Behavioral analysis and availability optimization of complex repairable industrial system using particle swarm optimization

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Abstract. The complexity in industrial system design under specific practical constraints has a great impact on the range of prediction in system behavior. The data collected in such conditions lead to the high range of uncertainties and the consequence is a possibility of low system performance. Thus, the main objective of the present study is to analyze the system behavior and remove the uncertainties up to the desired accuracy. For this, the mathematical formulation of the system is carried out using probabilistic approach i.e. Markov process. The input failure and repair rate parameters of various sub-systems used in the mathematical expression are considered as constant and statistically independent. Further, the particle swarm optimization (PSO) technique has been used to optimize the system performance in order to improve the system efficiency. A complex repairable system of ton container manufacturing plant has been considered to demonstrate the effectiveness of proposed methodology.

1. Introduction

The advancement in industrial systems recommends a continuous flow of work through a sequential flow of operations for higher system performance. The scheduled commitment to producing goods is only possible with minimum downtimes. The random failures of the subsystems make it a tedious task to maintain the system availability for a long duration of time. Thus the optimum maintenance policy is to be framed for the assurance of a reliable system. During the process, the failure of the system may occur due to a number of major and minor faults, which causes the low productivity or complete shutdown of the system. It may take few hours or days to bring back the system in working condition but during this period of time, an enormous production loss takes place. In these conditions, behavioral analysis and optimum availability evaluation for the system plays a vital role in order to solve the problem. The availability optimization problems have attracted the substantial attention of several researchers in the area of system engineering. Different PSO and GA based optimization problems have been proposed in the literature. Aggarwal et al. [1] presented the Markov modeling and reliability
analysis of urea synthesis system of a fertilizer plant. They used the GA approach to optimize the time-dependent system availability of butter oil production system. Bornatico et al. [2] proposed the PSO algorithm for a solar thermal system and also compared the results obtained with GA solution. Cura [3] used the PSO approach in portfolio optimization. Chiang et al. [4] demonstrated the Markovian system in periodic inspection and provided the optimum maintenance policy. Dayal et al. [5] demonstrated the reliability analysis of a repairable system in a fluctuating environment. Elegbede et al. [6] presented the GA approach to optimize the availability and cost of repairable parallel-series system. Garg [7] proposed a methodology for analyzing the behavior of the complex repairable system. Garg et al. [8] stated the PSO and IFS technique for reliability analysis. Goyal et al. [9] used the Markov approach to evaluate the steady-state availability multi-state repairable production system. Kachitvichyanukul [10] presented the comparison of GA, PSO and DE algorithms using the different optimization problems with the same number of function evaluations. Kumar et al. [12] presented the PSO approach for performance optimization of ethanol manufacturing system whereas Kumar et al. [13] described the application of PSO approach to optimize the performance of CSDGDB filling system of a beverage plant. Kanduja et al. [14] developed the performance model of stock preparation unit and screening unit in a paper plant. They also discussed the performance behavior analysis using GA approach. Marinakis et al. [15] studied the two nature inspired methods (Ant Colony and PSO techniques) for the optimization of financial classification problems. Modgil et al. [16] developed the performance model using Markov approach for the time-dependent system availability and long-run availability in the shoe industry. Rabbani et al. [17] provided the application of GA and PSO algorithms to obtain the optimum value of design parameters of a CCHP system. Sahoo et al. [18] used the GA approach in reliability allocation problem to maximize the overall system availability with the constraints reliability, cost and weight of each component. Tewari et al. [19] developed the performance model for yarn dyeing system of a textile industry and optimized the performance of urea crystallization system in a fertilizer plant using GA technique.

It has been observed from the literature that many researchers have done quality research work in the area of process industries such as sugar plant, paper industry, fertilizer plant and beverage plant etc. But now, new technologies and increased global demand make the system availability as fundamentally important in the field of heavy manufacturing industry also. Therefore a ton container manufacturing plant has been chosen for the present work.

2. System description
The Manufacturing process of the ton container requires a continuous flow of work in the system and the shell fabricating (SF) system is an important functionary of the plant. The continuous flow of work in the system can only be possible when all the subsystems are available to perform. In the process of shell fabrication, the carbon steel plates are cut in the desired rectangular size using computer numerical control (CNC) gas cutting machine. The fetch up and rolling machines are used to get the cylindrical shape. Further, long seam (LS) setup machine is used before L.S. Submerged arc welding (SAW) process which is followed by the testing of SAW weld though real-time radiography (RTR) process and finally the finished shell is processed for end disc installation.

The present study is done for the behavioral analysis and availability optimization of SF System. The schematic process flow diagram of the SF system is shown in figure 1. It consists of four subsystems as described below:

- **Subsystem A:** It consists of two CNC gas cutting machine in parallel. The shell fabrication starts with the cutting of raw material (12 mm thick carbon steel plates) in the desired rectangular size using CNC gas cutting machine.
- **Subsystem B:** It is a hydraulic power press machine which is used for the fetch-up process, in this process the carbon steel plates are bent in the required curvature to prepare for the rolling operation.
- **Subsystem C**: It consists of two rolling machines in parallel for the rolling purpose, which improves the strength of plate as well as to obtain the cylindrical shape of required diameter (900 mm).
- **Subsystem D**: It is a SAW welding machine and used to weld the edges of the round piece of the shell. It is used to weld the shell longitudinally so that it is known as long seam (L.S.) SAW welding machine. Further the testing of SAW weld is accomplished through RTR process and finally, the finished shell is processed for the end disc installation to the next section.

![Schematic process flow diagram of SF system](image)

**Figure 1.** Schematic process flow diagram of SF system

### 2.1. Assumptions
The following assumptions are made to carry out the mathematical modeling of SF system.

- Failure and repair rates parameters for each subsystem are constant and statistically independent.
- Performance wise a repaired unit is as good as new.
- Sufficient maintenance facility is available for each component. So, there is no waiting time to get the repair facility.
- All the units are initially operating and are in working state.
- The system may work as the reduced capacity state.

### 2.2. Notations

- \( A, B, C, D \): Represents the working states
- \( A^1, C^1 \): Represents the reduced capacity working states
- \( a, b, c, d, \): Represents the failure states
- \( \lambda_1, \lambda_2, \lambda_3, \lambda_4 \): Failure rates of \( A, B, C, D \)
- \( \lambda_5, \lambda_6 \): Failure rates of \( A \) and \( C \) in reduced capacity working state
- \( \mu_1, \mu_2, \mu_3, \mu_4 \): Repair rates of \( A, B, C, D \)
- \( \mu_5, \mu_6 \): Repair rates of \( A \) and \( C \) in reduced capacity working state
- \( P_0(t) \): Probability that the system is working in full capacity working state at time \( t \).
- \( P_i(t) \): Probability that the system is in \( i^{th} \) state at time \( t \).
- \( P' \): First-order derivatives of the probabilities.

### 3. Methodology

#### 3.1. Mathematical Modeling

The mathematical modeling of the system is carried out using simple probabilistic considerations and differential equations associated with the transition diagram (see figure 2) are developed on the basis of Markov approach. The first order differential equations are derived using the mnemonic rule as
stated by Khanduja et al. [14]. The following sets of differential equations associated with the SF system are generated using various probability considerations.

\[ P_0'(t) + \sum_{i=1}^{4} \lambda_i P_i(t) = \mu_1 P_1(t) + \mu_2 P_2(t) + \mu_3 P_3(t) + \mu_4 P_4(t) \]  
(1)

\[ P_1'(t) + \sum_{i=2}^{5} \lambda_i P_i(t) = \mu_2 P_1(t) + \mu_3 P_2(t) + \mu_4 P_3(t) + \mu_5 P_4(t) + \lambda_1 P_0(t) \]  
(2)

\[ P_2'(t) + \sum_{i=1}^{2} \lambda_i + \lambda_4 + \lambda_6 + \mu_3 P_2(t) = \mu_1 P_3(t) + \mu_2 P_3(t) + \mu_4 P_4(t) + \mu_5 P_6(t) + \lambda_3 P_0(t) \]  
(3)

\[ P_3'(t) + \sum_{i=4}^{6} \lambda_i + \lambda_2 + \mu_1 + \mu_3 P_3(t) = \mu_2 P_4(t) + \mu_4 P_5(t) + \mu_5 P_5(t) + \mu_6 P_6(t) + \lambda_4 P_1(t) + \lambda_3 P_0(t) \]  
(4)

\[ P_i'(t) + \mu_2 P_i(t) = \lambda_2 P_j(t) \]  
(5)

for \( i = 4, j = 0; i = 7, j = 1; i = 9, j = 2; i = 13, j = 3 \)

\[ P_i'(t) + \mu_4 P_i(t) = \lambda_4 P_j(t) \]  
(6)

for \( i = 5, j = 0; i = 8, j = 1; i = 10, j = 2; i = 15, j = 3 \)

\[ P_i'(t) + \mu_5 P_i(t) = \lambda_5 P_j(t) \]  
(7)

for \( i = 6, j = 1; i = 12, j = 3 \)

\[ P_i'(t) + \mu_6 P_i(t) = \lambda_6 P_j(t) \]  
(8)

for \( i = 11, j = 2; i = 14, j = 3 \)

The initial conditions at time \( t = 0 \):

\[ P_i(0) = \begin{cases} 1, & \text{if } i = 0 \\ 0, & \text{if } i \neq 0 \end{cases} \]
3.2. Long-run Availability
The subsystems of SF system are required to be available for the long duration of time. So, the long-run availability of the system is computed by substituting steady state conditions i.e. \((P^*) \rightarrow 0\) as the time \(t \rightarrow \infty\) for first-order differential equations (1 to 8) and solving these equations recursively we get:

\[
P_1 = T_2P_0 \quad P_2 = T_3P_0 \quad P_3 = T_4P_0 \quad P_4 = M_2P_0 \\
P_5 = M_4P_0 \quad P_6 = M_2T_2P_0 \quad P_7 = M_2T_2P_0 \quad P_8 = M_4T_2P_0 \\
P_9 = M_2T_3P_0 \quad P_{10} = M_4T_3P_0 \quad P_{11} = M_6T_3P_0 \quad P_{12} = M_5T_4P_0 \\
P_{13} = M_2T_4P_0 \quad P_{14} = M_6T_4P_0 \quad P_{15} = M_4T_4P_0
\]

where \(M_i = \frac{\lambda_i}{\mu_i}\) for \(i = 2, 4, 5, 6\) and

\[
T_4 = \left( \frac{\lambda_0T_2}{V_3} + \frac{\lambda_2T_2}{V_3} \right), \quad T_3 = \left( \frac{\mu_1\lambda_3T_2}{K_2V_2V_3} + \frac{\lambda_3}{K_2V_2} \right), \quad T_2 = \left( \frac{T_1}{K_3} \right), \\
T_1 = \left( \frac{\mu_2\lambda_3}{K_1V_1V_3} + \frac{\lambda_4}{K_1} \right), \quad K_3 = \left( 1 - \frac{\mu_1\mu_3\lambda_1\lambda_3}{K_1V_1V_2K_2V_2V_3} \right), \quad K_2 = \left( 1 - \frac{\mu_1\lambda_1}{V_2V_3} \right), \\
K_1 = \left( 1 - \frac{\mu_2\lambda_3}{V_1V_3} \right), \quad V_1 = (\lambda_3 + \mu_1), \quad V_2 = (\lambda_4 + \mu_3), \quad V_3 = (\mu_1 + \mu_3)
\]

Under normalized condition i.e. the sum of all the state probabilities is equal to one.

\[
\sum_{i=0}^{15} P_i = 1
\]

\[
P_0 = \frac{1 + T_2 + T_3 + T_4 + M_2 + M_4 + M_5(T_2 + T_4)}{M_6(T_3 + T_4)}
\]

The long-run availability \(A_v\) of SF system may be obtained by the summation of all the working and reduced capacity state probabilities i.e.

\[
A_v = P_0 + P_1 + P_2 + P_3 = P_0(1 + T_2 + T_3 + T_4)
\]

The maintenance data for the various sub-systems was collected from the maintenance history sheet. This data is translated into the parameterized form of failure and repair rate parameters as \(\lambda_1=0.004\), \(\mu_1=0.081\); \(\lambda_2=0.00033\), \(\mu_2=0.04\); \(\lambda_3=0.006\), \(\mu_3=0.07\); \(\lambda_4=0.0002\), \(\mu_4=0.3\); \(\lambda_5=0.0047\), \(\mu_5=0.09\); and \(\lambda_6=0.0051\), \(\mu_6=0.049\) for the various sub-systems. The long-run availability of the system is found 91.45% using above parameters in equation (9).

3.3. Particle Swarm Optimization
The PSO technique is comparatively an effective optimization method in most of the cases whose mechanics are inspired by social behavior of biological population Kennedy at al. [11]. Their behavior is unpredictable but consistent with keeping the most suitable distance from each other. The algorithm works by initializing the folk of birds randomly, where birds are known as “particles”. In PSO, the best solution is represented by the optimum position of a particle and the population is known as a swarm. The particles are initialized randomly with their position and velocity. The main goal of the entire particles is to find the optimum position in the space. In PSO every particle remembers its previous best position and the neighbor best as well. Therefore the memory capability is better as
compared to other algorithms (e.g. GA). Every time the best position reached is compared with the previous best position and personal (pbest) as well as global best (gbest) positions are updated.

Each particle updates its position towards a new even better position adjusting their velocity based on the previous experience of the particles. Once the new position is reached, the swarm of the particles is updated. This process is repeated until the optimum solution is not met. The velocity and position of the particle are updated using the following relations: [15]

\[
V_i = wV_i + c1 \cdot \text{rand} 1 \cdot (pbest_i - X_i) + c2 \cdot \text{rand} 2 \cdot (gbest - X_i)
\]

\[
X_i = V_i + X_i
\]

Where 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.

3.4. Genetic Algorithm

In order to compare the performance of PSO approach, the present study uses a Genetic Algorithm based approach also. Genetic algorithm (GA) technique has effectively been used to achieve the quality solution for both constrained and unconstrained optimization problems. GA determines the initial population randomly like PSO and fittest chromosomes represent the best solution. The chromosomes are evaluated for fitness value and best individuals are selected to become the parents of next generation. Crossover operator combines the best individuals to yield even better chromosomes. It propagates the good features of current population into the next generation, which will have better fitness value than the previous generation.

The mutation operator is used for rearranging the structure of chromosomes to avoid the possibility of new solution very similar to the previous solutions after several generations. The whole process is repeated until either the best fitness level of the population has been achieved or a maximum number of generations have been produced.

4. Computational Results

4.1. Behavioral Analysis of the System

In this section, the behavioral analysis has been conducted to identify the criticality of various subsystems. The failure and repair rate parameters of each sub-system are varied within a constrained range, keeping the other sub-system with constant parameters in this analysis. The designed ranges of failure and repair rate parameters are shown in table 1. The behavioral pattern in terms of the effect on system availability with respect to the variation in failure and repair rate parameters of various subsystems is shown in figure 3.

Table 1. Ranges of failure and repair rate parameters for SF system

| Sub-System | Ranges of failure rate parameters | Ranges of repair rate parameters |
|------------|----------------------------------|---------------------------------|
| A          | \( \lambda_1 = 0.004 - 0.016 \)  | \( \mu_1 = 0.081 - 0.2 \)       |
| B          | \( \lambda_2 = 0.0033 - 0.0153 \) | \( \mu_2 = 0.04 - 0.16 \)       |
| C          | \( \lambda_3 = 0.006 - 0.018 \)  | \( \mu_3 = 0.07 - 0.19 \)       |
| D          | \( \lambda_4 = 0.0002 - 0.0017 \)| \( \mu_4 = 0.3 - 1.8 \)         |
| A'         | \( \lambda_5 = 0.0047 - 0.0167 \)| \( \mu_5 = 0.09 - 0.21 \)       |
| C'         | \( \lambda_6 = 0.0051 - 0.00171 \)| \( \mu_6 = 0.049 - 0.169 \)     |
It is observed in the analysis that the long-run availability of SF system is highly influenced by the sub-system (B) and least affected by the sub-system (D) as compared to other sub-systems as shown in table 2. It shows the behavior of the system in terms of percentage changes in the long-run availability of the system with respect to the variation in the failure and repair rate parameters of various sub-systems. It is a useful method for making the perfect decisions of repair priorities for different sub-systems.

Table 2. Behavioral analysis of SF system

| Sub-System | Ranges of failure rates | Decrease in availability | Ranges of repair rates | Increase in availability | Repair priority |
|------------|------------------------|--------------------------|------------------------|--------------------------|----------------|
| A          | $\lambda_1 = 0.004-0.016$ | 0.45%                    | $\mu_1 = 0.081 - 0.2$  | 0.12%                    | III            |
| B          | $\lambda_2 = 0.0033 - 0.0153$ | 19.69%                   | $\mu_2 = 0.04 - 0.16$  | 5.49%                    | I              |
| C          | $\lambda_3 = 0.006 - 0.018$ | 1.04%                    | $\mu_3 = 0.07 - 0.19$  | 0.41%                    | II             |
| D          | $\lambda_4 = 0.0002 - 0.0017$ | 0.42%                    | $\mu_4 = 0.3 - 1.8$    | 0.05%                    | IV             |

4.2. Availability Optimization Using PSO and GA

In this section, the availability of the system is optimized using PSO and GA algorithms. The twenty independent runs are performed to get optimum results with the population size 45 and a maximum number of generations as 100 for each algorithm.
PSO settings: In our experiments, the cognitive component \( c_1 \) and the social component \( c_2 \) are taken as 1.5. The inertia weight \( w \) updated from 0.9 to 0.4 with the number of generation [15].

GA settings: The crossover function is taken as 0.8 and the mutation function in our experiments is taken as 0.01 [12].

The availability of the system is optimized using the same constrained ranges of failure and repair rate parameters of different sub-systems as shown in table 1. The optimum system availability is found to be 97.72% using the above PSO variables. Further, the effectiveness of the proposed evolutionary algorithm is verified by comparing the obtained results with the results obtained through other techniques i.e. GA and Markov process. The comparative results are shown in table 3. It can be observed from the results that the PSO performed well in optimizing the availability of the system by modifying the input failure and repair rate parameters. The convergence characteristic of PSO and GA is shown in figure A1 and figure B1 (see appendix).

### Table 3. Comparison of optimum availability using Markov process, GA and PSO.

| Failure & Repair rate Parameters | Markov Process (Population size = 45, Number of generations = 100) | GA (Population size = 45, Number of generations = 100) | PSO (Population size = 45, Number of generations = 100) |
|----------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|
| \( \lambda_1 \)                 | 0.004                                                       | 0.007                                                       | 0.0072                                                      |
| \( \mu_1 \)                      | 0.081                                                       | 0.207                                                       | 0.142                                                      |
| \( \lambda_2 \)                 | 0.0033                                                      | 0.004                                                       | 0.0033                                                      |
| \( \mu_2 \)                      | 0.16                                                        | 0.16                                                        | 0.16                                                        |
| \( \lambda_3 \)                 | 0.006                                                       | 0.006                                                       | 0.006                                                      |
| \( \mu_3 \)                      | 0.07                                                        | 0.14                                                        | 0.141                                                      |
| \( \lambda_4 \)                 | 0.0002                                                      | 0.001                                                       | 0.0008                                                      |
| \( \mu_4 \)                      | 0.3                                                         | 1.573                                                       | 1.29                                                        |
| \( \lambda_5 \)                 | 0.0047                                                      | 0.006                                                       | 0.0047                                                      |
| \( \mu_5 \)                      | 0.09                                                        | 0.209                                                       | 0.21                                                        |
| \( \lambda_6 \)                 | 0.0051                                                      | 0.005                                                       | 0.0051                                                      |
| \( \mu_6 \)                      | 0.049                                                       | 0.164                                                       | 0.162                                                      |
| Availability                     | 96.94%                                                      | 97.45%                                                      | 97.72%                                                      |

5. Conclusions

The present study depicts the perfect behavior of the system in order to identify the criticality of the various subsystems in terms of the effect on the system availability. For this, a mathematical model has been developed using Markov approach. Further, the optimum failure and repair rate parameters for various subsystems are obtained by solving the availability optimization model through particle swarm optimization technique and the results obtained through PSO are compared with GA solution. The major advantages of the proposed technique are that it reduces the range of prediction in system behavior and the results obtained in the present study are useful in maintenance planning to get higher system performance from the existing resources in the plant.
Appendix A

Figure A1. PSO convergence characteristic

Appendix B

Figure B1. GA convergence characteristic
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