Developing simulation based optimization mechanism for a novel stochastic reliability centered maintenance problem

S.H.A. Rahmati, A. Ahmadi*, and B. Karimi

Department of Industrial Engineering and Management Systems, Amirkabir University of Technology, Tehran, Iran.

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Reliability-Centered Maintenance (RCM); Stochastic production model; Condition-Based Maintenance (CBM); Shocking mechanism; Biogeography Based Optimization (BBO).

Abstract. This research investigates joint scheduling of maintenance and production planning. This novel integrated problem takes benefit of Reliability-Centered Maintenance (RCM) for monitoring and managing maintenance function of a stochastic complex production-planning problem, namely, Flexible Job Shop scheduling Problem (FJSP). The developed RCM works based on stochastic shocking of machines during their process time. In fact, it implements condition based maintenance approach regulated according to stochastic reliability concept. Comparison of the system reliability with critical levels determines the failure status of the machines. It activates two main types of reaction called preventive and corrective maintenance. Considering breakdown of the system between inspection intervals makes the proposed model more realistic. Moreover, maintenance activity times and their duration are considered stochastically. Because of the high complexity level of this joint system, Simulation-Based Optimization (SBO) approach is proposed for solving the problem. This SBO searches the feasible area through Genetic Algorithm (GA) and Biogeography Based Optimization (BBO) algorithm. Different test problems, statistical methods, and novel visualizations are used to discuss the problem and the algorithm, explicitly.

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1. Introduction

Production plans and the maintenance activities are joint concepts in real world. However, most of the production and scheduling problems assume all times machine availability [1]. In contrast to this assumption, real world problems face many situations in which machines break down or need maintenance. [2]. Moreover, inefficient maintenance can cause one third of maintenance costs being wasted due to unnecessary or improper maintenance activities [3]. Nonetheless, maintenance issues are not a considerable portion of the literature on production and manufacturing problems.

On the other hand, maintenance and reliability have a significant share of the literature on modeling and optimization [4-9]. Thus, taking benefit of this opportunity to realize and reinforce production-planning problems is of interest. One of these opportunities is a method called Reliability Centered Maintenance (RCM). Actually, the main goal of this paper is consistent introducing of RCM to production problem because of its importance in real environment. RCM has various industrial applications in the maintenance and reliability literature, including power distribution systems, subsea pulpiness, steel plants, chemical indus-

* Corresponding author. Tel.: +98 21 64545 354
E-mail address: abbas.ahmadi@aut.ac.ir (A. Ahmadi)

try, transportation, water distribution, and concrete bridge decays inspection [10-15].

RCM functionally controls the systems to reach a desired level by monitoring their reliability [16]. Moreover, it prioritizes maintenance activities by ranking the failures according to their effects on system reliability. In fact, RCM continuously monitors the reliability of the system and determines type of the required maintenance activities according to the levels of reliability [16]. Condition-Based Maintenance (CBM), in many cases, conducts the task of monitoring. CBM development owes to the recent emerging technologies such as radio frequency identification (RFID), Micro-Electro-Mechanical System (MEMS), wireless telecommunication, and Product Embedded Information Devices (PEID) [17]. In the next subsection, the literature on joint scheduling of maintenance and production planning is reviewed.

1.1. Integration of maintenance and general production problems


Chosikhi et al. [49] integrated a single-unit system with CBM and optimized the cost of maintenance and inspection time by determining the optimal inspection. They assumed that both corrective and preventive maintenance actions were perfect, which means after such actions, the system became as good as the new one. Besides, they assumed that durations of inspection, corrective maintenance, and preventive maintenance could be negligible. Kim and Ozturkoglu [50] developed a joint scheduling of single machine problem with multiple preventive maintenances. They proposed ant colony optimization and particle swarm optimization in order to solve this problem. Ying et al. [51] introduced different SMPs considering maintenance activity between two sequential jobs. Lin et al. [52] evaluated reliability of a multistate FFlexible FSSP with stochastic capacity. Huang and Yu [53] developed a two-stage multiprocessor FSSP with maintenance and clean production aims. Cui and Lu [54] investigated flexible maintenance in SMPS and solved their problem through the Earliest Release Date-Longest Processing Time (ERD-LPT), and Branch and Bound (B&B) algorithm.
1.2. Integration of maintenance and Flexible Job Shop scheduling Problem (FJSP)

Flexible job shop scheduling problem is a popular and complex flexible manufacturing problem [55,56]. In classical FJSP, most researches assume that all machines are available during their working process. Both areas of the optimization problems, i.e., model development [57-61] and solving method extension [62-76], can be found in the classical literature on FJSP. Demir and Isleyen [77] performed a comprehensive evaluation of the various mathematical models presented for the FJSP.

Zribi and Borne [78] assumed unavailability of machines due to preventive maintenance. Gao et al. [79] proposed preventive maintenance for FJSP in which the period of maintenance tasks was non-fixed and should be determined during the scheduling procedure. Wang and Yu [80] developed FJSP considering maintenance activities either in a time window or fixed beforehand. Moradi et al. [81] integrated FJSP and preventive maintenance by optimizing unavailability and makespan. Mohktari and Dadgar [82] introduced a joint FJSP and PM model that assumed the failure rates were time varying. In their model, the duration of PM activities was fixed. Aghamiri et al. [83] studied random machine breakdown in FJSP with simulation considerations. The related important studies are summarized in Table 1.

1.3. Gap analysis

According to the literature, a rare portion of the production studies is devoted to FJSP, CBM, and RCM. Therefore, this research reinforces FJSP problem through RCM concept. Real world assumptions, rarely considered in the literature, are assumed in the developed RCM. For instance, breakdown possibility is assumed between inspection intervals. Also, this study considers maintenance occurrence and duration time stochastically. In addition, it stochastically assumes recovery level of the system after preventive maintenance. Moreover, we use both types of maintenance strategies, called Corrective Maintenance (CM) and Preventive Maintenance (PM). CBM is used to detect the level of reliability [84].

The structure of the paper is as follows. Section 2 presents the related literature review of the problem. Section 3 discusses the elements of the proposed joint problem. The simulation-based approach related to the proposed RCM is developed in Section 4. Section 5 presents the proposed problem and its solving methodology through numerical examples. Finally, Section 7 concludes the paper.

2. Preliminaries of the developed joint problem

The considered production problem is a stochastic version of the simple FJSP. FJSP has two tasks, namely, allocating operations to machines and determining the sequence of allocated operations to each machine [72,79]. Simple FJSP consists of \( n \) jobs, \( J \) (\( J_i, i \in \{1, 2, \ldots, n\} \)); each job, \( i \) (\( J_i \), \( \ldots, J_n \)), includes \( n_i \) operations, \( O(O_{ij}, j \in \{1, 2, \ldots, n_i\}) \), that are processed on \( m \) machines, \( M(M_k, k \in \{1, 2, \ldots, m\}) \). The FJSP objective function of this paper is makespan (\( C_{\text{max}} \)) given below:

\[
C_{\text{max}} = \max\{C_k|k = 1, \ldots, n\},
\]

where \( C_k \) denotes completion time of machine \( k \) [74].

Figure 1 illustrates the FJSP example with 3 jobs, 4 machines, and 9 operations. This figure includes a table and a related Gant chart. In the table, the numbers present the processing times of operations on machines in addition to their sets of capable machines. The

![Figure 1. The machine capability table and Gant chart of a related feasible solution.](image-url)
<table>
<thead>
<tr>
<th>Ref. #</th>
<th>Year</th>
<th>Scheduling types</th>
<th>Objectives</th>
<th>Types of maintenance</th>
<th>Solving methodologies</th>
<th>Meta-heuristics</th>
<th>Exact</th>
<th>SBO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grave and Lee [18]</td>
<td>1999</td>
<td>Single machine</td>
<td>$C_{max}$, Lateness</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cassidy and Kutanoglu [27]</td>
<td>2005</td>
<td>Single machine</td>
<td>TWCT</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td>TE</td>
<td></td>
</tr>
<tr>
<td>Sortrakul et al. [28]</td>
<td>2005</td>
<td>Single machine</td>
<td>TWCT</td>
<td>*</td>
<td></td>
<td></td>
<td>GA</td>
<td></td>
</tr>
<tr>
<td>Maunier et al. [30]</td>
<td>2005</td>
<td>Single machine &amp; job shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
<td>B&amp;B</td>
</tr>
<tr>
<td>Chen [34]</td>
<td>2008</td>
<td>Single machine</td>
<td>$C_{max}$</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chen [40]</td>
<td>2009</td>
<td>Single machine</td>
<td>$C_{max}$</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td>B&amp;B</td>
<td></td>
</tr>
<tr>
<td>Pan et al. [42]</td>
<td>2010</td>
<td>Single machine</td>
<td>MWT</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low et al. [43]</td>
<td>2010</td>
<td>Single machine</td>
<td>$C_{max}$</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kim and Ozturkoglu [50]</td>
<td>2013</td>
<td>Single machine</td>
<td>$C_{max}$, TCT</td>
<td>*</td>
<td></td>
<td></td>
<td>GA</td>
<td></td>
</tr>
<tr>
<td>Ying et al. [51]</td>
<td>2016</td>
<td>Single machine</td>
<td>T, ML, TFT, MT</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cui &amp; Lu [54]</td>
<td>2017</td>
<td>Single machine</td>
<td>*</td>
<td></td>
<td></td>
<td>B&amp;B, ERD-LPT</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lin and Liao [52]</td>
<td>2007</td>
<td>Parallel machine</td>
<td>$C_{max}$</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liao and Sheen [55]</td>
<td>2008</td>
<td>Parallel machine</td>
<td>$C_{max}$</td>
<td>*</td>
<td></td>
<td></td>
<td>BSA</td>
<td></td>
</tr>
<tr>
<td>Berrih et al. [56]</td>
<td>2009</td>
<td>Parallel machine</td>
<td>$C_{max}$, Unavailability</td>
<td>*</td>
<td></td>
<td></td>
<td>NSGAII</td>
<td></td>
</tr>
<tr>
<td>Mellouli et al. [50]</td>
<td>2009</td>
<td>Parallel machine</td>
<td>TCT</td>
<td>*</td>
<td></td>
<td></td>
<td>DP, B&amp;B</td>
<td></td>
</tr>
<tr>
<td>Lee [19]</td>
<td>1999</td>
<td>Flow shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td>DP</td>
<td></td>
</tr>
<tr>
<td>Espinouse et al. [19]</td>
<td>2001</td>
<td>Flow shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chiang and Liu [20]</td>
<td>2003</td>
<td>Flow shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggoun et al. [25]</td>
<td>2004</td>
<td>Flow shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td>TS GA</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aliabadi and Artaba [26]</td>
<td>2004</td>
<td>Flow shop</td>
<td>Flow time</td>
<td>*</td>
<td>Heuristic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ruiz et al. [33]</td>
<td>2007</td>
<td>Flow shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td></td>
<td></td>
<td>Random, NEH, SA, GA, ACO</td>
<td></td>
</tr>
<tr>
<td>Safari et al. [44]</td>
<td>2010</td>
<td>Flow shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td>SA-TS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Naderi et al. [38]</td>
<td>2009</td>
<td>Flexible flow shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td>AIS, GA</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Huang &amp; Yu [56]</td>
<td>2016</td>
<td>Flow shop</td>
<td>$C_{max}$</td>
<td>*</td>
<td></td>
<td></td>
<td>PSO, ACO</td>
<td></td>
</tr>
</tbody>
</table>
Table 1. Literature review of the integration of scheduling and maintenance (continued).

<table>
<thead>
<tr>
<th>Ref. #</th>
<th>Year</th>
<th>Scheduling types</th>
<th>Objectives</th>
<th>Types of maintenance</th>
<th>Solving methodologies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zribi et al. [34]</td>
<td>2008</td>
<td>Job shop</td>
<td>$C_{\text{max}}$</td>
<td>*</td>
<td>Heuristic GA</td>
</tr>
<tr>
<td>Mati [38]</td>
<td>2010</td>
<td>Job shop</td>
<td>$C_{\text{max}}$</td>
<td>*</td>
<td>Heuristic</td>
</tr>
<tr>
<td>Ben Ali [40]</td>
<td>2011</td>
<td>Job shop</td>
<td>$C_{\text{max}}$, Cost</td>
<td>*</td>
<td>MOEA</td>
</tr>
<tr>
<td>Zhou et al. [47]</td>
<td>2012</td>
<td>Job shop</td>
<td>$C_{\text{max}}$, Cost</td>
<td>*</td>
<td>DP</td>
</tr>
<tr>
<td>Zribi and Borne [78]</td>
<td>2005</td>
<td>FJSP</td>
<td>$C_{\text{max}}$</td>
<td>*</td>
<td>Hybrid GA</td>
</tr>
<tr>
<td>Gao et al. [72]</td>
<td>2006</td>
<td>FJSP</td>
<td>$C_{\text{max}}$, TWL, CWL</td>
<td>*</td>
<td>GA</td>
</tr>
<tr>
<td>Wang and Yu [50]</td>
<td>2010</td>
<td>FJSP</td>
<td>$C_{\text{max}}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moradi et al. [74]</td>
<td>2015</td>
<td>FJSP</td>
<td>$C_{\text{max}}$, Unavailability</td>
<td>*</td>
<td>NSGAII</td>
</tr>
<tr>
<td>Mohababi and Dada [62]</td>
<td>2015</td>
<td>FJSP</td>
<td>$C_{\text{max}}$</td>
<td>*</td>
<td>SA</td>
</tr>
<tr>
<td>Ahmadi et al. [83]</td>
<td>2016</td>
<td>FJSP</td>
<td>$C_{\text{max}}$, Stability</td>
<td>*</td>
<td>NSGAII, NPGA</td>
</tr>
<tr>
<td>This Study</td>
<td></td>
<td>FJSP</td>
<td>$C_{\text{max}}$</td>
<td>*</td>
<td>BBO &amp; GA</td>
</tr>
</tbody>
</table>

The symbol ‘$inf$’ implies that the machine cannot operate the corresponding operation. The Gantt chart depicts combination of the sequence and the assignment for a sample solution.

This research realizes the basic FJSP production-planning problem through considering the real stochastic nature of the maintenance function. The main concept of the proposed approaches is RCM. RCM determines and classifies the failure modes and tries to keep the reliability of the system in a level that the occurrence of these modes is prevented [16]. In fact, it monitors the system status predictively to recognize the mode and do the required qualified actions in consequence [85-87].

The monitoring mechanism of the proposed RCM is based on the CBM approach. CBM determines the maintenance activities according to the actual condition of the systems [85]. In addition, the developed RCM mimics the faulting process [86] that degrades the considered reliability function of the machines, stochastically. In other words, CBM monitors the reliability degradation caused by stochastic shocking process. Simultaneously, it predicts and determines the appropriate maintenance actions according to the reliability status of the machines [16,85]. The failures considered in the research are of both types of CM and PM. Now, in case the reliability status falls beneath the first critical threshold, $L$, CBM suggests to have PM, and if it gets inferior to failure rate $LL$, a failure or breakdown occurs [87].

Figure 2 illustrates reliability deteriorating and failure modes, schematically. This figure plots the manner of reliability from two aspects. In the upper part, it introduces the stochastic variables of the problem, while in the lower part, on a generally similar figure, it focuses on the maintenance activities according to the state of reliability. The $S$ values in the figure denote the shock times that reduce machine reliability within simulation process. This example encompasses seven shocks, i.e., $S1$ to $S7$, presented on the horizontal axis. The $M$ values, i.e., $M1$ and $M2$, denote the time of the $j$th maintenance activity on the machine.

After shocks $S1$ to $S3$, reliability of the machine is still higher than $L$. Therefore, the machine does not require maintenance activity. Then, the fourth stochastic shock ($S4$) decreases the reliability of machine to the preventive maintenance bound $L$. Therefore, on the inspection time of $2T$, the PM maintenance activity is recognized. The PM maintenance activity recovers and improves the degradation level in $M1$. The machine works at this level of reliability until $S5$ occurs. Since the reliability level of machine after
Figure 2. The maintenance activities due to the degradation level.

Calculate the reliability level of machines \( \text{Rel}(m) \) in each new sample time

\[
\begin{align*}
\text{If } \text{Rel}(m) & \geq L \\
\text{Rel}(m)_{\text{new}} &= \text{Rel}(m)_{\text{old}} \\
\text{Else if } LL \leq \text{Rel}(m) & \leq L \\
\text{Rel}(m)_{\text{new}} &= \text{Rel}(m)_{\text{old}} + \text{RLPM} \\
\text{Else} \\
\text{Rel}(m)_{\text{new}} &= \text{Rel}(m)_{\text{old}} + \text{RLCM} = 1
\end{align*}
\]

End
End

Figure 3. The proposed reliability modification model.

shock \( S5 \) is higher than \( L \), no maintenance activity is required. However, \( S6 \) degrades the machine to even less than \( LL \); thus, corrective maintenance should be done. This corrective maintenance has two main distinctive differences with PM, namely 1) happening between the inspection intervals that cause breakdown of the machines, and 2) improving the reliability to a new machine reliability level or reliability zero in \( M2 \).

In Figure 2, the number represents the stochastic event types that occur during the working process of the machine as follows.

Number 1 is a stochastic variable that denotes machine reliability level \( (\text{Rel}(m)) \) or rel and follows exponential distribution with parameter \( (RL \sim \text{Exp}(\eta)) \). In fact, this number is a function of degradation of machine at each time \( (D_m(t)) \) according to the function in Eq. (2). In this equation, \( \beta_0 \) and \( \beta_1 \) are reliability deterioration rates and weighted average of critical levels, i.e., \( DM = (L + 4LL)/5 \). Machine degradation \( (DL_{eq}) \) or \( D_m(t) \) follows exponential distribution with parameter \( (DL_{eq} \sim \text{Exp}(\eta)) \). It should be noticed that in the equations of this paper, \( DL_{eq} \) and \( D_m(t) \) denote machine degradation and RL and \( \text{Rel}(m) \) denote machine reliability:

\[
\text{Rel}(m)(t) = \frac{e^{-\beta_0 D_m(t)}}{1 + e^{\beta_1 (D_m(t) - DM)}}.
\]

Number 2 denotes PM Duration (PMD) and it follows lognormal distribution (PMD \( \sim \) log normal\( (\mu_{PM}, \sigma_{PM}) \)).

Number 3 represents the improving or recovery level through PM (RLPM) activity, calculated through Eq. (3), and it follows lognormal distribution (RLPM – log normal\( (\mu_{PM'}, \sigma_{PM'}) \)).

\[
\text{Rel}_{\text{new}} = \text{Rel}_{old} + \text{RLPM}.
\]

\[
LL \leq \text{Rel}_{old} \leq L.
\] (3)

Number 4 denotes the CM Duration (CMD) and it follows lognormal distribution (CMD \( \sim \) log normal\( (\mu_{CM}, \sigma_{CM}) \)).

Number 5 represents the improving or Recovery Level through CM (RLCM) activity, calculated through Eq. (4), that either entirely removes the reliability of machine or makes it one.

\[
\text{Rel}_{\text{new}} = \text{Rel}_{old} + \text{RLCM}; \quad \text{Rel}_{old} \leq LL.
\] (4)

Number 6 denotes the stochastic time between two shocks (TBS) and it follows an exponential distribution (TBS \( \sim \) Exp(\( \lambda \))).

Figure 3 illustrates a brief explanation of the explained reliability modification process.
### 3. Simulation-Based Optimization (SBO) algorithm

The proposed SBO has two main elements, namely, optimization algorithm and simulation process. Two different meta-heuristic algorithms, namely, GA and BBO, conduct the optimization algorithm. Accordingly, this section is classified into three parts. The first two parts introduce the mentioned elements, respectively, and the third one integrates the whole elements and operators with each other.

#### 3.1. Optimization algorithm of the SBO

Before developing the optimization algorithms, separately, let us explain them, comparatively. GA and BBO, as population-based algorithms, have many similarities. Both algorithms include a set of individuals, called chromosomes and habitats, respectively. The fitness values of the individuals are called fitness and High Suitability Index (HSI), respectively. Other detailed comparisons of the algorithms are provided in [84].

#### 3.1.1. The BBO algorithm

BBO mimics the migration term of biogeography science [88,89]. The solution or habitat structure in this paper is a vector equal in length to the number of operations or total number of operations (TNOP). Each cell of this vector is an ordered pair in which the upper object is the operation name and the lower object is the assigned machine to that operation. Moreover, the first row of the solution structure shows the sequence of operations for operating on machines. Figure 4 illustrates a sample of solution structure related to the Gantt chart of Figure 1.

BBO implements different strategies in its mutation operator. In Sequencing Sub-Vector (SSV), it applies a hybrid strategy, including swap, reversion, and insertion, through a random process, as shown in Figure 5.

For the assignment sub-vector (MASV), BBO performs through machine changing from the capable table of each operation as in Figure 6.

For executing the migration, in sequencing part, permutation operator conducts the migration as in

---

**Figure 4.** The proposed solution habitat (solution) vector of the example in Figure 1.

**Figure 5.** The proposed hybrid SSV operator of the habitat.

---

<table>
<thead>
<tr>
<th>Habitat sequence</th>
<th>O₁₁</th>
<th>O₁₂</th>
<th>O₁₃</th>
<th>O₂₁</th>
<th>O₂₂</th>
<th>O₂₃</th>
<th>O₃₁</th>
<th>O₃₂</th>
<th>O₃₃</th>
</tr>
</thead>
<tbody>
<tr>
<td>Habitat machine assignment</td>
<td>M₁</td>
<td>M₂</td>
<td>M₃</td>
<td>M₄</td>
<td>M₅</td>
<td>M₆</td>
<td>M₇</td>
<td>M₈</td>
<td>M₉</td>
</tr>
</tbody>
</table>

\[
/\text{Generate a random number between 1 and 3 and call it Rand1/} \\
/\text{Generate a random permutation with TNOP and call it Randperm1/} \\
\]

If Rand1 = 1

- Execute swap operator
  \[
  a_1=\text{Randperm1(1)} \\
  a_2=\text{Randperm1(2)} \\
  SSV_1=SSV \\
  SSV_1(a_1)=SSV(a_2) \\
  SSV_1(a_2)=SSV(a_1)
  \]

Else if Rand1 = 2

- Execute reversion operator
  \[
  b_1=\text{min}\{\text{Randperm1(1)}, \text{Randperm1(2)}\} \\
  b_2=\text{max}\{\text{Randperm1(1)}, \text{Randperm1(2)}\} \\
  SSV_1=SSV \\
  \text{Reverse the order of the objects placed between the } b_1 \text{ and } b_2 \text{ in } SSV_1 \text{ or } SSV_1(b_1:b_2)=SSV(b_2\cdot1:b_1)
  \]

Else Rand1 = 3

- Execute insertion operator
  \[
  c_1=\text{Randperm1(1)} \\
  c_2=\text{Randperm1(2)} \\
  \text{if } C_1<C_2 \\
  SSV_1=\{SSV(1:c_1) \text{ SSV}(c_2 \text{ SSV}(1+c_1:c_2-1) \text{ SSV}(c_2+1:\text{end})} \\
  \text{else} \\
  SSV_1=\{SSV(1:c_2-1) \text{ SSV}(c_2+1\cdot c_1) \text{ SSV}(c_2 \text{ SSV}(1+c_1:\text{end})}
  \]
Figure 6. MASV operator of BBO.

<table>
<thead>
<tr>
<th>Habitat sequence</th>
<th>M₀</th>
<th>M₁</th>
<th>M₂</th>
<th>M₃</th>
<th>M₄</th>
<th>M₅</th>
<th>M₆</th>
<th>M₇</th>
</tr>
</thead>
<tbody>
<tr>
<td>Habitat machine assignment</td>
<td>M₀</td>
<td>M₁</td>
<td>M₂</td>
<td>M₃</td>
<td>M₄</td>
<td>M₅</td>
<td>M₆</td>
<td>M₇</td>
</tr>
</tbody>
</table>

<table>
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<th>M₁</th>
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<th>M₃</th>
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<th>M₇</th>
</tr>
</thead>
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<td>M₃</td>
<td>M₄</td>
<td>M₅</td>
<td>M₆</td>
<td>M₇</td>
</tr>
</tbody>
</table>

Figure 7. Proposed migration of sequencing.

Figure 8. Proposed migration of assignment.

Figure 7, and in assignment part, mask operator plays the role as in Figure 8.

3.1.2. The Genetic Algorithm (GA) operators

GA implements reproduction, mutation, and crossover as the conductive operators for searching the search space. Reproduction operator copies a set of elite chromosomes to the next generation [90].

3.2. The simulation agent of the algorithm

As mentioned in the developed scheduling model, the proposed FJSP contains different stochastic components, such as RL, PMD, RLPM, CMD, RLCM, or TBS, to encompass a realistic version of the RCM. These variables change the states of the solutions dynamically.

SBO, as a powerful tool of optimization, is involved in almost every aspect of stochastic programming [84]. Two general classes of stochastic optimization problems exist in the literature, namely, the parametric (static) and the control (dynamic) ones. The static optimization includes a set of static parameters for all states. However, in the control optimization, solutions change according to dynamic states [84]. Here, because of the stochastic nature of problem, dynamic strategy controls the simulation process. Figure 9 plots the general structure of the proposed SBO.

The input to Figure 8 is a solution from the optimization process and its output is the simulated version of the objective function. This SBO conducts a loop of simulation runs (Nruns) to obtain average and standard deviation of solutions for reporting a more robust solution. In this flowchart, dt regulates sample time of the simulation. Moreover, VT and LVT denote predetermined length between visit times and the obtained last visit time, respectively. Besides, the terms IJS{j}(i), IJF{j}(i), and IMB(m) in Figure 10 to Figure 12 are binary logical variables that represent ‘is operation j of job i started,’ ‘is operation j of job i finished,’ and ‘is machine m busy,’ respectively.

The reliability updating function of Figure 10 determines the level of reliability for machines and the
maintenance decision. Figure 11 includes the logic of the maintenance decision determination.

According to schedules, machine and job status determination functions are activated as given in Figure 12 and Figure 13, respectively. These functions determine the start and finish status of jobs plus the business status of machines at each moment of simulation.

The job status function includes the shocking time determination functions. Figure 14 illustrates the proposed shocking logic. SBO at these shock times updates the reliability level of machines during the operating times for the related assigned operations. Certainly, they have impact on the types of the maintenance decisions according to the reliability level obtained after the shock times.

4. Computational results

This section provides us with the numerical examples of the problem to have a detailed view of the developed stochastic problem and the simulation based algorithms. The general information of these test problems is provided in Section 2 and their detailed descriptions are in a file, called RCM, placed in ResearchGate site of the first two authors. In this section, the proposed SBO is compared with Genetic Algorithm (GA).

4.1. Parameter tuning

Parameters of the algorithms are tuned through Taguchi method [91].

Tables 2 and 3 show the determined levels of parameters of BBO and GA.

4.2. Outputs of the algorithms

Tables 4 and 5 present the outputs of the algorithms for the developed stochastic problem for GA and BBO, respectively. Moreover, these tables include the results of the algorithms for simple version of the problem as
Figure 10. Proposed reliability updating function.

Figure 11. The proposed maintenance decision function.

Figure 12. The proposed machine status determination function.
Figure 13. The proposed job status determination function.

Figure 14. The proposed shock creation function.

<table>
<thead>
<tr>
<th>Table 2. The factor levels of BBO.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A:</strong></td>
</tr>
<tr>
<td>Iteration size</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>10</td>
</tr>
<tr>
<td>30</td>
</tr>
<tr>
<td>50</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3. The factor levels of GA.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A:</strong></td>
</tr>
<tr>
<td>Iteration size</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>10</td>
</tr>
<tr>
<td>30</td>
</tr>
<tr>
<td>50</td>
</tr>
</tbody>
</table>
Table 4. Outputs of the algorithms for test problems.

<table>
<thead>
<tr>
<th>Problem #</th>
<th>GA</th>
<th>BBO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$C_{maxMean}$</td>
<td>Time 1</td>
</tr>
<tr>
<td>FJSP1</td>
<td>108</td>
<td>440.02</td>
</tr>
<tr>
<td>FJSP2</td>
<td>193</td>
<td>924.09</td>
</tr>
<tr>
<td>FJSP3</td>
<td>93</td>
<td>683.67</td>
</tr>
<tr>
<td>FJSP4</td>
<td>146.7</td>
<td>728</td>
</tr>
<tr>
<td>FJSP5</td>
<td>167.7</td>
<td>1255.8</td>
</tr>
<tr>
<td>FJSP6</td>
<td>76</td>
<td>690.4</td>
</tr>
<tr>
<td>FJSP7</td>
<td>261.9</td>
<td>1277.74</td>
</tr>
<tr>
<td>FJSP8</td>
<td>169.2</td>
<td>1197.9</td>
</tr>
<tr>
<td>FJSP9</td>
<td>206.95</td>
<td>2702</td>
</tr>
<tr>
<td>FJSP10</td>
<td>204.05</td>
<td>2496.35</td>
</tr>
<tr>
<td>Average</td>
<td>168.655</td>
<td>1239.597</td>
</tr>
</tbody>
</table>

Table 5. Outputs of the algorithms for test problems.

<table>
<thead>
<tr>
<th>Problem #</th>
<th>GA</th>
<th>BBO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$C_{max}$</td>
<td>Time 2</td>
</tr>
<tr>
<td>FJSP1</td>
<td>108</td>
<td>2.17</td>
</tr>
<tr>
<td>FJSP2</td>
<td>149</td>
<td>2.65</td>
</tr>
<tr>
<td>FJSP3</td>
<td>93</td>
<td>2.67</td>
</tr>
<tr>
<td>FJSP4</td>
<td>133</td>
<td>2.73</td>
</tr>
<tr>
<td>FJSP5</td>
<td>154</td>
<td>3.66</td>
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<tr>
<td>FJSP6</td>
<td>76</td>
<td>6.02</td>
</tr>
<tr>
<td>FJSP7</td>
<td>203</td>
<td>6.82</td>
</tr>
<tr>
<td>FJSP8</td>
<td>130</td>
<td>7.45</td>
</tr>
<tr>
<td>FJSP9</td>
<td>167</td>
<td>11.37</td>
</tr>
<tr>
<td>FJSP10</td>
<td>154</td>
<td>11.7</td>
</tr>
<tr>
<td>Average</td>
<td>137.6</td>
<td>5.724</td>
</tr>
</tbody>
</table>

A lower bound validation. The lower bound model is the simple version of the FJSP with any stochastic parameter or maintenance consideration. Obviously, in such situation, both $C_{max}$ and execution time of the algorithm present lower bound values for the developed stochastic problem. The simple problem does not encounter PM, CM, or breakdown. Moreover, it does not need inspection. Therefore, $C_{max}$ values are only dependent on the main operations and are in the worst case equal to the stochastic version. In terms of execution time, low time is required for processing only some operations in comparison with the case in which different maintenance components are also inserted besides the operations.

In each table, for the main developed problem, because of the stochastic nature of the problems, each test problem is run several times and the average ($C_{maxMean}$), standard deviation of $C_{max}$ ($C_{maxSTD}$) values, and average execution times (Time) are reported. In the simple model part of the tables, $Diff1$ is difference value of $C_{max}$ in stochastic model and simple lower bound model (i.e., $Diff1 = C_{max_{Stochastic}} - C_{max}$). Similarly, $Diff2$ shows difference of time values of the models (i.e., $Diff2 = Time_{1} - Time_{2}$).

In both Tables 4 and 5, the last columns represent the average values of the columns. Since $C_{max}$, standard deviation, and time objective functions are all to be minimized, the smallest values are the best ones.

Figure 15 compares the algorithms regarding three metrics of average $C_{max}$ ($C_{maxMean}$), average time, and average standard deviation for the obtained simulated solutions. As it is clear, GA is better than BBO only in time metric. Figure 16 carries out the comparison of the obtained outputs from the

Figure 15. Comparison of algorithms for the stochastic problem with maintenance considerations.
algorithms for the deterministic version or the lower bound problem.

As can be seen in Figure 17, algorithms do not have difference on $C_{\text{max}}$. Besides, although they have the same trend in time, the vertical dimensions of the outputs of algorithms are different.

Tables 6 and 7 conduct the statistical tests for the simple and stochastic versions. In fact, they prove that the algorithms in terms of $C_{\text{max}}$ are non-dominated and in terms of time, GA is superior.

Figures 18 compares the convergence plots of GA and BBO for the stochastic and simple problems regarding the mentioned metrics. Moreover, the real-time novel reliability monitoring illustration is presented in Figure 19 for problem FJSP9. GA is used for drawing these figures. This developed and innovative figure illustrates the developed reliability-centered maintenance approach in detail. In this figures, whenever a task is assigned to a machine, its reliability decreases during the task operation. Then, according to the mentioned logic behind the PM and CM, suitable maintenance reaction is taken.

Table 6. T-test for comparing GA and BBO regarding the metrics of Table 4.

<table>
<thead>
<tr>
<th>Metric name</th>
<th>$P$-value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{\text{max}}$ ($C_{\text{max}, \text{st}}$)</td>
<td>0.943</td>
<td>They are not considerably different</td>
</tr>
<tr>
<td>Time 1</td>
<td>0.044</td>
<td>GA outperforms BBO</td>
</tr>
<tr>
<td>Standard deviation ($C_{\text{max,STD}}$)</td>
<td>0.150</td>
<td>They are not considerably different</td>
</tr>
</tbody>
</table>

Table 7. T-test for comparing GA and BBO regarding the metrics of Table 5.

<table>
<thead>
<tr>
<th>Metric name</th>
<th>$P$-value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{\text{max}}$</td>
<td>0.926</td>
<td>They are not considerably different</td>
</tr>
<tr>
<td>Time 2</td>
<td>0.000</td>
<td>GA outperforms BBO</td>
</tr>
</tbody>
</table>
4.3. Discussion

As mentioned in Figure 2, our RCM problem assumes two determining levels, i.e., $L$ and $LL$. These levels are tuned to 0.81 and 0.11, respectively. According to this figure, 6 stochastic components are considered in the proposed RCM to make it realistic. These components and variables are also shown in Figure 20 for the main selected problem of FJSP9. In fact, this figure is same as Figure 19, but in reliability part, it only reports the outputs of Machine 2 for presentation simplicity.

Number 1 or RL and number 6 or TBM in Figure 20 depict a set of reliability degradations and set of shocks, respectively, due to activation of operation 1.1 on Machine 2. However, since the values of these variables are very small, the associated values are presented all together for a specific operation. RL is regulated according to the function in Figures 3 and 10. Shock times of TBM are generated according to Figure 14. Besides, the (3) values show the effect of PM (RLPM) on the reliability level of machine and they cause PM with duration denoted by number 2. The PM occurs when the degradation level goes less than the $L$ level at the inspection times or before them. Inspection times are presented in Gant chart part of the figure. CM recovery levels (RLCM) and their durations are pointed by numbers 5 and 4, respectively. CM happens when the reliability level violates $LL$ level. Activation of PM or CM and their durations are denoted by the maintenance decision function given in Figure 11. In the Gant chart part of the figure, machines and jobs
are scheduled through Figures 12 and 13, respectively. Figure 9 manages the whole simulation task.

Numbers 7 and 8 in this figure show the wasted time according to the maintenance requirement recognized with the autonomous detection engine of the simulation algorithm. It means that during the periods shown by numbers 7 and 8, operations \( O_{3,3} \) and \( O_{4,4} \) have been started, respectively, since they were degraded in the reliability figure. However, since their reliability levels have become less than \( LL \) and \( L \), respectively, they require CM and PM. Therefore, their main operations are interrupted and the maintenance operations are started. Certainly, since the jobs are not resumable in our problem, they are started from the beginning after their maintenance activities. To sum up, these figures prove that the designed algorithm can control the process autonomously.

5. Conclusion

This research focused on the maintenance consideration in production problems. A stochastic FJSP was developed by considering a modern maintenance system called RCM. This autonomous RCM monitored reliability level permanently and decided which maintenance activity should be done. Since the developed problem needed real-time checking of stochastic events, it was so complicated. Therefore, two SBO mechanisms, namely, GA and BBO, were developed to conduct the optimization problem. The required main and sub functions of the proposed algorithms were described in detail with sufficient examples. According to the results, the proposed RCM took benefit from its considered CBM concept properly. More importantly, it handled the considered assumptions and constraints during the optimization process completely. Moreover, different innovative and novel visualization techniques illustrated the proposed logics of the stochastic problem explicitly. Future work following this research may control the cost term of the maintenance within a multi-objective problem or develop other stochastic techniques, based on decomposition, to handle the same problem.

References


40. Chen, W.J. “Minimizing number of tardy jobs on a single machine subject to periodic maintenance”, Omega, 37, pp. 592-599 (2009).


**Biographies**

**Seyed Habib Rahmati** received the BSc and MSc degrees in Industrial Engineering in 2007 and 2010, respectively, from Qazvin Islamic Azad University (QIAU). Now, he is PhD Candidate in Industrial Engineering at Amir Kabir University of Technology. He joined the Qazvin Islamic Azad University (QIAU) in 2012 as faculty member of the Department of Industrial and Mechanical Engineering. His research interests are in stochastic optimization, maintenance and reliability models, scheduling, supply chain management, and business intelligence.

**Abbas Ahmadi** received the BSc degree in Industrial Engineering in 2000 from Amir Kabir University of
Technology, MSc degree in Industrial Engineering in 2002 from Iran University of Science and Technology, and PhD degree in Systems Design Engineering in 2008 from University of Waterloo. He joined Amirkabir University of Technology, Iran, in 2009, where he is at present Professor in the Department of Industrial Engineering and Management Systems. Dr. Ahmadi’s research interests are in supply chain management, business intelligence, swarm intelligence, computational intelligence, data and information management, system analysis and design, and cooperative intelligent systems. He has authored and co-authored several papers in journals and conference proceedings, chapters in books, and numerous technical and industrial project reports. Under his supervision, several students have completed their degrees.

Behrooz Karimi is Professor in the Department of Industrial Engineering and Management Systems at Amirkabir University of Technology. He received his BSc degree in Industrial Engineering in 1990 from Amirkabir University of Technology, MSc degree in Industrial Engineering in 1994 from Iran University of Science and Technology, and PhD degree in Industrial Engineering in 2001 from Amirkabir University of Technology. Dr. Karimi’s research interests are in supply chain management, computational intelligence, meta-heuristic, inventory control, and production planning.