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Prediction of Material Removal Rate in Wire Electrical Discharge Turning using Artificial Neural Networks and Adaptive Neuro-Fuzzy Models

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ABSTRACT

This work intended to assess the prediction and simulation effectiveness of the artificial neural network (ANN) with adaptive neuro-fuzzy inference system (ANFIS) approaches for modeling the material removal rate (MRR) in wire electrical discharge turning for fabrication of micro-pin made by Ti6Al4V. 16 experiments have been conducted according to full factorial design by varying four different WEDT input attributes namely pulse intensity, voltage open, wire tension and spindle speed. This dataset is aimed to be used for training and then, five more trials with random selection of input attributes is conducted to be established as the validation data. In developing the ANN model, Levenberg–Marquardt backpropagation training algorithm with ten neurons of hidden layer is employed and the Gaussian curve built-in membership function is used for developing the ANFIS model. The ANN and ANFIS model have been compared with experimental results. Both models indicated good predictions, however, the comparison revealed that the ANFIS model produced the closest result with the experiment compare than ANN.

Keywords: Artificial neural networks, full-factorial design, neuro-fuzzy inference system, WEDT

1. INTRODUCTION

Titanium alloy is classified as difficult-to-cut materials due to properties of high strength, low thermal conductivity and strong chemical reactivity with tool materials when encountered machining process by traditional method like turning, boring and milling which significantly reduce the tool life [1, 2]. To avoid extreme tool wear and chatter during machining, many researchers are looking at advanced machining processes with the usage of different source of energy to remove materials such as thermo-electric based like spark erosion machining, laser-based like laser machining, mechanical-based like abrasive jet machining, etc. [3–5].

Wire electrical discharge machining (WEDM) is one of the outstanding process among the most versatile advanced machining processes to perform machining for this kind of materials. Incorporating the WEDM process with a rotating workpiece can provide an effective solution for micro-sized fabrication of components that are made from difficult-to-machine material such titanium alloy [6, 7]. Turning process with WEDM is found to be an emerging sub-area and has high potential to attract more research interests. This process is synonym with the term wire electrical discharge turning (WEDT).

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The performance of WEDT process is identify through its control process parameters, which directly affect the outcome of the process. Naik and Narendranath [8] investigate the influence of machining parameters on MRR using Taguchi orthogonal array for turning Inconel 718. The residual error between predicted and experimental values is as much as 8.144%.

Kanthababu *et al*. [9] reported on the predictive modelling of MRR and surface roughness through statistic approach for turning process of Al 7075-based metal matrix composites. They used Box-Behnken approach to develop the prediction model for WEDT variable which are spindle speed, pulse-on time, pulse-off time and gap voltage. Izamshah *et al*. [10] generated prediction model through central composite design (CCD) of response surface methodology (RSM) to model the performance of rotary spindle in WEDT. The residual error of prediction on MRR and surface roughness are found to be less than 5%.

According to the literatures, MRR is found to be a vital performance measures in WEDT process because it represents the economics of machining and the production rate. By comparing WEDT and WEDM, WEDT is discovered as an unstable machining process due to the dynamic of workpiece motion. When the workpiece is in the rotating conditions, the pre-breakdown time of discharge is increased which leads to formation of short and arc pulse. Therefore, it is very challenging to identify and model the WEDT performance not to mention the nonlinear relationship between the parameters-responses and numerous numbers of controls variables that need to be adjust in order to obtain ideal machining conditions.

A lot of efforts have been done for modelling of the WEDT process in the perspective of empirical and statistical approach [11–13] and this approach has a limitation in prediction accuracy which is within the range of 5% to 25% [14, 15]. To the authors' best knowledge, there are no published works with regards to modelling through soft-computing technique for performance prediction of WEDT process for machining micro-sized components.

Therefore, this research aims to evaluate predictive capability of the two types soft-computing technique which are the artificial adaptive models-neural networks (ANN) and adaptive network-based fuzzy inference system (ANFIS). The experiments are designed using full factorial with intensity of pulse (Ip), voltage open (Vo), wire tension (WT) and spindle speed (SS) as input attributes, while MRR is the target attributes for WEDT in machining titanium alloy.

2. MATERIALS AND METHODS

The experimental works in this study is conducted using a non-submersible WEDM machine model Mitsubishi RA90 and integrated with a spindle unit to perform the turning operation as shown in Figure 1. The workpiece tested is a titanium alloys grade 5 (Ti6Al4V) with hardness 36 HRC. This kind of alloys is known to be challenging when processed by conventional machining [16]. Deionized water as dielectric fluid and 0.25 mm of diameter brass electrode wire has been used to turned raw size of 9.49 mm diameter workpiece into <1 mm of micro pin with machining length of 4 mm.

The MRR of machined workpiece is taken as the target function and is calculated by obtaining the differences in the weight of each workpiece before and after per unit machining time with the use of Mettler Toledo analytical balance as indicated in equation (1). Wi signifies the initial weight of the workpiece [mg], Wf signifies the final weight of the workpiece after machining [mg], and t signifies the time taken for machining to be completed [min].

$$MRR = (Wi - Wf) / t \ (mg/min) \tag{1}$$

In this study, input levels are decided based on the design of experiments specifically for full factorial design. Nowadays, the design of experiments is used widely in manufacturing engineering field [14], [17] including the integration with the soft-computing technique [18]. Four input levels are selected as process parameters which are the intensity of pulse, voltage open, tension of wire and rotational spindle speed. The input parameters and their level are presented in Table 1. This full factorial design yields 16 sets of trials as indicated in Table 2.

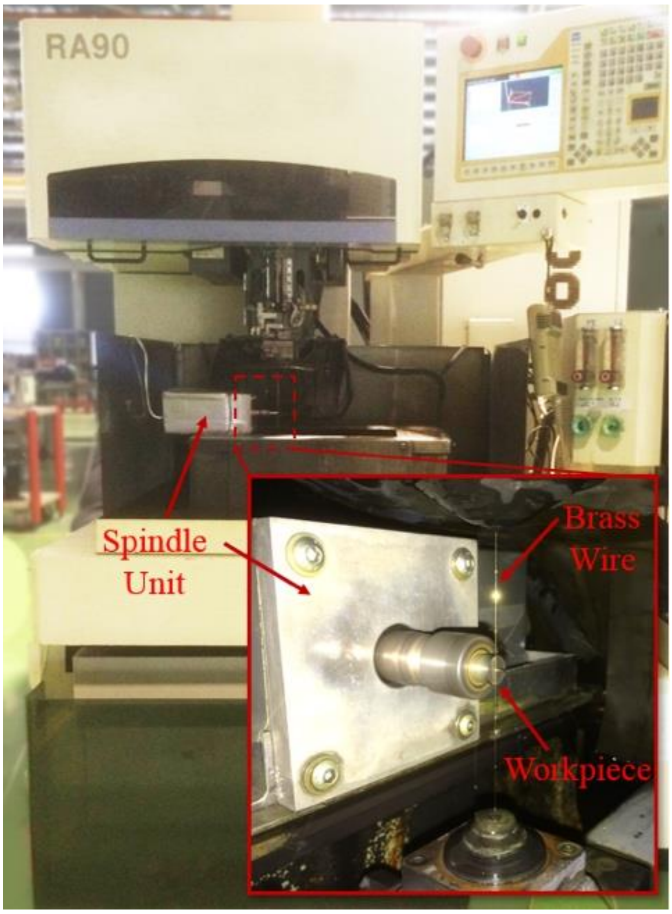

Figure 1. Non-submersible type of WEDM machine with precise spindle unit.

Table 1 Input Attributes, Level and Functions for WEDT Process

Input Attributes	Level	Functions
Intensity of Pulse (Ip)	8 to 10 Notch	To control the peak current concentration for the flow in the discharge gap specifically on normal pulse
Open Circuit Voltage (Vo)	6 to 8 Notch	To control the gap voltage level when there is no load High value represents high voltage
Wire Tension (WT)	12.2 to 14.8 Newton	To regulate the tension of the electrode wire High value represents high tension of wire applied
Rotational Spindle Speed (SS)	400 to 2400 rev/min	To regulate the speed of workpiece in rotational motion High value represents faster motion of the workpiece

Table 2 Experimental Design and Results

Trial	Intensity of Pulse (Notch)	Voltage (Notch)	Wire Tension (Newton)	Rotational Spindle Speed (rev/min)	Material Removal Rate (mg/min)
1	8	6	12.2	400	45.245
2	10	6	12.2	400	45.285
3	8	6	14.8	400	45.257
4	10	6	14.8	400	45.581
5	8	6	12.2	2400	45.308
6	10	6	12.2	2400	45.182
7	8	6	14.8	2400	44.596
8	10	6	14.8	2400	45.361
9	8	8	12.2	400	45.119
10	10	8	12.2	400	45.086
11	8	8	14.8	400	45.188
12	10	8	14.8	400	45.389
13	8	8	12.2	2400	45.032
14	10	8	12.2	2400	45.486
15	8	8	14.8	2400	45.091
16	10	8	14.8	2400	45.208

2.1 Artificial Neural Network (ANN)

ANN is a computing technique which is inspired from the human brain information process. It contains a number of simple computing units that works as artificial neurons that is also known as input nodes. Each unit is connected and organized to the parallel and feedforward in many layers [19]. This method is recognized as a quick prediction approach and is excellent to solve empirical and analytic physical models [20].

In this architecture, each one of the artificial neurons is defined by its input and output and is consists of a nodal set connected by synapses. In this research, the ANN model has been formed and constructed via Matlab Neural Network Toolbox in Matlab R2015a software. The element of network used in this study is a feedforward backpropagation and Levenberg-Marquardt method has been used as the learning algorithm. This method is found to be as one of the satisfactory set of rules to train the ANN model with less data [21].

The input-output database according to full factorial design has been separated into training, testing and validation which consist of 60%, 20% and 20%. Furthermore, hidden layer 10 that is chosen to be the acceptable key in performing model prediction is also used in this research study.

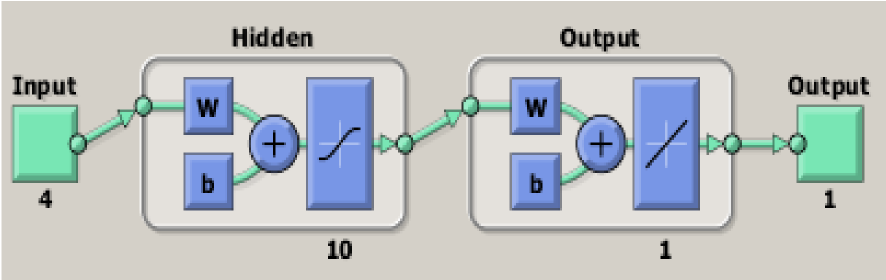

Figure 2. Network diagram for 4-10-1 used in this study.

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive network-based fuzzy inference system is an integration of the Takagi–Sugeno fuzzy inference system to the architecture of artificial neural network. ANFIS employed the hybrid-learning step and is able to predict the complex input-output natures in the basis of human-knowledge which involves membership functions, logic operators and fuzzy if-then rules [22, 23]. MRR is considered as target response to evaluate the performance of WEDT and is determined by four input variables which are the pulse intensity, voltage open, wire tension and spindle speed. The modelling of ANFIS has been performed using MATLAB R2015a with Fuzzy Logic Toolbox. The membership function employed in this study is the Sugeno type fuzzy reasoning along with gaussmf. The ANFIS model structure is illustrated in Figure 3, which consists of 16 rules with AND logical connector for all rules.

The collection data from the full factorial experimental design is randomly assigned for the training step to develop the ANFIS model for the MRR prediction which comprised of 16 input vectors with its MRR corresponding output vectors. The calculations of fuzzy inference of developed model is conducted just after the training is finish. In order to appraise the model prediction performance, 5 random input vectors from new dataset are used to train the ANFIS network, predicted the responses results, and compared with predicted experimental results.

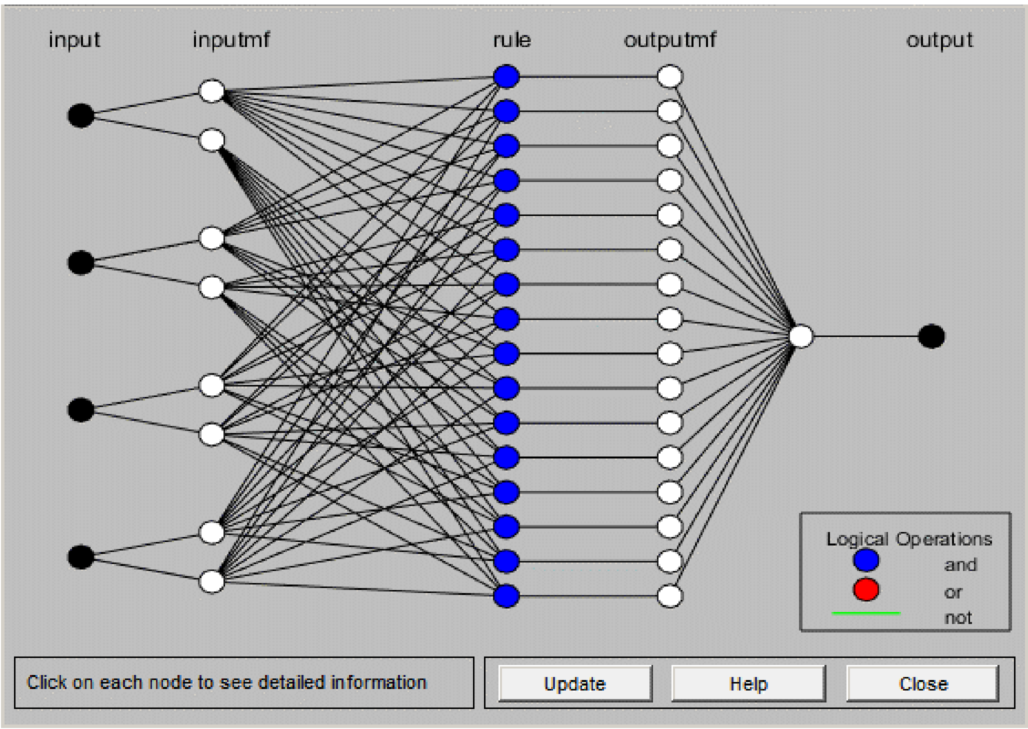

Figure 3. Four input with 16 rules of ANFIS model structure in this present study.

3. RESULTS AND DISCUSSION

3.1 ANN Modelling

The performance plot of training, validation and testing shown in Figure 4 indicated that the prediction error is reduced with the growing of epochs number and the training stops at epoch 3. The best validation performance is found at 0.015597 value of MSE which indicates reasonably good performance of the network. Figure 5 and Figure 6 indicated that the experimental results are well-correlated with the prediction results in which the output (predicted values) and (actual values) for the training, validation, testing and whole data sets that represent R are 1, 1, 1 and 0.96547, respectively.

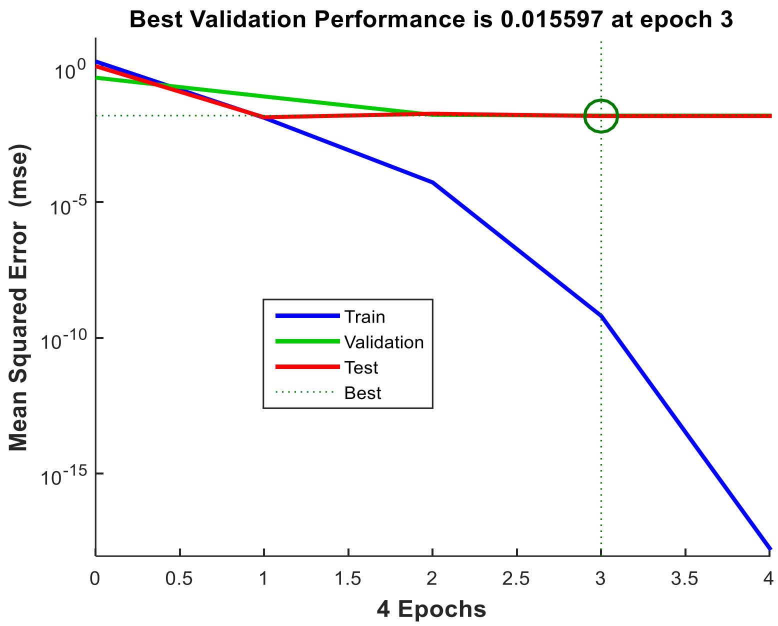

Figure 4. Performance plot that represents MSE of ANN models.

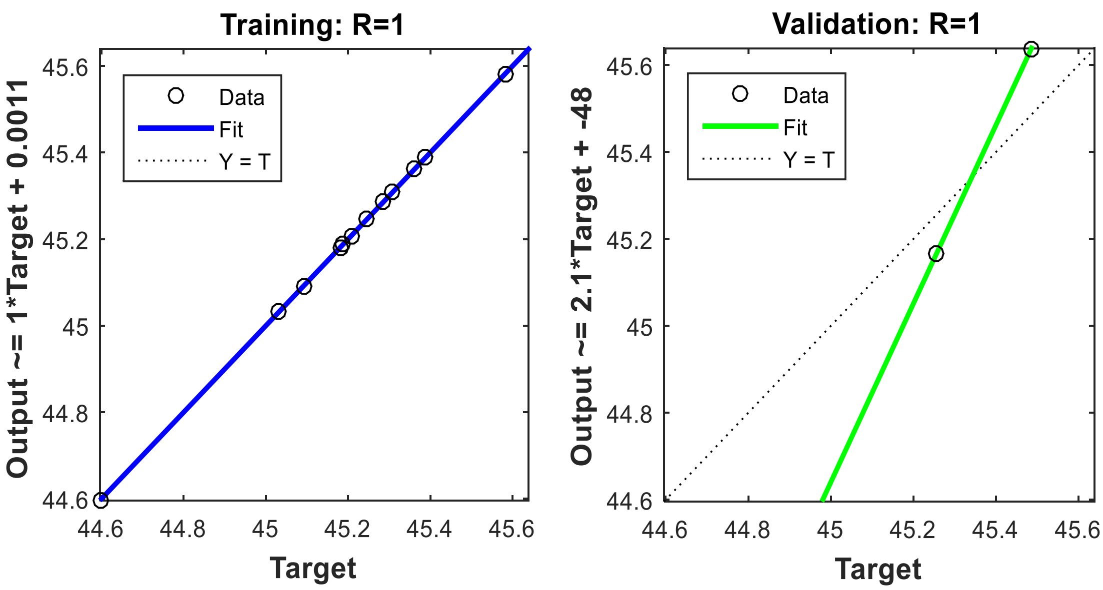

Figure 5. Performance plots of experimental data versus ANN model for training and validation.

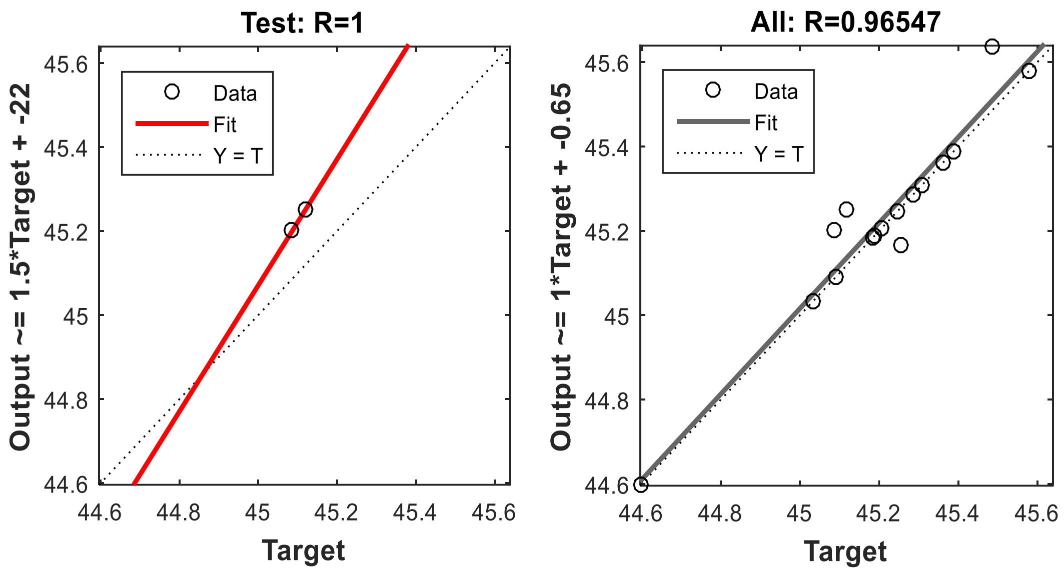

Figure 6. Performance plots of experimental data versus ANN model for testing and all data.

3.2 ANFIS Modelling

The MRR results on the experimental and prediction for ANFIS on 16 testing data are plotted and compared in Figure 7. It can be concluded that the prediction of ANFIS model is accurately matched with the experimental results. Therefore, it can be said that the ANFIS model is reliable and it can be used to perform the prediction. One of the ways to perform the prediction is by using rule viewer. Figure 8 depicts the rule viewers which shows the various inputs value of the ANFIS models with the computed output. From this rule viewer, the output values of MRR could be predicted by adjusting the input variables which are the pulse intensity, voltage open, wire tension and spindle speed.

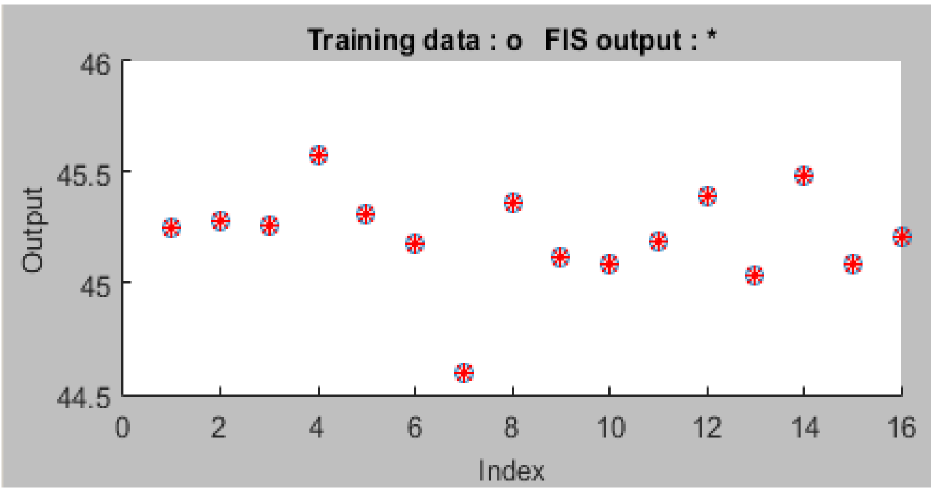

Figure 7. ANFIS, comparison between the experimental and predicted dataset.

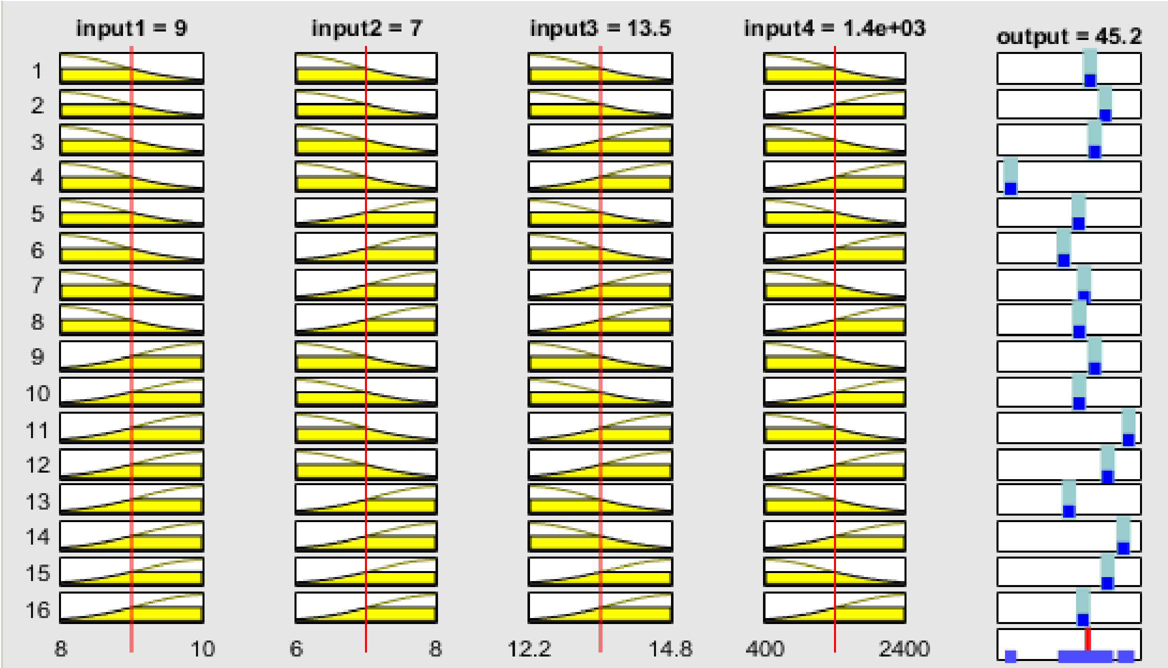

Figure 8. ANFIS rule viewer.

3.3 Performance Assessment of Predictive Capability

The effectiveness of the developed ANFIS and ANN models in predicting the MRR in WEDT, is evaluated by the accuracy of the prediction model. Firstly, both models are compared with the experimental and prediction data. Then, the models are validated with five additional data sets obtained from validation trials conducted experiments. Table 3 show the comparison of experiment and prediction results of ANN and ANFIS on the training data. Figure 9 illustrated that both models provide good estimation accuracy of MRR in WEDT. By referring to Table 3, the average residual error for ANN is 0.244% and for ANFIS, the average residual error is 0.053%. These results concluded that the high accuracy of MRR prediction can be achieved with ANFIS model because it is more closely matched to the experimental results.

In order to evaluate prediction capability of the proposed ANN and ANFIS model in this research study, the validation experiments are conducted. Table 4 shows the validation of WEDT process parameters and its results. Figure 10 illustrated the comparison plots among the experimental, ANN and ANFIS model. The results indicated that the minimum residual error for ANN model is at 0.13% which is quite high compared to ANFIS model at 0.039%. Therefore, this present study demonstrated that ANFIS has better prediction capability compared to ANN although the input-output dataset is not in the training or learning database.

Table 3 MRR Prediction Comparison Experiment, ANN and ANFIS

Trials	MRR Experiment (mg/min)	MRR Prediction-ANN (mg/min)	MRR Prediction-ANFIS (mg/min)	% Residual Error	
				ANN	ANFIS
1	45.245	45.218	45.246	0.061	0.002
2	45.285	45.406	45.311	0.266	0.057
3	45.257	45.219	45.303	0.085	0.101
4	45.581	45.502	45.600	0.173	0.042
5	45.308	45.070	45.297	0.525	0.024
6	45.182	45.323	45.199	0.314	0.039
7	44.596	44.574	44.610	0.049	0.032
8	45.361	45.285	45.382	0.166	0.046
9	45.119	45.008	45.038	0.244	0.178
10	45.086	45.231	45.118	0.322	0.070
11	45.188	45.181	45.176	0.015	0.027
12	45.389	45.389	45.392	0.002	0.007
13	45.032	45.021	45.051	0.024	0.043
14	45.486	45.118	45.493	0.808	0.016
15	45.091	44.717	45.145	0.831	0.119
16	45.208	45.197	45.187	0.023	0.046

Table 4 Validation Experiments results

	Validation 1	Validation 2	Validation 3	Validation 4	Validation 5
Pulse Intensity (Notch)	8	10	9	9	9
Voltage Open (Notch)	7	7	7	7	7
Wire Tension (Newton)	13.5	13.5	12.2	14.8	13.5
Spindle Speed (rev/min)	1400	1400	1400	1400	2400
MRR Experiment value (mg/min)	45.579	43.255	45.234	45.395	44.927
MRR Prediction-ANN value (mg/min)	45.001	45.307	45.174	45.133	45.038
MRR Prediction-ANFIS value (mg/min)	45.194	43.287	45.216	45.286	45.097
% Error ANN	1.27	4.74	0.13	0.58	0.25
% Error ANFIS	0.845	0.075	0.039	0.239	0.378

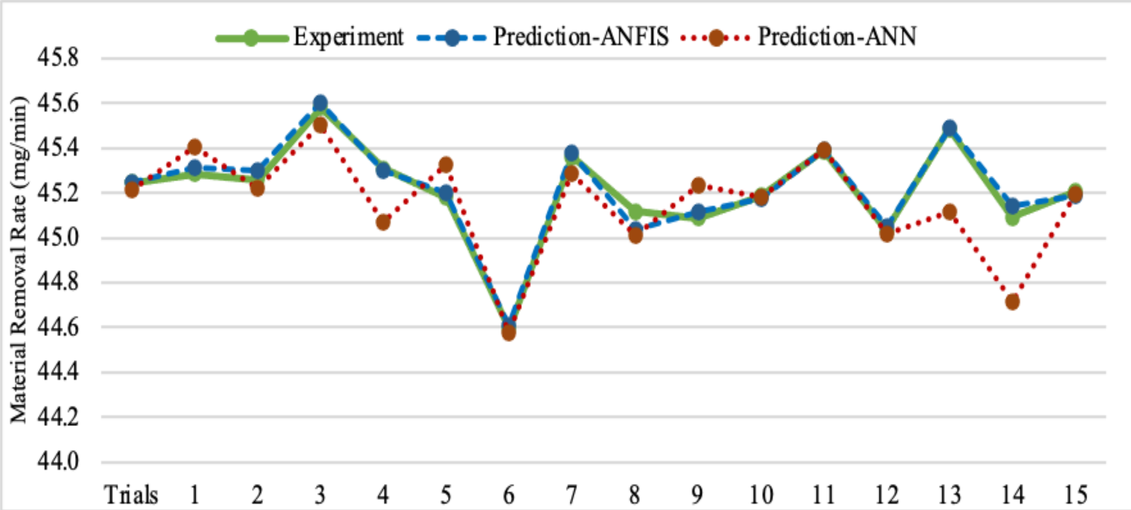

Figure 9. Comparison of experimental and predicted trials data set by the ANN and ANFIS models.

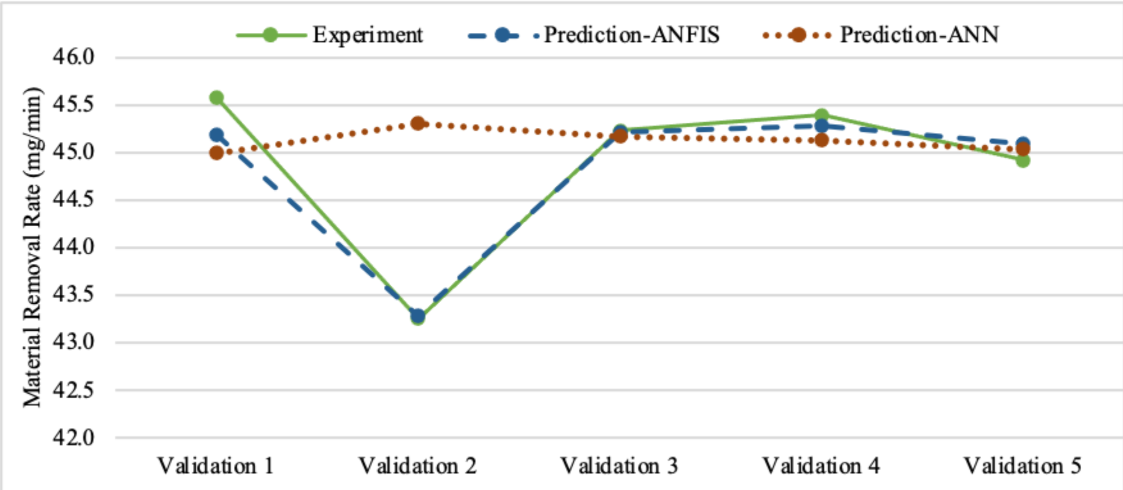

Figure 10. Comparison of experimental and predicted validation data set by the ANN and ANFIS models.

4. CONCLUSION

In this scholarly work, a comparative study between ANN and ANFIS has been performed for the evaluation of WEDT modelling on process performance to predict the MRR. The study begins with designing and performing the experimental works according to full factorial design that consists of 16 trials. The results of independent machining parameters including intensity of pulse, voltage open, tension of wire and rotational spindle speed are calculated over the weight differences for the MRR. Afterwards, dataset of the experimental results undergoes the training step for ANN and ANFIS to develop the ability to predict the MRR. The results of the performance assessment between ANN and ANFIS model in term predictive capability show that ANFIS model demonstrated high accuracy with residual error only at 0.039% compared to 0.13% for ANN model. Therefore, it can be concluded that ANFIS model is more accurate than ANN in modelling the machining process and reflect the advantages of combining fuzzy systems capabilities with neural networks.

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REFERENCES

[1] M.S. Kasim, C.H. Che Haron, J.A. Ghani; Advances in Materials and Processing Technologies, vol. **4**, no. 3 (2018) pp. 378–384.
[2] R. Azlan, R. Izamshah, M.S. Kasim, M. Akmal, & M. Nawi; International Journal of Applied Engineering Research, vol. **12**, no. 23 (2017) pp. 13506–13513.
[3] M.A. Ali, L. Suraya, H.I.K. Nor, et al., Applied Mechanics and Materials. vol. **465–466**, no. 1 (2014) pp. 1214–1218.
[4] N. Musa, J.B. Saedon, & M.S. Adenan, Journal of Mechanical Engineering, vol. **SI 8**, no. 1 (2019) pp. 130–139.
[5] W.N.F. Mohamad, M.S. Kasim, M.Y. Norazlina, M.S.A. Hafiz, R. Izamshah, & S.B. Mohamed, Results in Engineering, vol. **6** (2020) pp. 100101.
[6] Y. Sun, Y. Gong, Y. Liu, M. Cai, X. Ma, & P. Li, Archives of Civil and Mechanical Engineering, vol. **18**, no. 2 (2018) pp. 385–400.
[7] M. Akmal, R. Izamshah, & M.S. Kasim, "Cutting capabilities for macro-micro cylindrical shapes component by wire electrical discharge turning (WEDT)," in Proc. of Innovative Research and Industrial Dialogue, vol. 18, (2018) pp. 178–179.
[8] G.M. Naik & S. Narendranath, Journal of Mechanical Engineering and Biomechanics, vol. **2,** no. 2 (2017) pp. 8–14.
[9] M. Kanthababu, J.J.R. Jegaraj, & S. Gowri, International Journal of Manufacturing Technology and Management, vol. **30**, no. 3–4 (2016) pp. 216–239.
[10] R. Izamshah, M. Akmal, M.A. Ali, & M.S. Kasim, Advances in Materials and Processing Technologies, vol. **4**, no. 2 (2017) pp. 281–295.
[11] R. Izamshah, M. Akmal, M.S. Kasim, M.K. Sued, S.A. Sundi, & M. Amran, Journal of Advanced Manufacturing Technology (JAMT), vol. **12**, no. 1 (2018) pp. 1–12.
[12] J. George, J. Mathew, & R. Manu, Arabian Journal for Science and Engineering, vol. **45** (2020) pp. 5109-5127.
[13] S. R. Prakash, K. Rajkumar, & G. Selvakumar, "Pulse and work revolution parameters of wire electrical discharge turning on Ti-6Al-4V Alloy," In: M.S. Shunmugam and M. Kanthababu, Eds. Advances in Unconventional Machining and Composites, Lecture Notes on Multidisciplinary Industrial Engineering. pp. 611–620. Springer Singapore (2020).
[14] N. Yusof, B. Bais, N. Soin, J. Yunas, & B.Y. Majlis, Indonesian Journal of Electrical Engineering and Computer Science, vol. **15**, no. 1 (2019) pp. 113–121.
[15] M.F. Jaafar, M.S. Salleh, R. Izamshah, et al., International Journal of Mechanical & Mechatronics Engineering, vol. **19**, no. 1 (2019) pp. 43–56.
[16] M.S.A. Hafiz, M.S. Kasim, R. Izamshah, W.N.F. Mohamad, A. Abdullah, & M.F. Jaafar, The International Journal of Advanced Manufacturing Technology, vol. **105**, no. 7–8 (2019) pp. 3157–3163.
[17] N. M. Tuan, N. Q. Tuan, & T.T. Long, Journal of Mechanical Engineering Research and Developments, vol. **44**, no. 1 (2021) pp. 41-49.
[18] B.N. Asyirah, Z. Shayfull, S.M. Nasir, M. Fathullah, & M.H.M. Hazwan, "Optimisation of warpage on thin shell plastic part using response surface methodology (RSM) and glowworm swarm optimisation (GSO).," In: AIP Conference Proceedings (2017) pp. 1–11.
[19] O. F. Abdulateef, Journal of Mechanical Engineering Research and Developments, vol. **43**, no. 4 (2020) pp. 360-366.
[20] M.A.M. Zakaria, R.I.R. Abdullah, M.S. Kasim, & M.H. Ibrahim, EMITTER International Journal of Engineering Technology, vol. **7**, no. 1 (2019) pp. 261–274.

[21] S. Azmi, B. Mohd, R.M. Najib, & A.H. Saidin, "Prediction of titanium workpiece qualities machined by EDM die sinking using neural network," In: 4th National Conference on Research and Innovation, Perlis. (2018) pp. 1–7.

[22] M.R. Jamli & S. Fonna, Journal of Advanced Manufacturing Technology (JAMT), vol. **12**, no. 1 (3) (2018) pp. 153–164.

[23] S. A. M. Hashim, A. Z. Zainudin, & M. Kanagaraj. Politeknik Kolej Komuniti Journal Engineering Technology, vol. **4**, no. 1 (2019) pp. 159–171.