Preprints, 8th Vienna International Conference on Mathematical Modelling
February 18 - 20, 2015. Vienna University of Technology, Vienna, Austria

Improve wire EDM performance at different machining parameters – ANFIS modeling

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Abstract: This study presents an experimental investigation of wire electric discharge machining (WEDM) for improving the process performance. The effects of the machining parameters were investigated on the machining performance. Adaptive neuro-fuzzy inference system (ANFIS) was applied to determine the effect of significant parameters on WEDM performance. In addition, ANFIS was used to predict the cutting speed, surface roughness and heat affected zone in WEDM. The predicted cutting speed, surface roughness, and heat affected zone were compared with measured data, and the average prediction error for cutting speed, surface roughness, and heat affected zone were 3.41, 3.89, and 4.1 respectively.

Keywords: WEDM, Cutting speed, Surface roughness, Heat-affected zone, ANFIS

1. INTRODUCTION

Wire electrical discharge machining (WEDM) is an electro-thermal machining process for conductive materials. A metal wire electrode with de-ionized water is used to machine metal by the heat produced from electrical sparks. WEDM is able to machine complicated and precision parts for hard conductive materials (Sommer and Sommer, 2013, Maher et al., 2014c). WEDM is used to machine variety of materials for modern tooling applications. Besides that, WEDM is used to machine modern composite materials (Ho et al., 2004).

WEDM is a complex machining process controlled by a large number of process parameters. Any slight variations in one of the process parameters can affect the machining performance measures such as surface roughness and cutting rate. The most effective machining strategy is determined by identifying the different factors affecting the WEDM process, and seeking the different methods of obtaining the optimal machining condition and performance (Huang et al., 1999).

Several efforts have been made to determine optimal machining conditions for improving the productivity and achieving high quality via increase cutting rate and improve surface quality (Barzani et al., 2015). Nourbakhsh et al. (Nourbakhsh et al., 2013) studied the effect of injection pressure, servo reference voltage, time between two pulses and pulse width on surface integrity, wire rupture and cutting speed. They revealed that the cutting speed increases as pulse width increases. The surface roughness decreases as time between two pulses decreases. Besides that, experimental investigation of the effects of cutting parameters on surface roughness for the 1040, 2379 and 2738 steel material types have been successfully carried out and practical results for the WEDM process have been obtained (Gökler and Ozanözgü, 2000). Moreover, the recast layer has been observed to occur under different spark erosion conditions and it has many pockmarks, globules, cracks, and micro cracks. (Tomlinson and Adkin, 1992). Many investigations were done by earlier researchers and they observed that this layer was obvious under all machining conditions, including when water is used as dielectric material (Ramasawmy et al., 2005, Kruth et al., 1995, Jangra et al., 2011).

To obtain low surface roughness and heat affected zone, low discharge parameters with high dielectric flushing rate are required. However, they lower the cutting rate in WEDM. This implies that high cutting rate with least surface defects is difficult to obtain in a single setting of process parameters. In order to achieve an efficient machining, mathematical modeling between input WEDM parameters and output performance characteristics should be available to the manufacturers.

Two kinds of approaches, theoretical and empirical, have been commonly used in modeling of WEDM process (Patil and Brahmankar, 2010). Owing to the simplified and unavoidable assumptions, the theoretical models yield large errors between predicted and experimental results. On the other hand, empirical models are limited to specific experimental conditions. Taguchi method and response surface methodology (RSM) are the most used statistical techniques for determining the relationship between various input parameters and output responses (Hewidy et al., 2005, Myers and Anderson-Cook, 2009, Bobbili et al., 2013). Besides that, feed forward neural network was used to model the process and correlate the input parameters with the performance measures (Tarng et al., 1995). Moreover, ANFIS was used to model the process for predicting the machining performance (Çaydaş et al., 2009, Maher et al., 2014b, Maher et al., 2014a).

ANFIS is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can be used to construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and predetermined input-output data pairs for neural networks training. It provides a means for fuzzy modeling to learn information about the data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data (Maher et al., 2006).

Because the WEDM involves a lot of machining parameters and multi-performance characteristics, the objective of the present study is to investigate the effects of three machining parameters including peak current, pulse on time, and wire tension and develop ANFIS model for improve the three performance characteristics namely cutting speed, surface roughness, and heat affected zone for AISI 1050 carbon steel.

2. EXPERIMENTAL WORK

The machining parameters including peak current (IP), pulse on time (Ton), and wire tension (WT) were chosen in this study to investigate the effect on machining performance including cutting speed (CS), surface roughness (Ra), and heat affected zone (HAZ). Two machining parameters with three levels and one machining parameter with two levels were chosen according to machining recommendations as shown in Table 1. The other machining parameters were kept constant as a fixed value during experiments to optimize the process as gape voltage = 21volts; pulse off time = 2μs; flush pressure = 14kgf/cm²; water resistivity = $6x10^4$Ω.cm; and wire speed = 3m/min.

Table 1. Levels of machining parameters

Machining parameter	Levels		
	1	2	3
Pulse on time (μs)	0.15	0.20	0.25
Wire tension (g)	300	350	400
Peak current (A)	16	17	-

The experiments were performed using Computer numerical control (CNC) Sodick A500W WEDM machine tool. Hard brass wire with a diameter of 0.2 mm and tensile strength of 1000 N/mm² was used for machining blocks of AISI 1050 carbon steel under specific machining conditions. The raw material with dimension (100x60x25) mm is machined into dimension (5x5x25) mm for each specimen. The chemical compositions of AISI 1050 carbon steel are illustrated in Table 2. The electrical resistivity and thermal conductivity of AISI 1050 carbon steel are $1.63x10^{-5}$ Ω·cm and 49.8 W/ (m·K) respectively.

The CS is recorded directly from the WEDM machine tool monitor. The Ra was measured with a stylus-based profilometers (Mitutoyo SJ-201, 99.6% accuracy). Scanning electron microscope (SEM) is used to examine the surface characteristics of the machined part and used to measure the HAZ thickness.

Table 2. Chemical compositions of AISI 1050 carbon steel

Element	C	Mn	P	S	Fe
Weight, wt (%)	0.47-0.55	0.6-0.9	≤0.04	≤0.05	98.46-98.92

The average CS was calculated from the three-recorded data under the same conditions. The average Ra was calculated for three different measurements under the same conditions with a sampling length of Lc=2.5 mm at a specific area of the workpiece. The average HAZ thickness was calculated from three measurements using ESM. Eighteen sets of data were used for training ANFIS, as summarized in Table 3.

Table 3. Measured CS (mm/min), Ra (μm), and HAZ (μm) at different machining conditions

Machining parameters			Performance characteristics		
IP	Ton	WT	CS	RA	HAZ
16	0.15	300	0.59	2.46	10.23
		350	0.58	2.4	9.36
		400	0.63	2.36	9.89
	0.2	300	0.67	2.59	16.72
		350	0.69	2.51	16.79
		400	0.69	2.43	17.55
	0.25	300	0.84	2.85	19.44
		350	0.83	2.79	19.22
		400	0.85	2.72	19.44
17	0.15	300	0.82	2.52	13.35
		350	0.79	2.48	12.66
		400	0.79	2.45	12.69
	0.2	300	0.93	2.66	18.73
		350	0.96	2.59	19.16
		400	0.98	2.54	19.10
	0.25	300	1.1	2.90	20.84
		350	1.12	2.85	21.63
		400	1.13	2.76	21.76

3. ANFIS MODELING AND DISCUSSIONS

ANFIS is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can be used to construct an input–output mapping based on human knowledge as fuzzy if-then rules as well as predetermined input–output data pairs for neural network training. It provides a means for fuzzy modeling to learn information about the data set in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input–output data (Zalnezhad et al., 2013, Jang et al., 1997).

ANFIS was constructed through MATLAB, and 18 readings comprised the training data set as listed in Table 3. Different membership functions were used in training ANFIS. Two membership's functions of peak current and three membership functions of the other two parameters (pulse on time and wire tension) were chosen for creating the ANFIS model. The generalized bell membership function (gbellmf) gives the lowest training error of all performance measures, so it was adopted for the ANFIS training process in this study. The fuzzy rule architecture of ANFIS when gbellmf is adopted consists of 18 fuzzy rules generated from the input-output data set based on the Sugeno fuzzy model. During training, the 18 performance measure values were used to conduct 50 cycles of learning with an average error of 8.37×10^{-7}, 2.6×10^{-6}, and 1.5×10^{-5} for cutting speed, surface roughness, and heat affected zone respectively.

According to Fig. 1a, b pulse on time and peak current had considerable effect on cutting speed, while an increase in both pulse on time and/or peak current led to an increase in cutting speed, but wire tension had a minor effect on cutting speed. Increase pulse on time and peak current values are recommended for higher cutting speed. That is because the combination of pulse on time and peak current determine the spark energy and hence the amount of heat required to remove a specified volume of material. By increasing the pulse on time and peak current, large crater has to be cut per spark as shown in Fig. 2a, b; thus, the energy required is high. Consequently, this would increase the heat energy, leading to increase cutting speed (El-Hofy, 2005). The ANFIS model show that the maximum cutting speed is at the highest levels of peak current and pulse on time.

Figure 3a, b shows the effect of cutting parameters on the surface roughness based on ANFIS model. The surface roughness increases as peak current and pulse on time increase, but minor changes as wire tension increases. The SEM micrographs at 1500-x magnification of the machined surface at the lowest and highest levels of peak current and pulse on time are shown in Fig. 4a, b. The SEM micrographs show that the surface roughness with the highest levels of peak current and pulse on time is higher than the lowest levels of peak current and pulse on time. This is because of the discharge energy increases with peak current and pulse on time. Hence, larger craters are produced and lead to larger surface roughness on the workpiece (Kumar and Agarwal, 2012). This can be proved by the theory that shown in Fig. 2a, b and equation (1) (El-Hofy, 2005).

$$hm\ \alpha\ (V\ IP\ Ton)^{1/3} \quad (1)$$

The effects of pulse on time, peak current, and wire preloading on heat affected zone are shown in Fig. 5a, b. Pulse on time and peak current had great effect on the heat affected zone, but wire tension had minor effect on heat affected zone, while the heat affected zone width increases with increasing pulse on time and/or peak current as shown in Fig. 5a, b. Figure 6a, b introduce SEM micrograph 3000-x magnification of the heat affected zone. This micrograph verify that; the maximum width of heat affected zone is at the highest levels of peak current and pulse on time and the less heat affected zone width is at the lowest values of pulse on time and peak current. This is because of the heat energy increases with peak current and pulse on time. Hence, larger heat is produced on the machined surface and lead to larger heat affected zone on the workpiece (Saha et al., 2008).

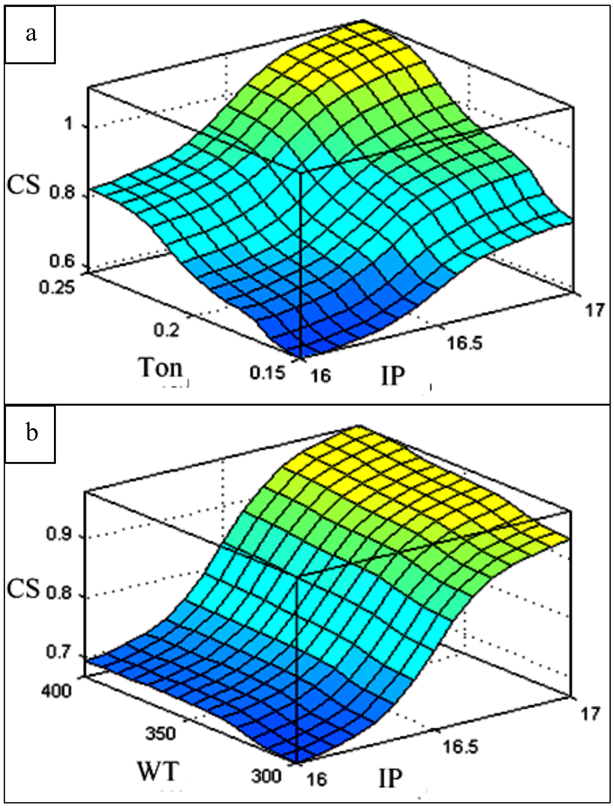

Fig. 1 The modeled cutting speed (CS) by ANFIS in relation to parameters change, a) CS in relation to change of Pulse on time (Ton) and peak current (IP), and b) CS in relation to change of wire tension (WT) and peak current (IP).

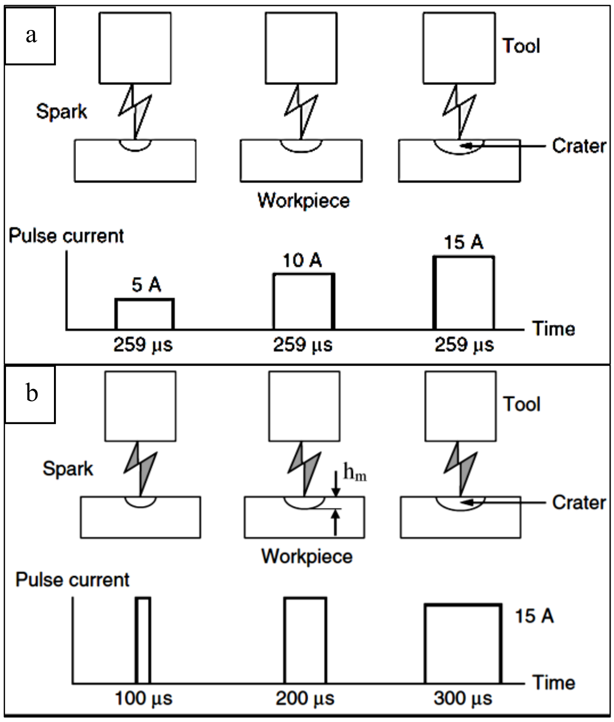

Fig. 2 Effect of spark energy on removal rate and surface roughness. a) Effect of pulse current on removal rate and surface roughness. b) Effect of pulse on time on removal rate and surface roughness.

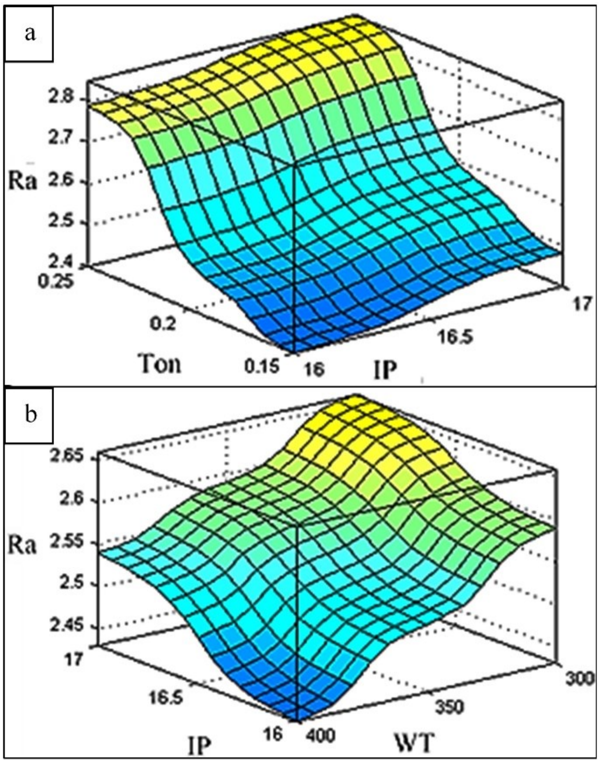

Fig. 3 The modeled Surface roughness (Ra) by ANFIS in relation to parameters change. a) Ra in relation to change of Pulse on time (Ton) and peak current (IP). b) Ra in relation to change of wire tension (WT) and peak current (IP).

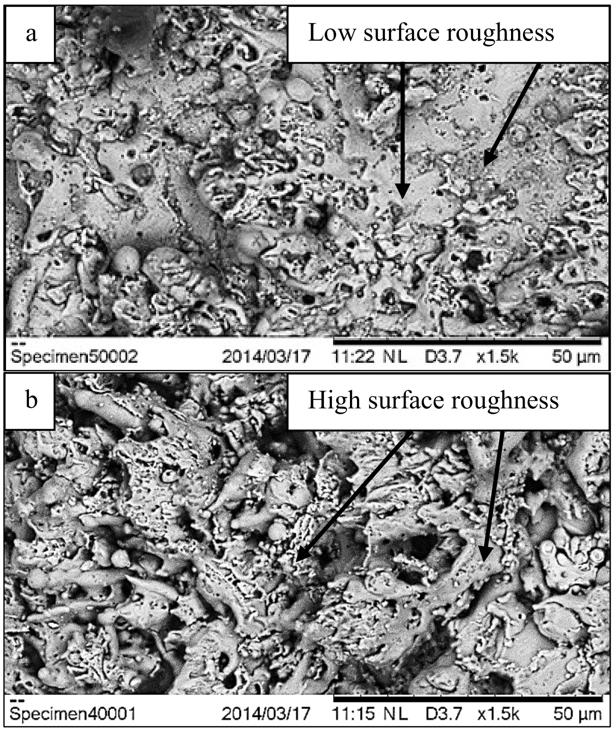

Fig. 4 SEM micrograph at different levels of spark energy. a) SEM micrograph at the lowest levels of peak current (IP=16A) and pulse on time (Ton=0.15µs). b) SEM micrograph at the highest levels of peak current (IP=17A) and pulse on time (Ton=0.25µs)

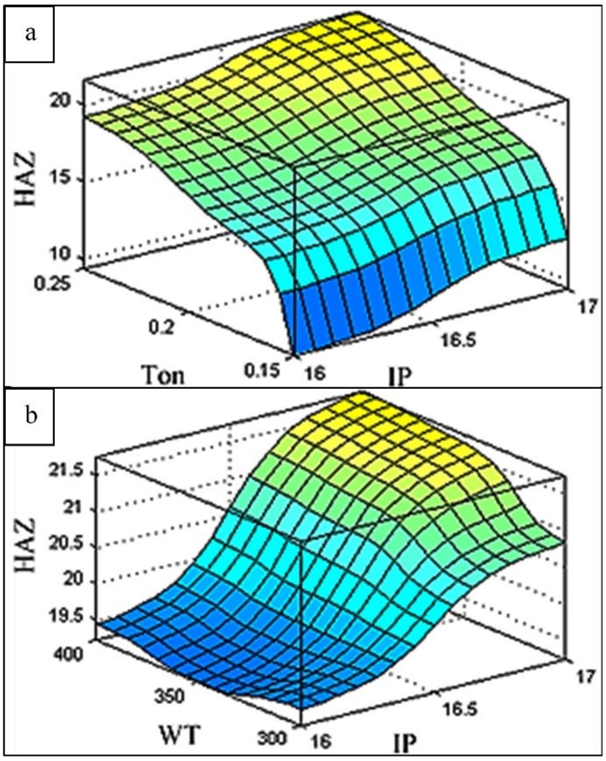

Fig. 5 The modeled Heat affected zone (HAZ) by ANFIS in relation to parameters change. a) HAZ in relation to change of Pulse on time (Ton) and peak current (IP). b) HAZ in relation to change of wire tension (WT) and peak current (IP).

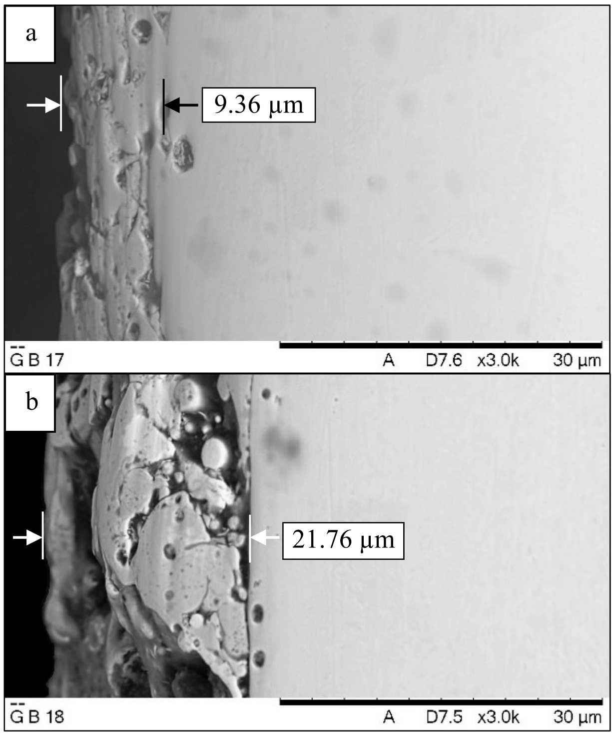

Fig. 6 SEM micrograph at different levels of spark energy. a) SEM for the lowest levels of peak current (IP=16A) and pulse on time (Ton=0.15µs). b) SEM micrograph for the highest levels of peak current (IP=17A) and pulse on time (Ton=0.25µs).

4. MODEL VERIFICATION

Four random readings were used as the testing data set. The measured CS, Ra, and HAZ values versus predicted values using the ANFIS model is shown in Table 4. The plot of four measured CS, Ra, and HAZ values versus predicted values using the ANFIS model is shown in Fig. 7. This figure presents a comparison of the measured and predicted CS, Ra, and HAZ of the testing data set of four following training using ANFIS. Appropriate assent is evident between the measured and predicted values. This close assent obviously displays that the ANFIS models can be used to predict the CS, Ra, and HAZ under consideration.

Table 4. Comparison of measured and predicted CS (mm/min), Ra (µm), and HAZ (µm) for the testing data set

Machining parameters			Performance characteristics						Error percent		
			Measured			ANFIS					
IP	Ton	WT	CS	Ra	HAZ	CS	Ra	HAZ	CS	Ra	HAZ
A	µs	g	m/min	µm	µm	m/min	µm	µm	E_i (%)		
16.5	0.175	325	0.79	2.39	17.41	0.762	2.53	16.6	3.54	5.86	4.65
		375	0.81	2.38	16.76	0.781	2.47	16.9	3.58	3.78	0.84
	0.225	325	0.90	2.85	18.49	0.941	2.79	19.6	4.44	2.11	6.00
		375	0.97	2.62	18.87	0.952	2.72	19.8	2.06	3.82	4.93
***E**$_{av}$*									**3.41**	**3.89**	**4.10**

To evaluate the Fuzzy model, the percentage error E_i and average percentage error E_{av} defined in Eqs. (2) and (3), respectively, were used.

$$E_i = \frac{|T_m - T_p|}{T_m} \times 100 \tag{2}$$

$$E_{av} = \frac{1}{m} \sum_{i=1}^{m} E_i \tag{3}$$

where E_i is the percentage error of sample number i; T_m is the measured value; T_p is the predicted value; i=1,2,3 is the sample number; and E_{av} is the average percentage error of m sample data. The obtained average percentage error is 3.41, 3.89, and 4.1 for CS, Ra and HAZ respectively. The low error level signifies that the CS, Ra, and HAZ results predicted by ANFIS are very close to the actual experimental results. The error values mean that the proposed model can predict CS, Ra, and HAZ satisfactorily.

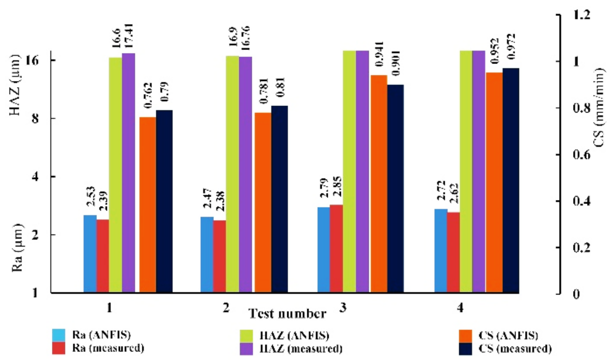

Fig. 7 Measured versus predicted CS, Ra, and HAZ

5. CONCLUSIONS

This study concludes that the peak current and pulse on time are the most significant parameters affecting the cutting speed, surface roughness and heat affected zone. The wire tension has minor effect on the cutting speed and heat affected zone but it has great effect on the surface roughness. ANFIS was successfully used to develop an empirical model for modeling the relation between the predictor variables (Ton, IP, and WT) and the performance parameters (CS, Ra, and HAZ). ANFIS model with gbellmf is accurate and can be used to predict cutting speed, surface roughness, and heat affected zone in wire electric discharge machining operation with average percentage errors 3.41, 3.89, and 4.1 respectively.

ACKNOWLEDGEMENTS

The authors acknowledge the financial support by the University Malaya Research Grant (Grant no.: (PPP) PG020-2013B) from the University of Malaya, Malaysia.

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