to face specific unexpected conditions in different time intervals, especially when performing some operations or considering processing times predicted by decision-makers, resource availability and cost usages for operations are open to changes. For this reason, considering the uncertainty in these problems is an important issue. On the other hand, resources used in these problems are mostly multi-skill machines and they need maintenance. Therefore, considering preventive and corrective maintenance between operations can be of importance in the future research. Moreover, some other practical constraints (such as sequence-dependent setup times or limited capacity of non-renewable resource) can be considered for the optimization of the RCPSP-MR model in production environments. Finally, in the proposed solving algorithm, the two phases are non-distinct. It means that, first, routes are assigned and then, sequencing is carried out and some interactions between the two phases are implemented. Developing an algorithm or the dispatching rules is recommended to involve the interactions between these two phases.

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