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MULTI OBJECTIVE MACHINING ESTIMATION MODEL USING ORTHOGONAL AND NEURAL NETWORK

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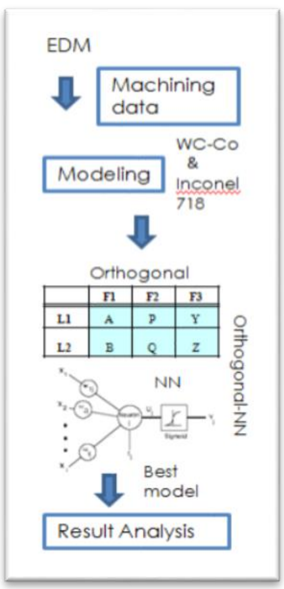
Graphical abstract



Abstract

Much hard work has been done to model the machining operations using the neural network (NN). However, the selection of suitable neural network model in machining optimization area especially in multi objective area is unsupervised and resulted in pointless trials. Thus, a combination of Taguchi orthogonal and NN modeling approach is tested on two types of electrical discharge machining (EDM) operations; Cobalt Bonded Tungsten Carbide (WC-Co) and Inconel 718 to observe the efficiency of proposed approach on different numbers of objectives. WC-Co EDM considered two objective functions and Inconel 718 EDM considered four objective functions. It is found that one hidden layer 4-8-2 layer recurrent neural network (LRNN) is the best estimation model for WC-Co machining and one hidden layer 5-14-4 cascade feed forward back propagation (CFBP) is the best estimation model for Inconel 718 EDM. The results are compared with trial-error approach and it is proven that the proposed modeling approach is able to improve the machining performances and works efficiently on two-objective problems.

Keywords: Orthogonal, neural network, multi objective, estimation model, electrical discharge machining

1.0 INTRODUCTION

Electrical discharge machining (EDM) is one of the most important and popular modern machining to machine hard to cut and complex metals through the use of electrical sparks. EDM is highly potential in the cutting process of super hard alloy with complex shapes that are particularly used in manufacturing, nuclear, automotive, dental, medical and surgical manufacturing. EDM provides an effective solution for machining hard materials such as titanium, nimonics, zirconium etc. With intricate shapes which are not possible by conventional machining. The basic mechanical structure of EDM is almost similar to the construction of conventional drilling and milling machine frames. The cost of EDM is very expensive due to high starting investment for the machine and the wire tool. EDM process is more economical if it is used to cut in low volume and greater variety. The selection of optimum machining parameters setting plays an important role in obtaining optimum performances.

Expensive equipments, long trials duration and requirement of skillful machinist are some of the reasons why there is a demand in improving the EDM optimization research area. Based on the literatures, there are four main concerns in EDM which are machine control, machining advancement, handling of tools and parameters optimization [1, 2]. Traditionally, machining parameters are selected manually based on the engineer and operator experiences [3]. The procedure of selecting parameters to gain the significance machining performances is extremely difficult due to the finest parameter combination is indefinite. This resulted to operational complications especially to the beginners and non-machining expertise. Inappropriate parameters estimation has contributed to a long production time, delay in production date and loss of formality. In general, during the early stage of development, the engineers and operators have very limited information and processing skills to cease the machining experiments within the time given and this resulted to unreasonable operational cost. To overcome the challenges in obtaining optimal solutions in a fast mode and minimum cost, new intelligent modeling and optimization techniques are suggested. Today, identification of different factors affecting the EDM performances and obtaining optimal machining conditions are still the most effective machining strategy. In this paper, we are focusing on the soft computing approaches to optimize and improve the multiple machining performances on WC-Co intermetallic alloys and hard to cut Inconel 718.

There are many modeling techniques proposed by previous researchers such as response surface methodology (RSM), regression [4], NN, support vector machine (SVM) [5], fuzzy logic (FL) [6] etc. For example, Padhee *et al*. [7] adopted RSM to model, the machining parameters; dielectric fluid, pulse on time, duty cycle and peak current of powder mixed EDM. Regression is also considered as one of the most well-known modeling technique employed by many researchers to overcome the machining optimization problems as mentioned by Zain *et al*. [8]. In term of multiple objectives, it is also surveyed that most of the researchers in the machining optimization area applied regression as a modeling technique to be integrated with the optimization algorithm. Kuriakose and Shunmugam [9] generated multiple linear regression to represent the relationship between the machining performances and parameters of WEDM process before optimizing it using non dominated sorting algorithm. Second order polynomial is employed by Palanikumar *et al*. [10]. Al-Ghamdi and Taylan [11] did a comparative study between two modeling techniques, ANFIS (neuro fuzzy inference system) and polynomial regression, and found ANFIS performed better result than polynomial regression. Yusoff *et al*. [12] combined orthogonal array, NN, regression and multi objective genetic algorithm to model and optimize machining parameters of WC-Co EDM.

Neural network is extensively used in solving the real world application [13, 14, 15, 16]. Nevertheless, in machining, Tsai and Wang [17] considered six types of neural networks to model removal rate of material in EDM and found that neuro fuzzy network performed the best. Juhr *et al*. [18] compared NN and nonlinear regression function and it is observed that NN is very much lenient and performed superior precision. Panda and Bhoi [19] summarized that one layer feed forward neural network model using logistic sigmoid transfer and Levenberg-Marquardt learning algorithm is quicker and more precise in estimating the removal rate value of EDM. Assarzadeh and Ghoreishi [20] employed two layer back propagation neural network modeling with Augmented Lagrange Multiplier algorithm and the percentage error results obtained is lower compared to the experimental result. Markopoulos *et al*. [21] applied back propagation neural network to estimate the surface roughness value using Netlab and Matlab software and found the software are flexible for estimation of surface roughness. Patowari *et al*. [22] challenged to model the EDM surface roughness using neural network and proved that the estimated results equivalent to the experimental results. Pradhan and Das [23] used Elman recurrent neural network to model AISI D2 EDM and the model generated 5.86% of percentage error which is considered low and has fulfilled the model estimation necessity. Mahdavinejad [24] employed NN to model EDM and found 3-5-5-2 network architecture simulated the lowest percentage error. Bharti *et al*. [25] used back propagation NN to optimize die sinking EDM on Inconel 718. Das and Pradhan [26] compared back propagation NN, radial basis NN, and recurrent NN to optimize surface roughness of EDM and found all models produced an acceptable estimation. Khan *et al*. [27] employed NN model to estimate the surface roughness and found that the approach helps in cost-efficient machining. Maity and Mishra [28] implemented neural network in the production of Inconel 718 EDM and produced satisfying results.

From the literature review conducted, none of the papers have considered particularly and thoroughly on how to obtain an ideal neural network model for machining optimization. Several researchers used variable mathematical trials [29], trial and error [30] and random selection trials [31, 20]. Therefore, in this present paper, we implemented combination of Orthogonal-NN on two types of machining operations. WC-Co EDM considered four input parameters and two objectives. Inconel 718 EDM considered five input parameters and four objectives. The capability of Orthogonal-NN is compared with the trial and error approach. The results are analysed and observed.

2.0 METHODOLOGY

The overall overview of this study comprises of three major stages as illustrated in Figure 1:

1) Machining data: Collection of machining experimental data that consist of the machining performances, parameters and

boundaries. Two types of machining operations, WC-Co EDM and Inconel 718 EDM are considered to test the viability of Orthogonal-NN. WC-Co EDM considered four machining parameters and two machining performances. Meanwhile Inconel 718 EDM considered five machining parameters and four machining performances.

2) Modeling: Development of estimation model for WC-Co EDM and Inconel 718 using NN and Orthogonal-NN. Compute the percentage error value and select the best model.
3) Result analysis: The actual machining experimental result is used as benchmark for result analysis. The result output of Orthogonal-NN and NN are also compared.

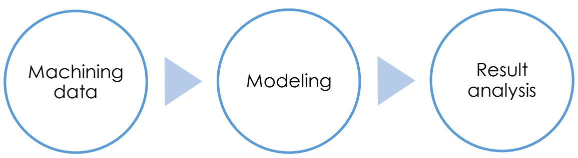


Figure 1 Basic flow of study

The machining data used in this study are obtained from experimental conducted by Kanagarajan *et al*. [32] and machining data of EDM on Inconel 718.

Kanagarajan *et al*. [32] machined the work piece of cobalt bonded tungsten carbide (WC-Co) in an Electronica die sinking EDM. The tool material used by the authors is an electrolytic grade copper with the size of 12 mm diameter. Kerosene is used as the dielectric fluid circulated by the jet flushing and the composites of the workpiece materials consist of 70% tungsten carbide and 30% cobalt. The machining performances considered are material removal rate (MRR) and surface roughness (Ra); meanwhile the parameters are rotation (S), current (T), pulse on time (U), flushing pressure (V). The boundaries considered for WC-Co EDM as given in Table 1.

Table 1 Machining boundaries of WC-Co EDM

Parameters	Lower Bound	Upper Bound
Rotational speed, rpm (S)	250	1000
Pulse current, A (T)	5	15
Pulse on time, μs (U)	200	1000
Flushing pressure, kg/cm2 (V)	0.5	1.5

The experiment of Inconel 718 machining used WEDM linear motor series AQ537L machine. The machining performances considered are material removal rate (MRR), surface roughness (Ra), cutting speed (Vc) and sparking gap (Sg). The machining performances considered are (i) pulse on time (A), pulse off time (B), peak current (C), feed rate (D) and flushing pressure (E). The machining boundaries of Inconel 718 EDM machining are given in Table 2.

Table 2 Machining boundaries of Inconel 718 EDM

Machining Parameters	Lower bound	Upper Bound
Pulse on time, μs (A)	0.80	1.3
Pulse off time, μs (B)	5	9
Peak current, Amp (C)	8	12
Feed rate, mm/min (D)	35	65
Flushing Pressure, bar (E)	5	45

Uncoated brass wire is selected as the wire tool to machine Inconel 718. The cutting measurement of Inconel 718 is 48 mm x 25 mm x 12. 5 mm. 10 mm length of work piece is cut with 1.5 mm gap between trials (see Figure 2). CNC controller board is used for cutting time measurement of cutting speed (Ra) and material removal rate (MRR). 5 mm is cut off samples for surface roughness measurement using Mitutoyo SJ-301. Mitutoyo Profile Projector PJ-3000 is used to measure the remaining 5 mm for bottom and top surfaces of the work piece. The measurement is calculated by considering the total average from the average of the horizontal and average of vertical directions.

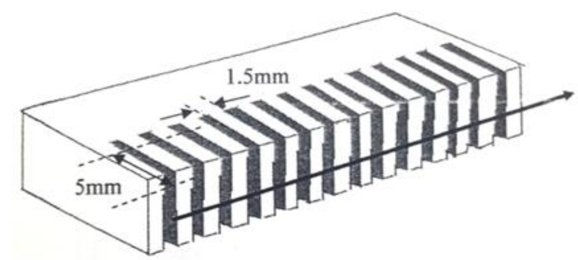


Figure 2 Cutting measurement of Inconel 718

Surface roughness (Ra) measurement in horizontal direction (x) is taken from 0.8 mm, length at five different distances and also a vertical direction. The total average of surface roughness (Ra) is based on equations (1), (2) and (3):

$$Ra_{(x)} = \frac{Ra_{(x1)} + Ra_{(x2)} + Ra_{(x3)} + Ra_{(x4)} + Ra_{(x5)}}{5} \quad (1)$$

$$Ra_{(y)} = \frac{Ra_{(y1)} + Ra_{(y2)} + Ra_{(y3)} + Ra_{(y4)} + Ra_{(y5)}}{5} \quad (2)$$

$$Ra = \frac{Ra_{(x)} + Ra_{(y)}}{2} \quad (3)$$

Where, $Ra_{(x)}$ in equation (1) is the average surface roughness on axis x. $Ra_{(y)}$ in equation (2) is roughness on y axis and Ra in equation (6) is overall average surface roughness. Twenty two runs of two level factorial experiments design with half fraction are performed on a linear motor Sodick AQ5371.

Including six replication of center bound runs. By dividing the distance of machining to the time of machining, the result of cutting speed is measured. The sparking gap value is calculated base on the measurement of kerf width at the top and bottom surface. Subtraction of the wire diameter from kerf width and divided into half is the calculation done to get one side gap. The measurement of material removal rate value is calculated based on weight of removal material per minute. The removal rate volume is obtained by multiplying the machining distance, kerf width and work piece thickness. By multiplying the removal volume with the density of Inconel 718 EDM, the mass of material removal is obtained. Material removal mass value is divided by the machining time and the value of material removal rate (MRR) is obtained.

From the machining data of WC-Co EDM and Inconel 718 EDM, the NN and Orthogonal-NN estimation models are developed using Matlab R2012a.

Using NN, the input data are associated with desired output to train the network. Therefore, NN has a very good capability to imitate the results of real experimentation by connecting the input data and desired output using neuron as the processing units. Each input is correlated with certain weight that takes a part of the input to the neuron for processing. The combination of neuron and input generates the output with the assistance of transfer function. An uncountable NN modeling trials is conducted for this study based on trial-error approach [30]. Various network functions are taken into consideration due to the complexity and the variety of NN functions. The best NN model is selected base on the percentage error value.

After excessive NN modeling trials, we found that there is a major problem with NN when there are too much guesswork in choosing the best network functions. To avoid time consuming and trial-error on unguided experimentation, we include Taguchi orthogonal array L256 in the process of network function selection combination Orthogonal-NN. There are four general steps included in the development of Orthogonal-NN model for this study; (i) the selection of Taguchi orthogonal factors (network functions) and levels, (ii) creation of L256 orthogonal array using Microsoft Excel, (iii) Orthogonal-NN modeling using Matlab R2012a, and (iv) selection of best Orthogonal-NN model base on percentage error value.

Seven network functions are taken into consideration which are; network type, number of hidden neurons, training function, performance function, transfer function, number of hidden layer and learning function. Four most popular network types; cascade forward backpropagation (CFBP), feed forward backpropagation (FFBP), Elman backpropagation (ELBP) and layer recurrent (LRNN) are considered in the selection. Sixteen level of hidden neuron (number of two to seventeen hidden neurons) are decided to be used. Fourteen level of training functions that we considered are; BFGS Quasi-Newton (TBFG), Bayesian regularization (TBR), conjugate gradient with Powell/Beale Restarts (TCGB), Fletcher-Powell conjugate gradient (TCGF), Polak-Ribiére conjugate gradient (TCGP), gradient descent backpropagation (TGD), gradient descent with momentum backpropagation (TGDM), gradient descent with adaptive lr backpropagation (TGDA), gradient descent with momentum & adaptive lr backpropagation (TGDX), Levenberg-Marquardt backpropagation (TLM), one step secant backpropagation (TOSS), random order incremental training with learning functions (TR), resilient backpropagation (TRP) and scaled conjugate gradient backpropagation (TSCG). The performance function considered are mean squared error with regularization (MSEREG), mean squared error (MSE) and sum squared error (SSE). The transfer functions considered are log sigmoid (logsig), hyperbolic tangent sigmoid (tansig) and linear (purelin). It is decided to use one and two as the level of hidden layer. Gradient descent with momentum weight and bias learning function (LGDM), and gradient descent weight and bias learning function (LGD) are the network learning factors considered.

The network functions are arranged based on the L256 combinatorial design that creates an effective and concise modeling trial which can avoid one by one extreme trial-error modeling attempt. A part of Orthogonal-NN matrix can be seen in Table 3.

Table 3 Part of L256 Orthogonal-NN matrix

L256	Factor						
	A	B	C	D	E	F	G
1	CFBP	TBFG	2	MSE	LOG SIG	one layer	LGD M
2	ELBP	TBR	3	MSE REG	Purel in	two layer	LGD
3	FFBP	TCGB	4	SSE	Tansi g	one layer	LGD M
4	LRNN	TCGF	5	MSE	LOG SIG	two layer	LGD
5	CFBP	TCGP	6	MSE REG	Purel in	one layer	LGD M
6	ELBP	TGD	7	SSE	Tansi g	two layer	LGD
251	CFBP	TBFG	3	MSE	LOG SIG	two layer	LGD M
252	ELBP	TBR	2	MSE REG	Tansi g	one layer	LGD
253	CFBP	TGDX	9	MSE	LOG SIG	two layer	LGD M
254	LRNN	TLM	8	MSE REG	Tansi g	one layer	LGD
255	CFBP	TOSS	7	MSE REG	Tansi g	two layer	LGD M
256	ELBP	TR	6	SSE	Purel in	one layer	LGD

Orthogonal-NN modeling is conducted for both Wc-Co EDM and Inconel 718 machining based on the combination of Orthogonal-NN matrix created. 256

trials of Orthogonal-NN models are generated for each machining operation and the best model need to be identified.

To choose the best model of NN and Orthogonal-NN, the percentage error of estimated results are calculated based on equation (4).

$$P_{Err} = (Pv - Av) / Av * 100\% \quad (4)$$

Where percentage error is P_{Err}, Pv is Orthogonal-NN or NN estimated value and Av is the actual machining data value.

3.0 RESULTS AND DISCUSSION

Percentage error or estimation accuracy for all Orthogonal-NN trials of WC-Co EDM and Inconel 718 EDM are calculated.

From 256 trials, the best-estimated results for WC-Co EDM, which have recorded less than 10% percentage error are sorted and given in Table 4.

Table 4 Percentage error for WC-Co EDM

L256	Percentage error (%)		
	Machining performances		Average
	MRR	Ra	
13	5.22	7.60	6.41
33	1.02	2.08	1.55
46	5.41	4.96	5.18
47	3.76	5.71	4.74
51	1.10	2.95	2.02
61	1.94	8.35	5.14
65	2.07	7.55	4.81
66	0.89	2.22	1.55
94	6.67	4.49	5.58
97	6.13	3.29	4.71
100	2.80	7.31	5.05
111	2.22	2.71	2.46
122	1.38	9.40	5.39
125	3.00	2.28	2.64
170	7.98	2.04	5.01
202	2.94	9.21	6.07
213	5.48	3.43	4.46
214	5.87	7.63	6.75
224	3.58	6.70	5.14
232	1.74	1.80	1.77
246	6.10	2.25	4.18

L232, layer recurrent (LRNN) 4-8-2 as illustrated in Figure 3 with Bayesian regularization training function (TBR), mean squared error performance function (MSE), tangent sigmoid transfer function (Tansig), gradient descent with momentum weight and bias learning function (LGDM) is chosen as the best Orthogonal-NN model for WC-Co EDM due to the equality of error for both machining performances. This is important to make sure both performances can be improved fairly without neglecting any of the objectives. The model is obtained in 34 seconds with 451 iterations.

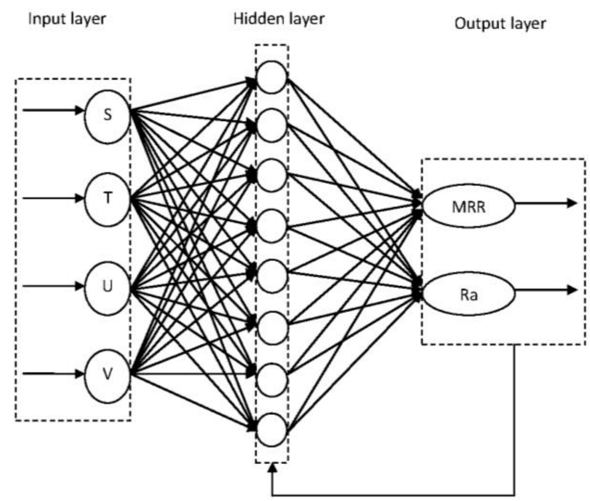


Figure 3 4-8-2 LRNN for WC-Co EDM

From two hundred and fifty-six combination trials for Inconel 718 EDM, there are two trials produced percentage error less than 10% as given in Table 5. To get the optimum model, the best network needs to be examined. The average of the percentage error is calculated to search for the ideal network model. As shown in Table 5, the lowest percentage error obtained for removal rate is from trial number 13, 8.18%. The lowest percentage error for surface roughness is 2.00%, also from trial number 13. 4.19% of percentage error is the lowest for cutting speed from trial number 129. The lowest percentage error for sparking gap is 4.48% from trial number 13. It can be seen that the average percentage error for trial number 13 is the lowest. Additionally, trial number 13 is dominant where three of the machining performances produced better percentage error compared to trial number 129. Therefore, trial no 13, cascade forward back propagation (CFBP) 5-14-4 as illustrated in Figure 4, with resilient back-propagation training function (TRP), MSE performance function, log sigmoid transfer function (Logsig), gradient descent with momentum weight and bias learning function (LGDM) is chosen as the best network model.

Table 5 Percentage error for Inconel 718

L256	Percentage error (%)				
	Machining performances				Average
	MRR	Ra	Vc	Sg	
13	8.18	2.00	5.96	4.48	5.16
129	8.20	3.80	4.19	6.05	5.56

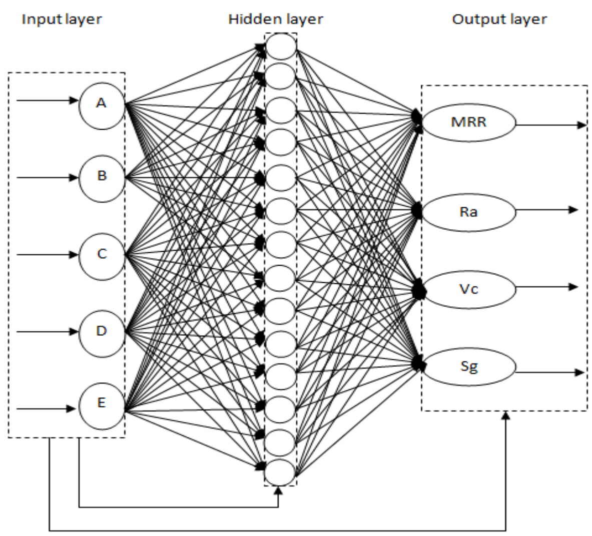


Figure 4 5-14-4 CFBP for WC-Co EDM

The results of the best Orthogonal-NN model are compared with the best NN model. Table 6 and Table 7 show the percentage error value of these two models for respective machining operation, WC-Co EDM and Inconel 718 EDM. From Table 6 and 7, it is revealed that Orthogonal-NN is a better approach to generate the best and optimal network model in estimating the machining operations compared to NN. The percentage error values of Orthogonal-NN are lower for most of machining performances and the average percentage error outperformed NN in both machining operations.

Table 6 Comparison between NN and Orthogonal-NN for WC-Co EDM

WC-Co EDM	Model	Percentage error (%)		
		MRR	Ra	Ave
NN	4-6-2 FFBP	2.77	8.52	5.65
Orthogonal-NN	4-8-2 LRNN	1.74	1.80	1.77

Table 7 Comparison between NN and Orthogonal-NN for Inconel 718 EDM

Inconel 718 EDM	Model	Percentage error (%)				
		MRR	Ra	Vc	Sg	Ave
NN	5-8-4 FFBP	6.54	2.69	6.19	6.85	5.57
Orthogonal-NN	5-14-4 CFBP	8.18	2.00	5.96	4.48	5.16

The plots comparison between experimental, estimated machining performances of NN and Orthogonal-NN for WC-Co EDM and Inconel 718 EDM are illustrated in Figure 5, 6, 7, 8, 9 and Figure 10. Figure 5 and Figure 6 show the performance comparison of material removal rate (MRR) and surface roughness (Ra) for WC-Co EDM. Figure 7, 8, 9 and Figure 10 show the performance comparison of material removal rate (MRR), surface roughness (Ra), cutting speed (Vc) and sparking gap (Sg) of Inconel 718 machining. As can be seen from the figures, the plots of Orthogonal-NN are closer to the experimental results compared to the results of NN. This verified that the results of Orthogonal-NN are acceptable and have higher accuracy than NN.

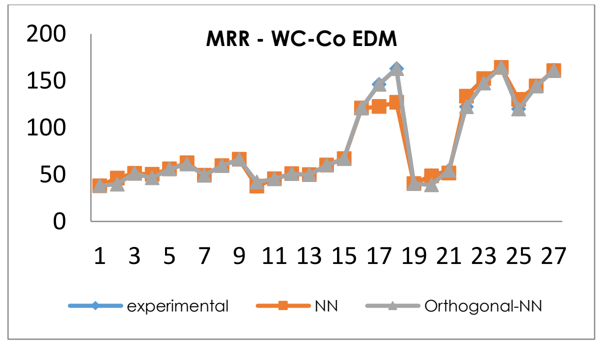


Figure 5 MRR performance comparison for WC-Co EDM

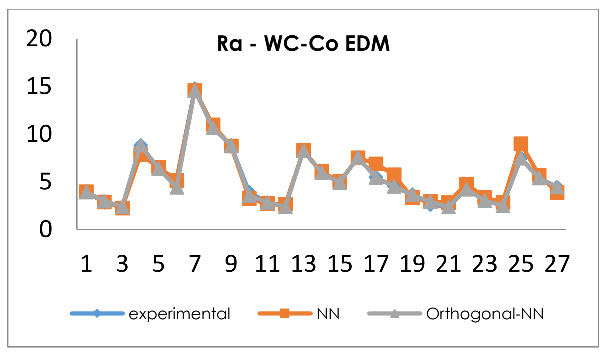


Figure 6 Ra performance comparison for WC-Co EDM

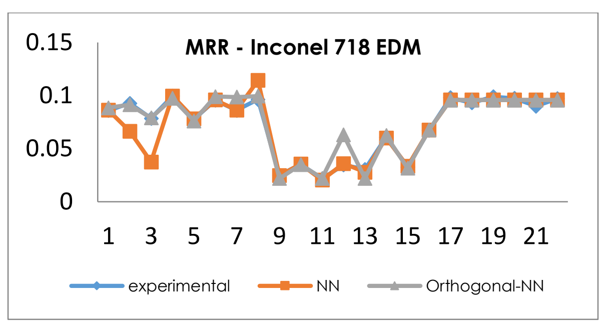


Figure 7 MRR performance comparison for Inconel 718

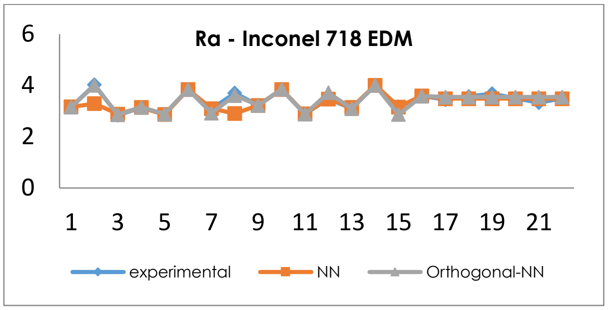


Figure 8 Ra performance comparison for Inconel 718

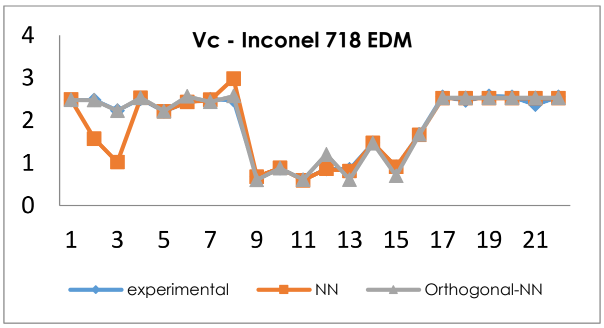


Figure 9 Vc performance comparison for Inconel 718

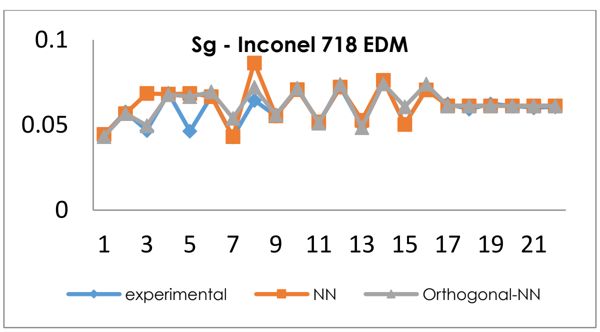


Figure 10 Sg performance comparison for Inconel 718

By considering the complex factors and levels, the real coverage required is about 32256 combination trials (4 factor A x 16 factor B x 14 factor C x 3 factor D x 3 factor E x 2 factor F x 2 factor G). It can be noted that the trial numbers is fixed to 256 and is reduced by 99.21% percent from total of actual required experimental trials.

4.0 CONCLUSION

The machining of WC-Co and Inconel 718 on EDM operation has been modeled using Orthogonal-NN. The experimental trials are conducted and compared with the real machining data to see the capability of the proposed approach. This approach is presented to estimate the machining parameters of EDM for achieving optimal performances such as maximum material removal rate, minimum surface roughness, maximum cutting speed and etc. This approach is highly recommended when there is only limited experimental data and correlation of input and output parameters. Based on the results, we concluded that:

1. Orthogonal-NN results are closer to the experimental results compared to NN and this proven that the for estimation model of EDM on two and four objectives machining problems are reliable.
2. Orthogonal-NN works impressively on two-objective problems with very low percentage error value (<2%) for every machining performance.
3. Orthogonal-NN generated model with better accuracy with organized experimentation and this reduced the unnecessary computational trials.

Machining is a very complicated task, even when a machinist uses the manual handbook, the desired solutions might not achieve due to various mechanical defect influences. This approach can be used by the machining operators in the early stage of machining operation for variety choices of parameters in order to achieve the optimum performances.

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