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Developing a mathematical model for predicting ultimate tensile strength to identify optimal machining parameters

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ABSTRACT

Identifying the ultimate tensile strength (UTS) for friction stir welded joints between AA6082-T6 and AA2014-T87 is crucial for ensuring material compatibility, optimizing welding parameters, and assessing mechanical performance. This information helps engineers design safer, more reliable structures and optimize the welding process, improving the utilization of these aluminum alloys in high-performance applications. Traditional methods for identifying UTS face challenges such as material variability, precise experimental setup, the influence of welding parameters, and are time-consuming and costly. This research aims to develop a mathematical model capable of identifying the UTS based on given inputs, specifically optimal tilt angle, travel speed, and rotational speed. The developed model is further utilized to identify the optimal machining parameters. Processing this manually or through trial and error is time-consuming and complex, highlighting the need to incorporate optimization techniques to determine the optimal parameters efficiently. This research involves several optimization techniques, among which the evolved wild horse optimization (EWHO) performs better, achieving a mean square error of 0.45. This is superior performance compared to other optimization techniques and employed prediction models. This approach saves time, reduces complexity, and enhances precision compared to manual or trial-and-error methods, ultimately improving the efficiency and reliability of material processing.

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1. INTRODUCTION

Friction stir welding (FSW) is a solid-state joining process that has transformed industries such as aerospace, automotive, shipbuilding, and railways since its invention in 1991 [1]. Unlike traditional welding methods [2], FSW uses a rotating tool to generate frictional heat, softening materials without melting them, resulting in a solid-state bond with fewer defects and better mechanical properties [3], [4]. Aluminum alloys AA6082-T6 and AA2014-T87 are popular for their strength-to-weight ratio, corrosion resistance, and machinability [5], [6], but welding these dissimilar alloys presents challenges in material compatibility, process optimization, and mechanical performance assessment [7]. Addressing differences in chemical composition and physical properties is crucial for bonding quality [8], [9], and precise control over welding parameters is needed for optimal joint quality [10]. Traditional methods for determining ultimate tensile strength (UTS) and optimal welding parameters are time-consuming and costly [11], [12], and experimental setups must be precise to account for thermal effects and residual stresses [13].

As an outcome, creating a reliable and effective model to determine the FSW UTS is crucial [14]. The goal of this research is to create a mathematical model that can predict UTS based on rotational speed, tilt angle, and travel speed [15], [16]. To do this, optimization techniques like genetic algorithm (GA) [17], evolutionary algorithm (EA) [18], particle swarm optimization (PSO) [19], wild horse optimization (WHO) [20], and enhanced wild horse optimization (EWHO) will be utilized. These techniques are evaluated using artificial intelligence-based models like artificial neural network (ANN) [21], radial basis function neural network (RBNN) [22], and k-nearest neighbors (KNN) [23]. The paper is structured with a literature review in section 2, methodology in section 3, model performance evaluation in section 4, and conclusions in section 5.

2. LITERATURE REVIEW

Thilagham *et al.* [24] suggested process parameters for welding AA6082-T6 and AA2014-T87, evaluating rotational speed, traversal speed, and tilt angle using the L9 orthogonal array. Jaroslaw Krzywanski [25] developed a modeling tool for predicting heat transfer coefficients in fluidized bed boilers, emphasizing the practical significance of such predictions. Krishnan *et al.* [26] highlighted the impact of process variables on FSW quality and created a mathematical model to forecast tensile strength using ANN. Dinkar and Deep [27] proposed improvements to the ant lion optimizer using a Cauchy distribution-based random walk and opposition-based learning to overcome local optima and slow convergence. Jamalian *et al.* [28] examined powder-assisted multi-pass FSW of AA5086-H34 joints, training an ANN to model FSW parameters and joint characteristics. Sayeed *et al.* [29] enhanced solar power generation forecasting by integrating optimization techniques into ANN models, achieving 97.2% prediction accuracy with their evolution of cub to predator technique, surpassing traditional methods.

3. PROPOSED METHODOLOGY

AA6082 and AA2014 are commonly utilized in aerospace and automotive applications for their high structural strength and excellent casting characteristics. In this study, two rolled aluminum plates (100×50×6 mm) were clamped and welded using a 3-T/HYD friction stir machine, with AA6082-T6 on the advancing side and AA2014-T87 on the retreating side. The welded plates were then cut into 100×100×6 mm specimens and tested for tensile properties. The research aims to develop a mathematical model using a sigmoidal function and involves fuzzy logic control (FLC) for generating the necessary data. The study also integrates EWHO techniques to identify optimal weights for predicting the UTS, incorporating oppositional-based learning and the Cauchy distribution to enhance the EWHO algorithm. Table 1 display the chemical analysis outcomes for the base materials.

Table 1. Chemical analysis results of base materials

Elements (wt %)	Si %	Fe %	Cu %	Mn %	Mg %	Cr %	Zn %	Ti %	Al %
AA2014	0.681	0.193	4.171	0.639	0.597	0.003	0.076	0.051	Balance
AA6082	1.16	0.169	0.035	0.54	0.831	0.005	0.002	0.017	Balance

3.1. Fuzzy logic controller

fuzzy logic control (FLC) is a key research area involving fuzzy set theory, reasoning, and logic [30]. It effectively addresses complex problems without needing a deep understanding of the underlying dynamics, using a knowledge base and fuzzy inference rules [31]. This research uses FLC to generate datasets for developing a mathematical model, mimicking human reasoning through rule-based implementation and handling uncertainty. Figure 1 shows the steps in designing an FLC.

3.2. Mathematical modelling

The primary purpose of developing a mathematical model is to predict the UTS for friction stir welded AA6082-T6 and AA2014-T87 alloys. This model aims to reduce the computational cost and time involved in experimentation. This research considers the sigmoidal function as a blind equation and tunes the mathematical model using the EWHO by adjusting the weights in the model. The developed mathematical model is expressed in (1) to (2). Developing this mathematical model through manual derivation and trial-and-error processes is time-consuming and complex. Therefore, integrating optimization techniques is essential to identify the optimal weights in the mathematical model, enabling effective prediction of the UTS.

$$f(x_1) = \frac{1}{1+exp^{-x_1}} = \frac{1}{\frac{1+exp(x_1)}{exp(x_1)}} = \frac{1}{\frac{1+exp(x_1)}{exp(x_1)}} = \frac{exp(x_1)}{1+exp(x_1)} \quad (1)$$

$$F_i = \sum_{j=1}^{NH} \zeta_i * \frac{exp(\sum_{i=1}^{NI} X_i \eta_i)}{1+exp(\sum_{i=1}^{NI} X_i \eta_i)} \quad (2)$$

x_1 is input vector, WHO is chosen for optimal weights in a mathematical model due to its balance of exploration and exploitation, adaptability to complex problems, and superior performance over other techniques like GA and PSO.

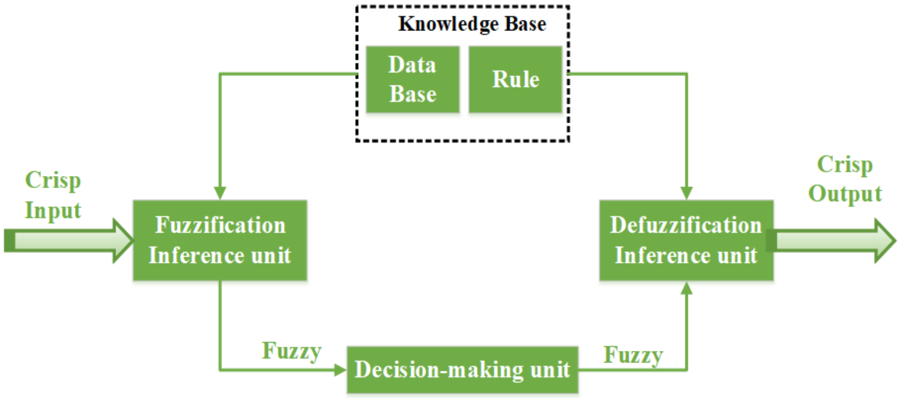

Figure 1. Fuzzy logic controller

3.3. Evolved wild horse optimization

The WHO is a mathematical model development tool that balances exploration and exploitation. However, it faces issues like premature convergence and computational intensity. The EWHO integrates opposition-based learning and the Cauchy distribution to improve its effectiveness. The EWHO process includes initial population generation, horse group organization, leader guidance, and optimal weight selection. Figure 2 depicts the EWHO flowchart.

3.3.1. Creating an initial population

Every optimization algorithm shares the same fundamental structure. The algorithm starts with $(\vec{x})=\{\vec{x_1}, \vec{x_2}, \ldots, \vec{x_n}\}$ an initial random population. The target function repeatedly evaluates this random population, and a target value is determined $(\vec{O})= \{O_1, O_2, \ldots, O_n\}$. A set of guidelines that form the basis of an optimization technique also helped. There is no assurance that a solution will be found in one run because population-based optimization approaches search for the ideal number of optimization issues. However, the likelihood of discovering the best global solution rises with enough random solutions and optimization stages (iteration). We first divide this initial population into a number of categories. If N is the number of members of the population, the number of groups is $G = [N \times PS]$. The PS, which we consider a control parameter for the suggested algorithm, is the proportion of stallions in the whole population. Thus, the number of groups determines the leader G (the stallion), and the remaining members $(N - G)$ are distributed equally among these groups. The algorithm first selects group leaders at random, and then selects them based on fitness, or the best fitness function, among the group members.

3.3.2. Opposition based solution

Considering opposition is more advantageous than creating random alternatives because an opposition candidate is usually closer to the answer. Running the current solution and its inverse concurrently can provide a better approximation, as an opposing pollen solution is more likely to be closer to the optimum than a random pollen solution.

$$OX_{i,G}^{j} = x_i + y_i - X_{i,G}^{j} \quad (3)$$

In (3), OX is the opposition-based solution and X refers randomly generated solution and x_i, y_i refers the minimum and the maximum values respectively. Generating both random and opposition-based solutions enhances solution diversity and improves the chances of finding the global optimum. These solutions are evaluated for effectiveness, leading to better optimization results by combining random exploration with systematic opposition.

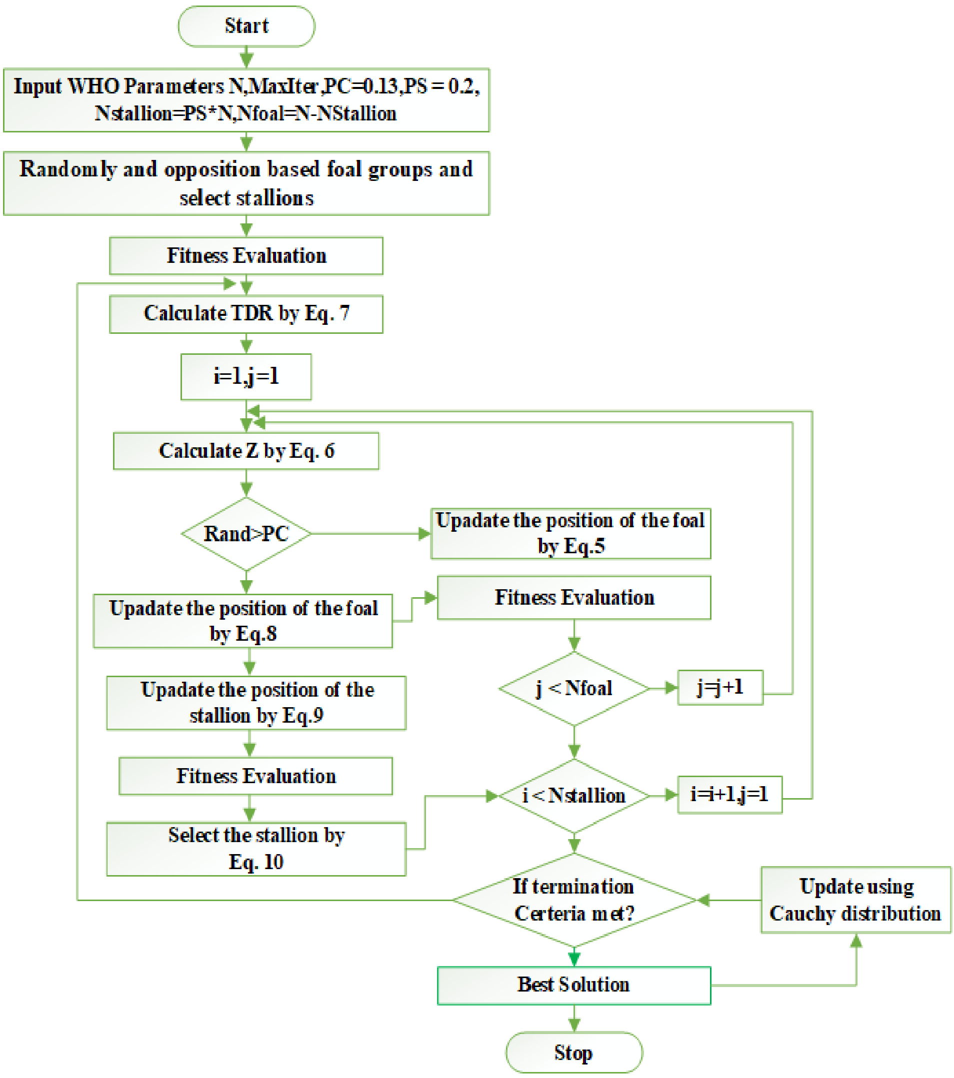

Figure 2. Flow chart of evolved wild horse optimization

3.3.3. Fitness0function

The fitness approach to evaluate how well a solution performs in comparison to the overall amount of validation data. In (4), N refers number of data points; x_i refers observed values; $\widehat{x_i}$ refers predicted values.

$$Mean\ Squared\ Error = \frac{1}{N}\sum_{i=1}^{N}(x_i - x_i)^2 \quad (4)$$

3.3.4. Grazing behavior

Most foals graze in the vicinity of their group, with the stallion marking the hub of the grazing area. The grazing behavior is simulated by (5), which leads the group members to move and search at different distances from the leader.

$$\overline{X}_{i,G}^{j} = 2F\,cos(2\pi RF) \times (Stallion^{j} - X_{i,G}^{j}) + Stallion^{j} \quad (5)$$

$X_{i,G}^{j}$ represents the current position of a group member, while $Stallion^{j}$ is the stallion's position. A random number R in the range [−2, 2] causes grazing at different angles around the leader. The COS function combining π (3.14) and R results in movement in various radius, determining the new position $\overline{X}_{i,G}^{j}$ of the group member when grazing.

$$P = \vec{R}_1 < TDR; IDX = (P == 0); F = R_2 \Theta IDX + \vec{R}_3 \Theta (\sim IDX) \quad (6)$$

where (6), P is a vector consisting of 0 and 1 equal to the dimensions of the problem, $\vec{R}_1$ and $\vec{R}_3$ are random vectors with uniform distribution in the range [0, 1], R_2 is a random number with uniform distribution in the range [0, 1], IDX indexes of the random vector $\vec{R}_1$ returns that satisfy the condition (P == 0). TDR is an adaptive parameter that starts with a value of 1 and decreases during the execution of the algorithm according to (7) and at the end of the execution of the algorithm reaches 0.

$$TDR = 1 - iter \times \left(\frac{1}{max\,iter}\right) \quad (7)$$

where in (7) $iter$ is the current iteration and $max\,iter$ represents the algorithm's maximum number of iterations.

3.3.5. Horse mating behavior

Horses exhibit a unique behavior where foals leave their family group before breeding to prevent inbreeding. Male foals join single groups before puberty, while females join different groups after puberty. This behavior is modeled using (8).

$$X_{G,k}^{p} = Crossover\left(X_{G,i}^{q}, X_{G,j}^{z}\right) i \neq j \neq k, p = q = end, \quad \text{Crossover} = \text{Mean} \quad (8)$$

where $X_{G,k}^{P}$ is the position of horse p from group k and leave the group and gives its place to a horse whose parents are horses that have to leave group i and j and have reached puberty. They have no family relationship and have mated and reproduced. $X_{G,i}^{q}$ the position of the foal q is from group i, which is a departure from the group, and after reaching the age of puberty, it mated with the horse z with the position $X_{G,j}^{z}$, which leaves group j.

3.3.6. Group leadership

Group leaders must lead their members to a central location called the water hole. Multiple groups approach and compete for it, with only the dominant group allowed to use it. Leaders guide their groups to the water hole, use it if dominant, or move away if another group is dominant. Equations (9) and (10) are proposed to manage this approach and distance.

$$\overline{Stallion_{G_i}} = \begin{Bmatrix} 2F\,cos(2\pi RF) \times (WH - Stallion_{G_i}) + WH if R_3 > 0.5 \\ 2F\,cos(2\pi RF) \times (WH - Stallion_{G_i}) - WH if R_3 \leq 0.5 \end{Bmatrix} \quad (9)$$

$$Stallion_{G_i} = \begin{Bmatrix} X_{G,i} & if\,cos\,t(X_{G_i}) < cos\,t(Stallion_{G_i}) \\ Stallion_{G_i} & if\,cos\,t(X_{G_i}) > cos\,t(Stallion_{G_i}) \end{Bmatrix} \quad (10)$$

where, $\overline{Stallion_{G_i}}$ is the next position of the leader of the i group, WH is the position of the water hole, $Stallion_{G_i}$ is the current position of the leader of the i group.

3.3.7. Exchange and selection of leaders

We first select the leaders at random in order to preserve the randomness of the algorithm. Leaders are selected based on fitness later in the algorithm. If a member of the group is physically fitter than the leader, the leader's and the corresponding member's positions will change according to (10).

3.3.8. Cauchy distribution

The Cauchy distribution enhances traditional WHO strategy by introducing larger steps, increasing search diversity, and balancing exploration and exploitation, leading to robust optimization and reliable convergence to optimal solutions. Equation (11) provides a definition for the Cauchy distribution function.

$$F(x; a, b) = \frac{1}{\pi} arctan\left(\frac{x-a}{b}\right) + \frac{1}{2} \tag{11}$$

Experimental analysis identifies location parameter and scale parameter b between 0 and 1, after multiple experiments with varying values.

3. RESULTS AND DISCUSSION

The mathematical model aims to predict UTS for given machining parameters and is evaluated using MSE, RMSE, R^2, and MAE. Experimental and model-predicted UTS are compared, showing EWHO with the smallest average difference (1.0 MPa) and highest accuracy. WHO and PSO also show good accuracy, while GA and EA are moderately accurate. ANN, RBNN, and KNN have lower precision. EWHO's superior performance is attributed to its advanced mechanisms that enhance solution diversity and avoid local optima, making it robust and reliable for predicting UTS. Figure 3 illustrates the prediction performance of the employed techniques.

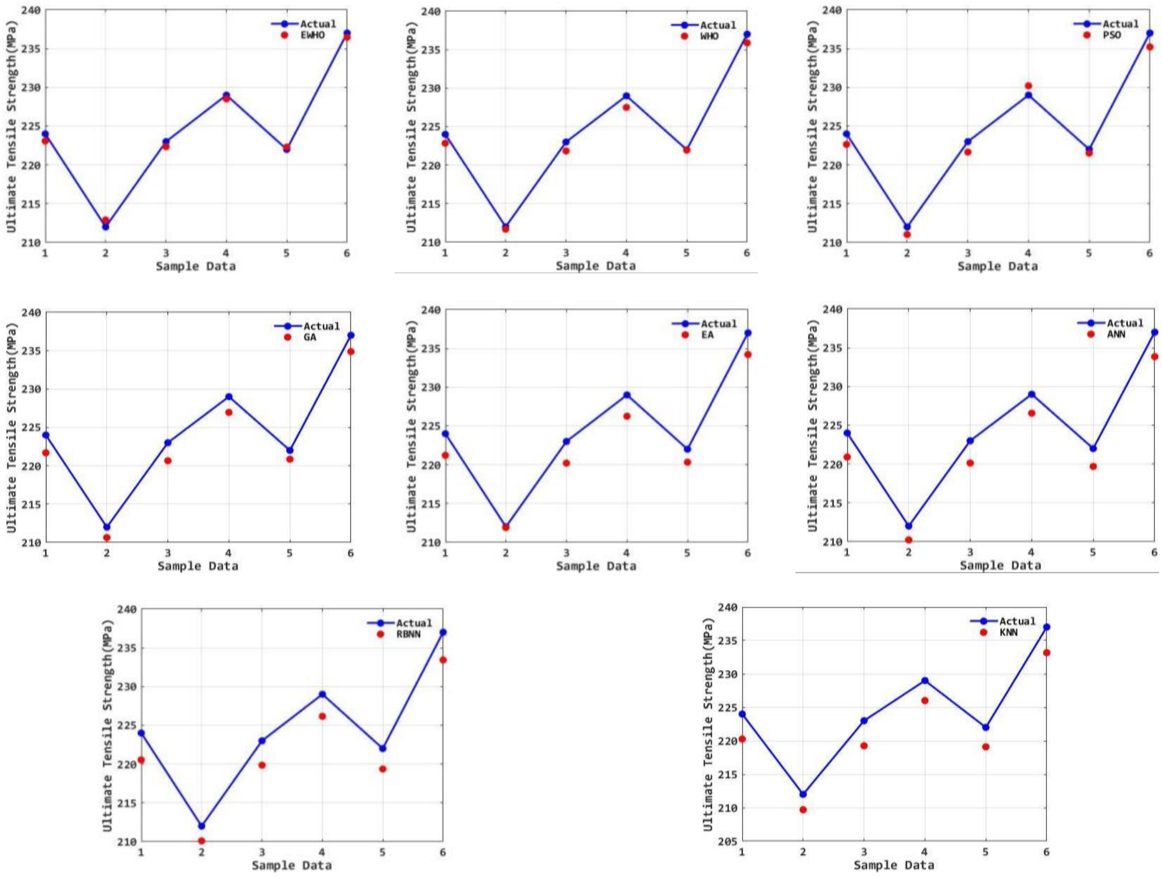

Figure 3. Predicting performance of employed techniques

3.1. Error measures

Error measures like MSE, RMSE, R^2, and MAE are crucial for evaluating a mathematical model's performance in predicting UTS. Figure 4 show that EWHO outperforms other techniques, with the lowest MSE, RMSE, highest R^2, and MAE, indicating superior accuracy and precision. WHO and PSO also perform well, while ANN, RBNN, and KNN have higher errors and lower reliability.

3.2. Convergence graph

A convergence graph shows the progress of optimization algorithms over time, comparing efficiency, stability, and convergence rates. EWHO shows the fastest convergence, achieving the lowest error value. WHO reduces error but at a slower rate, while PSO has a moderate rate. GA converges slowly, while EA has the slowest and least stable convergence. Figure 5 illustrates the MSE over iterations for various optimization techniques.

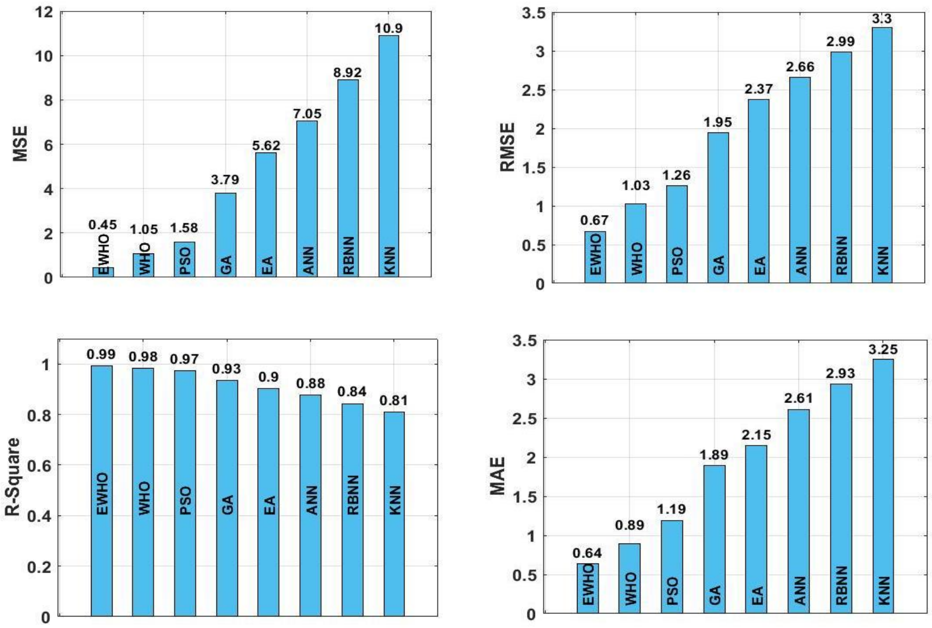

Figure 4. Performance of employed techniques for error measures

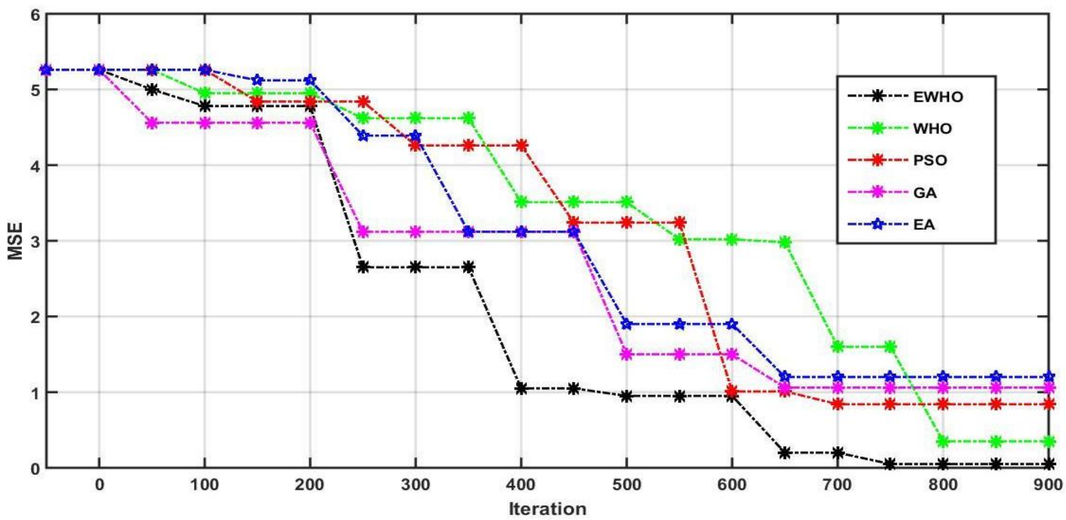

Figure 5. Convergence graph

4. CONCLUSION

Developing the mathematical model has been accomplished with EWHO-configured weights. As a result, the proposed approach reveals lower error values of 0.45, 0.67, and 0.64 from MSE, RMSE, and MAE, respectively. At the same time, the proposed model attains an R2 value of 0.99. The integration of opposition-based learning and the Cauchy distribution strategy, in conjunction with the traditional WHO approach, enhances the performance of EWHO in developing the mathematical model to predict the UTS effectively. The adequately trained mathematical model results indicate that it is much more robust and accurate in estimating the UTS when compared with the other optimization-configured and traditional prediction models. In the future, this research will aim to identify optimal tilt angle, travel speed, and rotational speed by using this developed mathematical model to predict UTS.

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