Availability-Cost Optimization of Butter Oil Processing System by Using Nature Inspired Optimization Algorithms

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Abstract

The challenge of upgrading the complex industrial systems is basically to cope up with the ever-increasing demands of the real world. For the maximum reliability of complex industrial systems, decisions of management depend on experience. This is because the pattern of the chance of success is not easy to predict due to limited and rough available information. Thus, the task of the researchers lies here to increase the operational time of the individual components of a system for maintaining higher system reliability to increase productivity and profit of an organization. In this paper, an optimum choice of the mean time between failure (MTBF), mean time to repair (MTTR), and associated costs in a suitable design unit has been showcased to bring as much efficiency as possible. The motive is to minimize the cost satisfying the availability constraints of the system by using a few recent nature-inspired optimization techniques named Grey Wolf Optimization (GWO) technique and Cuckoo Search Algorithm (CSA). The computational parameters produced to improve the efficiency of the designed system with the application of GWO and CSA techniques, which not only achieve the target of minimum cost but also stand out much competitively in terms of performance. The results obtained by these two algorithms for butter oil processing system are compared and this comparative study shows that the GWO is superior to CSA for this availability-cost optimization problem of butter oil processing system.

Keywords: **A**vailability, Reliability, Cost function, Metaheuristics, Grey Wolf Optimizer, Cuckoo Search Algorithm.

I. Introduction

It is not possible for any system to be perfectly reliable even if the researchers and the stakeholders work to the best of their efforts. So, the increasing complexity of present-day equipment has brought into focus two other aspects known as maintainability and availability. Maintenance plays a very crucial role as a preventive and corrective measure so as to achieve continuous and longer availability. Maintainability means the probability that the system will resume operation in a given prescribed time after the repairing is completed as per the specified condition. Availability is associated with the concept of maintainability. Availability refers to the probability that the system is operating within a given time. It means the proportion of time for which the system is available for use that is excluding the downtime (when it is under maintenance). Though availability is not an indicator of the number of failures but depends on both failure and repair rates and it integrates both reliability and maintainability. The input costs and availability are very important in any operation and are the deciding factors for increasing the reliability of any complex system. There are three types of availability depending upon the time elements. (a) Inherent availability (b) Achieved availability (c) Operational availability. To understand the different types of availability it is important to understand the concepts of MTBF and MTTR. MTBF is the mean time between the breakdowns or failures during which the system is unavailable and undergoes repairs. MTBM is the mean of the time periods between the maintenance which could be either scheduled (preventive) maintenance or corrective maintenance due to failure. MTTR is the average mean time calculated as the total repair time during a given period divided by the number of malfunctions during the same interval. For any system down time is the total time for which it is down for corrective or preventive maintenance. MTBF does not include the preventive maintenance. The Up time is the time for which system is under active operation. Now the three types of availability are explained as follows:

I. Inherent availability

Inherent availability is the availability in the presence of defined conditions in an ideal promoting environment without considering the preventive maintenance at any given time. It is expressed as

$$A_i = \frac{MTBF}{MTBF+MTTR} \tag{1}$$

Where, MTBF = $\frac{1}{\lambda}$ and MTTR =$\frac{1}{\mu}$

II. Achieved availability

Achieved availability refers to the chance that a system shall operate satisfactorily taking into account the preventive down time also. It is expressed as

$$A_c = \frac{MTBM}{MTBM+M} \tag{2}$$

Where MTBM is the mean time between the maintenance, which could be either scheduled (preventive) or corrective maintenance due to failure and M is the mean active--maintenance downtime resulting from both preventive and corrective maintenance.

III. Operational availability

Operational availability is the availability when the system operates under actual supply environment at any given time considering the administrative or supply downtime. It is expressed as

$$A_o= \frac{MTBM}{MTBM+MDT} \tag{3}$$

where MDT is the mean actual down time.

For achieving the goal of maximum reliability of any complex system matching the global standards and also making the estimated profit it is imperative for the management to specify the availability and cost related to each individual component reliability. Most recently for the minimization of the total costs of the system, various researchers have suggested the availability allocation models. The set availability of the system, which is already achieved after optimization as determined by some other technique, behaves as a constraint. The availability models can be classified as (a) formulation of a suitable model of system availability and (b) allocation of availability to each individual component depending upon the system requirements. The major focus of the paper is on required minimum performance of each component which can be done through failure avoidance of each component or redundancy allocation for it along with the cost minimization factor. Several researchers have devoted their study to the reliability optimization problems. Verma and Chari [43] emphasized the influence of common cause shock failures and individual failures individually as well as both together on the determination of availability of a repairable system and also developed related formulae. Ramirez and Bernal [35] used Evolutionary Algorithm for reliability and cost optimization for distribution networks expansion. Stochastic analysis of a Reheating-furnace system subject to preventive maintenance and repair was proposed by Upreti [42] using Markov model and exponential distribution. Garg and Sharma [9] studied reliability, availability and maintainability and did the analysis of these in synthesis unit in fertilizer plant. Different multi-objective and Single-objective constrained and unconstrained problems have been successfully solved to give competitive results using GWO. Fouad et al. [8] found additional number of neighboring nodal points using GWO technique. Mosavi et al. [27] applied three data sets including Iris, Lenses and Sonar to train the multi-layer perception neural networks, using GWO. Gupta and Saxena [10] applied GWO for finding parameters for the successful automatic power dispatch in two interconnected areas. Whereas, Jaya Bharati et al. [11] used crossover and mutation with GWO to solve economic power transmission problem. Zhang et al. [47] used GWO technique for minimizing the fuel cost and avoiding the threat areas in the (unmanned) ACV problem. Manikandan et al. [22] did the gene selection on the of micro array data using binary and mutated GWO approaches. Kamboj et al. [13] proposed GWO for the non-convex economic load dispatch problem. Multi–Objective GWO was proposed by Mirjalili et al. [25] in which an archive defining the global optimum solution is introduced into the original GWO for retrival of the Pareto Optimal solution. Kumar A [14] proposed GA and fuzzy logic for reliability of industrial systems. Kumar et al. [16] used GWO for complex system reliability optimization due to its highly efficient results to optimize reliability and cost of life support system in a space capsule and complex bridge system. Also, Kumar et al. [15] proposed the use of GWO for the comparison and analysis of availability and cost of the engineering systems in series configuration. Kumar et al. [17] continued further and proposed the use of GWO for the safety system of a nuclear power plant to optimize the reliability cost of the residual heat removal system. Negi et al. [28] presented a review and applications of the various forms and hybrids of GWO. Uniyal et al. [41] presented an overview of the reliability applications of few Nature inspired optimization techniques Various forms of GWO have been proposed to solve complex systems reliability optimization problems with very competitive results. In the case of WSNs. Li et al. [20] proposed Modified Discrete GWO (MDGWO) for multi-level image thresholding in which the optimized function Kapur's entropy was used along with the discrete nature of the threshold values. Mirjalili et al. [20] presented Multi-objective GWO (MOGWO) using Pareto-optimal solutions for solving global engineering problems. Other varied forms include Chaotic GWO [23] and Refraction Learning GWO [44]. No free lunch theorem [45] says that no single meta-heuristic can solve all complex problems of optimization. Pant et al. [31] proposed the method of solution for nonlinear system of equations using metaheuristics. Also, Pant et al. [30] presented an advanced approach of Particle Swarm optimization for reliability optimization. In addition to this they [29] also proposed a State of Art review of the flower pollination algorithm development. Pant et al. [32] also applied multi-objective particle swarm optimization (MOPSO) technique for solving reliability optimization problem. Pant et al. [33] presented modified PSO algorithm for nonlinear optimization problems. Li and Haimes [19] proposed decomposition method for the reliability optimization of large complex systems. Developed by Kennedy and Eberhart, [7] PSO has been used to solve many real-world engineering problems to get much competitive results. With further development Coelho [6] solved reliability-redundancy optimization problem using an efficient PSO approach for mixed integer programming problem. Kumar et al. [18] solved the reliability optimization problems of complex systems using CSA. Baskan [2] proposed CSA with L'evy Flights to determine optimal link capacity expansions in road networks. Buaklee and Hongesombut [5] proposed the CSA for solving optimal DG allocation in a smart distribution grid.

Hybridized Optimization Algorithms are those metaheuristics which use the characteristics of each of the involved algorithms in the best possible way in order to give much competitive results in terms of convergence rates, stability, efficiency and quality results than the individual algorithm alone. Some of these are GWO-ACO [1], GWO-GA [38], and GWO-ANN [40].

For optimal convergence rate and highly competitive results as compared to the existing methods leading to global optimum solution, nature inspired algorithm called the Metaheuristics can play a major role. Broadly, they are classified as population oriented (PSO, ACO, GWO, GA.) or trajectory oriented (SA).

Section II deals with the illustration of the different stages of the butter oil processing system. Section III explains GWO and CSA used for the minimization of expenditure in a butter oil processing system. The mathematical model devised for the optimization problem is presented in section IV. In section V the outcomes obtained by the GWO algorithm are discussed along with the investigation of the statistics and sensitivity analysis done thereby. Section VI proposes the conclusions and further scope of the research.

II. Demonstration of the industrial system considered

A butter oil processing plant is discussed below to demonstrate the suggested approach of GWO technique. It is assumed to be a repairable industrial system of a kind based in Northern India.

Description of six sub-units of butter oil processing and manufacturing industrial plant is presented below [36].

I. Separator (Sub-unit I):

Separator uses the law of centrifugal force to separate cream from the milk. To separate the cream (which contains fats) from the milk, chilled milk is introduced into the separator from the refrigerators. This removes 40-50% of fats from the milk and the skimmed milk which remains in the silos is used for making milk powder. Sub-part I is composed of three components in series which are motor, bearings and high-speed gearbox.

II. Pasteurizer (Sub-unit 2):

In this sub-unit pasteurization of cream is done. In this process cream is heated to at least 71°C which may go to 80-82°C in actual practice as long as the process of pasteurization is completed. It involves destruction of unwanted organisms and pathogenic organisms. The enzymes present become inactivated and the volatile substances are also removed. The substances which tan the contents also get removed in the heating process. Then on one side pasteurized milk goes out of this sub-unit through the outlets and on the other side storage of the pasteurized cream takes place in the double-coated tank for the next processing step. The flow of the milk gradually gets obstructed as some residue particles of milk stick around the outlet and form sludge with the passage of time leading to blockage in the outlet causing the sub-unit to fail. The sub-unit 2 has a series of motor and bearings.

III. Butter preparation without break (sub-unit 3):

The storage tank pours the butter into the butter preparation machine where butter is made continuously. Butter granules are formed due to continuous churning process in the machine which produces butter milk also. Then raw milk silos pump back the buttermilk produced during churning process. The butter granules formed are put to further processing with purpose of getting a homogeneous mass of butter. With the help of trolleys the homogeneous butter is shifted to melting vats. There is a series of gearbox, motor and bearings in the butter making machine.

IV. Melting vats (sub-unit 4):

This unit is a double coated tank for carrying out process of melting of butter. Heating butter to 107°C very gently evaporates water from the melting butter. After melting, it is important to keep the melted butter undisturbed for at least half an hour. This sub-unit is composed of mono block pumps, motors and bearings in series.

V. Butter-oil cleanser (sub-unit 5):

From the melting vats butter-oil is shifted to settling tanks to let the butter-oil settle for few hours. The butter-oil residue formed in the settling period is then removed and the residue free butter-oil is stored in the storage tanks. For storing butter-oil suitably, it is allowed to cool to 28-30°C. In this sub-unit a motor and gear box are connected in series.

VI. Packaging (sub-unit 6):

With the help of a pouch-filling machine, packets of processed butter are made in this sub-unit. The machine automatically fills, flows the packets and seals them. There is a printed circuit board and a pneumatic cylinder connected in series in this sub-unit [36].
All these sub-units are connected in series.

III. Nature Inspired Optimization techniques

I. Grey Wolf Optimizer:

I. The impulse that led to GWO

The two important phenomena that led to the development of the GWO algorithm are the social intelligence and hierarchical attitude among the wolves, which can be collectively defined as their social intelligence to carry out an efficient hunting mechanism. In the entire hunting process the four predominant types of wolves taking part can be categorized as alpha, beta, delta and omega in the of their leading capacity. These become the four candidates for initial solution. The alpha being the strongest leads the entire hunting process and the others follow to mechanism successful. This very effective mechanism has been simulated to develop an algorithm to find global optimum solution to many real-world engineering problems. The wolves of different capacities become the four candidates for solutions, which are improved in the iterations that follow, become the four candidates for initial solution.

II. Mathematical Model formulation of the GWO Algorithm

The detailed model:

- Tracking (approaching).
- Encompassing.
- Attacking.

The equations constructed to carry out the simulation are as follows.

$$D = \left|C.X_p(t) - X(t)\right| \tag{4}$$
$$X(t+1) = X(t) - A.D \tag{5}$$

Note that, in the equations, use of vectors help the use of the model to the required number of dimensions. Here, $X(t+1)$ expresses the location the wolf reaches in time $(t+1)$. $X(t)$ is the present location of the wolf, A is a coefficient matrix and D defines the location of the prey Xp. Here, A and C are represented as follows:

$$A = 2a.r_1 - a \tag{6}$$
$$C = 2.r_2 \tag{7}$$

where, r_1 and r_2 are random vectors in the interval [0,1]. The components of the vector a are linearly decreased from 2 to 0 over the course of iterations. The value of A ranges from -2 to 2 as there are random variables in the expression. The premises that alpha, beta and delta are the three best solutions in GWO is taken considering that they have good idea of the position due their strength in the entire population. So, the other wolf should try to update their position as follows:
where, r_1 and r_2 are random vectors in the interval [0,1]. The components of the vector a are linearly decreased from 2 to 0 over the course of iterations. The value of A ranges from -2 to 2 as there are random variables in the expression. The premises that the alpha, the beta and the delta are three best solutions in GWO is taken considering that they have good idea of the position due their strength in the entire population. So, the other wolf should try to modify their position as follows:

$$X(t+1) = \frac{1}{3}X_1 + \frac{1}{3}X_2 + \frac{1}{3}X_3 \tag{8}$$

where, $X_1, X_2,$ and X_3 are evaluated with the equations:

$$X_1 = X_\alpha(t) - A_1.D_\alpha$$
$$X_2 = X_\beta(t) - A_2.D_\beta$$

$$X_3 = X_\delta(t) - A_3 . D_\delta \tag{9}$$

Here, D_α, D_β, D_δ are calculated as follows:

$$D_\alpha = |C_1 . X_\alpha - X|$$
$$D_\beta = |C_2 . X_\beta - X|$$
$$D_\delta = |C_3 . X_\delta - X| \tag{10}$$

Initialize the grey wolf population $X_i\ (i = 1, 2, \ldots\ldots\ldots, n)$
Initialize a, A and C
Calculate the fitness of each search agent
$\vec{X}_\alpha$ = the best search agent
$\vec{X}_\beta$ = the second best search agent
$\vec{X}_\delta$ = the third best search agent

while (t < Max number of iterations)
  for each search agent
    Update the position of current search agent by equation (8)
end for
Update a, A, and C
Calculate the fitness of all search agents
Update $\vec{X}_\alpha$ $\vec{X}_\beta$ $\vec{X}_\delta$
t = t+1
end while
return $\vec{X}_\alpha$

Fig. 1 Pseudo code of the GWO algorithm

Pseudo code of the GWO algorithm is given in Figure 1 [24].

III. Proper survey (exploration) and effective utilization (exploitation) in the hunting mechanism:

Surveying enough before attacking is very important to make the process successful. The decisions of the surveying wolves lead to the effective positioning of the following wolves. To simulate this, the values of the parameters a and A have to be chosen in their ranges to so to get the best value of A. It has been established that IAI > 1. As the process of exploration or surveying and approaching reaches its peak then the attacking decisions depend on the parameter A and it should be and IAI < 1. Now here it is important that unless there is appropriate approaching of the prey, the attacking process won't be that effective. So, choosing the parameters within the range, according to the constraints is very important firstly to properly survey and explore the search space enough before utilizing and exploiting so as to avoid any local convergence of the solution. Thus, achieving global solution is the objective behind the required amount of investigation of the search space and utilizing the results of the investigation to get the optimum solution via proper exploitation as shown in fig. 2. GWO gives an efficiently converged result as compared to existing optimization methods like PSO, ACO, GA, cuckoo search, and few more.

II. Cuckoo Search Algorithm (CSA):

I. Cuckoo's breeding strategy

CSA [46] has its roots in the hostile and vigorous strategy of reproducing its young-ones in some species of fascinating bird cuckoo which can make beautiful sounds. The cuckoos belong to the

Cuculidae family of birds. Some of them are brood parasites which search for a nest of the host birds of different species probably to lay and hide their eggs. The host bird either tries to engage in direct conflict with invading cuckoo and tries to throw away the eggs of the invading cuckoos or leave its own nest and builds a new nest altogether. To increase their reproductivity some species of cuckoos like Tapera, mimic even some characteristics like color, pattern of the eggs and call of the chicks of the host species which really help in reducing abandoning of their eggs. Specific timing of egg laying in the host nest by cuckoos so that they can be hatched earlier than the host eggs is also a strategic pattern of cuckoos to throw the host eggs out of the nest. Cuckoos have developed basically three types of parasitic nature: nest takeover, cooperative parasitism and intraspecific parasitism. To increase the share of food for the cuckoo's chick in the host nest the cuckoo throws the host eggs out of the nest.

II. Idea of Levy Flights

Animals in nature, look for the food in an effective manner which is often much random and quasi-random way. Every next move is dependent on the present position. The shift to the new location and the direction chosen are probabilistic in nature which can hence be mathematically modelled. Levy flights [4, 34] characteristics have been observed in many animals and insects. Be it the landscape exploring by the fruit flies Drosophila melanogaster or the human behaviour such as the hunter gatherer Ju/'Hoansi [4] or the pattern of light all show the characteristics of Levy flights. The outstanding performances [37] shown by the application of such behaviour to the optimization problems for global optimal search have been tested successfully.

III. Cuckoo Search Model

Before presenting the actual model, the premises which lead to the model can be as follows.

- Every cuckoo in particular ensures laying one egg in one time in a nest chosen randomly;
- The highly potent eggs (solutions) of the ideal nests have the capability of being transferred to the next generations;
- The probability of revealing the stranger egg is from 0 and 1 which is approximately equal to the fraction of the number of nests being renewed and built. The probability obtained which can lead to removal of the stranger egg or building of a new nest by the host bird. Also, every cuckoo has only a fixed number of nests for laying their eggs.

The fitness of a solution is important and for a maximization problem it has a fixed ratio to the objective function.

A new solution x (t + 1) for say kth cuckoo can be generated by applying the L'evy flight feature as follows [38]

$$\mathrm{x\ (t{+}1)\ i = x\ (t)\ i} + \alpha \oplus \mathrm{L'evy}(\lambda) \tag{11}$$

where, $\alpha > 0$ is the size of the step and the suitable problems can be based on the same scale and it can be $\alpha = O(1)$. The product $\oplus$ represents the multiplication at each entry. The L'evy flight represent the random steps in the random walk whereas for the large steps L'evy distribution is applicable as follows:

$$\mathrm{L'evy} \sim \mathrm{u = t} - \lambda, \quad (1 < \lambda \leq 3) \tag{12}$$

This produces infinite mean and variance which explain the steps taken by the cuckoo in succession and is based on power-law step length distribution with a heavy tail. Since the probability of a cuckoo egg getting identified by the host bird is very less it is more important that the fitness function should be a function of the difference in solutions. Thus, random walk and random steps process chosen is very suitable. Pseudo code of CSA algorithm is given in Figure 2 [30].

begin

Objective function $f(x),\ x=(x_1,x_2,\ldots\ldots,x_d)^T$;

Initial a population of n host nests $x_i\ (i=1,2,\ldots\ldots,n)$;
while (t <MaxGeneration) or (stop criterion);
Get a cuckoo (say i) randomly by L´evy flights;
Evaluate its quality/fitness F_i;
Choose a nest among n (say j) randomly;
if ($F_i > F_j$),
Replace j by the new solution;
end
Abandon a fraction (p_a) of worse nests
[and build new ones at new locations via L´evy flights];
Keep the best solutions (or nests with quality solutions);
Rank the solutions and find the current best;
end while
Postprocess results and visualisation;

end

Fig. 2 Pseudo Code of Cuckoo Search Algorithm

IV. Formulation of the Mathematical model of the proposed problem

It is not possible to predict the behavior of a system perfectly even from the past records so, it is important to analyze the available parameters in an appropriate manner and some assumptions can be helpful in formulation of availability model the series-parallel system and use the GWO algorithm for cost optimization. Before formulating the mathematical model of the problem following important premises are notable.

- The components or sub system are not dependent on each other and so the failing and repairing of one the component is independent of the other and do not interfere with each other.
- The components do not fail simultaneously.
- The failure ($\boldsymbol{\lambda_i}$) repair rate (μ_i) are constants such that $\boldsymbol{\lambda_i} < \mu_i$.
- The repair and maintenance start in the event of failure of a component immediately with separate maintenance system available for each component.

The proposed optimization model requires expression for cost minimization along with the constraint that the system availability should be greater than the minimum availability criteria.

I. Availability and total cost

The constituent components of the proposed industrial system are as arranged and put in the reliability block diagram (RBD). The system consists of the series-parallel configuration for which the availability expressions with the basic parameters are as follows:

I. Series system.

$$Av_s = Av_1.Av_2.\ldots.Av_n \sim 1-\left(\frac{\lambda_1}{\mu_1}+\frac{\lambda_2}{\mu_2}+\ldots\ldots+\frac{\lambda_n}{\mu_n}\right) \tag{13}$$

where, $\lambda_s \sim \lambda_1+\lambda_2+\cdots+\lambda_n$ and $\mu_s \sim \frac{\lambda_1+\lambda_2+\cdots+\lambda_n}{\frac{\lambda_1}{\mu_1}+\frac{\lambda_2}{\mu_2}+\cdots\frac{\lambda_n}{\mu_n}}$

II. Parallel system

$$Av_s \sim 1-\frac{\lambda_1.\lambda_2\ldots\lambda_n}{\mu_1.\mu_2\ldots\mu_n} \tag{14}$$

where, $\lambda_s \sim \frac{\lambda_1.\lambda_2.....\lambda_n(\mu_1+\mu_2+\cdots\mu_n)}{\mu_1.\mu_2....\mu_n}$ and $\mu_s \sim \mu_1 + \mu_2 + ... \mu_n$

Here, Av_s and Av_i denote the availability of the system and i^{th} component, $\boldsymbol{\lambda_i}$ and μ_i denote the failure and repair rate respectively for the i^{th} component of the system and system failure and repair rate are denoted by

$\boldsymbol{\lambda_s}$ and μ_s.

The expressions for availability, failure rate and repair rate are from [3]. Thus, from the definitions and expressions for availability, following expression for availability ($\boldsymbol{Av_s}$) for the proposed system can be presented approximately as follows:

$$Av_s = f(\,MTBF_1, MTBF_2, \ldots\ldots, MTBF_n, MTTR_1, MTTR_2 \ldots\ldots.MTTR_n) \tag{15}$$

Failure rate of a system depends on MTBF. The higher value of the MTBF of any component causes decrease in the failure rate of the component. This generally leads to an increase in the cost sharply [21] and at the same time also the reliability of the system is increased as a whole. The relation between MTBF and manufacturing cost [39] can be expressed as follows:

$$CMTBF_i = \alpha_i.(MTBF_i)^{\beta_i} + \gamma_i \tag{16}$$

where, the manufacturing cost and $MTBF$ of the ith component are denoted by $CMTBF_i$ and $MTBF_i$ respectively, $\alpha_{i,}$ β_i and γ_i are constants which represent the physical properties of the i^{th} component and value of $\beta_i > 1$.

The output of a system depends on failure rate and reduces the efficiency of the system as a whole. Timely repairing of the failed component can help not to affect the efficiency and output of the system to some extent. Maintenance and repair of the failed component as soon as possible can be carried out with help of experts and repairing by standard equipment. $MTBF_i$ and repairing cost of the individual components ($CMTTR_i$) are linearly related to each other and mathematically can be represented as follows [12]:

$$CMTTR_i = a_i - b_i.(MTTR_i) \tag{17}$$

where, a_i and b_i are constants related to the i^{th} component of the system. From Equations (12) and (13), total cost can be expressed as:

$$T_c = \sum_{i=1}^{n}(\alpha_i.(MTBF_i)^{\beta_i} + \gamma_i)\ \ \sum_{i=1}^{n}(a_i - b_i.MTTR_i) \tag{18}$$

II. Optimization model for the cost minimization of butter oil plant:

Using equations, (1) and (4) optimization model of the problem is framed as follows:

Minimize T_c

Subject to $Av_s \geq A_{mini}$

$LbMTBF_i \leq MTBF_i \leq UbMTBF_i$

$LbMTTR_i \leq MTTR_i \leq LbMTTR_i$

$i = 1, 2, \ldots..6$ $All\ variables \geq 0$

$Av_s = 1 - [5\frac{MTTR_1}{MTBF_1} + \frac{MTTR_2}{MTBF_2} + \frac{MTTR_3}{MTBF_3} + \frac{MTTR_4}{MTBF_4}]$

$$T_c = \sum_{i=1}^{6}(\alpha_i.(MTBF_i)^{\beta_i} + \gamma_i) + \sum_{i=1}^{6}(a_i - b_i.MTTR_i) \tag{19}$$

$A_{mini} = 0.96$

where, lower and upper bounds of MTBF and MTTR for i^{th} component are denoted by $LbMTBF_i$, $UbMTBF_i$, $LbMTTR_i$, $UbMTTR_i$ out of the total 6 components of the given plant. GWO algorithm solves the formulated optimization problem quite efficiently. The values of α, β and γ are respectively taken as 0.92, 1.94 and 1250. The respective values of a and b are taken [14], [18], [150] and [50]. The range of lower and upper bounds of mean time between failure (MTBF) and mean time to repair (MTTR) for various components are 4000 hours to 4200 hours and 2 hours to 6 hours respectively.

V. Results and Analysis

GWO has an edge over other nature inspired optimization algorithms as in it the search agent and fitness function are not directly correlated. In GWO various search agents modify their position in accordance with the positions taken by the wolf alpha, beta, and delta. With this feature, GWO finds application to solve problem of any type of constraints with its mechanism remaining the same. This model for minimization of the expenditure in the butter oil processing plant system, uses the simplest method of constraints handling like penalty functions. For this cost minimization problem of butter oil processing plant, 100 grey wolves have been fixed and we run GWO algorithm with iterations around 200. On the other hand, in cuckoos search algorithm, number of nests have been fixed at 30 with the chance of finding the alien eggs/solutions is kept at 0.35. Total number of iterations have been set as 1000. After that, the GWO algorithm and Cuckoo search algorithm has been run in the MATLAB and table 1 shows the results, which are better the earlier in some respects definitely.

The search history of GWO algorithm is tabulated in the following manner for the same problem. The minimum system cost 5.61615071665e+07 obtained by GWO is similar to that obtained by CSA but there exists a difference in the function evaluation as shown in Fig. 3. GWO takes only 20000 function evaluations on the other hand CSA takes 60000 FE for the same cost. Both GWO and CSA are kept at system availability as shown in table 1.

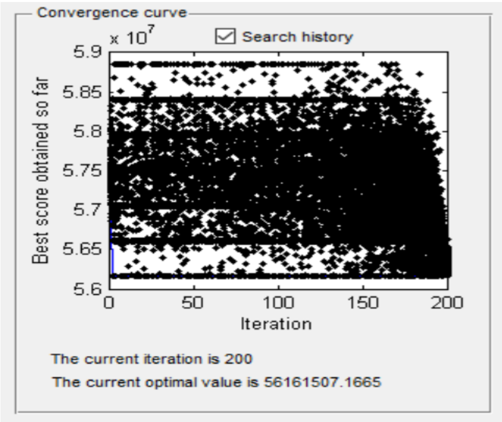

Fig. 3 Search history of GWO for butter oil processing plant

Table 1. Comparison results for butter oil processing plant

	Grey Wolf Optimizer (GWO)		Cuckoos Search Model (CSA)	
Components	**Mean Time Between Failure (MTBF in hours)**	**Mean Time to Repair (MTTR in hours)**	**Mean Time Between Failure (MTBF in hours)**	**Mean Time to Repair (MTTR in hours)**
Motors	4025	5	4025	5
Bearings	4100	3	4100	3
Gear Box	4075	5.5	4075	5.5
Pumps	4150	3.5	4150	3.5
Circuit Box	4070	3	4070	3
Cylinder	4115	3.5	4115	3.5
System Cost	5.61615071665e+07		5.616150716646019e+07	
System Availability	0.978716807		0.978716807	
Number of Iterations	200		1000	
FE	20000		60000	

VI. Conclusion and further scope:

For a series-parallel system, exact methods of reliability optimization are not enough to get effective results. This is because it may lead to an unnecessary rise in the costs of the whole system. Since the aim of any industrial unit is profit generation along with the satisfaction of the other constraints of weight, volume, maintenance policies, maximum performance in terms of reliability and availability so, nature inspired optimization algorithms like GWO and CSA work quite well under all these conditions to get better results as this butter-oil processing plant system show. These optimization techniques work to calculate the optimum values of MTBF and MTTR so well that they consider the constraints to gain maximum out of the series-parallel system even with limitations of its structure. The efficient results of the GWO and CSA algorithms to the present problems help the decision makers to derive the properties of the components to be chosen in future to get the best results. Together with this, comparatively GWO show high performance over CSA algorithms with regard to total number of functions evaluated and hence can save time of decision makers (DM). Hence, the DM can further decide about the policies of the design and repair based on GWO to improve the performance to meet the other constraints if any.

Declaration of Conflicting Interests:

The Authors have no conflict of interests.

References

[1] Ab Rashid, M. F. F. (2017). A hybrid Ant-Wolf Algorithm to optimize assembly sequence planning problem. Assembly Automation, 37(2), 238–248.

[2] Baskan, O. (2013). To determine optimal link capacity expansions in road networks using Cuckoo search algorithm with Levy flights, J. Appl. Math. 1– 11.

[3] Birolini, A. (2007). Reliability Engineering: Theory and Practice, 5th ed., Springer, New York, NY.

[4] Brown, C., Lie Bovitch, L.S., & Glendon, R. (2007). 'L´evy flights in Dobe Ju/'hoansi foraging patterns', Human Ecol., 35, 129-138.

[5] Buaklee, W., & Hong Pham, K. (2013). Optimal DG allocation in a smart distribution grid using Cuckoo search algorithm, ECTI Trans. Elect. Eng. Electron. Comm. 11(2), 16–22.

[6] Coelho, L. S. (2009). An efficient particle swarm approach for mixed integer programming problem in reliability-redundancy optimization applications. Reliability Engineering and System Safety, 94(4), 830-837.

[7] Eberhart, R., & Kennedy, J. (1995). A new optimizer using particle swarm theory. In: Proceedings of the sixth international Symposium on Micro Machine and Human Science.

[8] Fouad, M. M., Hafez, A.I., Hassanien, A.E., & Snasel, V. (2015). Grey wolves optimizer-based localization approach in WSNs. In: 11th international computer engineering conference (ICENCO). IEEE, pp 256–260.

[9] Garg, H., & Sharma, S. P. (2012). Behavioural analysis of synthesis unit in fertilizer plant. International Journal of Quality & Reliability Management, 29(2), 217-232. https://doi.org/10.1108/02656711211199928.

[10] Gupta, E., & Saxena, A. (2016). Grey wolf optimizer-based regulator design for automatic generation control of interconnected power system. Cogent Engineering. 3(1):1151612.

[11] Jaya Bharati, T., Raghunathan, T., Adarsh, B. R. & Suganthan, P. N. (2016). Economic dispatch using hybrid grey wolf optimizer. Energy 111:630–641.

[12] Juan, Y. S., Lin, S. S., & Kao, H. P. (2008). A knowledge management system for series-parallel availability optimization and design. Expert systems with Application, 34, 181-193.

[13] Kamboj, V. K., Bath, S. K., & Dhillon, J. S. (2015). Solution of non-convex economic load dispatch problem using grey wolf optimizer. Neural Comp App 27:1–16.

[14] Kumar, A. (2009). Reliability analysis of industrial system using GA and Fuzzy approach, Indian Institute of Technology Roorkee, Roorkee, (Ph.D. thesis).

[15] Kumar, A., Pant, S., & Ram, M. (2017). System Reliability Optimization Using Grey Wolf Optimizer Algorithm. Quality and Reliability Engineering International, Wiley, DOI: 10.1002/qre.2107.

[16] Kumar, A., Pant, S., & Ram, M. (2019). Multi-objective grey wolf optimizer approach to the reliability-cost optimization of life support system in space capsule. International Journal of System Assurance Engineering and management, 10(2),, 276-284 https://doi.org/10.1007/s13198-019-00781-1.

[17] Kumar, A., Pant, S., & Ram, S. M. (2019). Grey wolf optimizer approach to the reliability-cost optimization of residual heat removal system of a nuclear power plant safety system. Quality and Reliability Engineering international. Wiley, 1–12. https://doi.org/10.1002/qre.2499.

[18] Kumar, A., Pant, S., & Singh, S. B. (2016). Reliability Optimization of Complex System by using Cuckoos Search Algorithm, Mathematical Concepts and Applications in Mechanical Engineering and Mechatronics, IGI Global, 95-112.

[19] Li, D., & Haimes, Y. Y. (1992). A decomposition method for optimization of large-system reliability. IEEE Transactions on Reliability, 41, 183-188.

[20] Li, L., Sun, L., Kang, W., Guo, J., Chong, H., & Li, S. (2016). Fuzzy multilevel image thresholding based on modified discrete grey wolf optimizer and local information aggregation. IEEE Access 4:6438–6450.

[21] Li, Z. (2001). Availability allocation of series parallel system solved from object-oriented planning, Feng-Chia University, Taichung, Taiwan, (Master's thesis).

[22] Manikandan, S. P., Manimegalai, R., & Hariharan, M. (2016). Gene selection from microarray data: Current signal Transduction Therapy.

[23] Kohli, M. & Arora, S. (2018). Chaotic GWO for constrained optimization problems. Journal of Computational Design and Engineering, 5, 458-472.

[24] Mirjalili, S., Mirjalili, S., M., & Lewis, A. (2014). Grey wolf optimizer. Adv Eng. Soft. 69, 46–61.

[25] Mirjalili , S., Saremi, S., Mirjalili, S. M., & Coelho, L. S. (2016). Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization. Expert Sys App 47, 106–119.

[26] Mirjalili, S., Saremi, S., Mirjalili, S. M., & Coelho, L. S. (2016) Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization. Expert Syst. Appl. 47, 106–119.

[27] Mosavi, M. R., Khishe, M., & Ghamgosar, A. (2016). Classification of sonar data set using neural network trained by grey wolf optimization. Neural Net World, 26(4), 393.

[28] Negi, G., Kumar, A., Pant, S., & Ram, M. (2020). GWO: a review and applications, International Journal of System Assurance Engineering and management. https://doi.org/10.1007/s13198-020-00995-8.

[29] Pant, S., Kumar, A., & Ram, M. (2017). Flower Pollination Algorithm Development: A State of Art Review. International Journal of System Assurance Engineering and Management, Springer, 8 (2), 1858-1866.

[30] Pant, S., Kumar, A., & Ram, M. (2017). Reliability Optimization: A Particle Swarm Approach. Advances in Reliability and System Engineering, Springer International Publishing, 163-187.

[31] Pant, S., Kumar, A., & Ram, M. (2020). Solution of Nonlinear Systems of Equations via Metaheuristics, International Journal of Mathematical, Engineering and Management Sciences, 4 (5), 1108-1126.

[32] Pant, S., Kumar, A., Kishor, A., Anand, D., & Singh, S. B. (2015). Application of a Multi-Objective Particle Swarm Optimization Technique to Solve Reliability Optimization Problem. In the proceeding of IEEE Int. Conf. on Next Generation Computing Technologies, September 4-5, 1004-1007.

[33] Pant, S., Kumar, A., Singh, S. B., & Ram, M. (2017). A Modified Particle Swarm Optimization Algorithm for Nonlinear Optimization. Nonlinear Studies, 24(1), 127-138.

[34] Pavlyukevich, I. (2007). L´evy flights, non-local search and simulated annealing', J. Computational Physics, 226, 1830-1844.

[35] Ramírez-Rosado, I. J., & Bernal -Agustín, J. L. (2001). Reliability and costs optimization for distribution networks expansion using an evolutionary algorithm. IEEE Transactions on Power Systems, 16, 111-118.

[36] Rani, M., Garg, H., & Sharma, S. P. (2014) Cost minimization of butter oil processing plant using artificial bee colony algorithm, Mathematics and Computers in Simulation, 97, 94-107.

[37] Shlesinger, M. F. (2006). 'Search research'. Nature, 443, 281-282.

[38] Tawhid, M. A. & Ali, A. F. (2017). A Hybrid grey wolf optimizer and genetic algorithm for minimizing potential energy function. Memetic Computing, 9(4), 347–359.

[39] Tillman, F. A., Hwang, C. L., & Kuo, W. (1980). optimization of systems reliability, Marcel Dekker, New York. 17.

[40] Turabieh, H. (2016). A Hybrid ANN-GWO Algorithm for prediction of Heart Disease. American journal of operations Research, 6 136-146. Doi:10.4236/ajor.2016. 62016.

[41] Uniyal, N., Pant, S., & Kumar, A. (2020). An Overview of Few Nature Inspired Optimization Techniques and Its Reliability Applications. International Journal of Mathematical, Engineering and Management Sciences, 5 (4), 732-743.

[42] Upreti, I. (2012). Stochastic analysis of a Reheating-furnace system subject to preventive maintenance and repair, Galgotia's Institute of Management & Technology India, https://doi.org/10.1504/IJOR. 045664.

[43] Verma, S. M., & Chari, A. A. (1980). Availability and frequency of failures of a system in the presence of chance common-cause shock failures, Reliability Engineering 1(2), 127-142.

[44] Long, W., Wu, T., Cai, S., Liang, X., Jiao, J., & Xu, M. (2019). A Novel GWO with refraction learning. IEEE Access, 7, 57805-57819.

[45] Wolpert, D. H., & Macready, W. G. (1997). No free lunch theorems for optimization. *IEEE* transactions on Evolutionary computation, 1, 67-82.

[46] Yang, X. S., & Deb, S. (2009). 'Cuckoo search via L´evy flights', Proceedings of World Congress on Nature & Biologically Inspired Computing (NBIC, India), IEEE Publications, USA, pp. 210-214.

[47] Zhang, S., Zhou, Y., Li, Z., & Pan, W. (2016). Grey wolf optimizer for unmanned combat aerial vehicle path planning. Adv Eng Soft., 99, 121–136.