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ORIGINAL ARTICLE

Wear volume prediction of AISI H13 die steel using response surface methodology and artificial neural network

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ABSTRACT – Resistance to wear of hot die steel is dependent on its mechanical properties governed by the microstructure. The required properties for given application of hot die steel can be obtained with control the microstructure by heat treatment parameters. In the present paper impact of different heat treatment parameters like austenitizing temperature, tempering time, tempering temperature is studied using response surface methodology (RSM) and artificial neural network (ANN) to predict sliding wear of H13 hot die steel. After heat treating samples at austenitizing temperature of 1020°C, 1040°C and 1060°C; tempering temperature 540°C, 560°C and 580°C; tempering time 1hour, 2hours and 3hours, experimentation on pin-on-disc tribo-tester is done to measure the sliding wear of H13 die steel. Box-Behnken design is used to develop a regression model and analysis of variance technique is used to verify the adequacy of developed model in case of RSM. Whereas, multi-layer feed-forward backpropagation architecture with input layer, single hidden layer and an output layer is used in ANN. It was found that ANN proves to be a better tool to predict sliding wear with more accuracy. Correlation coefficient R^2 of the artificial neural network model is 0.986 compared to R^2 of 0.957 for RSM. However, impact of input parameter interactions can only be analysed using response surface method. In addition, sensitivity analysis is done to determine the heat treatment parameter exerting most influence on the wear resistance of H13 hot die steel and it showed that tempering time has maximum influence on wear volume, followed by tempering temperature and austenitizing temperature. The prediction models will help to estimate the variation in die lifetime by finding the amount of wear that will occur during use of hot die steel, if the heat treatment parameters are varied to achieve different properties.

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KEYWORDS
Sliding wear;
response surface methodology;
artificial neural network;
heat treatment parameters;
sensitivity analysis.

INTRODUCTION

H13 die steel is extensively used for extrusion, forging and die casting due to its elevated temperature strength, tempering resistance, ductility and moderate cost. H13 die steel is heat treated to have martensitic phase transfer which enables it to have high wear resistance. It is evident from the studies [1–4] that hot die steel wear resistance depends on its mechanical properties. Prediction model proves to be a useful tool in estimating the variation in die lifetime corresponding to the wear accruing during the use of hot die steel. To model and analyse, response surface methodology (RSM) is an effective tool capable of quantifying the relationship between input parameters and the obtained response considering the constraints of process parameters. A second order mathematical model is usually developed to identify the most suited input process parameters at which maxima or minima of the response lies. The best feature of RSM is the 2D and 3D plots, showing interactive impact on response of input process parameters [5, 6]. In recent years, artificial neural network (ANN) has been used in various areas of research such as medicine, engineering, mathematics, meteorology, neurology and economics [7]. Multi-layered neural network with backpropagation and differentiable transfer function is frequently used in the research works for materials science to perform pattern classification, function approximation and pattern association [8]. Backpropagation is the process of computing derivatives of network error, with respect too. network biases and weights.

Various researchers have studied the impact of heat treatment parameters on the properties and performance of different steels [2, 3, 9], but a gap still needs to be plugged is the study of hot die steel performance with respect to different heat treatment parameters being considered simultaneously. The present work set out to investigate the wear behavior of H13 die steel by considering all three key heat treatment parameters parallelly. This paper focuses on RSM and ANN techniques to study the variation in wear volume of H13 hot die steel occurring due to changes in properties obtained by different heat treatment parameters. Pin on disc tribo-tester is used for wear tests at room temperature in dry conditions. Hardness of various samples is measured with universal hardness tester (Make: Tinius Olsen, Model: FH-002-0001). Based on these experimental observations ANN and RSM models are developed to predict the wear volume of H13 hot die steel having different heat treatment parameters. Microstructure of samples undergone different heat treatments is observed using metallurgical microscope (Make: Dewinter, Model: Dmi victory) and field emission

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scanning electron microscope (Make: FEGQuanta, Model: 450) is used to examine the worn surface to check out for the difference in wear behaviour. ANN is trained and implemented using the MATLAB. ANN is trained number of times to find the model having weight matrix which gives minimum error and good results for the determination of wear volume with respect to the actual experimental values used as input set to train the network.

MATERIALS AND TESTING

H13 steel pin samples are made of 30mm length and 10mm diameter which is the standard sample size for pin on disc type tribo-tester (Make: Ducom, Model: 536A). Counter test material used is D2 steel disc of 8mm thickness and 100mm diameter. Schematic of pin sample and counter disc for dry sliding wear test are shown in Figure 1. Chemical composition of H13 pin and D2 disc material is given in Table 1.

Table 1. Composition pin and disc material made of H13 and D2 steel.

Steel	Weight percentage of alloying elements							
	C	Cr	Mo	Mn	V	Si	S	P
H13	0.356	5.100	1.264	0.346	1.123	0.964	0.025	0.022
D2	1.662	12.603	0.498	0.489	0.277	0.045	0.025	0.024

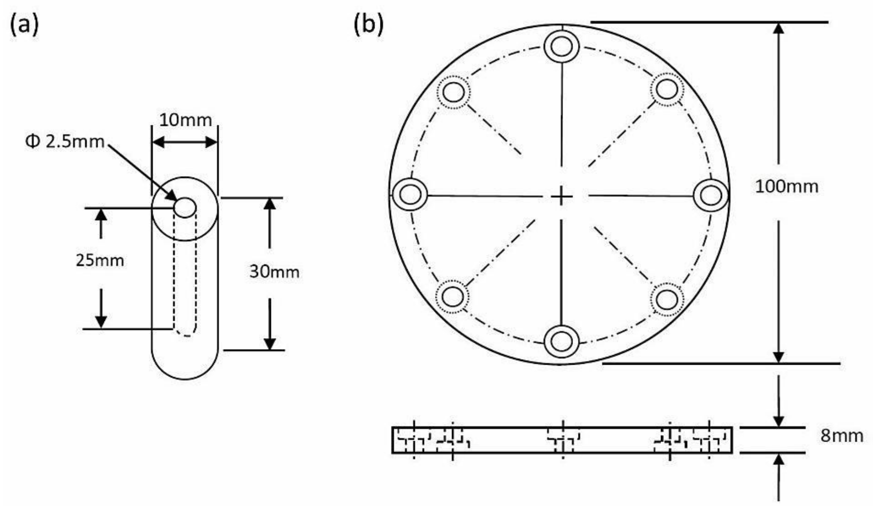

Figure 1. Schematic of: (a) pin sample and (b) counter disc for dry sliding wear test.

During heat treatment of H13 steel preheating is done at 620°C and 850°C. Different austenitizing temperature for H13 hot die steel are taken as per ASME standards [10] and austenitizing is done at 1020°C, 1040°C and 1060°C with soaking time of 20 minutes followed by marquenching at 350°C. Tempering is done at 540°C, 560°C and 580°C for 1 hour, 2 hours and 3 hours in pit furnace having air circulation.

Figure 2a, 2b & 2c shows the micrograph of as-quench samples austenitized at 1020°C, 1040°C and 1060°C. Sample austenitized at 1020°C has finer grain as compared to the moderate grain of sample austenitized at 1040°C whereas die steel austenitized at 1060°C has coarser grains. Figure 2d shows the martensite produced after marquenching from austenitizing temperature 1020°C and figure 2e shows the tempered martensite produced after tempering twice at 560°C for 2 hours.

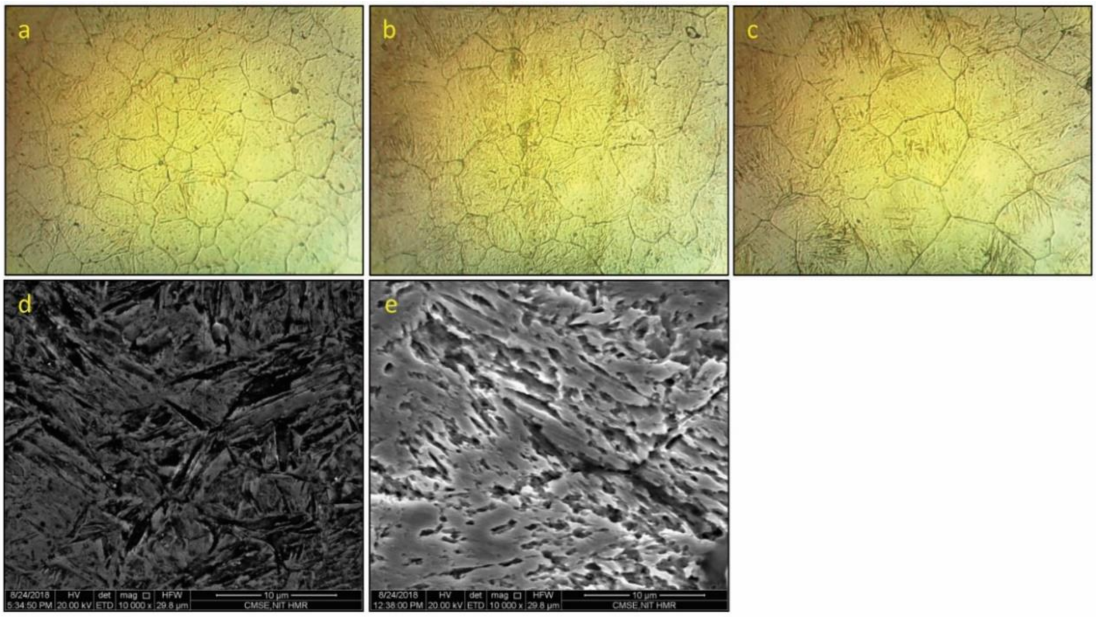

Figure 2. Micrograph at 1000x of as-quench samples austenitized at a) 1020°C, b) 1040°C and c) 1060°C respectively; FESEM images showing d) martensite and e) tempered martensite produced in samples austenitized at 1020°C.

Figure 3 shows the pin on disc type high temperature tribo-tester used for wear tests. The details of wear test setup are given in [11]. Winducom2010-POD software is used for acquiring experimental data.

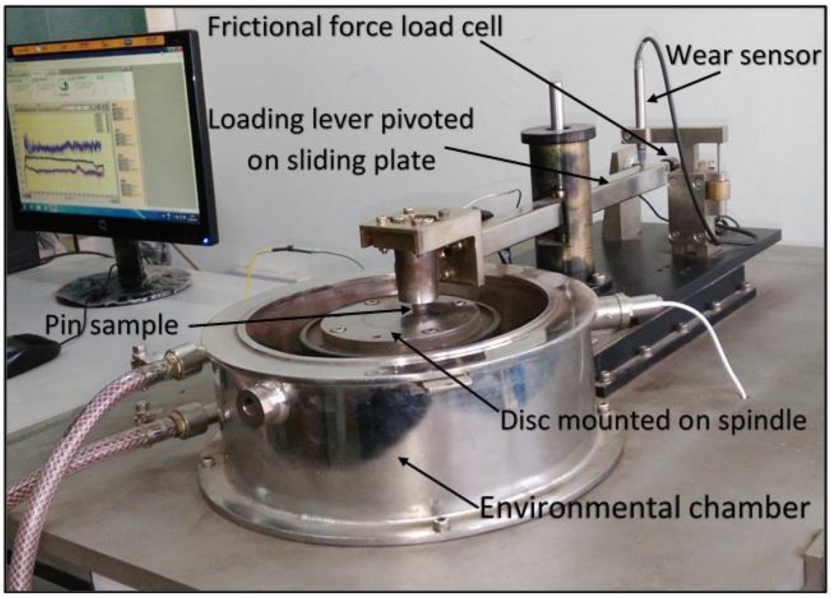

Figure 3. High temperature tribo-tester.

PREDICTION MODEL USING RESPONSE SURFACE METHOD

Development of Model

Box Behnken design (BBD) gives best solutions for RSM problems with three factors having three levels [12]. Generalized second order polynomial to find the suitable approximation for functional relationship of response surface (wear volume) with regressor variables (heat treatment parameters) is given as:

$$y = \beta_0 + \sum_{i=0}^{k} \beta_i x_i + \sum_{i=0}^{k} \beta_{ii} x_i^2 + \sum_{i} \sum_{j} \beta_{ij} x_i x_j + \epsilon \tag{1}$$

here β_0, β_i, β_{ii}, β_{0ij} are regression coefficients and ε is random error. In this paper value of k is 3 as there are three factors with three levels. Table 2 shows design matrix for DOE of wear volume with experimental and predicted responses of RSM model.

Multiple regression analysis is applied to develop a wear volume prediction model from the experimental data by finding the regression coefficients using BBD on Design Expert 7.0 software. The regression model for predicting wear volume (W_{vol}) in coded factors is given as:

$$W_{vol} = 1.38 - 0.12A - 0.097B + 0.35C - 0.28B^2 + 0.52C^2 + 0.37AC + 0.35BC \quad (2)$$

Table 2. Design matrix showing DOE for wear volume with experimental and predicted responses for response surface model.

Run	Coded Variable			Wear Volume (mm^3)					
				Experimental				RSM model	
	A	B	C	Test 1	Test 2	Test 3	Mean	Predicted	Residual
1	1	0	-1	1.10159	0.92166	1.01543	1.01289	1.05332	-0.04043
2	0	1	1	2.40145	2.16165	2.37248	2.31186	2.24696	0.06490
3	0	-1	1	1.66859	1.81225	1.82328	1.76804	1.74033	0.02771
4	0	0	0	1.25722	1.51221	1.50122	1.42355	1.38424	0.03931
5	0	0	0	1.34712	1.30264	1.38131	1.34369	1.38424	-0.04055
6	-1	0	-1	2.31057	2.22412	2.12252	2.21907	2.04708	0.17199
7	1	0	1	2.40242	2.23131	2.30184	2.41186	2.56872	-0.15686
8	-1	-1	0	1.20155	1.23317	1.22248	1.21907	1.29767	-0.07860
9	0	0	0	1.24825	1.33329	1.40248	1.32801	1.38424	-0.05623
10	0	0	0	1.49125	1.30246	1.32741	1.37371	1.38424	-0.01053
11	-1	0	1	2.28635	1.89723	1.97495	2.05284	1.99728	0.05556
12	-1	1	0	1.00941	1.11576	0.82846	0.98454	1.10326	-0.11872
13	0	1	-1	0.80223	0.72090	0.76165	0.76159	0.81312	-0.05153
14	1	-1	0	1.40184	1.16873	1.08278	1.21778	1.08651	0.13127
15	0	0	0	1.34429	1.48352	1.37946	1.40242	1.38424	0.01818
16	0	-1	-1	1.68525	1.49384	1.68047	1.61985	1.70857	-0.08872
17	1	1	0	1.05973	1.10128	0.80423	0.98841	0.89210	0.09631

A: Austenitizing temperature (-1 is 1020°C, 0 is 1040°C and 1 is 1060°C)
B: Tempering temperature (-1 is 540°C, 0 is 560°C and 1 is 580°C)
C: Tempering time (-1 is 1 hour, 0 is 2 hours and 1 is 3 hours)

ANOVA results for wear volume are summarized in Table 3. Value of probability >F is less than 0.05, it means that the developed model is significant at 95 confidence interval. Adequate signal to noise ratio should always be greater than 4 and for the developed model its value is 18.26, which ensures the effectiveness of model. Correlation coefficient R2 of the model is 0.957. The value of R2 close to unity means proposed model is reliable for predicting wear volume [13].

Analysis of Results

Perturbation plot showing the effect of heat treatment parameters on wear volume is shown in Figure 4. Factor A, austenitizing temperature shows a linear relationship with wear volume. It has been found that the hardness of H13 die steel increases with increase in austenitizing temperature from 1020°C to 1060°C which helps to decrease the wear volume. This increase of hardness in H13 hot die steel is due to the alloying elements Chromium and Vanadium as they further increase the hardness of martensitic matrix for higher austenitizing temperature [2]. Figure 5 shows the increase in hardness for increase in austenitizing temperature for as-quench H13 die steel. Factor B, tempering temperature when raised from 540°C to 580°C results in first increase and then decrease of wear volume, it is due to the precipitation of alloy carbides initially and then decrease in martensite tetragonality producing BCC ferritic matrix of tempered martensite [14].

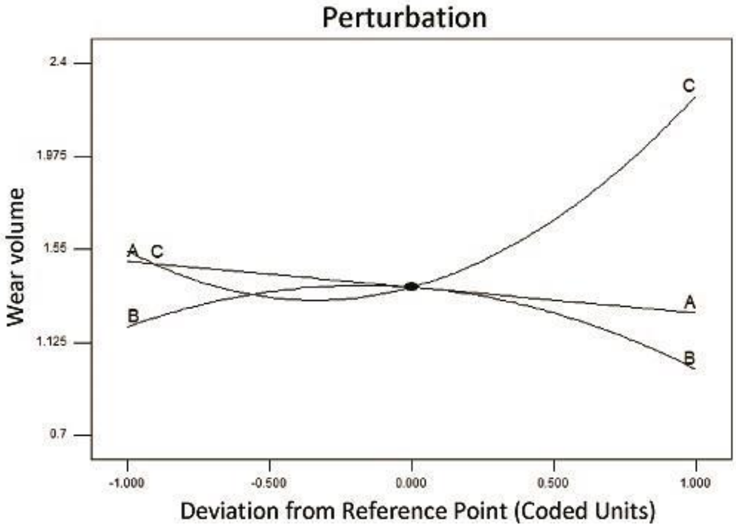

Figure 4. Perturbation plot for wear volume.

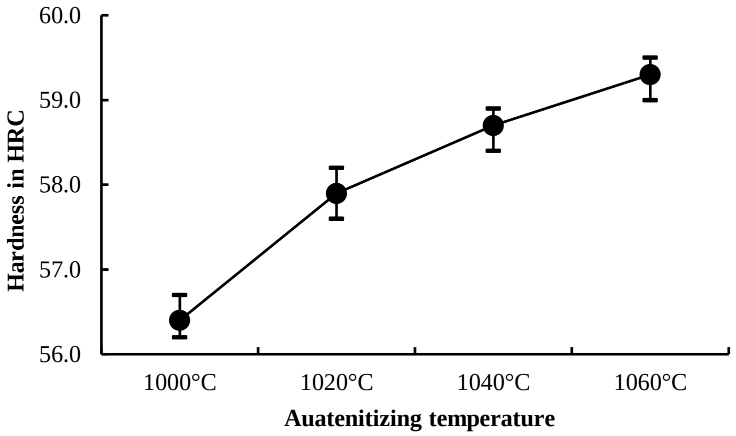

Figure 5. Hardness change with austenitizing temperature.

Table 3. ANOVA results for wear volume.

Model terms	Sum of Squares	Degree of Freedom	Mean Square	F value	Prob>F	
Model	3.62	7	0.52	28.71	< 0.0001	significant
A	0.11	1	0.11	6.20	0.0345	
B	0.076	1	0.076	4.21	0.0705	
C	1.00	1	1.00	55.66	< 0.0001	
AC	0.54	1	0.54	29.82	0.0004	
BC	0.49	1	0.49	27.30	0.0005	
B^2	0.33	1	0.33	18.06	0.0021	
C^2	1.14	1	1.14	63.23	< 0.0001	
Residual	0.16	9	0.018			
Lack of Fit	0.16	5	0.031	19.78	0.0064	significant
Pure error	6.296E-003	4	1.574E-003			
Cor Total	3.78	16				
Std. Dev.	0.13		R-Squared	0.9571		
Mean	1.49		Adj. R-Squared	0.9238		
C.V.%	9.00		Pred R-Squared	0.6902		
PRESS	1.17		Adeq Precision	18.268		

A: Austenitizing temperature, B: Tempering temperature, C: Tempering time

Factor C, tempering time when varied from 1 hour to 3 hours, the wear volume first decreases and then shows a sharp increase with further increasing of the tempering time. The high hardness of H13 hot die steel at lesser tempering time is due to some freshly formed martensite from retained austenite. When the tempering time is further increased, H13 steel shows a decrease in hardness because of more carbon combining with iron to form cementite, hence decreasing the carbon supersaturation in the martensitic matrix [15].

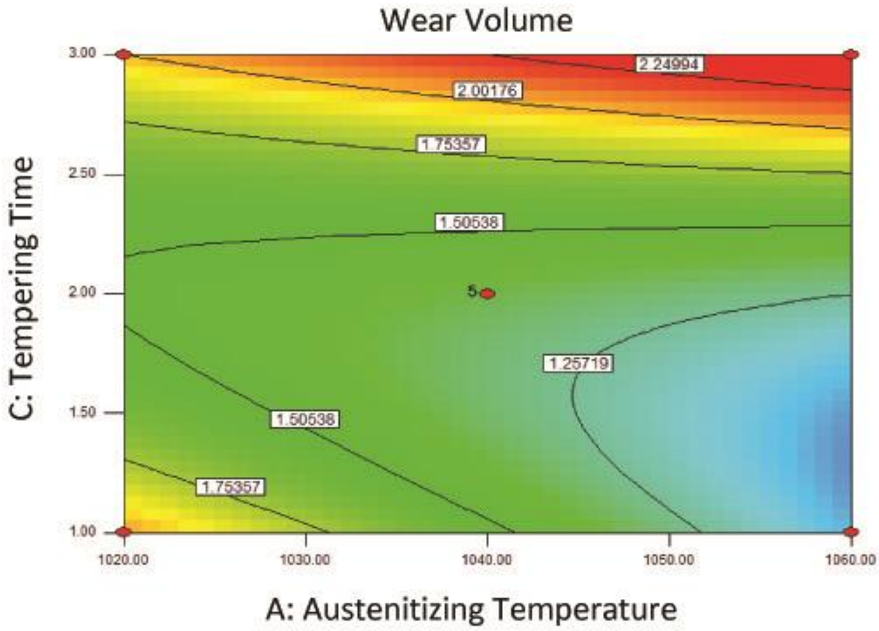

Figure 6. Interaction plot of tempering time and austenitizing temperature for wear volume.

One of the key features of RSM is its ability to analyze impact of interaction of input parameters on the response surface. Figure 6 shows the response surface plot for the interaction between factor A and factor C. Specimen having austenitizing temperature 1060°C and tempering time of 1.25 hour shows least wear volume whereas the maximum wear volume has accrued for sample having austenitizing temperature of 1060°C and tempering time of 3 hours. This effect has also been found in the wear tests, Figure 7a and 7b shows the wear surface for samples hardened at 1060°C and tempered twice for 1 hour and 3 hours respectively. It is quite evident from the wear behavior that higher tempering time reduces the wear resistance of H13 die steel. It is due to the decrease in hardness of H13 steel with longer tempering time as coarsening of martensitic crystals takes place with reduction in dislocation density [16].

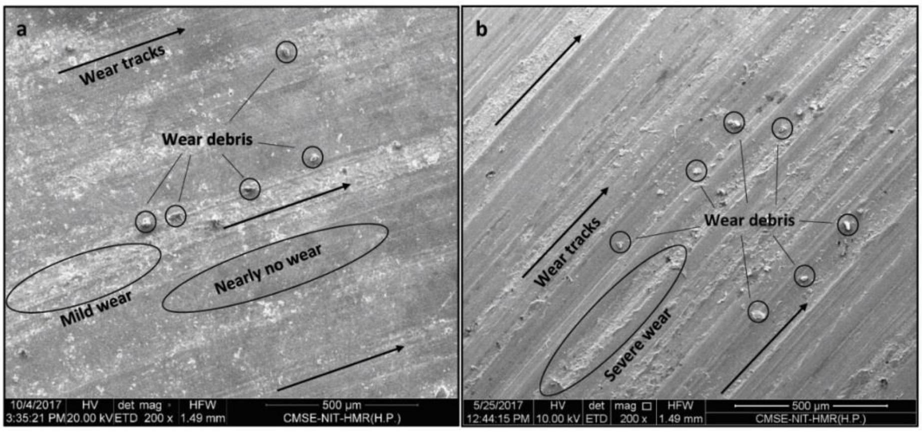

Figure 7. Wear tracks for samples heat treated at a) austenitizing temperature 1060°C and tempering time 1 hour; b) austenitizing temperature 1060°C and tempering time 3 hours.

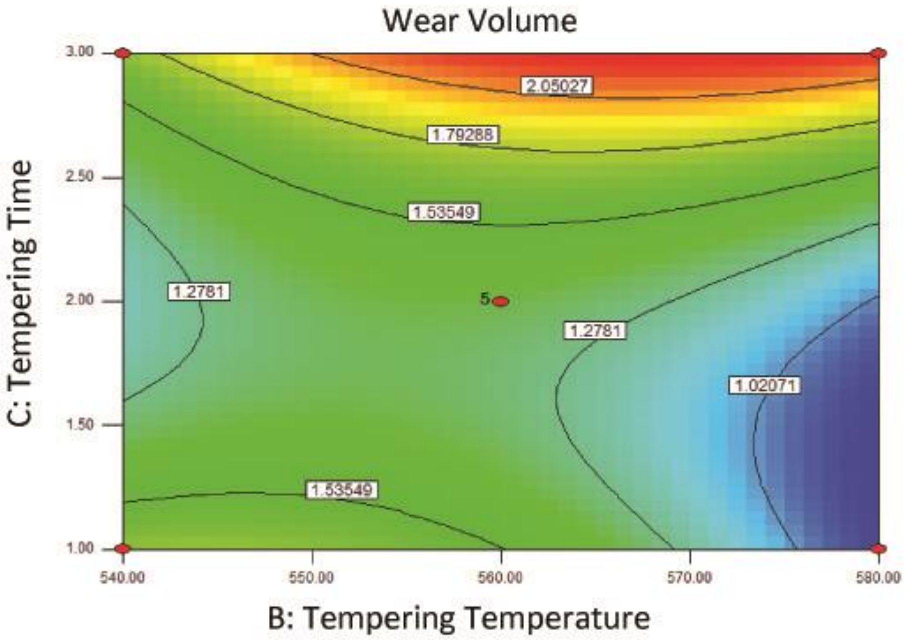

Figure 8. Interaction plot of tempering time and tempering temperature for wear volume.

Response surface plot for factor B and factor C is shown in Figure 8. It shows that specimens tempered at 580°C for 1 hour exhibits minimum wear volume whereas maximum wear volume has been observed on sample tempered at 560°C for 3 hours. The reason for this is secondary hardening occurring at higher tempering temperatures, allowing Molybdenum & Chromium to precipitate and diffuse as fine alloy carbides [16].

PREDICTION MODEL USING ARTIFICIAL NEURAL NETWORK

ANN is a computational system similar to biological neurons structure in human brain. The interconnection between neurons are governed by network function [17]. A weight is associated with input to every neuron to determine the strength of interconnection between neurons. These weights are modified with every iteration to evaluate the contribution of all interconnections toward the network. During the training of ANN according to the transfer function weights are modified by the network response to the input matrix [18]. This plays a key role in ANN's ability to have learning and memory. Multi-layer feed-forward backpropagation ANN architecture consisting of 3 neurons in input layer for three heat treatment parameters, a hidden layer with n_i neurons and output layer having 1 neuron for wear volume is used. Learning parameters used for training the network are given in Table 4. Input output data for training of ANN model for wear volume prediction is the same as being used for developing RSM model. The number of neurons in the hidden layer (n_i) have an important effect on neural network functioning [19]. Therefore, value of n_i is varied from 1 to 20 to find the most suited number of neurons for hidden layer. For each value of n_i i.e. 1 to 20 network has been trained 50 times as per the training parameters given in Table 4. The impact of n_i on the performance of neural network in terms of regression coefficient is shown in Figure 9. It is found that n_i with value 10 gives the best results for the present case for wear volume prediction with respect to heat treatment parameters of H13 die steel. Figure 10 shows the ANN architecture considered in present study having input, hidden and output layers.

Table 4. Learning parameters for the training of artificial neural network model.

S. No.	Training parameter	Value
1	training algorithm	traingd
2	transfer function	tan-sigmoid
3	number of epochs	10000
4	learning rate	0.01
5	tolerance for mean square error	0.00001

Table 5. Training data and predicted response matrix for wear volume of H13 die steel using artificial neural network model.

Run	Wear Volume (mm^3)					
	Experimental				ANN model	
	Test 1	Test 2	Test 3	Mean	Predicted	Residual
1	1.10159	0.92166	1.01543	1.01289	0.96860	0.04429
2	2.40145	2.16165	2.37248	2.31186	2.31034	0.00152
3	1.66859	1.81225	1.82328	1.76804	1.74553	0.02251
4	1.25722	1.51221	1.50122	1.42355	1.39219	0.03136
5	1.34712	1.30264	1.38131	1.34369	1.39219	-0.04850
6	2.31057	2.22412	2.12252	2.21907	2.26736	-0.04829
7	2.40242	2.23131	2.30184	2.41186	2.31105	0.10081
8	1.20155	1.23317	1.22248	1.21907	1.21934	-0.00027
9	1.24825	1.33329	1.40248	1.32801	1.39219	-0.06418
10	1.49125	1.30246	1.32741	1.37371	1.39219	-0.01848
11	2.28635	1.89723	1.97495	2.05284	1.93646	0.11638
12	1.00941	1.11576	0.82846	0.98454	0.97212	0.01242
13	0.80223	0.72090	0.76165	0.76159	0.74921	0.01238
14	1.40184	1.16873	1.08278	1.21778	1.31511	-0.09733
15	1.34429	1.48352	1.37946	1.40242	1.39219	0.01023
16	1.68525	1.49384	1.68047	1.61985	1.61981	0.00004
17	1.05973	1.10128	0.80423	0.98841	0.95192	0.03649

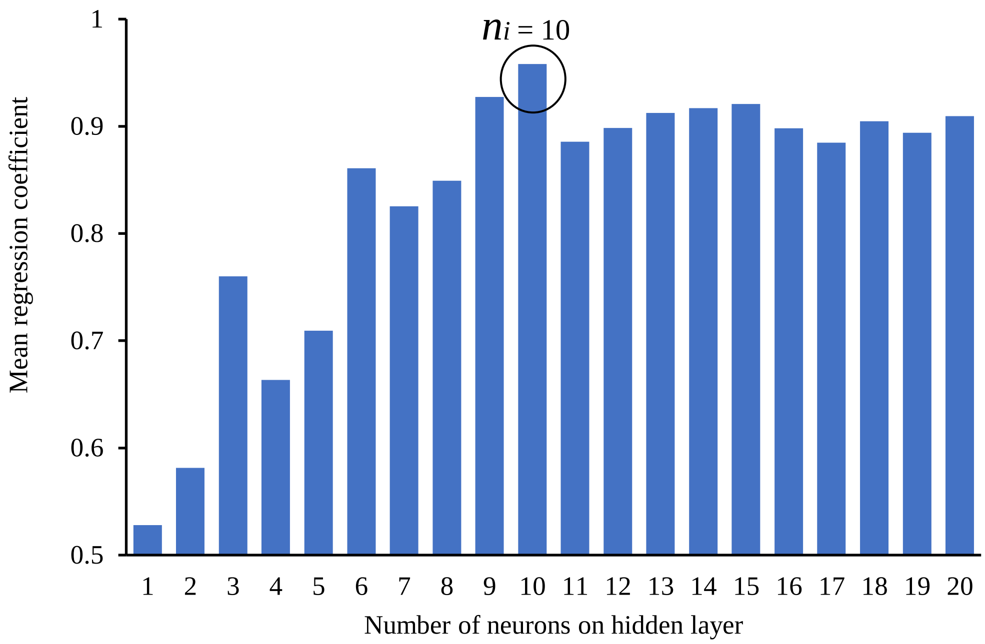

Figure 9. n_i vs ANN regression coefficient.

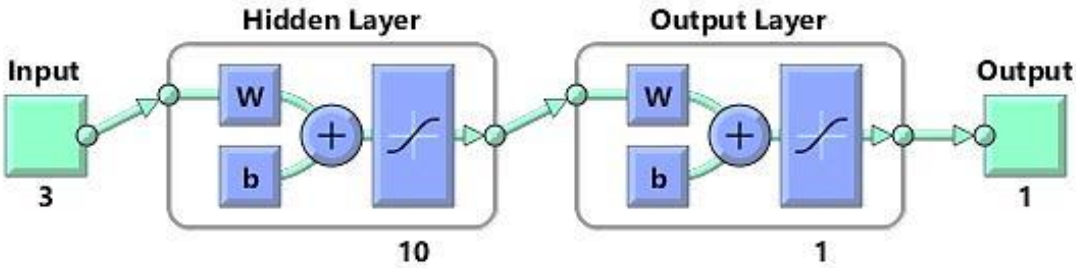

Figure 10. Artificial neural network architecture showing different layers.

To achieve better results lots of training runs are conducted and the selected trained network with best result was achieved after 8371 iterations. The trained network gave a regression coefficient of 0.986 i.e. close to unity which indicates good reliability of the developed ANN model for predicting wear volume. Figure 11 shows the ANN training plot with output and target values for wear volume of H13 die steel. Table 5 shows the predicted results with residuals for ANN model.

COMPARISON OF RSM AND ANN RESULTS

Most optimization methods vary one variable at a time and keep others constant to optimize the response, but they fail to indicate the impact of interactions between the input variables on response. To overcome this issue RSM is an effective tool. It is widely used for developing, improving and also optimizing the processes having several input variables and analyzing how their complex interactions affect the performance of response variable [20]. However, RSM based models are restricted to small number of input parameters, and also not suitable for highly non-linear processes. On the other hand, ANN is a superior tool compared to other methods in modelling non-linear behaviors of complex processes [21]. It has features of self-learning for highly non-linear descriptions which helps in finding complex relationships between input and output variables [22].

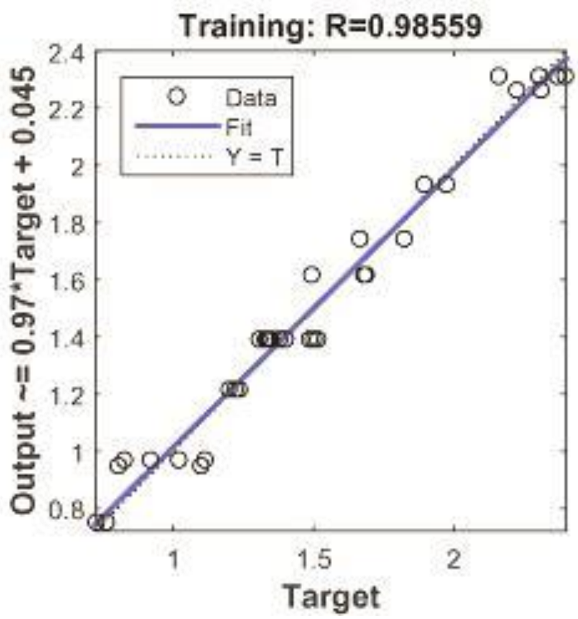

Figure 11. ANN training plot.

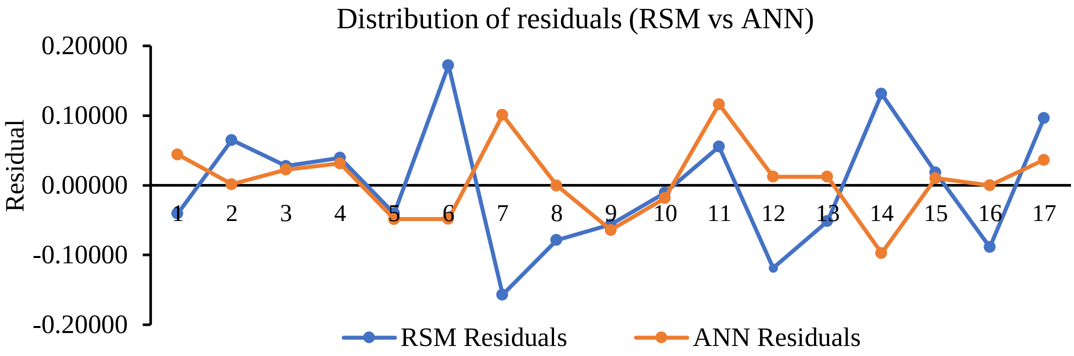

Figure 12. Distribution of residuals for RSM and ANN.

SENSITIVITY ANALYSIS

Sensitivity analysis is a method to identify critical process parameters exerting the most influence upon model response. Sensitivity equations are achieved by partially differentiating the response function regression model given by equation 2 with respect to input parameters. The sensitivities derived in Eqs. (3), (4) and (5) represent the wear volume sensitivity for austenitizing temperature (A), tempering temperature (B) and tempering time (C), respectively:

$$\frac{\partial W_{vol}}{\partial A} = -0.12 + 0.37C \tag{3}$$

$$\frac{\partial W_{vol}}{\partial B} = -0.097 - 0.56B + 0.35C \tag{4}$$

$$\frac{\partial W_{vol}}{\partial C} = 0.35 + 1.04C + 0.35 \tag{5}$$

Positive sensitivity w.r.t. a certain process parameter indicates that the response function will increase with increase in that parameter, while negative sensitivity indicates the vice-versa [23]. The sensitivities of austenitizing temperature (A), tempering temperature (B) and tempering time (C) on wear volume are presented in Figure 13, 14 and 15 by solid bars with respect to various heat treatment conditions as planned by DOE. Sensitivity analysis shows that a small change in tempering time produces large changes in wear volume i.e. -1.06 to 1.76 in coded units, whereas, the sensitivity of wear volume w.r.t. tempering time is -1.007 to 0.813 and for austenitizing temperature it ranges only -0.49 to 0.25. It means that wear resistance of H13 hot die steel is most sensitive to tempering time than to tempering temperature and least sensitive to austenitizing temperature.

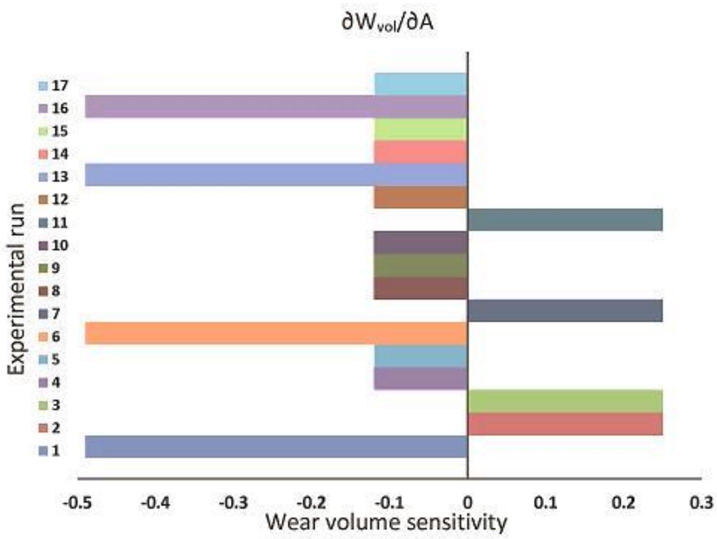

Figure 13. Austenitizing temperature sensitivity.

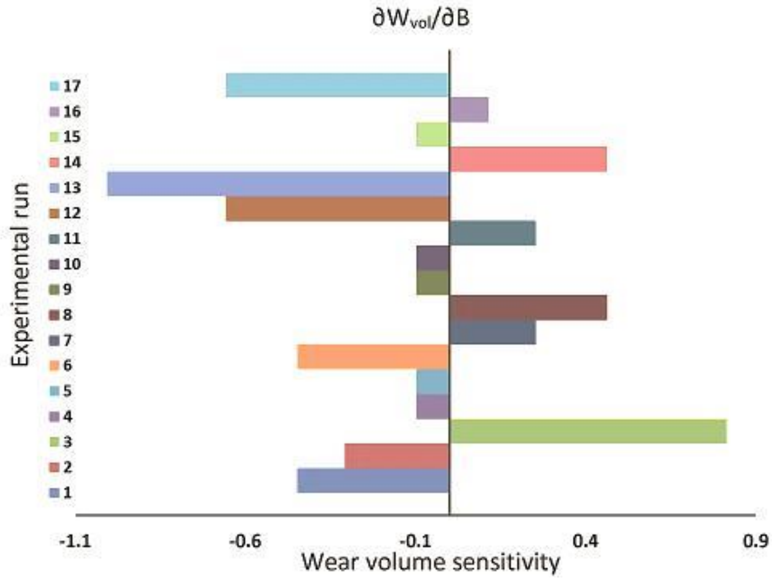

Figure 14. Tempering temperature sensitivity.

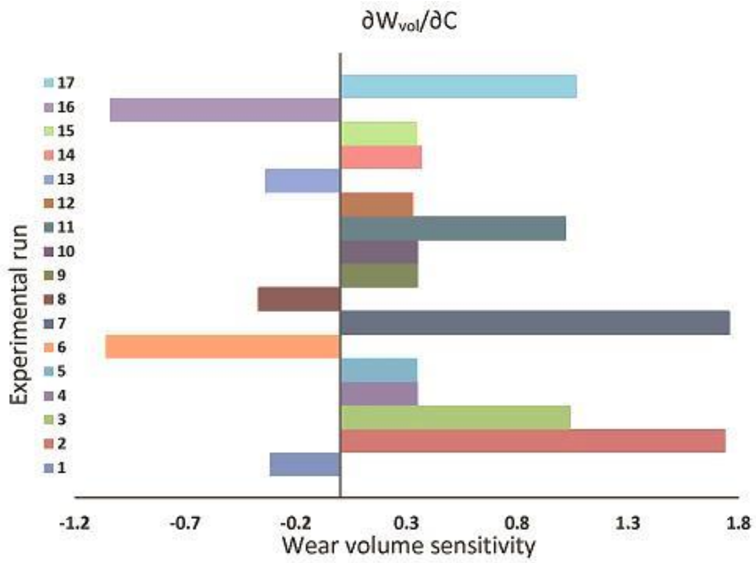

Figure 15. Tempering time sensitivity.

CONCLUSIONS

RSM and ANN models are developed and the prediction results by ANN model have been found to be closely matching with the experimental results. Conclusive remarks made from this investigation are listed as follows:

1. Minimum wear volume of 0.37595 mm^3 is obtained for austenitizing temperature 1059.7°C, tempering temperature 579.9°C and tempering time 1.24 hours.
2. Results showed that ANN is a better tool having correlation coefficient R^2 of 0.986 than RSM which have R^2 of 0.957 for the estimation of wear volume of H13 hot die steel. However, impact of input parameter interactions can only be analyzed using RSM model.
3. Sensitivity analysis revealed the ranking for heat treatment parameter influencing the wear volume H13 steel. Tempering time has maximum impact ranging from -1.06 to 1.76, followed by tempering temperature having impact of -1.007 to 0.813 and austenitizing temperature having least impact of -0.49 to 0.25 in coded units respectively.
4. The proposed RSM and ANN models within the investigated range of heat treatment parameters have proven to be reliable tool for identifying significant relationship capable of predicting wear volume of H13 hot die steel. The proposed models can be used for selecting the value of heat treatment parameters to achieve minimal wear of H13 hot die steel.

REFERENCES

[1] X. H. Cui, S. Q. Wang, M. X. Wei, and Z. R. Yang, "Wear Characteristics and Mechanisms of H13 Steel with Various Tempered Structures," *J. Mater. Eng. Perform.*, vol. 20, no. 6, pp. 1055–1062, 2011.

[2] Y. Guanghua *et al.*, "Effects of heat treatment on mechanical properties of h13 steel," *Met. Sci. Heat Treat.*, vol. 52, no. 7, pp. 393–395, 2010.

[3] A. Bahrami, S. H. M. Anijdan, M. A. Golozar, M. Shamanian, and N. Varahram, "Effects of conventional heat treatment on wear resistance of AISI H13 tool steel," *Wear*, vol. 258, no. 5–6, pp. 846–851, 2005.

[4] M. Gojic, L. Kosec, and P. Matkovic, "The effect of tempering temperature on mechanical properties and microstructure of low alloy Cr and CrMo steel," *J. Mater. Sci.*, vol. 33, pp. 395–403, 1998.

[5] M. Manohar, J. Joseph, T. Selvaraj, and D. Sivakumar, "Application of Box Behnken design to optimize the parameters for turning Inconel 718 using coated carbide tools," *Int. J. Sci. Eng. Res.*, vol. 4, no. 4, pp. 620–642, Apr. 2013.

[6] N. Senthilkumar, T. Tamizharasan, and S. Gobikannan, "Application of Response Surface Methodology and Firefly Algorithm for Optimizing Multiple Responses in Turning AISI 1045 Steel," *Arab. J. Sci. Eng.*, vol. 39, pp. 8015–8030, 2014.

[7] B. Wang, J. H. Ma, and Y. P. Wu, "Application of artificial neural network in prediction of abrasion of rubber composites," *Mater. Des.*, vol. 49, pp. 802–807, 2013.

[8] L. A. Gyurova and K. Friedrich, "Artificial neural networks for predicting sliding friction and wear properties of polyphenylene sulfide composites," *Tribol. Int.*, vol. 44, pp. 603–609, 2011.

[9] M. X. Wei, S. Q. Wang, L. Wang, X. H. Cui, and K. M. Chen, "Effect of tempering conditions on wear resistance in various wear mechanisms of H13 steel," *Tribol. Int.*, vol. 44, no. 7–8, pp. 898–905, 2011.

[10] *ASM Handbook Volume 4 - Heat Treating*. ASM International, 1991.

[11] V. Jagota and R. K. Sharma, "Interpreting H13 steel wear behavior for austenitizing temperature, tempering time and temperature," *J. Brazilian Soc. Mech. Sci. Eng.*, vol. 40, no. 4, 2018, doi: 10.1007/s40430-018-1140-6.

[12] D. C. Montgomery, *Design and Analysis of Experiments*, 8th ed. John Wiley and Sons Ink., 2012.

[13] S. Negi, R. K. Sharma, and S. Dhiman, "Experimental Investigation of SLS Process for Flexural Strength Improvement of PA-3200GF Parts," *Mater. Manuf. Process.*, vol. 30, no. 5, pp. 644–653, 2015.

[14] G. R. Speich and W. C. Leslie, "Tempering of steel," *Metall. Trans.*, vol. 3, pp. 1043–1054, May 1972.

[15] G. B. Olson, *Martensite: a tribute to Morris Cohen*. ASM International, 1992.

[16] G. Roberts, G. Krauss, and R. Kennedy, *Tool Steels*, 5th Edition. ASM Internationa, 1998.

[17] M. R. S. Yazdi, G. S. Bagheri, and M. Tahmasebi, "Finite Volume Analysis and Neural Network Modeling of Wear During Hot Forging of a Steel Splined Hub," *Arab. J. Sci. Eng.*, vol. 37, pp. 821–829, 2012.

[18] Z. Zhang, N. M. Barkoula, J. K. Kocsis, and K. Friedrich, "Artificial neural network predictions on erosive wear of polymers," *Wear*, vol. 255, pp. 708–713, 2003.

[19] S. Taghvaei and R. Vatankhah, "Detection of Unstable Periodic Orbits and Chaos Control in a Passive Biped Model," *Iran. J. Sci. Technol. Trans. Mech. Eng.*, vol. 40, no. 4, pp. 303–313, 2016.

[20] V. Muthukumar, N. Rajesh, R. Venkatasamy, A. Sureshbabu, and N. Senthilkumar, "Mathematical Modeling for Radial Overcut on Electrical Discharge Machining of Incoloy 800 by Response Surface Methodology," *Procedia Mater. Sci.*, vol. 6, pp. 1674–1682, 2014.

[21] I. Salehi, M. Shirani, A. Semnani, M. Hassani, and S. Habibollahi, "Comparative Study Between Response Surface Methodology and Artificial Neural Network for Adsorption of Crystal Violet on Magnetic Activated Carbon," *Arab. J. Sci. Eng.*, vol. 41, pp. 2611–2621, 2016.

[22] J. P. Davim, V. N. Gaitonde, and S. R. Karnik, "Investigations into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models," *J. Mater. Process. Technol.*, vol. 205, pp. 16–23, 2008.

[23] H. Joardar, N. S. Das, G. Sutradhar, and S. Singh, "Application of response surface methodology for determining cutting force model in turning of metal matrix composite," *Measurement*, vol. 47, pp. 452–464, 2014.