Modelling Titanium Machined Workpiece Qualities Using Fuzzy Logic

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Abstract

Titanium is an expensive material with superior qualities and preferred by manufacturing industries. The industries must consider machining operations and parameters selection to minimise the material waste and machining failure. Material waste related directly to machining operation used. Thus, EDM Die Sinking is the selected machining operation because of its extensive in reducing material waste. Moreover, machining failure which effected to machined workpiece qualities are associated with machining parameters. Furthermore, determining the machining parameter practically made by experienced machinist and is made by trial and error manner. Therefore, this paper aims to put forward Titanium workpiece qualities in relation to EDM Die Sinking machining parameters relation with Fuzzy Logic model. For comparison, ANN will also model the relation. The models development begins with data selection, modification, and composition. Then the selected models are designed with their features. Fuzzy Logic model features include selection of membership functions, feature range points for input-output, and fuzzy logic rules. In addition, for Neural Network model, Feed Forward Backpropagation Network is applied. Afterward, the network architecture and functions used is decided. Finally, the estimation performance of the models with various model designs are compared. Fuzzy Logic and ANN models best performance in estimating Surface Roughness is similar i.e. 83.3% detection rate. Fuzzy Logic with 97.2% detection rate is the best dimensional accuracy estimation performance. And the best dimensional accuracy estimation performance for ANN is 91.7%. The best performance model is substantial to the related industries because the model can reduce material waste and machining failure. Besides, the model simplified the parameters estimation and easy to new machinist.

Keywords: EDM die sinking, fuzzy logic, neural network

1.0 Introduction

Steel (St) usage great challenge in manufacturing industries is Titanium (Ti) material. Economic-wise, St is much cheaper material, approximately 2% of Ti price. But, quality-wise, Ti superior qualities seemly to widen manufacture product varieties. Ti superior qualities include almost as steel tough, 45% lighter than steel, good rigidity, and corrosion resistance (David & William, 2015). Thus, Ti usage is a better material selection than St, in manufacturing industries.

The use of Ti is limitless in the industries. Aerospace's Ti parts applied as firewalls, exhaust ducts, and aircrafts frames (Ahmed et al., 2014). Ti superior strength and light weight enable wider and bigger aircraft designs (Gudmundson, 2013). Rotor, compressor blade, nacelle, and hydraulic components are engine use example (Kalpakjian & Smith, 2014). Plus, user products include tennis racket, golf club, cookware, and frames for bicycle, spectacle, and firearms are made of Ti. Also, Ti is human body tolerant, is used for implant parts – dental, orthopaedic, hip-ball and joint replacement socket (Brunette et al., 2012). Ti corrosion resistance quality enables equipment to contact chemical e.g. tank, valve, and vessel (Lee et al., 2010). Also, this enable for marine applications, e.g. propeller shaft, rigging and salt water aquarium heater-chiller (Schneider et al., 2014). And in military, Ti is used for housing undersea surveillance devices (Thiollay et al., 2016) and submarine parts (Brandt & Panoch, 2015).

Economy-wise, Ti machining operation priority is the lowest material loss probability. Machining with forces e.g. CNC Lathe and CNC Milling, are off-interest in this study. The machining still has moderate product failure probabilities and high material losses. But this is advantageous for Electro Discharged Machining by Die Sinking (EDMDS). The machining is low in material losses, while machining. Besides, EDMDS is used no force in machining, resulted minimal product failure. Generally, workpiece qualities machined by EDMDS include surface roughness (SR), dimensional accuracy (DA), and surface quality. Surface qualities defined the heat-affected on surface layer – differ than surface roughness. Dimensional accuracy expressed the difference between the electrode and formed cavity size. These centered this study interest on EDMS machining.

By the correlation, machinist estimates machining features for required product's qualities. Thus, this is disadvantage to a new machinist to estimate the machining features. New machinist estimation common practice is through trial and error (Geetha et al., 2013 and Gupta & Jain, 2014). And, no record of the correlation, worsen this issue. Even, experienced machinist, take years to estimate well the features. Fortunately, numerical models provide the shortest and systematic way to estimate the correlation. Researchers correlate input-output features with number of numerical models. For instance, a well know model, i.e. Neural Network (Nahato et al., 2015; Mohd Hashim et al., 2017; Zain et al., 2010). Conventional numerical models also used to correlate the input-output. The models include Regression (Kovac et al., 2013), k-Nearest Neighbour (Mohd Hashim et al., 2016), and Naive Bayes Classifier (Mohd Hashim et al., 2016). Fuzzy logic is getting popular to model input-output correlation, e.g. Patchami et al. (2010) correlates process capability and production quality. Carrera & Mayorga (2008) correlates supplier criteria and new product development. Kovac et al. (2013) correlates product surface roughness and milling machine features. In a big scale, Pourghasemi et al. (2012) correlates landslide conditioning factors and susceptible areas. These are studies model multitude systems with Fuzzy Logic (FL).

This paper proposes models to correlate between machining and product quality features. The paper is dissimilar, though data are Singh & Singh (2011) tapped. Singh & Singh (2011) compares the Ti machining characteristics using Taguchi Method. And Singh & Singh (2011) used Analysis of Variance (ANOVA) to determine the optimum Ti machined qualities include Material Removal Rate, Tool Ware Rate, and SR, and DA.

The optimum Ti machined qualities are valid for 95% accuracy (Singh & Singh, 2011). In contrast, this paper model correlates numerically product qualities and machining features. The selected numerical model is Fuzzy Logic. And for performance comparison, Neural Network (ANN) models the correlation on similar dataset. These models are designed by replicating Singh & Singh (2011) data pattern.

The subsequent sections of this paper are as follows. Elaboration on input and output features use in this paper is in Section 2. Section 3 and section 4 highlights the numerical models – Fuzzy Logic and Neural Network. Result, discussion, and conclusion present in section 5 and 6.

2.0 Input and output features

EDM Die Sinking has too many features to set prior to machining. On electrical features, discharge voltage, peak current, average current, pulse on, pulse off, polarity, pulse frequency, duty factor, and spark gap must be set. And, deciding which non-electrical features include workpiece material, electrode material, dielectric type, and flushing pressure. Although, non-electrical features are few, but workpiece and electrode materials are many. Logically, workpiece and electrode are made of any electrically conductive material. Thus, these many features are considered disadvantaged for machining with EDMDS (Maher et al., 2015). To avoid cluttered with these many input features, hence only a few are selected. The rest features are set constant and not within this study. Thus, these features would not be discussed in this paper.

Table 1: The Modified Data

Sy.	Input Feature: Electrode Material – Current – Workpiece Material	Output Feature: SR	Output Feature: DA	Sy.	Input Feature: Electrode Material – Current – Workpiece Material	Output Feature: SR	Output Feature: DA
T01	NT Ti–2A–NT Ti	0.595	0.06	L07	CT Ti–2A–NT Ti	0.591	0.10
T02	NT Cu–6A–NT Ti	0.632	0.07	L08	CT Ti–4A–NT Ti	0.606	0.10
T03	NT CuCr–6A–NT Ti	0.631	0.07	L09	CT Ti–6A–NT Ti	0.622	0.09
T04	CT Cu–2A–NT Ti	0.597	0.09	L10	CT Cu–4A–NT Ti	0.612	0.10
T05	CT CuCr–4A–NT Ti	0.609	0.09	L11	CT Cu–6A–NT Ti	0.629	0.09
T06	NT Ti–2A–CT Ti	0.587	0.02	L12	CT CuCr–2A–NT Ti	0.594	0.10
T07	NT CuCr–4A–CT Ti	0.603	0.04	L13	CT CuCr–6A–NT Ti	0.627	0.09
T08	CT Ti–6A–CT Ti	0.633	0.05	L14	NT Ti–4A–CT Ti	0.599	0.04
T09	CT Cu–2A–CT Ti	0.607	0.04	L15	NT Ti–6A–CT Ti	0.618	0.04
T10	CT Cu–4A–CT Ti	0.623	0.05	L16	NT Cu–2A–CT Ti	0.593	0.03
T11	CT Cu–6A–CT Ti	0.638	0.05	L17	NT Cu–4A–CT Ti	0.605	0.03
T12	CT CuCr–4A–CT Ti	0.618	0.06	L18	NT Cu–6A–CT Ti	0.628	0.04
L01	NT Ti–4A–NT Ti	0.609	0.07	L19	NT CuCr–2A–CT Ti	0.591	0.03
L02	NT Ti–6A–NT Ti	0.628	0.07	L20	NT CuCr–6A–CT Ti	0.624	0.04
L03	NT Cu–2A–NT Ti	0.603	0.06	L21	CT Ti–2A–CT Ti	0.601	0.05
L04	NT Cu–4A–NT Ti	0.613	0.06	L22	CT Ti–4A–CT Ti	0.617	0.05
L05	NT CuCr–2A–NT Ti	0.599	0.06	L23	CT CuCr–2A–CT Ti	0.605	0.05
L06	NT CuCr–4A–NT Ti	0.612	0.07	L24	CT CuCr–6A–CT Ti	0.635	0.06

Note: Sy. – Symbol; Ti – Titanium; Cu – Cuprum; CuCr – Cuprum Cromium; NT – Non Treated; CT – Cryogenic Treatment; SR – Surface Roughness (μm); Dimensional Accuracy (mm); Example of supplied flow average current, 2A = 2 Ampere; Gray Color Highlight Line – Learning Dataset.
(Modified from: Singh & Singh, 2011)

The input features are electrode material, workpiece material, and average current. And, the selected output features are Dimensional Accuracy (DA) and Surface Roughness (SR). Talysurf measuring instrument measures the surface roughness. The SR is the average value of surface peak and base distance. DA measures the average difference of electrode diameter and workpiece cavity. Since electrode forms workpiece cavity, hence the lower DA the better quality. Electrode with 6mm diameter, forms circle cavity on workpiece, in this study. The features are tapped data from Singh & Singh (2011), shown in Table 1. Original data are modified by reducing input and output features. The electrode is made of Ti, Chromium-Cuprum, and Cuprum. These materials, are categorized into Non-treated and Cryogenic Treated. The workpiece is made of Ti and also classed into Non-treated and Cryogenic Treated materials. The average current applied is 2, 4, and 6 amperes. To consider all these inputs, L9 Taguchi Orthogonal Array (Singh & Singh, 2011) [Full Factorial] experimental design is applied. Based on the design the possible number of data is 36 (6 electrode material types × 2 workpiece material types × 3 levels of average current).

The aforementioned paragraph stated the use of FL and ANN models. The data in Table 1 must be designed according to the model's requirement. The first requirement is sufficient amount of data for the learning process. Previous researcher with 24 data is sufficient in estimating overview (Ioannis & Dimitrious, 2010; Zain et al., 2010; and Kant & Sangwan, 2015). Hence, 36 data in the study are above the lowest referred amount. Researchers divided data into learning and testing dataset. And 70%:30% are the preferred ratio between learning to testing dataset (Nahato et al., 2015 and Zahran et al., 2013). In this paper, learning dataset size is 24 (67%) and test dataset is 12 (33%). Besides, the learning dataset must have sufficient information that represents all input and output features (Natarajan et al., 2011). Logically, learning dataset must have association with testing dataset. Thus, good estimation can be achieved. For this, data is pre-process into L for learning and T for testing dataset. This separation for L and T classes are listed in Table 1.

3.0 Fuzzy logic

Fuzzy logic (FL) is an effective predictor compared to the conventional numerical model. Conventional model requires clear information to design the exact numerical model. Thus, huge analysis on data and related equations are compulsory. But FL is good in dealing indeterminate and unclear information. In addition, the model is not relying on the exact numerical model. Fuzzy Logic is distinguished by the use of specified linguistic. For example, 'bottom' and 'top' for specific descriptions.

$$R = \{R_1, R_2, R_3, \dots, R_n) \quad (1)$$

$$if\ X1 = C1\ AND\ X2 = T1\ AND\ X3 = W2\ THEN\ Y1 = L1\ AND\ Y2 = L2 \quad (2)$$

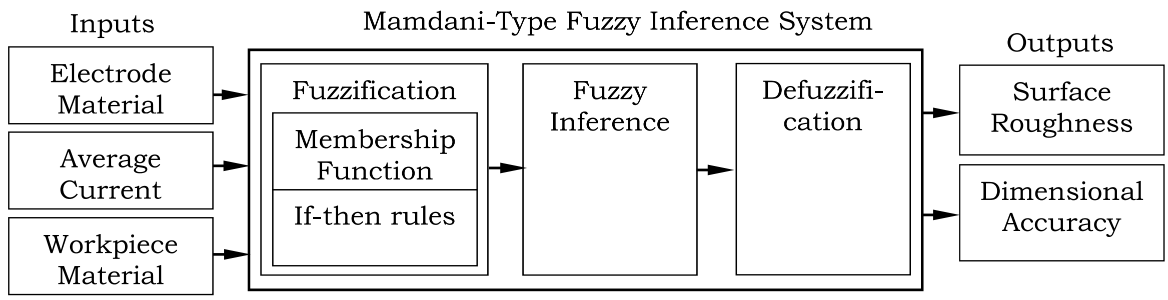
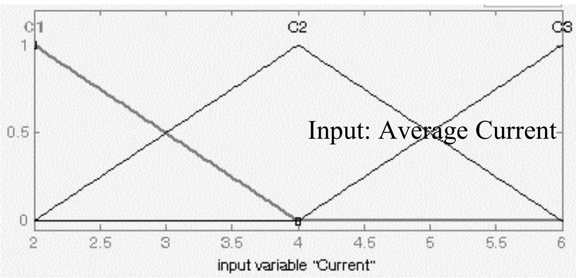
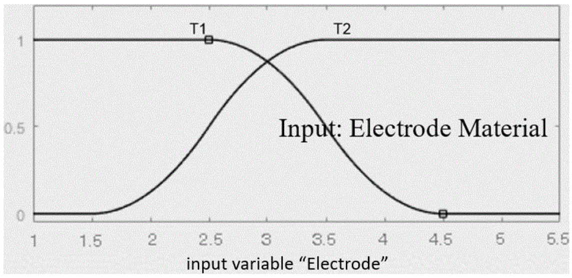


Figure 1: The fuzzy logic model

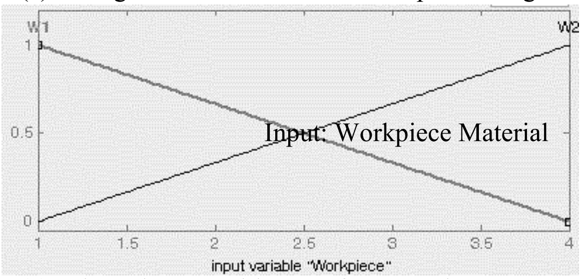
For the case of system with multiple inputs and multiple outputs. Knowledge based (R) contains n rule as in equation (1). Suppose, the n^th^ rule is in the form of equation (2). The variable such as $C1$, $W2$, and L2 are linguistic values. These space values, defined by fuzzy sets of X and Y accordingly. Ideally, the mapping of R and if-then rules, generate two outputs i.e. $L1$ and $L2$. Evaluation on all input-output if-then rules are inessential (Kovac et al., 2013). Lesser rules can be set, if this is done by experienced operator. Due to inexperience on the matter, detail if-then rules are applied in this study.



(a) Triangular MF with ± 2.0 feature points range



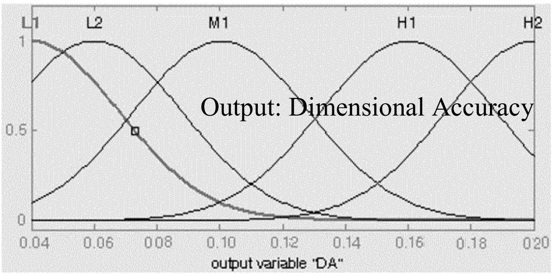
(b) Sigmodally-shape MF with ± 2.0 feature points range



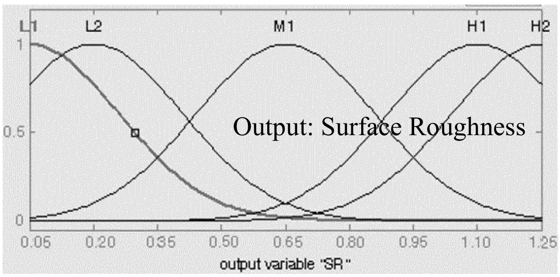
(c) Triangular MF with ± 3.0 feature points range

Note:
The feature point ranges referring to first and second half of the complete graph range. The clear picture is as in Figure 2(c). Half of the graph within the whole range of the figure.

The value range and the horizontal axis represent the value coded for the labels and features.



(d) Gaussian MF with ± 0.10 feature points range



(e) Gaussian MF with ± 0.6 feature points range

Figure 2: Membership function and feature range points applied to input and output features

This paper uses Mamdani-Type Fuzzy Inference System in modelling FL as in Figure 1. The model operates in three stages i.e. Fuzzification, Fuzzy Inference, and Defuzzification. Fuzzification stage is the setting of membership function (MF) and if-then rules. The samples of MF from each input and output feature show in Figure 2. The figure shows overlap of MF graphs with feature point range. For model's learning, it replicates the 24 set of if-then rule is shown in Table 2. This is based on data symbols with L01 to L24 as in Table 1. By fuzzy operators, MF graph spaces are mapped by this if-then rules. This mapping is operated by Fuzzy Inference. Then, the generated result is transformed into quantifiable output by Defuzzification.

The model is tested with testing dataset, i.e. T01 to T12 to generate two outputs.

The setting of MF numbers applied for each feature is labelled and listed in Table 3. The MF input based on number of features it refers to. The MF code is defined in number which set range as Figure 2. Meanwhile, the output is set into five conditions in Table 3. The low to high sequence is as follows L1, L2, M, H1, and H2. The range setting is based on the output values cover. These settings are shown in Figure 2(d), Figure 2(e), Table 2, and Table 3. Thus, all of these settings, required for 3645 numbers of tests.

Table 2: The rule of the fuzzy logic

	X1		*X2*		*X3*		*Y1*		*Y2*	
1	*if X1 =*	C1	*AND X2 =*	T1	*AND X3 =*	W2	*then Y1 =*	L1	*AND Y2 =*	L1
2	*if X1 =*	C1	*AND X2 =*	T2	*AND X3 =*	W2	*then Y1 =*	L2	*AND Y2 =*	L2
3	*if X1 =*	C1	*AND X2 =*	T3	*AND X3 =*	W2	*then Y1 =*	L2	*AND Y2 =*	L2
4	*if X1 =*	C1	*AND X2 =*	T1	*AND X3 =*	W1	*then Y1 =*	L2	*AND Y2 =*	M1
5	*if X1 =*	C1	*AND X2 =*	T2	*AND X3 =*	W1	*then Y1 =*	M1	*AND Y2 =*	M1
6	*if X1 =*	C2	*AND X2 =*	T2	*AND X3 =*	W1	*then*		*Y2 =*	M1
7	*if X1 =*	C1	*AND X2 =*	T3	*AND X3 =*	W1	*then*		*Y2 =*	M1
8	*if X1 =*	C2	*AND X2 =*	T6	*AND X3 =*	W1	*then*		*Y2 =*	M1
9	*if X1 =*	C3	*AND X2 =*	T6	*AND X3 =*	W2	*then Y1 =*	H2	*AND Y2 =*	M1
10	*if X1 =*	C3	*AND X2 =*	T4	*AND X3 =*	W1	*then Y1 =*	H1	*AND Y2 =*	H1
11	*if X1 =*	C1	*AND X2 =*	T5	*AND X3 =*	W1	*then*		*Y2 =*	H1
12	*if X1 =*	C3	*AND X2 =*	T5	*AND X3 =*	W1	*then*		*Y2 =*	H1
13	*if X1 =*	C2	*AND X2 =*	T6	*AND X3 =*	W1	*then*		*Y2 =*	H1
14	*if X1 =*	C3	*AND X2 =*	T6	*AND X3 =*	W1	*then Y1 =*	H1	*AND Y2 =*	H1
15	*if X1 =*	C1	*AND X2 =*	T4	*AND X3 =*	W1	*then Y1 =*	L2	*AND Y2 =*	H2
16	*if X1 =*	C2	*AND X2 =*	T4	*AND X3 =*	W1	*then Y1 =*	M1	*AND Y2 =*	H2
17	*if X1 =*	C2	*AND X2 =*	T5	*AND X3 =*	W1	*then*		*Y2 =*	H2
18	*if X1 =*	C1	*AND X2 =*	T6	*AND X3 =*	W1	*then Y1 =*	L2	*AND Y2 =*	H2
19	*if X1 =*	C2	*AND X2 =*	T2	*AND X3 =*	W2	*then Y1 =*	M1	*AND Y2 =*	L2
20	*if X1 =*	C1	*AND X2 =*	T6	*AND X3 =*	W2	*then Y1 =*	M1		
21	*if X1 =*	C3	*AND X2 =*	T1	*AND X3 =*	W1	*then Y1 =*	H1		
22	*if X1 =*	C3	*AND X2 =*	T2	*AND X3 =*	W2	*then Y1 =*	H1		
23	*if X1 =*	C2	*AND X2 =*	T5	*AND X3 =*	W2	*then Y1 =*	H1		
24	*if X1 =*	C3	*AND X2 =*	T5	*AND X3 =*	W2	*then Y1 =*	H2		

Table 3: Parameters applied to membership functions

Feature	Label / Name of Function	Feature Point Ranges As Code	Representation of Code	Membership Function
Average Current	C1 C2 C3	± 2.0; ± 4.0; ± 6.0;	2A, 4A, and 6A for Average Current values.	*Input:* Gaussian, triangular, and sigmodally-shape.
Electrode	T1 T4 T2 T5 T3 T6	± 1.0; ± 4.0; ± 2.0; ± 5.0; ± 3.0; ± 6.0;	Six types of electrodes.	
Workpiece	W1 W2	± 2.0; ± 3.0;	Two types of workpieces.	
Surface Roughness	L2 L1 H1 M H2	± 0.10; ± 0.30; ± 0.40; ± 0.50; ± 0.60; ± 0.70; ± 1.0;	Five levels of SR values.	*Output:* Gaussian, triangular, and sigmodally-shape.
Dimensional Accuracy	L2 L1 H1 M H2	± 0.02; ± 0.03; ± 0.05; ± 0.08; ± 0.10;	Five levels of DA values.	

4.0 Neural network

Selecting ANN networks set the whole stages of ANN model operation. Feed Forward Backpropagation (FFB) Network is selected since FFB recorded with high performances (Belkacem et al., 2017; Kant & Sangwan, 2015; and Natarajan et al., 2011). FFB algorithm learns by replicating data pattern. Replication involve evaluating the output difference value between generated and learning dataset. Based on the difference, a set of weights are generated to replicate data pattern. The generation of weights are repeated (Zain, et al., 2010) to generated the better set of weights. And the smallest difference ends this repetition, that also represent the weights are the best to replicate data pattern by producing the closest to actual output.

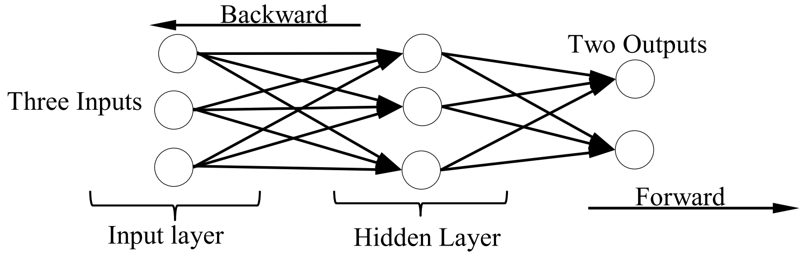


Figure 3: ANN model with Feed Forward Backpropagation Network and 3-3-2 Architecture

Besides, the network set of four functions must be selected – training, learning, performance, and transfer functions. The selected functions are shown in Figure 4. Based on the functions, 252 combinations of estimation tests are required. This is based on full factorial test, 14 Training Functions × 2 Learning Functions × 3 Performance Functions × 3 Transfer Functions. The number represents functions used for each function.

Training Function

- BFGS quasi-Newton backpropagation
- Bayesian regularization backpropagation
- Gradient descent backpropagation
- Resilient backpropagation
- One-step secant backpropagation
- Levenberg-Marquardt backpropagation
- Scaled conjugate gradient backpropagation
- Conjugate gradient backpropagation with Powell-Beale restart
- Conjugate gradient backpropagation with Fletcher-Reeves updates
- Conjugate gradient backpropagation with Polak-Ribiére updates
- Gradient descent with momentum backpropagation
- Gradient descent with adaptive learning rate backpropagation
- Gradient descent with momentum and adaptive learning rate backpropagation
- Random order incremental training with learning functions

Learning Function

- Gradient descent weight and bias learning function
- Gradient descent with momentum weight and bias learning function

Performance Function

- Mean squared normalized error performance function
- Mean squared normalized error and biases performance function
- Sum squared error performance function

Transfer Function

- Hyperbolic tangent sigmoid transfer function
- Linear transfer function
- Log-sigmoid transfer function

Figure 4: Sub-functions List for Four Functions Applied to ANN Model

The ANN model architectures must also be set. Four architecture designs are used in this study. The selected design is single hidden layer and represent by 3–3–2, 3–4–2, 3–5–2, and 3–10–2 symbols. Three neurons for input features and two neurons for two output features are constant parameter. The architectures differentiated by hidden layer neuron number.

Neuron in hidden layer represents the middle number. For instance, to picture this architecture shown in figure 3. In order consider these model architecture factors, hence for full factorial 1008 prediction tests are required (4 model architectures × 252 tests = 1008 tests).

5.0 Result and discussion

The model's result is based on the model's performance in detection rate (dR). The rate of detection is the value as in equation (3) (Natarajan et al., 2011). By the equation, the detected number of right estimations will be divided with the total number of samples. In this study, the number of samples is represented by the 12 number of testing data. The following sub-sections use 'detection rate' term for model's performance. Since too many tests are required, resulted so many detection rates finding. Thus, only the top 16th dR discusses in this section. The finding clear picture visualised through these rates.

5.1 Fuzzy logic

Based on 3645 tests, the top 16 dR shown in Figure 5. The best dR is 83.3% for SR and 97.2% for DA. The best dR determines the best MF for the model. MF input is Gaussian for Average Current and Triangular for electrode and workpiece. And the best MF output is Gaussian for SR and Triangular for DA. Based on Figure 5, the best dR refers to test number 2. Sigmodally-shape MF is ineffective to correlate the input-output features. Besides, based on record from Figure 5 the average of dR values are determined. The results are DA average of dR value is above 90% (92.71%) and SR average of dR value is below 90% (60.76%).

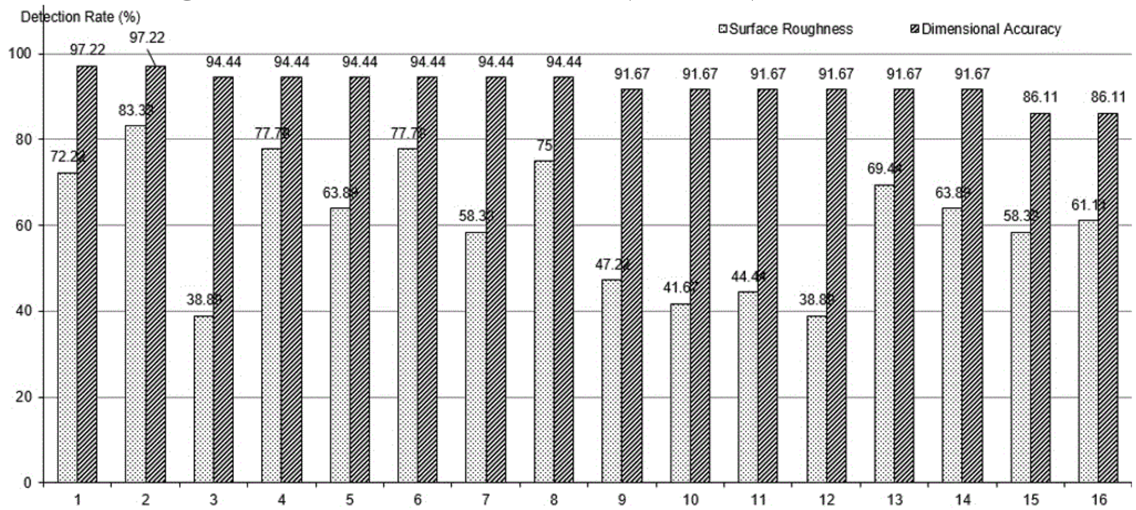


Figure 5: The Top 16th Fuzzy Logic Surface Roughness and Dimensional Accuracy Detection Rate Results (%)

$$Detection\ Rate = \frac{Number\ of\ Right\ Detection}{Total\ Number\ of\ Sample} \times 100\% \qquad (3)$$

5.2 Neural network

The dR values are used to discuss the model performances. The model performances are classified into number of neuron in hidden layer and set of functions. Besides, further discussion is related to output features i.e. surface roughness (SR) and dimensional accuracy (DA). Based on the detection rate (dR) performance result, the discussion is simplified to focus on the top 16 best detection rates. This is due to showing all of the 1008 records of dR is not effective for a comparison study. In line with the aim to determine the model best set of functions, therefore the most effective for the aim is by charting among the best dR.

Table 4 shows the combination of four set of functions for the top 16 best dR of workpiece qualities i.e. SR and DA. The combination of four functions in Table 4 contains only five training functions, two learning functions, three performance functions, and two transfer functions. The table lists the combination of four functions in acronym of each function and the actual name of the function is presented at the bottom of the table. In relation to Table 4, Figure 6 shows the top 16 best for both the best SR and the best DA detection rates in percentage. Based on these dR, only 18 out of 1008 combinations of four functions are pictured in Figure 6, and labelled in alphabetical A to R to represent the top 16 best dR of SR and DA. Besides the figure shows only 14 set of function combinations are agreed for classifying correct SR and DA. The rest four set of function combinations are agreed either for classifying correct SR or DA.

Table 4: The Top 16th for combination of four functions for ann model detection rate

	Function					Function					Function			
Sy.	TR	LR	PR	TF	Sy.	TR	LR	PR	TF	Sy.	TR	LR	PR	TF
A	RBP	GMB	MEP	HTS	G	OSB	GWB	MRI	LTR	M	RBP	GWB	MEP	LTR
B	RLF	GWB	MRI	HTS	H	CPB	GMB	MRI	LTR	N	LMB	GMB	MEP	LTR
C	SCB	GWB	MRI	HTS	I	OSB	GMB	MRI	LTR	O	OSB	GWB	MRI	LTR
D	RBP	GWB	MRI	LTR	J	LMB	GWB	SSE	LTR	P	RLF	GMB	SSE	LTR
E	RBP	GMB	MEP	LTR	K	LMB	GWB	MEP	LTR	Q	RLF	GWB	MEP	LTR
F	SCB	GWB	MEP	LTR	L	RLF	GWB	MEP	LTR	R	CPB	GWB	MRI	LTR

Note: Sy. – Symbol; TR – Training; LR – Learning; PR – Performance; TF – Transfer; RBP – Resilient Backpropagation; RLF – Random order Incremental Training with Learning Functions; SCB – Scaled Conjugate Gradient Backpropagation; OSB – One-step Secant Backpropagation; LMB – Levenberg-Marquardt Backpropagation; CPB – Conjugate Gradient Backpropagation with Powell-Beale Restarts; GMB – Gradient Descent with Momentum Weight and Bias Learning; GWB – Gradient Descent Weight and Bias Learning; MEP – Mean Squared Normalized Error Performance; MRI – Mean Squared Normalized Error Performance Function with Regularization Implemented; SSE – Sum Squared Error Performance; HTS – Hyperbolic Tangent Sigmoid; LTR – Linear Transfer.

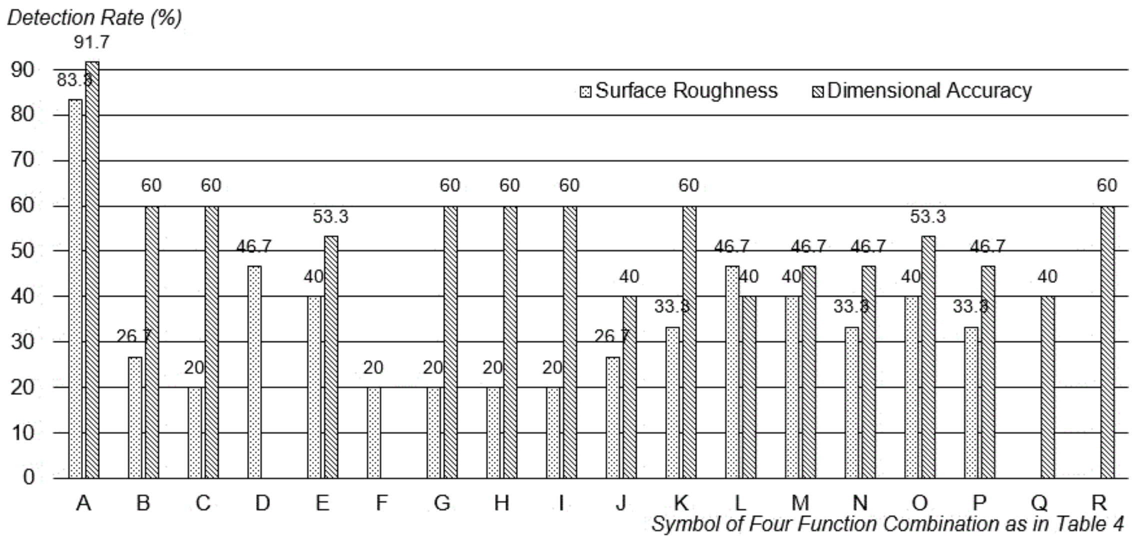


Figure 6: The Top 16th ANN surface roughness and dimensional accuracy detection rate results (%)

The result of number of hidden neuron performances show in Figure 7. The figure shows the best detection rate for selected neuron numbers in hidden layer in this study labelled horizontally i.e. three (3), four (4), five (5), and ten (10) neurons. The performance of four neurons in hidden layer shows the best performance for dR of both workpiece qualities. The best dR performance is 83.3% for SR and 91.7% for DA. The lowest performance is architecture with ten neurons in hidden layer for both workpiece qualities. The lowest detection rate is 33.3% for SR and 26.7% for DA.

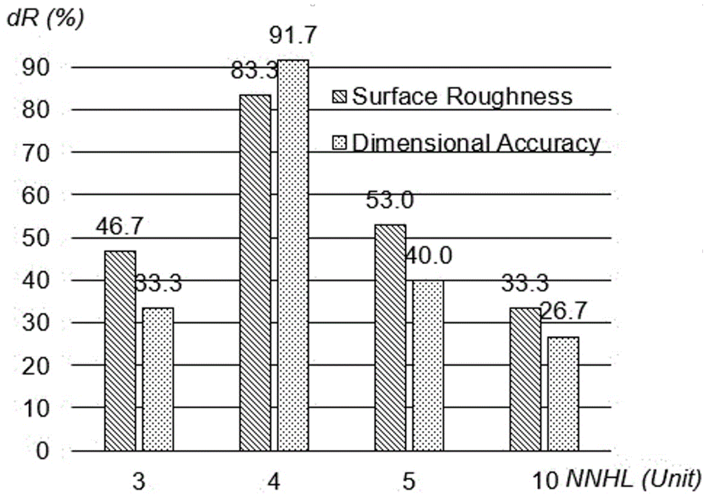


Figure 7: The best detection rate (dR) by neuron numbers in hidden layer (NNHL)

The rest combination of functions are resulted weak dR and not listed in the Table 4. The functions include Log-Sigmoid Transfer for transfer function and nine functions for the training function. The nine functions are Bayesian Regularization Backpropagation, Conjugate Gradient Backpropagation with Fletcher-Reeves Updates, Conjugate Gradient Backpropagation with Polak-Ribiére Updates, Gradient Descent Backpropagation, Gradient Descent with Momentum Backpropagation, Gradient Descent with Adaptive Learning Rate Backpropagation, Gradient Descent with Momentum, and Adaptive Learning Rate Backpropagation, and BFGS Quasi-Newton Backpropagation.

6.0 Conclusion

Based on FL and ANN performance, both models are effective to correlate the input-output features. Comparatively, for this case study, FL outperforms ANN model in term of detection rate of workpiece qualities. Though, dR for SR is similar for both models, but FL's are better at estimating DA. Also, both models agree that estimating DA is more effective than SR. Besides, although EDMS has too many input-output features, this paper focusing only on three inputs and two outputs. Therefore, for future study, other features should be the focus. In addition, the use of ANFIS model may help in reducing if-then rules for the FL model. Pragmatically, the proposed models are more economical than trial and error method. Trial and error method required too much time, experienced worker, and a lot of material waste for estimation tests.

On the other hand, by ANN and LF models, the preparing time for estimation tests are shorts, few, and systematic. Thus, less material waste is required. In addition, shorter time is required to train machinist for estimating the input-output parameters relation than to has experienced machinist.

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