The current issue and full text archive of this journal is available on Emerald Insight at:
**www.emeraldinsight.com/0265-671X.htm**



Received 15 February 2018
Revised 1 November 2018
25 December 2018
Accepted 3 January 2019

RELIABILITY PAPER

# Performance modeling and optimization for complex repairable system of paint manufacturing unit using a hybrid BFO-PSO algorithm

Amit Kumar
*Department of Mechanical Engineering,*
*Seth Jai Parkash Mukand Lal Institute of Engineering and Technology,*
*Yamunanagar, India*
Vinod Kumar
*Department of Mechanical Engineering,*
*National Institute of Technology Kurukshetra, Kurukshetra, India, and*
Vikas Modgil
*Department of Mechanical Engineering,*
*DeenBandhu Chhotu Ram University of Engineering and Technology, Sonipat, India*

## Abstract

**Purpose** – The purpose of this paper is to optimize the performance for complex repairable system of paint manufacturing unit using a new hybrid bacterial foraging and particle swarm optimization (BFO-PSO) evolutionary algorithm. For this, a performance model is developed with an objective to analyze the system availability.

**Design/methodology/approach** – In this paper, a Markov process-based performance model is put forward for system availability estimation. The differential equations associated with the performance model are developed assuming that the failure and repair rate parameters of each sub-system are constant and follow the exponential distribution. The long-run availability expression for the system has been derived using normalizing condition. This mathematical framework is utilized for developing an optimization model in MATLAB 15 and solved through BFO-PSO and basic particle swarm optimization (PSO) evolutionary algorithms coded in the light of applicability. In this analysis, the optimal input parameters are determined for better system performance.

**Findings** – In the present study, the sensitivity analysis for various sub-systems is carried out in a more consistent manner in terms of the effect on system availability. The optimal failure and repair rate parameters are obtained by solving the performance optimization model through the proposed hybrid BFO-PSO algorithm and hence improved system availability. Further, the results obtained through the proposed evolutionary algorithm are compared with the PSO findings in order to verify the solution. It can be clearly observed from the obtained results that the hybrid BFO-PSO algorithm modifies the solution more precisely and consistently.

**Research limitations/implications** – There is no limitation for implementation of proposed methodology in complex systems, and it can, therefore, be used to analyze the behavior of the other repairable systems in higher sensitivity zone.

**Originality/value** – The performance model of the paint manufacturing system is formulated by utilizing the available uncertain data of the used manufacturing unit. Using these data information, which affects the performance of the system are parameterized in the input failure and repair rate parameters for each sub-system. Further, these parameters are varied to find the sensitivity of a sub-system for system availability among the various sub-systems in order to predict the repair priorities for different sub-systems. The findings of the present study show their correspondence with the system experience and highlight the various availability measures for the system analyst in maintenance planning.

**Keywords** PSO, Sensitivity analysis, Markov process, BFO-PSO, Long-run availability, Paint manufacturing system

**Paper type** Research paper

International Journal of Quality & Reliability Management
Vol. 36 No. 7, 2019
pp. 1212-1228

0265-671X
DOI 10.1108/IJQRM-02-2018-0041

**Nomenclature**

| | |
|---|---|
| A, B, C, D, E | Full capacity working state |
| $D^1$, $E^1$ | Reduced capacity working state |
| a, b, c, d, e | Failed state |
| $\lambda_1$, $\lambda_2$, $\lambda_3$, $\lambda_4$, $\lambda_5$ | Failure rate parameters of A, B, C, D and E, respectively |
| $\lambda_6$, $\lambda_7$ | Failure rate parameters of D and E in reduced capacity state |
| $\mu_1$, $\mu_2$, $\mu_3$, $\mu_4$, $\mu_5$ | Repair rate parameters of A, B, C, D and E, respectively |
| $\mu_6$, $\mu_7$ | Repair rate parameters of D and E in reduced capacity state |
| $P_0$ | Probability of full capacity working state |
| $P_1$ to $P_3$ | Probability of reduced capacity working state |
| $P_4$ to $P_{19}$ | Probability of failed state |
| $P_i'(t)$ | First-order derivative of $i$th state *w.r.t.* time $t$ |

## 1. Introduction

System availability is always being considered one of the major problems for the industries as it affects directly to the overall industrial performance in terms of maximum utilization of various operating systems. The inaccuracies in the maintenance planning highly influence the system performance and their effects become magnified with increased complexity of the system or the number of the sub-systems/machines used is large. The visual inspection is not enough for the system analyst to predict the perfect system behavior. It is also necessary to analyze all the factors which cause the system failures. These complex industrial systems are the main challenges for system analyst in maintaining the availability of various operating systems for a long period of time without failure. In recent years, evolutionary tools have become popular optimization methods to solve complex engineering problems of industrial systems (Garg and Rani, 2013). It predicts not only the system behavior but provides various availability measures to devise a suitable maintenance policy for better system performance. Therefore, several evolutionary tools have been applied to the complex engineering problems for the purpose of getting maximum performance by utilizing existing operating systems. Different aspects of availability analysis and performance optimization are explored in the literature. Arabi and Jahromi (2013) used the redundancy technique to improve system availability. The availability of the system is optimized considering the redundancy and repair facility allocation. Di Bona, Forcina and Silvestri (2016) applied a new approach based on integrated factor method for reliability allocation using an aerospace system prototype and compared with other traditional methods in order to validate the proposed method. Di Bona, Forcina, Petrillo, De Felice and Silvestri (2016) proposed a new reliability allocation method, i.e. critical flow method (CFM) for complex systems with series-parallel configuration and the proposed method is validated using a real case study of a cooling system through the comparison with conventional methods. (Garg, 2013; Garg and Sharma, 2012) analyzed the system behavior by utilizing the rough and imperfect data of the complex repairable system. They have used the Lambda–Tau technique for behavior analysis of the system whereas Garg and Rani (2013) presented the PSO and IFS technique for reliability analysis of the industrial system. Gupta *et al.* (2007) used the matrix method to solve the governing differential equations to analyze the system reliability and used Runge–Kutta fourth-order method to solve the same differential equations to verify the solution. Hajeeh (2015) developed the optimization models to study the perfect behavior of operating systems in order to maintain the balance between the cost and performance of the repairable system. Kachitvichyanukul (2012) reported the application of GA, PSO and DE algorithms using the different optimization problems with the same number of function evaluations. Kajal and Tewari (2012) proposed the GA approach for performance optimization in the dairy industry. Kennedy and Eberhart (1995) presented the particle swarm optimization (PSO) technique whose mechanics is inspired by the social behavior of the biological population. Khanduja *et al.* (2010; Khanduja *et al.*, 2011) developed the performance model in a paper plant and presented the GA technique for the optimization of system performance. Kora and Kalva (2015) proposed the hybrid BFPSO technique to detect the bundle branch block for heart circulatory system. Kumar and Garg (2016) applied the PSO technique to improve the availability of a repairable system in brewery plant. Kumar and Ram (2013) investigated the reliability and sensitivity analysis of a coal handling system of thermal power plant. Kumar *et al.* (2018) selected the ethanol manufacturing plant to demonstrate the application of PSO algorithm for performance optimization whereas Kumar and Tewari (2017) used the PSO technique to optimize the availability of various sub-systems in a beverage plant. Raju *et al.* (2018) used a hybrid PSO-BFO algorithm for the optimization of FDM process parameters in order to improve the mechanical and surface quality of complex objects manufactured through the 3D printer. Modgil *et al.* (2013) developed the performance model using Markov approach for the time-dependent system availability in a shoe industry. Pang (2015) proposed a new computer network technology based Markov model for failure prediction in a manufacturing industry. Rabbani *et al.* (2018) employed the GA and PSO algorithms to obtain the optimal value of design parameters of a CCHP system. Sharma and Vishwakarma (2014) described the GA approach for the availability optimization of refining system in the sugar industry. Yadav and Zhuang (2014) reported the effectiveness of a reliability allocation approach considering the modified criticality factors. A case example is considered to demonstrate the proposed approach.

Keeping in view the use of different evolutionary algorithms for parameter optimization in various industries, this paper proposed a new hybrid BFO-PSO algorithm for performance optimization of the complex industrial system. The main aim of the methodology presented in the paper is to optimize the performance for a multi-state repairable system of paint manufacturing unit. For this, a hybrid BFO-PSO algorithm is applied to obtain maximum system performance by rectifying the uncertain data up to a desired degree of accuracy. To explain the findings of this study computational results are presented in two sections. In the first section (4.1), the system behavior is analyzed to find the sensitivity of each sub-system for system availability. The second section (4.2) discusses the details of solving performance model through BFO-PSO and PSO algorithms. In this section, the optimal combinations of failure and repair rate parameters are obtained for various sub-systems in order to improve the system efficiency. The obtained results are highly useful for the system analyst in the development of suitable maintenance scheduling for maximum utilization of various operating systems, which finally leads to higher system performance.

## 2. System description

The liquid paint is a composite of mainly three constituents, i.e. pigments, binders and solvents (thinners). Some other additional additives are also blended in the solution to get the required properties for specific purposes or applications. Generally, paint is a blend of a finely divided pigment dispersed in a combination of different constitutes. The paint manufacturing system comprises following five sub-systems in series and parallel configuration. The schematic process flow diagram of the paint manufacturing system is shown in Figure 1:

(1) Sub-system A: it consists of a mixer which is used to achieve homogeneity between the different constituents. It is a single component and the failure of this component lead to complete failure of the system.

(2) Sub-system B: it consists of a grinding mill which is used for the grinding of composite solution in fine particles and also to improve its homogeneity. It is a

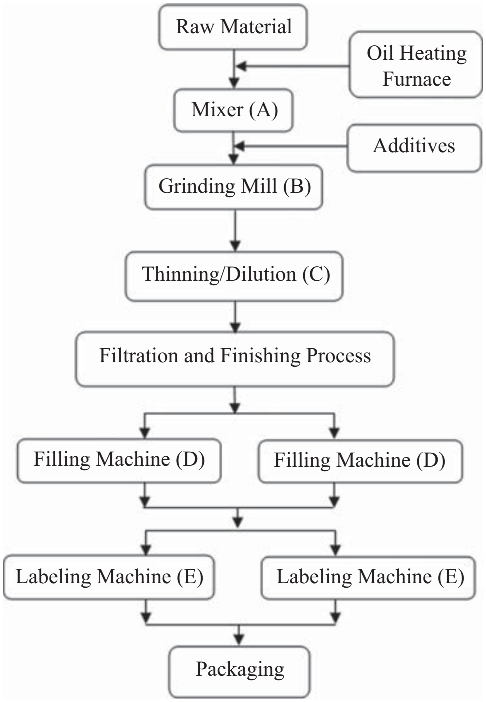


**Figure 1.** Schematic process flow diagram of paint manufacturing system

single component and the failure of this component lead to complete failure of the system.

(3) Sub-system C: it includes another mixer for thinning and dilution, where the solvents and other additives are added. It is a single component and the failure of this component lead to complete failure of the system.

(4) Sub-system D: it includes two filling machines which are arranged in parallel. In this sub-system, the empty containers are filled with the paint (final product). The failure of one component reduces the productive capacity of the unit. The complete failure occurs when both components remain in the failed state.

(5) Sub-system E: it consists of two labeling machines which are arranged in parallel. It is used for labeling the paint containers. The failure of one component reduces the productive capacity of the unit. The complete failure occurs when both components remain in the failed state.

The oil heating furnace and filtration/finishing process (Figure 1) never fail. So, it does not affect the performance of the system. The sub-system A, B and C are subjected to major failures while the sub-system D and E are subjected to minor failures. The major failures cause the complete failure of the system while the minor failures can be repaired during the reduced capacity working state.

### *2.1 Assumptions*

It is difficult to predict the future system behavior as all the collected information represents the past behavior of the system. Thus in order to find the optimal failure and repair rate parameters, the following assumptions are made to carry out the performance modeling of the paint manufacturing system:

- Failure and repair rate parameters of the sub-systems are statistically independent.
- Failure and repair rate parameters obey the exponential distribution.
- There are no simultaneous failures among the sub-systems.
- Repaired components are considered as good as new.
- Separate maintenance facility is available for each component. So, there is no waiting time for repair.
- All the components are initially operating and are in working state.
- The system may work as reduced capacity.

Based on the above assumptions and notations performance modeling and state transition diagram of the paint manufacturing system have been developed.

## 3. Methodology

### *3.1 Performance modeling*

The performance modeling of the system is carried out using simple probabilistic considerations and differential equations associated with the transition diagram are developed according to the mnemonic rule (Khanduja *et al.*, 2011). The performance modeling of the system is described in diagrammatic form (Figure 2), which is known as the state transition diagram. The State 0 represents the full capacity working state, the State 1–3 represents the reduced capacity working state and the State 4–19 represents the failed state. Probability considerations give the following differential equations associated with the transition diagram:

$$P_0'(t)+\sum_{i=1}^{5}\lambda_i P_0(t)=\sum_{i=1}^{3}\mu_i P_{i+3}(t)+\mu_4 P_1(t)+\mu_5 P_2(t), \tag{1}$$

$$P_1'(t)+\left(\sum_{i=1}^{3}\lambda_i+\sum_{i=5}^{6}\lambda_i+\mu_4\right)P_1(t)=\sum_{i=1}^{3}\mu_i P_{i+6}(t)+\mu_5 P_3(t)+\mu_6 P_{10}(t)+\lambda_4 P_0(t), \tag{2}$$

$$P_2'(t)+\left(\sum_{i=1}^{3}\lambda_i+\lambda_4+\lambda_7+\mu_5\right)P_2(t)=\sum_{i=1}^{3}\mu_i P_{i+10}(t)+\mu_4 P_3(t)+\mu_7 P_{14}(t)+\lambda_5 P_0(t), \tag{3}$$

$$P_3'(t)+\left(\sum_{i=1}^{3}\lambda_i+\sum_{i=6}^{7}\lambda_i+\sum_{i=4}^{5}\mu_i\right)P_3(t)=\sum_{i=1}^{3}\mu_i P_{i+14}(t)+\sum_{i=6}^{7}\mu_i P_{i+12}(t)+\lambda_4 P_2(t)+\lambda_5 P_1(t), \tag{4}$$

$$P_i'(t)+\mu_1 P_i(t)=\lambda_1 P_j(t)\quad \text{where } i=4,7,11,15 \text{ and } j=0,1,2,3, \tag{5}$$

$$P_i'(t)+\mu_2 P_i(t)=\lambda_2 P_j(t)\quad \text{where } i=5,8,12,16 \text{ and } j=0,1,2,3, \tag{6}$$

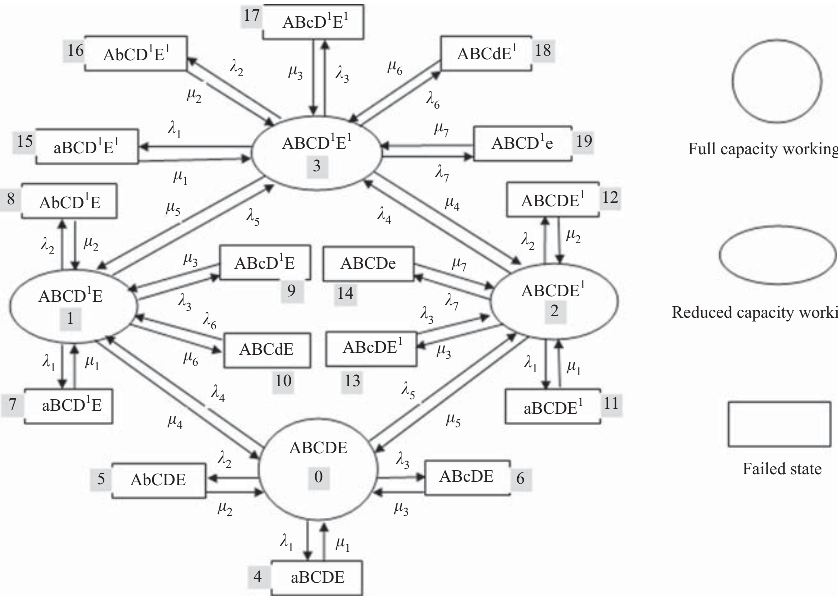


**Figure 2.**
State transition diagram of paint manufacturing system

$$P_i'(t)+\mu_3 P_i(t) = \lambda_3 P_j(t) \quad \text{where } i = 6, 9, 13, 17 \text{ and } j = 0, 1, 2, 3, \tag{7}$$

$$P_i'(t)+\mu_6 P_i(t) = \lambda_6 P_j(t) \quad \text{where } i = 10, 18 \text{ and } j = 1, 3, \tag{8}$$

$$P_i'(t)+\mu_7 P_i(t) = \lambda_7 P_j(t) \quad \text{where i} = 14, 19 \text{ and } j = 2, 3. \tag{9}$$

The initial conditions are:

$$P_i(0) = \begin{cases} 1, \text{if} i = 0 \\ 0, \text{if} i \neq 0 \end{cases}.$$

*3.1.1 Long-run availability*. All the sub-systems must be available for the long duration of time to achieve higher system performance. So, the long-run or steady-state availability of the system is computed by substituting steady-state conditions, i.e. *(P′)* → 0 as the time $t \to \infty$ for first-order differential Equations (1)–(9) and solving these equations recursively one gets:

$$P_1 = K_2 P_0 \quad P_2 = K_3 P_0 \quad P_3 = K_4 P_0$$

$$P_4 = M_1 P_0 \quad P_5 = M_2 P_0 \quad P_6 = M_3 P_0$$
$$P_7 = M_1 K_2 P_0 \quad P_8 = M_2 K_2 P_0 \quad P_9 = M_3 K_2 P_0$$
$$P_{10} = M_6 K_2 P_0 \quad P_{11} = M_1 K_3 P_0 \quad P_{12} = M_2 K_3 P_0$$
$$P_{13} = M_3 K_3 P_0 \quad P_{14} = M_7 K_3 P_0 \quad P_{15} = M_1 K_4 P_0$$

$$P_{16} = M_2K_4P_0 \quad P_{17} = M_3K_4P_0 \quad P_{18} = M_6K_4P_0$$
$$P_{19} = M_7K_4P_0,$$

where $M_i = \lambda_i/\mu_i$ $i = 1, 2, 3, 6, 7$ and:

$$K_2 = \left(\frac{\mu_5K_4}{V_1}\right)+\frac{\lambda_4}{V_1}, \ K_3 = \left(\frac{\mu_4K_4}{V_2}\right)+\frac{\lambda_5}{V_2}, \ K_4 = K_1/T_1, \ K_1 = \frac{\lambda_4\lambda_5}{V_2}+\frac{\lambda_5\lambda_4}{V_1},$$

$$T_1 = V_3-\frac{\lambda_4\mu_4}{V_2}-\frac{\lambda_5\mu_5}{V_1}, \ V_1 = \lambda_5+\mu_4, \ V_2 = \lambda_4+\mu_5, \ V_3 = \mu_4+\mu_5.$$

The probability of full capacity working state $P_0$ is obtained using normalizing condition i.e. the sum of all the state probabilities is equal to one:

$$\sum_{i=0}^{19} P_i = 1,$$

$$P_0 = \begin{bmatrix} 1+K_2+K_3+K_4+M_1+M_2+M_3+K_2(M_1+M_2+M_3+M_6) \\ +K_3(M_1+M_2+M_3+M_7)+K_4(M_1+M_2+M_3+M_6+M_7) \end{bmatrix}^{-1}.$$

The long-run availability ($A_{v.}$) of paint manufacturing system may be obtained by the summation of all the working and reduced capacity state probabilities, i.e.:

$$A_{v.} = P_0+P_1+P_2+P_3 = P_0(1+K_2+K_3+K_4). \tag{10}$$

The data collected from the maintenance history sheet is translated into the parameterized form of failure and repair rate parameters as $\lambda_1 = 0.0049$, $\mu_1 = 0.3$, $\lambda_2 = 0.037$, $\mu_2 = 0.5$, $\lambda_3 = 0.005$, $\mu_3 = 0.44$, $\lambda_4 = 0.067$, $\mu_4 = 0.4$, $\lambda_5 = 0.09$, $\mu_5 = 0.46$, $\lambda_6 = 0.077$, $\mu_6 = 0.54$, $\lambda_7 = 0.094$, $\mu_7 = 0.7$ for each sub-system, respectively. The long-run availability of the system is obtained 87.40 percent using these parameters in Equation (10).

### *3.2 Particle swarm optimization*

PSO technique is one of the evolutionary optimization algorithms and is based on social behavior observed in bird folks and fish colonies (Kennedy and Eberhart, 1995). In PSO, the population of solutions is known as a swarm and each member of the swarm is called a particle, which is initialized randomly with its position and velocity. The best position of the particle represents the best solution in the study. The algorithm allows particles to move toward its best position at each one of the iterations. This movement depends on the current velocity and position of the particle. The best position attained is compared with the previous best position in each step, as the particle remembers its previous best position and the neighbor's previous best as well. The main goal of all particles is to achieve the optimum solution in the multi-dimensional search space. Once the new best position is attained the personal best (*pbest*) as well as global best (*gbest*) positions are updated. The algorithm terminates the optimization process when, either relatively best position has been attained or computational limitations (i.e. the maximum number of iterations) has been reached. The velocity and position of the particle are updated using the following relations:

$$V_i = w \times V_i + c1 \times rand1 \times (pbest_i - X_i) + c2 \times rand2 \times (gbest - X_i), \tag{11}$$

$$X_i = X_i + V_i, \tag{12}$$

where $V_i$ and $X_i$ represent the velocity and position of $i$th particle, respectively, $c1$ and $c2$ are the cognitive and social components range from 0 to 2, $rand1$ and $rand2$ are the random numbers between 0 and 1. The inertia weight $w$ ranges from 0.4 to 1.4, which controls the convergence behavior of the PSO algorithm. In the present paper, the value of the inertia weight linearly decreases with each iteration, from initial value $w_{\max} = 0.9$ to final value $w_{\min} = 0.4$ using the relation $w = w_{\max} - (w_{\max} - w_{\min}) \times (ite/ite_{\max})$, where $ite$ represents the iteration number and $ite_{\max}$ is used for the maximum number of iterations (Garg, 2013).

### *3.3 Hybrid bacterial foraging and particle swarm optimization*

The BFO and PSO both are the nature-based optimization algorithms. BFO algorithm is based on the food searching process of *E. Coli* bacterial elements (Kora and Kalva, 2015) whereas PSO follows the food hunting process observed in the birds. Here, in this work, a newly developed hybrid optimization method is proposed. The hybridization of two optimization algorithms has been done with the objective to achieve the better optimal solution in competitively less time. The BFO has been selected for the reason that this algorithm performs equally well in both linear and non-linear optimization problems whereas the PSO controls the direction of bacteria. The use of PSO with BFO not only offers the optimal solution faster but also adjusts the bacteria direction toward the better convergence. The working procedure of the proposed hybrid BFO-PSO evolutionary algorithm is discussed below:

- Step 1: The initialization of BFO and PSO variables as shown in Table III.
- Step 2: The position and direction of bacterial element initialized randomly.
- Step 3: At each chemotaxis step, the fitness value and the movement of the bacterial element is simulated through swimming and tumbling via flagella. The position of bacteria element is computed using the following equation:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}, \tag{13}$$

  where $\theta^i(j, k, l)$ represents $i$th bacteria at $j$th chemotactic $k$th reproductive and $l$th elimination-dispersal step. *C(i)* is the step size taken in the random direction indicated by a vector ($\Delta$) whose elements lie in (−1, 1).

- Step 4: in the swarming step, the previous position of bacteria is compared with the next position and if it is found less than the position of subsequent bacteria is computed again using Equation (13). Once the new best position is attained the local best position, as well as the global best position, is updated.
- Step 5: the present position of bacteria is termed as the current position of particle for PSO. In this step, PSO is used to tune the direction of bacteria and the velocity/direction of each bacteria/particle is further updated using the Equation (14):

$$\begin{aligned}\text{New velocity} = {} & w \times \text{previous velocity} + c1 \times rand1 \\ & \times (\text{local best position} - \text{current position}) + c2 \times rand2 \\ & \times (\text{global best position} - \text{current position}),\end{aligned} \tag{14}$$

where $w$, $c1$, $c2$, $rand1$ and $rand2$ are initialized as PSO variables. This new velocity is termed as the direction of bacteria in BFO (Kora and Kalva, 2015):

$$\text{Velocity} = \text{Direction.}$$

- Step 6: after completion of chemotaxis and swarming loop for all initialized steps then the reproduction step takes place for shorting the bacterial elements with high fitness value. The bacterial elements with lower fitness value are dispersed or killed with a deciding probability of 0.25 and other healthy bacterial elements split into two, which disperse into a new location.
- Step 7: this whole cycle of the algorithm is repeated until an optimum solution (best position of bacteria) is not attained or the maximum number of iterations is not produced.

## 4. Results

### *4.1 Sensitivity analysis*

This section reports the results of sensitivity analysis conducted in terms of the effect on the long-run availability of the system with respect to the various combinations of failure and repair rate parameters for each sub-system. In this analysis, the input parameters of each sub-system are varied within a constrained range, keeping the other sub-systems with constant parameters. Figure 3 provides behavioral plots representing failure and repair rate parameters along the $x$-axis and $y$-axis, respectively from minimum to maximum range as provided in Table I, while the corresponding variation in availability along the $z$-axis shows the system behavior pattern.

It can be observed from the behavior pattern that the long-run availability is highly affected by the sub-system (B) as compared to the other sub-systems as shown in Table II. The system availability is reduced by 11.88 percent when the failure rate of the sub-system (B) is changed from 0.037 to 0.127. Similarly the system availability is increased by 3.79 percent when the repair rate of the sub-system (B) is changed from 0.5 to 1.4 and the maximum availability can be obtained, i.e. 91.19 percent using the combinations of failure and repair rate parameters as $\lambda_1 = 0.0049$, $\mu_1 = 0.3$, $\lambda_2 = 0.037$, $\mu_2 = 1.4$, $\lambda_3 = 0.005$, $\mu_3 = 0.44$, $\lambda_4 = 0.067$, $\mu_4 = 0.4$, $\lambda_5 = 0.09$, $\mu_5 = 0.46$, $\lambda_6 = 0.077$, $\mu_6 = 0.54$, $\lambda_7 = 0.0094$, $\mu_7 = 0.7$. This observation depicts the perfect behavior of the system and helps in predicting the repair priorities for different sub-systems.

### *4.2 Optimization modeling*

*4.2.1 BFO-PSO and PSO variables settings*. In order to have uniformity in analyzing results common variables such as population size and the number of iterations used are kept to be the same for each algorithm i.e. BFO-PSO and PSO. Population size and the maximum number of iterations are taken as 80 and 800, respectively. In order to get the optimal results, 30 independent runs have been performed at each step. The algorithm terminates when, either the best solution has been reached or a maximum number of iterations has been produced. The optimization modeling has been implemented in Matlab 15. The values of BFO and PSO variables used in the present study are shown in Table III (Garg, 2013; Kora and Kalva, 2015).

*4.2.2 Performance optimization using BFO-PSO and PSO*. A large number of trails were carried out to optimize the system performance by varying the variables (i.e. population size and number of iterations) one by one with a step size keeping the second variable constant for each evolutionary algorithm. The effect of number of bacterial elements/ population size on the system performance (i.e. Availability) using BFO-PSO and basic PSO evolutionary algorithm is shown in Tables IV and V and represents graphically in Figure 4. At first, the system performance (i.e. availability) is computed using BFO-PSO. In this analysis, the population size

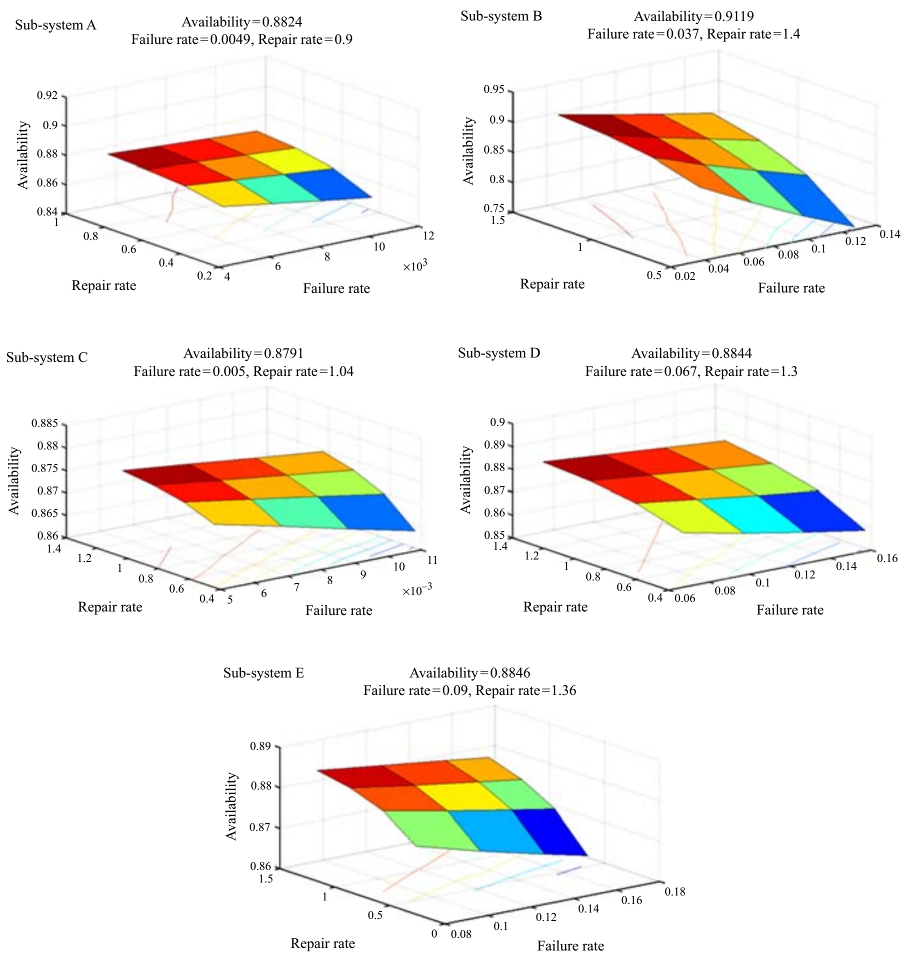


**Figure 3.** Effect of failure and repair rate parameters of different sub-systems on the system availability

| Sub-systems | Failure rate parameters range | Repair rate parameters range |
|---|---|---|
| A | $\lambda_1 = 0.0049–0.0109$ | $\mu_1 = 0.3–0.9$ |
| B | $\lambda_2 = 0.037–0.127$ | $\mu_2 = 0.5–1.4$ |
| C | $\lambda_3 = 0.005–0.011$ | $\mu_3 = 0.44–1.04$ |
| D | $\lambda_4 = 0.067–0.157$ | $\mu_4 = 0.4–1.3$ |
| E | $\lambda_5 = 0.09–0.17$ | $\mu_5 = 0.46–1.36$ |
| $D^1$ (reduced state) | $\lambda_6 = 0.077–0.167$ | $\mu_6 = 0.54–1.44$ |
| $E^1$ (reduced state) | $\lambda_7 = 0.094–0.174$ | $\mu_7 = 0.7–1.6$ |

**Table I.** Ranges for parameterized data collection of paint manufacturing system

is varied from 10 to 80 with a step size of 10 keeping the number of iterations constant at 800. The system performance is found to be 95.77 percent at a population size 60, it provides the best possible combinations of failure and repair rate parameters as $\lambda_1 = 0.0052$, $\mu_1 = 0.8835$, $\lambda_2 = 0.0481$, $\mu_2 = 1.0130$, $\lambda_3 = 0.0056$, $\mu_3 = 1.0801$, $\lambda_4 = 0.0704$, $\mu_4 = 1.2658$, $\lambda_5 = 0.0950$, $\mu_5 = 1.2590$, $\lambda_6 = 0.0824$, $\mu_6 = 1.4218$, $\lambda_7 = 0.0961$, $\mu_7 = 1.5019$ as shown in Table IV.

Similarly, the system performance (i.e. availability) is computed using PSO. In this analysis, the population size is again varied from 10 to 80 with a step size of 10 keeping the number of iterations constant at 800. The system performance is found to be 95.65 percent at a population size 40, it provides the best possible combinations of failure and repair rate parameters as $\lambda_1=0.0050$, $\mu_1=0.8891$, $\lambda_2=0.0370$, $\mu_2=1.3968$, $\lambda_3=0.0052$, $\mu_3=0.9975$, $\lambda_4=0.0727$, $\mu_4=$ 1.2315, $\lambda_5=0.0954$, $\mu_5=1.2436$, $\lambda_6=0.0778$, $\mu_6=1.3743$, $\lambda_7=0.0955$, $\mu_7=1.3874$ as shown in Table V.

**Table II.** Sensitivity analysis for the paint manufacturing system

| Sub-system | Ranges of failure rates | Decrease in availability (%) | Ranges of repair rates | Increase in availability (%) | Repair priority |
|---|---|---|---|---|---|
| A | 0.0049–0.0109 | 1.5 | 0.3–0.9 | 0.84 | IV |
| B | 0.037–0.127 | 11.88 | 0.5–1.4 | 3.79 | I |
| C | 0.005–0.011 | 0.69 | 0.44–1.04 | 0.51 | V |
| D | 0.067–0.157 | 1.48 | 0.4–1.3 | 1.04 | III |
| E | 0.09–0.17 | 1.07 | 0.46–1.36 | 1.06 | II |

**Table III.** BFO and PSO variables

| BFO variables | Value |
|---|---|
| Number of chemotactic steps *Nc* | 10 |
| Maximum allowed length of swim *Ns* | 4 |
| Number of reproduction steps *Nre* | 4 |
| Number of elimination-dispersal events *Ned* | 2 |
| Probability of elimination and dispersal *Ped* | 0.25 |
| Number of bacterial elements (i.e. population size) *S* | 80 with a step size of 10 |
| Number of bacteria reproduction (splits) per generation *Sr* | *S*/2 |
| Number of iterations (i.e. number of generations) | 800 with a step size of 100 |
| PSO variables | Value |
| Cognitive component *c*1 | 1.5 |
| Social component *c*2 | 1.5 |
| Inertia weight (*w*) | 0.4–0.9 |
| Number of particles (i.e. population size) | 80 with a step size of 10 |
| Number of iterations | 800 with a step size of 100 |

**Table IV.** Effect of population size on the availability of paint manufacturing system using BFO-PSO

| | Population size | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Parameters | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 |
| $\lambda_1$ | 0.0072 | 0.0073 | 0.0066 | 0.0054 | 0.0049 | 0.0052 | 0.0053 | 0.0049 |
| $\mu_1$ | 0.8073 | 0.8188 | 0.6629 | 0.7864 | 0.8760 | 0.8835 | 0.8818 | 0.8819 |
| $\lambda_2$ | 0.0433 | 0.0752 | 0.0723 | 0.0451 | 0.0384 | 0.0481 | 0.0434 | 0.0481 |
| $\mu_2$ | 1.2976 | 0.9902 | 1.3778 | 1.3827 | 1.1197 | 1.0130 | 1.1982 | 1.1236 |
| $\lambda_3$ | 0.0078 | 0.0058 | 0.0060 | 0.0055 | 0.0055 | 0.0056 | 0.0060 | 0.0052 |
| $\mu_3$ | 0.6984 | 0.9927 | 0.8254 | 1.0238 | 1.0570 | 1.0801 | 1.0480 | 1.0813 |
| $\lambda_4$ | 0.0720 | 0.0802 | 0.0882 | 0.0690 | 0.0722 | 0.0704 | 0.0705 | 0.0715 |
| $\mu_4$ | 1.0431 | 0.9189 | 1.1732 | 1.0942 | 1.2112 | 1.2658 | 1.1782 | 1.1212 |
| $\lambda_5$ | 0.0943 | 0.0943 | 0.0943 | 0.0962 | 0.0935 | 0.0950 | 0.0937 | 0.0941 |
| $\mu_5$ | 0.9072 | 1.0785 | 1.1246 | 1.1869 | 1.3352 | 1.2590 | 1.2182 | 1.2802 |
| $\lambda_6$ | 0.1075 | 0.0848 | 0.0878 | 0.0787 | 0.0844 | 0.0824 | 0.0825 | 0.0839 |
| $\mu_6$ | 1.1621 | 1.2015 | 1.2622 | 1.1517 | 1.3560 | 1.4218 | 1.3052 | 1.3588 |
| $\lambda_7$ | 0.1584 | 0.0960 | 0.0958 | 0.0956 | 0.0964 | 0.0961 | 0.0977 | 0.0973 |
| $\mu_7$ | 0.8012 | 1.3945 | 1.368 | 1.3357 | 1.4800 | 1.5019 | 1.5354 | 1.394 |
| Availability | 0.9399 | 0.9461 | 0.9481 | 0.9523 | 0.9565 | 0.9577 | 0.9570 | 0.9559 |

| Parameters | 10 | 20 | 30 | Population size 40 | 50 | 60 | 70 | 80 |
|---|---|---|---|---|---|---|---|---|
| $\lambda_1$ | 0.0063 | 0.0093 | 0.0053 | 0.0050 | 0.0051 | 0.0057 | 0.0054 | 0.0053 |
| $\mu_1$ | 0.7164 | 0.8149 | 0.7698 | 0.8891 | 0.8639 | 0.7646 | 0.8451 | 0.7695 |
| $\lambda_2$ | 0.0387 | 0.0372 | 0.0374 | 0.0370 | 0.0378 | 0.0380 | 0.0370 | 0.0375 |
| $\mu_2$ | 1.3573 | 1.2632 | 1.3295 | 1.3968 | 1.3859 | 1.3672 | 1.3762 | 1.3968 |
| $\lambda_3$ | 0.0051 | 0.0073 | 0.0062 | 0.0052 | 0.0057 | 0.0050 | 0.0051 | 0.0052 |
| $\mu_3$ | 0.5623 | 0.9326 | 0.8303 | 0.9975 | 1.0160 | 0.9778 | 0.9780 | 0.9286 |
| $\lambda_4$ | 0.0974 | 0.0861 | 0.0728 | 0.0727 | 0.0673 | 0.0701 | 0.0761 | 0.0736 |
| $\mu_4$ | 0.7311 | 1.2320 | 0.9862 | 1.2315 | 1.2831 | 0.9986 | 1.2830 | 1.2627 |
| $\lambda_5$ | 0.1034 | 0.1143 | 0.1080 | 0.0954 | 0.0939 | 0.0921 | 0.0931 | 0.0954 |
| $\mu_5$ | 0.7949 | 1.2537 | 1.2666 | 1.2436 | 1.2910 | 1.1651 | 1.3426 | 1.2321 |
| $\lambda_6$ | 0.1343 | 0.0820 | 0.0839 | 0.0778 | 0.0773 | 0.0791 | 0.0861 | 0.0784 |
| $\mu_6$ | 1.4118 | 1.1973 | 1.3889 | 1.3743 | 1.3580 | 1.4087 | 1.2523 | 1.4289 |
| $\lambda_7$ | 0.1181 | 0.0947 | 0.1069 | 0.0955 | 0.0996 | 0.0974 | 0.0987 | 0.1165 |
| $\mu_7$ | 1.4974 | 1.2319 | 1.1735 | 1.3874 | 1.5239 | 1.3314 | 1.4080 | 1.5428 |
| Availability | 0.9375 | 0.9438 | 0.9490 | 0.9565 | 0.9560 | 0.9529 | 0.9551 | 0.9544 |

**Table V.**
Effect of population size on the availability of paint manufacturing system using PSO

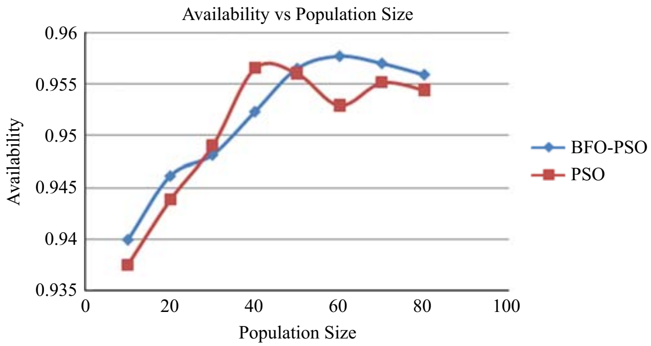


**Figure 4.**
Effect of population size on the system availability

Again, the system performance is computed with respect to the variation in number of iterations for each algorithm. The effect of number of iterations on the system performance (i.e. Availability) using BFO-PSO and basic PSO evolutionary algorithms is shown in Tables VI and VII and represents graphically in Figure 5. In this analysis, the number of iterations is varied from 100 to 800 with a step size of 100 keeping the population size constant at 60. The system performance is found to be 95.72 percent using BFO-PSO at a number of iterations 300, it provides the best possible combinations of failure and repair rate parameters as $\lambda_1 = 0.0053$, $\mu_1 = 0.8586$, $\lambda_2 = 0.0461$, $\mu_2 = 1.3356$, $\lambda_3 = 0.0056$, $\mu_3 = 1.0471$, $\lambda_4 = 0.0743$, $\mu_4 = 1.2300$, $\lambda_5 = 0.0944$, $\mu_5 = 1.2423$, $\lambda_6 = 0.0811$, $\mu_6 = 1.3321$, $\lambda_7 = 0.0976$, $\mu_7 = 1.3831$, as shown in Table VI.

Similarly, the system performance (i.e. availability) is computed using PSO. In this analysis, the number of iterations is varied from 100 to 800 with a step size of 100 keeping the population size constant at 40. The system performance is found to be 95.61 percent at a number of iterations 700, it provides the best possible combinations of failure and repair rate parameters as $\lambda_1 = 0.0051$, $\mu_1 = 0.8873$, $\lambda_2 = 0.0372$, $\mu_2 = 1.3952$, $\lambda_3 = 0.0053$, $\mu_3 = 1.0005$, $\lambda_4 = 0.0758$, $\mu_4 = 1.2922$, $\lambda_5 = 0.0935$, $\mu_5 = 1.3516$, $\lambda_6 = 0.0851$, $\mu_6 = 1.3457$, $\lambda_7 = 0.1120$, $\mu_7 = 1.5437$ as shown in Table VII.

The effectiveness of the proposed algorithm is tested by comparing the results with PSO as both the techniques follow the deterministic and probabilistic rules from current iteration

**Table VI.**
Effect of number of iterations on the availability of paint manufacturing system using BFO-PSO

| Parameters | Number of iterations 100 | 200 | 300 | 400 | 500 | 600 | 700 | 800 |
|---|---|---|---|---|---|---|---|---|
| $\lambda_1$ | 0.0052 | 0.0053 | 0.0053 | 0.0054 | 0.0057 | 0.0052 | 0.0052 | 0.0051 |
| $\mu_1$ | 0.4852 | 0.8263 | 0.8586 | 0.8289 | 0.8628 | 0.8809 | 0.8863 | 0.8647 |
| $\lambda_2$ | 0.0550 | 0.0382 | 0.0461 | 0.0375 | 0.0405 | 0.0490 | 0.0414 | 0.0387 |
| $\mu_2$ | 1.2821 | 1.2337 | 1.3356 | 1.0642 | 1.0986 | 1.0194 | 1.3847 | 1.2865 |
| $\lambda_3$ | 0.0075 | 0.0059 | 0.0056 | 0.0054 | 0.0065 | 0.0061 | 0.0056 | 0.0054 |
| $\mu_3$ | 0.8782 | 0.9914 | 1.0471 | 1.0852 | 1.0711 | 1.0407 | 1.0973 | 1.0759 |
| $\lambda_4$ | 0.1239 | 0.0735 | 0.0743 | 0.0682 | 0.0755 | 0.0736 | 0.0745 | 0.0723 |
| $\mu_4$ | 0.7439 | 0.8816 | 1.2300 | 1.1282 | 1.2031 | 1.1722 | 1.2396 | 1.1655 |
| $\lambda_5$ | 0.1229 | 0.0934 | 0.0944 | 0.0942 | 0.0938 | 0.0922 | 0.0943 | 0.0944 |
| $\mu_5$ | 1.0829 | 0.9740 | 1.2423 | 1.2882 | 1.2610 | 1.2167 | 1.2621 | 1.2084 |
| $\lambda_6$ | 0.1115 | 0.0983 | 0.0811 | 0.0846 | 0.0809 | 0.0815 | 0.0806 | 0.0839 |
| $\mu_6$ | 1.2467 | 1.1542 | 1.3321 | 1.2692 | 1.3789 | 1.3892 | 1.3923 | 1.3793 |
| $\lambda_7$ | 0.1103 | 0.0957 | 0.0976 | 0.0966 | 0.0974 | 0.0974 | 0.0976 | 0.0967 |
| $\mu_7$ | 1.4021 | 1.5660 | 1.3831 | 1.5043 | 1.4201 | 1.4126 | 1.5058 | 1.4984 |
| Availability | 0.9376 | 0.9502 | 0.9572 | 0.9558 | 0.9564 | 0.9569 | 0.9563 | 0.9560 |

**Table VII.**
Effect of number of iterations on the availability of paint manufacturing system using PSO

| Parameters | Number of iterations 100 | 200 | 300 | 400 | 500 | 600 | 700 | 800 |
|---|---|---|---|---|---|---|---|---|
| $\lambda_1$ | 0.0051 | 0.0081 | 0.0056 | 0.0051 | 0.0072 | 0.0054 | 0.0051 | 0.005 |
| $\mu_1$ | 0.8665 | 0.7389 | 0.7065 | 0.8011 | 0.8425 | 0.7999 | 0.8873 | 0.8588 |
| $\lambda_2$ | 0.0387 | 0.0383 | 0.0377 | 0.0391 | 0.0372 | 0.0372 | 0.0372 | 0.0378 |
| $\mu_2$ | 1.2976 | 1.3705 | 1.3416 | 1.3733 | 1.3404 | 1.3994 | 1.3952 | 1.3932 |
| $\lambda_3$ | 0.0075 | 0.0071 | 0.0054 | 0.0056 | 0.0062 | 0.0053 | 0.0053 | 0.0050 |
| $\mu_3$ | 0.7166 | 0.8687 | 0.9813 | 0.9391 | 0.7519 | 1.0185 | 1.0005 | 0.9830 |
| $\lambda_4$ | 0.1376 | 0.0915 | 0.0738 | 0.0801 | 0.0739 | 0.0789 | 0.0758 | 0.0715 |
| $\mu_4$ | 0.8378 | 0.7946 | 1.2117 | 1.1750 | 0.9974 | 1.1366 | 1.2922 | 1.1248 |
| $\lambda_5$ | 0.1660 | 0.1339 | 0.1305 | 0.1070 | 0.0976 | 0.0973 | 0.0935 | 0.0928 |
| $\mu_5$ | 1.0576 | 0.8724 | 1.2682 | 0.9959 | 1.2319 | 1.2315 | 1.3516 | 1.3120 |
| $\lambda_6$ | 0.1171 | 0.0958 | 0.1551 | 0.1063 | 0.1301 | 0.0777 | 0.0851 | 0.0792 |
| $\mu_6$ | 1.3608 | 1.2482 | 1.2942 | 1.4067 | 1.2065 | 1.1262 | 1.3457 | 1.2133 |
| $\lambda_7$ | 0.1019 | 0.0970 | 0.1074 | 0.1182 | 0.1023 | 0.1111 | 0.1120 | 0.0943 |
| $\mu_7$ | 1.1567 | 1.5045 | 1.1946 | 1.5987 | 1.5938 | 1.3828 | 1.5437 | 1.4955 |
| Availability | 0.9343 | 0.9403 | 0.9462 | 0.9499 | 0.9463 | 0.9534 | 0.9561 | 0.9559 |

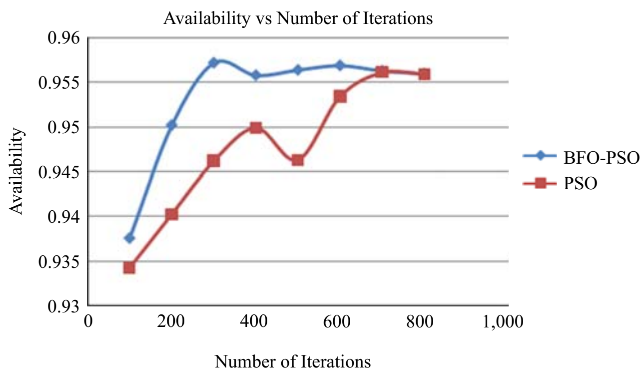


**Figure 5.**
Effect of number of iterations on the system availability

to next. The comparative study shows that the BFO-PSO algorithm estimated the system performance with higher accuracy as compared to PSO, although the maximum difference is 0.12 percent only as shown in Table VIII. Thus, the results obtained through BFO-PSO algorithm contributes to the system analyst and reduces the range of prediction which finally leads to more sound decisions in maintenance planning. The convergence characteristic of basic PSO and BFO-PSO is shown in Figure 6.

## 5. Conclusions

In this paper, the sensitivity analysis has been conducted by utilizing the uncertain data of system concerned and traced out the best system performance for a paint manufacturing unit. In the proposed methodology, a Markov process-based performance model has been constructed to analyze the effect of failure and repair rate parameters of various sub-systems, more closely, on system performance. In order to increase the system efficiency and to obtain the optimal combinations of failure and repair rate parameters for

| System | Markov process | Performance evaluation using PSO (population size = 40, number of generations = 800) | BFO-PSO (population size = 60, number of generations = 800) |
|---|---|---|---|
| Paint manufacturing system | $\lambda_1 = 0.0049$, $\mu_1 = 0.3$ | $\lambda_1 = 0.0050$, $\mu_1 = 0.8891$ | $\lambda_1 = 0.0052$, $\mu_1 = 0.8835$ |
| | $\lambda_2 = 0.037$, $\mu_2 = 1.4$ | $\lambda_2 = 0.0370$, $\mu_2 = 1.3968$ | $\lambda_2 = 0.0481$, $\mu_2 = 1.0130$ |
| | $\lambda_3 = 0.005$, $\mu_3 = 0.44$ | $\lambda_3 = 0.0052$, $\mu_3 = 0.9975$ | $\lambda_3 = 0.0056$, $\mu_3 = 1.0801$ |
| | $\lambda_4 = 0.067$, $\mu_4 = 0.4$ | $\lambda_4 = 0.0727$, $\mu_4 = 1.2315$ | $\lambda_4 = 0.0704$, $\mu_4 = 1.2658$ |
| | $\lambda_5 = 0.09$, $\mu_5 = 0.46$ | $\lambda_5 = 0.0954$, $\mu_5 = 1.2436$ | $\lambda_5 = 0.0950$, $\mu_5 = 1.2590$ |
| | $\lambda_6 = 0.077$, $\mu_6 = 0.54$ | $\lambda_6 = 0.0778$, $\mu_6 = 1.3743$ | $\lambda_6 = 0.0824$, $\mu_6 = 1.4218$ |
| | $\lambda_7 = 0.094$, $\mu_7 = 0.7$ | $\lambda_7 = 0.0955$, $\mu_7 = 1.3874$ | $\lambda_7 = 0.0961$, $\mu_7 = 1.5019$ |
| Availability (%) | 91.19 | 95.65 | 95.77 |

**Table VIII.** Comparison of performance evaluation for paint manufacturing system using Markov process, PSO and BFO-PSO

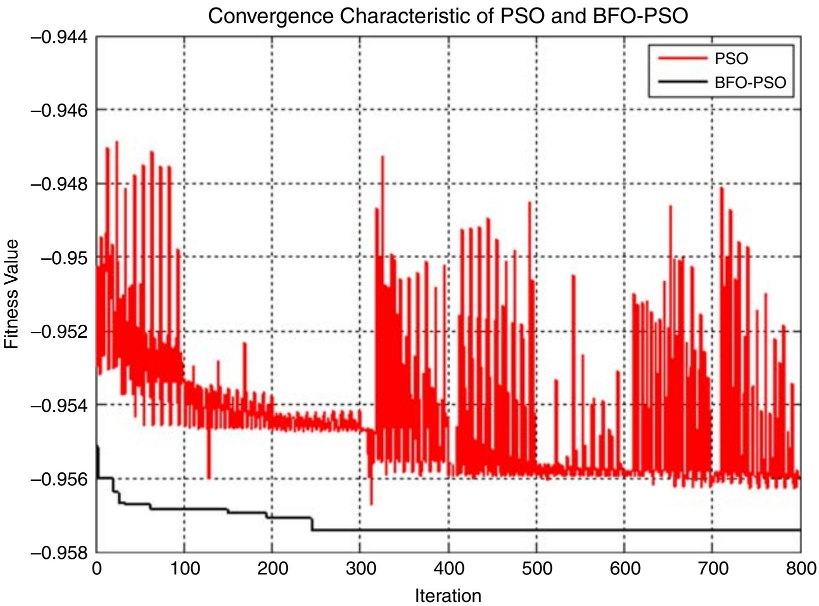


**Figure 6.** Convergence characteristic of PSO and hybrid BFO-PSO algorithms

various sub-systems, the performance optimization model has been solved through a hybrid BFO-PSO algorithm and their results are compared with basic PSO findings. The following observations can be made from the availability results:

- the sensitivity of various sub-systems can be analyzed in more realistic manner using the proposed methodology;
- it can be easily identified that the sub-system B (Grinding Mill) is more sensitive than other sub-systems in terms of the effect on system availability;
- the maintenance priorities can be easily set up using the obtained results;
- the availability of the system has been increased up to 95.77 percent using the hybrid BFO-PSO algorithm;
- in this study, we have observed that the accuracy, frequency of getting optimal results and convergence speed of the BFO-PSO algorithm is higher than the basic PSO algorithm;
- a major conclusion of this study is that hybrid BFO-PSO based algorithm performs well in determining the optimal input parameters so as to increase the efficiency of the system; and
- the results obtained from the present study can be utilized for further improvement in the system design as a future course of action.

### References

Arabi, A.A.Y. and Jahromi, A.E. (2013), "Availability optimization of a series system with multiple repairable load sharing subsystems considering redundancy and repair facility allocation", *International Journal of System Assurance Engineering Management*, Vol. 4 No. 3, pp. 262-274.

Di Bona, G., Forcina, A. and Silvestri, A. (2016), "A new reliability allocation approach for a thermonuclear system", *Quality and Reliability Engineering International*, Vol. 32 No. 5, pp. 1677-1691.

Di Bona, G., Forcina, A., Petrillo, A., De Felice, F. and Silvestri, A. (2016), "A-IFM reliability allocation model based on multicriteria approach", *International Journal of Quality & Reliability Managment*, Vol. 33 No. 5, pp. 676-698.

Garg, H. (2013), "Performance analysis of complex repairable industrial systems using PSO and fuzzy confidence interval based methodology", *ISA Transactions*, Vol. 52 No. 2, pp. 171-183.

Garg, H. and Rani, M. (2013), "An approach for reliability analysis of industrial systems using PSO and IFS technique", *ISA Transactions*, Vol. 52 No. 6, pp. 701-710.

Garg, H. and Sharma, S.P. (2012), "Behavior analysis of synthesis unit in fertilizer plant", *International Journal of Quality & Reliability Managment*, Vol. 29 No. 2, pp. 217-232.

Gupta, P., Lal, A.K., Sharma, R.K. and Singh, J. (2007), "Analysis of reliability and availability of serial processes of plastic-pipe manufacturing plant: a case study", *International Journal of Quality & Reliability Management*, Vol. 24 No. 4, pp. 404-419.

Hajeeh, M.A. (2015), "Performance and cost analysis of repairable systems under imperfect repair", *International Journal of Operational Research*, Vol. 23 No. 1, pp. 1-14.

Kachitvichyanukul, V. (2012), "Comparison of three evolutionary algorithms: GA, PSO, and DE", *Industrial Engineering & Management Systems*, Vol. 11 No. 3, pp. 215-223.

Kajal, S. and Tewari, P.C. (2012), "Performance optimization for skim milk powder unit of a dairy plant using genetic algorithm", *IJE Transactions B: Applications*, Vol. 25 No. 3, pp. 211-221.

Kennedy, J. and Eberhart, R. (1995), "Particle swarm optimization", *Proceedings of the IEEE International Conference on Neural Networks*, *Perth*, Vol. 4, pp. 1942-1945.

Khanduja, R., Tewari, P.C. and Chauhan, R.S. (2011), "Performance modeling and optimization for the stock preparation unit of a paper plant using genetic algorithm", *International Journal of Quality & Reliability Management*, Vol. 28 No. 6, pp. 688-703.

Khanduja, R., Tewari, P.C. and Kumar, D. (2010), "Mathematical modeling and performance optimization for the digesting system of a paper plant", *IJE Transactions A: Basics.*, Vol. 23 Nos 3/4, pp. 215-225.

Kora, P. and Kalva, S.R. (2015), "Hybrid bacterial foraging and particle swarm optimization for detecting bundle branch block", *SpringerPlus*, Vol. 4 No. 1, pp. 1-19.

Kumar, A. and Garg, R.K. (2016), "Decision support system for maximum availability of series-parallel system using particle swarm optimisation", *International Journal of Intelligent Enterprise*, Vol. 3 No. 2, pp. 148-169.

Kumar, A. and Ram, M. (2013), "Reliability measures improvement and sensitivity analysis of a coal handling unit for thermal power plant", *IJE Transactions C: Aspects*, Vol. 26 No. 9, pp. 1059-1066.

Kumar, A., Kumar, V. and Modgil, V. (2018), "Performance optimisation for ethanol manufacturing system of distillery plant using particle swarm optimisation algorithm", *International Journal of Intelligent Enterprise*, Vol. 5 No. 4, pp. 345-364.

Kumar, P. and Tewari, P.C. (2017), "Performance analysis and optimization for CSDGB filling system of a beverage plant using particle swarm optimization", *International Journal of Industrial Engineering Computations*, Vol. 8 No. 3, pp. 303-314.

Modgil, V., Sharma, S.K. and Singh, J. (2013), "Performance modeling and availability analysis of shoe upper manufacturing unit", *International Journal of Quality & Reliability Management*, Vol. 30 No. 8, pp. 816-831.

Pang, J. (2015), "A new Markov model of reliability assurance and failure prediction using network technology", *4th International Conference on Computer Science and Network Technology (ICCSNT 2015)*, pp. 776-780.

Rabbani, M., Mohammadi, S. and Mobini, M. (2018), "Optimum design of a CCHP system based on Economical, energy and environmental considerations using GA and PSO", *International Journal of Industrial Engineering Computations*, Vol. 9 No. 1, pp. 99-122.

Raju, M., Gupta, M.K., Bhanot, N. and Sharma, V.S. (2018), "A hybrid PSO-BFO evolutionary algorithm for optimization of fused deposition modelling process parameters", *Journal of Intelligent Manufacturing*, pp. 1-16, available at: https://doi.org/10.1007/s10845-018-1420-0

Sharma, S.P. and Vishwakarma, Y. (2014), "Availability optimization of refining system of sugar industry by markov process and genetic algorithm", *International Conference on Reliability, Optimization and Information Technology-ICROIT 2014*, pp. 29-33.

Yadav, O.P. and Zhuang, X. (2014), "A practical reliability allocation method considering modified criticality factors", *Reliability Engineering and System Safety*, Vol. 129, pp. 57-65.

## About the authors

Amit Kumar obtained his Bachelor of Engineering (2006) and Master of Engineering (2010), all in Mechanical Engineering from Kurukshetra University, Kurukshetra, Haryana India. He is pursuing his PhD in Industrial Engineering from Department of Mechanical Engineering at National Institute of Technology, Kurukshetra, Haryana, India. He has seven years of teaching and two years of industrial experience. Currently, he is working as Assistant Professor in Department of Mechanical Engineering at Seth Jai Parkash Mukand Lal Institute of Engineering and Technology, Radaur, Yamunanagar, Haryana, India. His research areas are reliability engineering, mathematical modeling, stochastic behavioral analysis of complex industrial system and maintenance engineering. Amit Kumar is the corresponding author and can be contacted at: er.meet@gmail.com

Dr Vinod Kumar obtained his B.Sc in Engineering (1989) and M. Tech in Mechanical Engineering (1992) from REC Kurukshetra, Haryana, India. He obtained his PhD in Mechanical engineering (2008) from Kurukshetra University, Kurukshetra, Haryana, India. Currently, he is working as Associate Professor in Department of Mechanical Engineering at National Institute of Technology, Kurukshetra,

Haryana, India. He has 25 years of teaching and research experience. His research interests include manufacturing system, tribology and machine design.

Dr Vikas Modgil obtained his Bachelor of Engineering, Master of Engineering and PhD, all in Mechanical engineering from Kurukshetra University, Kurukshetra, Haryana, India (2002), Sant Longowal Institute of Engineering and Technology, Longowal, Sangrur, Punjab, India (2004) and National Institute of Technology, Kurukshetra, Haryana, India (2013), respectively. Currently, he is working as Assistant Professor in Department of Mechanical Engineering at Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Sonipat, Haryana, India. He has 12 years of teaching and research experience. His research interests include reliability engineering, performance optimization, mathematical modeling, decision support system, etc.