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Comparison of classical and heuristic methods for solving engineering design problems

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Abstract: This paper presents an innovative application of the Ant Colony Optimization (ACO) algorithm to optimize engineering problems, specifically on welded beams and pressure vessels. A simulation study was conducted to evaluate the performance of the new ACO algorithm, comparing it with classical optimization techniques and other heuristic algorithms previously discussed in the literature. The algorithm was executed 20 times to obtain the most efficient results. The best performance outcome in the welded beam simulation was 1.7288, achieved after 540 iterations using 1000 ants, with a computation time of 6.27 seconds. Similarly, the best performance result in the pressure vessel simulation was 5947.1735, obtained after 735 iterations using 1000 ants and completed in 6.97 seconds. Compared to similar results reported in the literature, the new ACO algorithm demonstrated superior performance, offering an outstanding solution. Additionally, users can utilize this new ACO algorithm to quickly acquire information about welded beam design and prefabrication through simulation.

Keywords: Ant colony, engineering design, MATLAB, optimization, welded beam design, pressure vessel

1. Introduction

Optimization is generally used to achieve the best possible result within the determined goals and constraints. The optimization steps include creating basic configurations, defining design variables, formulating the objective function, and selecting and implementing suitable optimization problems [1].

Optimization techniques are often divided into two categories: mathematical and heuristic methods. Mathematical methods strive to find the most accurate analytical solution, while heuristic methods exhibit a more practical approach [2-3]. Some heuristic algorithms are used to solve engineering problems. These include ant colony optimization (ACO) [4], genetic algorithms (GA) [5], particle swarm optimization (PSO) [6], bat algorithms (BA) [7], firefly algorithms (FA) [8] and butterfly algorithms [9].

Studies can be conducted on the instinctual behaviors of animals like ants, bats, and fireflies using heuristic approaches. These instincts enable ants to search for food, birds to gather, and fish to move in schools, organizing these animals [10]. Scientists have studied insect behaviors and developed successful optimization algorithms in this context. These techniques have been successfully applied to many scientific fields and engineering problems. They possess a high level of flexibility in solving engineering problems [11].

Moreover, in recent years, many hybrid algorithms have been proposed by combining these algorithms to solve engineering problems [12]. Hybrid algorithms are created by taking the relatively better aspects of heuristic algorithms, depending on the characteristics and complexity of the problem being solved. One of the successful heuristic applications that can be modified and used in optimization problems is the ACO algorithm [13]. Solutions to optimization problems are also complex due to the high application areas and variability of engineering problems. To facilitate this, the computing power of computer programs is used [14]. One of the programs that

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can be easily used to solve algorithms is MATLAB [15].

This study originated from the need to address specific engineering challenges in welded beam design and pressure vessel optimization, which are critical in ensuring structural integrity and cost-effectiveness in industrial applications. These design problems are characterized by complex constraints, such as minimizing material usage while maintaining structural strength and handling pressure conditions within safety limits. Traditional methods often struggle to navigate these challenges, leading to suboptimal designs efficiently. To overcome these issues, we employed Ant Colony Optimization (ACO) as a heuristic method and Sequential Quadratic Programming (SQP) as a classical optimization method. Recognizing the limitations of existing approaches, the ACO algorithm was modified to handle better the unique constraints and complexities of these design problems. The modifications include enhancements that leverage the advantageous aspects of ACO, making the algorithm more effective in exploring the solution space and avoiding local optima. The new ACO code was implemented in MATLAB, and its performance was compared against results obtained using other techniques reported in the literature. The enhanced ACO algorithm improves solution accuracy and provides valuable insights into welded beam design and pressure vessel optimization during pre-production. By offering a more robust solution framework, this study aims to contribute to cost and time savings for professionals and industries in these critical fields.

2. Literature View

Due to the challenging nature and extensive application areas of engineering problems in manufacturing and aerospace industries, numerous studies have been carried out to find solutions [16]. With the increased number of variables in problems, finding solutions using traditional methods has become difficult. Efforts have been made to simplify the solution and find the best one, leading to the development of metaheuristic algorithms. One such metaheuristic algorithm, ACO [17], has been used to solve many application problems in different areas of daily life [18]. ACO was analytically expressed first in 1930 and began to be frequently used after 1950. Since then, it has successfully solved various problems today [19].

A literature review was conducted on engineering problems, including welded beam design. The review found that previous studies had defined these problems, objective functions, constraints, variables, and solutions using various optimization techniques. These studies were examined to develop the solution further while considering the same definitions. The studies examined are given below.

Welded Beam has been described by Rao [20], Ray & Liew [21], Grković & Bulatović [22], and Cagnina *et al.* [23]. The design problems presented aim to determine the minimum cost due to shear stress, bending stress in the Beam, buckling load, and end deflection of the Beam. Pressure vessels have been previously described by Renato & Leandro Dos Santos [24], Zahara & Kao [25], He & Wang [26], and Huang *et al.* [27]. The design problem involves minimizing the weight of the spring while adhering to certain restraints on minimum deflection, shear stress, surge frequency, and limits on the outside diameter and design variables. Coelho & Mariani [28], Ray & Liew [21], Grković & Bulatović [22], Cagnina *et al.* [23], and Tanriver & Ay [29] have conducted ACO optimization studies on these problems.

Hasan *et al.* [30] studied optimal power flow analysis in power distribution networks, solved with the Sequential Quadratic Programming (SQP) algorithm. Wang *et al.* [31] studied optimization-based transient control of turbofan engines via a sequential quadratic programming approach.

While these studies have provided valuable contributions, the modified new ACO algorithm presented in this paper demonstrates improved efficiency and accuracy in solving these complex engineering problems by better navigating large solution spaces and avoiding local optima. In addition, unlike the literature, a classical optimization solution has been run and compared with the new ACO algorithm results so that the readers could better understand the algorithm's performance.

3. Methodology

Using the information accumulated in the form of pheromone trails laid by artificial colony ants, consecutively shorter feasible tours are formed. Thus, the best results are recorded at the end of the specified iteration to arrive at the problem solution. Computer simulations using programming languages have shown they can produce reasonable solutions to ACO examples [32].

This study combines these two methods to achieve a more effective and reliable solution. The primary ACO method's code has been modified to create a new algorithm for this goal. This new ACO algorithm's code has been tested for functionality and compared with results in the literature using MATLAB software.

3.1. Sequential Quadratic Programming (SQP)

Sequential Quadratic Programming (SQP) is among the classical methods used to solve optimization problems. SQP is used to solve nonlinear objective and constraint function problems [33, 34]. It is used in MATLAB with the fmincon code. SQP solves the optimization problem iteratively by solving a series of Quadratic Programming (QP) subproblems. Each QP subproblem approximates the original problem at the current iterate. x_k.

Quadratic Approximation: The Lagrangian function using a quadratic model is below.

$$\mathcal{L}(x_k + \Delta x, \lambda_k, \mu_k) \approx \mathcal{L}(x_k, \lambda_k, \mu_k)$$

$$+ \nabla_x \mathcal{L}(x_k, \lambda_k, \mu_k)^T \Delta x + \frac{1}{2} \Delta x^T \nabla_{xx}^2 \mathcal{L}(x_k, \lambda_k, \mu_k) \Delta \quad (1)$$

Linearize Constraints: Linearize the constraints around the current iterate x_k Is below.

$$c_i(x_k + \Delta x) \approx c_i(x_k) + \nabla c_i(x_k)^T \Delta x \leq 0, \; i = 1, \dots, m \quad (2)$$

$$h_j(x_k + \Delta x) \approx h_j(x_k) + \nabla h_j(x_k)^T \Delta x = 0, \; j = 1, \dots, p \quad (3)$$

Solve QP Subproblem: Solve the QP subproblem to find the search direction Δx below.

$$\min_{\Delta x} \; S(x) \;\; \nabla f(x_k)^T \Delta x + \frac{1}{2} \Delta x^T \nabla_{xx}^2 \mathcal{L}(x_k, \lambda_k, \mu_k) \Delta x \quad (4)$$

$$\text{Subject to} \quad \nabla c_i(x_k)^T \Delta x + c_i(x_k) \leq 0, \; i = 1, \dots, m$$

$$\nabla h_j(x_k)^T \Delta x + h_j(x_k) = 0, \; j = 1, \dots, p$$

Update Iterates: The solution estimates are below.

$$x_{k+1} = x_k + \alpha_k \Delta x \quad (5)$$

where α_k Does a line search determine a step size?

3.2. ACO Max-Min Ant System

Wilson and Hölldobler [35] discovered that ants communicate via pheromone signals. It helps to understand how ants reach a food source upon their discovery and how they clear obstacles. Pheromones act as a communication medium among ants. The ant colony optimization algorithm is based on the natural behaviors of ants. The algorithm was first studied by Dorigo *et al.* [36] in a reference paper. The pheromones of ants enable information to be transmitted in the colony. Pheromones are the chemicals secreted by ants, and upon secretion, their trails survive for a short period. The more frequently ants visit the same place, the more pheromones they deposit on that path. In ant colony optimization, through a formulated decision mechanism, artificial ants inspired by real ants can communicate by depositing these trails on edges.

Besides their skills in finding the shortest way from food sources to anthills without using their sense of sight, they also can adapt. They can find the new shortest way if the current way they follow is not the shortest way anymore due to external factors. We can explain the behavior pattern of ants as they move casually until they find a pheromone trail. Then, based on the pheromone concentration on the trail, ants decide if they will follow the trail. Therefore, the more ants following a trail there are, the more likely other ants are following the trail [37].

Upon detecting pheromone trails, it becomes clear how ants find food and exhibit cooperative behavior. The classical ant colony algorithm is a meta-intuitive method based on an agent population aiming to solve intermittent optimization problems through behaviors emerging from swarm intelligence. Some additional features of the ant colony algorithm can be categorized as follows: Single artificial control architecture is the same for some units and has scalable characteristics. The solution to a given problem can be applied to other versions of the same problem, which is multifaceted. With minimum modification, it can be used in combinatorial optimizations such as second-degree assignment problems and the planning approach of mobile robots. As a multi-agent system, they can be used for general-purpose planning methods to handle ambiguity, including the noise of sensors and actuators of detection systems. As a search engine based on population, they sometimes tried to optimize positive feedback problems; however, as their goal is to optimize continuous functions, some modifications were made [38]. In the beginning, ants follow a straight line, and in the meantime, releasing the mentioned pheromones onto the path, they help the following ants find their way. The movements of ants, with the help of pheromones that they naturally release, and their path have been illustrated. As they cannot track pheromone trails when their path is blocked, ants primarily choose one of the two paths they can follow. As the transition from the short way for a unit of time will be longer, the amount of the dropped pheromone will also be more significant. Accordingly, in time, there will be a rise in the number of ants that prefer the shorter way. After a while, all ants will choose the shorter way. By checking trails, the ants that move randomly before will probably decide to take the direction of a more intense pheromone trail. As the algorithm was developed inspired by ant colonies, it is called the ACO algorithm.

In order to accelerate the ACO algorithm's speed, which is relatively complicated, various studies were tested successfully utilizing updating some parameters [39]. ACO algorithms have been studied in three categories: original ant system, maximum-minimum ant system and ant colony system. In addition to the pheromone update done in the optimization process, this algorithm initiates a local pheromone update. This update is also called an offline pheromone update. Following each iteration, all ants perform a local pheromone update, and each ant applies it only to the last edge covered. $\mathrm{T_{ij}}$ is shown below.

$$\tau_{ij} = \tau_{ij} . (1 - Q) + \tau_0 . Q \quad (6)$$

Q is the evaporation coefficient; its quantity is $0 \leq Q \leq 1$. $\tau 0$ is the initiation value of the pheromone.

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The primary purpose of the local pheromone update is to diversify the search performed by ants after each iteration. Decreasing pheromone concentration on traversed edges encourages subsequent ants to choose another edge and produce a different solution. Several ants' probability of producing an identical solution gets lower during iteration. The local pheromone update works similarly to the max and min in ant systems. It is also applied by a single ant at the end of each iteration. Likewise, the best update is considered at the end of each iteration, but the ACO algorithm is different, as shown below.

$$\tau_{ij} = \begin{cases} \tau_{ij}.(1-q) + \Delta\tau_{ij}.q, \\ if\ (i,j) belongs\ to\ best\ tour, \\ \tau_{ij}, \qquad otherwise, \end{cases} \tag{7}$$

An essential difference between the ant system and the ant colony system can be seen in the ants' decision rule in the solution process. In ACO, the rule below is employed.

The probability of an ant moving from city i to city j depends on a random variable q between the $0 \leq q \leq 1$ interval. If this Value is the new rate $q \leq q0$, $j = argmax_{c_{il} \in N(s^P)} \{\tau_{il}\, \eta_{il}{}^{\beta}\}$, is employed. Otherwise, the following in below is employed.

$$P_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}\ \eta_{ij}^{\beta}}{\sum_{c_{ij} \in N(s^P)} \tau_{ij}^{\alpha}\ \eta_{ij}^{\beta}},\ if\ C_{ij} \in N(S^P) \\ 0, \qquad otherwise \end{cases} \tag{8}$$

3.3. Modified Ant Colony Optimization Algorithm

The algorithm we propose is a modification of the Ant Colony Optimization (ACO) algorithm. This modification is designed to enhance the adaptability of the algorithm and improve solution quality. The key points and how this new algorithm works is shown below.

Adaptive α and β Values: In each iteration of the algorithm, the importance of pheromone (α) and heuristic information (β) is dynamically adjusted. It makes the solution search process more flexible and may help avoid local minima.

Pheromone Update: All pheromone trails (τ) are updated in each iteration. The new pheromone value is increased based on the current pheromone value and the function value of the best solution in that iteration. That gives more weight to reasonable solutions.

Queen Ant (queen. Value): The best solution is stored as the "queen ant," and the Value of this solution influences the future search directions of other ants.

Status Check and Output: The algorithm checks the best solution in each iteration and if this solution is better than the previous best, it is accepted as the new best solution.

To integrate these proposed modifications into the existing ant optimization, it is necessary to update the functions to reflect the specified changes while maintaining the basic structure of the algorithm. This will include the pheromone update mechanism and the adaptive adjustment of α and β. Additionally, storing and updating the best solution ("queen ant") will be necessary. This approach can be practical in complex optimization problems, such as various engineering design problems. The parameter definition is given in ▶**Table 1**.

Table 1. New ACO Parameters Definition

max_iterations	The maximum number of iterations for the algorithm
ant_population	The size of the ant population
evaporation_rate (ρ)	The rate at which the pheromone evaporates
alpha (α)	The parameter that controls the importance of pheromone in the ant's decision-making process
beta (β)	The parameter that controls the importance of distance in the ant's decision-making process.
queen. Value	The best solution is stored as the "queen ant"

Only the solution obtained from the best ant pheromone trail is updated in the modified ant colony algorithm, and with determined modifications, the new ACO algorithm is obtained. In the first stage, m number of ants should be determined as a parameter. This parameter is based on the quality of the first solution and the I iteration number that represents the change number in the second loop. In the first loop, all ants randomly choose a location and take a value for each variable. Once each ant finds its location, through minval values optimized for variable values selected by ants, the Value of the function is determined. When the values of the function are obtained for each ant, it is evaluated which ant has chosen the best solution, and the Value of that solution is saved as minfunction. All ants obtain the best solution locally from first stage minfunction in the second loop. Pheromone update for the best Value is performed as shown in below.

$$\tau(i) = 0.1\left(1 - \eta_{ij}\right).\tau(i) \tag{9}$$

αj and βj is given to correct the solution of each iteration. In the first iteration, this Value is given in a code, and this Value is selected depending on the intervals of possible solutions of variables in lower and upper band. Also, for each following iteration, correction values of α and β is done as in below.

$$\alpha_j = 0{,}05\,.\,\alpha_i \quad ; \quad \beta_j = 0{,}05\,.\,\beta_i \tag{10}$$

This procedure, explained in the second step, is an iter-

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ation repetition in the second loop and is programmed to repeat to correct the solutions up to the maximum iteration number. Optionally, the best Value can be defined in the code. If a value is defined and a solution better than required cannot be obtained after a given iteration number, the entire loop can be repeated. Once the best solution values are obtained, these values are recorded, and their function values are defined. A simple optimization code of the new ACO algorithm is given in ▶**Figure 1**.

```
Algorithm MACO
for t = 1 : maxiteration
MACO= createMaco ( graph, colony , antnumber, τ, η, α , β);
function [ graph ] = createGraph()
Update α and β;
α_j = 0,05 . α_i ;   β_j = 0,05 . β_i

Determine optimun value and best function value
for i = 1 : antnumber
 τ(j) = τ(i) + 0,005. min_function

 if minfunction < bestfunction;
    function = new function;
   end

queen.value= bestvalue;
to update τ ;
τ = 0.1*( 1 - rho) .* τ;

output = [ 'MACO (Modified ACO) #' ,'Iteration #' ,
value1 ,
 ' optimum Function value = ' , value2];
disp(output)
```

Figure 1. Modified ant colony optimization code

4. Result

Optimization is a method of optimizing a system using mathematical operations to obtain the best possible result. It involves determining the basic configurations, defining the design variables, specifying the objective function, selecting the appropriate optimization algorithms, and applying the optimization procedures. These steps collectively define the optimization process. Optimization can be applied in various fields, such as bolt strength [40], drilling [41,42], cutting parameters [43, 44, 45], machinability of steels [46], and thermal performance [47]. This paper applies optimization to solve the welded Beam and pressure vessel engineering problem.

In the literature, the studies conducted with heuristic optimization methods are used to solve and compare engineering problems. Therefore, to measure the performance of this algorithm in other problems and to compare the results, the pressure vessel model was also included in the calculation in addition to the welded beam design. In addition, unlike the literature, a classical optimization solution was run and compared with the new ACO algorithm results so that the readers could better understand the algorithm performance.

4.1. Welded Beam Problem Definition

The objective is to design a beam subjected to some constraints fixed through the welding method with a minimum cost using the new ACO algorithm. Design variables are x_1, x_2, x_3, x_4 and constraints of shear stress, bending stress forming on the Beam, buckling load on the Beam and end deflection. Welded Beam is shown in ▶**Figure 2** [20],[21], [22], [23].

There are some constraints to optimizing welded beams at minimum cost. These are shear stress τ (g_1), bending stress on beam σ (g_2), buckling force PC (g_7), deflection δ (g_6) and other constraints that are stated below. Values are given as follows: the size of the weld h(x_1), the length of the welded part of the beam l(x_2), the width of the beam t(x_3) and the beam thickness b(x_4). The objective, constraint functions and coefficients are given by obtaining them from the literature [20],[21], [22], [23].

The objective function is shown in Equation 11.

$$f(x) = (1.10471\, x_1^2\, x_2 + 0.04811\, x_3\, x_4\, (14.0 + x_2) \tag{11}$$

Constraint conditions and design variables are shown in Equation 12-34

$$g_1(x) = \tau(x) - \tau_{max} \le 0 \tag{12}$$

$$g_2(x) = \sigma(x) - \sigma_{max} \le 0 \tag{13}$$

$$g_3(x) = x_1 - x_4 \le 0 \tag{14}$$

$$g_4(x) = 0.10471\, x_1^2 + (0.04811\, x_3\, x_4\, (14.0 + x_2)) - 5 \le 0 \tag{15}$$

$$g_5(x) = (0.125 - x_1) \le 0 \tag{16}$$

$$g_6(x) = \delta(x) - \delta_{max} \le 0 \tag{17}$$

$$g_7(x) = P - P_c(x) \le 0 \tag{18}$$

$$0{,}125 \le x_1 \le 2 \tag{19}$$

$$0{,}1 \le x_2 \le 10 \tag{20}$$

$$0{,}1 \le x_3 \le 10 \tag{21}$$

$$0{,}1 \le x_4 \le 2 \tag{22}$$

Where:

$$\tau(x) = \sqrt{(\tau')^2 + 2\frac{\tau'\tau''}{2R}x_2 + (\tau'')^2} \tag{23}$$

$$\tau'' = M\frac{R}{J}, M = P\left(L+\frac{x_2}{2}\right) = 6000\left(14+\frac{x_2}{2}\right), \tau' = \frac{P}{\sqrt{2x_1x_2}} \tag{24}$$

$$\tau'' = M\frac{R}{J} \tag{25}$$

$$M = P\left(L+\frac{x_2}{2}\right) = 6000\left(14+\frac{x_2}{2}\right) \tag{26}$$

$$R = \sqrt{\frac{{x_2}^2}{4} + \left(\frac{x_1+x_3}{2}\right)^2} \tag{27}$$

$$J = 2\left\{\sqrt{2x_1x_2}\left[\frac{{x_2}^2}{12} + \left(\frac{x_1+x_3}{2}\right)^2\right]\right\} \tag{28}$$

$$\sigma(x) = \frac{6PL^3}{x_4{x_3}^2} \tag{29}$$

$$\delta(x) = \frac{4PL}{E\,{x_3}^3\,x_4} \tag{30}$$

$$P_c(x) = \frac{4.013\sqrt{\frac{{x_3}^2{x_4}^6}{36}}}{L^2}\left(1-\frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right) \tag{31}$$

4.2. Pressure Vessel Problem Definition

The new ACO algorithm was used to achieve minimum cost in pressure vessel design. The design variables are the thickness of the shell *Ts* (x_1), the thickness of the head (x_2), the inner radius R (x_3), and the length of the vessel L (x_4). Pressure Vessel is shown in ▶**Figure 3** [20], [21], [22], [23].

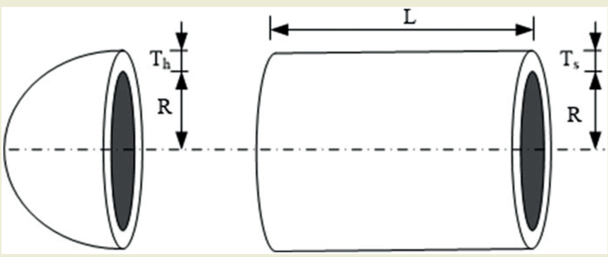

Figure 3. Schematic View of The Pressure Vessel [20], [21], [22], [23].

The objective, constraint functions and coefficients are given by obtaining them from the literature [20], [21], [22], [23].

The objective function is shown in Equation 35.

$$f(x) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 + 19.84x_1^2x_3 \tag{34}$$

Constraint conditions and design variables are shown in Equations 35-44.

$$g_1(x) = -x_1 + 0.0193x_3 \le 0 \tag{35}$$

$$g_2(x) = -x_2 + 0.00954x_3 \le 0 \tag{36}$$

$$g_3(x) = -\pi x_3^2x_4 - \frac{4}{3}\pi x_3^3 + 1{,}296{,}000 \le 0 \tag{37}$$

$$g_4(x) = x_4 - 240 \le 0 \tag{38}$$

$$g_5(x) = 1.1 - x_1 \le 0 \tag{39}$$

$$g_6(x) = 0.6 - x_2 \le 0 \tag{40}$$

$$0 \le x_1 \le 100 \tag{41}$$

$$0.6 \le x_2 \le 0 \tag{42}$$

$$10 \le x_3 \le 200 \tag{43}$$

$$10 \le x_4 \le 200 \tag{44}$$

4.3. New ACO Algorithm and Sequential Quadratic Programming (SQP) Results Comparison

Considering the objective and constraint functions given for the welded beam design, it was run 20 times to obtain the best result. The best result in the new ACO algorithm is 1.7225, and the best result in the SQP algorithm was obtained at 1.9667. The MATLAB result screen is shown in ▶**Figure 4**.

Considering the objective and constraint functions given for the pressure vessel design, it was run 20 times to obtain the best result. The best result in the new ACO algorithm is 5947.1735, and the best result in the SQP algorithm was obtained at 5955.8184. The MATLAB result screen is shown in ▶**Figure 5**.

4.4. New ACO Algorithm and Literature Results Comparison

Considering the objective and constraint functions given for the welded beam design, it was run 20 times to get the best result. The best result was obtained with 540 iterations, 1000 ants and 6.27 seconds. In addition, the best result for the new ACO was compared with those obtained for the same problem in the literature. Result summaries are given in ▶**Table 2**.

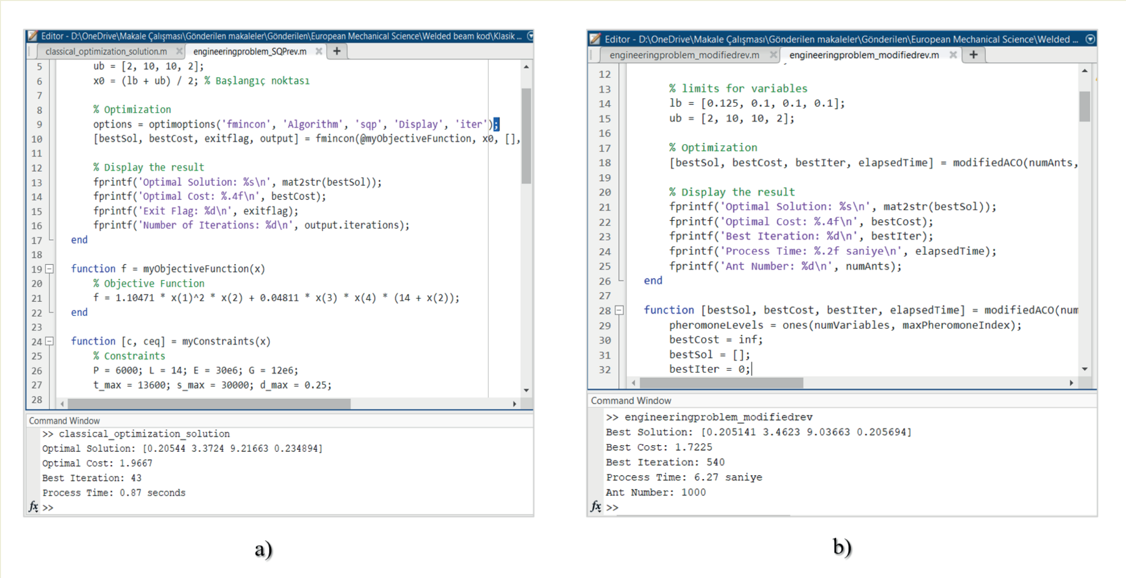

Figure 4. Welded Beam MATLAB Result Screen a) The new ACO b) SQP

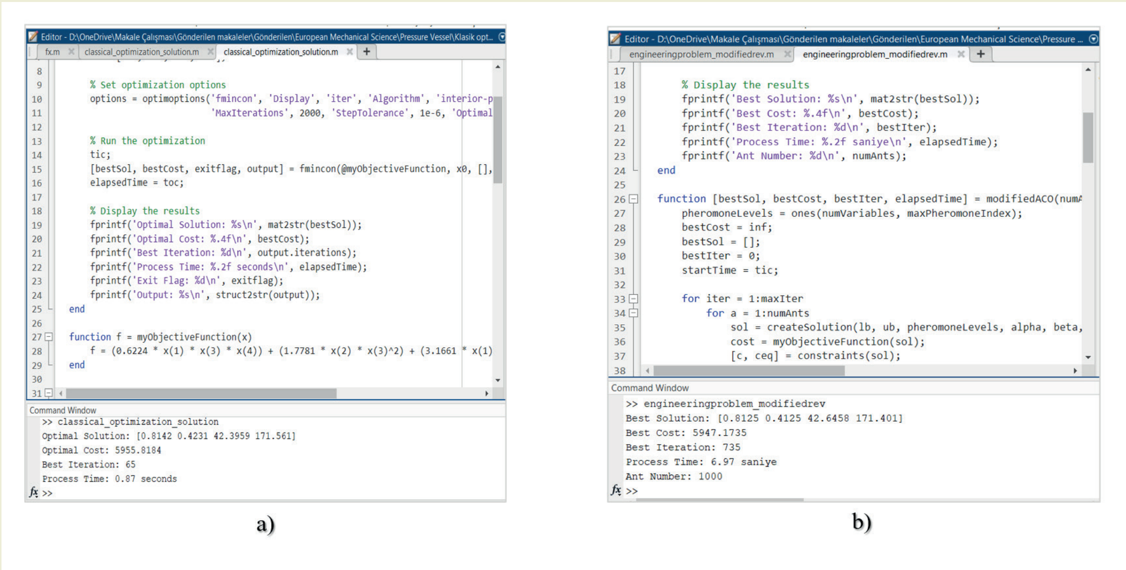

Figure 5. Pressure Vessel MATLAB Result Screen a) The new ACO b) SQP

Comparisons of welded beam design results with literature are as follows.

Eskandar *et al.* have conducted their research using the Water Cycle algorithm (WCA), Colelo with the Genetic Algorithm (GA), Zhao *et al.* with the Hybrid Genetic Algorithm with flexible allowance technique (GAFAT), and Grković & Bulatović have carried out their studies using a modified Ant Colony algorithm (MACA). When the new ACO algorithm was applied, the best solution was found to be 1.7225

The new ACO algorithm result is 0.13% better than Eskander *et al.*'s study (WCA) [48]. Although the algorithm solved with 540 iterations, WCA solved with 750 iterations. The new ACO algorithm result is 1.47 % better than Coello's study (CA) [49]. Although the algorithm solved with 540 iterations, GA solved with 11 iterations. The new ACO algorithm result is 0.13% better than Zhao *et al.* 's study (GAFAT) [50]. Although the algorithm solved with 540 iterations, SA solved with 3000 iterations. The new ACO algorithm result is 0.39 % higher than Grković & Bulatović's work (MACA) [22]. Although the algorithm solved with 1000 ants, MACA solved with 10000 ants. Considering the objective and constraint functions given for the pressure vessel design, it was run 20 times to get the best result. The best result was obtained with 735 iterations, 1000 ants and 6.97 seconds. In addition, the best result for the new ACO was compared with those obtained for the same problem in the literature. Result summaries are given in ▶**Table 3**.

Table 2. Comparison of The Results for Welded Beam Design

Definition	Eskandar et al. (WCA)	Colelo (GA)	Zhao et al. (GAFAT)	Grković & Bulatović (MACA)	This Paper
x_1	0.205728	0.2088	0.20572964	0.202611802838422	0.205141
x_2	3.470522	3.4205	3.47048867	3.538184790851369	3.462302
x_3	9.036620	8.9975	9.03662391	9.038385657692625	9.036633
x_4	0.205729	0.2100	0.020572964	0.205720941513918	0.205694
Best f(x)	1.724856	1.74830941	1.724852	1.729335567988	1.7225
Iteration	750	11	3000	-	540
Ant number	-	-	-	10000	1000
Process time (sec)	-	-	-	-	6.27

Table 3. Comparison of The Results of Pressure Vessel Design

Definition	Eskandar et al. (WCA)	Colelo (GA)	Zhao et al. (GAFAT)	Grković & Bulatović (MACA)	This Paper
x_1	0.7781	0.8125	0.8125	0.82217025865521	0.8125
x_2	0.3846	0.4375	0.4375	0.40638075763737	0.4125
x_3	40.3196	40.3239	42.0984455959	42.6028471508185	42.6458
x_4	_200.0000	200.0000	176.6365958424	170.484922696647	171.4015
Best f(x)	6288.7445	6288.7445	6059.7143	5964.5059570367	5947.1735
Iteration	1000	11	9000	-	735
Ant number	-	-	-	10000	1000
Process time	-	-	-		6.97

Comparisons of welded beam design results with literature are as follows.

Eskandar *et al.* have conducted their research using the Water Cycle algorithm (WCA), Colelo with the Genetic Algorithm (GA), Zhao *et al.* with the Hybrid Genetic Algorithm with flexible allowance technique (GAFAT), and Grković & Bulatović have carried out their studies using a modified Ant Colony algorithm (MACA). When the new ACO algorithm was applied, the best solution was 5947.1735. The new ACO algorithm result is 5.43 % better than Eskander *et al.*'s study (WCA) [48]. Although the algorithm solved with 735 iterations, WCA solved with 1000 iterations. The new ACO algorithm result is 5.43 % better than Coello's study (CA) [49]. Although the algorithm solved with 735 iterations, GA solved with 11 iterations. The new ACO algorithm result is 1.85% better than Zhao *et al.* 's study (GAFAT) [50]. Although the algorithm solved with 735 iterations, SA solved with 9000 iterations. The new ACO algorithm result is 0.29 % higher than Grković & Bulatović's work (MACA) [22]. Although the algorithm solved with 1000 ants, MACA solved with 10000 ants. From this, it is clear that new has achieved success among the results in the literature. Thus, it is clear that new ACO can be reliably used in bow design solutions.

5. Conclusions

This study presents a solution for welded Beam and pressure vessel design using a modified ant colony optimization (ACO) algorithm. The algorithm was enhanced to improve performance compared to previous techniques in the literature. The MATLAB-based implementation was tested 20 times for the new ACO and SQP methods.

The best result was achieved in welded beam design with 540 iterations, 1000 ants, and 6.27 seconds. When the algorithm was applied, the best solution was 1.7225 in the new ACO algorithm and 1.9667 in the SQP algorithm. The new ACO algorithm result is 0.13% better than Eskander *et al.*'s study (WCA). Although the algorithm solved with 540 iterations, WCA solved with 750 iterations. The new ACO algorithm result is 1.47 % better than Coello's study (CA). Although the algorithm solved with 540 iterations, GA solved with 11 iterations. The new ACO algorithm result is 0.13% better than Zhao *et al.* 's study (GAFAT). Although the algorithm solved with 540 iterations, SA solved with 3000 iterations. The new ACO algorithm result is 0.39 % higher than Grković Bulatović's work (MACA). Although the new ACO solved with 1000 ants, MACA solved with 10000 ants.

The best result was achieved in pressure vessel design with 735 iterations, 1000 ants, and 6.97 seconds. When the algorithm was applied, the best solution was

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5947.173 in the new ACO algorithms and 5955.8184 in the SQP algorithm. The new ACO algorithm result is 5.43 % better than Eskander *et al.*'s study (WCA). Although the algorithm solved with 735 iterations, WCA solved with 1000 iterations. The new ACO algorithm result is 5.43 % better than that of Coello's study (CA). Although the algorithm solved with 735 iterations, GA solved with 11 iterations. The new ACO algorithm result is 1.85% better than Zhao *et al.* 's study (GAFAT). Although the algorithm solved with 735 iterations, SA solved with 9000 iterations. The new algorithm result is 0.29 % higher than Grković & Bulatović's work (MACA). Although the algorithm solved with 1000 ants, MACA solved with 10000 ants.

From this, it is clear that the new algorithm has succeeded among the results in the literature. Thus, the algorithm can be reliably used in welded beam design and pressure vessel solutions. Users can quickly learn about welded beam design, pressure vessel design and prefabrication through simulation using the new ACO algorithm. Therefore, the aim is to contribute to cost and time savings for Industry, professionals and users in this field. Further research and development of the algorithm is believed to yield more optimal results. Heuristic optimization methods such as particle swarm and other different classical optimization techniques can be used to measure the algorithm's applicability to other design problems. In addition, it is suggested that the algorithm be extended to other engineering design challenges, such as composite material design, to verify its versatility and effectiveness.

Research ethics

Ethical approval is not required.

Author contributions

Conceptualization: [Kursat Tanriver], Methodology: [Kursat Tanriver], Formal Analysis: [Kursat Tanriver], Investigation: [Kursat Tanriver], Resources: [Kursat Tanriver], Data Curation: [Kursat Tanriver], Writing - Original Draft Preparation: [Kursat Tanriver], Writing - Review & Editing: [Mustafa Ay], Visualization: [Mustafa Ay], Supervision: [Mustafa Ay], Project Administration: [Mustafa Ay]

Competing interests

The authors declare that there is no competing financial interest or personal relationship.

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Data availability

Data may be made available on request.

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