# COST AND RELIABILITY OPTIMIZATION OF A COMPLEX SYSTEM USING MULTI-OBJECTIVE GREY WOLF OPTIMIZATION TECHNIQUE

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**Abstract**

*Modern engineering systems increasingly focus on multi-objective optimization. Nature-inspired optimization techniques have shown superior efficiency and effectiveness compared to many traditional methods across various parameters. This work demonstrates the reliability and cost optimization of a complex bridge system using the Multi-Objective Grey Wolf Optimization algorithm (MOGWO). The bridge system in question is a series-parallel system. A key performance highlight is the use of an archive for search agents to generate a Pareto optimal front (PoF) with a minimal number of iterations. Among the various solutions in the PoF, the solution set that best meets the multi-objective criteria is preferred. Additionally, statistical analyses are conducted to further validate the competitiveness of the results.*

**Keywords**: Nature-inspired optimization techniques, Cost minimization, reliability optimization, multi-objective grey wolf optimization

## I. Introduction

Addressing the challenges of real-world nonlinear problems requires models that achieve multiple objectives simultaneously. This necessity arises from the need to maximize reliability while minimizing costs within the expansive search space of reliability issues. Balancing these opposing objectives without compromise is crucial for optimal results. Therefore, multi-objective optimization techniques are employed as effective methods to achieve the desired outcomes under given constraints. Finding the optimal solution is challenging, but nature-inspired optimization techniques have proven highly effective, consistently producing competitive Pareto optimal solution (PoS) sets. In this article, we use an efficient MOGWO technique to optimize the reliability and cost of a complex bridge system.

As compared to single objective optimization problem (SOOP) producing only a single optimum solution, in multi-objective optimization problem (MOOP) a number of solutions are obtained as a Pareto optimal set. Thus, MOOP determines the desirable set of trade-off solutions for the decision makers to choose their best trade-off solution. As a result, nature inspired optimization methods are being extensively used for achieving the opposing objectives for their efficiency in producing competitive results. Multi-objective optimization algorithms converge to a true approximate global optimal solution as it gives the option of choosing from among a set of Pareto optimal solutions (PoS) satisfying the desired trade-offs between the objectives. This is the result of multi-objective formulation of the problem which explores design parameters of the system with high variation. Better exploration ensures selection from more diversified large search space. This algorithm helps in dealing with local fronts, insolvable areas, separation of the optimum and less diverse nature of solution. This leads to (i) speedy attainment of the global optimum due to the quick sharing of information between the search agents and (ii) better exploration to choose from varied design characteristics and requirements of operations. Efficiency of the multi-objective optimization techniques is based on a number of PoS obtained during the optimization mechanism.

Kumar et al. [1] presented a brief description of the nature of reliability optimization problems along with the different terminologies involved. The authors briefed about various metaheuristic techniques of reliability optimization and also solved problems of complex bridge structure and life support system in a space capsule applying cuckoo search algorithm (CSA). Kumar et al. [2] calculated the availability cost optimization of the butter oil processing plant using GWO technique and compared with the results obtain by CSA. The authors established that Grey Wolf Optimizer (GWO) outperformed the results of CSA. Mirjalili et al. [3] proposed a novel GWO technique based on the social hierarchical behaviour of grey wolves used by them for the hunting mechanism. Nastasi G. et al. [4] applied three variants of genetic algorithm for the problem of multi-objective strategies optimization of steel making industry. The authors gave detailed statistical results with the significant outcomes of the applied techniques.

Zhang and Li [5] proposed an efficient decomposition method of dividing the MOOP into a number scalar optimization sub problems to reduce computational complexity. The authors showed that a set of evenly distributed solutions can be generated with the method used thus highlighted the scalability and sensitivity factor of the technique experimentally. So, to satisfy the multi-objectives covering a variety of design characteristics such computational algorithm is required which avoid local stagnation and also derivatives in the mathematical formulation of the problem. Multi-objective problems have therefore driven a lot of research towards development of meta-heuristics inspired by nature. Nebro et al. [6] proposed the speed-constrained Multi-objective PSO algorithm (SMPSO) and analysed different leader selection schemes. The author suggested based on tests that the hyper volume indicator to guide leader selection is the best for multi-objective PSO algorithms. Pradhan and Panda [7] introduced an extended Cat Swarm Optimization algorithm aimed at identifying non-dominated solutions throughout the search process by employing Pareto dominance principles. This algorithm utilizes an external archive for storage. Their findings suggest that this new method is a promising option for tackling MOOPs.

Shi and Kong [8] investigated enhancements to the multi-objective ACO and introduced the Elitist Multi-objective Ant Colony Optimization (EMOACO) method, which accelerates the parallel search for multiple objectives. Their results demonstrate that EMOACO improves global optimization capabilities and population diversity compared to the basic MOACO, as it quickly converges to PoS and offers a dependable foundation for decision-making. Mirjalili et al. [9] introduced the MOGWO, which incorporates a fixed-size external archive into the GWO for storing and retrieving PoS. This integration helps define the social hierarchy and simulate the hunting behavior of grey wolves. Additionally, Hancer et al. [10] developed a multi-objective artificial bee colony (MOABC) algorithm for feature selection in classification tasks. Their research demonstrated that among the three filter fitness evaluation criteria tested—mutual information, fuzzy mutual information, and a proposed fuzzy mutual information—the proposed fuzzy mutual information yielded the best results in terms of classification accuracy and the number of features selected. Zhou et al. [11] surveyed the development of MOEAs such as decomposition based MOEA, coevolutionary variant of MOEA, MOEA variant for multimodal problems and MOPs of dynamic, noisy, combinatorial and discrete nature. The authors highlighted the advantages of MOEAs in terms of approximation of the Pareto optimal set from a population of solutions cover the conflicting objectives.

Marler & Arora [12] did an extensive survey of the non-linear multi-objective optimization (MOO) techniques consisting of priori, posteriori and the no articulation preferences method. The authors presented a detailed description of the advantages and the limitations of the MOO techniques including a detailed description of the Genetic algorithm. The survey also highlighted the often, ignored ideas and their utility in engineering problem solving with the emphasis on the fact that there is no best single approach for solving real world optimization problems. Zitzler [13] proposed a novel MOO approach called Strength Pareto Evolutionary Algorithm (SPEA) to investigate the development of heterogeneous hardware/systems and to explore software implementations of multidimensional nature for the digital signal processors. The authors also compared the MOO algorithms developed so far with the experimentally and quantitatively and also investigated the effect of elitism and population size. Deb [14] presented a framework of the principles, application and recent developments in the Evolutionary MOO. The authors discuss the Evolutionary MOO's applicability in multiple criterion decision making (MCDM) procedures to handle of a large number of objectives and also outlined the concepts of multi-objectification and innovation.

Zitzler et al. [15] introduced an enhanced version of the Strength Pareto Evolutionary Algorithm (SPEA), named SPEA2. This improved algorithm incorporates three novel strategies: a fine-grained fitness assignment method, a density estimation technique, and an advanced truncation technique. The comparison of the proposed improved SEPA algorithm with other latest methods reveals better performance of SEPA 2. Messac & Mattson [16] presented a Physical programming-based method for generation of well distributed PoS to obtain an Optimization-Based Design (OBD). The authors presented that the characteristics an OBD may possess are its ability generate all PoS with reasonable ease despite the changes in the parameters of the optimization method. Song et al. [17] presented MOO with parameter matching method based on NGA II algorithm. The authors obtained PoS using PHEV integrated optimization simulation platform with fuel economy effect is increased by 2.26%. Kumar et al. [18] proposed to compute various availability measures applying MOGWO in a nuclear power plant. The authors basically aim to optimize technical specifications for residual heat removal system for safety system of the plant. Tiwari et al. [19] proposed an improved version of the Archive-based Micro Genetic Algorithm called AMGA2 which incorporates a selection strategy for the reducing the chance of missing out on enough exploration of the desirable search space. The algorithm retains a collection of wide range of best solution along with a working population of small size.

Emary et al. [20] proposed MOGWO based feature selection strategy. The authors showed that the results of present version of MOGWO and better performance of present algorithm. Makhadmeh et al. [21] presented MOGWO for minimizing the electricity bill and peak-to-average ratio (PAR) and increasing the comfort level of users of smart homes. The authors established a better performance of the MOGWO for power scheduling problem as compared to GA. Dilip et al. [22] introduced a MOGWO aimed at optimizing the power flow problem. They addressed emission, fuel cost, and active power loss as individual objectives and derived Pareto-optimal solutions (PoS) for two multi-objective scenarios: minimizing fuel cost alongside emission value, and minimizing fuel cost along with active power loss. Their results showed significant competitiveness in these scenarios. Xia et al. [23] proposed a multi-objective optimal function for Hydraulic turbine governing system (HTGS) under multiple operation conditions by applying novel MOGWO with searching factor called sMOGWO. The authors employed two improvements which include addition of more no-domain solutions with adjustment of control parameters for exploration in the latter period of the process of optimization to finally make the algorithm more effective.

Petrovic et al. [24] developed a MOGWO for scheduling material transport systems using a single mobile robot within an intelligent manufacturing system. They quantitatively assessed and compared the effectiveness of their algorithm against three other algorithms—MOGA, MOAOA, and MOPSO—using four metrics: Generational Distance (GD), Inverted Generational Distance (IGD), Spacing (SP), and Maximum Spread (MS). Experimental results demonstrated the efficiency of their proposed method. Additionally, Darvish [25] applied a non-dominated sorting MOGWO-based fractional-order sliding mode controller (FOSMC) to precisely regulate the active and reactive power of a DFIG-based wind turbine. The FOSMC was designed to handle uncertainties and unmodeled dynamics in the nonlinear, multivariable, time-varying system of the DFIG, showing valid performance.

The present paper optimizes the reliability cost of a complex bridge structure consisting a series parallel configuration. Section II describes the MOO technique, MOGWO algorithm along with the motivation for the algorithm. Section III describes the mathematical formulation of the problem. The discussion of numerical solution, along with graphical representation of the solution of the problem is presented in section IV. The conclusion and future scope are given in section V.

## II. Multi-Objective Grey Wolf Optimization Optimizer (MOGWO)

General representation of a linear or nonlinear MOOP is given as

$$Maximize\ (\ Minimize): F(x) = \{f_1(x), f_2(x), \ldots, f_h(x)\}. \tag{1}$$

Subject to:

$$p_i(x) \geq 0,\ i = 1,\ 2, \ldots .\, o$$
$$q_i(x) = 0,\ i = 1,\ 2, \ldots .\, n$$
$$H_i(x) \leq x_i \leq G_{i,}\ i = 1,\ 2, \ldots .\, m.$$

There is inherent complexity of the reliability optimization problems having vast exploration area for finding the global optimum solution from among the large population of the candidate solutions which may have the risk of late or early convergence to near optimal solution. Apart from these problems there is a major problem of obtaining more than one objective with the choice trade-offs for suiting the different preferences of the decision makers. Here comes the role of MOO techniques. Also, MOO approach is divided into priori approach converting the different objectives into single objective by using weights the decision makers give to the objectives for the sake of preferences of the different objectives and the other approach being the posterior retaining the multi-objective nature of the problem giving a chance to the model parameters to shape the optimization to the fullest for attaining the global best solutions of pareto optimal set. To avoid the local stagnation problem of the conventional MOO techniques using the deterministic methods applying the mathematical and computer science study, the modern stochastic methods are producing much better results. MOWGO is one of the well-known recent stochastic optimization techniques for MOOP.

Proposed by Mirjalili et al. [3] Grey wolf optimization (GWO) technique has been extended to MOGWO technique by Mirjalili et al. [9]. GWO technique is an optimization method which involves the simulation of the unique hunting mechanism adopted by the grey wolves by following three steps of surveying, encircling and attacking with their social hierarchical behavior. In the technique the search space exploration is done for the candidate solutions and the they are divided into four categories like those of the alpha, beta, delta and the rest as the omega category in the decreasing order of their fitness (hierarchical ability of the wolves). At the end of every iteration the hierarchy is updated. Based on the unique hunting mechanism involving a balanced exploration and exploitation approach the GWO technique has been developed into MOO technique to achieve the different conflicting objectives of increasing availability and reliability of complex systems along with the cost minimization objective.

The following terms are worth noting:

- Pareto Dominance: For two vectors $x = (x_1, x_2, \ \dots..x_k)$ and y $= (y_1, y_2, \ \dots.y_k)$, $x > y$ if $\forall\, j \in 1, 2, \dots\dots, k$, $[f(x_j) \geq f(y_j)] \wedge [\exists j \in 1, 2, 3 \dots..k: f(x_j)]$
- PoS: $x \in X$ is called PoS if and only if $\nexists\, y \in \mathrm{X}$ for $\mathrm{F(y)} > \mathrm{F(x)}$. The Pareto optimal set $P_s$ is the set of all PoS.
- PoF: The set of values of the objective functions for Pareto solution set that is $P_i = \{\mathrm{F}(x): x \in P_s\}$. The PoF consisting of the values of the objectives for different POF the best suitable values are preferred to satisfy the operating conditions.

The GWO algorithm simulates the hunting mechanism of the wolves for a single optimal solution. MOGWO on the other hand produces a set of solutions called as POS which is a result of the following two strategies employed in MOGWO technique.

(i) An archive responsible for sorting non-dominated PoS

An archive is an ordinary collection of PoS. It has a maximum capacity so the entry of a new solution (new member) to the archive is possible only if the new solution dominates at least one member of the archive or if both the new solution and each of the members of the archive are equally dominating. In case the archive is full then the entry is possible only after the grid mechanism is run followed by the re-arrangement of the segmentation of the search space and omission of one the solutions of the most crowded segment (hypercube). The accommodation of the new solution in the least crowded segment or outside the segment increases the diversity of the final PoS.

(ii) Leader selection strategy that assists to choose (Roulette Wheel method)

As against the three best solutions obtained in the GWO to guide the other search for the global optimum solution, in MOGWO the Pareto optimality restricts the comparison of the solutions. To compensate for this aspect of MOGWO there is a leader selection strategy in which the least crowded segment is offered one of its non-dominated solutions as the alpha, beta or delta wolves.

Probability of selection is given by $P_i = \frac{C}{N_i}$;

$c > 1$ and $N_i$ is the number of obtained PoS in the ith segment.

As three best solutions (or leaders) have to be selected so if there are less than three solutions in the least crowded segment then second least crowded segment is considered for the leader selection and the process continues if there is not enough non-dominated leaders in this segment as well. This process is important to maintain the selection of the different kinds of leaders and explore the un-explored areas of the search space.

Thus, the grid mechanism and leader selection strategies enhance the diversity of the archive as the optimization process advances. Also, the Roulette Wheel method helps to overcome the problem of local front for the MOGWO. MOGWO possesses almost same characteristics of GWO except for the fact that GWO tries to maintain and upgrade the three best solutions whereas the MOGWO does the sorting of the archive members in terms with respect to dominated and non-dominated solutions. Following Figure 1 shows code of the MOGWO [26].

Initialize the grey wolf population Xi (i = 1, 2, , k)

Initialize a, A, and C

Calculate the objective values for each search agent

Find the non-dominated solutions and initialized the archive with them Xα=Select Leader(archive)

Exclude alpha from the archive temporarily to avoid selecting the same leader Xβ= Select Leader(archive)

Exclude beta from the archive temporarily to avoid selecting the same leader Xδ= Select Leader(archive)

Add back alpha and beta to the archive t=1;

**while** (t < Max number of iterations)

**for** each search agent

Update the position of the current search agent

end for

Update a, A, and C

Calculate the objective values of all search agents Find the non-dominated solutions

Update the archive with respect to the obtained non-dominated solutions

**If** the archive is full

Run the grid mechanism to omit one of the current archive members Add the new solution to the archive

end if

**If** any of the new added solutions to the archive is located outside the hypercubes Update the grids to cover the new solution(s)

end if

Xα=Select Leader(archive)

Exclude alpha from the archive temporarily to avoid selecting the same leader Xβ= Select Leader(archive)

Exclude beta from the archive temporarily to avoid selecting the same leader Xδ= Select Leader(archive)

Add back alpha and beta to the archive t=t+1

end while

return **archive**

**Figure 1:** *Pseudo code for MOGWO*

## III. Mathematical Formulation of Complex Bridge System (CBS)

The system has a total of five components (Fig. 2) each having component reliability $r_j$, $j = 1,2,3,4,5$ .

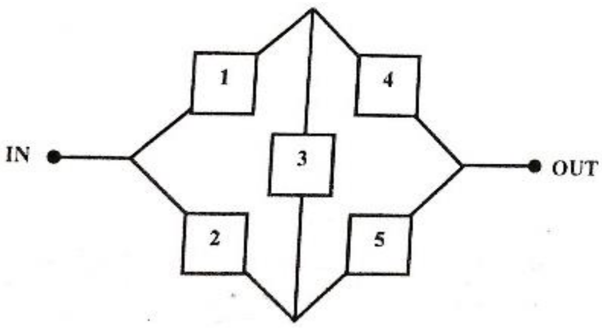


**Figure 2:** *CBS Block Diagram*

The overall reliability of system, which is probability of success of system, is given by

$$R_s = r_1 r_4 + r_2 r_5 + r_2 r_3 r_4 + r_1 r_3 r_5 + 2 r_1 r_2 r_3 r_4 r_5 - r_1 r_2 r_4 r_5 - r_1 r_2 r_3 r_4 - r_2 r_3 r_4 r_5 - r_1 r_2 r_3 r_5 - r_1 r_3 r_4 r_5 \quad (2)$$

The cost of j[th] component is taken as

$$c_j = a_j exp\left(\frac{b_j}{(1-r_j)}\right),\ j = 1,2,3,4,5 \tag{3}$$

Thus, the overall system cost is given by,

$$C_S = \sum_{i=1}^{5} a_i \exp\left[\frac{b}{(1-r_i)}\right] \tag{4}$$

The MOOP proposed here is to determine the reliability of components, which minimize both system unreliability and system cost is presented as follows.

To find $(r_1,\ r_2,\ r_3,\ r_4, r_5)$ to minimize $(Q_S, C_S)$
subject to,
$0.5 \le r_j \le 1,\ \ j = 1,\ 2,\ 3,\ 4,\ 5$ where
$a_i$=1 and $b_i$, =0.0003, $\forall i,\ i = 1,\ 2,\ \ldots,5$

## IV. Results and Discussion

The MOGWO technique used to is successfully used to achieve two opposing objectives of maximizing reliability $R_s$ and minimizing cost $C_s$ . This is done by the POF obtained in the course of the iterations using MATLAB (Fig. 3). The numerical results involve following parameter settings.
Grey wolves =500
Max Iterations= 1000
Archive size =100
Alpha wolves 0.1 % of the Grid Inflation Parameter
Beta wolves 4 % of the Leader selection pressure parameter.
Gamma = 2% (which could be deleted being extra)
N Grid = 10 % per each dimension of the hyper volume of the search space.

**Table 1:** *Examples of non-dominated optimal solution obtained by MOGWO*

| **Solutions (Sol.)** | | **Sol. 1** | **Sol. 2** | **Sol. 3** | **Sol. 4** |
|---|---|---|---|---|---|
| **Optimum variables** | $r_1$ | 0.647078 | 0.955759 | 0.874055 | 0.920607 |
| | $r_2$ | 0.813646 | 0.985532 | 0.85428 | 0.823586 |
| | $r_3$ | 0.666308 | 0.830469 | 0.550224 | 0.828131 |
| | $r_4$ | 0.809893 | 0.968221 | 0.724388 | 0.851756 |
| | $r_5$ | 0.757558 | 0.816819 | 0.918158 | 0.862526 |
| **Optimum system cost** | $C_s$ | 5.006178 | 5.040651 | 5.009874 | 5.011445 |
| **Optimum system reliability** | $R_s$ | 0.866563 | 0.992170 | 0.942139 | 0.961015 |
| **Solutions** | | **Sol. 5** | **Sol. 6** | **Sol. 7** | **Sol. 8** |
| **Optimum variables** | $r_1$ | 0.784118 | 0.967767 | 0.677376 | 0.816032 |
| | $r_2$ | 0.894535 | 0.837209 | 0.721532 | 0.786603 |
| | $r_3$ | 0.630719 | 0.574196 | 0.588316 | 0.624724 |

| | | | | | |
|---|---|---|---|---|---|
| | $r_4$ | 0.607285 | 0.962570 | 0.692794 | 0.854300 |
| | $r_5$ | 0.917022 | 0.890661 | 0.691226 | 0.745382 |
| **Optimum system cost** | $C_s$ | 5.009438 | 5.022695 | 5.004686 | 5.007079 |
| **Optimum system reliability** | $R_s$ | 0.930796 | 0.987236 | 0.786834 | 0.906191 |

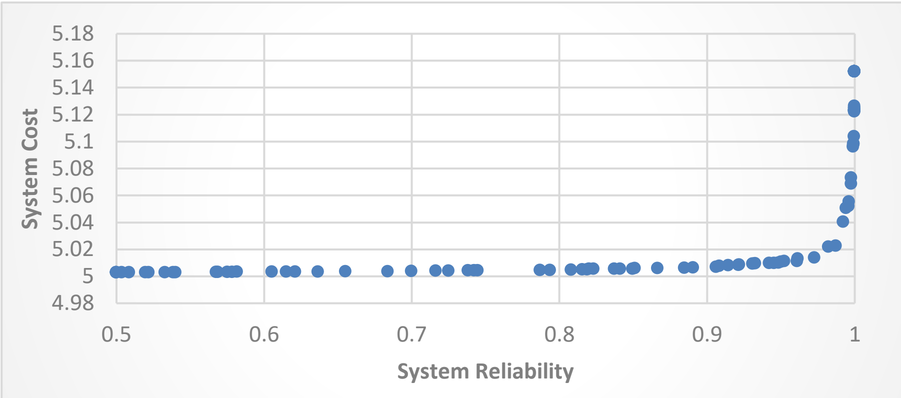


**Figure 3:** *PoF solutions for the Complex Bridge system by MOGWO*

**Table 2:** Convergence results of $R_s$ *and* $C_s$ (1000 runs) MOGWO

| | **Repository size = 100** | **Mean** | **Median** | **S. D** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|---|
| **MOGWO** | System Reliability (Rs) | 0.854069 | 0.943724 | 0.176146 | 0.500000 | 0.999798 |
| | System Cost (Cs) | 5.054642 | 5.009944 | 0.062221 | 5.003001 | 5.152273 |

## V. Conclusion and Further Scope

MOGWO technique with its two module strategies of an archive of solutions for storing and retrieving the best solutions during the progress of the optimization process along with the selection of leader gradually lead to achieve diverse PoS. On one hand the grid mechanism improved the non-dominated solutions in the archive the leader selection mechanism geared the best coverage and convergence. Thus, the exploration and exploitation balance is maintained.

- The above Table 1 presents the numerical results. It includes the estimation of the optimum reliabilities and costs in different run of the MATLAB.
- Total eight sets of PoS corresponding to the optimum reliabilities and cost using MOGWO have been presented in the Table.
- Table 2 presents the average values of optimum reliabilities and costs using simple statistical tools like mean, median and standard deviation.
- Table 2 gives the minimum and maximum values of the mean of all eight PoS. Minimum r= 0.500000 and maximum r= 0.999798 whereas costs range from minimum value 5.003001 to

maximum value of 5.15227.

- By and large the results are competitive as compared to the those of MOPSO.
- Figure 2 indicates very clearly that for the reliability less than r = 0.786834 the minimum cost is approximately same around 5 and less than 5.004686 and also that the minimum cost constantly increases with the increase in the reliability. The highest reliability 0.992170 corresponds to the cost of 5.009874.
- Figure 2 also shows that for reliability is almost same for the values of the minimum cost of 5.009874 approximately.

In the future, MOGWO can be instrumental in evaluating and prioritizing multiple objective problems for solving complex systems with redundant components, ensuring high performance, and achieving optimal cost and efficiency. This approach can be applied in various fields, including telecommunications, optimal power load transmission, artificial neural networks, space program reliability optimization, mutation processes, and other biological and medical areas. The Pareto optimal front (PoF) and multi-criteria decision-making (MCDM) techniques can be utilized to select the most suitable optimal solutions from the PoF, ensuring efficiency throughout the entire operation of complex multi-state systems.

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