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Prediction of Response in R-μEDM Process using Adaptive Neuro-based Fuzzy Inference System (ANFIS) Model

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Abstract

In this study, an adaptive neuro-based fuzzy inference system (*ANFIS*) has been proposed to model a relationship between machining parameters such as voltage, feed rate, capacitance and response parameter such as *'deviation in length'*. The present work uses the results of the experiment carried out on Reverse-*μEDM* (*R- μEDM*) reported in a particular literature. In this literature the diameter of the bulk rod has been reduced to *212 μm* with the help of tool electrode made of copper plate. Thereafter, developed *ANFIS* model (offline prediction method) has been used to predict the unknown parametric conditions. The predicted results of the *'deviation in length'* are closely correlated with the experimental results. The statistical indicators such as R^2, *RMSE*, *MAPE* and *Cov* are found to be *0.9727*, *16.0405*, *21.6690* and *17.6269* respectively. The results prove that the *ANFIS* can be applied successfully in the response parameter of Reverse-*μEDM* such as *'deviation in length'*.

Keywords: Micro *EDM*, Fuzzy Logic, Modelling, Neural Network, *ANFIS*, Micro-rod.

1. INTRODUCTION

Recent development in micro-manufacturing processes uses miniaturized parts and components within the range of *1-500 μm*. This miniaturized parts & components offer unique advantages in terms of efficient use of space, energy & material requirements. This uniqueness contributes a lot in the field of micro-machining. Micro-manufacturing finds its wide applications in producing dies, punches, injection moulds, surgical components, electronic & domestic appliances, finishing components for aerospace and automobile industries [1].

Micro Electrical Discharge Machining (*μEDM*) is a process, where a material is eroded from the workpiece through the use of a series of high-frequency discrete spark created when both the tool and the workpiece electrode are dipped inside a liquid dielectric solution. Reverse-*μEDM (R-μEDM),* the variant of *μEDM,* works on the same principle as that of *μEDM*. It works on reverse polarity where workpiece (metal rod*)* is connected to the spindle through collet with anode (positive terminal), and the tool electrode is kept on the worktable, is attached to the cathode (negative terminal) [2]. *R-μEDM* has the ability to fabricate components with multiple micro features and high aspect ratio micro structures [3]. Singh et al. have done experimentation with the use of Taguchi based design of experiment *(DOE)* technique for machining microtool using *R-μEDM* and investigated the effect of machining parameters on the various response measures [4]. The effect of tool wear on fabricated microrods using *R-μEDM* on both the obtained length of the arrayed microrods and over the diameter along the machined surface has been investigated with different levels of process parameters such as voltage, feed rate and capacitance [5].

Literature shows that the exact mechanism of the material removal from the workpiece during sparking process is still controversial, even though the existence of well-known physical laws [6, 7]. This is the reason why the modelling or correlating of process parameters with response measures is difficult to establish accurately. Tsai et al. [7] have concluded in their research that *μEDM* parameters have been modelled accurately with *ANFIS*, even though *μEDM* is well-known for its stochastic and complicated nature. Suganthi et al. have designed *ANFIS* model and made an attempt to establish a relationship between the input parameters like feed rate, capacitance, gap voltage and threshold value on output responses such as metal removal rate, surface roughness and tool wear ratio. They observed that *ANFIS* based model outperforms the *ANN*-based model, in predicting the various response measures [8]. Maher et al. have used *ANFIS* model to develop an empirical model for modelling the relationship between the predictor variables including peak current *(IP),* pulse on time *(Ton),* and wire tension *(WT)* and machining performance parameters including cutting speed *(CS),* surface roughness *(Ra),* and heat affected zone *(HAZ)* [9]. Caydas et al. presented the use of *ANFIS* method based on the full factorial experimentation for predicting surface roughness and white layer thickness *(WLT)* in the *WEDM* process [10]. ANFIS has also been applied successfully in others areas of research. Soft computing technique like ANFIS has successfully demonstrated its learning and predicting potential for the stock market return prediction on the Istanbul Stock Exchange (ISE) National 100 Index [11]. Wang and Elhag [12] have developed an ANFIS model for bridge risk assessment to judge maintenance priority ranking of bridge structures using if-then rules between bridge risk scores and risk ratings. Anfis model has shown assurance for differentiating between normal and glaucomatous eyes using Stratus OCT data [13].

The present paper objective is to model a *R-μEDM* process, which is the extension work carried out by Singh et al. [4] where authors performed an experimental investigation on different levels of process parameters over response measures. In this particular study, experimental data of the above work is used, and focus has been made to develop an adaptive neuro-based fuzzy interface system *(ANFIS)* for the prediction of response parameter such as *'deviation in length'* of the fabricated micro-rods. Later, the developed model has been used to predict the response parameter and compared it with the experimental results. Voltage, feed rate, and capacitance have been used as machining parameters and 'deviation in length' as response parameter.

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2. METHODOLOGY

The experimental data that has been taken in this study are based on Taguchi design of experiment (*DOE*) reported in the literature by Singh et al. [4]. The different levels of machining parameters and response measure which have been considered are shown in Table 1.

Table 1: Process Parameters and response measure

Variable Parameters	Levels	Values
Capacitance (*pF*)	2	100, 1000
Voltage (*V*)	4	80, 100, 120, 140
Feed rate (*µm/sec*)	4	5, 10, 15, 20
Fixed Parameters		
Workpiece electrode	Tungsten rod of diameter *800 µm*	
Tool electrode	Copper plate having *293 µm* thickness and pre-drilled micro hole of *212 µm* diameter	
Dielectric fluid	Hydrocarbon oil	
Response Measure	Deviation in length	

3. Adaptive neuro-fuzzy inference system (ANFIS)

Application of Artificial Intelligence is impressive virtually in all the field of manufacturing. It is determined from the literature that, it is very difficult to understand the complete physical mechanism/phenomena of the *µEDM* process. An attempt has been made to develop a model based on given input and output using *ANFIS* as shown in Fig. 1, where *ANFIS* model is trained by training data, and then the prediction of the dynamic response parameter has been made. *ANFIS* architecture in case of two inputs, x and y, and one output is shown in Fig. 2.

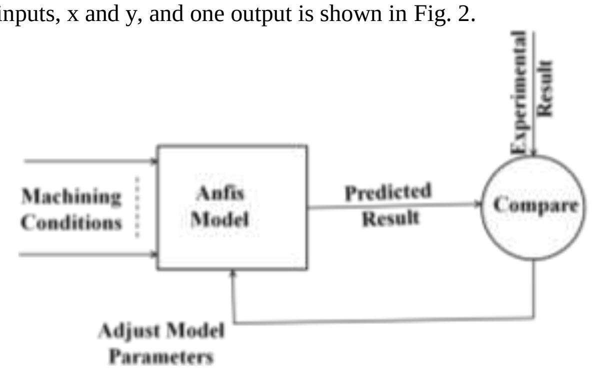

Fig. 1 Model block diagram

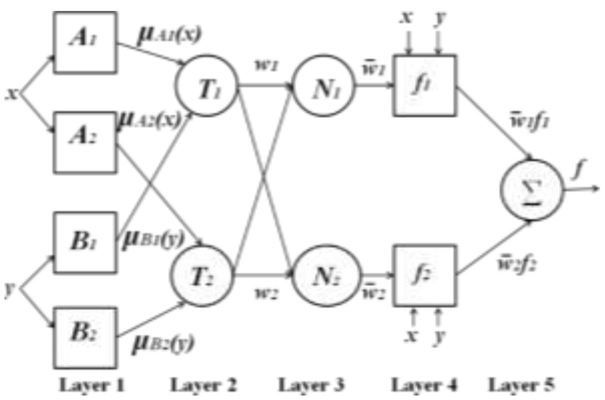

Fig. 2 Architecture of ANFIS model for R-µEDM process.

4. RESULTS AND DISCUSSION

For establishing the correlation or mathematical modelling between input and output, *ANFIS* approach has been used. To train the *ANFIS* model, the experimental data set with their response values are used which is taken from the research work of Singh et al. [4]. Triangular *(trimf)*, Trapezoidal *(trapmf)*, simple Gaussian curve *(gaussmf)*, two-sided composite of two different Gaussian curve *(gauss2mf)*, two sigmoidal *(dsigmf)*, or generalized bell *(gbellmf)* membership function are used as input membership function, where output membership function is linear and constant. Each input parameter consists of 2, 3, or 4 numbers of same membership functions at a time with linguistic term such as Low *(L)*, High (H), or Low *(L)*, Medium *(M)*, High *(H)*, or Very low *(VL)*, Low *(L)*, High *(H)*, Very high *(VH)* respectively. As the number of same membership function increases or decreases for a particular model, then there is an increase or decrease in the number of rules, which is the order of *8, 12, 18, 27, 36 and 64*. Output membership function is incorporated with each of the different combination of membership function and number of rules. For generating/constructing the fuzzy inference system *(FIS)* with the help of input and output data set, grid partition method has been used. Hybrid learning algorithm which consists of a mixture of backpropagation algorithm and least squares method has been used for tuning the *FIS*. Actual, it tunes or adjusts the membership function parameters during the training. Total *72 ANFIS* model has been developed, after considering the combination which includes type of input and output membership function and a number of rules.

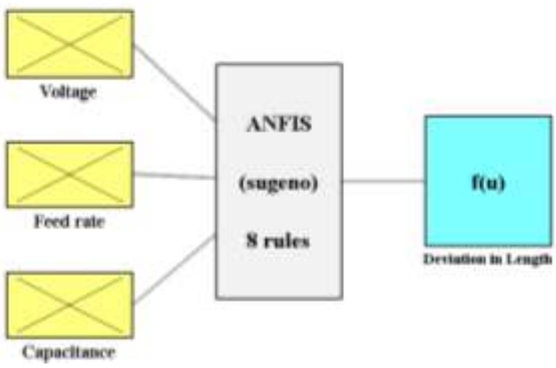

Fig. 3 Block diagram of ANFIS Editor

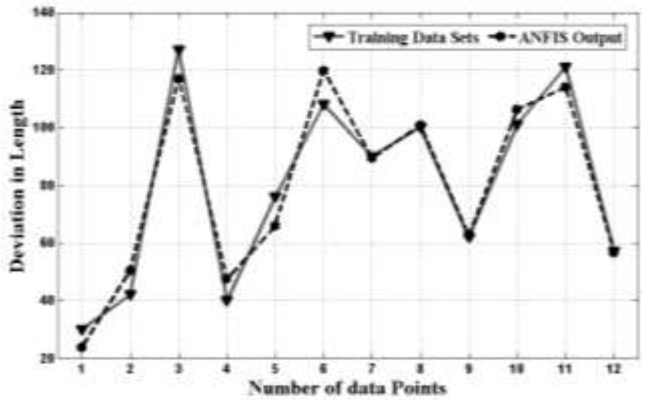

Fig. 4 Training data sets Vs ANFIS outputs

Four datasets of input parameters have been selected randomly from the paper of Singh et al. [4] for predicting the response measure using the developed *ANFIS* models. Thereafter comparison of predicted response measure *(P)* has been made with the experimental response measure *(E)*. To check the performance of the model, several criteria are used which is shown below.

(1) *R-Square (R^2)*:

where n is the number of data associated with the response measure.

(2) *Root Mean Square Error (RMSE)*:

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n} (E - P)^2}{n}}$$

(3) Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{\sum_{m=1}^{n} \left| (E - P)/E \right|}{n} X\ 100$$

(4) Coefficient of variation (Cov):

$$Cov = \frac{RMSE}{\left| \bar{E} \right|} X\ 100$$

Performance of the each *ANFIS* model has been presented in Table 2. From Table 2, it is observed that the triangular and constant are the input and output membership function respectively with *8* number of rules provide betters result based on the training error. Block diagram of the ANFIS Editor which consists of three inputs and one output with 8 rules is shown in Fig. 3 and the corresponding training error (trend of training data sets Vs ANFIS outputs) which is found to be 6% in this model is shown in Fig. 4. For validation, four experimental data sets have been use for prediction using selected ANFIS model and the corresponding plotting which shows the comparison between experimental data and predicted data is presented in Fig. 5.

Table 2: ANFIS result on different input and output function with different no. of rules

		No. of	Linear				Constant			
		Rules	R^2	RMSE	MAPE	Cov	R^2	RMSE	MAPE	Cov
Inputs Membership Types	Trimf	8	0.8636	35.8550	40.4292	39.4011	**0.9727**	**16.0405**	**21.6690**	**17.6269**
		12	0.9489	21.9365	27.1032	24.1060	0.8955	31.3841	39.7213	34.4880
		18	0.8621	36.0520	42.7657	39.6176	0.8621	36.0520	42.7657	39.6176
		27	0.9525	21.1575	26.6489	23.2500	0.8621	36.0520	42.7657	39.6176
		36	0.9525	21.1558	26.6431	23.2482	0.8621	36.0520	42.7657	39.6176
		64	0.8621	36.0520	42.7657	39.6176	0.8621	36.0520	42.7657	39.6176
	Trapmf	8	0.9522	21.2301	26.4764	23.3297	0.9712	16.4877	22.0799	18.1183
		12	0.9462	22.5225	27.9649	24.7500	0.9534	20.9670	25.0748	23.0407
		18	0.8621	36.0520	42.7657	39.6176	0.8621	36.0520	42.7657	39.6176
		27	0.8621	36.0520	42.7657	39.6176	0.8621	36.0520	42.7657	39.6176
		36	0.8621	36.0520	42.7657	39.6176	0.8621	36.0520	42.7657	39.6176
		64	0.8621	36.0520	42.7657	39.6176	0.8621	36.0520	42.7657	39.6176
	Gaussmf	8	0.9366	24.4443	22.0826	26.8619	0.9275	134.7786	183.0123	148.1084
		12	0.9424	23.3000	29.5725	25.6044	0.9534	20.9673	25.0746	23.0410
		18	0.9465	22.4644	28.9418	24.6862	0.9513	21.4129	27.0086	23.5307
		27	0.9445	22.8699	29.3871	25.1318	0.9510	21.4841	27.1699	23.6089
		36	0.9501	21.6852	28.3273	23.8299	0.9525	21.1550	26.7524	23.2472
		64	0.9524	21.1790	27.1337	23.2736	0.9524	21.1717	26.7322	23.2656
	Gauss2mf	8	0.9521	21.2481	26.4082	23.3495	0.9682	17.3002	18.4147	19.0113
		12	0.9462	22.5177	27.9459	24.7447	0.9534	20.9670	25.0748	23.0407
		18	0.9525	21.1670	26.6609	23.2605	0.9524	21.1785	26.6091	23.2730
		27	0.9524	21.1743	26.6728	23.2685	0.9524	21.1790	26.6100	23.2736
		36	0.9525	21.1574	26.6457	23.2499	0.9524	21.1778	26.6082	23.2723
		64	0.9525	21.1535	26.6469	23.2456	0.9524	21.1778	26.6082	23.2723
	dsigmf	8	0.9522	21.2268	26.5142	23.3261	0.9706	16.6518	22.1161	18.2987
		12	0.9461	22.5340	27.9750	24.7626	0.9534	20.9529	25.0411	23.0252
		18	0.9524	21.1791	26.6822	23.2738	0.9523	21.1985	26.6426	23.2950
		27	0.9524	21.1790	26.6806	23.2737	0.9523	21.1985	26.6426	23.2950
		36	0.9525	21.1540	26.6577	23.2461	0.9524	21.1761	26.6157	23.2705
		64	0.9525	21.1490	26.6728	23.2406	0.9524	21.1759	26.6166	23.2702
	gbellmf	8	0.9501	21.6878	25.6221	23.8328	0.1846	105.6627	141.5550	116.1129
		12	0.9438	23.0079	28.8403	25.2834	0.9534	20.9637	25.0756	23.0371
		18	0.9538	20.8565	25.9892	22.9192	0.9602	19.3739	17.7063	21.2900
		27	0.9535	20.9454	26.1849	23.0169	0.9593	19.5750	16.9439	21.5110
		36	0.9523	21.1994	26.2937	23.2960	0.5752	63.2768	60.8762	69.5349
		64	0.9479	22.1621	24.4525	24.3539	0.8233	40.8129	33.6976	44.8494

The model is considered to be better if the statistical value like *RMSE*, *MAPE*, *Cov* approaches zero and R^2 value approaches one. The predicted results R^2, *RMSE, MAPE and Cov* associated with the selected *ANFIS* model are *0.9727, 16.0405, 21.6690 and 17.6269* respectively are shown in Table 2. Based on the performance of the model, it can be said that the *ANFIS* is an appropriate technique for the prediction of *µ-EDM* parameters. Variation of Deviation in Length Vs feed rate and voltage is shown in Fig. 6. Results show that deviation in length increases with increase in voltage and feed rate.

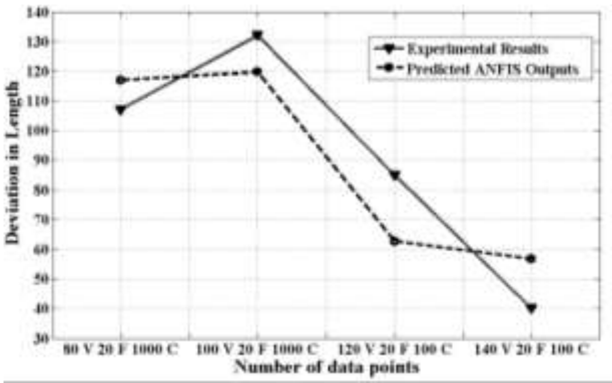

Fig. 5 Experimental results Vs Predicted ANFIS outputs

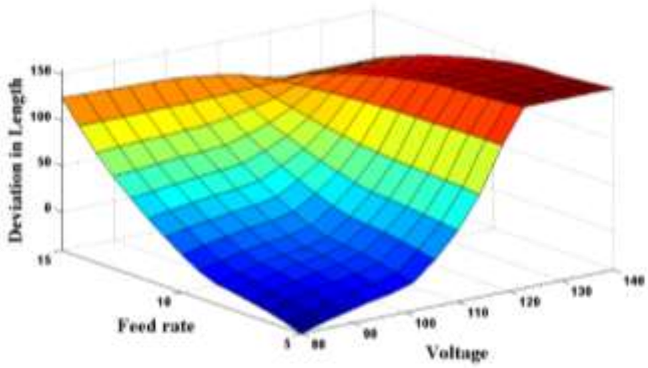

Fig. 6 Variation of “Deviation in Length” with the variation of feed rate and voltage

5. CONCLUSION

In the present study, authors have proposed an *ANFIS* model in order to provide an accurate relationship between machining parameters such as voltage, feed rate, and capacitance, and response parameter like *‘deviation in length’* for fabrication micro-tool using *R-µEDM*. The *ANFIS* model with triangular input membership function and constant output membership function with *8* rules outperforms the other *ANFIS* models used in the study. The results of the best *ANFIS* model in terms of R^2, *RMSE, MAPE, and Cov* are *0.9727, 16.0405, 21.6690 and 17.6269* respectively. It is seen from the results that the proposed *ANFIS* based model performs well and can be used for accurate prediction in case of machining micro rod using *R-µEDM*.

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