Modeling of friction stir welding process using adaptive neuro-fuzzy inference system integrated with harris hawks optimizer

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Abstract

Friction Stir Welding (FSW) has been paid more attention in recent years due to its efficiency in welding materials that are difficult to weld by conventional fusion welding methods. There are several parameters that affect FSW process, so it is important to understand the relationship between different process parameters to maximize the quality and strength of the joint. This paper proposed an alternative method to predict FSW parameters and make a decision using a modified version of the adaptive neuro-fuzzy inference system (ANFIS) integrated with harris hawks optimizer (HHO). HHO was used to search for optimal values of ANFIS parameters and to determine the optimal operating conditions of the FSW process. The shared effect of welding speed, tool rotational speed, and plunge force on the mechanical properties of welded aluminium plates was simulated. The proposed model, called ANFIS-HHO, was used to predict the mechanical properties of FSW Al plates in terms of ultimate tensile strength (UTS) as functions of welding speed, tool rotational speed, and plunge force. The adequacy of the model was tested; the predicted data were in good agreement with the experimental data. The tool rotational speed and the empirical force index (EFI) have a significant impact on the mechanical properties of the welded joints. ANFIS-HHO technique was found to be a powerful optimization tool for predicting FSW parameters to achieve high joint strength.

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https://doi.org/10.1016/j.jmrt.2019.09.060
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1. Introduction

Aluminum alloys especially AA2219 have been used in the aerospace industry for manufacturing wings and fuselage frames due to their superior mechanical properties such as high strength-to-weight ratio and ductility [1–3]. Welding of AA2219 aluminum alloys using conventional fusion welding at high welding temperature by melting and re-solidification processes of the fusion zone may deteriorate the mechanical properties of the joint. As it may result in the formation of a thick and brittle intermetallic compound layers and eutectic phases in the weld interface which consequently cause a strong decrease in the mechanical properties of the joint such as hardness, strength and ductility [4].

Friction Stir welding (FSW) technique has been proposed as a good alternative to the conventional fusion welding of high strength aluminum alloys [5]. FSW process has many advantages over conventional fusion welding such as avoiding porosity and solidification cracks as well as the absence of parent metal melting [6–10]. FSW was first introduced in 1991 as a new joining technique which initially applied for joining aluminum alloys [11]. The main idea of FSW is quiet simple: a rotating tool of non-consumable material with a well-designed shoulder and pin is used to heat the workpiece, stir the material, and restrain the soft metal below the shoulder of the tool which causes plastic deformation in the metal and leads to solid state joining in the surrounding area [12].

There are several parameters that affect FSW technique such as material properties, tool design, clamp design, and welding conditions as shown in the cause and effect fishbone diagram presented in Fig. 1. Elangovan et al. [13] revealed that tool geometry plays an important role in the mechanical properties and microstructure of aluminum joints, where five different tool pin geometries (straight cylindrical, tapered cylindrical, threaded cylindrical, square and triangular) have been utilized to produce joints. It has been concluded that the geometry of the square tool pin produces metallurgically and mechanically sound joints without defects compared to other tested tool pin geometries. FSW aluminum joints were produced using dual-pin tool, and concluded that the microhardness and tensile values across the nugget region were relatively improved compared with single-pin joints [14].

Welding speed (V), tool rotational speed (N), tool pin profile, and tool axial force (Fz) have a significant effect on the tensile behavior of dissimilar FS welded joints [15,16]. Effect of process parameters (tool rotational speed, axial force, and welding speed) on the tensile strength of friction stir welding A356/C355 aluminum alloys joint has been investigated using response surface methodology [17]. FSW of AA6061 using Inconel 601 tool has been carried out in different combinations of traverse speed and tool rotation to assess joint performance in terms of ultimate tensile strength and micro-hardness [18].

Recently, Kumar et al. [19] identified the optimal FSW process parameters for maximizing the tensile strength of friction stir welded AISI 316L butt joints as a function of tool transverse speed, tool rotational speed, axial force and tilt angle of the tool. Other welding process parameters such as plunge depth and gap-tolerance have been also investigated. Iqbal et al. [20] introduced an attempt to obtain the optimum value of plunge depth during FSW of aluminum alloy pipe using point tracking method and the results were validated experimentally. Ma et al. [21] investigated the effect of gap-tolerance on joint efficiency and welding defects during butt welding of 2A14-T6 aluminum alloy. More experimental investigations should be carried out to understand the relationship between different process parameters to augment the quality of welded joints in terms of tensile strength. Therefore, the selection and control of various parameter of the welding process is highly desirable. Several prediction techniques have been used to correlate the output to the process inputs via developing mathematical models to figure out the relationship between process input parameters and corresponding output variables such as response surface methodology (RSM) and artificial neural network (ANN).

RSM is a powerful tool that can be used to develop an appropriate approximation for the relationship between independent input variables and response variables to characterize joint characteristics [22]. Many researchers [23–26] have demonstrated that the design of experiments methods can be utilized to develop empirical methodologies to statistically analyze the fusion welding process. In recent decades, ANN based modeling has gained increasing importance in the materials joining field. ANN is a powerful modeling tool that mimics the natural behavior of human brain and is used to model complex problems of a non-linear nature in various engineering applications [27]. The basic element of the ANN model is neuron. Neurons are interconnected via artificial links known as synapses. ANNs are able to learn non-linear relationship between the process inputs and outputs with excellent generalization capabilities without involving in solving complex mathematical models using numerical and analytical approaches [28–31]. Details about ANN modeling techniques are provided elsewhere [32]. Andersen et al. [33] applied ANN, for first time, in welding applications as a tool to predict the shape of a welding bead during gas tungsten arc welding process. There are further investigations into ANN applications to develop predictive models of FSW joints [34–40]. ANN was used to predict the correlation between FSW process parameters and mechanical properties of welded aluminum plates such as yield strength, tensile strength, elongation, and hardness of welded joints [37]. In addition, the integration of various metaheuristic approaches [41–43] and ANN such as genetically optimized (GA) ANN has been pro-

![Fig. 1 – Cause and effect fishbone Diagram.](image-url)
posed in intelligent decision making [38]. Both of GA and ANN were applied to optimize FSW process and predict their responses, respectively. FSW is a complex process with unexpected behavior that may affect the prediction accuracy of RSM and ANN models. Thus, the need for linguistic-based models arises. Therefore, Fuzzy logic (FL) has been proposed as an alternative to RSM and ANN to estimate the characteristics of the FSW process.

Adaptive neuro-fuzzy inference system (ANFIS) is a hybrid predictive model in which ANN and FL are integrated to create a mapping relationship between inputs and outputs [44]. The structure of the ANFIS model consists of five layers, wherein each layer is constructed by several nodes. Like ANN, in the ANFIS model, inputs for each layer are obtained by nodes from the previous layer. ANFIS has shown promising applications in predicting the performance of manufacturing processes. Although ANFIS is a powerful tool for prediction and optimization of many applications such as manufacturing [45], machining [46-54], acoustics [55], and materials processing [56], very few studies on optimization of FSW process parameters using ANFIS model have been reported in literature [57].

In this paper, a new method for predicting ultimate tensile strength (UTS) of AA2219-T87 FSW joints is presented. This technique is based on the integration between ANFIS and Harris Hawks optimizer (HHO), where the optimal values of ANFIS parameters are determined using HHO. There are two main stages implemented in the proposed model: the training stage and the testing stage. The experimental dataset is randomly divided into two sets: a training set and a testing set. In the training stage, the algorithm generates a set of solutions that represent the parameters configuration. Then for each generated solution, ANFIS is created, based on the current solution. The learning process is performed using the training set. The quality of the configuration (solution) is computed using a pre-defined objective function to select the best solution. Once the best solution is identified, all existing solutions are updated by applying the HHO operators and these steps are repeated until the stopping criterion is fulfilled. In the meantime, the evaluation stage begins with the selection of the trained ANFIS model based on the optimal configuration and then the test set is applied to it. The target output is then calculated, and the performance of the model is evaluated using statistical measures.

2. Background

In this section, we will discuss the basic information about ANFIS and HHO.

2.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a hybrid artificial intelligence model in which fuzzy logic is integrated with ANN. This integration results in superior enhancement in the accuracy and the robustness of the hybrid model as well as avoiding the drawbacks of both models. In ANFIS, Takagi–Sugeno inference technique is implemented via creating nonlinear input/output mapping using the fuzzy IF–THEN rules. ANFIS model consists of five main layers as shown in Fig. 2 and summarized as follows:

In the Layer 1, the inputs x and y are subjected to generalized Gaussian membership function $\mu$ to produce a new output $O_{i}$, which can be expressed by the following equations:

$$O_{i} = \mu_{A_{i}}(x), \ i = 1, 2, O_{i} = \mu_{B_{i-2}}(y), \ i = 3, 4$$

(1)

$$\mu(x) = e^{-(x-r_{i}/\sigma_{i})^{2}}$$

(2)

where $A_{i}$ and $B_{i}$ denote the membership values of the $\mu$. $r_{i}$ and $\sigma_{i}$ denote the set of hypothesis parameters.

In the second, the output of each node is calculated as follows:

$$O_{2i} = \mu_{A_{i}}(x) \times \mu_{B_{i-2}}(y)$$

(3)

Then, the output of the second layer is normalized in Layer 3 using the following equation:

$$O_{3i} = \frac{\omega_{i}}{2} \sum_{i=1}^{\omega_{i}} \tilde{O}_{3i}$$

(4)

Then, the output of layer 3 is passed through the adaptive nodes of Layer 4 as follows:

$$O_{4i} = \tilde{O}_{f_{i}} = \tilde{O}_{i}(p; x + q; y + r)$$

(5)

where $p$, $q$ and $r$ denote the consequent parameters of the $i$-th node.

Finally, the overall output of the model is calculated as follows:

$$O_{5} = \sum_{i} \tilde{O}_{f_{i}}$$

(6)

ANFIS suffers from some drawbacks such as trapping in local optima and slow convergence of training especially for wider search space. Therefore, there is a need to use hybrid methods integrated with ANFIS to overcome these problems arises.

2.2. Harris hawks optimizer (HHO)

HHO begins by determining the initial value for a set of agents $X$ that represent the solution for the tested problem. The next step is to evaluate these agents by calculating the fitness function and then searching for the best solution ($a_{b}$) (i.e., the location of prey). HHO then uses a set of phases to update the current agents that depend on random variables as described in algorithm 1. These phases are discussed with more details in the following:

2.2.1. Exploration phase

In this phase, the position of current agent will be updated depends on either the information from other agents and the
best solution (second branch of Eq. (7)) or random agent from the population (first branch of Eq. (7)).

\[
X (t + 1) = \begin{cases} 
X_r (t) - r_1 |X_r (t) - 2r_2 X (t)| & q \geq 0.5 \\
X_b (t) - X_m (t) - r_5 (lb + r_4 (ub - lb)) & \text{otherwise}
\end{cases}
\]  

(7)

In Eq. (7), \(X_m\) and \(X_r\) are the average of agents, and the random agent, respectively, at current iteration \(t\). The parameters \(r_1, r_2, r_3, r_4, q\) are random numbers generated from the interval \([0,1]\), where the main purpose of \(q\) is to represent the ability of HHO to switch between the two branches of Eq. (7) where the first branch is used when \(q \geq 0.5\) otherwise the second branch is used.

2.2.2. Change from exploration to exploitation

In this phase, the HHO uses the escape energy of the rabbit (E) defined in Eq. (8) to simulate the transfer of searching from exploration to exploitation.

\[
E = 2E_0 \left(1 - \frac{t}{T}\right)
\]  

(8)

Where \(E_0 \in [-1,1]\) represents the initial value of E, this value is used to indicate either the physically flagging of the rabbit (i.e., \(-1 \leq E_0 < 0\)) or its strengthening (i.e., \(0 \leq E_0 < 1\)). In addition, \(T\) and \(t\) are the maximum number of iterations and the current iteration, respectively. Moreover, in the case \(|E| \geq 1\) then HHO will explore the search space otherwise, HHO will change its status to the exploitation phase.

2.2.3. Exploitation phase

HHO in this phase uses various strategies to simulate the process of attacking the rabbit and this depends on the prey’s ability to escape. These strategies are detailed below.

2.2.4. Soft besiege

This strategy is used when \(r \geq 0.5\) and \(|E| \geq 0.5\) (where \(r\) represents the prey’s ability to escape). This means that the rabbit still has enough escape energy, so the harris hawks select the best solution from the population to update the solution \(X (t)\) in the current iteration \(t\). This can be formulated using the following equation:

\[
X (t + 1) = \Delta X (t) - E |J \times X_b (t) - X (t)| \cdot \Delta X (t) = X_b (t) - X (t) \cdot J = 2 (1 - r_5)
\]  

(9)

In Eq. (9), \(J\) represents the random jump strength of the prey and this is used to represent the process of escape from the hawks. \(r_5 \in [0,1]\) represents a random value.

2.2.5. Hard besiege

This strategy is used when \(r \geq 0.5\) and \(|E| \geq 0.5\) this means the prey still has energy, so the hawks encircle the rabbit, and this is performed using Eq. (10)

\[
X (t + 1) = X_b (t) - E |J \times X_b (t) - X (t)|
\]  

(10)

In the case \(r < 0.5\) and \(|E| < 0.5\), this indicates that the rabbit has energy but the probability of escaping is not high, so hawks try to catch it. Therefore, HHO simulates this by using a set of steps that begins by selecting the next step as in Eq. (11)

\[
Y = X_b (t) - E |J \times X_b (t) - X (t)|
\]  

(11)

The current movement is compared with the previous dive and the best one is selected. Hawks begin to dive irregularly and quickly when the value of \(Y\) is not good and this emulated by using the levy flight as in Eq. (12)

\[
Z = Y + S \times \text{levy} (D)
\]  

(12)

Where \(\text{levy} (D)\) represents the levy flight function with dimension \(D\), whereas \(S \in \mathbb{R}^{1 \times D}\) is a random vector. According to the previous behaviors the current solution can updated either using Eq. (11) or Eq. (12) as follows:

\[
X (t + 1) = \begin{cases} 
Y & \text{if } \text{Fit} (Y) < \text{Fit} (X (t)) \\
Z & \text{if } \text{Fit} (Z) < \text{Fit} (X (t))
\end{cases}
\]  

(13)

2.2.6. Hard besiege with progressive rapid dives

HHO uses this strategy when \(r < 0.5\) and \(|E| < 0.5\) which means that the rabbit has not enough \(E\). This strategy is like the soft besiege, however, the hawks decrease the distance of their
average position and the rabbit. Therefore, the following equation is used

\[
X (t + 1) = \begin{cases} 
Y & \text{if } \text{Fit} (Y) < \text{Fit} (X (t)) \\
Z & \text{if } \text{Fit} (Z) < \text{Fit} (X (t)) 
\end{cases}.
\]

\[
Y = X_b (t) - E [J \times X_b (t) - X_m (t)]. \tag{14}
\]

where Z is given in Eq. (12).

The HHO strategy is summarized in Algorithm 1

**Algorithm 1 HHO**

**Inputs:** The size of population \( N \), and the total number iterations \( T \)

Set the random population \( X_i (i = 1, 2, 3, \ldots, N) \)

while (terminating state is not occurred) do

Compute the fitness values of hawks

Find the best solution \( X_b \).

For \( i = 1 : N \)

Update the value of \( E_0 \) and \( J \).

Update the \( E \) by Eq. (8).

If \( |E| > 1 \) then

Update the location vector by Eq. (7)

if \( r \geq 0.5 \) and \( |E| > 0.5 \) then

Update the location vector by Eq. (9)

else if \( r \geq 0.5 \) and \( |E| < 0.5 \) then

Update the location vector by Eq. (10)

else if \( r < 0.5 \) and \( |E| > 0.5 \) then

Update the position vector by Eq. (13)

else if \( r < 0.5 \) and \( |E| < 0.5 \) then

Update the location vector by Eq. (14)

**Outputs:** The best solution.

### 3. Proposed model

The structure of the proposed model for predicting the ultimate tensile strength (UTS) of AA2219-T87 FSW joints is given in Fig. 3. The proposed method is based on improving the performance of the conventional ANFIS model by determining its parameters based on the HHO algorithm.

The proposed model, called ANFIS - HHO, begins by setting the initial value for the position of \( N \) hawks (solutions). Each of these hawks represents the parameters of ANFIS, so we have \( N \) ANFIS models. The next step is to compute the fitness function of each solution because it is used to evaluate the quality of each solution and is formulated in Eq. (15). However, before computing fitness function, the data is divided into two main sets: training set and testing set which represent 70% and 30% of the original data, respectively. The training set is then used to train ANFIS with the current solution (i.e., its parameters).

\[
\text{Fit} = \sqrt{\frac{\sum_{i=1}^{NS} (y_i - \hat{y}_i)^2}{NS}} \tag{15}
\]

In Eq. (15), \( \hat{y}_i \) is the prediction value of \( y_i \). Thereafter, the best solution is determined \( X_b \) (it has the smallest \( \text{Fit} \)). The next is an update of solutions using HHO strategies as discussed earlier. After reaching the terminal conditions, the test set is used to test the ANFIS model with the parameters determined from the best solution and compute the prediction quality of the test set.

### 4. Experiments

To verify the accuracy of the proposed model, experimental data of literature [20] were used. In that work, FSW butt joints were conducted for the aluminum plate AA2219-T87 (609 × 152 × 8.13 mm). The chemical composition of the base metal alloy is tabulated in Table 1. FSW was achieved using load control. A two-piece fixed pin was used which has a scrolled shoulder made of H13 steel with a diameter of 30.48 mm, 0.76 mm deep, a spiral scroll with a pitch equals 2.92 mm, and a counterclockwise (CCW) helix. An interchangeable tapered cone pin, made of MP159 Nickel-Cobalt, with a shoulder diameter of 10.16 mm and a length of 7.112 mm at the bottom, was used.

The welding experimental plan involves three independent process parameters including welding speed, tool rotational speed, and plunge force. The examined ranges of process parameters are shown in Table 2. After welding process, the top surfaces of the joint were grounded. The specimens were then prepared for tensile tests. The tensile test is performed according to ASTM E8/8M-11 at 1.0 mm/min cross head speed for three tensile specimens for each weld schedule. The geometry and dimensions of tensile specimens are shown in Fig. 4.

To obtain engineering strain values, an extensometer was attached at the center of the specimens. Table 3 shows 73 sets of experimental observations of the measured tensile strength used to construct the ANFIS model. Four FSW process parameters of the (\( N, V, F_z, \text{EFI} \)) were employed in this study where, EFI denotes an empirical force index derived from the three process parameters (\( N, V \) and \( F_z \)). EFI can be calculated using Eq. (16).

\[
\text{EFI} = \frac{F_z}{C_i (R)^{0.5}} \tag{16}
\]

where, \( F_z \) denotes the plunge force and \( R \) is the dimensionless speed ratio which is calculated as a function of \( N \) and \( V \), where, \( (R) \) can be written as Eq. (17).

\[
R = \frac{2 \pi r N}{V} \tag{17}
\]
5. Results and discussion

5.1. Comparison of experimental values, ANFIS predicted values, and ANFIS-HHO values for UTS

The results of the proposed model have been compared with those found in the literature using the same training to test ratio (70:30) and the proposed model showed a better accuracy in terms of root mean square error (RMSE) (22.76 MPa) compared with results found in the literature (29.7 MPa). Fig. 5 shows a graphical comparison of the experimental values versus the predicted values of ANFIS and the modified values of ANFIS-HHO. The correlation between the experimental data and ANFIS-HHO prediction is much better than ANFIS prediction thanks to the HHO strategy that successfully predicts the FSW parameters and obtains the optimal UTS.

In addition, we used the percentage error $E_i$ and the average percentage error $E_{av}$ to evaluate the performance of ANFIS-HHO technique. The $E_i$ and $E_{av}$ are defined in Eqs. (18) and (19) respectively.

\[
E_i = \left(\frac{UTS_i - UTS_i^P}{UTS_i}\right) \times 100 \tag{18}
\]

\[
E_{av} = \frac{1}{n} \sum_{i=1}^{n} E_i \tag{19}
\]

Where, $E_i$ denotes the percentage error of the experiment number $i$; $UTS_i$ denotes the experimental UTS of the experiment number $i$; $UTS_i^P$ denotes the predicted UTS created by ANFIS-HHO technique; $i = 1, 2, 3, \ldots$; $n$ is the experiment number.

Where $(2\pi r)$ is the pin-tool circumference, and $r$ is the radius of pin tool. The values of $C_1$ and $C_2$ are 256.93 and 0.561, respectively. These constants have been determined experimentally [39].
number; and $E_{av}$ denotes the average percentage error of $n$ experimental results. Fig. 6 shows a comparison between the prediction error for ANFIS and ANFIS-HHO models. The highest prediction percentage error for the ANFIS-HHO model is 64.46% while the highest prediction percentage error for ANFIS is 80.21% indicating a better prediction of the proposed technique. It is also observed that the average prediction percentage error for ANFIS-HHO prediction is 9.87% while the average percentage error for ANFIS model prediction is 13.24%. Accordingly, the error resulting from ANFIS-HHO is less than that of ANFIS model which means that the UTS results predicted by ANFIS-HHO are consistent with the experimental results. From the above-mentioned discussion, the ANFIS-HHO strategy is strong and reliable in predicting tensile strength for FSW.

5.2 Checking validity of the model

Fig. 7 (a, b) illustrates the validity of the ANFIS-HHO and ANFIS models based on UTS. Experimental and predicted values are scattered on both sides of the line for the two models. The UTS values are falling on the straight line for the ANFIS-HHO as shown in Fig. 7 (a), which means that the errors are scattered typically indicating the perfect fitness of the model, while the random scattering of the values is noticeable for the ANFIS as shown in Fig. 7 (b) which indicates a lower degree of fitness.
The above considerations show an excellent capability of the HHO prediction model.

5.3. Statistics for ANFIS and ANFIS-HHO models

Statistical results in terms of the coefficient of determination ($R^2$), the root mean square error (RMSE), the mean relative estimate error (MRE), the mean absolute error (MAE), and the coefficient of variance (COV) are shown in Table 4. It is observed that $R^2$ equals 0.980 and 0.985 for the ANFIS-HHO model, and ANFIS model, respectively, which means that predicted values for both models are highly correlated with the experimental results. On the other hand, the RMSE value of ANFIS-HHO (22.763) is much lower than the ANFIS model (47.170), and the MRE, MAE, and COV values of ANFIS-HHO are lower than the values of the ANFIS model, hence the prediction of HHO has much adequacy, and it can be used to optimize the parameters of ANFIS model and predict the (UTS) without significant error.

5.4. The influence of the size of training set on the performance of ANFIS-HHO models

After verifying the accuracy of the proposed model compared with the conventional ANFIS model, different training to test ratios have been examined to select the optimal ratio that maximize the model accuracy where two additional models (50:50 and 80:20) were trained and tested. It was observed that the RMSE for 50:50 model decreased from 47.53 MPa to 25.42 MPa for both ANFIS and ANFIS-HHO models, while RMSE for 80:20 model decreased from 41.27 MPa to 22.51 MPa which means that the 80:20 model is the best model because it has the lowest RMSE compared with other models as shown in Fig. 8. On the other hand, ANFIS-HHO modified values have better fitness compared to the experimental values due to the role of HHO in selecting the optimal values of ANFIS parameters to get the best solution (UTS value). Thus, the proposed ANFIS-HHO model is robust and can be used to predict the UTS values of FSW joints in a specified range of input parameters to achieve the required joint strength.

5.5. Effect of the welding parameters on UTS

As a result of studying the effect of welding parameters, it was noticed that the tool rotational speed is the most effective parameter on the tensile strength. The UTS for all joints is less than the UTS of the base material (475 MPa), regardless of tool rotational speeds used in the manufactured joints. It was observed that the joint fabricated with a rotational speed of 350 rpm, an empirical force index of 0.9, a welding speed of 236.98 mm/min, and a plunge force of 26.69 KN, achieved maximum tensile strength. Fig. 9 shows the effect of the rotational speed on UTS of AA2219 aluminium alloy joints. When the rotational speed increases from 250 rpm, the UTS also increases and the maximum value is achieved.

Fig. 7 – Fitting of UTS data (a) ANFIS-HHO model (b) ANFIS model.

Fig. 8 – RMSE for the developed models.
at 350 rpm. When the rotational speed exceeds 350 rpm, the UTS of the joint decreases until it reaches the minimum value at 450 rpm. Increasing the tool rotational speed increases the heat generation due to friction caused by the increased temperature, which leads to a decrease in tensile properties due to the metallurgical transformation such as re-precipitation, solubilisation, grain growth at the weld zone, and lowering of dislocation density that causes poor microstructure [58]. It is also clear that the predicted values of ANFIS-HHO have a better agreement with the experimental values than the predicted values of ANFIS.

### 5.6. Effect of empirical force index (EFI)

Using EFI is one of the best ways to study the effect of welding parameters on the mechanical properties of the joint as it combines the three main parameters in the FSW process (N, V, Fz) and thus gives an accurate prediction of joint strength. Fig. 10 illustrates EFI versus the experimental values of UTS, ANFIS values, and ANFIS-HHO values at the rotation speed of 350 rpm where the highest tensile strength is attained. For EFI values deviating from 0.9, a gradual decrease in UTS to the left and right of 0.9 occurs due to defects formed during welding. On the other hand, the prediction of the ANFIS-HHO model with UTS values is much better than the ANFIS model indicating the strength of the ANFIS-HHO proposed model to find optimal welding variables.

### 6. Conclusion

In this work, the effects of FSW input parameters on the mechanical properties of FSW butt joints of AA2219-T87 aluminum plate have been simulated in terms of UTS. A new hybrid ANFIS-HHO model is proposed to predict the UTS for welded joints. The ANFIS model was trained with experimental data then optimized by HHO algorithm where HHO is used to search the optimal ANFIS model with the most appropriate parameters. The effect of the training to test ratio on model accuracy has been also investigated. The developed model resulted in optimal solution with lowest RMSE value of 22.76 MPa. It was observed that the tool rotational speed is the most effective parameter in tensile strength. The empirical force index has a strong effect on the mechanical properties of welds due to its dependence on welding parameters. The performance of the ANFIS-HHO model was found to be a feasible option for modeling the FSW process and searching for the optimal solutions. ANFIS-HHO technique is also recommended for other engineering applications.

### Conflicts of interest

The authors declare no conflict of interest.

### Acknowledgement

The authors would like to gratefully acknowledge the support of the National Science Foundation of China (Grant no. 15175205 and No. 151605174).

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