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JUDUL: OPTIMIZATION OF MACHINING PARAMETERS OF TITANIUM ALLOY IN ELECTRIC DISCHARGE MACHINING BASED ON ARTIFICIAL NEURAL NETWORK

SESI PENGAJIAN: 2010/2011

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OPTIMIZATION OF MACHINING PARAMETERS OF TITANIUM ALLOY IN ELECTRIC DISCHARGE MACHINING BASED ON ARTIFICIAL NEURAL NETWORK

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Report submitted in partial fulfillment of the requirements
for the award of the degree of
Bachelor of Mechanical Engineering with Manufacturing Engineering

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I hereby declare that the work in this project is my own except for quotations and summaries which have been duly acknowledged. The project has not been accepted for any degree and is not concurrently submitted for award of other degree.

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ABSTRACT

This report presents the artificial neural network model to predict the optimal machining parameters for Ti-6Al-4V through electrical discharge machining (EDM) using copper as an electrode and positive polarity of the electrode. The objective of this paper is to investigate how the peak current, servor voltage, pulse on- and off-time in EDM effect on material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR). Radial basis function neural network (RBFN) is used to develop the Artificial Neural Network (ANN) modeling of MRR, TWR and SR. Design of experiments (DOE) method and response surface methodology (RSM) techniques are implemented. The validity test of the fit and adequacy of the proposed models has been carried out by doing confirmation test. The optimum machining conditions are estimated and verified with proposed ANN model. It is observed that the developed model is within the limits of the agreeable error with experimental results. Sensitivity analysis is carried out to investigate the relative influence of factors on the performance measures. It is observed that peak current effectively influences the performance measures. The reported results indicate that the proposed ANN models can satisfactorily evaluate the MRR, TWR as well as SR in EDM. Therefore, the proposed model can be considered as valuable tools for the process planning for EDM and leads to economical industrial machining by optimizing the input parameters.

ABSTRAK

Laporan ini membentangkan kajian tentang *artificial intelligence model* untuk meramal parameter yang terbaik bagi pemesinan Ti-6AL-4V dengan menggunakan mesin nyahcas elektrik (EDM) dan tembaga dengan polarity posifit sebagai elektrod. Tujuan kajian ini adalah until megkaji bagaimana arus puncak, kuasa voltan, masa pemberhentian pulsa dan masa pembukaan pulsa dalam EDM mempengaruhi kadar pemesinan bahan (MRR), kadar kehausan alat (TWR) dan kekasaran permukaan (SR). *Radial basis function neural network* (RBFN) digunakan untuk membina *Artificial Neural Network* (ANN) untuk permodelan MRR, TWR dan SR. Kaedah desain eksperimen (DOE) dan metodologi respon permukaan (RSM) telah dilaksanakan. Kesahihan dan ketepatan model yang dicadangkan dibuktikan dengan menjalankan ujian pengesahan. Keadaan memesin yang terbaik ditafsir dan disahkan dengan model ANN yang telah dicadangkan. Daripada model yang dibina, dapat diperhatikan bahawa ralat antara model yang dibina dengan keputusan eksperimen masih dalam kadar yang boleh diterima. Analisis sensitivity dilakukan untuk mengkaji pengaruh relatif oleh factor-faktor mesin terhadap prestasi yang diukur. Keputusan yang dilaporkan menunjukkan bahawa model ANN boleh menilai MRR, TWR dan SR. Oleh yang demikian, model yang dicadankan boleh dianggap sebagai satu alat untuk merancang pemesinan EDM dan dapat member hermat dalam industry pemesinan dengan memasukkan parameter pemesinan yang optima.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

W_{w1}	Weight of workpiece before machining
W_{w2}	Weight of workpiece after machining
T	Time taken for the machining
W_{e1}	Weight of electrode before machining
W_{e2}	Weight of electrode after machining
Y	Performing parameter
X	Response to neural network
W	Weight matrix
f	Model of process that is being used in the training
v	Induced local fields produced
x	Input signal
w	Synaptic weight
H_l	Hidden layer one
Z_j	Hidden layer two
O_k	Hidden layer three
Y_o	Output at the output layer
w_{li}	Synaptic weight from the input neuron
i (x_i)	Input neuron
w_{jl}	Synaptic weight form neuron *l* in the first hidden layer to the neuron *j* in the second hidden layer
w_k	Synaptic weight from neuron *j* in the second hidden layer to the neuron *k* in the last hidden layer to the output neuron *o*.

LIST OF ABBREVIATIONS

EDM	Electric-Discharge machine
EWW	Loss electrode
MRR	Material removal rate
SR	Surface Roughness
TWR	Tool wear rate
WRW	Weight loss of workpiece

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Titanium alloy is increasing use in many industrial and commercial applications because of its excellent properties. The largest consumer of titanium alloys is the aerospace industry and is increasingly more used in chemical machine building, shipbuilding and auto industry, in equipment fir the oil and gas industry, food industry , medicine and civil engineering. Application of Ti-6Al-4V are use in engineering application because of its outstanding corrosion resistance, fatigue resistance, and sufficient corrosion resistant in many environment especially in high strength applications.

Ti-6Al-4V is $\alpha+\beta$ alloys which contain a larger amount of β stabilizers (4-6%). Beta alloys can be heat treated to develop variety of microstructures and mechanical property combinations. Alloy VT6 has the following chemical composition (wt. %): Al, 5.5–7.0; V, 4.2–6.0. The content of impurities should not exceed (wt. %): C, 0.10; Fe, 0.30; Si, 0.15; O_2, 0.20; N_2, 0.05; H_2, 0.015 (Moiseyev, 2006). Titanium alloy is hard to be machine due to the properties of it. Hence Electrical discharge machining (EDM) is used. EDM is a non conventional, thermo electric process in which the material from work pieces is eroded by series of discharge sparks between the work and tool electrode immersed in a liquid dielectric medium (Yang et al., 2009). EDM technology are develop and are widely use in applications such as die and mild machining, micro-machining, and prototyping. Among all EDM processes, die sinker EDM is widely use (Fonda et al., 2008). Die sinking EDM is a machining process where positive feature shapes on the workpieceare mapped from the negative features in the electrode. It is relatively low machining process and it require electrode made specially for machining of a given product. The advantage of EDM machine is its ability to produce small, even micro features. The EDM process is used mostly for making dies and moulds (Valentilic et al., 2009). In order to get a good quality parts with minimum cost there are several parameter in the EDM that have to be control. There are the polarity, pulse on duration, discharge voltage and discharge current are several parameter that need to be control.

Advance in information and communication technology have force industrial activities to use computers in each phase of manufacturing process. This has put computerization at the forefront of competitive factors in manufacturing business. Hence Artificial Intelligence (AI) is introduce into the industry. AI is a branch of computer science dealing with the design of computer systems that exhibit characteristic associated with intelligence in human behavior including reasoning, learning, self-improvement, goal-seeking, self maintenance, problem solving and adaptability (Shin and Xu, 2009). In other words it is the discipline concerned with the development and application of computational tools that mimic or are inspired by natural intelligence to execute tasks with performances similar to or higher than those of natural systems. There are a lot of different tool in AI. Neural Network (NN) is one of the technique use in AI. NN is a computational model of the human brain that assumes that computation is distributed over several simple interconnected processing elements called neurons or nodes, which operate in parallel. NNs can capture domain knowledge from examples. Do not archive knowledge in an explicit form such as riles or data bases, can readily handle both continuous and discrete data, and have good generalization capability. NNs can be employed as mapping devices, pattern classifiers or patters completers. Application in manufacturing engineering range from modeling, prediction, control, classification and pattern recognition, to data association, clustering, signal processing and optimization

1.2 PROBLEM STATEMENT

Titanium alloy in industry has high strength-weight ratio, high temperature strength and exceptional corrosion resistance. Titanium alloy are difficult to be machine due to its chemically reactive with almost all cutting tool materials and its low thermal conductivity and low modules of elasticity impairs machinability. In EDM, electrode and workpiece does not make direct contact. Therefore titanium can be machined effectively using EDM (Hascalik and Caydas, 2007). EDM machining, the selection of proper parameter is important. Improper combination of parameter may cause low material removal rate (MRR) and also high tool wear ratio (TWR) which impose high cost on manufacturer. Effective machining needs high surface quality with minimum electrode erosion. Optimization of EDM parameter by finding the correct combination of the parameter available in EDM will enhance the machining productivity and reliability.

1.3 OBJECTIVES

The objectives of this project are as follows:

i) To investigate the machining characteristic on titanium alloy (Ti-6Al-4V).

ii) To optimize the EDM machining parameter of Ti-AL-4V in term of MRR, TWR base on artificial neural network model.

1.4 PROJECT SCOPES

This research is limited to machining by using EDM die sinking, the material used which is Ti-Al-4V and also EDM parameter that will be consider in the research are the dielectric fluid, polarity, pulse-on-duration, discharge current and discharge voltage. Because of cost and availability limitation the electrode that is use is copper. Copper with its properties of high density, low electrical resistively and high hardness make it suitable for this research. MRR can be calculated by measuring the amount of material being removed after a certain period of machining and the electrode wear ratio is calculated after measuring the weight of the electrode and workpiece before and after machining. Radial Basis Function (RBF), Neural Networks is use for modeling of this research.

1.5 OVERVIEW OF REPORT

This report consists of five chapters. Chapter 1 presents background, problem statement, objectives and the scope of the project. Chapter 2 discusses the literature review related to EDM, titanium, alloy and AI. The methodology of this study which includes method, strategy and approaches are explain in Chapter 3. Results, analysis and discussion of this study are stated in Chapter 4. Chapter 5 presents the conclusion and recommendation of this project.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter provide a review of past research related to EDM machining and its parameter, titanium alloys and also AI. The review offers different approach in this present project so that it can be properly modified to add to the present of literature as well as to justify the scope and direction of present research effort.

2.2 ELECTRICAL DISCHARGE MACHINING

2.2.1 History of EDM

EDM machining techniques was discovered by and English Scientist in the 1770s but it is not fully taken advantage until 1943 when Russian scientist learned how the erosive of the technique could be controlled and used for machining purposed. EDM machining was very imprecise and riddled with failures during the 1770s and is commercially developed in mid 1970s. Wire EDM began to viable technique that held shape the metalworking industry we see today. In mid 1980s, the EDM techniques was transfer to a machine tool. This migration made EDM more widely available and appealing over traditional machining process.

2.2.2 EDM Machining

EDM is a machine use to cut hard material or material which is difficult to machine with traditional techniques. It is often being categories as non-traditional or non-conventional group of machining method. This method can be use to machine all type of metal including alloys which are hard to be machine by conventional machine. It is also can be use to cut complex shape and geometry with small shaped angles and detailed contours or cavities within parts and assembly. EDM are commonly used in tool and die industry to produce mould and die component. Currently EDM has become a integral part for making prototype and production parts but it only work with material that are electrically conductive (Jameson, 2001). There are two types of EDM machine which is Die-sinking EDM or also known as ram EDM, and Wire EDM. Die-sinking EDM machine need the electrode to be in the exact opposite shape of the workpiece, while wire EDM uses continuous wire as electrode. Machining occur by controlling the sparks between the electrode and the workpiece in the presence of dielectric fluid where the electrode can be considered to act as cutting tool.

Dielectric fluid is usually a petroleum product or deionized water usually die sinker machines use hydrocarbon dielectric fluids. Dielectric fluid functions for spark machining is that it prove a known electrical barrier between the electrode and workpiece, cooling for the electrode and workpiece, cooling for the vaporized material that becomes the EDM chip upon solidification and for removal of the EDM spark debris form the sparking gap. Dielectric fluid is an insulator that resist the flow of electricity until voltage is high enough to cause the fluid to change into an electrical conductor applied which is called the ionization point. As the spark electricity flow between the electrode and the workpiece, heat is generated, and dispersed within the electrode and surround the sparking area. The dielectric fluids help to remove heat as it surround the sparking area. It also cools and remove chip. As vapor cloud is form in the sparking-gap area which is then cool and solidifies produce a sphere with a hollow center known as the EDM chip. This chip is then remove by having dielectric fluid flowing through the sparking gap and then transport the chips out of the sparking area.

2.2.3 EDM Parameters

There are a lot of studies had been done in finding a good combination of parameter in EDM machining regardless the type of material to be machine nor the electrode that is used in the machining. Apart from that, modeling by using various types of artificial intelligent tools had also been performed. A study of EDM machining of titanium alloy (Ti-6Al-4V) had been performed by Hascalik and Caydas (2007). From their research, it had been found that the value of MRR, EWR and surface roughness has the tendency to increase with increasing current density and pulse duration. Even though in increases with pulse duration, at a long pulse duration such as 200 μs, it will decrease MRR and the surface roughness of the workpiece machine.

Krishna et al. (2009) has development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm. They found that in EDM machining, the current increases at constant voltage surface finish reduces tremendously. For machining of titanium, the machining current less than or equal to 15 is more suitable. From this research, they had come out with a conclusion that it has good surface finish at voltage 40V and at constant current of 16A. ANN models are develop for surface roughness which can predict the behavior of these material when machined on EDM. The developed models are within the limits of agreeable error for all performance measures considered. Investigation into the electric discharge machining of hard tool steel using different electrode material done by Singh et al. (2004) uses copper, copper tungsten , brass and also aluminum as electrode. From their research, work piece machine by copper and aluminum electrodes offer higher MRR. Copper and copper tungsten over comparatively low electrode wear or the tested work material. At high values of currents, copper and aluminum offer low surface roughness. Hence copper is a better electrode material.

Erden (1983) has made a research on the effect of materials on the mechanism of electric discharge machining. From this research, spark gap is consider when selecting an electrode size to achieve a particular hole diameter. Frontal spark gap determines the ultimate depth of the blind hole. The variation between discharge in term of their electrical characteristic and strike location within the gap is influenced by several factors. It is established that only spark pulses are responsible for metal erosion. Short circuit, open circuit arcing pulses are collectively termed as ineffective pulse. It has been experimentally investigated that during EDM there is an appreciable amount of diffusion of metals from the tool electrode to the work material and vice versa. In order to the maximize quality and minimum cost in EDM machining, optimization on the parameter that will effect this factor is important. There are few important parameter that need to be considered in EDM machining. There are:

i) Source voltage can be determine by the width of gap between the electrode and workpiece, higher voltage creates current and spark across wider gap.
ii) Discharge current is the value of the current applied to the electrode during pulse on-time in EDM. It is one of the primary input parameter of an EDM process and together with discharge duration and relatively constant voltage for given tool and workpiece materials.
iii) Arc gap is the distance between the electrode and workpiece during the process of machining also know as sparking gap.
iv) Pulse on-time is the time of which current is applied to the electrode during each EDM cycle. The materials removed is directly proportional to the quantity of energy applied during pulse on-time. This energy is controlled by the current and the on-time.
v) Pulse off-time is the waiting interval during two pulse on-time periods. Melted and solidified particles are removed form the setting during this period.

Apart from electrical parameter, non electrical parameter also influence the performance of EDM machining which are the electrode used and also dielectric fluid. The electrode that are commonly use is EDM machining are tungsten, copper tungsten, silver tungsten, yellow brass, chrome plated material, zinc alloys, tungsten carbide, copper and graphite. Copper electrode are commonly used in resistance capacitance circuits where higher voltages are employed while graphite electrodes are commonly used in application requiring low tool wear and high material removal. Brass material are mainly used in pulse type circuits because of their good machinability (Salman et al,. 2008)The properties of some electrode are shown in the Table 2.1.

Table 2.1: Properties of electrode (Hascalik and Caydas, 2007)

Material	Gaphite	Copper	Aluminium
Density (g/cm^3)	1.77	8.905	27.5
Melting point (°C)	3300	1083	660
Electrical resistively (μΏ cm)	1400	8.9	14.2
Hardness (HB)	7	100	40

Two commonly used dielectric fluid are kerosene and distilled water. Dielectric fluid act as an insulator until enough voltage is supply to cause it to change to electrical conductor (Jameson, 2005). Water is a good insulator but it has several disadvantages to be use as dielectric fluid where it causes rust towards the electrode, workpiece and also the machine itself, and also during electric discharge it separates water into pure hydrogen and pure oxygen which is a very explosive pair. Kerosene is a better choice of dielectric fluid where it does not have rust problem and no dangerous gases are produced. The choosing of dielectric fluid is based on the type of material ad the process that are made or used.

2.3 TITANIUM ALLOY

Titanium alloy is to be consider as a rather new material used in the market for manufacturing purpose. It has been become one of the essential metal materials for modern machine building. The use of titanium alloy . various engineering field is due to its high specific strength and high temperature strength within a broad temperature range, and also high corrosion resistance. Comparing to other metal, titanium have lower values of thermal conductivity, electrical resistance and thermal expansion.

Titanium alloy are divided into three groups which is alloys based on solid α- and β- solution, alloy based on solid solutions with some chemical compound and alloy based on chemical compound. Titanium exists in two allotropic modifications which is high temperature and low temperature. α- titanium exists at temperature below 882°C and β-titanium at higher temperature up to the melting point (Moiseyev, 2006).The largest consumer of titanium alloys is the aerospace industry. Recent decade, titanium and it alloys have been increasingly more used in chemical, machine building, shipbuilding, medicine, auto industry, food industry and also in equipment for the old and gas industry. In aircraft, the use of titanium alloy reduces the weight of aircraft construction and gives a higher weight efficiency. Figure 2.1 and Figure 2.2 shows some of the application of Ti-6Al-4V in automotive and biomedical industries.

Figure 2.1: Parts make by Ti-6AL-4V

Figure 2.2: Femur bone implant

In this research high strength titanium alloy is use which is Ti-6Al-4V also known as VT6. Ti-6Al-4Vare used worldwide as commercial material. Table 2.2 and Table 2.3 below shows the chemical and mechanical properties of Ti-6Al-4V.

Table 2.2: Chemical composition of Ti-6Al-4V alloy (wt.%) (Hascalik and Caydas, 2007)

Chemical composition	%
Ti	89.464
Al	6.08
V	4.02
Fe	0.22
O	0.18
C	0.02
N	0.01
H	0.0053

Table 2.3: Mechanical properties of Ti-6Al-4V (Hascalik and Caydas, 2007)

Work material	**Ti-6Al-4V**
Hardness (HV20)	600
Melting point (°C)	1660
Ultimate tensile strength (MPa)	832
Yield strength (MPa)	745
Impact-toughness (J)	34
Elastic modulus (GPa)	113

2.4 ARTIFICIAL INTELLIGENCE

Manufacturing of complex system can be conceptually thought as being an integrated whole of complex interacting subsystem. A manufacturing system takes in customer needs, feedback and part of society total energy and transform them to produce outputs or product with more efficiency. In concerned with the development and application to perform this task, Artificial Intelligence (AI) tool had been develop.

AI is a branch of computer science dealing with the design of computer system that exhibit characteristic associated with intelligent in human behavior. It is concern with the development and the application of computational tools that are inspired by natural intelligence to perform task with similar or higher performance that those of natural system. AI have brought new opportunities and challenges for researches to deal with complex, uncertain problems and systems, which is difficult or could not be solved by traditional method. Many traditional approaches that have been developed for mathematically well defined problems with accurate models may lack in autonomy and decision making ability and hence cannot provide adequate solutions under uncertain fuzzy environments (Shin and Xu, 2009).

Numerous AI tools, techniques and paradigms have been applied such as Fuzzy Logic (FL), Neuro-Fuzzy, Simulate Annealing (SA), Neural Network and many more. The processing core of FL is based on a collection of IF-THEN rules where IF part is called the antecedent and THEN part is called consequent. Fuzzy rules sets usually have several antecedents that are combined using fuzzy operator. Neuro-Fuzzy is a natural link between symbolic and sub-symbolic approaches in AI. It work in real time circumstances and handle uncertainties as NN but, it is usually does not incorporate automatic learning abilities and adaptive features. SA is to lead the material to a state corresponding to a global minimum of its internal energy. It is usually use to solve discrete variable problems. NN can capture domain knowledge from examples, do not archive knowledge in an explicit form such as rules or databases, can readily handle both continuous and discrete data, and have a good generalization capability. Hence in this research NN is being used.

2.4.1 Artificial Neural Network

Artificial Neural Network (ANN) is a AI tools that are suitable for representing the input-output relationship of nonlinear system. Due to its smoothing and global approximation capabilities, if a sufficient amount of data is available, NN can be trained to provide a suitable mapping between input and output variables . NN is basically a computational model at human brain than assumes that computational is distributed over several interconnection processing element called neurons or nodes (Luo and Unbehauen, 1998). The key featured of NN are asynchronous parallel and distributed processing nonlinear dynamics, global interconnection of network, self organization and high speed computational capability. There are three types of layer in neural system is shown in Figure 2.3. Input layer receive data from outside the neural network, output layer send data out of the network and hidden layer whose input and output units signals remain within the network. The basic model of NN are the discrete-time Hopfield neural network, the continuous time Hopfield neural network, cellular neural networks, multilayer perceptron network (MLP), self organizing systems, radial basis function network and high neural network.

It is adaptive, where the system parameters are changed during operation, normally called the training phase. It is built with step-by-step procedure systematically to optimize a performance criterion or to follow some implicit internal constraint, commonly referred to as learning rule. The input or output training data are fundamental in neural network technology. They convey the necessary information to discover the optimal operating point. The ANN parameters are fixed and the system is deployed to solve the problem at hand after the training phase which is called the testing phase. For supervised method, an input is given to the NN while a target response set is given at the output. Then an error will be develop from the difference between the desire output or response and the system output which is next fed back to the system where it adjusts the parameter of the system symmetrically according to the learning rule. It is repeated until the performance is acceptable.

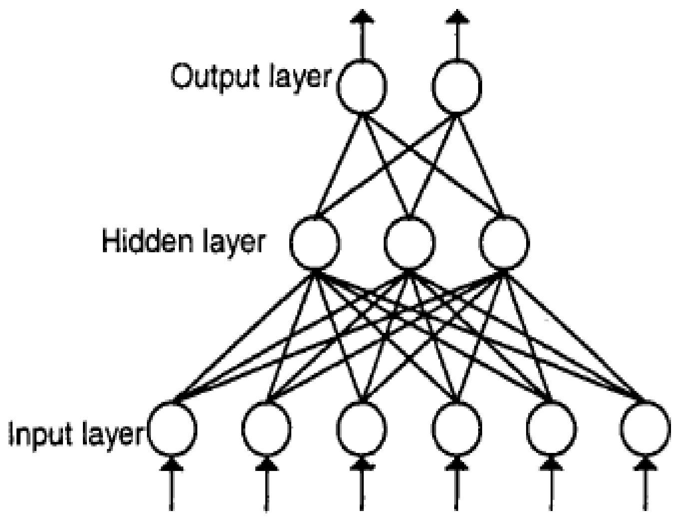


Figure 2.3 MLP network with one hidden layer. (Luo and Unbehauen, 1998)

In ANN, the network topology, the performance function, the learning rule and the criterion to stop the raining phase are chosen. Instead of conducting traditional engineering design that exhaustive subsystem specifications and intercommunication protocols are necessary, the system adjust the parameters automatically. Even though some information is hard to bring into the design and it is difficult to incrementally refine the solution when the system does not work in a proper way, ANN solution are time efficient in terms of development and resources. It also provides performance that is difficult to match with other technologies.

2.4.2 ANN Topology

There are two main type if ANN topology. There are feed-forward networks and recurrent neural network which is also known as feedback network. Feed-forward networks allow signal to travel one way only which is from input to output. There is no feedback or loop. The data processing can extend over multiple units. Recurrent neural network can have signals travelling in both directions by introducing loops network. The dynamic properties of the network are important. In some applications, the change of the activation values of the output neurons are significant such that the dynamical behavior constitutes the output of the neural network. While some undergo a relaxation process such that the neural network will evolve to a stable state is which these activations do not change anymore. Examples of feed-forward neural work are Constructive Algorithm Adeline., and Kohonen Network and Hopfield Network are examples of recurrent network.

In this project hybrid networks is used. Hybrid network is neither feed-forward network or recurrent neural network but it is a combined network, especially those which couple a self-organizing with feed-forward layer. Hybrid network are divided in to several type such as ART architectures, Counterpropagation networks, Maximum entropy, Spline network and Radial Basic Function (RBF). However RBF is used in this research.

2.4.3 Training of ANNs and its Learning Method

The memorization of patterns and the subsequent response of the network can be categorized into to paradigms which are associative mapping and regularity detection. Associative mapping is network that learns to produce a particular pattern on the set of input unit whenever another particular pattern is applied on the set of input units. Regularity detection is at which the units learn to respond to particular properties of the input patterns (Christos Stergiou and Dimitrios Siganos). The ANN has to be configured such that the application of a set of input produces the desired set of outputs. Various method to set the strength of the connection exist. One way is to set the weights explicitly, using a priori knowledge which is know as fixed networks. Another way is to rain the ANN by feeding it teaching patterns and letting it change its weight according to some learning rule or known as adaptive networks.

The learning methods use for ANN is classified in to two distinct categories which are supervised learning and unsupervised learning. Supervised learning or associative learning, input and matching output patterns are provided into the network. These input and output pairs can be provided by an external teacher, or by the system which contains the ANN. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning (Christos Stergiou and Dimitrios Siganos). Supervised learning concentrate on determining the set of weight that minimizes error. A common method used is the least mean square (LMS) convergence. Unsupervised learning or self organization is which an output unit is trained to respond to cluster of pattern within the input. The system will discover statistically salient features of the input population. The system must develop its own representation of the input stimuli. Reinforcement learning is another learning method in ANN, this type of learning may considered as an intermediate form of the two types of learning before this. The learning machines does some action on the environment and gets a feedback response from the environment. The learning system grades its action based on the environmental response and accordingly adjust its parameter.

The behavior of an ANN depends on both the weight and the input-output function. This function are categorize into three there are linear, threshold and sigmoid. In linear unit, the output activity is proportional to the total weighted output while in threshold units, the output is set at one of two levels, depending on whether the total input is greater than or less than some threshold value. Sigmoid units bear a greater resemblance to real neurons than to linear or threshold units. The output varies continuously but not linearly as the input changes(Christos Stergiou and Dimitrios Siganos).

2.4.4 Radial Basis Function

Radial Basis Function (RBF) network is an approached by viewing the design as a curve-fitting problem in high dimensional space. Learning is equivalent to finding a multidimensional function that provides a best fit to the training. Correspondingly, regularization is equivalent to the used of this multidimensional surface to interpolate the test data. The viewpoint is the real motivation behind RBF method in the sense that it draws upon research work on traditional strict interpolations in a multidimensional space. In neural network, the hidden units form a set of function that compose of a random basis for the input patterns.

The design of RBF network consists of three separate layers. The input layers which contain the source nodes, second later the hidden layer of high dimension and the output layer gives the response of the network to the activation patterns applied to the input layer. RBF have a static Gaussian function as a nonlinearity for the hidden elements. The Gaussian function responds only to a small region of the input space where the Gaussian is centered. Centers of RBF are determined with reference to the distribution of the input data without referring to the prediction task. Representational resources that are irrelevant to the learning task may be wasted on areas of the input space. One of the common solutions is to associate each data point with its own centre. This can make the linear system to solved in the final layer rather large, and needs shrinkage techniques to avoid over fitting.

The only parameters that are adjusted in the learning process are the linear mapping form hidden layer to output layer, hence RBF network do not suffer from local minima in the same way as Multi-Layer Perceptrons. The linearity ensures that the error surface to be quadratic. The minimum value can be easily found. This can be found in one matrix operation in regression problem. Gaussian Processes are trained by maximizing the probability, minimizing the error of the data under the model in a Maximum Likehood framework. RBF can be competitive in regression applications when the dimensionality of the input space is relatively small.

2.5 CONCLUSION

This chapter presented the summary of previous studies and facts related to this project which discuss the parameter of EDM machining, composition and application of titanium alloy and AI. The methodology used to perform this project is in the next chapter.

CHAPTER 3

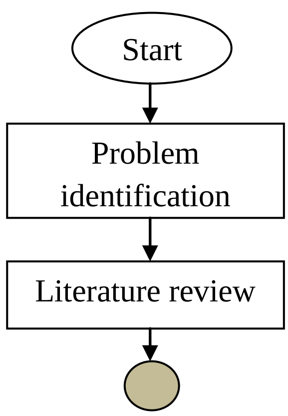
METHODOLOGY

3.1 INTRODUCTION

This chapter presents the design of experiment for this project which include EDM process, evaluation of machining performance in term of SR, TWR and MRR, experiment setup and ANN modeling.

3.2 FLOW CHART OF PROJECT

This project is started by problem identification which is followed by reviewing previous work done by other researcher to serve as a guide in this project. The experiment started by determining the combination of parameter, cutting the workpiece, weight measuring, machining, collect relevant data and measure the surface roughness, develop an ANN model and lastly do validation on the model developed. Flow chart in Figure 3.1 shows the overall flow of this project.



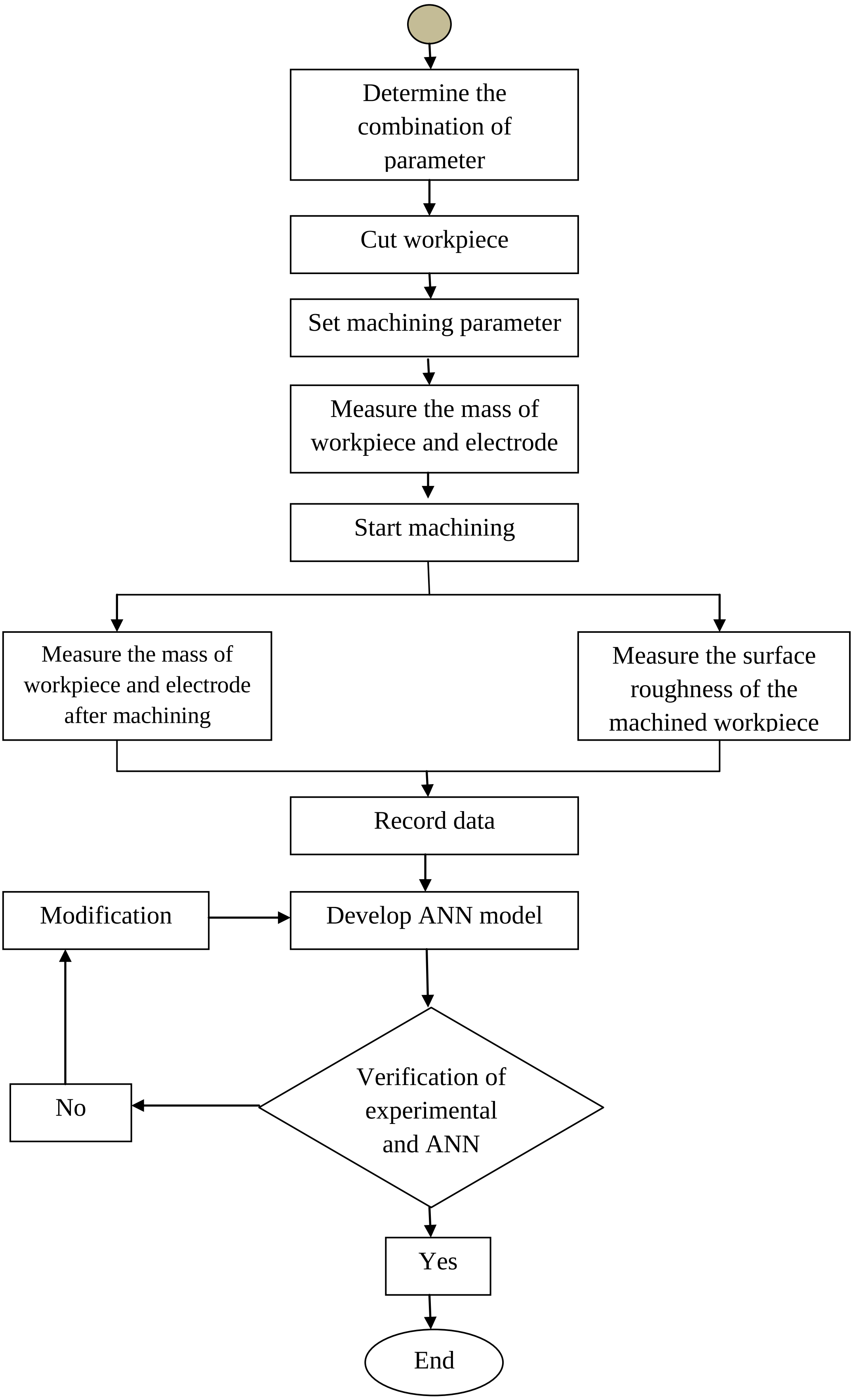


Figure 3.1: Flow chart of project

3.3 EDM PROCESS

In EDM process, materials are remove by using spark erosion process, where material is remove without any physical contact between electrode and workpiece. The electrode is position away from the workpiece with a small differential distance which is call sparking gap. Both electrode and the workpiece are submerged in dielectric fluid as shown in Figure 3.2. Dielectric fluid is used to maintain the sparking gap between the electrode and the workpiece, cools the heated material to form EDM chip and also to remove EDM chips from the sparking area. Dielectric material is usually hydrocarbon oil where in die-sinker EDM kerosene is used and in wire EDM usually deionized water is used. There will be no sparking and no material will be removed if the electrode and workpiece come into contact in die-sinking or wire-cut types of EDM machines.

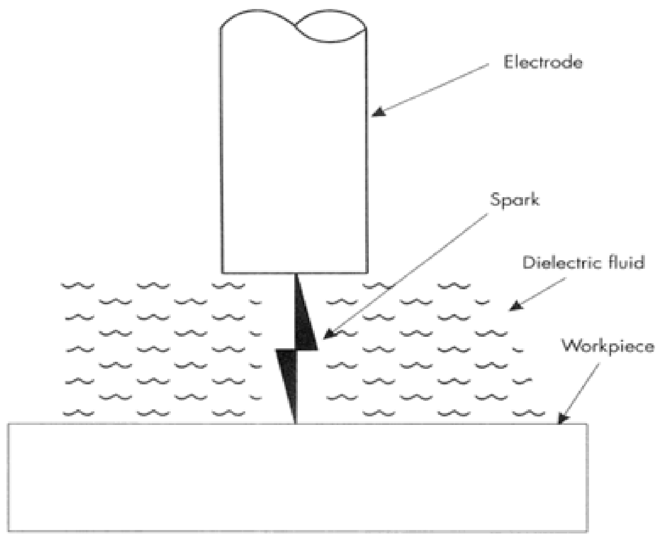


Figure 3.2: Basic components of EDM (Jameson, 2005)

When power is supply to the machine, current flow between the electrode and workpiece in the form of spark. At this time spark voltage causes the dielectric fluid to change from an insulator to a conductor and spark will occur. Spark will occur at a point where the electrode and the workpiece are at the closest distance. When spark occurs, the area is very hot but small hence the dielectric fluid quickly cools the vaporized material, the electrode and workpiece surface. Each spark result in localized heating and particles of metal become to molten having a very small area and at the end of the pulse duration the molten metal particles are flashed away by the dielectric fluid and remaining liquid material resolidifies (Hascalik and Caydas, 2007). When the spark is turned off, the dielectric fluid deionizes and the fluid returns to being an electrical insulator. Only one spark occur at one time and spark occur in a range of 2 000 to 500000 spark per second. The sparking process is shown in Figure 3.3.

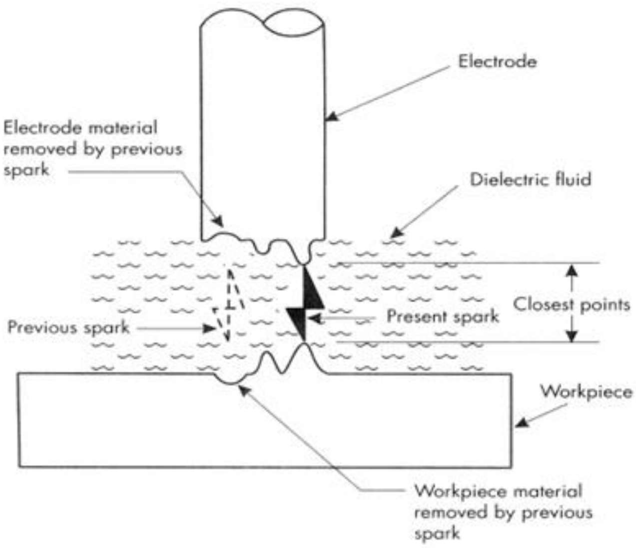


Figure 3.3: Sparking process (Jameson, 2005)

The material removal rate (MRR), of EDM machining is slow where additional time and cost is needed compare to conventional machining. Although it has certain disadvantages, EDM can be used for machining hard and tough materials and also weak material can be machines without distortion since there is no direct contact between cutting tool and work piece. Instead it also can produce complex shape which is difficult to be produce by using conventional machines.

3.4 MACHINING PERFORMANCE EVALUATION

In EDM machining the performance can evaluate in terms of material removal rate (MRR), tool wear ratio (TWR) and also surface roughness of the machine parts. Machining performance is dependent on the optimization if the parameters of EDM machining. A good machining parameter are when the MRR is maximize, TWR and surface roughness of the parts machine are minimize.

Machining is a term to describe variety of material removal process in which a cutting tool removes unwanted material from a workpiece to produce the desired shape. MRR represents the volume or mass of workpiece removed in unit time. Maximum MRR shows that it uses less time to remove the same amount of material. The MRR (Luis et al,. 2005):

$$WRW = W_{w1} - W_{w2} \tag{3.1}$$

$$MRR = \frac{WRW}{T} \tag{3.2}$$

where, W_{w1} is the weight of workpiece before machining and W_{w2} the weight of workpiece after machining, *WRW* is the weight loss of the workpiece and *T* time taken for the machining.

EDM process is a spark erosion method, eroding workpiece by high frequency spark discharge. Electrode wear occur during EDM machining, which will reduce the machining accuracy in the geometry of the workpiece. Electrode wear impose high cost for manufacturer to replace the eroded electrode with new one die to die making. Instead of the cost, electrode wear also effect the surface roughness of the parts machine. To reduce cost to produce replace electrode, the material remove must be maximize while minimizing the erosion of the electrode by optimizing several parameter such is current, voltage, pulse on-time, pulse off-time and also by selecting the suitable electrode for the type of material to be machine. TWR is define by the ration of weight of material removed from electrode (EWW) to the weight of material removed from part (WRW) which is given by Equation (3.3) and (3.4) (Luis et al., 2005):

$$\mathrm{TWR} = \frac{\mathrm{EWW}}{\mathrm{WRW}} \tag{3.3}$$

$$\mathrm{EWW} = \mathrm{W_{e1}} - \mathrm{W_{e2}} \tag{3.4}$$

where W_{e1} and W_{e2} are the weigh of electrode before and after the machining respectively, while EWW is the loss electrode and T is the time taken during the machining.

The surface roughness of an EDM product can be defined as a chip forming process where chips are spherical debris melted by sparks. The surface roughness is worsen with increase of current. A large discharging energy will causes violent sparks and impulsive forces and results in a deeper and larger erosion crater on the surface. Cooling process after the spilling molten metal, residues are remaining at the periphery of the crater to form a rough surface.

3.5 ANN MODELLING

In order to develop an ANN model to predict the MRR, TWR and SR. Radial basis function neural network (RBFN) model is is used to develop the ANN model. RBFN is built into a distance criterion with respect to a center and is applied in neural network as replacement for sigmoid hidden layer characteristic in Multi-Layer Perceptrons. RBFN have two layers of processing. Input is mapped onto each RBF in the hidden layer. The output layer is a combination of hidden layer values representing the mean predicted output. The interpretation of this output layer is like a regression model in statistic. The output layer is a typical sigmoid function of a linear combination of hidden layer values representing the mean predicted output. The interpretation of this output layer value is like a regression model in statistic.

The training and testing of neural network is perform by using experimental data which is shown in Table 3. The mathematical relation between the performance factors and response are described in Eq. (3.5) and Eq. (3.6).

$$Y=f(X,W) \tag{3.5}$$

$$v=\sum_i w_i x_i \tag{3.6}$$

where, Y represents the performing parameter, X is the response to the neural network, W is the weight matrix, f is the model of process that is being used in the training, v

represents the induced local field produced, x as the input signal and w as the synaptic weight.

The inputs of the network at the nodes of the hidden layer and the output layer are combined by using Eq. (3.7) and Eq. (3.8) respectively.

$$H_l = f(v_l) = f(\sum_i w_{li} x_i) \tag{3.7}$$

$$Z_j = fi\ (H_l),\ O_k = f(Z_j) \text{ and } Y_o = f(O_k) \tag{3.8}$$

where H_l, Z_j and O_k are the output at the hidden layer one, two and three respectively; Y_o is the output at the output layer and w_{li} is the synaptic weight from input neuron i (x_i) to the neuron l in the first hidden layer. Combining Eq. (3.5) - Eq. (3.8), the relation for the output of the network can be set as Eq. (3.9):

$$Y_o = f(O_k) = f(\sum_k w_{ok} f(\sum_j w_{kj} f(\sum_l w_{jl} f(\sum_i w_{li} x_i)))) \tag{3.9}$$

where w_{jl} is the synaptic weight from neuron l in the first hidden layer to the neuron j in the second hidden layer, w_{kj} is the synaptic weight from neuron j in the second hidden layer to the neuron k in the third hidden layer and w_{ok} is the synaptic weight from neuron k in the last hidden layer to the output neuron o.

3.6 MACHINE AND EQUIPMENT

The equipment used for this research are:

(i) CNC EDM wire cut. This is use to cut out the workpiece.
Brand: Sodick CNC wire cut
Model: AQ535L
Number of axes: 3 axes (X, Y and Z)

Figure 3.4: Sodick CNC wire cut

(ii) CNC EDM die sink. This is use to drill a hole in Ti-6AL-4V workpiece for this experiment.

Brand: Sodick CNC die sink

Model: AQ55L

Number of axes: 3 axes (X, Y and Z)

Figure 3.5: Sodick CNC die sink

ii) Precision balance is use to measure the mass of the workpiece and electrode before and after the machining process.

Brand: Precisa

Model: 92SM – 202A DR

Readability: 0.01mg/0.1mg

Figure 3.6: Balance machine

iii) Perthometer is use to measure the surface roughness of the machined workpiece.

Brand: Mohr

Model: Perthometer S2

Figure 3.7: Perthometer S2

3.7 EXPERIMENT SETUP

The experiment were performed on a numerical control programming EDM AQ55L with constant gap of 1mm and positive polarity for electrode is use. The dielectric used is kerosene with supply voltage of 120V and duty factor of 0.8 is used in this experiment. The titanium alloy material Ti-6Al-4V was machined with copper tool electrode. Table 3.1 shows the experimental setting.

Table 3.1: Experimental Settings.

Parameters	Description
Work piece material	Ti-6Al-4V
Work piece size	25 mm × 25 mm × 20 mm
Electrode material	Copper
Electrode size (diameter × length)	20 mm × 44 mm
Electrode polarity	Positive
Dielectric fluid	Commercial Kerosene
Applied voltage	120 V
Servo voltage	70 V
Flushing pressure	1.75 MPa
Machining time	40 minutes

3.7.1 Machining of workpiece

The workpiece is cut according to the dimension of 21.50mm × 21.0mm × 13.16mm as being shown in the Figure 3.8 from a plate if Ti-6Al-4V by using CNC EDM wire cut machine. The electrode size is 20mm in diameter. The experiments were designed on the basis of axial point central composite designs using response surface method , and by using Minitab, the design of experiment of level 5 is obtain. Table 3.2 shows the machining parameter and their level. The weight of the electrode and workpiece were measured before and after the machining by using a percision balance with readability of 0.1mg. Each machining was operated for 40 minutes. The sets of combination parameter that was generated by using response surface method earlier serve as the input data. The sets of parameter combination are shows in Table 3.3 After the machining and the weight are taken, the workpiece surface roughness is obtained by using perthometer.

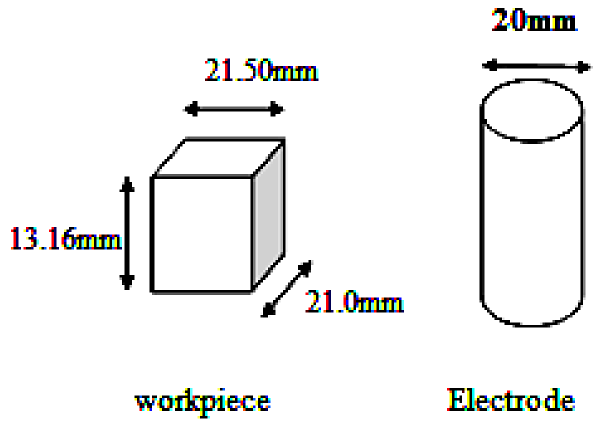


Figure 3.8: Material and electrode dimension

Table 3.2: Machining parameter and their levels.

Process	**Level** -2	**Level** -1	**Level** 0	**Level** 1	**Level** 2
Peak Current (A)	1	8	15	22	29
Pulse on time (µs)	10	95	180	265	350
Pulse off time (µs)	60	120	240	180	300
Servo voltage	75	85	95	105	115

Table 3.3: Parameter combination

Sample	**Peak current (A)**	**Pulse on time (s)**	**Pulse off time (s)**	**Servo voltage (V)**
1	15	180	180	95
2	8	265	240	85
3	29	180	180	95
4	15	180	180	95
5	15	180	180	75
6	15	180	180	95
7	8	95	120	85
8	22	265	240	85
9	8	265	240	105
10	15	180	180	95
11	8	95	240	105
12	15	180	60	95
13	8	265	120	85
14	22	95	120	105
15	22	95	240	105
16	8	95	120	105
17	22	265	240	105

Table 3.3: Continued

18	22	265	120	85
19	1	180	180	95
20	15	180	180	95
21	15	180	300	95
22	15	180	180	95
23	22	95	240	85
24	22	265	120	105
25	22	95	120	85
26	15	180	180	115
27	8	265	120	105
28	15	10	180	95
29	8	95	240	85
30	15	350	180	95
31	15	180	180	95

3.7.2 Modeling of ANN

The model used is RBFN with three hidden layer. The architecture of RBFN are shown in Figure 3.9.

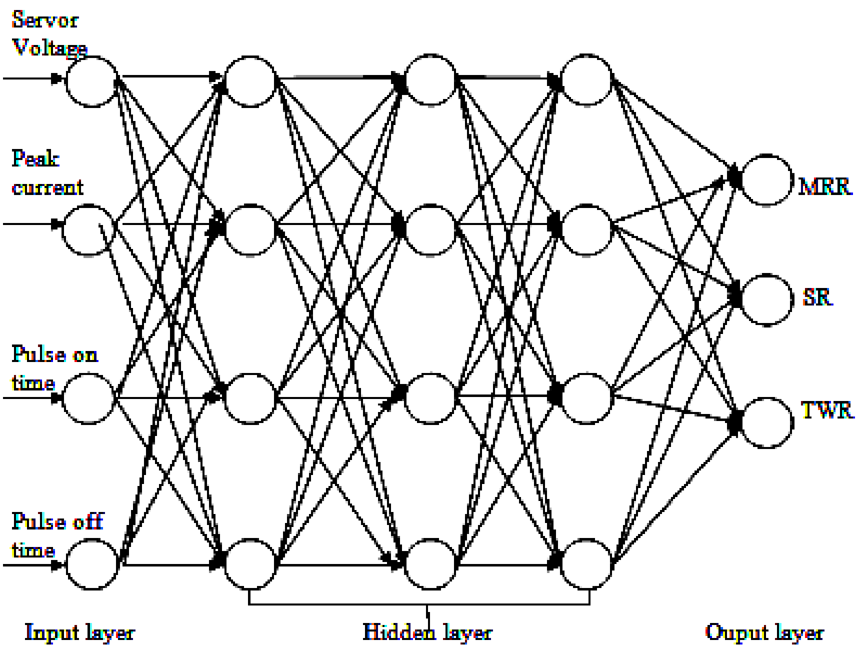


Figure 3.9: Architecture of RBFN model

The model used is RBFN with three hidden layer. Hyperbolic tangent function of sigmoid (TanhAxon) is used to calculate the output at both the hidden layer and also the output layer. The function of TanhAxon are shown in Eq. (3.10) and the output was compared with the measured output using mean square error (MSE) as in Equation (3.11). For training, levenberg-manquardt is used and the threshold was set at 0.0001. The model is train in batch mode. The maximum number of epoch used is 1600.

$$f(v) = \tanh(v) \tag{3.10}$$

$$E = \frac{1}{N}\sum_{o=1}^{N}(T_o - Y_o)^2 \tag{3.11}$$

A number of networks are constructed, each of them is trained separately, and the best network is selected based on the accuracy of the predictions in the testing phase. The general network is supposed to be 4–3–3, which implies four neurons in the input layer, 3 neurons in the hidden layer and 3 neurons in the output layer. These are done by using NeuroSolution 6 software by following the steps below. The output obtain from the experiment which is in the result table in the following chapter is used to generate ANN model.

3.8 CONCLUSION

In this chapter, EDM machining process, experiment setup and ANN modeling steps are being presented. By using the procedure in the experiment setup, experiment are carried to obtain results which will be presented in Chapter 4.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 INTRODUCTION

In this session, the experimental data are recorded in table and this data is used for ANN modeling. After the ANN modeling, the difference between experimental and predicted output is determined. From the modeling, the optimize parameter for the machining of Ti-6AL-4V can be determined in term of the best MRR, TWR and SR. Hence the effect of the parameter towards the output in this research is determined.

4.2 EXPERIMENTAL DETAILS

The experiment data as shown in Table 4.1 is used in the modeling of ANN as input parameter and desired output respectively. In this project, RBF used in ANN \modeling as in RBF network the best fit is used for the training to predict the output from the finding of multidimensional function. Sigmoid function is used in this modeling because it bear a greater resemblance to real neurons that to linear or threshold units. Table 4.2 shows the output generated by using ANN.

Table 4.1: Experimental data

No. Expt.	Input data				Output data		
	Servo voltage (V)	**Peak current (A)**	**Pulse on time (μs)**	**Pulse off time (μs)**	**SR (μm)**	**MRR (mg/min)**	**TWR**
1	95	15	180	180	4.319	2.0268	0.0229
2	85	8	265	240	1.747	1.0878	1.5291
3	95	29	180	180	6.110	6.5512	0.0234
4	95	15	180	180	4.326	1.9854	0.0934
5	75	15	180	180	4.660	2.9146	0.1096
6	95	15	180	180	5.334	0.9366	0.1641
7	85	8	95	120	2.529	1.7244	1.3197
8	85	22	265	240	5.983	4.2902	0.1017
9	105	8	265	240	3.108	0.4878	4.0550
10	95	15	180	180	4.268	2.2561	0.0259
11	105	8	95	240	2.851	0.3927	2.8713
12	95	15	180	60	3.461	2.6220	0.0242
13	85	8	265	120	2.638	1.3122	1.1896
14	105	22	95	120	4.358	143.0707	0.0045
15	105	22	95	240	4.043	3.1634	0.0616
16	105	8	95	120	2.976	0.5415	0.8153
17	105	22	265	240	5.402	3.3854	0.1376
18	85	22	265	120	5.617	5.8120	0.0721
19	95	1	180	180	1.999	0.1415	6.4310
20	95	15	180	180	4.799	2.4293	0.0270
21	95	15	180	300	5.413	1.7098	0.1054
22	95	15	180	180	4.684	2.1146	0.0188
23	85	22	95	240	5.544	3.4195	0.1405
24	105	22	265	120	6.535	3.8024	0.0783
25	85	22	95	120	6.041	4.4465	0.2660
26	115	15	180	180	6.213	1.3415	0.564
27	105	8	265	120	3.989	0.8488	0.0676
28	95	15	10	180	4.322	1.2073	0.4202
29	85	8	95	240	2.316	1.3780	0.7611
30	95	15	350	180	3.833	2.7024	0.0298
31	95	15	180	180	3.709	2.0488	0.0452

4.3 ANN RESULTS

Table 4.3 shows the convergence of the output error, mean square error (MSE) with the number of iterations (epochs) during the training of the network.

Table 4.2: Experimental and ANN predicted data

	Experimental data			ANN predicted		
No.expt	**SR**	**MRR**	**TWR**	**SR Output**	**MRR Output**	**TWR Output**
1	4.319	2.0268	0.0229	4.491286	1.971086	0.056757
2	1.747	1.0878	1.5291	1.747000	1.087800	1.529100
3	6.11	6.5512	0.0234	6.110000	6.551200	0.023400
4	4.326	1.9854	0.0934	4.491286	1.971086	0.056757
5	4.66	2.9146	0.1096	4.660000	2.914600	0.109600
6	5.334	0.9366	0.1641	4.491286	1.971086	0.056757
7	2.612	1.7244	1.3197	2.612000	1.724400	1.319700
8	5.983	4.2902	0.1017	5.983000	4.290200	0.101700
9	3.108	0.4878	4.055	3.108000	0.487800	4.055000
10	4.268	2.2561	0.0259	4.491286	1.971086	0.056757
11	2.851	0.3927	2.8713	2.851000	0.392700	2.871300
12	3.461	2.622	0.0242	3.461000	2.622000	0.024200
13	2.638	1.3122	1.1896	2.638000	1.312200	1.189600
14	4.358	143.0707	0.0045	4.358000	143.070700	0.004500
15	4.043	3.1634	0.0616	4.043000	3.163400	0.061600
16	2.976	0.5415	0.8153	2.976000	0.541500	0.815300
17	5.402	3.3854	0.1376	5.402000	3.385400	0.137600
18	5.617	5.8512	0.0721	5.617000	5.851200	0.072100
19	1.999	0.1415	6.431	1.999000	0.141500	6.431000
20	4.799	2.4293	0.027	4.491286	1.971086	0.056757
21	5.413	1.7098	0.1054	5.413000	1.709800	0.105400
22	4.684	2.1146	0.0188	4.491286	1.971086	0.056757
23	5.544	3.4195	0.1405	5.544000	3.419500	0.140500
24	6.535	3.8024	0.0783	6.535000	3.802400	0.078300
25	6.041	4.4465	0.266	6.041000	4.446500	0.266000
26	6.213	1.3415	0.0564	6.213000	1.341500	0.056400
27	3.989	0.8488	0.0676	3.989000	0.848800	0.067600
28	4.322	1.2073	0.4202	4.322000	1.207300	0.420200
29	2.316	1.378	0.7611	2.316000	1.378000	0.761100
30	3.751	2.7024	0.0298	3.751000	2.702400	0.029800
31	3.709	2.0488	0.0452	4.491286	1.971086	0.056757

MSE is one of the way to quantify the difference between ANN predicted and the true value of the quantity from the experimental result. It measure the average error by which the predicted value duffers form the quantity to be predicted. After 474 epoch, the MSE between the desired and actual output is 0.001194516 where the training is stopped. Table 4.3(a) represent the error between the desired output and predicted ANN output. The error of output generated by using ANN compare to the desire output in terms of SR, MRR and TWR are shown in Table 4.3(b). It can be seen that the accuracy of MRR, TWR and SR are 99.999%, 99.98% and 98.53% respectively.

Table 4.3: Error analysis of MRR, SR and TWR for the network

Best Network	**Training**
Epoch #	474
Minimum MSE	0.001194516
Final MSE	0.001194516

(a)

Performance	**SR**	**MRR**	**TWR**
MSE	0.050349143	0.044880613	0.000562047
NMSE	0.02929424	7.22888×10^{-5}	0.000296066
MAE	0.086654387	0.066741027	0.009289403
Min Abs Error	2.05565×10^{-9}	1.1966×10^{-9}	1.29688×10^{-11}
Max Abs Error	0.842714268	1.034485717	0.107342856
r	0.98524401	0.999963855	0.999851956

(b)

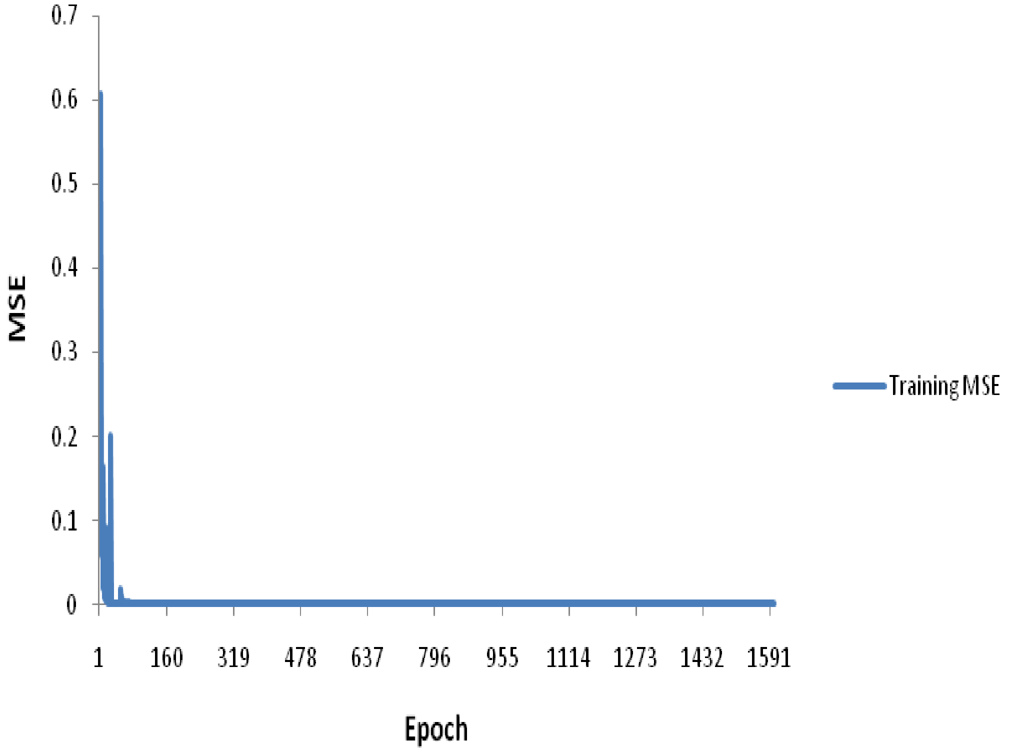


Figure 4.1: Learning behavior of ANN model

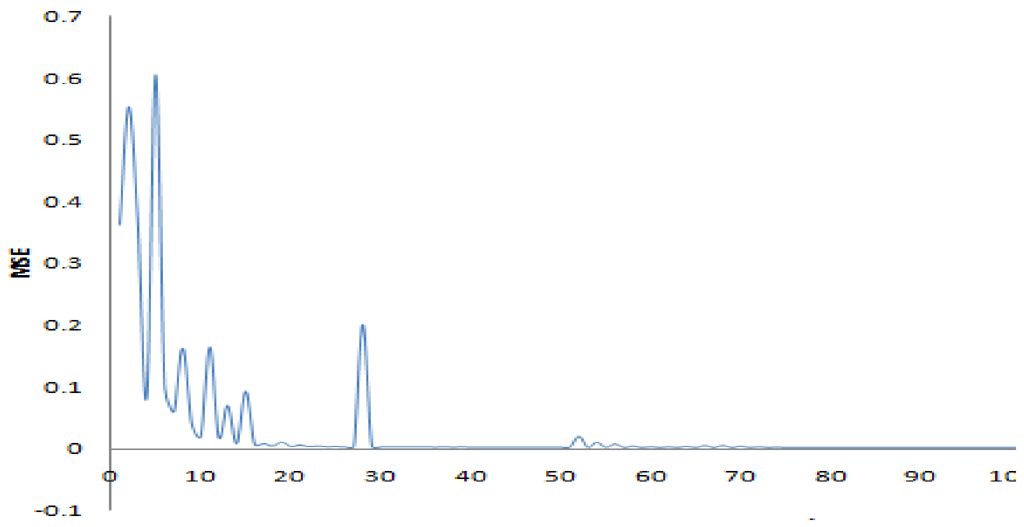


Figure 4.2: Enlarge Figure 4.1 from 0 epoch to epoch 90

From Figure 4.1, at the beginning of the training, the output value is far from the targeted value but it get closer as epochs increases as the network slowly learn the relationship between the input and output of the training samples until the epoch stop. In sensitivity analysis, the effect of different input parameters towards the output is analyze. It can be seen that the, peak current effect the output response the most followed by servo voltage, while pulse on time and pulse off time both gives almost similar effect on the output. Peak current serve as one of the primary parameter in EDM machining. The machining parameter effects the SR the most and has the smallest effect on the TWR. Table 4.4 and Figure 4.3 show the result of sensitivity analysis.

Table 4.4: Sensitivity analysis

Sensitivity	**SR**	**MRR**	**TWR**
Servo voltage	0.688406544	0.458291076	0.042164026
Peak Current	0.831760848	0.864021914	0.060062428
Pulse on time	0.410801856	0.248125045	0.038801849
Pulse off time	0.433807762	0.387179951	0.033671973

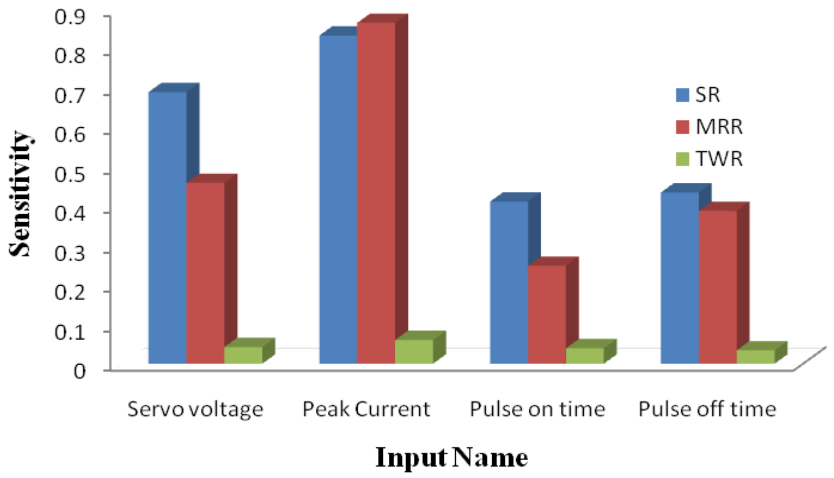


Figure 4.3: Sensitivity diagram

Figure 4.4 shows the effect of various input voltage to its response output. Generally SR increases as the servo voltage increases while MRR decreases and TWR are at almost at a constant rate. As servo voltage approach 93A, the SR and started to decreased. It is observed that the minimum surface roughness and TWR obtained at servo voltage 95V.

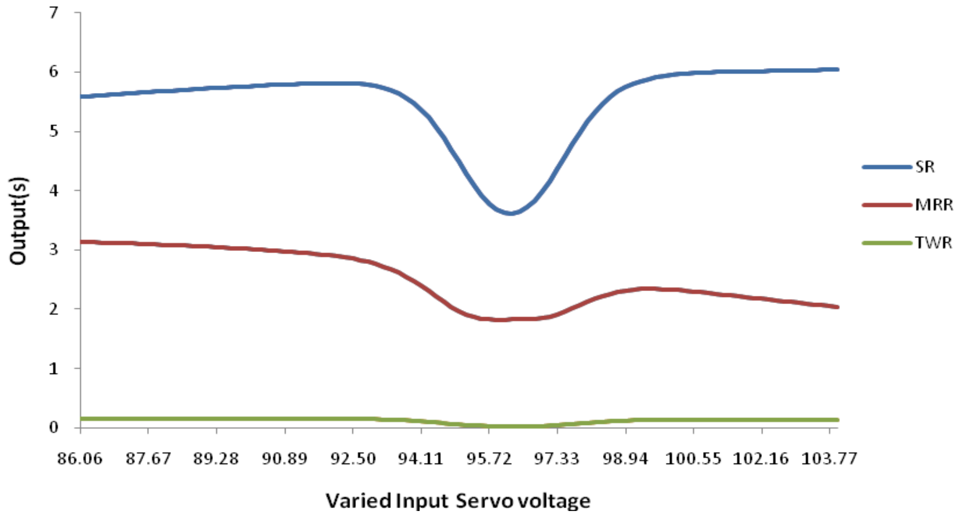


Figure 4.4: Variation of machining parameter for various input servo voltage

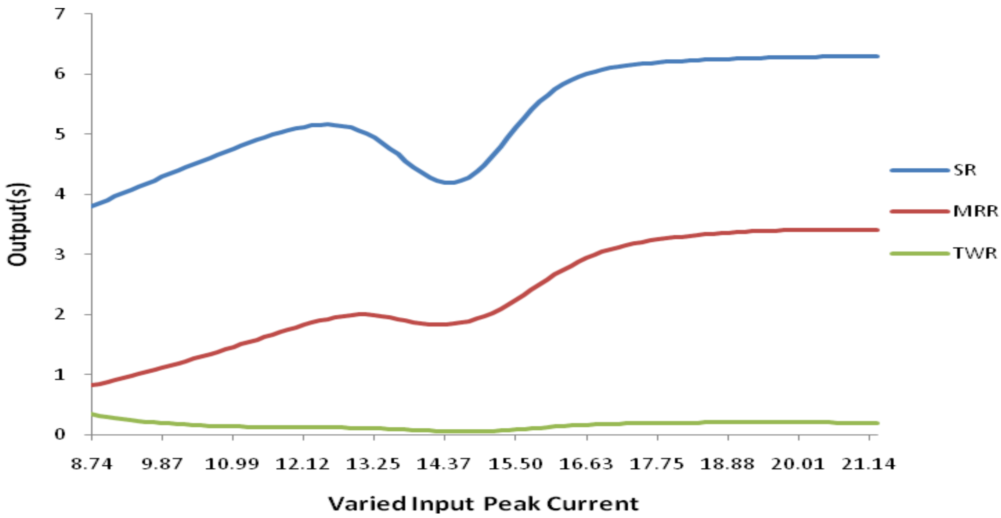


Figure 4.5: Variation of machining parameter for various for various input peak current

Figure 4.5 shows that the value of SR, MRR and TWR has the tendency to increase as the peak current increases. Peak current is the value of current applied to the electrode during pulse on-time in EDM. The higher the peak current, the higher the rate of the spark to occur that will increase the MRR. The optimize current for best SR is at

15A. Pulse on-time and pulse off-time shows the time of which current is applied to the electrode during each EDM cycle and the waiting interval during two pulse on-time respectively. Longer pulse on-time allow more material to be removed because the time interval for the spark to occur has increase. SR and TWR decreases as pulse on-time increases while MRR increases. While for pulse off-time, SR increase, MRR decreases but it does not show much effect on the TWR. During pulse off-time, melted and solidified particle are removed from the setting. The optimize pulse on-time and pulse off-time for the best SR is at 180μs. Figure 4.6 and Figure 4.7 shows effect of various input pulse on-time and pulse off-time toward the output response.

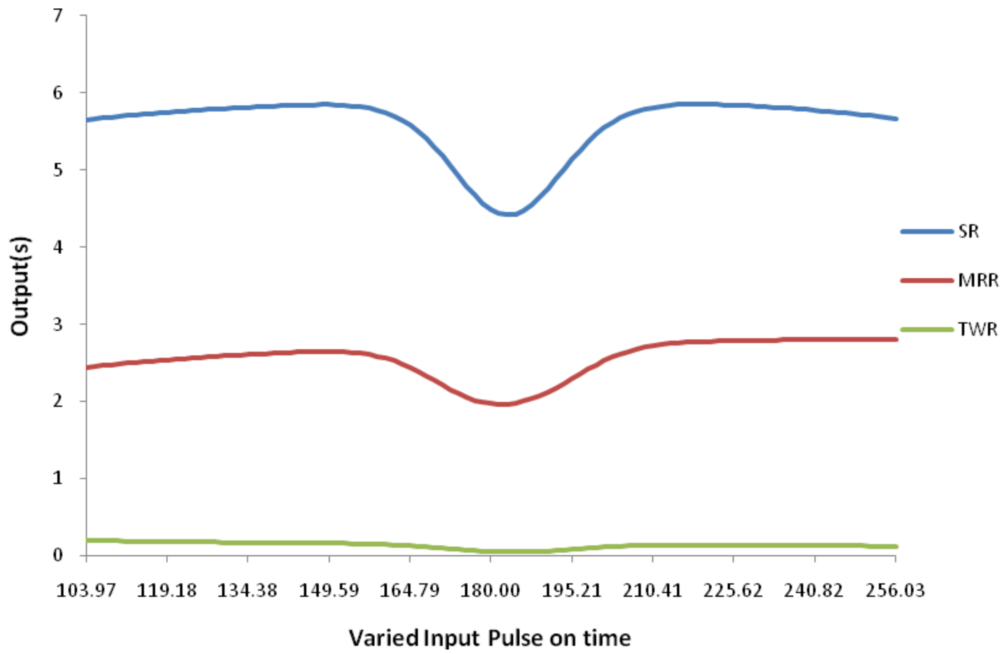


Figure 4.6: Variation of machining parameter for various of varies input pulse on-time

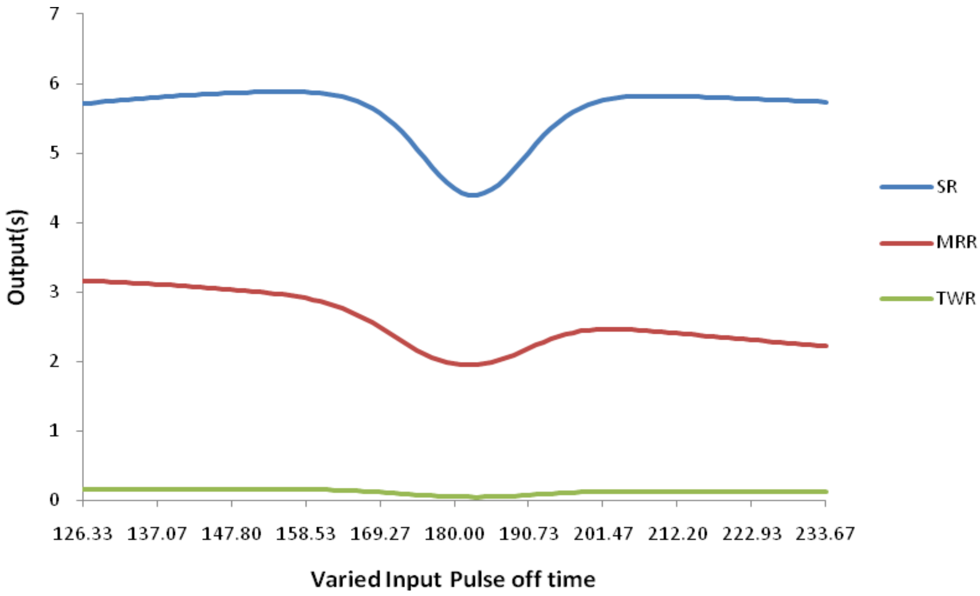


Figure 4.7: Variation of machining parameter for various input pulse off-time

4.4 COMPARISON OF EXPERIMENTAL AND ANN PREDICTED

Comparing between the experimental and ANN predicted results, there are slightly difference in its value. This is shown in Figure 4.8 to Figure 4.10 where SR output, TWR output and MRR output represent ANN predicted value.

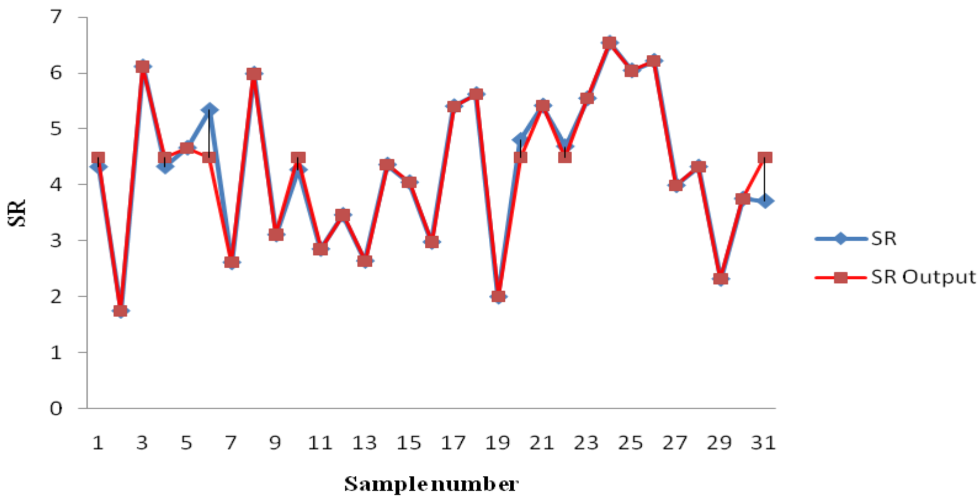


Figure 4.8: Difference between ANN predicted and experimental SR

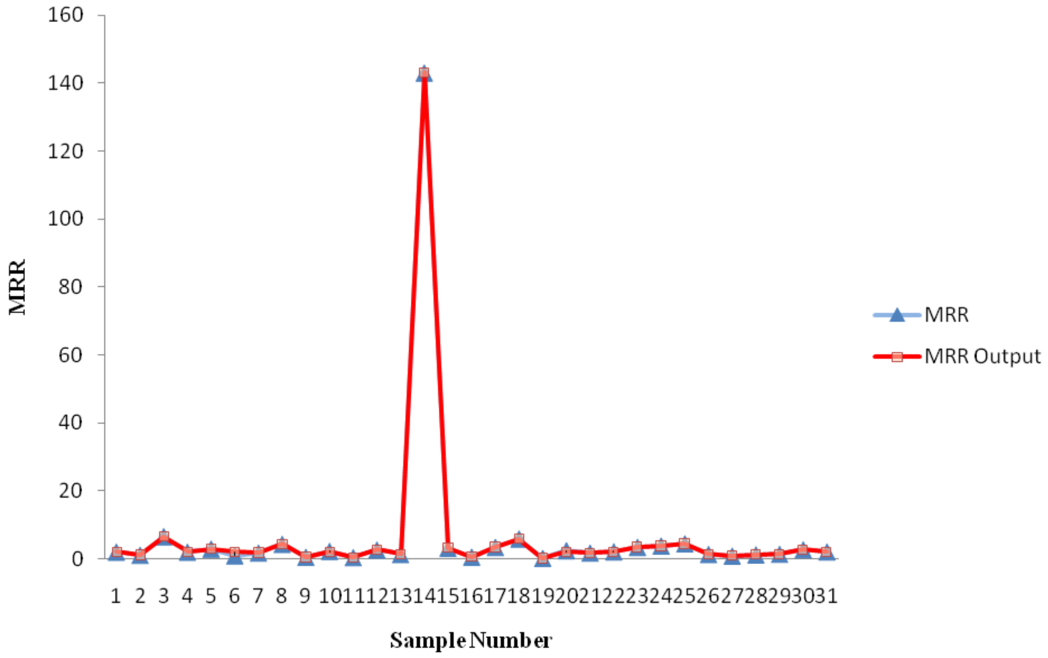


Figure 4.9: Difference between ANN predicted and experimental MRR

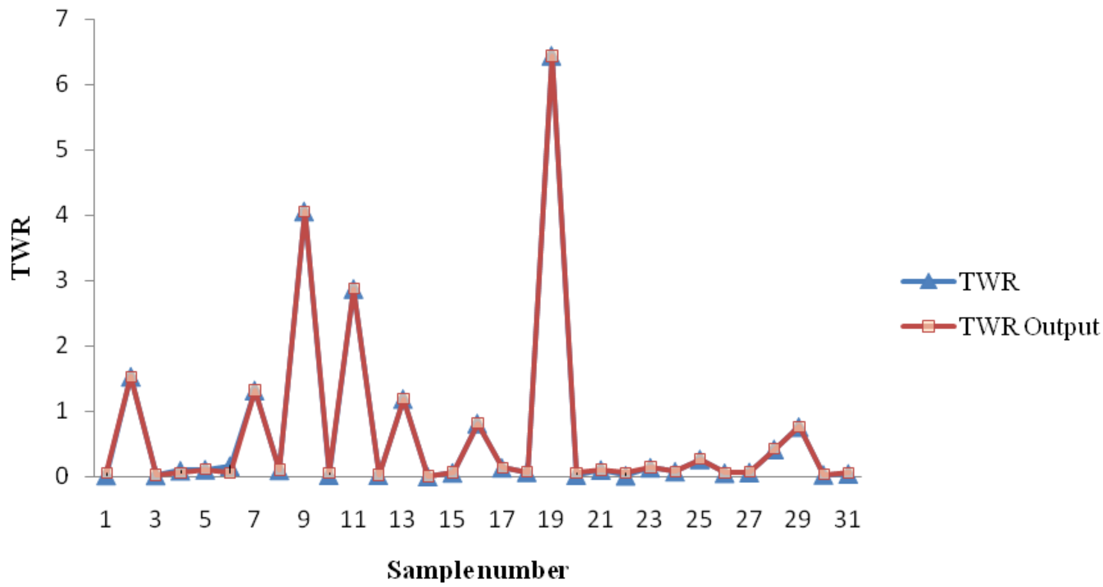


Figure 4.10: Difference between ANN predicted and experimental TWR

4.5 CONFIRMATION TEST

Experimental results and the result predicted by ANN are almost the same. Hence this prove that the network can be employed for production. EDM machining condition used in confirmation test are as presented in Table 4.5. Table 4.6 is generated by performing this confirmation test.

Table 4.5: EDM input parameters for confirmation test

Peak current (A)	**Pulse on time (μs)**	**Pulse off time (μs)**	**Servo voltage (V)**
8	265	300	85
15	180	180	105
22	265	180	85

Table 4.6: Error for ANN predicted results with experiment.

No. of Expt.	**Experiment**	**Prediction**	**Error (%)**
Material Removal Rate			
1	1.3450	1.378	2.45
2	2.6161	2.702	3.28
3	1.7497	1.971	12.65
		Average error	6.13
Tool Wear Rate			
1	0.8251	0.7611	7.76
2	0.0281	0.0298	6.05
3	0.5845	0.5676	2.84
		Average error	5.55
Surface Roughness			
1	2.106	2.316	9.97
2	3.783	3.751	0.85
3	4.754	4.491	5.86
		Average error	5.56

The output of the network in terms of MSE during training of the network and the error between the desired response and ANN predicted is in the range of 5-6%. This error are within an acceptable range. Performance parameter of EDM in terms of MRR, TWR and SR can be evaluates practically and effectively by using ANN.

4.6 CONCLUSION

In this chapter, the difference between ANN predicted and experimental data is obtain and ANN modeling has be prove to be accurate in predicting the parameter in EDM machining of TI-6Al-4V with average error of 5% to 6%. The optimize machining parameter are concluded in the following chapter.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 INTRODUCTION

This chapter include the conclusion for the whole project and some recommendation to improve the results.

5.2 CONCLUSION

ANN model is developed for four parameters which can predict the behavior of these parameters when machined on Ti-6Al-4V. The developed model is within the limits of agreeable error when experimental and model values are compared for all performance measures considered. From the sensitivity analysis it is concluded that peak current is having highest influence on all performance measures. Around 15 A peak current, 180 µs pulse on time, 180 µs pulse off time and 95V servo voltage yields the best surface roughness. The electrode wear rate initially decreases with pulse on time henceforth increase as on time increase. The similar effect was observed in the case of pulse off time nevertheless the longest on time generates maximum TWR whilst the same result occurred at shortest off time. As for MRR and TWR the servo voltage is around 85V and 95V respectively and peak current of 21A and 8A respectively. The results reveal that the lower the ampere the higher the electrode wear rate and vice versa. The lowest value of electrode wear rate is acquired while the peak current around 18A.

5.2 RECOMMENDATION

In the experiment, there are several factors that contribute to the experimental error which bring to the difference between experimental result and ANN predicted. Hence several changes can be made in performing gathering the result from experiment. In the case of wet electrode and workpiece by the dielectric fluid during the machining, instead of wiping it off by using cloth, it is a better result if the electrode and workpiece can be dry by using high pressure blower. Higher level of experiment and more sets of parameter should be generated to gather more data so that more accurate sets of parameter to optimize the machining of Ti-6AL-4V can be obtained.

REFERENCES

Erden,A. 1983. Effect of materials on the mechanism of electric discharge machining. *Trands ASME*. **105:** 132

Fonda, P., Wang, Z., Yamazaki, K. and Akutsu, Y. 2008 A Fundamental study on Ti-6Al-4V's thermal and electrical properties and their relation to EDM productivity. *Journal of Material Processing Tehnnology*. **202** (1): 583-589.

Hascalik, A. and Caydas, U. 2007. Electrical discharge machining of titanium (Ti-6l-4V). *Applied Surface Science* **253**: 9007-9016.

Jameson, E.C. 2005. *Electrical discharge machining.* United State of America: Society Of Manufacturing Engineer.

Joshi, V.A. 2006. *Titanium alloys an atlas of structures and fracture features.* Baco Raton: CRC Press.

Krishna, M.R.G., Rangajanardhaa, G., Hanumantha, R.D. and Sreenivasa, R.D. 2009. Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm. *Journal of Materials Processing Technology* **209:** 1512-1520

Luis, C.J., Puerkas, J. and Villa G. 2005. Material removal rate and electrode wear study on the EDM of silicon carbide. *Journal of Material Processing Technology* **164-165:** 889-896.

Luo, F. and Unberhauen, R. 1998. *Applied neural networks for signal processing*. New York: The Syndicate of The University of Cambridge.

Moiseyev, V.N. 2006. *Titanium alloys Russian aircraft and aerospace applications.* Baco Raton: CRC Press.

Salman,O., Cengiz,M. and Kayacan. 2008. Evolutionary programming method for modeling the EDM parameter for roughness. *Journal of Material Processing Technology* **200:** 347-353.

Shin, Y.C. and Xu, C. 2009. *Intelligent systems modeling, optimization, and control.*Baco Ralton: CRC Press.

Singh, S., Maheshwari, S. and Pandey, P.C. 2004. Some investigation into the electric discharge machining of hardened tool steel using different electrode materials. *Journal of Materials Processing Technology* **149:** 272-277.

Valenticic, J., Filipuc, B., and Junkar, M. 2009. Machine learning induction of a model for online parameter selection in EDM rough. Machining.*Int J Adv Manuf Technol.* **41**:865-870.

Yang, S., Srinivas, J., Mohan, S., Lee, D.M. and Balaji, S. 2009. Optimization of electric discharge machining using simulated aneealing. *Journal of Materials Processing Thecnology*. **209** (9): 4471-447.5