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2&3-DIMENSIONAL OPTIMIZATION OF CONNECTING ROD WITH GENETIC AND MODIFIED CUCKOO OPTIMIZATION ALGORITHMS*

S. A. MOEZI[1**], E. ZAKERI[2], Y. BAZARGAN-LARI[3] AND A. ZARE[4]

[1,2,4]Young Researchers and Elite Club, Shiraz Branch, Islamic Azad University, Shiraz, I. R. of Iran
Email: moezi2000@gmail.com
[3]Dept. of Mechanical Engineering, Shiraz Branch, Islamic Azad University, Shiraz, I. R. of Iran

Abstract– In this paper, a connecting rod was modeled and analyzed by finite element method. By using genetic algorithm (GA) and modified cuckoo optimization algorithm (MCOA), the material properties and some geometrical specifications were optimized. Cost function was a combination of weight and stress. The connecting rod was under a load of 21.8 kN which obtained 360° crank angle at 5700 rev/min. The reduction percentages of weight in 2-D analysis were 45.47% and 50.34% based on GA and MCOA, respectively. The reduction percentages of stress were also 1.26% and 2.20% based on GA and MCOA, respectively. The values of reduction percentages in 3-D analysis showed the same trends.

The results showed that applying each of the algorithms was efficient. Meanwhile, the results of MCOA were better than GA, because of the smaller number of iterations and the initial population, which resulted in increasing the rate of convergence (i.e. decreasing computational time) and accuracy of answers. It can be mentioned that MCOA is an efficient and reliable algorithm and can be used as a benchmark for future works.

Keywords– Connecting rod, optimization, finite element analysis, GA, MCOA

1. INTRODUCTION

In any automobile a connecting rod is used to transmit the thrust load of piston that comes from combustion chamber into a rotary motion of the crankshaft and so is a highly dynamically loaded component. The material and geometry of this rod is of great importance from the viewpoint of maximum stress because both tensile and compressive stresses are produced due to the pressure loading. According to design engineers, a connecting rod must be very rigid and strong, but as light as possible. Therefore, the connecting rod is generally designed in the form of I-section to accommodate maximum rigidity and strength with minimum weight. By using a constant material, the maximum stress produced in the connecting rod may be decreased by optimum design of its geometry.

Traditionally, engineers performed the optimization process by trial and error, and optimization was a matter of intuition and know-how. This is, of course, an old-fashioned, costly, and imperfect process of optimization. The current trend is to utilize more and more numerical softwares that simultaneously analyze and optimize many possible designs in an automated process. Optimization makes it possible to manage energy and resources, save time and costs, and ultimately lead to greater accuracy in a device and easier use of it [1-4].

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**Corresponding author

The main purpose of connecting rod optimization is to determine its optimal shape, which includes the shape and size of it, according to an objective function (such as weight, stress, cost and …). The optimization of connecting rod was already started in 1983 by Webster et al. [5]. Since that time, many optimization techniques have been offered in order to solve design optimization problems. Some of these methods are tabu search, genetic algorithm, simulated annealing, particle swarm optimization algorithm, ant colony algorithm, and immune algorithm [6].

Charkha and Jaju [7] performed Finite Element Analysis (FEA) and optimized a connecting rod using COMSOL software by considering fatigue analysis. Weight was used as the objective function that should be reduced. Shenoy [8] explored the weight and cost reduction opportunities in order to produce an optimized forged steel connecting rod. Shenoy and Fatemi [9] studied optimization of a steel forged connecting rod considering weight and production cost reduction, under a cyclic load. Yang et al. [10] described a modular software system and a successful process for performing component shape optimization. Mirehei et al. [11] performed a fatigue analysis on universal tractor (U650) connecting rod in order to determine the fatigue life of it due to cyclic loading. Cioata and Kiss [12] introduced a method which was used to verify the stress and deformation in the connecting rod using the FEA with ANSYS software.

The FEA is a powerful computational technique for solving a variety of complex engineering problems subjected to various boundary conditions. There is no need to describe the FEA, since it has become an essential step in the design process of a physical object in various engineering fields (Madenci and Guven [13]). One of the powerful softwares in analyzing engineering problems with the FEA is COMSOL, which is utilized in the present paper.

There are numerous optimization methods available. Among these methods, however, two procedures were used in this paper: Genetic Algorithm (GA) and Modified Cuckoo Optimization Algorithm (MCOA). A Brief discussion about these two methods will be presented in the following sections.

GA and COA have been used widely by many researchers. Moezi et al. focused on the existence of an optimal shape of buckle, called BELT, optimized by GA [14]. Jafarsalehi et al. tried to develop an efficient distributed collaborative optimization method for the design of remote sensing small satellite mission in low earth orbit. They used GA for the system level optimization [15]. In 2012, Dejam et al. used Cuckoo and Tabu algorithms to solve Quadratic Assignment Problem (QAP) as a combinatorial optimization problem. They compared their results with other meta-heuristic algorithms and showed that the combination of Cuckoo and Tabu algorithms is better than other single algorithms [16]. Mohamad et al. used Cuckoo algorithm in order to predict the surface roughness of Abrasive Water Jet (AWJ). They showed that the Cuckoo algorithm can improve machining performances of the AWJ. They also found that Cuckoo algorithm is capable of giving an improved surface roughness as it outperformed the results of two established computational techniques, artificial neural network and support vector machine [17]. Teimouri and Sohrabpoor applied COA for analyzing electro-chemical machining process [18]. Rabiee and Sajedi presented a method by COA to solve job scheduling in grids computational design and implementation [19]. RamaMohana Rao and Naresh Babu presented an efficient and reliable evolutionary-based approach to obtain a solution for optimal power flow (OPF) problem by employing the nature inspired meta-heuristic optimization algorithm COA to determine the optimal settings of control variables [20]. Mellal et al. applied a model dealing with the replacement of obsolete items in degrading tools in manufacturing systems, based on COA. They also presented a case study to illustrate the methodology [21]. Ziabari et al. used GA, COA and Particle Swarm Optimization Algorithm (PSO) to compute the optimal parameters for the generalized back-stepping controller of flexible joint manipulator system [22]. Singh and Rattan employed COA for the optimization of linear and non-uniform circular antenna arrays.

Their results revealed the superior performance of COA as compared to other techniques, for design of both linear and circular antenna arrays [23]. Ajami et al. presented the elimination of undesired harmonics in a multilevel inverter with equal DC sources by using COA. They used this method to solve the nonlinear transcendental equations of selective harmonic elimination problem. Their results showed that COA is more efficient than Bee algorithm (BA) and GA in eliminating the selective harmonics which cause the lower total harmonic distortion in the output voltage [24].

Along with the development of the COA method by Rajabioun [25], the novel evolutionary algorithm suitable for continuous nonlinear optimization problems, MCOA was first introduced and used by Kahramanli [26]. He presented MCOA and applied this new method to two constrained continuous engineering optimization problems. His results indicated that the MCOA is a powerful optimization technique that may yield better solutions to engineering problems.

The main goal of the present paper is to obtain optimum sizes for a prescribed connecting rod, considering both weight and cost in a single objective function. The basic analysis was done by using the finite element (FE) software COMSOL. MCOA was applied to determine the optimal values for the connecting rod geometry and its material properties. This paper is organized as follows: In section 2, three optimization methods, GA, COA and MCOA, are introduced briefly. In section 3, the basic model of the connecting rod is described and finally, in section 4, the results are presented according to the two optimization methods, GA and MCOA.

2. OPTIMIZATION METHODS

Generally speaking, optimization is the process of enhancing the performance of something towards our desire. From the mathematical point of view, it is a process of finding global extremum of some objective functions. Among several optimization approaches, two well-known techniques GA and COA (and also MCOA), which were inspired from natural processes, are discussed briefly in the following subsections.

a) Genetic algorithm

GA makes use of natural selection and the concept of genetics. The basic idea of GA is to look for optimum solutions using an analogy to the theory of evolution. While iterating (called "evolution" in GA terminology) to converge to a solution, the decision variables (or "genes") are manipulated to create new design populations (or new sets of "chromosomes"). Once a new design population is organized, each new design is calculated using an objective function (called "biological fitness function"). The fittest populations survive and the process progresses till the least fit ones are withdrawn.

In this approach, it is easy to include constraints either in the fitness function or candidate design. In this case, if a design defies a constraint, its fitness is set to zero and it is not present in the next evolution level. GA does not require sensitivity inspection. It is an interesting method for multi-objective problems [27, 28].

b) Cuckoo optimization algorithm

Similar to other evolutionary algorithms, COA starts with an initial population of cuckoos that have some eggs to lay in some host birds' nests. Fortunate eggs, which are more similar to the host bird's eggs, can grow up and become a mature cuckoo. Other eggs are detected by host birds and expelled. The grown eggs disclose the fitness of the nests in that area; and so the more eggs that survive there, the more profit gained. Therefore, the location in which more eggs endure will be the COA extremum [25].

Cuckoos search for the most appropriate area to lay eggs in order to maximize their eggs survival rate. After the remained eggs grow up and become mature cuckoos, they produce some populations. Each population has its residence region to inhabit. The best residence of all populations will be the target for the cuckoos in other populations. They will reside somewhere near the best residence. According to the number of each cuckoo egg and also the cuckoo's distance to the best residence, the egg laying radii is assigned to it. Then, cuckoos start to lay eggs in some random nests inside this radius. This process continues until the best position with maximum gain is obtained. The most important point is that most of the cuckoo habitants are gathered around the same optimum point [25].

According to the above explanation, the main steps of COA are as follows:

1- Formation of initial population place of cuckoos or habitats by some random points
2- Laying of some eggs in some host birds' nests
3- Definition of Egg Laying Radius (ELR) for each cuckoo
4- Egg laying each cuckoo in its ELR
5- Destroying the cuckoo eggs which are identified by a host bird
6- Growing up of some eggs similar to the host bird's eggs and becoming mature cuckoos
7- Evaluation of the suitability of the grown eggs nests
8- Limiting number of the cuckoos in the environment by eliminating the cuckoos that live in inappropriate places
9- Categorizing the cuckoos, selecting the best category and the best habitat
10- Allowing for the creation of a new population of cuckoos near the best habitat
11- If the stop condition is available, the algorithm stops; Otherwise, go to step 2.

c) Modified cuckoo optimization algorithm

In this method, the COA, which was proposed by Rajabioun [25], has been used. In order to solve the problem by COA, first, a matrix that contains the habitat of cuckoos must be created. For this purpose, the initial population shall be defined. If N is the population size of the search space is D-dimensional, the place of i-th cuckoo is defined as follows:

$$X_i = (x_{i1}, \quad x_{i2}, \quad \ldots \quad , x_{id}), \quad i = 1, 2, \ldots N$$

Then a random number of eggs is assigned to the initial population. In nature, each cuckoo lay between 5 to 20 eggs. This value is used as the upper and lower bounds for egg laying of each cuckoo. Another habit of the cuckoos is that they lay eggs in maximum distance from their habitat, which is known as egg-laying radius (ELR). *ELR* in COA is formulated as follows:

$$ELR = \alpha \times \frac{\text{Number of current cuckoos eggs}}{\text{Total number of eggs}} \times (\text{var}_h - \text{var}_l)$$

var_h and var_l are the upper and lower limits of the range of the optimization problem parameters. α is a positive constant which is defined for the maximum radius.

In the MCOA method, the author has used the *ELR* formulation of the COA method in order to describe his method. In the COA method, the *ELR* for each cuckoo is fixed. It is better, though that the *ELR* is large at first and is gradually reduced. This leads to accuracy in the final answer. Therefore this formulation is changed in the MCOA method and causes the reduction of the optimization parameters ranges in any t-increment, as follows:

$$t = \frac{\text{Max\_iter}}{c}$$

$$e = \text{var}_h - \text{var}_l$$

$$a = (\text{iteration}/t) + 1$$

$$e_{new} = \frac{e_{old}}{a}$$

where c is a positive constant number that is selected in the interval (0, 20] and the Max_iter is the maximum number of iterations selected for the problem.

As a result, the formulation for the ELR is corrected as follows:

$$ELR = \alpha \times \frac{\text{Number of current cuckoos eggs}}{\text{Total number of eggs}} \times e_{new}$$

After correcting this radius, the rest of the algorithm is the same as the COA.

3. NUMERICAL SOLUTION STUDY

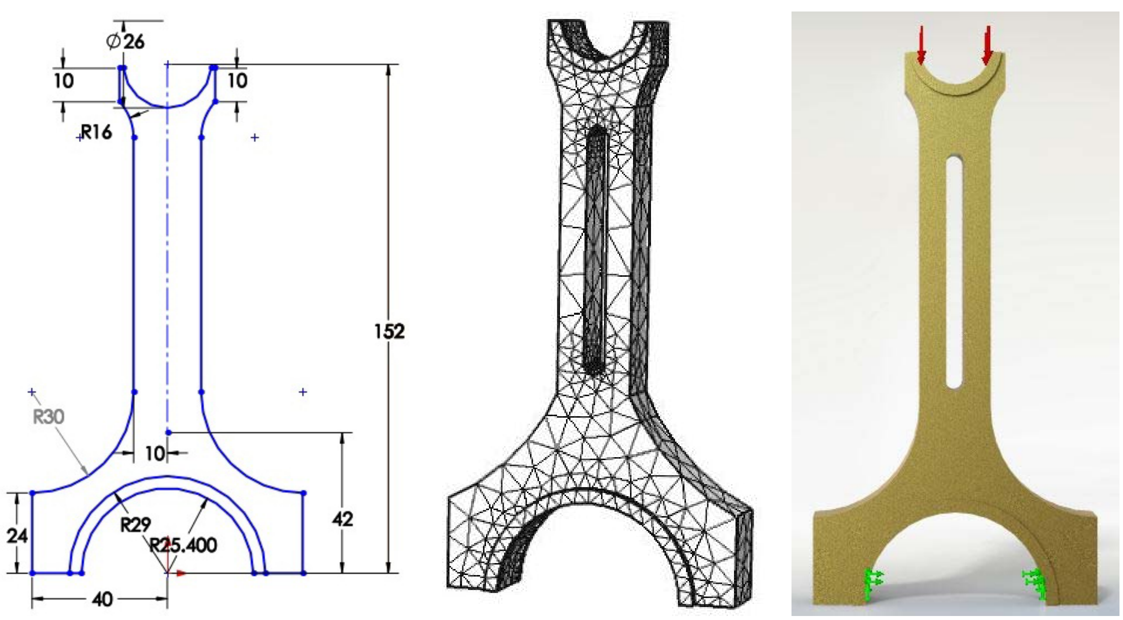
The numerical study of connecting rod optimization consists of three parts: structural stress analysis, optimization process and solving process. Structural stress analysis was performed by using COMSOL software. Optimization process was done by Matlab, which will be explained.

a) Structural stress analysis

What is analyzed hereafter is 2-D and 3-D model of a connecting rod that was developed using SolidWorks software. The initial sizes of the model are depicted in Fig. 1a.

Finite element mesh generation was performed in two states of 2- and 3-D. Mesh parameters of the corresponding models are presented in Tables 1 and 2. The whole FE models are also depicted in Fig. 1b. A fine mesh was adopted for the FE models to ensure accuracy of the calculated results. The material of structural model is high-strength steel and obeys Hooke’s law. The initial parameters of steel are Young’s modulus (which is 200 Gpa), Poisson’s ratio (which is 0.29) and mass density (which is 7858 kg/m3).

The loading applied to the connecting rod was 21.8 kN dynamic tensile force at 360° crank angle and 5700 rev/min, at which maximum tensile stress occurs [9]. The connecting rod was cut through two ends symmetrically, compressive loading was imposed on the upper end and the lower end was fixed. Figure 1(c) shows the whole model with the specified BCs and loadings.



(a) (b) (c)

Fig. 1. Connecting rod model: a) initial sizes; b) 3-D FE mesh; c) BCs and loadings

b) Optimization approach

The connecting rod was optimized in 2&3-D by using two optimization methods, GA and MCOA. MCOA was adopted because of its speed, convergence rate and accuracy in responses. To compare and verify the answers of MCOA, GA was selected as an efficient method.

The objectives of the present paper are two-fold: weight and stress. MCOA, however, is not a multi-objective method. Thus, a single-objective function was used to overcome this problem. In order to be able to compare the results of MCOA with GA, the same single objective function was used in GA. The assumption used in two-objective optimization was a constraining weight.

Table 1. Mesh parameters of 2-D model

Property	Value
Maximum element size	10.2
Minimum element size	0.0456
Resolution of curvature	0.3
Maximum element growth rate	1.3
Minimum element quality	0.5657
Average element quality	0.8969
Triangular elements	800
Edge elements	204
Vertex elements	30

Table 2. Mesh parameters of 3-D model

Property	Value
Maximum element size	15.2
Minimum element size	2.74
Resolution of curvature	0.6
Resolution of narrow regions	0.5
Maximum element growth rate	1.5
Minimum element quality	0.05492
Average element quality	0.6448
Tetrahedral elements	4295
Triangular elements	2290
Edge elements	574
Vertex elements	84

There are three ways in constraining the problem:

1- Constraints of type $g(x) = a$: For this type, which is the simplest one, an expression in the form of $(g(x) - a)^2$ is calculated as penalty and then added to the objective function by a coefficient. It can be seen that if $g(x) = a$, zero number is added to the objective function and practically no penalty is assigned to the optimization algorithm.

2- Constraints of type $g(x)\langle a$: The procedure of solving an optimization problem considering this kind of constraint is adding the expression $VT = \frac{(g(x) - a) + |g(x) - a|}{2}$ to the cost function. $g(x)$ can be any linear or nonlinear expression of the problem variables vector. The superiority of VT term is that in constraints of type $g(x)\langle a$, VT is zero and in situations where $g(x)$ is more than the constraint by e (i.e. $g(x) = a + e$), it is exactly e itself. In fact, the cost function will be fined commensurate to the amount of deviation with constraint.

3- Constraints of type $g(x)\rangle a$: In this type, by multiplication of -1, the constraint can be converted to $G(x)\langle A$; because it can be written as $-g(x)\langle -a$. Thus, the approach to this constraint would be the same as $g(x)\langle a$, just multiplication of -1 is needed.

If cost function doesn't satisfy the specified constraint, penalizing it would be the easiest way, but it is often not a practical way. A better way may be to use an expression which determines the deviation from constraint and also the needed penalty. This kind of penalizing notifies the optimization algorithm of how far it is from satisfaction of the constraint and therefore how much penalty should be used.

According to the abovementioned explanations, in the present paper, weight function was constrained and the following linear combination assumption was used to convert the multi-objective cost function to a single-objective one:

$$\text{Cost} = c \times \text{Stress} + d \times \text{Weight}$$

First, the limit bounds of two desired functions were found and then they were multiplied by two constants of c and d (For example in 2-D optimization, c and d were valued as 240,000 and 1, respectively).

These two constants were adopted so that the values of two cost functions are almost equal and a new cost function, called "Cost", was created and used in optimization process.

c) Solving process

The aim of this study was to optimize a connecting rod, considering cost (which includes weight and stress) as the objective function. Therefore some material and geometric properties were assumed to be interchangeable: these were upper and lower hole radii (R_1 and R_2, respectively), the length and width of rectangular hole (H and B, respectively), Young's modulus E, Poison's ratio ν and density ρ for 2-D analysis and connecting rod and bearing thicknesses (t_1 and t_2, respectively), the length and width of rectangular hole (H and B, respectively), Young's modulus E, Poison's ratio ν and density ρ for 3-D analysis. The prescribed parameter values will be presented in the results section.

The algorithm of solving optimization problem is shown in the flowchart depicted in Fig 2. In the flowchart, "I" means number of iterations, "N" means maximum number of iterations, "E" means the changes in cost function and finally "e" means the tolerance assumed in the solution.

4. COMPARATIVE STUDY

The connecting rod was optimized by using two optimization algorithms, GA and MCOA. In order to better evaluate the application of these methods in solving the optimization of automotive connecting rod, it was considered in both 2D and 3D modes. As mentioned before, the advantage of MCOA over COA is that the ELR is large at first, and then its value is gradually reduced. This allows the search results to be followed in a smaller range and also faster convergence to the optimal value is obtained.

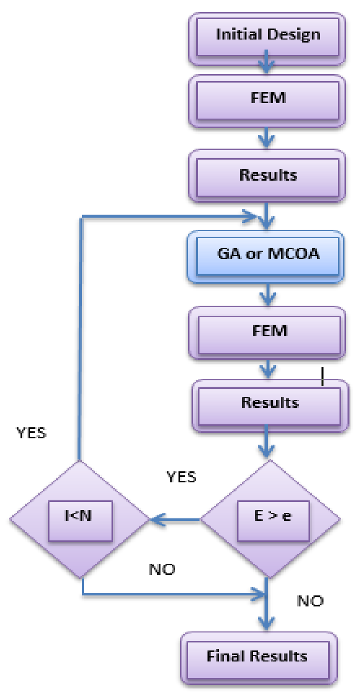


Fig. 2. Algorithm flowchart of solving optimization problem

Table 3 shows the properties of the two methods, GA and MCOA. According to this table, initial number of cuckoos is smaller than population size of genes. In this study, using trial and error, the optimum value 5 and 10 for MCOA parameter c was considered in 2D and 3D modes, respectively. According to the 100 iterations intended to solve the problem, the ELR was reduced after every 20 and 10 iterations in 2D and 3D modes, respectively.

The results of both of the algorithms (i.e. material variables and geometric parameters), before and after optimization are tabulated in Tables 4 and 5. The connecting rod model was analyzed by COMSOL software before and after optimization. Contours of 2-D stress analysis, which were optimized by GA and MCOA are depicted in Fig. 3. Cost functions (including stress and weight) of 2&3-D, before and after optimization by GA and MCOA, are also tabulated in Table 6. Comparing the values obtained and reported in the tables and also in the diagrams shows a good performance of the two methods, especially MCOA.

Table 3. Properties of GA and MCOA

GA		MCOA	
Population Size	20	Number of Cuckoos	5
Generation	100	Min Number of Eggs	2
Crossover	0.95	Max Number of Eggs	4
Tolerance	1e-6	Generation	100
Mutation	0.04	Tolerance	1e-13
Initial Penalty	10	Number of Clusters	1
Penalty Factor	100	Radius Coefficient	5

Table 4. Variable parameters of 2-D connecting rod, before and after optimization

Design Variable	Lower bound	Upper Bound	Initial Design	Optimized by	
				GA	MCOA
R_1	10	13	13	10.763	13
R_2	27	35	29	34.472	34.976
H	25	65	60	31.626	64.508
B	3	6	5	4.2	6
E	98e09	200e09	200e09	197.38e09	99.9e09
ρ	4000	8000	7858	4101.3	4000.3
ν	0.29	0.38	0.29	0.352	0.380

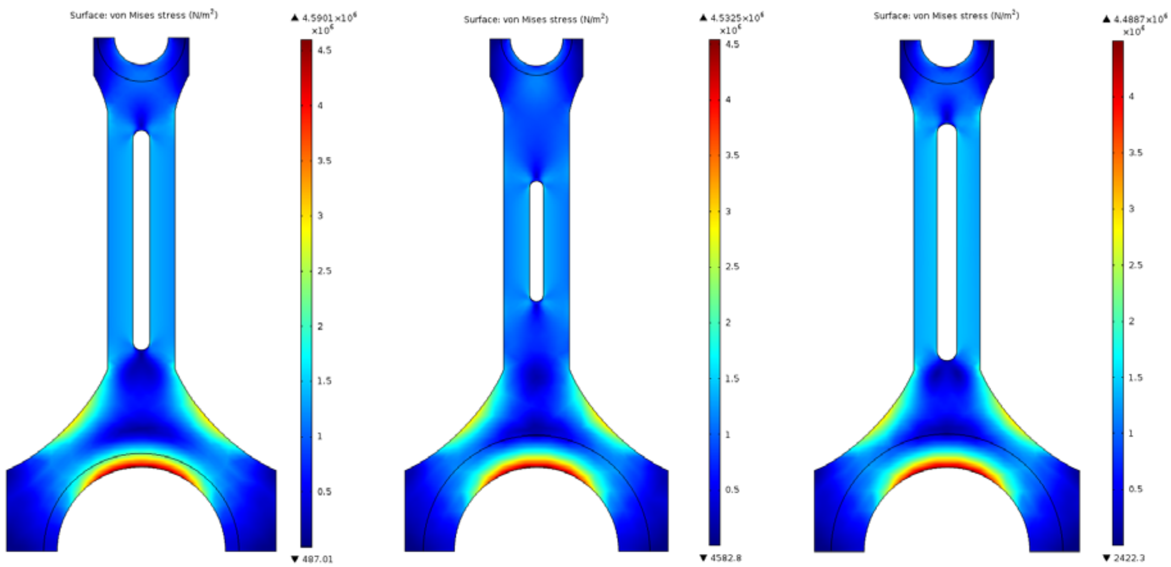
Table 5. Variable parameters of 3-D connecting rod, before and after optimization

Design Variable	Lower bound	Upper Bound	Initial Design	Optimized by	
				GA	MCOA
t_1	13	17	16	13	13.875
t_2	2	4	4	2	2.002
H	25	65	60	50.612	64.99
B	3	10	10	8.895	10
E	100e09	200e09	200e09	100e09	100e09
ρ	4400	8000	7858	4400	4400
ν	0.28	0.37	0.29	0.28	0.28

Table 6. The results of 2&3-D FEM analysis, before and after optimization by GA and MCOA

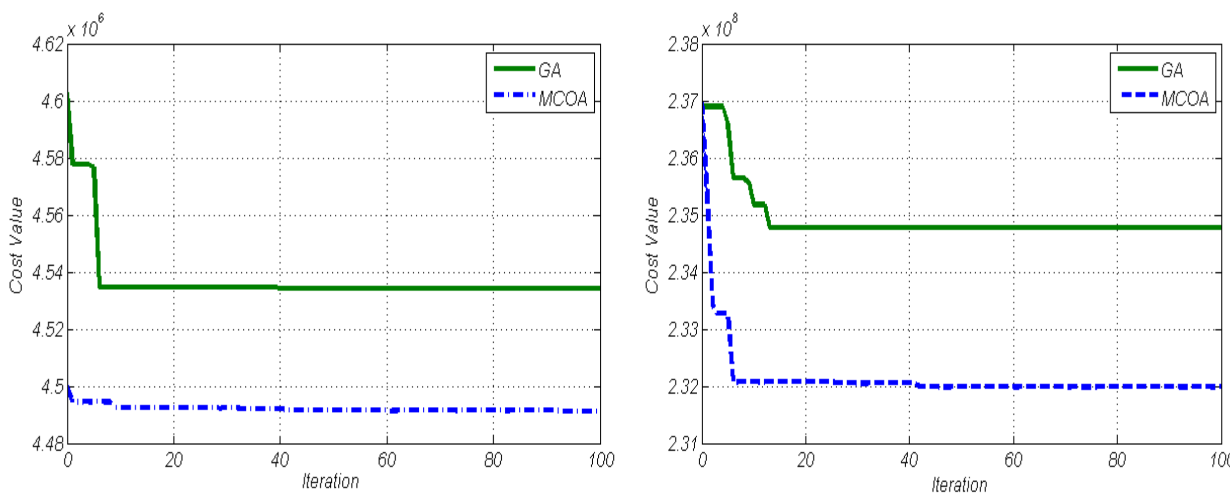
Design Variable	Initial value	After optimization by		Percentage of change	
		GA	MCOA	GA	MCOA
2-D					
Von-Mises (10^6 N/m^2)	4.59	4.53	4.49	-1.26	-2.20
Weight (Kg/m)	30.61	16.69	15.20	-45.47	-50.34
3-D					
Von-Mises (10^8 N/m^2)	2.35	2.16	2.15	-8.00	-8.60
Weight (Kg)	0.46	0.22	0.22	-53.48	-53.48

Comparison of decay trends of the cost function in optimization by GA and MCOA of 2-D and 3-D connecting rod are depicted in Fig. 4. As shown in these two figures, even though the initial population of the MCOA is less than GA, the convergence and accuracy of MCOA is much better than GA, such that after 40 iterations, the MCOA achieves the optimum value with higher speed, in both 2D and 3D modes. Therefore it can be concluded that convergence rate of MCOA is much higher than that of GA.



(a) **(b)** **(c)**

Fig. 3. Contours of 2-D stress analysis: a) before optimization; b) after optimization by GA; c) after optimization by MCOA



(a) (b)

Fig. 4. A Comparison of decay trend of cost function in GA and MCOA: a) 2-D; b) 3-D

5. CONCLUSION

In this paper, the application of MCOA, which is the modified version of COA, was presented to solve the optimization problem of automobile engine connecting rod. Stress analysis of the connecting rod in two modes of 2-D and 3-D was performed by the powerful COMSOL software. In this study, a function of maximum Von Mises stress and weight of the rod was chosen as the cost function, in which seven parameters related to the geometry and material of the rod were considered. According to the results obtained, the following concluding remarks can be stated:

1- Convergence speed and accuracy of MCOA is much more than GA; because after a smaller number of iterations, the solution converges to a more precise value in MCOA, compared to that in GA.
2- According to the 2-D results tables, the reduction percentages of weight were 45.47% and 50.34% based on GA and MCOA, respectively. The reduction percentages of stress were also 1.26% and 2.20% based on GA and MCOA, respectively. The values of reduction percentages in 3-D analysis showed the same trends. This showed that the reduction percentages of stress and weight based on MCOA are more than GA.
3- The results showed that applying each of the algorithms is efficient. Meanwhile, the results of MCOA were much better than GA; because of the smaller number of iterations and initial population, which resulted in increasing the rate of convergence (i.e. decreasing computational time) and accuracy of answers.

According to the results of this research it can be mentioned that MCOA is an efficient and reliable algorithm for future research in the field of engineering problems, especially in matters of optimization.

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