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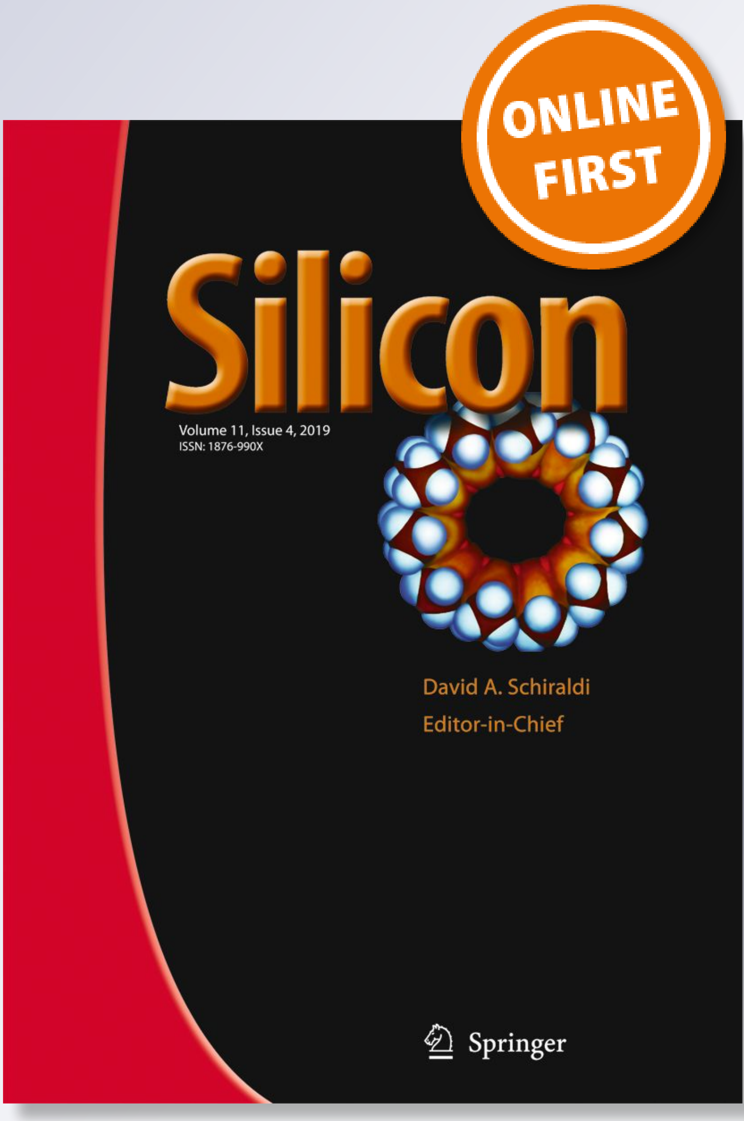

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ORIGINAL PAPER

Experimental Investigation of White Layer Thickness on EDM Processed Silicon Steel Using ANFIS Approach

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Abstract
Since the white layer thickness influences the surface quality of the machined specimens using electrical discharge machining process, the prediction of such parameter is highly important in the present scenario. Adaptive network based fuzzy inference system based white layer thickness prediction on machining processed silicon steel has been attempted in the present study. Three machining process parameters such as open circuit voltage, peak current and duty factor have been utilized for the training purpose owing their importance on determining white layer thickness. The accuracy of the prediction has been analyzed by comparing the predicted values from the architecture testing with the real time measured values. From the experimental results, it has been found that the developed adaptive network based fuzzy inference system can predict the average white layer thickness in an efficient way with accuracy of 96.8%. It has also been observed that the electrical process parameters have highly contributed on determining average white layer thickness.

Keywords ANFIS · EDM · Prediction · White layer

1 Introduction

In the present scenario, silicon steel is being utilized in electrical appliances and manufacturing applications owing to its distinctive characteristics. Since the alloy is high strength nature, it is very tedious process to machine such material with complex shapes using traditional processes. Electrical discharge machining (EDM) process is generally used to machine such hard material due to its merits of high tolerance, surface finish and negligible cutting force ability [1]. In EDM process, the material removal is happened using thermal energy produced by the electrical discharge plasma column [2]. Since the spark plasma produces higher thermal energy, the material is melted and vaporized [3]. The melted workpiece is resolidifed over the machined surface and formed the white layer (or) recast layer with the thickness of μm [4].

Figure 1 shows the white layer formation over the machined specimen in EDM. The surface quality of the EDM processed specimen is mainly influenced by the white layer thickness (WLT) over the machined workpiece. The modification of the white layer thickness plays on vital role in EDM process enhancement research areas [5]. The prediction of the performance measures with respect to the input process parameters can develop a better empirical model of any process. Since the thickness of the recast layer is characterized by the machining process parameters in EDM, the prediction of the WLT in terms of process parameters is. It is very important to improve the accuracy of the prediction on performance measure. An adaptive neuro fuzzy inference system (ANFIS) model has been applied to predict current-voltage curve [6]. It has been found that ANFIS model can predict the performance measures in proton exchange membrane fuel cell. The prediction of the surface roughness in end-milling process has been attempted to analyze the effects of the membership functions with ANFIS model [7]. It has been inferred that ANFIS

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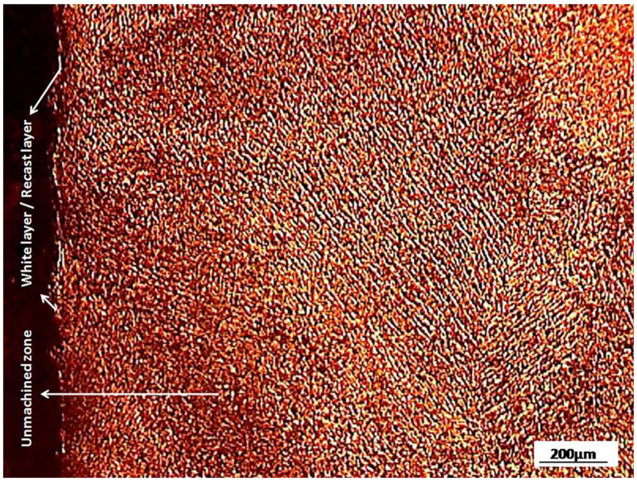


Fig. 1 White layer formation over the machined surface in EDM process

model can produce very high accuracy about 96%. It has been presented an approach to predict the surface roughness and cutting zone temperature on turning process of stainless steel using various multi-layer coated tungsten carbide tools [8]. It has been observed that the prediction can closely approach the performance measures in any process [9].

The selection of dielectric medium can considerably influence the thickness of white layer on machining nickel alloy in EDM process [10]. The thickness of the recast layer thickness can be modified by changing the open circuit voltage and pulse parameters in EDM process [11]. The modification of WEDM process can enhance mechanism of the machining process which has resulted on reducing recast layer thickness of the machined specimen [12]. The plasma energy could reduce the thickness of the recast layer in EDM process under diluted insulating medium [13]. The recast layer thickness distribution can affect the product life of aeronautical alloys machined in EDM process. The modelling and estimation of the layer thickness could increase the efficacy of the process mechanism [14]. The prediction of white layer thickness can effectively help on determining the process parameter combination to enhance the surface quality in EDM process [15].

Even though many research works have been done on prediction of the performance measures in EDM process, only very little attention has been given to predict the white layer thickness in terms of electrical process parameters and influence of machining process parameters on WLT of machined specimens using EDM process. In the present study, an attempt has been made to introduce ANFIS based prediction of WLT over the machined silicon steel and analyze effect of the machining process parameters on WLT.

2 Experiments and Methods

2.1 Experimental Design

Silicon steel is widely utilized in the electrical appliances and manufacturing industries. The chemical composition of silicon steel is shown in Table 1 [16]. A blind hole drilling processes with depth of 5 mm have been done using EDM process to machine silicon steel with tungsten carbide tool electrode. Owing to its importance on determining surface quality, white layer thickness has been considered as the performance measure in the present study.

Open circuit voltage (V_G), peak current (I_P) and duty factor (DF) has been chosen as the EDM process parameters to analyze their influence on white layer thickness. Totally 48 experimental training combinations have been used in the ANFIS method. The process variable settings of open circuit voltage values of 40, 60, 80 and 100 V with peak current of 3, 6, 12 and 24 A. The duty factor has been chosen as 0.4, 0.6 and 0.8 [17–19]. Since the white layer has dissimilar thickness over the machined surface, average white layer thickness (WLT) has been taken for prediction purpose as reported by Muthuramalingam (2019) [20]. The measured WLT values under different process parameters combination is shown in Tables 2 and 3.

2.2 ANFIS Methodology

An adaptive network-based fuzzy inference system (ANFIS) is a technique that integrates fuzzy logic and artificial neural network principles [6–8]. In this process, a neural network algorithm is used to tune the structure and rules of the fuzzy inference system (FIS). The architecture of the ANFIS network is shown in the Fig. 2.

The ANFIS architecture normally consists of five levels. The functions of each level are as follows:

Level 1: The input variables are assigned to the corresponding membership function. This stage depicts the fuzzification stage of the fuzzy logic system. This is actually a variable node, where the structure of

Table 1 Chemical composition of silicon steel

Elements	C	Si	Cu	Mn	P	S	Mo	Cr	Ni	Al	Fe
% composition	0.035	0.44	0.38	0.55	0.013	0.022	0.022	0.025	0.033	0.33	Remain

Table 2 EDM training performance measures for ANFIS model

S.No	V_G (V)	I_P (A)	DF	Average white layer thickness (μm)
1.	40	3	0.4	1.136
2.	40	3	0.6	1.219
3.	40	3	0.8	1.356
4.	40	6	0.4	1.301
5.	40	6	0.6	1.465
6.	40	6	0.8	1.68
7.	40	12	0.4	1.625
8.	40	12	0.6	1.958
9.	40	12	0.8	2.238
10.	40	24	0.4	2.282
11.	40	24	0.6	2.945
12.	40	24	0.8	3.602
13.	60	3	0.4	1.218
14.	60	3	0.6	2.954
15.	60	3	0.8	1.475
16.	60	6	0.4	1.468
17.	60	6	0.6	1.728
18.	60	6	0.8	2.012
19.	60	12	0.4	1.954
20.	60	12	0.6	2.452
21.	60	12	0.8	2.958
22.	60	24	0.4	2.838
23.	60	24	0.6	3.931
24.	60	24	0.8	4.918
25.	80	3	0.4	1.305
26.	80	3	0.6	1.465
27.	80	3	0.8	1.635
28.	80	6	0.4	1.629
29.	80	6	0.6	1.968
30.	80	6	0.8	2.385
31.	80	12	0.4	2.287
32.	80	12	0.6	2.958
33.	80	12	0.8	3.605
34.	80	24	0.4	3.567
35.	80	24	0.6	4.928
36.	80	24	0.8	6.235
37.	100	3	0.4	1.383
38.	100	3	0.6	1.595
39.	100	3	0.8	1.895
40.	100	6	0.4	1.794
41.	100	6	0.6	2.205
42.	100	6	0.8	2.735
43.	100	12	0.4	2.616
44.	100	12	0.6	3.438
45.	100	12	0.8	4.345
46.	100	24	0.4	4.26
47.	100	24	0.6	5.906
48.	100	24	0.8	7.548
Mean				2.633
Standard deviation				1.439
Standard error				0.208

the membership is a variable that is tuned accordingly.

Level 2: The firing strength of each rule for all the nodes are calculated using the fuzzy AND operation. This is a fixed node and it is the first layer of the neural network algorithm.

Level 3: At all the nodes, the ratio of the rule's firing strength or weight (w) is calculated. This is also a fixed node

Table 3 Validation of ANFIS testing values for WLT prediction

S.No	V_G	I_P	DF	WLT (μm)		
				Measured value	Predicted value	% error
1.	40	9	0.4	1.429	1.484	3.71
2.	40	9	0.6	1.697	1.733	2.08
3.	40	9	0.8	2.067	1.985	4.13
4.	40	15	0.4	1.732	1.691	2.42
5.	40	15	0.6	2.089	2.06	1.41
6.	40	15	0.8	2.481	2.363	4.99
7.	40	18	0.4	1.781	1.872	4.86
8.	40	18	0.6	2.442	2.33	4.81
9.	40	18	0.8	2.791	2.749	1.53
10.	60	9	0.4	1.729	1.792	3.52
11.	60	9	0.6	2.107	2.219	5.05
12.	60	9	0.8	2.682	2.622	2.29
13.	60	15	0.4	2.148	2.13	0.85
14.	60	15	0.6	2.682	2.731	1.79
15.	60	15	0.8	3.212	3.304	2.78
16.	60	18	0.4	2.296	2.408	4.65
17.	60	18	0.6	3.263	3.17	2.93
18.	60	18	0.8	3.803	3.891	2.26
19.	80	9	0.4	1.872	1.96	4.49
20.	80	9	0.6	2.385	2.473	3.56
21.	80	9	0.8	3.032	2.99	1.4
22.	80	15	0.4	2.263	2.381	4.96
23.	80	15	0.6	2.923	3.104	5.83
24.	80	15	0.8	3.892	3.826	1.73
25.	80	18	0.4	2.832	2.717	4.23
26.	80	18	0.6	3.532	3.633	2.78
27.	80	18	0.8	4.451	4.52	1.53

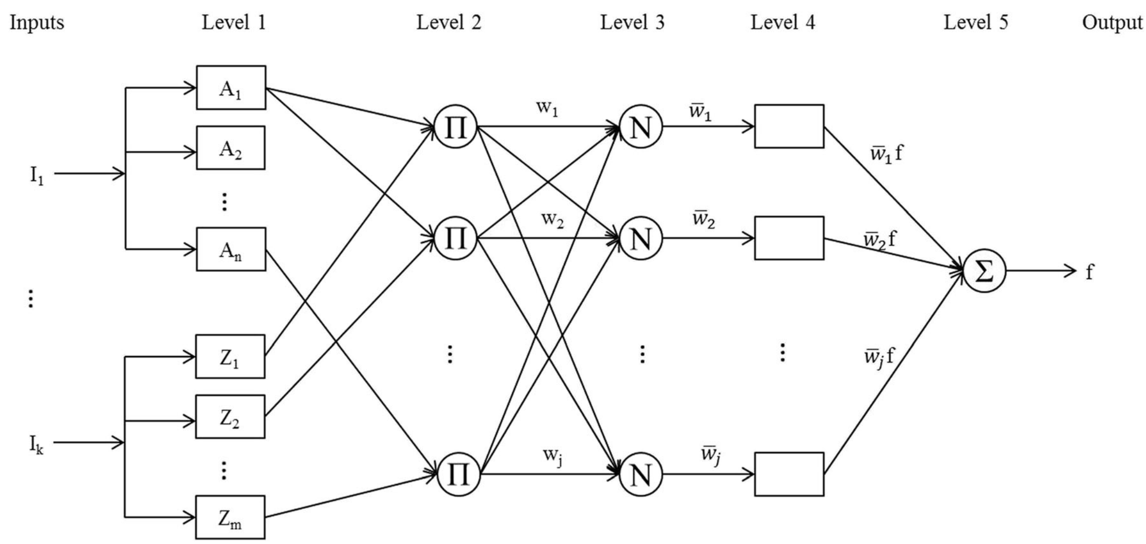


Fig. 2 ANFIS structure and architecture

and it is normally a hidden layer of neural network algorithm.

Level 4: The nodes calculate the parametric functions using a number of iterations. Thus the rule-base of the fuzzy inference system is tuned.

Level 5: This stage corresponds to the defuzzification stage of the fuzzy system and aggregates all incoming singles to a single output function.

3 Results and Discussion

3.1 Performance of Developed ANFIS Model

Totally 48 machining experiments have been conducted on machining silicon steel using EDM process for the reason of ANFIS training under different input process parameters combinations as shown in Table 1 . The developed ANFIS model has been tested with 27 different set of machining process parameters combination to verify the accuracy of the predicted white layer thickness values as shown in Table 2. During training in ANFIS, 48 sets of experimental data have been utilized to conduct 500 factors of learning. The initial value for the adaptation of parametric pace has been considered as 0.01.

The membership function of EDM machining parameter within the architecture has been divided into three zones such as small, medium and large areas. Figure 3 shows the initial and final membership functions of input process parameters such as open circuit voltage, peak current and duty factor. From the figure, it has been observed that medium area has been the most extensive and both the sides of the medium area gradually shrink toward the centre to form a triangular area. It has also been observed that the change in all three zones has been significant.

The ANFIS model has been developed using 48 sets of input machining process parameters. The ANFIS structure for three input one output factors is shown in Fig. 4. The predicted testing data has to be validated with experimental values for checking the accuracy of the ANFIS prediction of WLT. Hence the WLT values of the machined specimens have been computed experimentally and compared with the predicted values of WLT. Table 2 shows the comparison between the predicted and experimental data of AVLT after ANFIS model training.

Figure 5 shows the scatter diagram and accuracy plot of the predicted values and measurement values of the WLT of 27 combinations of ANFIS testing data. In scatter diagram, the predicted values of WLT have been distributed around the 45° line. It has been inferred from the scatter of the predicted values, the accuracy of the prediction can be enhanced with the developed ANFIS model. It has also been observed that only less error has been noticed with measured and predicted values. It has been proved that the developed ANFIS has achieved an excellent accuracy in the prediction of WLT as shown in Table 2.

3.2 Influence of Machining Parameters on WLT Prediction

Figure 6 shows the influence of the machining process parameters on WLT prediction. Since the electrical process parameters highly influences the performance

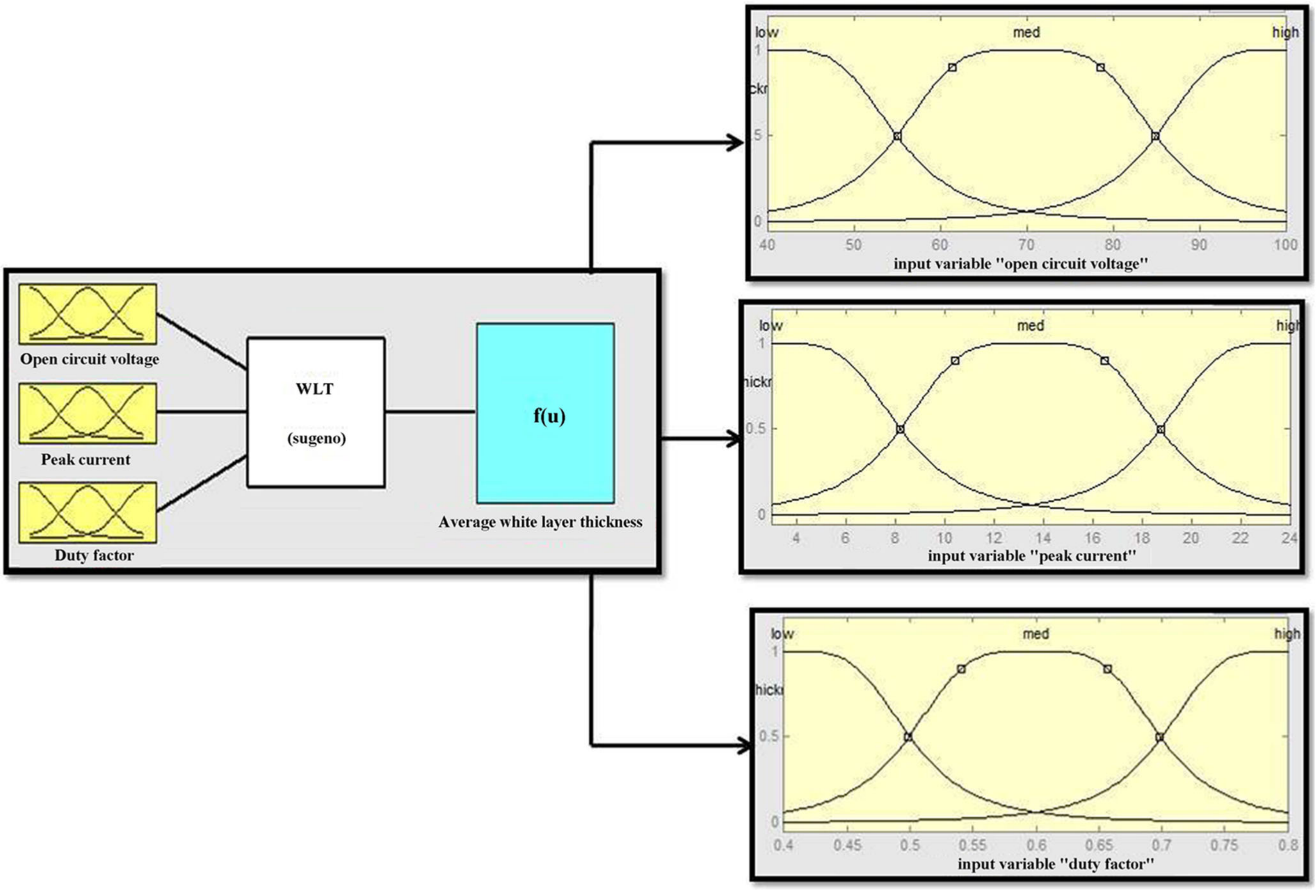
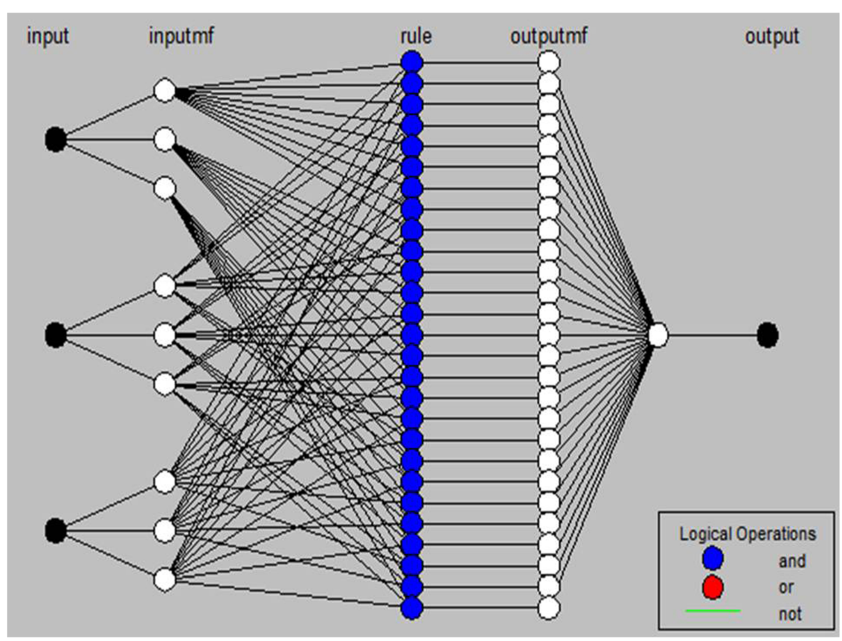


Fig. 3 Membership relationship between EDM process parameters

measures in EDM process, the influence of those parameters such as open circuit voltage, peak current and duty factor on white layer thickness has to be analyzed. The WLT prediction under different process parameter

Fig. 4 ANFIS architecture for three input process factors



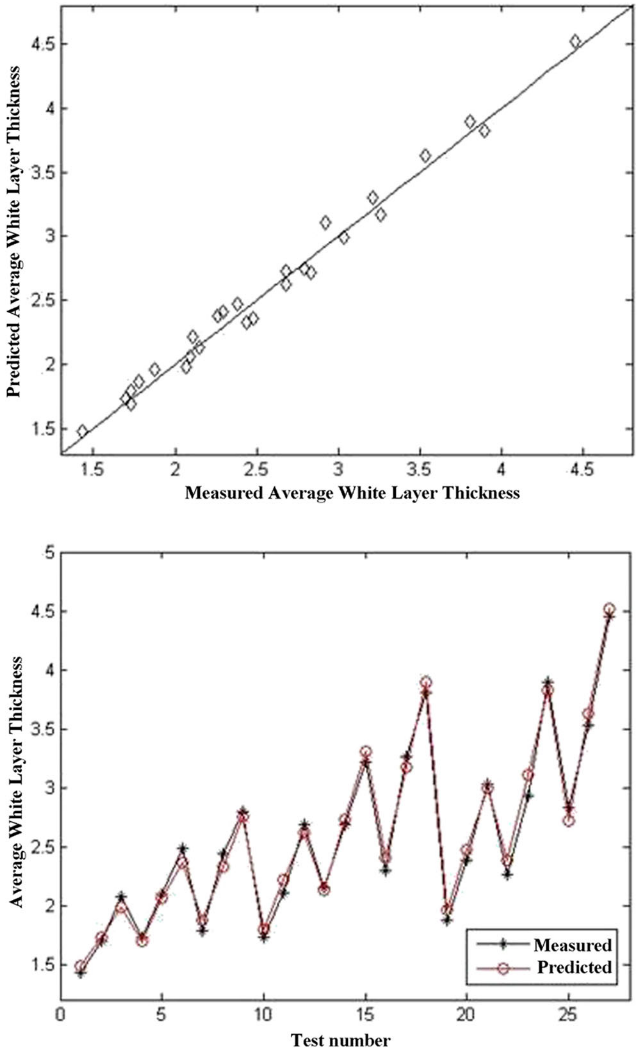


Fig. 5 Scatter diagram between measures and predicted values for predicting WLT

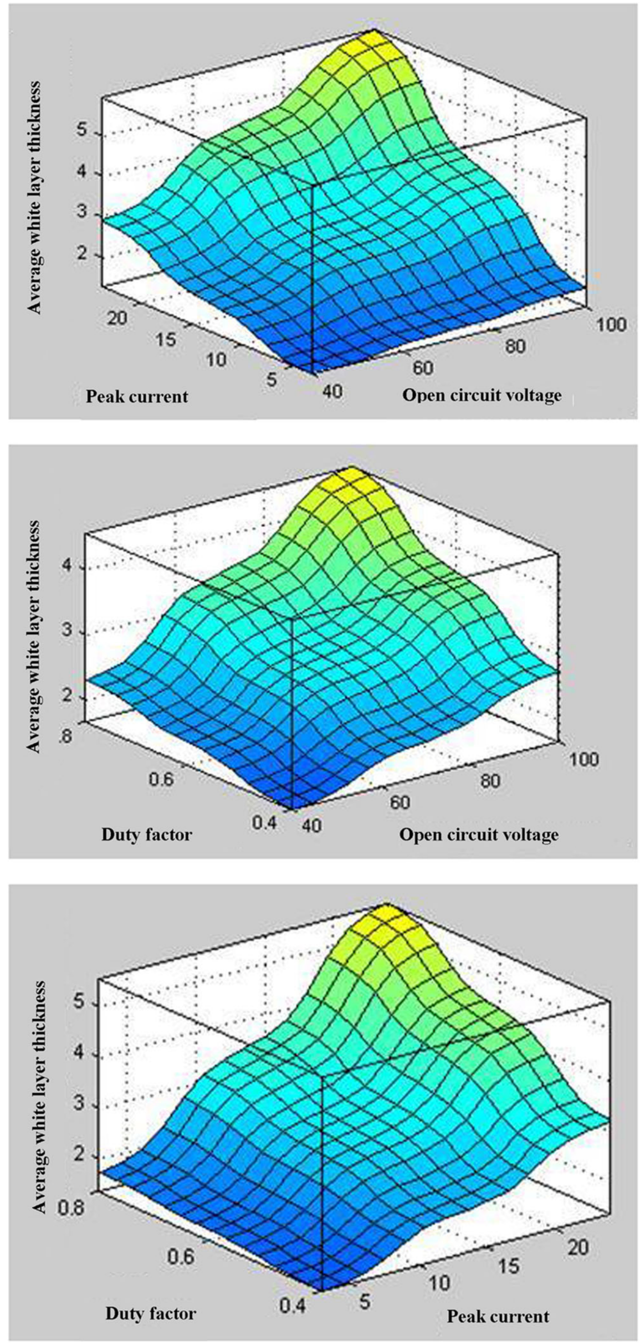


Fig. 6 Influence of input process factors on WLT prediction

combinations have been plotted using response surface approach. The duty factor indicates the period of applied spark energy across the tool electrode and the workpiece. Owing to the importance of duty factor on producing white layer formation, it has been observed that WLT has been increased with higher duty factor. It has also been observed that the WLT has been increased open circuit voltage and peak current due to its importance on determining the discharge energy in EDM process.

4 Conclusion

In the present study, an attempt has been made to introduce ANFIS approach to predict average white layer thickness while machining silicon steel using EDM process with 48 combinations of machining process parameters. The ANFIS model has been validated by comparing experimental and predicted values to analyze the accuracy of the model. From the experimental results, the following conclusions have been made.

(1) The developed ANFIS model can predict the average white layer thickness with an accuracy of 96.8%
(2) The electrical process parameters can highly contribute on determining white layer thickness.

References

1. Muthuramalingam T, Mohan B (2013) Influence of discharge current pulse on machinability in electrical discharge machining. Mater Manuf Process 28(4):375–380
2. Patowari PK, Mishra UK, Saha P, Mishra PK (2011) Surface integrity of C-40 steel processed with WC-Cu powder metallurgy green compact tool in EDM. Mater Manuf Process 26(5):668–676
3. Ekmekci B, Elkoca O, Tekkaya AE, Erden A (2005) Residual stress state and hardness depth in electric discharge machining: de-ionized water as dielectric liquid. Mach Sci Technol 9(1):39–61
4. Rajendran S, Marimuthu K, Sakthivel M (2012) Study of crack formation and resolidified layer in EDM process on T90Mn2W50Cr45 tool steel. Mater Manuf Process 28(6):664–669
5. Muthuramalingam T, Mohan B, Jothilingam A (2014) Effect of tool electrode resolidification on surface hardness in electrical discharge machining. Mater Manuf Process 29(11-12):1374–1380
6. Vural Y, Ingham DB, Pourkashanian M (2009) Performance prediction of a proton exchange membrane fuel cell using the ANFIS model. Int J Hydrogen Energ 34(22): 9181–9187
7. Lo SP (2003) An adaptive-network based fuzzy inference system for prediction of workpiece surface roughness in end milling. J Mater Process Technol 142(3): 665-675
8. Aydin M, Karakuzu C, Ucar M, Cengiz A, Cavuslu MA (2013) Prediction of surface roughness and cutting zone temperature in dry turning processes of AISI304 stainless steel using ANFIS with PSO learning. Int J Adv Manuf Technol 67(1–4): 957–967
9. Benardos PG, Vosniakos GC (2003) Predicting surface roughness in machining: a review. Int J Mach Tool Manuf 43(8):833–844
10. Li C, Xu X, Li Y, Tong H, Ding S, Kong Q, Zhao L, Ding J (2019) Effects of dielectric fluids on surface integrity for the recast layer in high speed EDM drilling of nickel alloy. J Alloys Compd 783(1): 95–102
11. Li CJ, Li Y, Tong H, Zhao L (2016) Thinning process of recast layer in hole drilling and trimming by EDM. Proc CIRP 42(1):575–579
12. Wu X, Li S, Jia Z, Xin B, Yin X (2019) Using WECM to remove the recast layer and reduce the surface roughness of WEDM surface. J Mater Process Technol 268(1):140–148
13. Muthuramalingam T (2019) Effect of diluted dielectric medium on spark energy in green EDM process using TGRA approach. J Clean Prod 238(1):117894
14. Izquierdo B, Plaza S, Sánchez JA, Pombo I, Ortega N (2012) Numerical prediction of heat affected layer in the EDM of aeronautical alloys. Appl Surf Sci 259(1):780–790
15. Yildiz Y (2016) Prediction of white layer thickness and material removal rate in electrical discharge machining by thermal analyses. J Manuf Process 23(1):47–53
16. Muthuramalingam T, Mohan B, Vignesh S (2018) Performance analysis of pulse generators on residual stress of machined silicon steel using EDM process. Silicon 10(5):1785–1792
17. Newton TR, Melkote SN, Watkins TR, Trejo RM, Reister L (2009) Investigation of the effect of process parameters on the formation and characteristics of recast layer in wire-EDM of Inconel 718. Mat Sci Eng A-Struct 513-514(1):208–215
18. Muthuramalingam T, Mohan B (2013) Influence of tool electrode properties on machinability in spark erosion machining. Mater Manuf Process 28(8):939–943
19. Muthuramalingam T, Mohan B, Rajadurai A, Prakash MAA (2013) Monitoring and fuzzy control approach for efficient electrical discharge machining process. Mater Manuf Process 29(3):281–286
20. Muthuramalingam T (2019) Measuring the influence of discharge energy on white layer thickness in the electrical discharge machining process. Measurement 131:694–700

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