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PERFORMANCE OPTIMIZATION OF RUBBER TUBE EXTRACTION SYSTEM USING NATURE BASED ALGORITHMS

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Abstract

Reliability and maintenance engineering is a powerful tool which enables the industries to find ways of costs savings and operational improvement opportunities. In this paper, the rubber tube extraction system is considered to evaluate the availability of the system under different maintenance conditions. The methodology employed for analysis purpose is based upon Markov Modeling in which failure and repair rates of the units comprising the system are taken as constant. Differential equations are derived and solved by Laplace transform to attain state probabilities. Solving reliability problems using meta-heuristic algorithms have attracted increasing thought in recent years. Various recent nature based algorithms are considered to solve availability optimization problem. The computational results were carried out on different algorithms and their experimental results are exhibited and compared with best obtained solutions. The analysis enables to find the local maxima of the objective function, which will help plant personnel to increase the daily production with optimum parameters.

Key Words: Markov Modelling, Availability, Genetic Algorithm, Whale Optimization Algorithm, Particle Swarm Optimization

1. Introduction

The present competitive scenario for the industry increased the necessity to design and develop highly reliable systems. The increasing competition for industries make their profits slimmer day by day. The concept of reliability engineering has gained the attention of industry leaders in the current business scenario. Reliability engineering is a powerful engineering tool which enables industries to find ways of cost savings and other operational improvement opportunities (Barlow & Wu, 1978).The basic objective of the reliability engineering is to explore methods and statistical tools to evaluate and exhibit reliability, maintainability and availability (RAM) of the system or component. Generally, Maintenance may be Corrective (CM) or Preventive (PM). A well-scheduled PM model reduces superfluous shutdowns because of unplanned failure. PM can be ideal or faulty. An ideal PM is presumed to reinstate the system as new; whereas faulty PM brings in repair state (Manzini, Regattieri, Pham, & Ferrari, 2010).An effective PM model is an indispensable need for present process industry to increase productivity and profits. The PM can also be helpful in preserving the quality of the products.

With the development of industrial engineering, various complex industrial system designs come into existence. The increasing necessity for high reliable systems demands the exploration of reliability optimization. Optimization will enable more precise and competent methods for optimal system reliability, which assures efficiency and system safety (Wu et al., 2011) Reliability of systems has been a research area for many scientists and engineers. An industrial system can have a series, parallel or series-parallel configurations (Srinath, 2005). Aksu & Turan (2006) presents reliability and availability valuation of pod propulsion system using failure mode and effect analysis, fault tree analysis (FTA) and Markov analysis complementarily. Umemura & Dohi (2010) discussed the embedded Markov Chain approach in continuous-time and discrete-time scales stochastic behavior of an electronic system to maximize its steady-state availability. Sharma and Kumar (2008) used RAM analysis on a urea production process plant to minimize system failures, maintainability requirements and optimizing equipment availability. Hassan et al. (2016) proposed Markov model for LNG processing plant for availability and PM. The optimum PM policy had been determined to maximize the availability. A comprehensive review on multi-component maintenance optimization was conducted by Nicolai & Dekker (2006). The research was based on mathematical modeling of industrial systems. Gupta & Goyal (2010) discussed the effect multi repair facilities and multi repair the bubble gum production system bubble gum production system. In order to cope with optimization problems arising in system reliability, important contributions have been made since 1960. Many researchers applied heuristic approaches to study the reliability problems (Tillman & Hwang, 1977). Hikita et al. (1992) reported nonlinear mixed-integer programming formulation and the surrogate dual method for optimizing redundancy and component reliability at various stages of a system. Genetic algorithms (GA) are nature inspired algorithms, generally used to solve combinatorial nature optimization problems (Holland, 1975). Yokota et al. (1996) and Hsieh et al. (1998) applied GA to solve reliability optimization problems. They reported, the solutions obtained by GAs can solve reliability problems efficiently and effectively. A design of a mixed configuration system comprising of multiple component available out of several k-out-of-n: G subsystems had been optimized using GA. A problem-specific genetic algorithm (GA) is developed and demonstrated to analyze series-parallel systems and to determine the optimal design configuration when there are multiple component choices available for each of several k-out-of-n: G subsystems (Doit & Smith, 1996).Kennedy & Eberhart (1995) developed an efficient particle swarm optimization (PSO) algorithm based on Gaussian distribution and chaotic sequence to optimize the reliability systems. Kuo and Wan (2007) presented a good comprehensive review in recent trends in optimal reliability problem and summarized various techniques. Another hybrid algorithm combining two heuristic techniques Particle swarm optimization (PSO) and genetic algorithms (GA) denoted by GA-PSO. This hybrid technique creates individuals in a new generation by crossover and mutation operations of GA and by mechanisms of PSO (Sheikhalishahi et al., 2013).

Yang and Deb (2013) proposed an efficient metaheuristic algorithm namely, Cuckoo search (CS). It mimics the behavior of the cuckoo species which lays their eggs in the nests of other birds. CS found to be highly effective method in solving global optimization problems of reliability and redundancy designs (Valian & Valian, 2013). This hybrid algorithm enhances the accuracy and convergence rate of the cuckoo search algorithm. Simulations by ICS reveal the effectiveness of the algorithm. Metaheuristic algorithms are frequently nature-inspired. They are the most widely used algorithms for achieving optimization. Kanagaraj & Jawahar (2011) proposed meta-heuristic optimization algorithm CS-GA to solve reliability problems. This algorithm is based on cuckoo search (CS) hybridized with genetic algorithm (GA). A new swarm intelligence optimization technique called a dragonfly algorithm (DA) was developed by Mirjalili (2016). This technique able to improve the initial random population and converges towards the global optimum. Mirjaliliet al. (2016) proposed a meta-heuristic algorithm called Grey Wolf Optimizer (GWO).The algorithm mimics the leadership hierarchy and the hunting mechanism of grey wolves in nature. Mirjalili (2015) proposed Moth-Flame Optimization (MFO) algorithm inspired from the navigation method of moths in nature called transverse orientation. MFO proves to be a better optimization technique in solving problems with constrained and unknown search spaces. Another nature-inspired algorithm, Ant Lion Optimizer (ALO) proposed by Mirjalili (2015). ALO mimics the hunting mechanism of antlions in nature. ALO proves its excellence in solving constrained problems with diverse search spaces. Recently, Mirjalili and Lewis (2016) proposed a newly developed nature based algorithm called Whale Optimization Algorithm (WOA) based on social behavior of humpback whales. In their research, authors optimize number of practical engineering problems with this technique.

To our best knowledge no, comparative study has addressed the availability optimization with nature-based algorithms of the production system with PM under faulty and ideal condition. The objective of this study is to illustrate the behavior of different algorithms with the similar level of input variables for availability. This is accomplished by deriving the full availability (A_{FC}) and overall availability (A_{OC}) using Markov modelling for evaluation and optimization. For this Rubber tube extraction system, a subsystem of Rubber tyre tube manufacturing plant located in Punjab, India. (Because of confidentiality issues, the name of the company is not quoted) is considered and the real time data of repair rates, failure rates, PM rates and transition rates are taken. Moreover, literature review suggests that most of the work on reliability optimization is done by taking a hypothetical system and data. Except genetic algorithm, very less work is done in the field of reliability optimization. Present work focuses on the applicability of different optimization techniques on the real practical problem.

2. System Description

The rubber sheets from warming mill is transfer to strainer, where the sheets are treated to remove foreign particles of metal or dust. These sheets are then, sent to refinement mill where the powdered accelerators (Sulphur, CBS and TMT) are impinged on sheets to enhance the rubber properties. The tubes will be formed with the help of extruders and cut with cutters according to the size. Figure 1 describes the various subsystems of Rubber tube extraction system. The rubber tube extraction system consists of three subsystems. Subsystem “S”, consists of one unit namely Strainer subjected to both revealed and unrevealed failures. Subsystem “R”, consists of one unit namely Refinement Mill subjected to both revealed and unrevealed failures. Subsystem “E” consists of five parallel systems, each comprising of one extruder and one cutter in the series. This subsystem can work with three items in reduced capacity. If three or more than three items are failed, the subsystem - E will be in failed state.

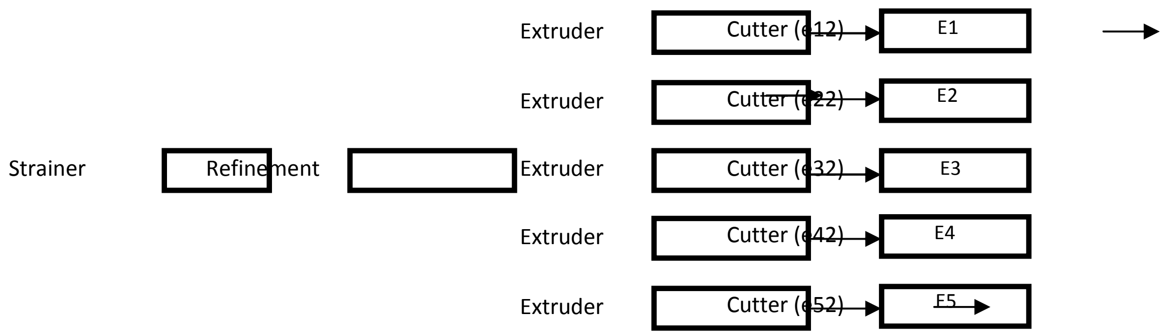

Figure 1: Various subsystems of Rubber tube extraction system.

2.1 Notations

Various subscripts used for mathematical analysis of the system are as below:-

"o" :indicates system is functional

"g" :indicates system is good enough but not functional.

"r" :indicates system is under breakdown and in repair.

"q" :indicates system is waiting for repair.

"p" : indicates system is not functional and under preventive maintenance

λ_6 and λ_7 : indicates failure rates of S and R respectively.

μ_6 and μ_7 : indicates repair rates of S and R respectively.

α, β : indicates transition rates of systems S & R , to go to degraded state.

θ, ϕ : indicates PM rate of a "S" and "R" .

η :constant probability that PM is carried out unsatisfactorily and causes the system to go to failed state immediately thereafter.

(1-η) :represents constant probability that PM is carried out satisfactorily and this makes the system to operate immediately thereafter.

λ_{ia} : Respective failure rate of the two series units e_{i1} and e_{i2}. As e_{i1} and e_{i2} are working in series therefore $\lambda_i = \lambda_{i1} + \lambda_{i2}$.

$\mu_e(x)$:refer overall repair rate of the complete system initiated on failure of four or more parallel working units of subsystem B.

$E_{m,n}^{x,y}$: Represents the working status of the subsystem B which consists of five identical units e_1, e_2, e_3, e_4 and e_5 working in parallel. Further each E_i consists of two units working in series viz. e_{i1}, e_{i2} where i = 1,2,3,4,5. The subscript 'm' represents the number of operating units of E while 'n' represents the number of failed units of E. Pair $\binom{x}{m}$ designates the working status of 'm' operating units, while pair $\binom{y}{n}$ represents the repair status of 'n' failed units and this pair can further be expanded as $\binom{y+y+y+y}{ei+ej+ek+el}$ if 'n' becomes more than one.

$$n = e_i \; when \; n = 1$$
$$n = e_i + e_j \; when \; n = 2$$
$$n = e_i + e_j + e_k \; when \; n = 3$$
$$n = e_i + e_j + e_k + e_l \; when \; n = 4$$

$P_i(t)$:State probability that the system is in i[th] state at time t.
$P_o(t)$: State probability that the system at time't' is working at full capacity.

2.2 Assumptions

In analyzing the system, following assumptions made -

1. Initially, all the units are in a functional state.
2. Units may be functional, failed or degraded.
3. After repair, each unit will function as new.
4. The various failure, repair, transition and PM rates are taken constant.
5. At an instance, PM of only one subsystem can be performed.
6. The PM will only be initiated, if no subsystem is under repair.
7. A single repair unit exists in plant for repair and maintenance.
8. Subsystems "S" and "R" are priority items whereas Subsystem-E is second priority unit because it consists of five subunits working in parallel.
9. On pre-empting the repair of E units to perform the repair of higher priority subsystems S and R, there is a delay in the repair of these E units. This delay in repair reduces the repair rate and this effect is exhibited by using $\mu_i^*(x)$ in place of$\mu_i(x)$. $\mu_i^*(x) = \frac{\mu_i(x)}{\gamma_i}$, where γ_i is the delay factor and $\gamma_i > 1.$ $(i = 1,2,3,4,5)$in the present work we take$\gamma_i = 1.35$.
10. The subsystem E will be working only, if at least two units remain functional. On failure of four or more units, the subsystem will be in failed state.

3. Mathematical Modelling

The system starts from a particular state at time 't' and reaches failed state, PM state or remains in the operational state during the time interval Δt. The mathematical formulation of the model is carried out using first order differential – difference equations associated with the state transition diagram of the system. Various probability considerations give the following differential equations associated with the Rubber tube extraction system. These equations are solved for determining the steady state availability of the system.

$$P_0'(t) + F_0P_0(t) = \mu_i^*P_5(t) + \mu_j^*P_{15}(t) + \mu_k^*P_{30}(t) + \mu_6P_1(t) + \mu_7P_3(t) + \mu_eP_{35}(t) + \theta(1-\eta)P_2(t) + \phi(1-\eta)P_4(t) \quad \ldots (1)$$

$$P_5'(t) + F_1P_5(t) = \lambda_iP_0(t) + \mu_7P_8(t) + \mu_6P_6(t) + \theta(1-\eta)P_7(t) + \phi(1-\eta)P_9(t) \quad \ldots (2)$$

$$P_{10}'(t) + F_3P_{10}(t) = \lambda_jP_5(t) + \mu_7P_{13}(t) + \mu_6P_{11}(t) + \theta(1-\eta)P_{12}(t) + \phi(1-\eta)P_{14}(t) \quad \ldots(3)$$

$$P_{15}'(t) + F_4P_{15}(t) = \mu_i^*P_{10}(t) + \mu_7P_{18}(t) + \mu_6P_{16}(t) + \theta(1-\eta)P_{17}(t) + \phi(1-\eta)P_{19}(t) \quad \ldots(4)$$

$$P_{20}'(t) + F_5P_{20}(t) = \lambda_kP_{10}(t) + \mu_7P_{23}(t) + \mu_6P_{21}(t) + \theta(1-\eta)P_{22}(t) + \phi(1-\eta)P_{24}(t) \quad \ldots(5)$$

$$P_{25}'(t) + F_6P_{25}(t) = \lambda_kP_{15}(t) + \mu_i^*P_{20}(t) + \mu_7P_{29}(t) + \mu_6P_{26}(t) + \theta(1-\eta)P_{28}(t) + \phi(1-\eta)P_{27}(t) \quad \ldots(6)$$

$$P_{30}'(t) + F_7P_{30}(t) = \mu_j^*P_{25}(t) + \mu_7P_{33}(t) + \mu_6P_{31}(t) + \theta(1-\eta)P_{32}(t) + \phi(1-\eta)P_{34}(t) \quad \ldots(7)$$

$$P_{35}'(t) + \mu_eP_{35}(t) = \lambda_lP_{20}(t) \quad \ldots(8)$$

$$P_{5a+1}'(t) + \mu_6P_{5a+1}(t) = \lambda_6P_{5a}(t) + \theta\eta P_{5a+2}(t) \quad \ldots(9)$$

$P'_{5a+2}(t) + \theta P_{5a+2}(t) = \alpha P_{5a}(t)$ …(10)

$P'_{5a+3}(t) + \mu_7 P_{5a+3}(t) = \lambda_7 P_{5a}(t) + \phi\eta P_{5a+4}(t)$ …(11)

$P'_{5a+4}(t) + \phi P_{5a+4}(t) = \beta P_{5a}(t)$, for a=0,1………5 …(12)

Where,

$F_0 = \alpha + \beta + \lambda_6 + \lambda_7 + \lambda_i$

$F_1 = \alpha + \beta + \lambda_6 + \lambda_7 + \lambda_j + \mu_i^*$

$F_2 = \alpha + \beta + \lambda_6 + \lambda_7 + \lambda_k + \mu_i^*$

$F_3 = \alpha + \beta + \lambda_6 + \lambda_7 + \lambda_k + \mu_j^*$

$F_4 = \alpha + \beta + \lambda_6 + \lambda_7 + \lambda_l + \mu_i^*$

$F_5 = \alpha + \beta + \lambda_6 + \lambda_7 + \mu_j^*$

$F_6 = \alpha + \beta + \lambda_6 + \lambda_7 + \mu_k^*$

Taking Laplace Transform of above (1-12) equations, the equations will be,

$sP_0(s) + F_0P_0(s) = \mu_i^*P_5(s) + \mu_j^*P_{15}(s) + \mu_k^*P_{30}(s) + \mu_6P_1(s) + \mu_7P_3(s) + \mu_eP_{35}(s) + \theta(1-\eta)P_2(s) + \phi(1-\eta)P_4(s)$ …(13)

$sP_5(s) + F_1P_5(s) = \lambda_iP_0(s) + \mu_7P_8(s) + \mu_6P_6(s) + \theta(1-\eta)P_7(s) + \phi(1-\eta)P_9(s)$ …(14)

$sP_{10}(s) + F_2P_{10}(s) = \lambda_jP_5(s) + \mu_7P_{13}(s) + \mu_6P_{11}(s) + \theta(1-\eta)P_{12}(s) + \phi(1-\eta)P_{14}(s)$ …(15)

$sP_{15}(s) + F_3P_{15}(s) = \mu_i^*P_{10}(s) + \mu_7P_{18}(s) + \mu_6P_{16}(s) + \theta(1-\eta)P_{17}(s) + \phi(1-\eta)P_{19}(s)$ …(16)

$sP_{20}(s)) + F_4P_{20}(s) = \lambda_kP_{10}(s) + \mu_7P_{23}(s) + \mu_6P_{21}(s) + \theta(1-\eta)P_{22}(s) + \phi(1-\eta)P_{24}(s)$ …(17)

$sP_{25}(s) + F_5P_{25}(s) = \lambda_kP_{15}(s) + \mu_i^*P_{20}(s) + \mu_7P_{29}(s) + \mu_6P_{26}(s) + \theta(1-\eta)P_{28}(s) + \phi(1-\eta)P_{27}(s)$ …(18)

$sP_{30}(s) + F_6P_{30}(s) = \mu_j^*P_{25}(s) + \mu_7P_{33}(s) + \mu_6P_{31}(s) + \theta(1-\eta)P_{32}(s) + \phi(1-\eta)P_{34}(s)$ …(19)

$sP_{35}(s) + \mu_eP_{35}(s) = \lambda_lP_{20}(s)$ …(20)

$sP_{5a+1}(s) + \mu_6P_{5a+1}(s) = \lambda_6P_{5a}(s) + \theta\eta P_{5a+2}(s)$ …(21)

$sP_{5a+2}(s) + \theta P_{5a+2}(s) = \alpha P_{5a}(s)$ …(22)

$sP_{5a+3}(s) + \mu_7P_{5a+3}(s) = \lambda_7P_{5a}(s) + \phi\eta P_{5a+4}(s)$ …(23)

$sP_{5a+4}(s) + \phi P_{5a+4}(s) = \beta P_{5a}(s)$ …(24)

Solving recursively the above equations (13 to 24) we get,

$P_n(s) = K_nP_0$ where n=1, 2, 3, 4, 5……..35 …(25)

Where,

$K_1 = \frac{\lambda_6 + \alpha\eta}{\mu_6}$, $K_2 = \frac{\alpha}{\theta}$, $K_3 = \frac{\lambda_7 + \beta\eta}{\mu_7}$, $K_4 = \frac{\beta}{\phi}$

$K_5 = \frac{\lambda_i}{(s + F_1 - \lambda_7 - \lambda_6 - \alpha - \beta)}$, $K_{10} = \frac{K_5\lambda_j}{(s + F_2 - \lambda_7 - \lambda_6 - \alpha - \beta)}$,

$K_{15} = \frac{\mu_i^*K_{10}}{s + F_3 - \lambda_7 - \lambda_6 - \alpha - \beta}$, $K_{20} = \frac{\lambda_kK_{10}}{(s + F_4 - \lambda_7 - \lambda_6 - \alpha - \beta)}$,

$K_{25} = \frac{\lambda_kK_{15} + \mu_i^*K_{20}}{(s + F_5 - \lambda_7 - \lambda_6 - \alpha - \beta)}$, $K_{30} = \frac{\mu_j^*K_{25}}{(s + F_6 - \lambda_7 - \lambda_6 - \alpha - \beta)}$,

$K_{35} = \frac{\lambda_l}{\mu_e}K_{20}$, $K_{5+a} = K_aK_5$, $K_{10+a} = K_aK_{10}$, $K_{15+a} = K_aK_{15}$,

$K_{20+a} = K_aK_{20}$, $K_{25+a} = K_aK_{25}$, $K_{30+a} = K_aK_{30}$, *where* $a = 1,2,3,4,5$

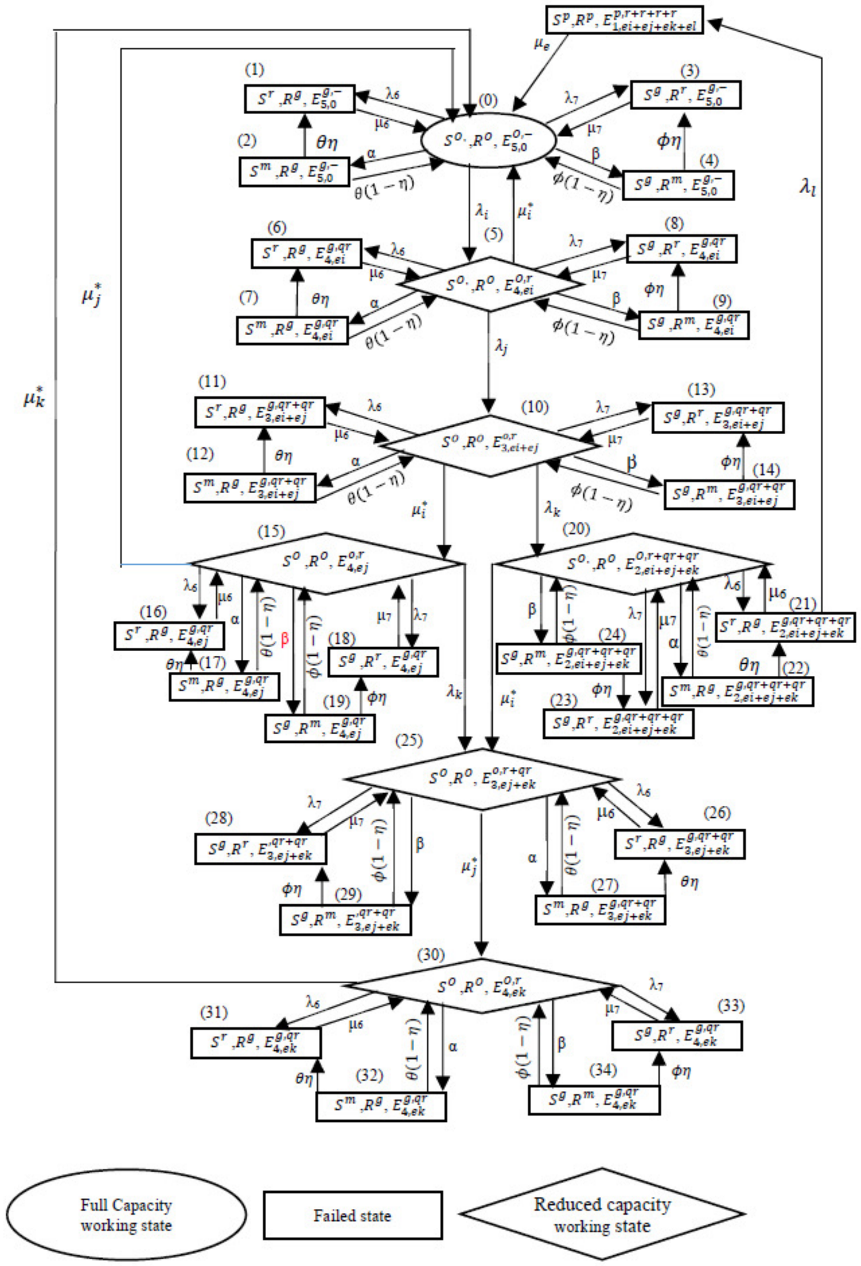

Figure 2: Transition diagram of Rubber Tube Extraction system

Taking Laplace transform of equation- (1), using initial conditions and relations, we get

$$P_0(s) = \frac{1}{s + F_0 - \mu_i^* K_5 - \mu_j^* K_{15} - \mu_k^* K_{30} - \mu_6 K_1 - \mu_7 K_3 - \mu_e K_{35} - \theta(1-\eta)K_2 - \phi(1-\eta)K_4} \quad \ldots(26)$$

The full Availability function A_{FC} (s) for the system is given as,

$$A_{FC}(s) = P_0(s) \quad \ldots(27)$$

Inversion of $A_{FC}(s)$ gives the full availability function $A_{FC}(t)$

The overall Availability function A_{OC} (t) for the system is given as,

$$A_{OC}(s) = P_0(s) + P_5(s) + P_{10}(s) + P_{15}(s) + P_{20}(s) + P_{25}(s) + P_{30}(s)$$
$$= P_0(s)(1 + K_5 + K_{10} + K_{15} + K_{20} + K_{25} + K_{30}), \quad \ldots(28)$$

where $P_0(s)$ is given by equation (26)

Inversion of $A_{OC}(s)$ gives the overall availability function $A_{OC}(t)$

The steady state probabilities are required to calculate the long run availability of the system. The steady state behavior of the system can be analyzed by setting t→ ∞ and d/dt → 0 in equations (18) to (34).

We get,

$$F_0 P_0 = \mu_i^* P_5 + \mu_j^* P_{15} + \mu_k^* P_{30} + \mu_6 P_1 + \mu_7 P_3 + \mu_e P_{35} + \theta(1-\eta)P_2 + \phi(1-\eta)P_4 \quad \ldots(29)$$

$$F_1 P_5 = \lambda_i P_0 + \mu_7 P_8 + \mu_6 P_6 + \theta(1-\eta)P_7 + \phi(1-\eta)P_9 \quad \ldots(30)$$

$$F_2 P_{10} = \lambda_j P_5 + \mu_7 P_{13} + \mu_6 P_{11} + \theta(1-\eta)P_{12} + \phi(1-\eta)P_{14} \quad \ldots(31)$$

$$F_3 P_{15} = \mu_i^* P_{10} + \mu_7 P_{18} + \mu_6 P_{16} + \theta(1-\eta)P_{17} + \phi(1-\eta)P_{19} \quad \ldots(32)$$

$$F_4 P_{20} = \lambda_k P_{10} + \mu_7 P_{23} + \mu_6 P_{21} + \theta(1-\eta)P_{22} + \phi(1-\eta)P_{24} \quad \ldots(33)$$

$$F_5 P_{25} = \lambda_k P_{15} + \mu_i^* P_{20} + \mu_7 P_{29} + \mu_6 P_{26} + \theta(1-\eta)P_{28} + \phi(1-\eta)P_{27} \quad \ldots(34)$$

$$F_6 P_{30} = \mu_j^* P_{25} + \mu_7 P_{33} + \mu_6 P_{31} + \theta(1-\eta)P_{32} + \phi(1-\eta)P_{34} \quad \ldots(35)$$

$$\mu_e P_{35} = \lambda_l P_{20} \quad \ldots(36)$$

$$\mu_6 P_{5a+1} = \lambda_6 P_{5a} + \theta\eta P_{5a+2} \quad \ldots(37)$$

$$\theta P_{5a+2} = \alpha P_{5a} \quad \ldots(38)$$

$$\mu_7 P_{5a+3} = \lambda_7 P_{5a} + \phi\eta P_{5a+4} \quad \ldots(39)$$

$$\phi P_{5a+4} = \beta P_{5a} \quad \ldots(40)$$

Where,

$$Z_1 = \frac{\lambda_6 + \alpha\eta}{\mu_6}, \quad Z_2 = \frac{\alpha}{\theta}, \quad Z_3 = \frac{\lambda_7 + \beta\eta}{\mu_7}, \quad Z_4 = \frac{\beta}{\phi},$$

$$Z_5 = \frac{\lambda_i}{F_1 - \lambda_7 - \lambda_6 - \alpha - \beta}, \quad Z_{10} = \frac{Z_5 \lambda_j}{F_2 - \lambda_7 - \lambda_6 - \alpha - \beta},$$

$$Z_{15} = \frac{\mu_i^* Z_{10}}{F_3 - \lambda_7 - \lambda_6 - \alpha - \beta}, \quad Z_{20} = \frac{\lambda_k Z_{10}}{F_4 - \lambda_7 - \lambda_6 - \alpha - \beta},$$

$$Z_{25} = \frac{\lambda_k Z_{15} + \mu_i^* Z_{20}}{F_5 - \lambda_7 - \lambda_6 - \alpha - \beta}, \quad Z_{30} = \frac{\mu_j^* Z_{25}}{F_6 - \lambda_7 - \lambda_6 - \alpha - \beta},$$

$$Z_{35} = \frac{\lambda_l}{\mu_e} Z_{20}, \quad Z_{5+a} = Z_a Z_5, \quad Z_{10+a} = Z_a Z_{10}, \quad Z_{15+a} = Z_a Z_{15},$$

$$Z_{20+a} = Z_a Z_{20}, \quad Z_{25+a} = Z_a Z_{25}, \quad Z_{30+a} = Z_a Z_{30},$$

From eq. 29 , we get

$$P_0 = \frac{1}{F_0 - \mu_i^* Z_5 - \mu_j^* Z_{15} - \mu_k^* Z_{30} - \mu_6 Z_1 - \mu_7 Z_3 - \mu_e Z_{35} - \theta(1-\eta) Z_2 - \phi(1-\eta) Z_4}$$

…(41)

Using normalizing condition,

$$\sum_{i=1}^{35} P_i = 1, we\ get$$

$$P_0 = \left(1 + \sum_{i=1}^{35} Z_i\right)^{-1} \quad …(42)$$

The full Availability function A_{FC} for the system is given as,

$$A_{FC} = P_0 \quad …(43)$$

Inversion of A_{FC} gives the overall availability function A_{FC}.

The overall Availability function A_{OC} (t) for the system is given as,

$$A_{OC} = P_0 + P_5 + P_{10} + P_{15} + P_{20} + P_{25} + P_{30}$$

$$= P_0(1 + Z_5 + Z_{10} + Z_{15} + Z_{20} + Z_{25} + Z_{30}), \quad …(44)$$

where P_0 is given by equation (41)

Inversion of $A_{OC}(s)$ gives the overall availability function $A_{OC}(t)$

The A_{FC} and A_{OC} can be evaluated by substituting the values of different variables in above equations. The values of different variables have been taken from the real data available with the maintenance department. The various values are $\lambda_i = \lambda_j = \lambda_k = \lambda_l = 0.012$, $\lambda_6=0.01$, $\lambda_7=0.012$, $\mu_i = \mu_j = \mu_k = \mu_l = 0.35$, $\mu_6=0.2$, $\mu_7=0.2$, $\mu_e=0.009$, $\alpha=0.004$, $\beta=0.005$, $\theta=0.4$, $\phi=0.5$.

Substituting values in equation (43), the value of A_{FC} is

$$A_{FC} = 0.8454, \eta = 0$$

$A_{FC} = 0.8131, \eta = 1$

Substituting values in equation (44), the value of A_{OC} is

$$A_{OC} = 0.8849, \eta = 0$$

$A_{OC} = 0.8510, \eta = 1$

4. Computation Results, Analysis and Discussion

To optimize the performance and availability of the system, different nature based algorithms are used for best results. The algorithms were coded in C++ language. The computations were done on AMD A10-8700P (x64 based Processor-64 bit) Windows 10 Compute Cores 4C+6G, 1.8 GHz Having 8 GB of memory. The task of optimizing with different algorithms was performed in 40 runs, with each run iterated until the best solution was found. The local maxima were found by using the maximum and minimum value of the input variables. The values are chosen such that the extreme values are ± 25% of the mean values as shown in Table 1.

Parameter	λ_i	λ_6	λ_7	μ_i	μ_6	μ_7	μ_e	α	β	θ	φ
Minimum	0.009	0.0075	0.009	0.2625	0.15	0.1125	0.15	0.00625	0.00375	0.3	0.375
Maximum	0.015	0.0125	0.015	0.4375	0.25	0.1875	0.25	0.01125	0.00625	0.5	0.625

Table 1: Minimum and Maximum values of parameters used in the analysis

We compare the different ten nature based algorithms from literature, namely:

GA -Genetic Algorithm
PSO -Particle Swarm Optimization
CS -Cuckoo Search Algorithm
CS-GA -Cuckoo Search- genetic algorithm
GA-PSO -Genetic Algorithm- Particle Swarm Optimization
GWA -Grey Wolf Algorithm
MFO -Moth Flame Optimization
DAO -Dragonfly Algorithm
ALO -Ant Lion Algorithm
WOA -Whale Optimization Algorithm

The numerical results are shown in Tables 2–5, where the best solutions are reported corresponding to optimization technique. For measuring the improvement, MI% (maximum improvement percentage) can be used to measure the percentage improvement of the solutions found by the algorithms to the present availability and is described as:

$$MI\% = \left(\frac{A_{algo} - A_{mean}}{A_{mean}}\right) * 100$$

Where,

A_{algo}= best system availability obtained corresponding to the algorithm

A_{mean}= Present availability of the system as described in section 2.3

By using MI%, it shows the change in the availability of the system from the mean. In high reliable systems, a small increment in reliability is often difficult to be achieved.

Algorithm	A_{FC}	λ_i	λ_6	λ_7	μ_i	μ_6
GA	0.886833	0.009214	0.007745	0.009623	0.437348	0.249758
PSO	0.906047	0.009001	0.0075002	0.0095001	0. 437381	0.243258
CS	0.906114	0.009003	0.0075002	0.0095006	0. 437499	0.248756
CS-GA	0.906294	0.009	0.0075	0.0095001	0. 437498	0.249997
GA-PSO	0.906295	0.009	0.0075	0.0095	0. 437496	0.25
GWA	0.905838	0.009004	0.007508	0.0095003	0. 437412	0.249916
MFO	0.906099	0.009005	0.0075001	0.0095002	0. 437466	0.248569
DAO	0.90614	0.009007	0.0075003	0.0095	0. 437485	0.249999
ALO	0.905976	0.009008	0.007501	0.0095001	0. 437499	0.249999
WOA	0.906295	0.009	0.0075	0.0095001	0. 4375	0.2499998

Algorithm	μ_7	μ_e	α	β	θ	φ
GA	0. 24932	0.011231	0.003751	0.003795	0.499999	0.623986
PSO	0. 249262	0.011245	0.003	0.003768	0.497906	0.624365
CS	0. 249358	0.011247	0.003001	0.003765	0.499899	0.624953
CS-GA	0. 2495	0.011246	0.003	0.00375	0.499912	0.625
GA-PSO	0. 2495	0.011247	0.003	0.00375	0.5	0.625001
GWA	0. 2493	0.011246	0.003001	0.003786	0.499848	0.624788
MFO	0. 249400	0.011246	0.003008	0.003758	0.498528	0.624997
DAO	0. 249363	0.011246	0.003007	0.003798	0.499758	0.624997
ALO	0. 249402	0.011221	0.003005	0.003776	0.499988	0.624997
WOA	0. 249362	0. 011245	0.003	0.003751	0.499996	0.624996

Table 2: Best result for the A_{FC} with various nature based algorithms when PM is ideal

Algorithm	A_{FC}	λ_i	λ_6	λ_7	μ_i	μ_6
GA	0.878854	0.009158	0.007627	0.0096221	0. 437441	0.239952
PSO	0.878914	0.009008	0.007504	0.0095951	0. 437475	0.241211
CS	0.879441	0.009003	0.007501	0.0095055	0. 437395	0.24998
CS-GA	0.87943	0.009	0.0075	0.0095018	0. 4375	0.24999
GA-PSO	0.879270	0.009001	0.0075	0.0095	0. 4375	0.25
GWA	0.879123	0.009012	0.007601	0.0095037	0. 43721	0.249841
MFO	0.879312	0.009014	0.007707	0.0095511	0. 437423	0.248952
DAO	0.879443	0.009025	0.007512	0.0095062	0. 437489	0.249999
ALO	0.879443	0.009	0.0075	0.0095001	0. 437499	0.249998
WOA	0.879423	0.009091	0.007612	0.009508	0. 437452	0.24125

Algorithm	μ_7	μ_e	A	β	θ	φ
GA	0. 249418	0.011231	0.003368	0.003759	0.499984	0.624997
PSO	0. 249399	0.011245	0.003022	0.0037511	0.499999	0.624874
CS	0. 249425	0.01124	0.003041	0.0037574	0.499952	0.624922
CS-GA	0. 249399	0.011243	0.003235	0.0037512	0.499966	0.624985
GA-PSO	0. 2494999	0.0112479	0.003001	0.0037501	0.5	0.62499
GWA	0. 249444	0.011246	0.00301	0.0037592	0.499156	0.624995
MFO	0. 249441	0.011243	0.003012	0.0037522	0.499965	0.624959
DAO	0. 249969	0.0112421	0.003061	0.0037541	0.499852	0.62492
ALO	0. 2495	0.011221	0.003	0.0037501	0.499988	0.625
WOA	0. 249402	0. 011245	0.003005	0.0037595	0.499588	0.62491

Table 3: Best result for the A_{FC} with various nature based algorithms when PM is faulty

Algorithm	**A_{OC}**	**λ_i**	**λ_6**	**λ_7**	**μ_i**	**μ_6**
GA	0.954102	0.009041	0.007568	0.009504	0. 437325	0.2497521
PSO	0.96125	0.009000	0.007502	0.009513	0. 437380	0.2497899
CS	0.961825	0.009000	0.0075	0.0095	0. 437498	0.24999985
CS-GA	0.961907	0.009012	0.007502	0.009512	0. 4375	0.24989965
GA-PSO	0.963845	0.009	0.0075	0.0095	0. 437492	0.24989965
GWA	0.960803	0.009000	0.007502	0.009501	0. 437428	0.24999016
MFO	0.961998	0.009055	0.007500	0.009515	0. 437474	0.24999852
DAO	0.961022	0.009035	0.007500	0.009506	0. 437413	0.2499523
ALO	0.962559	0.009000	0.0075	0.009503	0. 437473	0.24999852
WOA	0.963841	0.009002	0.0075	0.009502	0. 437953	0.25

Algorithm	**μ_7**	**μ_e**	**α**	**β**	**θ**	**φ**
GA	0. 249399	0.01124	0.003118	0.003871	0.489458	0.624999
PSO	0. 249261	0.011245	0.003009	0.003755	0.499906	0.624865
CS	0. 249499	0.011241	0.003024	0.003756	0.498998	0.624953
CS-GA	0. 249499	0.011243	0.003009	0.003757	0.5	0.625
GA-PSO	0. 249499	0.011248	0.003001	0.00375	0.499999	0.624999
GWA	0. 249495	0.01125	0.0030004	0.003777	0.499948	0.624882
MFO	0. 249389	0.01125	0.003005	0.003765	0.499997	0.624995
DAO	0. 249357	0.0112421	0.0030065	0.003778	0.499998	0.624995
ALO	0. 249491	0.01125	0.003005	0.003859	0.499997	0.624995
WOA	0. 249425	0. 011235	0.003008	0.003759	0.5	0.624999

Table 4: Best result for the A_{OC} with various nature based algorithms when PM is ideal

Algorithm	A_{OC}	λ_i	λ_6	λ_7	μ_i	μ_6
GA	0.920833	0.009214	0.007745	0.009623	0. 437348	0.249758
PSO	0.934523	0.0090001	0.0075	0.009502	0. 437489	0.249985
CS	0.931547	0.0090002	0.007505	0.0095	0. 437395	0.24998
CS-GA	0.942568	0.0090032	0.0075	0.0095	0. 437451	0.25
GA-PSO	0.945426	0.009	0.0075	0.00955	0. 437352	0.24995
GWA	0.935248	0.0090002	0.007601	0.0095	0. 4374	0.249854
MFO	0.93241	0.0090004	0.0075	0.0096	0. 437459	0.24995
DAO	0.935395	0.0090003	0.007523	0.009511	0. 437477	0.249981
ALO	0.945405	0.0090002	0.007513	0.0095	0. 437476	0.249966
WOA	0.945426	0.009	0.007509	0.0095	0. 437489	0.249999

Algorithm	μ_7	μ_e	α	β	θ	Φ
GA	0.24932	0.011238	0.003751	0.0037951	0.499999	0.623986
PSO	0. 2494	0.01125	0.003	0.003775	0.499999	0.62458
CS	0. 249495	0.011246	0.003004	0.003761	0.499951	0.624999
CS-GA	0. 249499	0.011241	0.003	0.003781	0.499999	0.624875
GA-PSO	0. 2495	0.01125	0.003001	0.00375	0.5	0.62498
GWA	0. 24999	0.011246	0.003001	0.003777	0.499525	0.62412
MFO	0. 2495	0.011244	0.003006	0.003769	0.499965	0.624999
DAO	0. 249395	0.0112421	0.003	0.0037526	0.499951	0.624875
ALO	0. 249476	0.01125	0.003001	0.0037516	0.499991	0.624877
WOA	0. 249496	0. 01125	0.003	0.0037501	0.499999	0.62492

Table 5: Best result for the A_{OC} with various nature based algorithms when PM is faulty

Algorithm	**M I %**			
	A_{FC} (η=0)	**A_{FC} (η=1)**	**A_{OC} (η=0)**	**A_{OC} (η=1)**
GA	4.67651	8.080128	5.559324	4.69865
PSO	6.944417	8.087497	6.350117	6.255202
CS	6.952325	8.152321	6.413688	5.916831
CS-GA	6.973688	8.151841	6.42433	7.169918
GA-PSO	6.973689	8.131188	6.63722	7.494872
GWA	6.919747	8.113103	6.220705	6.337634
MFO	6.950554	8.136408	6.432874	6.014954
DAO	6.955394	8.152497	6.324891	6.354348
ALO	6.936036	8.152497	6.494941	7.492484
WOA	6.973689	0.009	0.007509	0.0105

Table 6: M I % of availability with various algorithms

By critically observing, Table 2 indicates that the best solution of A_{FC} when PM is ideal, obtained by GA-PSO and WOA is 0.906295 which is better to other optimization techniques. Table-3 indicates the best solution of A_{FC} when PM is faulty, obtained by DAO is 0.879443. Table-4 indicates that the best solution of A_{OC} when PM is ideal, obtained by GA-PSO is 0.963845. Table-5 indicates the best solution of A_{OC} with faulty PM, obtained by WOA is 0.945426. The MI% in table 6 indicates the increment in the availability of the system. The corresponding input values also represented in the tables.

5. Conclusion

This paper presented a comparative analysis of various nature-based algorithms to optimize the availability of a series-parallel continuous production system. Various thirteen nature based algorithms are used to find the local maxima of the availability of the system under ideal and faulty PM. The best values obtained and the MI % is shown in table-7.

For any system, failure rates can be decreased. Eliminating or making a system failure free is not possible. The present study optimizes the system by taking ± 25% of the present values of failure rates, repair rates, transition rate and PM rates. The local maxima has been found. By making necessary changes and adjusting the parameters, the same system can be optimized for higher reliability. The various algorithms indicate the values of parameters corresponding to the availability. Simulation results show the vital role of hybrid algorithms in reliability optimization. Hybrid algorithms combine two different algorithms and improves the efficiency of the algorithms. We can conclude from the Results (Table2- 6) that best results are found with hybrid algorithm GA-PSO and recently developed DAO and WAO. The application of these algorithms may prove to be beneficial in increasing the availability of the system in the given constraints.

Availability	PM	Optimization Technique	MI%
A_{FC}	Ideal	GA-PSO & WOA	6.973689
	Faulty	DAO	8.152497
A_{OC}	Ideal	GA-PSO	6.63722
	Faulty	WOA	7.49487

Table 7: Summary of best-obtained results

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