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AISI4140 Steel Hard Turning Tool Wear Prediction with the aid of optimally configured Artificial Neural Network

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Abstract

The wear on cutting tools is inevitable in turning operations, detection of tool failure is essential in automated manufacturing for proper maintenance. The state of cutting tool is a critical factor in any metal cutting process because dull or damaged cutting tool reduces surface quality and dimensional accuracy of work piece and damages the machine tool. The significant research objective identifies tool wear on Hard Turning of AISI4140 steel with the aid of Artificial Neural Network (ANN) for a given cutting speed, feed rate and depth of cut as input parameters. The research integrates optimization techniques to identify optimal hidden layers and their corresponding neurons. The techniques involved in this process are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Chimp Optimization Algorithm (ChOA) and Oppositional based Chimp Optimization Algorithm (OChOA). The proposed OChOA unveils superior performance over comparative techniques and the regression based model.

Keywords: Artificial Neural Network (ANN), tool wear, algorithm, speed, feed.

Introduction

The use of hardened steel in different engineering components subjected to significant fatigue and thermal impacts has received a lot of consideration [1]. Gear teeth, railway tracks, axels, forging and extrusion dies, engine mounting, camshafts, and heavy-duty machine basements are some of the principal industries where high-strength alloys play an important part [2]. There are several varieties of hardened steel. AISI 4140 steel material hardened with high wear resistance is widely used in a variety of applications, including aircraft landing gear, axles, aircraft frames, forming dies, car crankshafts, and rollers, among others. However, the material's hardness makes it difficult to machinability, particularly when turning, whereas life of the tool could be reduced. Turning on materials with a hardness above 45 HRC can be termed as hard turning. Hard turning has been commonly utilized due to the production of a high-quality surface as well as wear resistance. As the result, a tremendous effort has lately been preceded on hard turning [3]. In general, the process of hard turning includes the machining of materials with extremely high hardness, which results in significant machining forces and the substantial quantity of heat generation. High tool wear is caused by the prevailing machining conditions in hard turning [4]. Hence, for machinability in hardened AISI 4140 steel material, it is critical to obtain a long tool life as well as acceptable surface quality [5, 6]. Because current tool wear levels have a direct impact on workpiece surface quality and even machine tool performance [7]. Alternatively, statistics reveal that cutting forms about 70%–80% of the components, whereas cutting tools breakdown accounts nearly 20% for downtime of machine. As a result, prediction of tool wear is important for improving the safety and dependability of machining tools, considering its broad use in practically each manufacturing branch [8]. However, predicting tool wear during machining, particularly turning, is a challenging problem. Traditional ways of using process parameters that impact tool wear are accessible, however there are some parameters that are peculiar to the machining process and current prediction models fail [9]. As a result, this could be critical to design effective tool wear monitoring systems for real-time and accurate tool wear monitoring during process of machining. Because tool wear causes tool breakage, it can lead to more significant repercussions such as workpiece scratching and scraping, manufacturing system paralysis, and even operator casualties [7]. To that purpose, various researchers in the literature have developed Artificial Intelligence approaches including Artificial Neural Networks for anticipating tool wear machining [10].

Literature Review

Generally, tool wear is an inherent phenomenon when hard turning hardened steels using coated carbide tools. Rajeev et al. (2018) [11] proposed Artificial Neural Network, Fuzzy Logic, and Regression Models-based techniques for prediction of tool wear in hard turning of AISI4140 steel. The work piece in concern is made of AISI4140 steel that has been hardened to 47 HRC. The proposed models were constructed based on the study findings that were actually implemented with the experimental design (Response surface methodology). Inputs are cutting speed, feed, and depth of cut, and output is wear. Findings show that proposed ANN-based model outperformed Regression Analysis and Fuzzy Logic in terms of accuracy.

Suresh et al. (2021) [12] had developed ANN (artificial neural network) and RSM (Response surface method)-based methods investigate machining settings impact on the wear of different cutting tools types in AISI H13 hardened die steel turning. Ceramic inserts with multilayer chemical vapour deposition (CVD) coated, uncoated, and physical vapour deposition (PVD) coated had been used. To estimate tool wear, RSM and ANN models were used. The study took into account the following machining parameters: cutting time, feed rate, cutting speed and depth of cut. To organise as well as perform trials in a systematic manner, CCD (central composite design) methodology was used. Models of ANN and RSM were constructed and had demonstrated a higher level of accuracy ($R2 > 98.5\%$ and MSE 0.2%), ensuring greater predictability. Adhesive wear and abrasive wear at low machining parameters and higher machining parameters exhibited by Cutting tools.

Chen, Shao-Hsien, and Zhi-Rong Luo, (2020) [13] had proposed back-propagation ANN for predicting and verifying tool wear during machining of stainless steel 2316ISO-B MOD based on cutting chip color. The correlation between chip surface chromaticity and cutting tool wear was demonstrated through tests in this work, and a technique for evaluating and predicting tool wear based on chip colour was proposed. At the moment, the cutting tools' life prediction can be measured and predicted indirectly with vibration and current. Cutting test and verification studies verified average percentage of error between predicted value about 1.73% and actual value about 1.66% of tool wear. Therefore, the ANN-based proposed model could efficiently and rapidly predict tool wear with mean error percentages of 1.73% and 1.66%, and maximum error ranges of 0.0012 mm and 0.0097 mm, respectively.

Mikołajczyk et al. (2018) [14] had proposed ANN and image processing-based techniques for predicting tool life automatically during turning operations of C45 carbon steel. Initially, under same constant processing conditions, experimental data in three cutting edges were obtained. And, tool wear parameter (VB) was evaluated using traditional techniques and calculated by Neural Wear, customised software package integrates flank wear image recognition with ANNs. Secondly, using data from initial two cutting edges, ANN model of tool life can be developed, and the model was then tested on two distinct subsets for third cutting edge. Finally, results confirmed that ANN modelling combination as well as image recognition software has the potential to be turned into valuable industrial tool for low-cost tool life estimate in turning operations.

Segreto et al. (2020) [15] had proposed ANN-based machine learning paradigms as well as wavelet sensor signal analysis for estimating the tool wear during turning of Inconel 718. During experimental turning trials, multiple sensor monitoring system on the basis of measurement of cutting force, signals of vibration acceleration and acoustic emission has been used. WPT decomposition was used to extract features of diverse signal from the detected sensor signals. Using correlation measurements, the most relevant features were chosen to be used in ANN-based machine learning paradigms for estimation of tool wear. Finally, the accurate estimation of tool wear accomplished by wavelet sensor signal analysis application and ANN-based machine learning paradigms provided here might pave the way on effective intelligent tool condition monitoring system implementation in Inconel 718 turning.

Khishe, M., and Mohammad Reza Mosavi (2020) [16] introduced a unique metaheuristic algorithm termed ChOA (Chimp Optimization Algorithm), which was influenced through individual intelligence and sexual motivation of chimps within their group hunting that differs from other social predators. Sexual motivation as well as chimp intelligence's mathematical model was proposed. There are four chimps categories are used to simulate diverse intelligences: attacker, barrier, chaser, and driver. Furthermore, four major hunting stages were implemented: driving, chasing, blocking, and attacking. Regarding convergence speed, exploration and exploitation and probability of being stuck in local minimums, the findings had been compared with various newly proposed meta-heuristic algorithms. Statistical tests had been also used to determine results' significance. According to findings, the ChOA excels existing techniques of benchmark optimization.

Proposed Methodology

This research consider hardened AISI 4140 steel (47 HRC) having the dimension of 80mm diameter and 250mm length as the work piece and the entire experiments were carried out in heavy duty kirloskar lathe. The oxide layers are machined and centre holes are drilled before heat treatment. The Ti(C, N) coated carbide of SECO make is utilized as the cutting tool. The Tool holder used is PCL NR2525 M12 type. Tool wear values are measured after a machining length of 200mm. The following table 1 shows the experimental values for a given inputs cutting speed, speed rate, depth of cut and the output response Tool Wear. The data obtained in the course of experimentation is utilized to develop an ANN model. The ANN model's outcome wear value is compared with the experimental wear to adjudge the model's performance. The proposed approach is to identify the optimal hidden layers and their corresponding neurons for identifying the tool wear. The techniques used in this process is OChOA, integrating opposition strategy enhance the performance in traditional ANN while predicting tool wear.

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Table 1 Experimental tool wear and hardened AISI 4140 steel machining parameters.

Machining Input parameters				**Output Response Factor**
Trial	*Cutting Speed*	*Speed Rate*	*Depth of cut*	*Wear*
1	170	0.08	0.45	0.145
2	70	0.1	0.3	0.065
3	120	0.1	0.45	0.12
4	120	0.1	0.45	0.12
5	170	0.1	0.6	0.17
6	120	0.12	0.3	0.116
7	70	0.1	0.6	0.121
8	120	0.1	0.45	0.12
9	120	0.12	0.6	0.16
10	70	0.08	0.45	0.075
11	70	0.12	0.45	0.1
12	120	0.1	0.45	0.12
13	120	0.1	0.45	0.12
14	120	0.08	0.6	0.14
15	120	0.08	0.3	0.09
16	170	0.1	0.3	0.14
17	170	0.12	0.45	0.17

Artificial Neural Network (ANN)

ANN is a real learning framework that is utilised in psychological brain science and AI. ANN is an adjusted computational model that attempts to replicate the neural structure and functioning of the human cerebrum. It includes an interconnected system of artificially produced neurons that serve as information exchange pathways. ANN is versatile and adaptable, learning and altering in response to each unique interior or external stimulus. As a component of succession and pattern recognition systems, data processing, robotics, and modelling, ANN is being utilized.

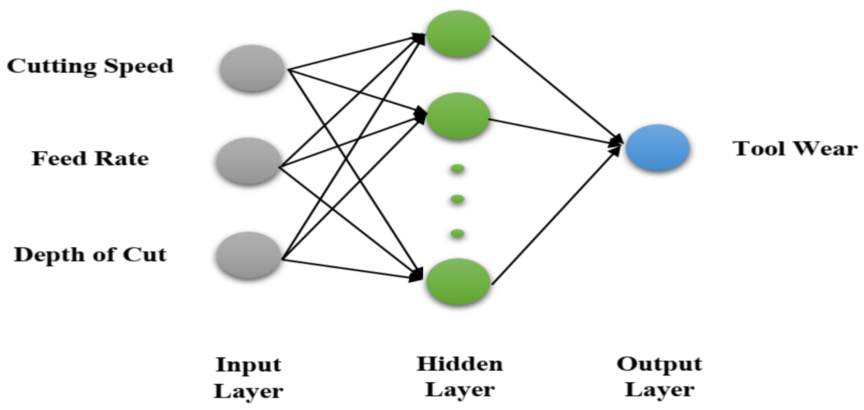

Figure 2 Neural network structure

Generally, Figure 2 shows that ANN has three layers termed as input layer, hidden layer, and output layer. Every layer has been made up of a certain number of neurons. In each neuron's input layer has been interconnected with a hidden layer of neuron, whereas each hidden layer of neuron could be correlated with output layer through random weight. Weights supplied to all the interconnected layers at random.

Input layer

In this case, 61-features are considered to be feeding input in the first layer known as the input layer G_1, G_2, *up to* G_n, which is used in input neurons u_1, u_2 *up to* u_n, and each neuron in input layer has been interconnected with neurons in hidden layer with random weight $w_{11}, w_{12}...w_{ij..}$. To rebuild the structure of ANN through manually configuring the optimal number of hidden layers and associate neurons takes a long time to compute; thus, an optimization technique should be used to save the complex procedure. $HR_1, HR_2, \ldots HR_n$, represent number of neurons within hidden layer that could be connected to neuron's output layer. Each neuron in hidden layer could be associated with an irregular weight to neurons in the output layer $w_{11}, w_{12}, \ldots w_{ij.}$. A multilayer perceptron is a hyperbolic tangent form with sigmoidal activation function.

The basic function of hidden neurons could be estimated using equation (1).

$$P_f = \sum_{j=1}^{N} G_i \times w_{ij} \tag{1}$$

Where P_f refers to a basic function, w_{ij} refers to input layer weight, whereas i refers to the number of inputs combined with this basic function to form active function, which employs sigmoid function in response to the condition shown below,

$$\tan sig\,(P_f) = \frac{2}{(1+\exp(-2 * P_f)) - 1} \tag{2}$$

Levenberg–Marquardt algorithm

LM method could be common as well as widely utilised training optimization technique. LM defeats techniques of existing conjugate point as well as enable tendency drop in a wide aggregation of problems. This could be as same as EBP, which comprises figuring of inclination vector; similarly, LM selects Jacobian.

Chimp optimization algorithm

Inspiration

ChOA (Chimp Optimization Algorithm) can be termed as metaheuristic algorithm which was influenced by chimps' sexual motivation as well as individual intelligence in group hunting. It distinguishes them from remaining social predators. One of only two species in African great ape is Chimps (also known as Chimpanzees). In each group, chimps are not all that comparable based on intelligence as well as ability, and perform out members of the colony duties. Each person's ability is valuable during certain situation.

In chimp colony, drivers, barriers, chasers, and attackers are four categories of chimps, each represents unique capabilities, yet such diversities are essential for successful hunt. Without catching the prey, drivers chase it. Barriers construct a dam in a tree to obstruct the prey progression. Chasers move quickly behind the prey in order to catch the prey. Lastly, attackers forecast prey's escape route in order to inflict it (the prey) back towards chasers or down into lower canopy. This vital job (attacking) is favourably related to age, intelligence, and physical ability. Chimps might change sides in span of a hunt or remain in the same one throughout. In general, chimp hunting is separated into two phases: exploration, and exploitation. Exploration has driving, blocking, and chasing the prey, whereas exploitation contains attacking prey. Then, in following section, all of these ChOA concepts are mathematically represented.

Mathematical model and algorithm

Mathematical models of an independent group, driving, blocking, chasing, and attacking has been proposed in this section. Following that, the corresponding ChOA algorithm can be provided.

Opposition based initialization

To regulate size of opposition's step, a_i and b_i should dynamically update regarding current population's search space. This shows that every dimension's minimum and maximum values in current population can be utilized for calculating the opposite solution other than boundaries of predefined interval ($[a_i, b_i]$). Pigeons are aided in their search for better positions by dynamic opposition, which speeds up convergence. It is possible to compute a new opposition-based approach:

$$OP_{i,j} = a_j^p + b_j^p - P_{i,j} \tag{3}$$

Here $P_{i,j}$ denotes j-th position vector of i-th chimp within population, $OP_{i,j}$ denotes opposite position of $P_{i,j}$, a^p_j as well as b^p_j respectively denote j-th dimension's minimum and maximum values in current population. Figure 2 shows flowchart of oppositional based chimp optimization algorithm and table 1 shows pseudo-code of proposed technique.

Fitness computation

The following mathematical modelling MSE utilize to evaluate and identify optimal hidden layers and their corresponding neurons.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y_i})^2 \tag{4}$$

Where, MSE represent Mean Square Error, n represent the number of data points, Y_i denotes observed values and $\hat{Y_i}$ represents predicted values

Driving and chasing the prey

Prey could be hunted throughout phases of exploration as well as exploitation, as stated previously. Eqs. (5) and (6) are proposed to mathematically model driving and pursuing prey.

$$d = \left| c.x_{prey}(t) - m.x_{chimp}(t) \right| \tag{5}$$

$$x_{chimp}(t+1) = x_{prey}(t) - a.d \tag{6}$$

Here number of the current iteration referred by t, coefficient vectors denoted by a, m, and c, vector of prey position is referred by X_{prey} whereas position vector of a chimp is referred by X_{chimp}. Vectors of a, m, and c can be computed using Eqs. (7), (8) and (9), separately.

$$a = 2.f.r_1 - f \tag{7}$$

$$c = 2.r_2 \tag{8}$$

$$m = chaotic\_value \tag{9}$$

Here, **f** represents reduced non-linearly from 2.5 to 0 using process of iteration (phase of exploitation and exploration). Whereas random vectors in range [0,1] has been denoted $\mathbf{r_1}$ and $\mathbf{r_2}$. At last, **m** denotes chaotic vector calculated in terms of different chaotic map whereas such vector denotes chimps' sexual motivation effect during process of hunting.

Attacking method (exploitation phase)

Two methods are aimed to mathematically model chimp attacking behaviour: Chimps evaluate location of prey (by driving, blocking, and chasing) and encircling prey. Then, four optimal solutions achieved, which are preserved, and remaining chimps could be compelled for updating its positions in accordance with locations of best chimp. Eqs. (10) – (12) express this relationship.

$$\begin{aligned} d_{Attacker} &= |c_1 x_{Attacker} - m_1 x|, d_{Barrier} = |c_2 x_{Barrier} - m_2 x|, \\ d_{Chaser} &= |c_3 x_{chaser} - m_3 x|, d_{Driver} = |c_4 x_{Driver} - m_4 x|. \end{aligned} \tag{10}$$

$$\begin{aligned} x_1 &= x_{Attacker} - a_1(d_{Attacker}), x_2 = x_{Barrier} - a_2(d_{Barrier}), \\ x_3 &= x_{Chaser} - a_3(d_{Chaser}), x_4 = x_{Driver} - a_4(d_{Driver}). \end{aligned} \tag{11}$$

$$x(t+1) = \frac{x_1 + x_2 + x_3 + x_4}{4} \tag{12}$$

Here, four best groups estimate the prey's position, while existing chimps update their positions in its vicinity at random.

Prey attacking (utilization)

As previously mentioned chimps attack prey, which terminate the hunt as soon as the prey stops moving in last stage. **F** value should be decreased to mathematically represent the attacking process. It is also worth noting that **f** reduces the variation range of **a**. Then, **a** could be the random variable for interval [−2**f**, 2**f**]. f decreases from 2.5 to 0 during period of iterations. Whereas random a values are within range [−1, 1], a chimp's next position can found between current position and prey position.

Based on who have already been shown, ChOA permits chimps to attack the prey by updating their locations based on attacker, barrier, chaser, and driving chimps' positions. Conversely, ChOAs may get trapped in local minima, thus existing operators must take precautions to minimise such problem. Despite of that the proposed driving, blocking, and chasing mechanism depicts the process of exploration in some ways, ChOA requires additional operators to emphasise the phase of exploration.

Searching for Prey (exploration)

As stated earlier, chimps' exploration is mostly based on attacker, barrier, chaser, and driving chimps' location. They divide to hunt prey, then aggregate to attack prey. Another component of ChOA affects phase of exploration about c value. Elements of c vector could be random variables within interval [0, 2] in Eq. (8). In Eq. (9), it gives random weights on prey for reinforcing (c >1) or lessen (c<1) prey location effect in distance determination. This intends to help ChOA for improving its stochastic behaviour with process of optimization and minimizing to get trapped in local minima. **c** can often require for generating random values which execute process of exploration in both initial iterations, and final iterations.

Social incentive (sexual motivation)

As stated earlier, obtaining meet as well as subsequent social motivation (sex as well as grooming) during last stage enables chimps to relinquish its activities of hunting. As a result, they strive to gather meat in a chaotic manner. This chaotic behaviour in the last step aids chimps in overcoming the two issues of entrapment in local optima as well as slow convergence rate while solving high-dimensional problems.

This section describes chaotic maps that were utilised to increase ChOA's performance. Six chaotic maps were utilised. These chaotic maps are deterministic algorithms with random behaviour. In Saremi, Mirjalili, & Lewis, 2014, primary point of all maps is the value 0.7 in this article. To model this simultaneous behaviour, it is being assumed that there is a 50% chance of selecting either chaotic model or normal updating position mechanism for updating chimps' position while optimization. Eq. (13) expresses mathematical model.

$$x_{chimp}(t+1) = \begin{cases} x_{prey}(t) - a.dif\mu < 0.5 \\ Chaotic\_valueif\mu \geq 0.5 \end{cases} \tag{13}$$

Where μ represents random number in [0, 1].

Pseudo-code of OChOA

Initialize population of chimp x_i (i=1,2, …,n) and oppositional based population Eq. (3)
Initialize **f, m, a** and **c**
Initialize hidden layers and neuron
Calculate every chimp position
Divide chimpanzees randomly into independent groups
Until stopping condition could be fulfilled
Calculate each chimpanzees fitness Eq. (4)
$\mathbf{x}_{Attacker}$=best search agent Eq. (10)
$\mathbf{x}_{Chaser}$=second best search agent Eq. (10)
$\mathbf{x}_{Barrier}$=third best search agent Eq. (11)
$\mathbf{x}_{Driver}$=fourth best search agent Eq. (11)
  while (t<maximum number of iterations)
      for every chimpanzees:
          Extract group of chimpanzees
          Utilize their group strategy for updating **f, m** and **c**
          Utilize **f, m** and **c** to compute **a,** then **d**
        end for
          for every search chimpanzees
              if (μ<0.5)
                  if $(\|a\| < 1)$
            Update current search agent position using Eq. (6)
                  else if $(\|a\| < 1)$
                      Choose random search agent
                end if
              else if(μ>0.5)
             Update current search position through Eq. (13)
              end if
         end for
     Update **f, m, a** and **c**
     Update $\mathbf{x}_{Attacker,}$ $\mathbf{x}_{Driver,}$ $\mathbf{x}_{Barrier,}$ $\mathbf{x}_{Chaser}$
    t=t+1
  end while
return $\mathbf{x}_{Attacker}$

In short, ChOA searching method begins with the generation of stochastic population of chimps (candidate solutions). Chimps could be categorized as four different groups in random: attacker, barrier, chaser, and driver.

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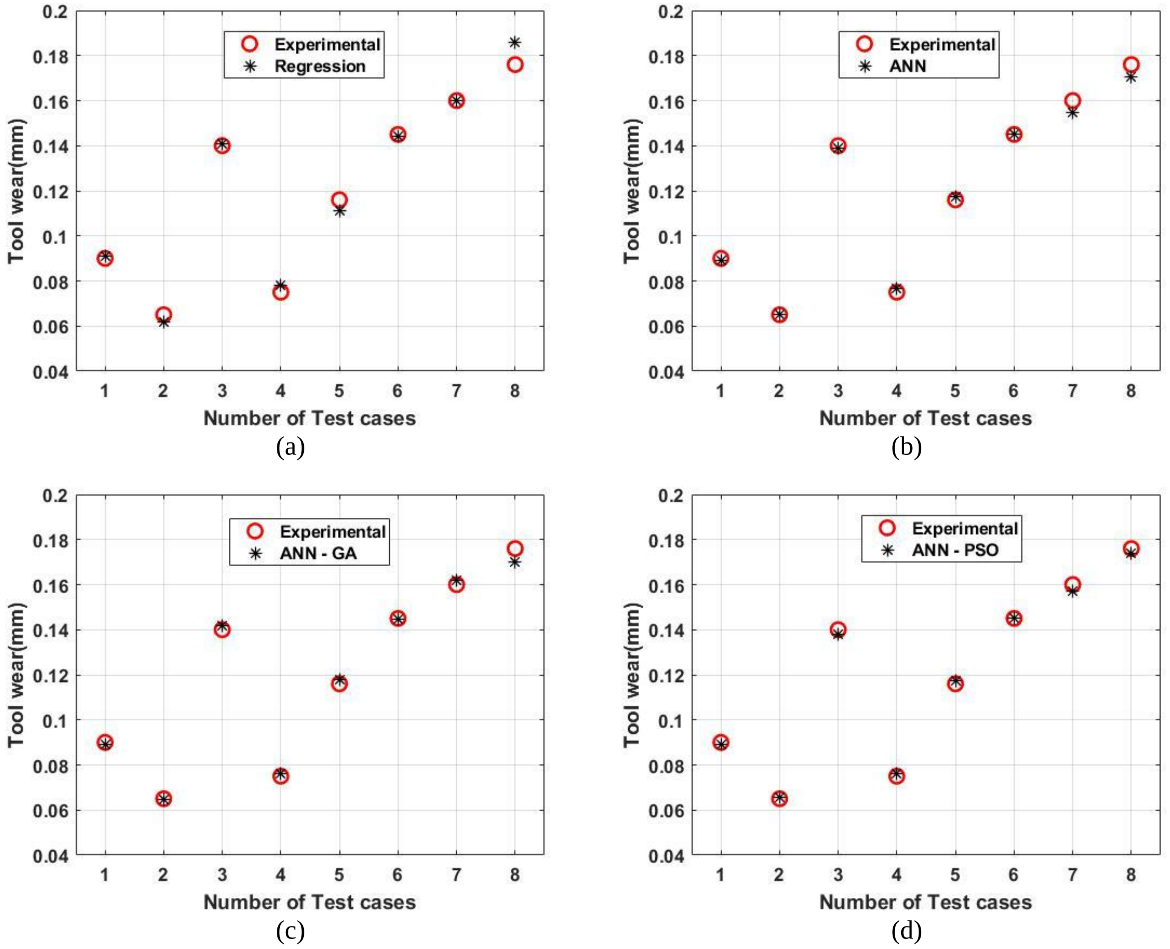
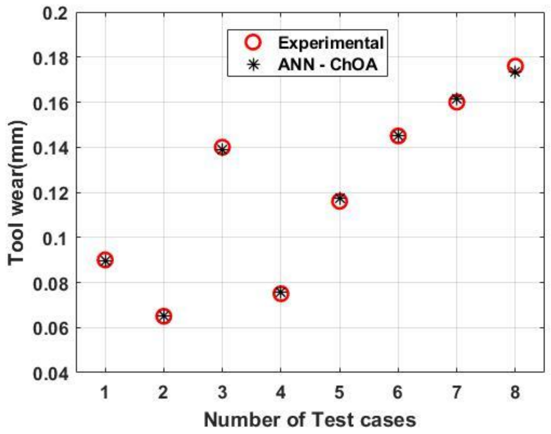
Using the group technique, each chimp modifies its **f** coefficients. Attacker, barrier, chaser, and driver chimps assess potential prey positions during iteration period. Every candidate solution changes their position with relation to prey. Adaptive tuning of vectors of **c** and **m** results in both avoidance of local optima as well as faster convergence curve. To improve process of exploitation and attacking on the prey, **f** value is decreased from 2.5 to zero. Inequality | a | > 1 causes candidate solutions to diverge; they progressively converge around the prey. The above pseudo-code explains of OChOA.

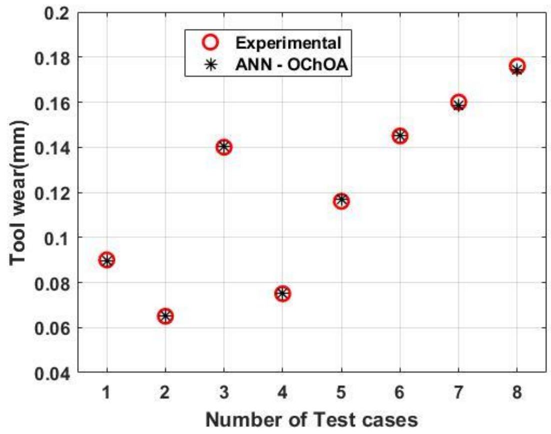
Results and Discussion

The results investigate the performance of proposed reconfigured ANN with traditional ANN and regression analysis. It is evident from the results that incorporating optimization technique in finding optimal hidden layers and their corresponding neurons exhibits better performance over comparative techniques. The figure 2 shows the performance of employed techniques w.r.t experimental value in finding tool wear. The figure 2 (a) shows the tool wear predicted values from regression, (b) shows the traditional ANN (LM) algorithm, (c) unveils ANN configured by GA, (d) exhibits the ANN configured by PSO, (e) shows ANN configured by ChOA and (f) exhibits the ANN configured by OChOA. Incorporating opposition strategy elevates the ANN's performance in predicting tool wear for a given inputs unveils clearly with minimized MSE showed in figure 4. The figure 5 depicts training performance of ANN-OChOA in terms of validating and testing.





(e)



(f)

Figure 2 Experimental and the predicted output from different techniques

Table 2 Shows the experimental and the predicted tool wear values from different techniques

S.No	Experimental	Regression	ANN (LM)	ANN-OChOA	ANN-ChOA	ANN-PSO	ANN-GA
1	0.09	0.091	0.0891	0.0898	0.0894	0.0893	0.08906
2	0.065	0.062	0.0653	0.06501	0.0652	0.0655	0.0646
3	0.14	0.141	0.139	0.1402	0.139	0.138	0.142
4	0.075	0.078	0.0766	0.07512	0.07589	0.0764	0.07638
5	0.116	0.111	0.1174	0.11705	0.1172	0.1173	0.1178
6	0.145	0.144	0.1451	0.145098	0.14523	0.1451	0.1448
7	0.16	0.16	0.1549	0.1585	0.1616	0.157	0.1617
8	0.176	0.186	0.1706	0.1742	0.1732	0.174	0.17

Table 2 shows the superior performance of proposed ANN-OChOA on predicting tool wear. Incorporating the opposition based solution in traditional ChOA improve the performance of finding optimal hidden layers and their corresponding neurons. Table 3 shows the optimal configuration from different employed techniques. The proposed model configured ANN having three hidden layers and their corresponding neurons are 21, 20 and 23 respectively. Figure 3 shows the MATLAB outcome ANN's optimal configuration from OChOA.

Table 3 Optimal configuration from the techniques

Techniques	**Hidden layer-1**	**Hidden layer-2**	**Hidden layer-3**
ANN-OChOA	21	20	23
ANN-ChOA	22	20	-
ANN-PSO	32	21	15
ANN-GA	18	22	-

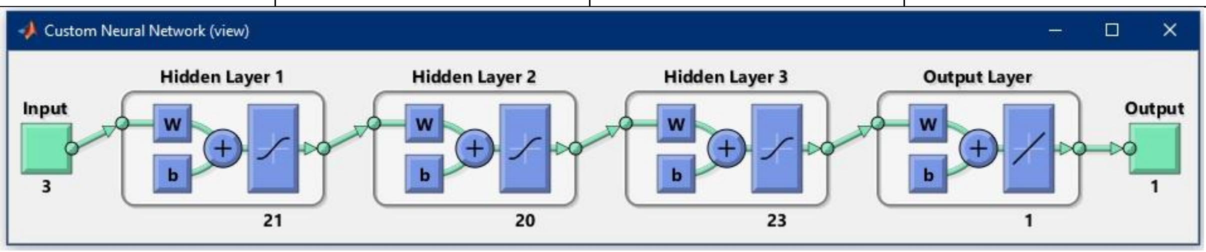


Figure 3 OChOA configured ANN model

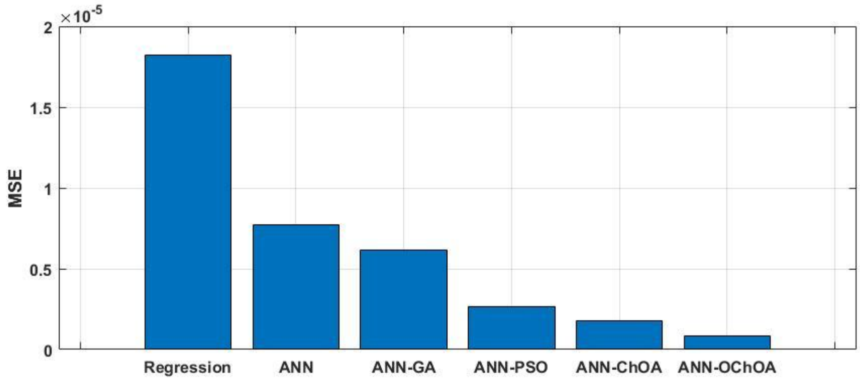


Figure 4 MSE for employed techniques

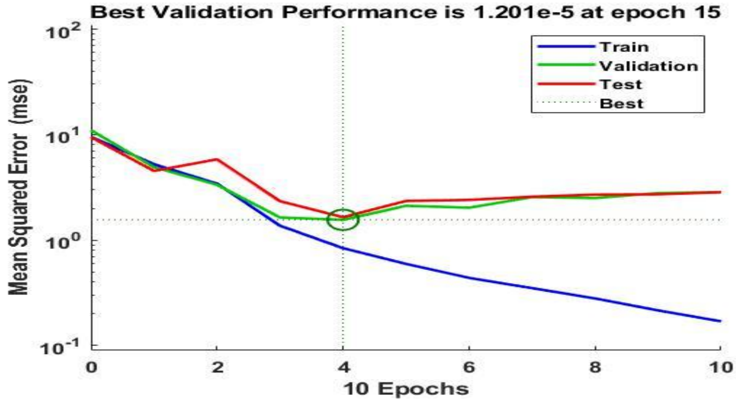


Figure 5 MSE performance validations for ANN-OChOA

Conclusion

This research involves predicting tool wear model has been formulated based on the data obtained during hard turning of AISI4140. The research integrates opposition based solution generation strategy on traditional ChOA to find ANN's optimal hidden layers and their corresponding neurons. It is evident from the graphs that incorporating opposition strategy gives better performance in predicting tool wear; the proposed approach configured ANN model having three hidden layers and each layers having 21, 20 and 23 neurons respectively. The proposed ANN configured model having the MSE of 0.00062225 that is comparatively better than employed techniques and far better than regression based model. In future, the research involves more optimization techniques to reduce the error value and thus increasing the predicting accuracy.

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