OPTIMISATION OF LASER CUTTING PARAMETERS OF

OIL PALM WOOD

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ABSTRACT

Materials derived from Oil palm wood are still not widely used in furniture industry. There are many machining operations that can be implemented to process the oil palm wood into the final product. This project experimentally investigates the cutting quality of oil palm wood produced/processed using a CO_2 laser cutting machine. The quality of the cut has been monitored by measuring the upper kerf width. Another aim of this project is to evaluate the effect of processing parameters of CO_2 laser cutting such as laser power, inert gas pressure, cutting speed and focal point position on the cutting quality of the oil palm wood. A statistical analysis of the result has been conducted in order to determine the effect of each parameter on the cut quality. From the analysis for dried sample (Sample X), laser power has a very big effect on upper kerf width (34.08%). Simulation and prediction of CO_2 laser cutting of oil palm wood have been done by feed forward back propagation Artificial Neural Network (ANN). Experimental data of Taguchi orthogonal array L9 was used to train the ANN model. The simulation results were evaluated and verified with the experiment. In some cases, the prediction errors of Taguchi ANN model was found larger than 10% even using a Levenberg Marquardt training algorithm. To overcome the problem, a hybrid genetic algorithm-based Taguchi ANN (GA-Taguchi ANN) has been developed. The potential of genetic algorithm in optimization was utilized in the proposed hybrid model to minimize the error prediction for regions of cutting conditions away from the Taguchi based factor level points. The hybrid model was constructed in such a way to realize mutual input output between ANN and GA. The simulation results showed that the developed GA-Taguchi ANN model managed to reduce the maximum prediction error below 10%. The model has significant benefits in many manufacturing processes.

ABSTRAK

Kayu kelapa sawit ialah satu bahan yang mana masih tidak digunakan dengan meluas dalam industri perabot. Terdapat banyak operasi permesenan yang boleh digunakan untuk memproses kayu kelapa sawit ke bentuk produk akhir. Projek ini menyiasat secara eksperimen kualiti pemotongan kayu kelapa sawit dengan menggunakan mesin pemotong laser CO_2. Kualiti potongan telah dipantau dengan mengukur kelebaran garitan atas. Satu lagi tujuan projek ini ialah untuk menilai parameter pemprosesan pemotongan laser CO_2 seperti kuasa laser, tekanan gas lengai, kederasan memotong dan kedudukan tumpuan utama di kualiti memotong kayu kelapa sawit. Satu analisis statistik hasil telah dijalankan teratur untuk kesan setiap parameter di kualiti memotong untuk dipastikan. Daripada analisis sampel kering (Sampel X), kuasa laser memberi kesan yang lebih tinggi untuk kelebaran garitan atas (34.08%), Simulasi dan ramalan keratan laser CO_2 kayu kelapa kelapa sawit telah dibuat dengan menggunakan teknologi Artificial Neural Network (ANN). Data tatasusunan Taguchi ortogon L9 ada digunakan bagi melatih model ANN. Keputusan simulasi telah dinilaikan dan mengesahkan dengan eksperimen. Dalam beberapa kes, kesilapan-kesilapan ramalan model Taguchi ANN lebih besar daripada 10% meskipun dengan Levenberg Marquardt berlatih algoritma. Untuk mengatasi masalah seumpama, satu kacukan Taguchi ANN berasaskan algoritma genetik (GA-Taguchi ANN) telah dimajukan. Potensi algoritma genetik dalam pengoptimuman telah digunakan dalam model kacukan dicadangkan meminimumkan ramalan ralat kerana kawasan-kawasan memotong syarat-syarat jauh dari Taguchi berpangkalan mata aras faktor. Model kacukan dibina dalam jalan sebegitu menunaikan input output saling antara ANN and GA. Keputusan simulasi menunjukkan bahawa model GA-Taguchi ANN maju boleh mengurangkan ralat ramalan maksimum di bawah 10%. Model ini mempunyai faedah penting dalam proses pembuatan.

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ANN   Artificial Neural Network

MC   Moisture Content

MD   Material Density

GA   Genetic Algorithm

NPM   Noise Performance Measure

OPT   Oil Palm Trunk

S/N   Signal to Noise Ratio

TPM   Target Performance Measure

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Appendix B: List of Conferences

CHAPTER 1

INRODUCTION

1.1   Research Background

Oil palm industry is one of the largest agricultural plantation sectors in Malaysia with a planted area of 4.69 million hectares and producing over 8 million tons of oil annually. But, the oil only consists of 10% of the total biomass produced in the plantation. The remainder consists of huge amount of celluloses materials such as oil palm trunk, fronds, and empty fruit bunches. The efficient use of such residues is vital in order to minimize the environmental burdens associated with the disposal of the oil palm residues, thus ensuring the future growth of Malaysia's palm oil industry (Nordin, K 2004).

The oil palm trunk is converted to oil palm wood after the replantation take place. Manufacturing of an oil palm wood was initiated by Malaysian Palm Oil Board (MPOB) in the early 1980s. It has been long observed that this type of wood has high market value due to its lightweight property, ease of manufacture and eco-friendly. Use of oil palm trunk (OPT) in wood processing not only revives the ailing plywood industry but also provide an opportunity for the industry to grow. In one study, industrial manufacturing of plywood from OPT was demonstrated to be successful and profitable (Husin, Mokhtar, & Hassan, 2003).

Wood is a complex an isotropic material characterized by several hierarchical levels of organization (Trtik et al., 2007). Structural features of all the levels, from the macroscopic to the sub-microscopic scale, contribute to the properties of wood.

Different types of wood show different mechanical properties. Ratanawillai (2006) investigated mechanical properties at different portions of the OPT. It was found that the mechanical properties (in term of tensile, bending, hardness and impact test) of OPT were approximately two times lower than those of teak and rubber wood (Thanate Ratanawillai, 2006). Teak is quite often used as a reference species for standardization of wood property evaluation and end-use classification of tropical hardwood (K.M. Bhat, 2001). Besides that, processing of the stem was found difficult, particularly at the region near the bark due to the presence of silica in the cells.

The machining of wood process by cutting is a demanding technological process because of it is specific structure. There are many successful CO_2 laser cutting applications have been reported since 1986, (Barnekorv et al. 1986) but, machining of wood by laser still has not been widely accepted by wood industry nowadays. A considerable amount of literature has been focused on the use of CO_2 laser cutting of wood. As an example, Yusoff et al. (2008) studied the Malaysian light hardwood have been cut using CO_2 laser. In spite of that, have some researcher studied the laser cutting of processed wood. As an example is an experiment in laser cutting of medium density fiberboard (MDF) (H.A. et al., 2011; Lum et al., 2000).

There are a lot of factors that influence the laser cutting of wood. This can be referred to the machining of normal wood which results in complex interactions between the laser beam and wood. Each parameters and variables are depends among each others (fixed and dependent variables). For example, when the beam penetration becomes greater, the thicker wood can be cut with increasing power. Among the factors that influence the laser cutting of wood are focal point, type of assist gas, gas pressure, work piece thickness, density, moisture content, laser power, polarization and etc

(Barnekorv, et al., 1986). Zhou and S.M.Mahdavian (2004) cut different non-metallic materials using 60 W low power lasers. When this laser power used to cut the wood, the slow cutting speed required and cutting kerfs are always charred. More energy is required for deeper cutting depth. They also stated that the content of water inside the wood greatly affect the laser cutting quality.

Eltahwani et al. (2011) reported that many researchers conducting their experiments using a statistical technique like Design of Experiment (DOE) and artificial neural network (ANN). The aim to use this technique is to optimizing the behaviours of a certain manufacturing process, such as optimizing laser cutting processes that have been conducted by Castaneda JCH (2009) or laser welding processes by Benyounis KY (2008).

In this research, the effect of each parameter or factor on the quality measures will be determined. This research conducted, in conjunction to recognize the best machining condition and the effectiveness of CO_2 laser for oil palm wood in cutting process. For the output of this research, the wood industries may manipulate this new technology in order to improve the productivity and increase quality of their products. Thus this CO_2 laser wood cutting system can work for the company to produce those high qualities of production with a minimum of waste and total ease of use. To achieve this, the best machining condition of laser cutting need to be well determined to prevent any burn or minimize the char formation of wood while conducting the cutting process. Hence, this work aims to investigate the effect of CO_2 laser cutting process parameters of oil palm wood based on cut quality and then determined the optimal cutting conditions, which would lead to the desired quality features at a reasonable operating cost.

1.2   Problem Statement

Wood nowadays has been widely used on many applications, from construction to furniture. Hence the processing of this material has become more important to satisfy the ever increasing demand of it in the market. The processing involves machining and cutting of the wood. However, in this project, the focus is on the cutting process of oil palm wood. There are a lot of cutting methods which are used today to cut this material. It falls into two major types of cutting processes – conventional and non-conventional. A question arises though as what the difference between these methods? How they differ between each other in terms of cutting mechanism and applications. Also, what are the cutting parameters of these cutting processes that we can control? Another problem is that how the changes of the parameters of cutting can affect the quality of cutting on the wood. By changing one parameter, the cutting quality such as kerf width might change as well, so it is important to identify and gain knowledge on the parameters.

1.3   Objectives

a) To investigate the cut quality (kerf width) of CO_2 laser cutting of oil palm wood.

b) To identify the factors affecting laser cutting of oil palm wood such as laser power, cutting speed, focal point position, material density and moisture content.

c) To predict the optimization of CO_2 laser cutting of oil palm wood using analytical and numerical methods.

1.4   Scope of Research

The scope of study of this project includes CO_2 laser cutting and Oil Palm Wood. The principal and mechanism of CO_2 laser cutting will be studied in order to develop good understanding about the project. Different material can be machined using CO_2 laser which can be categorised into 2 major groups: metal and non-metal. However, focus will be given to machining of non-metal material using CO_2 laser as it is more relevant to this project. This study is limited to the machining of oil palm wood that have two different section with have two different material density and two different moisture content. Extensive study on oil palm wood will be conducted to understand about its characteristics and properties.

There are many parameters which need to be manipulated when using CO_2 laser. However, in this project only four parameters that will be studied which is laser power, focal point position, cutting speed and pressure of inert gas. By varying these parameters level using the design of experiment by Taguchi Method $L_9(3^4)$, the oil palm wood will be cut using CO_2 laser. The analysis will be focused on upper kerf width.

1.5 Arrangement/ Organization of the Dissertation

This dissertation consists of five chapters. The chapters included as follow:

Chapter 1: Introduction

- A brief introduction of this project, it also includes the importance of study, research problem statement, objectives, scope and limitations of the study and the methodology applied in carrying out the research.

Chapter 2: Literature Review

- A review of the previous studies done by other researchers and explanation of the theory and principle related to the project.

Chapter 3: Research Methodology

- A detailed description on the methodology of the project, include the experiment preparation, experiment setup, machine and equipments used, procedure of experiment, design of experiment and data collection methods.

Chapter 4: Result and Discussion

- Results collected and analyzed, and discussion of the results are presented.

Chapter 5: Conclusion and Recommendation

- Conclusion for this project and recommendation of further improvement for future work.

1.6 Contribution of the Study

This research is essential to provide the information for machining using CO_2 laser to select the optimum combination of input cutting parameters to achieve the optimum laser cutting output quality. This experimental study was meant to utilize and optimize the usage of continuous wave CO_2 laser cutting of oil palm wood. The new method of optimization will minimize the number of experiment improved quality of final products.

CHAPTER 2

LITERATURE REVIEW

2.1   Oil Palm Wood

Malaysia is among the world's top producers of palm oil plantation with a planted area of 4.85 million hectares in 2010 (Sulaiman et al., 2012). The success of oil palm industries in Malaysia is in terms of producing and marketing palm oil, palm kernel oil and the other products from the tree itself. Besides the oil, there are also huge amounts of oil palm by-products such as oil palm shells, oil palm fronds (during harvest of fresh fruit bunch) and oil palm trunk (from the field during replanting), being generated by industries.

Oil palm normally passed their economic age, on an average after 25th years and is due replanting. During replanting, the bole together with length of felled palm trunk is in the range of 7 meter to 13 meter, with the average diameter of 45 cm to 65 cm. Kamaruddin et al (1997) illustrated that the form curve of oil palm trunk is neilod (convex) in the region of its buttress until a point of inflection which is located approximately 2.5 meter above the ground.

It was found that the mechanical properties (in term of tensile, bending, hardness and impact test) of oil palm trunk were approximately two times lower than those of teak and rubber wood (Thanate Ratanawillai, 2006). In addition, its structure property is different in comparison to forestry trees since it does not have a secondary growth which typically displays growth rings, cambium, ray cells, sapwood and heartwood (Kilmann & Lim, 1985). The growth and increase in diameter of the trunk

are as a result from the overall cell division and cell enlargement of the fiber of vascular bundles and parenchymatous tissue.

Oil palm trunk consist of complex arrangement of fiber in which surrounded by the fine parenchymatous tissue. The density of the oil palm trunk is dependent on the density of the arrangement of the fiber in which the density variation pattern is found to be declining towards the inner part of the log while the bottom part of the log contains higher density of fiber as compared to the top portion (Balfas, 2006; Feng, Tahir, & Hoong, 2011). The variation densities from top to bottom ranged from 200-700 kgm^{-3} and the variation of moisture content ranged from 200%-300% (Kilmann & Lim, 1985).

The length of single fibre of the oil palm trunk ranges from 1.23 to 1.37mm with its fibre-wall area varies from 188.51 to 295.28 μm^2 depending on the location within the tree trunk (Hasan, 2005). This author also stated that the fibers from the lower portion of OPT are significantly stronger than those from the top potion of the same oil palm trunk. The mechanical properties of single fiber of oil palm trunk are as shown in Table 2.1.

Table 2.1: Mechanical properties of single fiber of Oil Palm Trunk

Mechanical Properties	Value
Fracture Stress	263.65 to 530.63 MPa
Fracture Strain	5.97% to 7.56%
Modulus of Elasticity	4059.74 to 6469.42MPa

Choo et al., (2010) stated that the density of oil palm wood is increases from the pitch to the bark because the number of fiber is increasing from the pitch to the bark. The illustration of cross-section of oil palm trunk is as shown in the figure 2.1. The basic density is obtained using green volume and oven dry weight of each trunk

specimen in accordance with ISO 3131:1975 procedures. The calculation of density is as follows:

$$\text{Density, kg.m}^{-3} = \frac{\text{Weight at Oven Dry Specimen, kg}}{\text{Volume of Green Specimen, m}^3} \qquad (2.1)$$
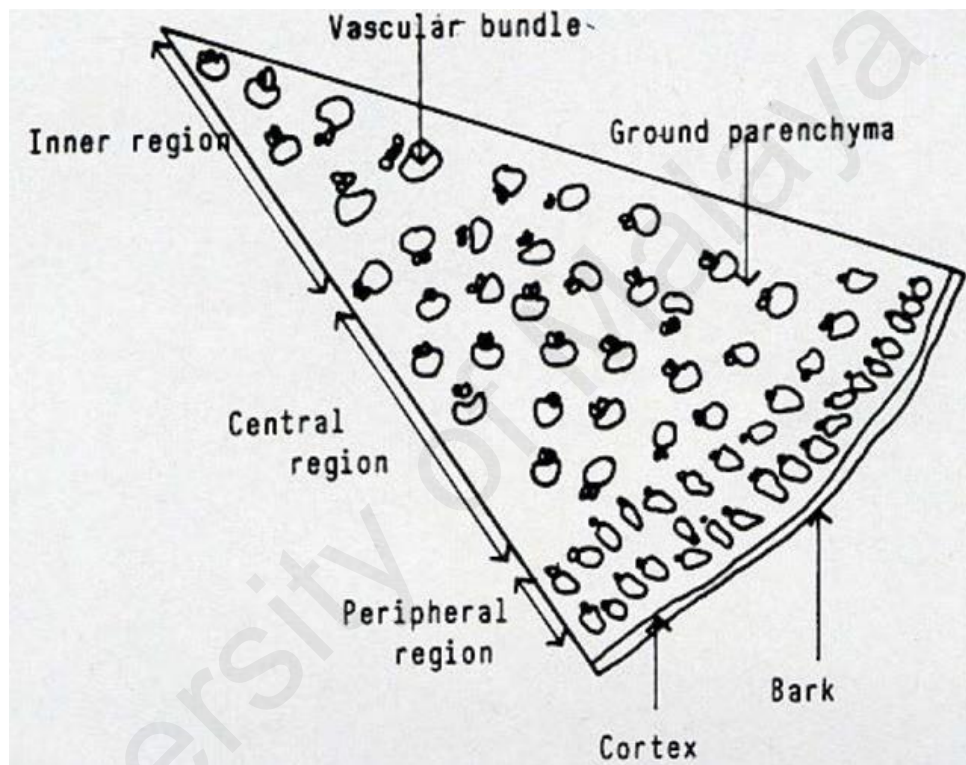
Figure 2.1: Cross section of oil palm trunk [(Kilmann & Lim, 1985)]

The moisture content of freshly felled OPT varies between 140% to 500% (Balfas, 2006; Kilmann & Lim, 1985). Choo, et al., (2010) and Feng, et al., (2011) described that the stem portion with moisture content of 300% and above, as within the center (pitch) and its intermediate inner zones (slightly below the bark). This author also stated that this percentage is covered 86.29% of the total cross sectional area of oil palm trunk. The trend of moisture content increment from bark to pitch is because the

distribution of the tissue (parenchymataous cells) which retain more moisture than fiber (vascular bundles) (Ramle et al., 2012).

The moisture content is defined as the ratio of the mass of removable water to the dry mass of the wood in accordance with ISO 3130:1975 and the calculation is as follows:

$$\% \text{ moisture content} = \frac{[\text{Total weight of specimen and moisture -1}]}{\text{oven dry weight}} \times 100 \qquad (2.2)$$

2.2 Principles And Mechanism Of CO_2 Laser

Laser is an acronym of light amplification by stimulated emission of radiation and it is basically a device which emits light through a process of optical amplification based on the stimulated emission of photon. Atom consists of proton, nucleus and electron. The electron has its natural orbit that it occupies, orbiting the nucleus of the atom. However, if an atom is energized, the electron can move to a higher orbit. The atom is now in the excited state. At this state, the electron moves up to a higher energy level as mentioned before and it becomes unstable. Eventually, the electron will move back to its natural orbit. A photon of light is produced whenever an electron in a higher orbit falls back to its natural orbit. This phenomenon happens at random time and in random direction, generating an incoherent light. This process is called spontaneous emission.
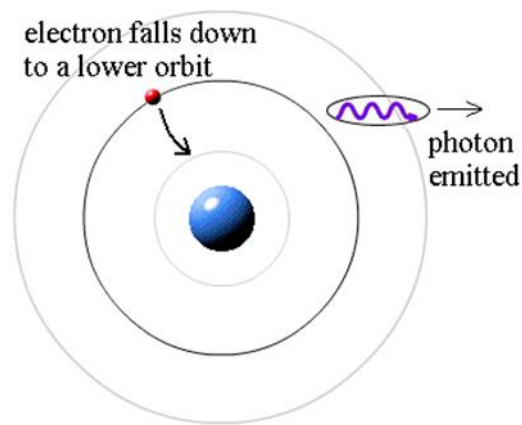
Figure 2.2: Emission of photon

CO_2 laser cutting is a technology that utilize laser to cut materials. It has been widely used since it was introduced. The first commercial use of CO_2 laser cutting was to cut plywood die boards for packaging industry (Powell, 1998). Now it can be employed to machine both metal and non-metallic materials. For example, Yilbass (2011) recently studied laser cutting of alloy steel, Haynes 188.

Generally, laser cutting is a thermal process. The material is cut using the heat from the laser (Powell, 1998). During cutting, a generated laser beam is focused onto the workpiece. The workpiece will then burn or melt, leaving a clean cutting edge.

CO_2 laser had been used in this project to analyze the cutting quality of an oil palm wood. Non-metallic materials cutting using CO_2 laser are said to be very efficient (Yusoff, et al., 2008). This is because the non-metallic materials are highly absorptive to the CO_2 laser's wavelength (H.A. Eltawahni, et al., 2011; Powell, 1998).

The mechanism of CO_2 laser cutting is simple. First is the generation of high intensity beam of an infrared light by the laser. The produced beams are then focused onto the surface of the workpiece using a converging lens. The surface of the

workpiece is heated by the focused beam and this establishes a localized melt throughout the depth of the workpiece. The melted material is then removed from the heated area by pressurized gas jet. The localized area of material removal is moved across the surface of the workpiece, thus generating a cut. The cut can be generated by either keeping the laser beam stationary or moving the workpiece or by moving the laser beam across the surface of the workpiece while keeping the workpiece stationary. There exists a hybrid system which allows the combination of these two options. Using this system, linear cuts and two dimensional parts can be produced. However, more complex system is needed for three dimensional parts. Figure 2.2 gives a better image on the mechanism of laser cutting.
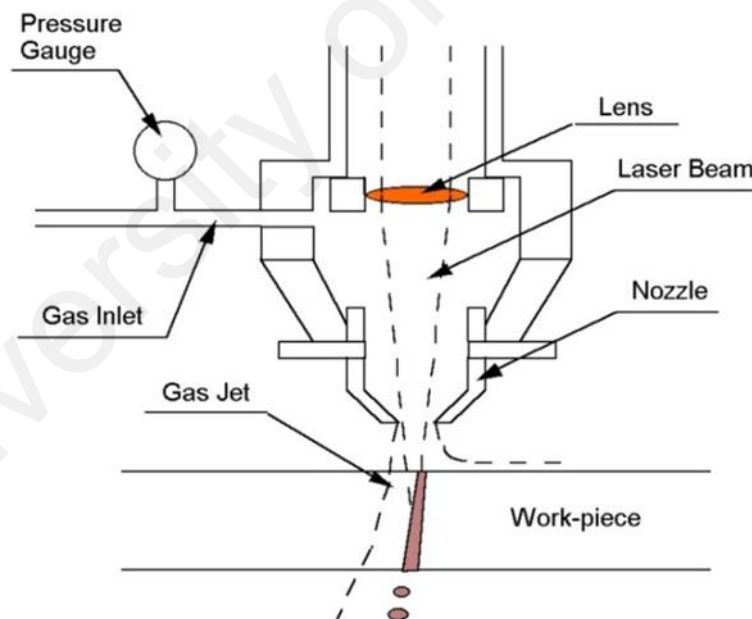
Figure 2.3: Schematic diagram of a laser cutting process

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Material that have successful cutting using a CO_2 laser depends on three fundamental parameters (Jackson et al. 1995; Caiazzo et al., 2005; Dubey & Yadava, 2008a).

- Absorption efficiency of the workpiece for energy at 10.6μm wavelength
- Rate at which heat is conducted away from the cutting zone
- Temperature at which the workpiece is vaporized/melted.

2.3 Machine and parameter

Machining parameters are the parameters used for a machine to produce the intended results. In the case of machining using laser, the cutting speed, laser power, material thickness and its composition, type and pressure of assist gas, and mode of operation (continuous or pulsed mode) are the parameter that always considered by many researcher (Caiazzo et al., 2005; Dubey & Yadava, 2008b). The focus distance of the focusing lens also is one of the machining parameters in laser cutting (Karatas et al, 2006).

According to Lum et al. (2000), some of the important parameters for laser cutting are as follow:

- Pressure of Assist Gas
- Type of Assist gas
- Laser Cutting Speed
- Focal Point Position

Detailed experiments by I. Choudhury & Shirley, (2010), Davim et al. (2008) and Yusoff, et al. (2008) verified that the variation of cutting speed and laser power in laser cutting process are very important parameters to achieve the best quality and efficiency of laser cutting processes.

2.4 Laser Power

Laser power is the optical power level emitted by the laser. The laser power is expressed in Watt, W. Cutting using laser is a thermal cutting process which utilize heat from the laser beam to cut the workpiece . The higher the laser power used, the higher the heat that is generated. Thus, this is an important factor in laser cutting. The control on this parameter is crucial to produce a successful cut using laser. Lan et al. (2011) stated that if the laser power used is too low, the laser beam might not penetrate through the workpiece. However, the workpiece will get burned and charred if a very high power is used. It is also closely related to the cost of the processing. Higher power means higher cost.

In previous study, an experiment was conducted to investigate the relationship between cutting speeds, laser power and kerf width on three different thicknesses of a material. Eltahwani et al. (2011) in their research conclude that the increases of kerf width are when the laser power increases but when the cutting speed increases, the kerf width will decrease. In addition, this author also stated that these two factors have the main effect on the lower kerf width.

2.5 Cutting Speed

Cutting speed is another important parameter in CO_2 laser cutting. This parameter determines the amount of time the workpiece is exposed to the laser beam, and hence the amount of energy that can be absorbed (Barnekorv, et al., 1986). It is expressed in mm/min. By changing the cutting speed, the energy input to the cutting zone at any particular point along the cut line will be changed as well. If the maximum cutting speed is exceeded, then the laser might not penetrate through the workpiece during cutting resulting in incomplete cut. Combination of high laser power and low cutting speed during cutting will cause the energy input to the cutting zone to be much higher than needed to cut the workpiece. As the result, the workpiece will be overheated and burned.

Different material will have different maximum cutting speed which will ensure successful cutting using laser. Even for different wood type, the requirement for cutting speed is different. A study of CO_2 laser cutting of Malaysian light hardwood was previously performed by Yusoff et al. (2008). They managed to come out the relationship between type of wood with different properties and processing parameters such as laser power and cutting speed in terms of optimum cutting condition.

Thickness of the workpiece also has effect on the cutting speed that should be used. An investigation using different combination of CO_2 laser cutting parameters on MDF wood composite material have been conducted previously (H.A. Eltawahni, et al., 2011). Three different thicknessess of workpiece have been used in the experiment.

They found that the optimum cutting speed needed to achieve the best cutting quality is not the same. With increasing cutting speed, the roughness value will also increase.

Lum et al. (2000) stated that cutting speed is an important economic variable because the lower unit cost of product required higher the cutting speed with lower cycle time. For each thickness of material, there is a range of acceptable maximum and minimum cutting speed values, including an optimum value with regard to quality.

Yilbas (1996) showed that self-burning occur when a mild steel is cut at very low cutting speed. The cuts were of irregular width and contained holes of varying diameter spaced irregularly along the cut.

2.6 Assisted and Inert Gas

Assisted Gas is one of the important parameter in laser cutting processes. Lum et al. (2000) stated that one of the important of shield gas in CO_2 laser cutting is removes the material from the cut zone. This shielding gas also can protect the lens from the smoke emitted from the vaporized material. The author also stated that the lower gas pressure obtainable when the bigger of nozzle diameter sized.

Many researchers have done their research using oxygen as an assist gas for laser cutting processes (Dubey & Yadava, 2008a; Salem et al., 2008). Self-burning occurs when oxygen pressure increased because the rate of reaction and the oxidation process is proportional to the oxygen concentration (Yilbas, 1996). In a study done by Lum et al. (2000), they found that the surface roughness result obtained for each

thickness of MDF remained the same even with an increase in the shield gas pressure or using a different type of shield gas but nitrogen did help in reducing the charring effect. The used of nitrogen gas as an assist gas produces smoother and brighter cut surfaces with smaller kerf width compared to oxygen (Ghany & Newishy, 2005)

In a study done by Salem et al. (2008), it was observed that the heat affected zone (HAZ) width increased when the pressure values lower than 4 bar because of additional source of heat. The author also stated that increasing the gas pressure, the HAZ width decreased. It is because increasing the gas pressure would blows the formed drosses away while in the molten state and hence decreased the possibility of excessive generated heat in the HAZ.

2.7 Stand of Distance and Focal Point Position

Standoff distance is the distance between the workpiece and the nozzle of the laser machine (Sivarao, Brevern, El-Tayeb, & Vengkatesh, 2007). Standoff distance can be closely related to the focal point position on the workpiece. Focal point is the point at which the laser beam meets after reflection or refraction. The length depends on the focal length of the lens used in the machine. There are many possible location of focal point relative to the workpiece as shown in the figure 2.3.
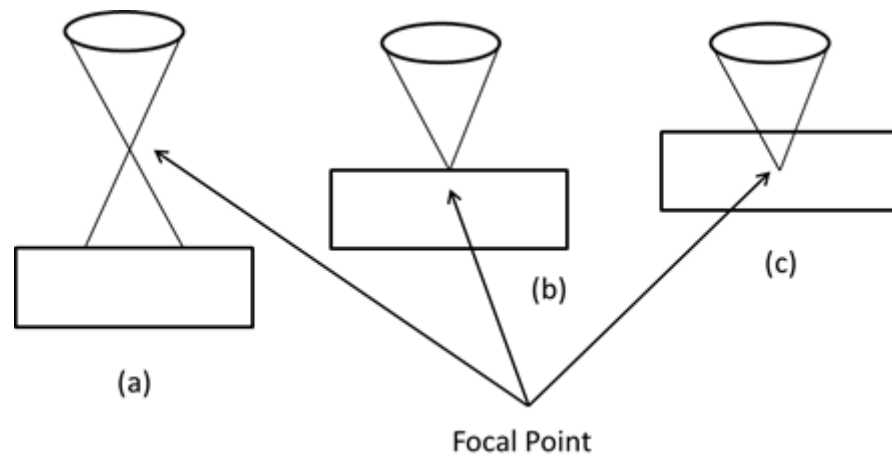
Figure 2.4: Possible locations of the focal point relative to the workpiece

(Barnekorv, et al., 1986)

(a) Above workpiece, (b) On top of the workpiece and (c) Middle of workpiece.

The quality and cutting efficiency are affected by the focal point position relative to the workpiece (Barnekorv, et al., 1986; H.A. Eltawahni, et al., 2010; Lum, et al., 2000). If the focal point is located above the surface, the energy density will reduce resulting in greater kerf width and the surface of the workpiece to be charred. If the focal point is located on top of the surface of the workpiece, the energy density will become maximum at the surface but diminishes as the thickness of the workpiece increases. The energy density is more uniform throughout the thickness when the focal point is at or slightly above the middle of the workpiece. In the latter case, smaller and uniform kerf width can be achieved. The surface will be smoother and has less char. Also, deeper cuts are possible.

2.8 Cut Quality

After the machining parameters are all set for laser cutting machine, the process will take place and the responding effect are called the response parameters. Response parameters for laser cutting method that widely known are the kerf width (Figure 2.5), surface roughness (Figure 2.6), and heat-affected zone (Figure 2.7) (Bamforth et al., 2006; Dubey & Yadava, 2008b; Kaebernick et al., 1999; Karatas, et al., 2006). Charring effect and cutting depth is also the known as response parameter for laser cutting processes (B. H. Zhou & S.M.Mahdavian, 2004). Previous study has been done by H.A. Eltawahni, et al., (2010). In their experiment, the effect of laser cutting parameter and different thickness of material on roughness and kerf width was studied. In their finding, they have stated that the average upper kerf width decreases as the cutting speed, and air pressure increase but the kerf width increases when laser power increase.

Yung et al. (2001) found that increasing in the average laser power will increase the size of HAZ. Li Zheng et al. (2010) in the study of laser maching of fiber reinforcement composited and discovered that heat conduction in the transverse direction to the fiber axis is slower than in the parallel directions. This is because the different fiber orientations in CO_2 laser machining results will give a non-uniform HAZ size. Cutting speed also will influence the heat affected zone width. Based on the result obtained by Mathew et al. (1999)**,** the cutting speed controls the interaction time. Experiment was conducted using the Nd:YAG laser on the carbon fiber reinforced plastic and HAZ was found to be inversely proportional to the interaction time. When the cutting speed is higher, interaction time will be less and thus HAZ will also be less. Besides, at higher speeds some of the laser radiation is deflected and the efficiency of

the process may reduce. They noted that the both cutting speed and laser power over interaction time are related to the carburized residues. As the power gets higher, thicker layer of charred material is formed. With reduction in the cutting speed and laser power, charred material tends to form a good quality cut.

MRR or the Material Removing Rate is the response parameters that show the amount of material being removed during laser cutting process in certain period. The formula for MRR is (Yusoff, et al., 2008):

$$MRR \ (\mathrm{m}^3 \ \mathrm{min}^{-1}) = thickness(t) \ x \ cutting \ speed(s) \ x \ kerf \ width \ (w) \quad\quad (2.3)$$
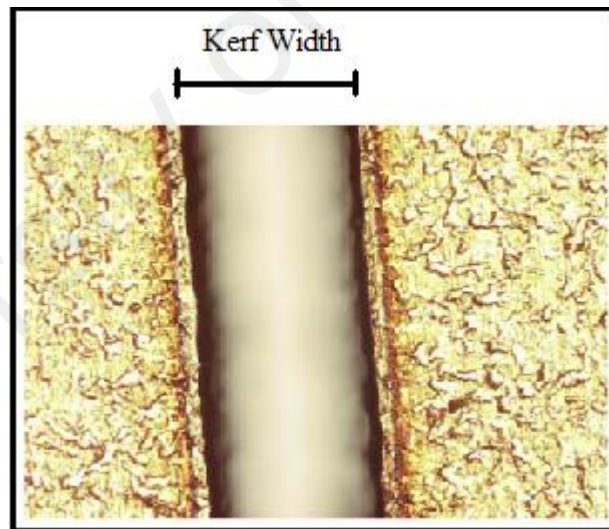
Figure 2.5: Example of the kerf width on workpiece
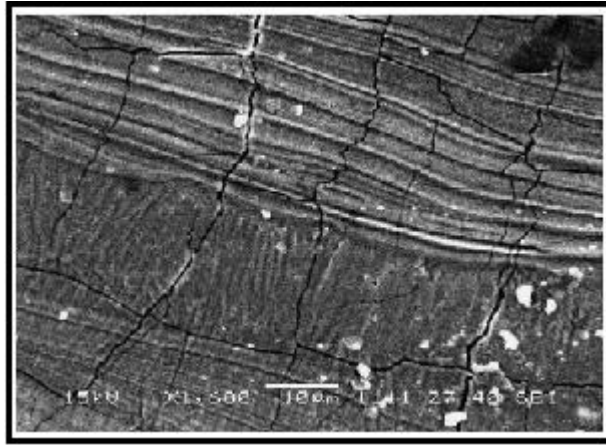
Figure 2.6: Example of surface roughness of workpiece
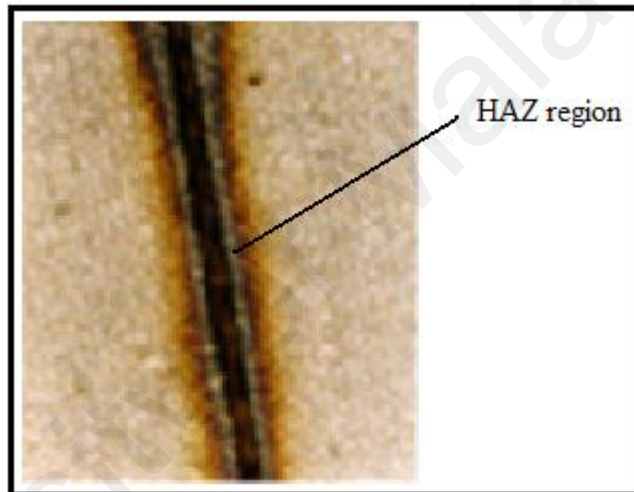
Figure 2.7: Example of the HAZ region on workpiece

2.9 Design of Experiment (DOE)

Design of experiment (DOE) is one of the methods used for experimental study. It is a statistical approach in which mathematical model is develop through experimental run. The main purpose of the DOE is to design an experiment which will improve the understanding of the relationship between the products produced, the process parameter that is used to produce the product and the desired performance

characteristics (Senthilkumar, et al., 2010). DOE is actually based on the fractional factorial experiment that allows an experiment to be conducted with only a fraction of all the possible experimental combination of parameters value. Orthogonal array are used in order to aid the designing of the experiment, by specifying the combination of parameters needed to conduct a certain experiment (Mahapatra & Patnaik, 2006). System design is an initial functional design that might be far from optimum in terms of quality and cost. The objective of parameter design is to identify the product parameter values under the optimal process parameter values and to optimize the settings of the process parameter values for improving quality characteristics (Y. Li et al., 2000; Tarng & Yang, 1998).

In this study, DOE has been employed for optimization purposes. One of the techniques used is Taguchi method. The main objective of this method is to determine the optimum setting of input parameters, neglecting the variation caused by uncontrollable factors or noise factor (Anand, 2010). This method also known as a tool for designing of high quality systems that provides an efficient, simple and systematic approach for optimization of cost, quality and performance (Y. S. Tarng & Yang, 1998). This method is valuable when the design parameters are discrete and qualitative. Taguchi parameter design can reduce the sensitivity of the system performance to sources of variation and optimize the performance characteristics through the settings of design parameters (Bachtiyar et al., 2009).

Quality loss function concept and the experiment design theory are the combination of Taguchi method that has been used in developing robust designs of products and processes (Kurt, et al., 2008; Tsao & Hocheng, 2004). This method makes the work simpler and is the powerful tool of the design of a high quality system. By

applying Taguchi method based on orthogonal arrays, cost and experiments time can be reduced (Öktem, Erzurumlu, & Çöl, 2005). Usually the number of experiment are prohibitively large but by using Taguchi approach, the number of experiments can be reduces to certain smaller number and this has then significantly contribute to reduction in cost and time. Orthogonal array is one of the methods created to reduce the variance for the experiment by optimum setting of control parameters (Datta, et al., 2006). It has then provides a set of well balanced and minimum number of experiment.

Next, a response table can be developed conducted to investigate the effect of the parameter on the final product quality. After that, Analysis of Variance (ANOVA) analysis can be carried out.

2.10   Analysis of Variance

Analysis of Variance (ANOVA) is a method used to analyse the data obtained from the experiment run. It is a statistical technique that can be used to evaluate whether there are differences between mean across several population with the average value across group's population. It uses a set of equation to conduct an analysis for a set of result (Montgomery, 2001). It is also one of the most useful ways of partitioning the variability of a process into identifiable sources of variation and the associated degree of freedom in an experiment. ANOVA used collection of statistical model and it is beneficial to help determining factors that has the most significant effect on output responses. We also can determine the parameter values which maximize the achievement of performance characteristics and determine the parameters that have no significant effect on performance; so tolerances can be relaxed. In addition, it also

provides value of variability of response contributing to the factors (Santhakumar, et al., 2009). Furthermore, ANOVA is used as a platform to indicate the relationship between the input parameter and the output response directly. Following step-by-step calculations were used complete the ANOVA table.

a) The average response for each experiment

b) The overall experiment average

c) The response table

d) The total sum of squares

e) The sum of squares due to mean

f) The sum of squares due to factor

g) The sum of square due to error

h) The mean sum of square

2.11   Artificial Neural Network

Human generally bad at calculations or at any kind of computing. A negligible percentage of human beings can multiply two 3-digits numbers in their heads. The basic function of human intelligence is to ensure survival in nature, not to perform precise calculations. The human brain can process millions of data or visual and it shows the abilities to learn from generalize from learned rules, experience and recognize patterns. Brain is far better than computer because of the ability of billions of neuron computational ability in parallel (Kaiser, 2007). It is in effect a very good engineering tool that performs these tasks in addition to carry out approximations, low precision, or less generality, depending on the problem to be solved.

The origin of Connectionist architectures can be traced to Psychology, Physiology and Computer Science. The artificial neural networks (ANN) try to follow the functionality of the human brain. ANN are able to learn from data. They create a mapping between some input and output data. The basics of ANN are artificial Neuron, learning algorithm and network topology encoding scheme (Luger & Stubblefield, 1998). In 1958, Frank Rosenblatt create neural network linearly separable by perceptron with multilayered networks (Luger & Stubblefield, 1998).

In other words, ANN create a function between some input and output data. Once they are trained, the outputs of unknown inputs with arbitrary high precision can be predicted and this capability is known as generalization (Shukla, et al., 2010).
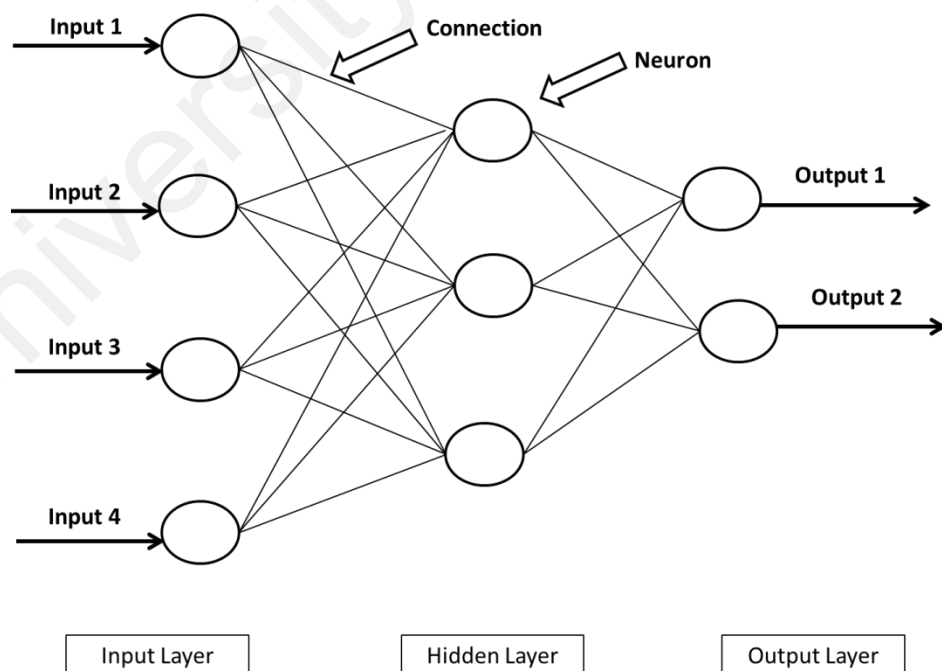
Figure 2.8: A typical multi-layered perceptron ANN architecture

Inputs is important in ANN because it contains the candidates that affect the output by a reasonable amount. However, the system become slower if too many input inside the system. If the system has several characteristic which may not give a fine contribution to the output, that contribution may be ignored from the list of inputs. The type of output and the number of outputs according to the problem need to be decided because the system can only give valid outputs and not the abstract. The complexity of the system low if the number of outputs is limited (Shukla, et al., 2010).

The computational complexity of the ANN is decided by the number of layers. To avoid saturation of network, the input and output values are normalized. Normalization is a sets of the input and output values in between desired limits. This equation represent the general formula for computing the corresponding output for any input. The equation of normalization is as follow (Yang, et al, 2011) :

$$D_{nor} = D_{min} + \frac{V_{orig} - V_{min}}{V_{max} - V_{min}} (D_{max} - D_{min}) \qquad (2.3)$$

Where

D_{min} = minimum normalization value

D_{max} = maximum normalization value

V_{min} = minimum value

V_{max} = maximum value

V_{orig} = original value

ANN uses back-propagation algorithm for training. From the study by (Kizilkan.O, 2011) in thermodynamic analysis using ANN, he found that when the number of neuron is increases will improve the connection networks of model. (Anderson & Donaldson, 1995) stated that biological networks works in parallel and

ANN follow von Neumann architecture. The process known as training is the ability of ANN to learn the data presented. ANN learned from the available experience (input/output datasets) and captured the functional relationship between the input and output parameters. (Kuo, 1998). To train the ANN, the input need to apply and the output need to obtained for each itereation by updating the weights and biases. Each single iteration is known as epoch (Shukla, et al., 2010). This author also stated that the learning rate is the rate of system to learns the data and normally measured between 0 and 1.

This system may stop the training according to the one of the stopping condition. The criteria of stopping conditions are as follow (Shukla, et al., 2010):

- The training stopped when the time taken to execute exceeds more than a threshold.

- The training stopped when maximum number of epochs exceeded.

- The training stopped when the error measured by the system reduces to a specific value.

- The training stopped when the error on validation data start to increase.
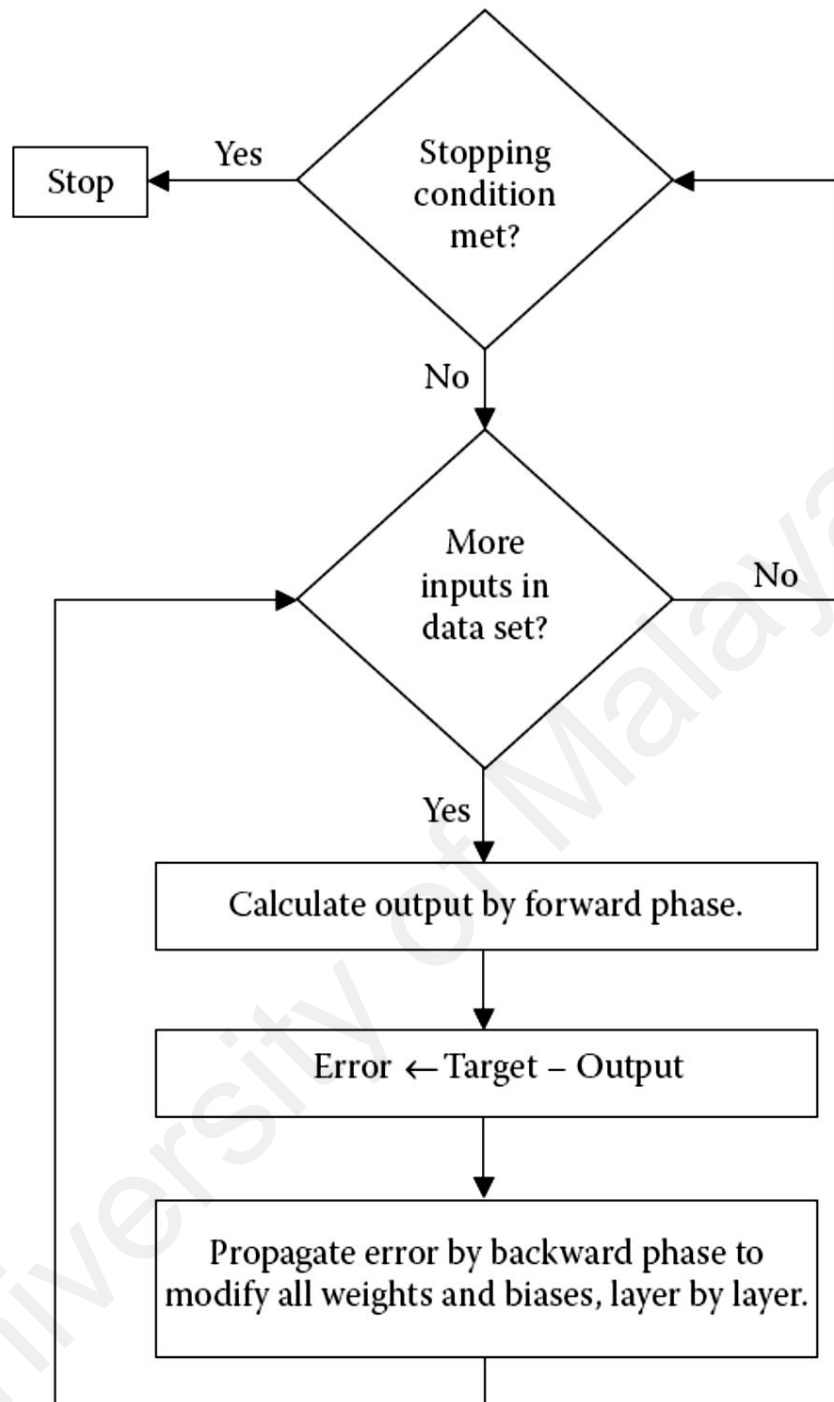
Figure 2.9: Back Propagation (BP) Algorithm Flow Chart [source: (Shukla, et al., 2010)]

In the study of extrusion processed by Shihani Kumbhar et al. (2006), they claimed that ANN modeling execute better than Response surface methodology RSM. The author found that ANN definitely performs better when the problem is complex

nonlinear while RSM is only using regression and linear modeling to complete the surface. Tsai et al. (2008) utilizing ANN for optimization of laser cutting process parameter. In this paper, they performed 27 sets of experimental data and tested by 14 sets of experimental data from a practical laser cutting using Levenberg–Marquardt back-propagation training algorithm.

The traditional ANN model has the inherent disadvantage of requiring a large number of training samples. Lin ZC (2010) and Ching-Been et al. (2011) proposed a combined Taguchi Artificial Neural Network model, which is different from the conventional ANN model, in order to reduce the number of training data. This method was used to construct a prediction model for a CO_2 laser cutting experiment. They claimed that Taguchi network has good predictive results for all regions and the prediction model of Taguchi artificial neural network serves as a reference for fabrication application and performance.

2.12   Genetic Algorithm

Optimization is the mathematical discipline which is concerned in finding and searching the minimum and maximum of functions with possibly subject to constraints. Optimization parameters are critical for an optimization problem. The value of objective and constraint functions cannot be defined if no existent of optimization parameters.

Genetic Algorithm (GA) is a search method that mimics the process of naturalevolution. This method is used to generate useful solutions to optimization

problems. This technique is required to optimize an objective function by varying some variables or parameters. GA operates on population of strings with the strings coded to represent some underlying parameter-set (Agapie, Florin Fagarasan, & Stanciulescu, 1997). Re-production, cross-over and mutation are applied to string populations to generate new populations. In the study by Guo-qianget al. (2004) in Genetic Alghorithm, the author stated that GA are different from other conventional optimization methods in 4 ways:

- GA work with a coding of parameter-sets and not parameters themselves.

- GA search from a population of points and not a single point

- GA use objective function information and not derivatives

- GA use stochastic rules and not deterministic ones

There are six important features of GA:

1. **Encoding** and known as population.

2. **Selection** is an operator which defines the way individuals in the current population are selected for reproduction.

3. **Crossover** is an operator which defines how chromosomes of parents are mixed in order to obtain genetic codes of their offspring (e.g. one–point, two–point, uniform crossover, etc). This operator implements the inheritance property (offspring inherit genes of their parents).

4. **Mutation** is an operator which creates random changes in genetic codes of the offspring.

5. **Fitness Function** basically determines which possible solutions get passed on to multiply and mutate into the next generation of solutions. It

is a function which represents the main requirements of the desired solution of a problem (i.e. cheapest price, shortest route, most compact arrangement, etc).

6. **Stopping Condition**. The GA proceeds in an iterative manner and runs generation by generation. This procedure continues, and the solutions generally keep improving until the solutions being generated are sufficiently optimized or the number of generations exceeds a certain number or time taken.

2.13 Summary

In summary, the chapter reviews some of the characteristics of oil palm wood particularly on moisture content and material density. It uses in furniture industry has receive much attention in recent years due to their positive material characteristics after undergoing necessary treatment. Similarly, important factors which influence the CO_2 laser processing of such materials was discussed to some extent, such as laser power, cutting speed, inert gas pressure and focal point position. Since these parameters were found to be interdependent, optimal processing parameters are not easily determined. For this reason, the following chapters investigate and evaluate the application of some established optimization techniques in processing oil palm wood, which include Taguchi, ANNOVA, Artificial Neural Network and Genetic Algorithm.

CHAPTER 3

RESEARCH METHODOLOGY
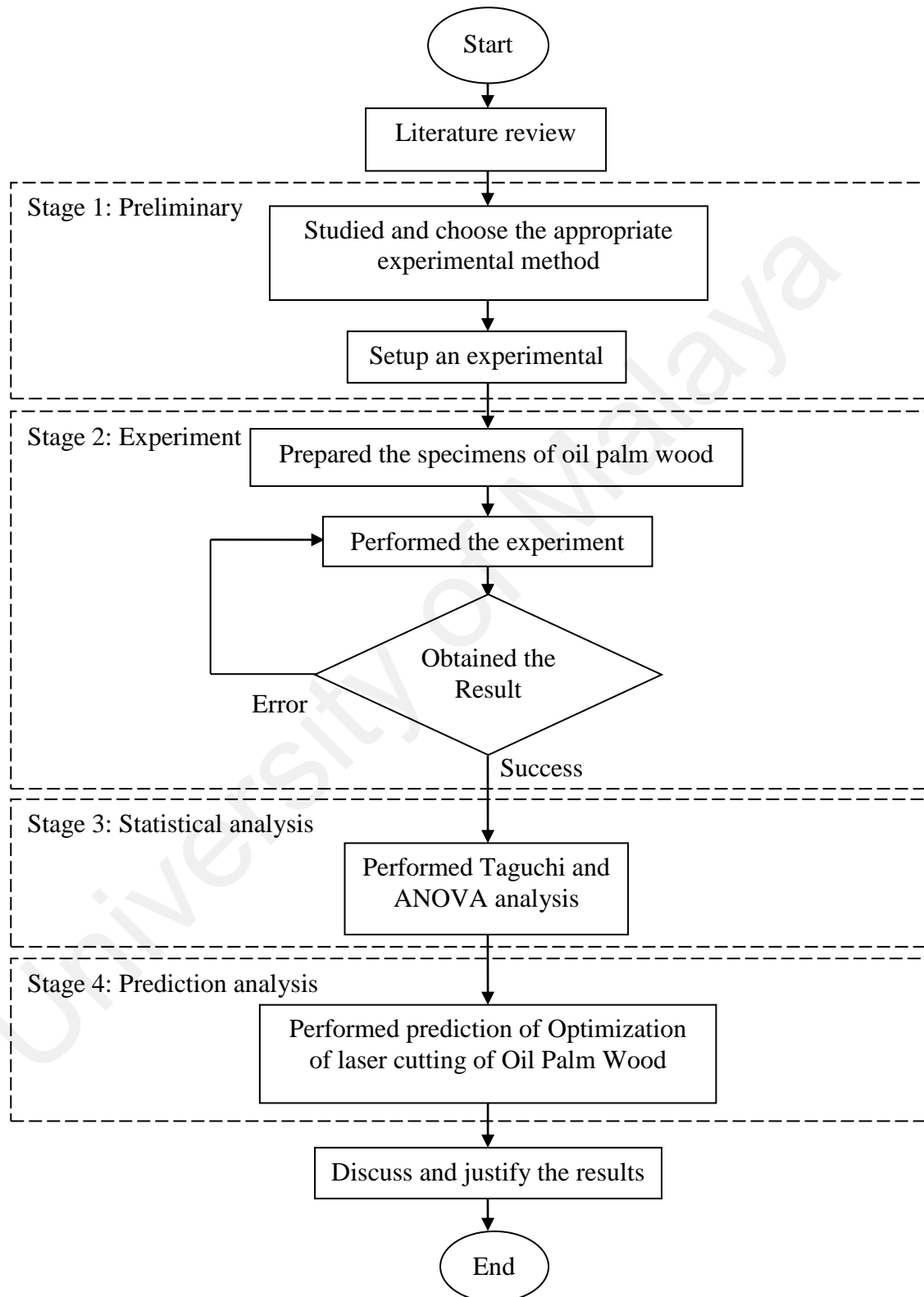
Figure 3.1: Flow chart of research procedures

3.1 Material Used

Material used for this research is the oil palm wood. The wood is come from the oil palm tree that reach 25th years. For this research, we only take the sample at the bottom portion of that tree that is 5 feet from the ground. A large chunk of oil palm was cut into two sections. One section is dried inside the oven and another one is kept fresh. For each section, we only take 2 sample of oil palm wood as shown in the figure. Each sample has a thickness of 12 mm. The preparation of this sample is as shown in the Figure 3.1 and the explanation of this preparation is as follow.

1. At first, a section of the tree measuring about one meter long was cut and its bark was removed using a debarking machine. The measured diameter was 270 $\pm$ 5mm (Figure 1a).

2. The section was further cut using a mechanical saw, leaving the central portion measuring about 120 mm thick (Figure 1b) and divided equally into two equal blocks (Figure 1c).

3. One of the blocks (Figure 1d) was then completely dried in the oven at 60^{0}C for 25 days (Sulaiman, et al, 2012). This process ensures that the blocks are free from moisture and not over-dried.

4. Finally, two different samples for each blocks (sample V and W for Fresh block and Sample X and Y for Dried block) were collected at two different portions of the dried block, located 48 mm and 108 mm from the centre of the original trunk, respectively (Figure 1e). Each sample has an equal thickness of 12 mm.
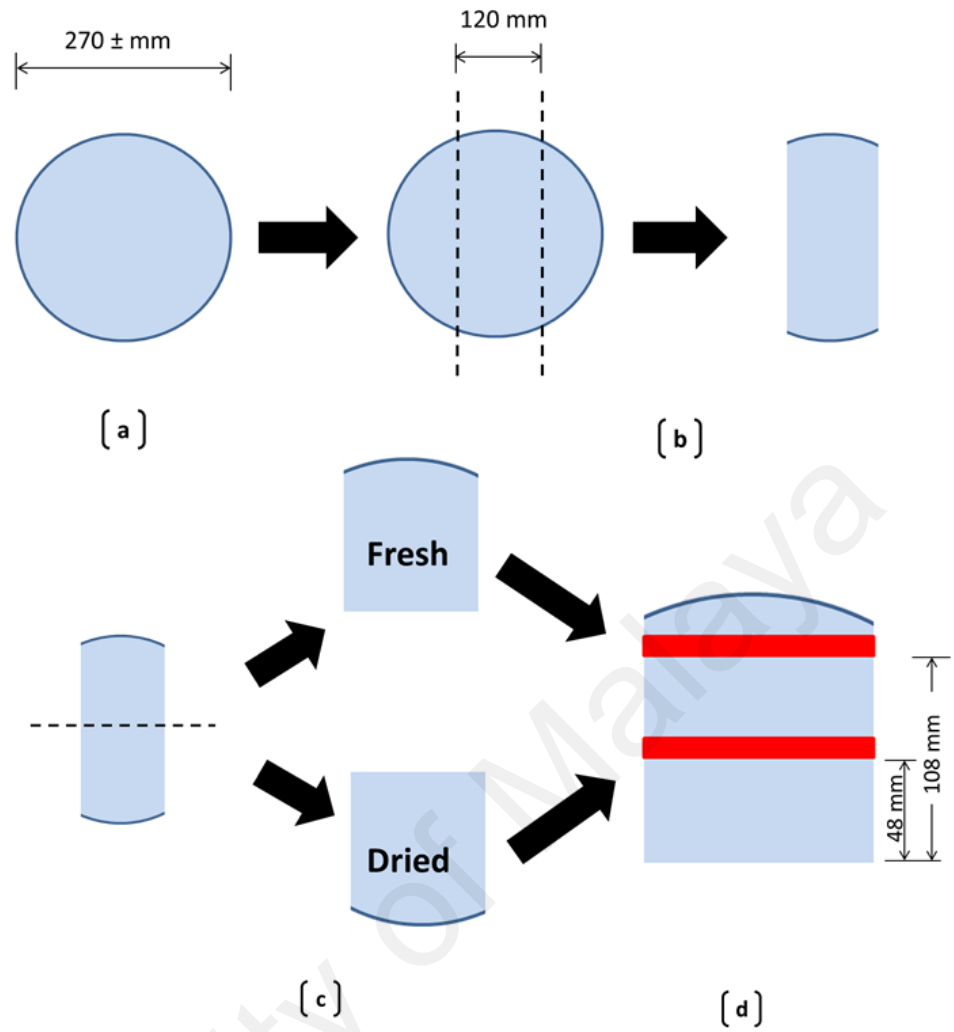
Figure 3.2: The step of preparation of oil palm wood samples

The density and moisture content for all samples as calculated using equation (2.1) and (2.2) are shown in the Table 3.1.

Table 3.1: Moisture Content and Material Density of oil palm wood Sample

Sample	Moisture Content, %	Material Density, kg/m^3
Sample V	342.39	425
Sample W	267.22	632
Sample X	82.27	419
Sample Y	85.20	636
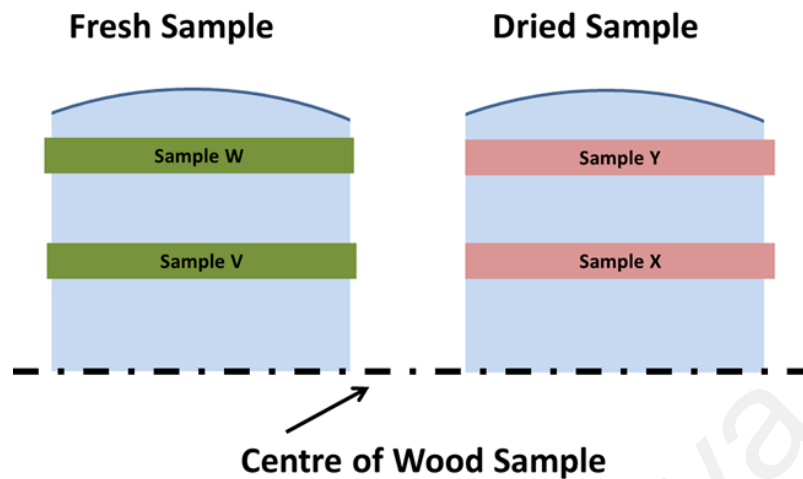
Figure 3.2: Sample of oil palm wood

3.2 Machine And Equipment Used

Throughout the duration of this study, several machines and equipment have been used in order to conduct the experiment and to perform data collection. A laser will be used in a nonconventional method for cutting oil palm wood. For CO_2 laser cutting process, HELIUS 2513 laser machine was used. This machine is integrated within a workstation to aid the laser cutting process. Assist gas is used to aid the laser cutting process. There are two assist gasses used with this machine which are cutting gases and laser gases. But, for this research, the cutting gases that we used are nitrogen. For laser gas, the gases are composed of premix 55% Nitrogen gases, 40% Helium gases and 5% Carbon Dioxide gases.

Other machine used in this project includes a sawing machine which was utilized as the preparation of samples of material. To take the measurement of the kerf width, Sometech Microscope are used respectively. Sometech Microscope works by using two software which are Capture Flux and Image Tool. Capture Flux software is

used to take the picture of the kerf, while the Image Tool software is used to measure the kerf width.

Figure 3.3: Sometech microscope

Figure 3.4: Vertical sawing machine

Figure 3.5: LVD HELIUS 2513 CO$_2$ Laser Machine

3.3 Parameters and variables

There are many parameters that involve in laser cutting operation. To name a few, they are assist gas pressure, cutting speed, laser power, focal point position, type of assist gas and standoff distance. These parameters have effect on the quality of cut on the product using laser cutting. In this project, four parameters will be investigated. They are laser power, cutting speed, inert gas pressure, and focal point position. While conducting the experiment, some of the parameters will be kept constant and will not be investigated. HELIUS 2513 laser machine are capable of delivering the laser power ranging from 100 watts to 3000 watts. The minimum cutting speed it can offer is 1 mm/min and the maximum cutting speed of 5000 mm/min. For inert gas pressure, the ranges taken to be studied are from 30 psi to 50 psi. The focal point position is varied from -6 mm to 0 mm.

Table 3.2: Constant parameter for CO_2 laser cutting.

Parameters	Values
Delay time (s)	1
Nozzle diameter (mm)	3
Corner power (%)	70
Type of inert gas (cutting gas)	Nitrogen gases
Focal length of lens (mm)	190.5
Material thickness	12

3.4 Design of Experiment

As stated earlier, four parameters will be investigated which are laser power, cutting speed, inert gas pressure and focal point position. These parameters will contain three levels which are low, medium and high. Thicknesses of the oil palm wood used are constant throughout the experiment which is 12 mm. The level determined for each parameter is based on the studies of previously related work. The values for the parameters are shown in Table 3.3.

Table 3.3: List of cutting condition selected.

Parameters/level	Level 1	Level 2	Level 3
Laser power (watt)	800	900	1000
Pressure of inert gas (psi)	30	40	50
Cutting speed (mm/min)	200	600	1000
Focal point position (mm)	-6	-3	0

If full factorial method is used for this experiment to include all the possible combination of levels, there will be 81 experiments need to be conducted. By employing the orthogonal array L_9 (3^4), the number of experiment will be reduced to 9 experiments. The orthogonal array is shown below.

Table 3.4: The L9 orthogonal array (3^4).

Experiment no	Parameter			
	Laser Power (level)	Cutting Speed (level)	Inert gas pressure (level)	Focal Point Position (level)
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	1
8	3	2	1	3
9	3	3	2	1

Table 3.5: L9 orthogonal array and the corresponding value for each experiment.

Experiment no	Parameter			
	Laser power (watt)	Cutting Speed (mm/min)	Inert gas pressure (psi)	Focal Point Position (mm)
1	800	200	30	-6
2	800	600	40	-3
3	800	1000	50	0
4	900	200	40	0
5	900	600	50	-6
6	900	1000	30	-3
7	1000	200	50	-3
8	1000	600	30	0
9	1000	1000	40	-6

3.6 Data Measurement

Before the experiment can be conducted, the shape or profile of the desired product must be designed first. The laser machine will cut the workpiece according to the design of the desired product. In this project, the shape of the product is rectangular with a dimension of 20mm x 30mm. The shape is designed using AutoCAD software.

2D design of the product will be generated using AutoCAD software and then exported

into the LVD HELIUS CO_2 laser machine software to generate the cutting path.
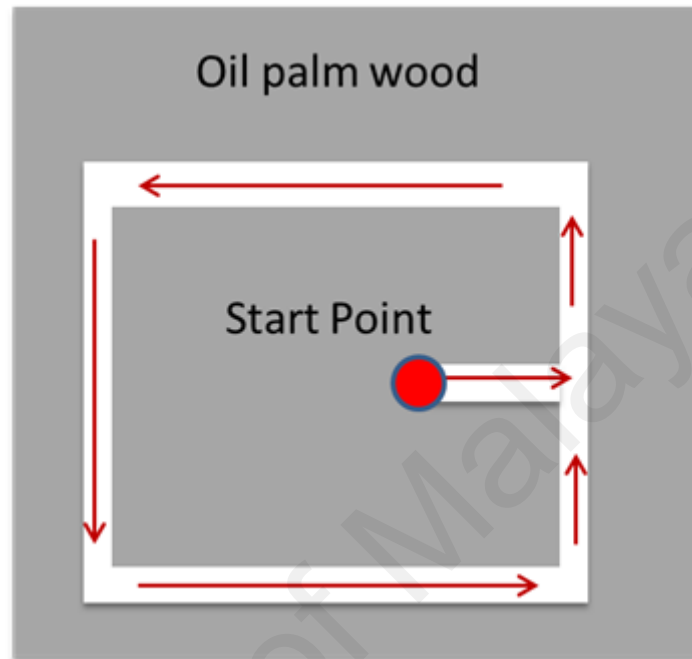
Figure 3.7: The cutting path (red arrow) of laser on oil palm wood
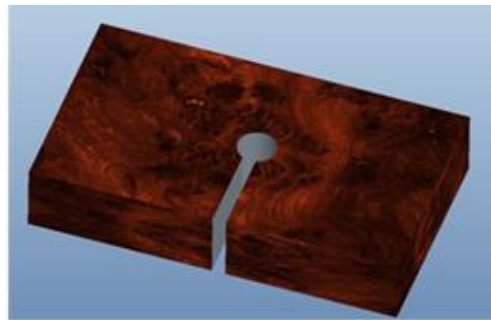
Figure 3.8: Part that successful cut using CO_2 laser :

(a) Part of experiment number 9 for Sample X

(b) 3-D part drawing using 3D CAD software

At this stage, the data measurement on the upper kerf width on the cut surface will be taken from the part which already have been cut using CO_2 laser. The upper kerf width is measured using Sometech Microscope. This microscope is integrated with a computer which made the measuring process possible. For the measurement of the upper kerf width, 40 x magnifications were used. When the workpiece is placed under the lens, Capture Flux software are used to capture the image of the kerf on the workpiece. After that, the measureIT software will be used to draw a line on the image, indicating the length of the kerf width. When the line is drawn, the software will automatically calculate the five readings of upper kerf width that will be taken for analysis purpose as shown in the figure 3.9.
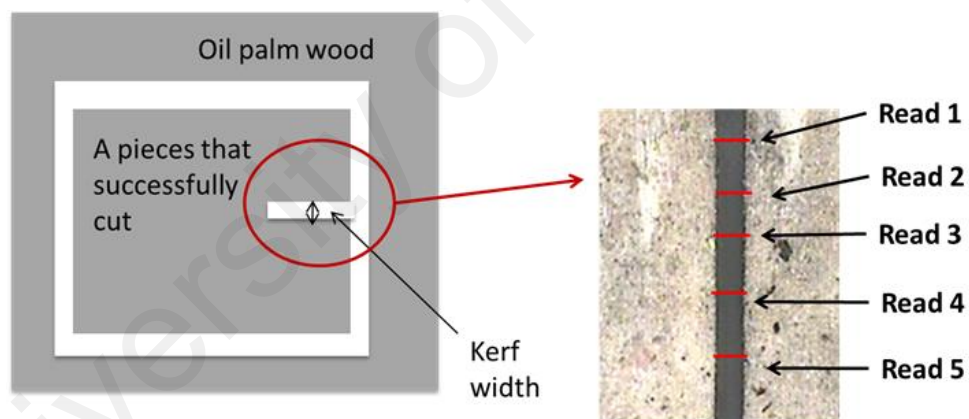
Figure 3.9: Measurement of upper kerf width

3.7 Artificial Neural Network Model (ANN)

Figure 3.10 shows a schematic diagram of general model of Laser Cutting/Training and simulation process using an ordinary ANN and Taguchi ANN models. Four controllable independent parameters and one dependent parameter (independent with each other which mean the source of parameter for the calculation of

dependent parameters are different) have to be focused on the estimation of error in predictions of kerf width in CO_2 laser cutting of oil palm wood.

There are a number of factors which affect the output quality in designing ANN model. These factors are the number of inputs and input data, number of outputs in the output layer, the number of neurons in hidden layer and the number of hidden layers. The output variable (kerf width) variation is measured by the signal to noise ratio (S/N). The ANN model is based on feed forward back propagation that uses Levenberg Marquardt for training, Mean Square Error for performance, tangent sigmoid functions for hidden layers, and the process training is taken as supervised learning. Taguchi L9 orthogonal is used for training, simulation and test of the ANN model. Both input and output of experimental Taguchi L9 orthogonal array for oil palm wood laser cutting is normalized before it is used for training the ANN model.
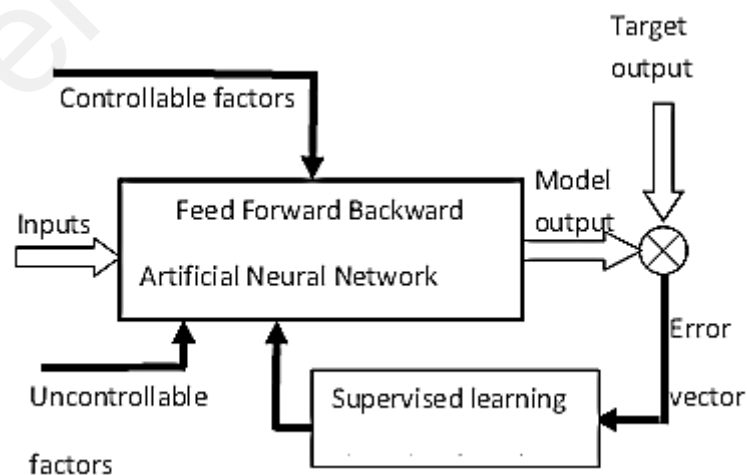
Figure 3.10: Computation style of ANN and Taguchi ANN-model for Laser cutting process (Training and simulation)

```
        ┌─────────────────┐
        │    Taguchi      │
        │  experimental   │
        │   Method L9     │
        └────────┬────────┘
                 │
                 ▼
        ┌─────────────────┐
        │   Kerf width    │
        │  response, S/N  │
        └────────┬────────┘
                 │
                 ▼
        ┌─────────────────┐
        │   Normalized    │
        │   inputs and    │
        │  outputs data   │
        └────────┬────────┘
                 │
                 ▼
        ┌─────────────────┐
        │ Neural Network  │
        │     Model       │
        └────────┬────────┘
                 │
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        ┌─────────────────┐
        │ Error evaluation│
        └────────┬────────┘
                 │
                 ▼
        ┌─────────────────┐
        │    Optimum      │
        │ prediction results│
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```
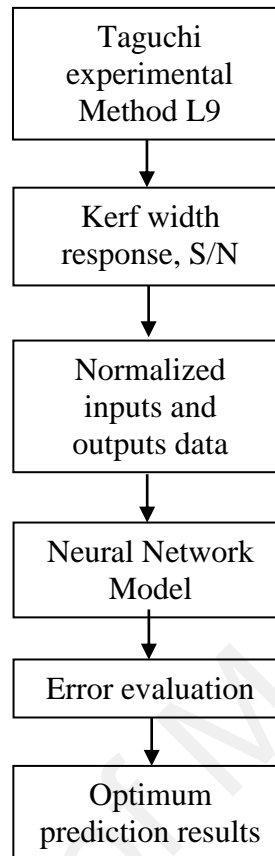
Figure 3.11: Flow chart of Taguchi Neural network for optimum prediction of kerf width in CO_2 laser cutting of Oil Palm Wood

3.5 Hybrid Optimization Model

A genetic algorithm-based Taguchi ANN (GA-Taguchi ANN) model for prediction and simulation of CO2 laser cutting process has been developed. Figure 4 shows the layout of GA-Taguchi ANN model. As it is known, the GA provides a near-optimal solution for a complex problem having large number of variables and constraints. This potential is utilized in the proposed hybrid model to minimize the error prediction for regions of cutting conditions away from the Taguchi based factor level points. The model is constructed in such a way to realize mutual input output due to the hybrid of ANN and GA. Therefore, the experimental Taguchi L9 orthogonal array for oil palm wood laser cutting is normalized before it is used for training the

ANN model. The GA generates normalized random inputs for the trained ANN and the output is again presented to the GA for error optimization. If the error level is less than 10% then the predicted results for kerf width (S/N) is confirmed.
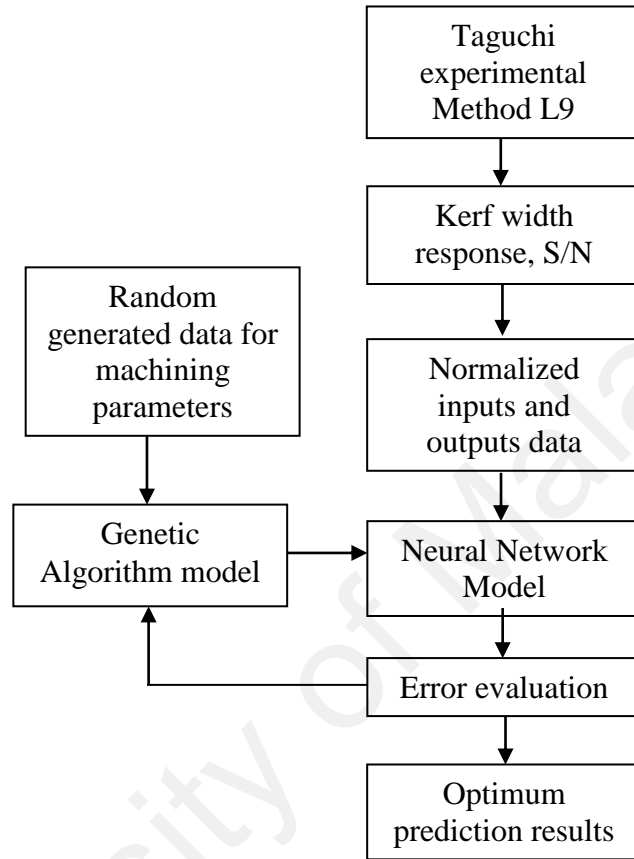
Figure 3.12: A flowchart of GA-Taguchi-Neural network for optimum prediction of kerf width in CO_2 laser cutting of Oil Palm Wood

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

In this chapter, the result of the experiment and the analysis of the result will be covered. For analysis, Analysis of Variance (ANOVA) is used. Using this method of analysis, the optimum cutting parameter level is determined and the contribution factor of each cutting parameter on the quality characteristics can be evaluated. In this experiment, the purpose is to study on the effect of machining parameters for CO_2 laser such as laser power, cutting speed, inert gas pressure and focal point position on different sample of oil palm wood. The tables and graphs have been plotted to make it easier for the analysis of the effects.

4.2 Data Collection

One of the crucial side-effects of laser cutting process on any materials is the kerf width. It is defined as the amount of material that have been melted and vaporized by the laser. In laser cutting of wood substrate, carefully controlled process could avoid excessive burning and vaporization while maintaining good kerf quality. From previous studies, many factors have been identified as the reasons behind the variation of the kerf width such as the laser power, cutting speed and type of assisting gas but there are no study is focusing on the effect that those factors have on the kerf width of oil palm wood. The details on equipment and method that had been used to generate the data were already explained in Chapter 3. The type of data had been collected is upper kerf width for each specimen with five replicate. The experimental data will be analysed

using target performance measure (TPM) and noise performance measure (NPM) technique to determine the effect of each process variable on the quality of the upper kerf width. The TPM on the contrary measures mean response or output and identifies control factors that largely affect the mean response and it is given by

$$\text{TPM} = \sum \frac{x_i}{N_i} \tag{4.1}$$

where x_i is the measured value of upper kerf width for i-th reading and N_i is the number of measurements taken.

For NPM analysis, the quality is benchmarked against signal-to- noise (S/N) ratio. In order to obtain a good cut quality of an oil palm wood, the upper kerf width is preferable to be small. For this reason, the smaller the better criterion of S/N was chosen that is defined as

$$\text{NPM} = -10 \ \log_{10} \left[\ \frac{1}{n} \sum_{i=1}^{n} (\theta_i)^2 \ \right] \tag{4.2}$$

where θ_i is the measured value of upper kerf width for i-th reading and n is the number of measurements taken.

Those experiment data is recorded in tabular form as shown in Table below:

Table 4.1: Experimental Result for Kerf Width, Mean and Signal to Noise Ratio (S/N) for Sample V

Run	Read 1 (μm)	Read 2 (μm)	Read 3 (μm)	Read 4 (μm)	Read 5 (μm)	Mean (μm)	S/N (dB)
1	580.20	583.79	585.18	585.18	585.18	583.91	-55.33
2	398.15	402.55	402.55	400.35	398.15	400.35	-52.05
3	468.98	469.15	470.00	470.00	470.00	469.63	-53.44
4	560.00	560.00	558.58	558.58	558.58	559.15	-54.95
5	638.85	638.85	638.85	638.85	638.85	638.85	-56.11
6	519.58	519.58	539.57	539.57	519.58	527.58	-54.45
7	583.58	583.58	583.33	583.33	583.33	583.43	-55.32
8	539.58	539.58	539.58	539.58	540.00	539.66	-54.64
9	696.00	696.00	698.30	698.30	698.30	697.38	-56.87

Table 4.2: Experimental Result for Kerf Width, Mean and Signal to Noise Ratio (S/N) for Sample W

Run	Read 1 (μm)	Read 2 (μm)	Read 3 (μm)	Read 4 (μm)	Read 5 (μm)	Mean (μm)	S/N (dB)
1	690.33	690.33	692.68	692.68	690.33	691.27	-56.79
2	513.85	513.85	512.35	513.35	515.55	513.79	-54.22
3	572.53	572.53	572.53	573.85	572.53	572.79	-55.16
4	693.14	691.58	693.14	693.14	692.68	692.74	-56.81
5	750.95	747.85	750.95	748.88	748.88	749.50	-57.50
6	627.58	627.58	626.88	626.88	627.58	627.30	-55.95
7	703.21	703.21	703.21	703.21	703.00	703.17	-56.94
8	654.88	654.00	653.18	653.18	654.00	653.85	-56.31
9	806.11	803.88	806.11	806.11	806.88	805.82	-58.12

Table 4.3: Experimental Result for Kerf Width, Mean and Signal to Noise Ratio (S/N) for Sample X

Run	Read 1 (μm)	Read 2 (μm)	Read 3 (μm)	Read 4 (μm)	Read 5 (μm)	Mean (μm)	S/N (dB)
1	1331.65	1331.65	1330.15	1330.00	1331.65	1331.02	-62.48
2	1294.38	1294.38	1294.38	1294.38	1295.00	1294.50	-62.24
3	1238.65	1238.65	1239.15	1238.15	1238.15	1238.55	-61.86
4	1318.65	1320.68	1318.65	1318.65	1320.68	1319.46	-62.41
5	1344.33	1344.33	1349.85	1349.85	1349.85	1347.64	-62.59
6	1288.98	1289.00	1288.98	1288.98	1289.00	1288.99	-62.21
7	1401.33	1401.33	1403.64	1403.64	1403.64	1402.72	-62.94
8	1299.68	1299.68	1301.72	1301.72	1299.68	1300.50	-62.28
9	1348.69	1348.69	1346.00	1348.69	1348.69	1348.15	-62.59

Table 4.4: Experimental Result for Kerf Width, Mean and Signal to Noise Ratio (S/N) for Sample Y

Run	Read 1 (μm)	Read 2 (μm)	Read 3 (μm)	Read 4 (μm)	Read 5 (μm)	Mean (μm)	S/N (dB)
1	1235.00	1233.15	1233.15	1235.00	1235.68	1234.40	-61.83
2	1205.86	1205.86	1205.86	1207.00	1207.00	1206.32	-61.63
3	1150.15	1150.15	1150.15	1150.15	1150.15	1150.15	-61.22
4	1231.15	1231.15	1230.00	1230.00	1231.15	1230.69	-61.80
5	1251.15	1250.65	1250.00	1250.00	1250.65	1250.49	-61.94
6	1198.00	1198.00	1197.65	1197.65	1198.00	1197.86	-61.57
7	1301.86	1301.86	1301.00	1301.00	1301.00	1301.34	-62.29
8	1210.00	1210.00	1210.46	1210.46	1210.46	1210.28	-61.66
9	1269.00	1269.89	1269.89	1269.00	1269.89	1269.53	-62.07

Sample V and W is fresh sample of oil palm wood. Result for the upper kerf width for Sample V is shown in table 4.1. The highest mean value of kerf width is 697.38 μm in experiment number nine and the signal-to-noise ratio (S/N) value is -56.8694 dB. Smallest mean value is 400.35 μm in experiment number two and the signal to noise value is -52.0489 dB.

Result for the upper kerf width for Sample W is shown in table 4.2. The highest mean value of kerf width is 805.82 µm in experiment number nine and the signal-to-noise ratio (S/N) value is -58.12 dB. Smallest mean value is 513.79 µm in experiment number two and the signal to noise value is -54.21 dB.

Sample X and Y is fresh sample of oil palm wood. Result for the upper kerf width for Sample X is shown in table 4.3. The highest mean value of kerf width is 1402.72 µm in experiment number seven and the signal-to-noise ratio (S/N) value is -62.94 dB. Smallest mean value is 1238.55 µm in experiment number three and the signal to noise value is -61.86 dB.

Result for the upper kerf width for Sample Y is shown in table 4.4. The highest mean value of kerf width is 1301.34 µm in experiment number seven and the signal-to-noise ratio (S/N) value is -62.29 dB. Smallest mean value is 1150.15 µm in experiment number three and the signal to noise value is -61.22 dB.

4.3 Data Analysis

The data from previous section should be analysed. The statistical method was selected in order to derive the data so that the effects and dependents of the variables and parameter can be seen clearly. Since, the laser power, cutting speed, pressure of inert gas, focal point position and the different characteristic properties of oil palm wood hugely contributed to the upper kerf width in laser cutting processes. The NPM and TPM analysis for each sample is discussed in sub-section of this Chapter.

4.3.1 Data Analysis for Sample V

The response of each factor on the kerf width in NPM and TPM analysis is shown in table 4.5 and table 4.6 respectively. Based on the both table, the most significant factor affecting on the kerf width in CO_2 laser cutting of oil palm wood is focal point position. The second significant factor affecting the kerf width is laser power. Cutting speed and pressure of inert gas are the third and fourth significant factor affecting the kerf width respectively. In order to obtain a good cut quality of an oil palm wood, the kerf width is preferably to be small. Thus, the smaller the better criterion is applied for the kerf width. The optimum level of parameter is the level which yields the smallest kerf width in the experiment. Therefore the optimum parameter level are laser power on level 1 (800 W), cutting speed on level 2 (600 mm/min), and focal point position on level 2 (-3 mm). However, there are different in optimum level for pressure of inert gas in NPM and TPM analysis. For NPM analysis, the optimum level for pressure of inert gas is on level 2 (40 psi) while in TPM analysis, the optimum level for pressure of inert gas is on level 1 (30 psi).

Table 4.5: Control factor NPM / Signal to Noise Ratio (S/N) factor response table of the analysis of the Taguchi Design Experiment Method Analysis (Smaller is Better)

Level	Power	Speed	Pressure	Focal Point Position
1	-53.60	-55.20	-54.81	-56.10
2	-55.17	-54.27	-54.62	-53.94
3	-55.61	-54.92	-54.95	-54.34
Delta	2.01	0.93	0.33	2.16
Rank	2	3	4	1

Table 4.6: Control factor response table of the TPM analysis of the Taguchi Design Experiment Method Analysis

Level	Power	Speed	Pressure	Focal Point Position
1	484.6	575.5	550.4	640.0
2	575.2	526.3	552.3	503.8
3	606.8	564.9	564.0	522.8
Delta	122.2	49.2	13.6	136.3
Rank	2	3	4	1

The optimum cutting parameter level for upper kerf width using CO_2 laser cutting in NPM and TPM analysis is shown in table 4.7 and table 4.8 respectively.

Table 4.7 Optimum parameter level and its corresponding value for upper kerf width in NPM analysis

Parameter	Level	Value
Laser power	1	800 W
Cutting speed	2	600 mm/min
Inert gas pressure	2	40 psi
Focal Point Position	2	-3 mm

Table 4.8 Optimum parameter levels and its corresponding value for upper kerf width in TPM analysis

Parameter	Level	Value
Laser power, (A)	1	800 W
Cutting speed , (B)	2	600 mm/min
Inert gas pressure, (C)	1	30 psi
Focal Point Position, (D)	2	-3 mm
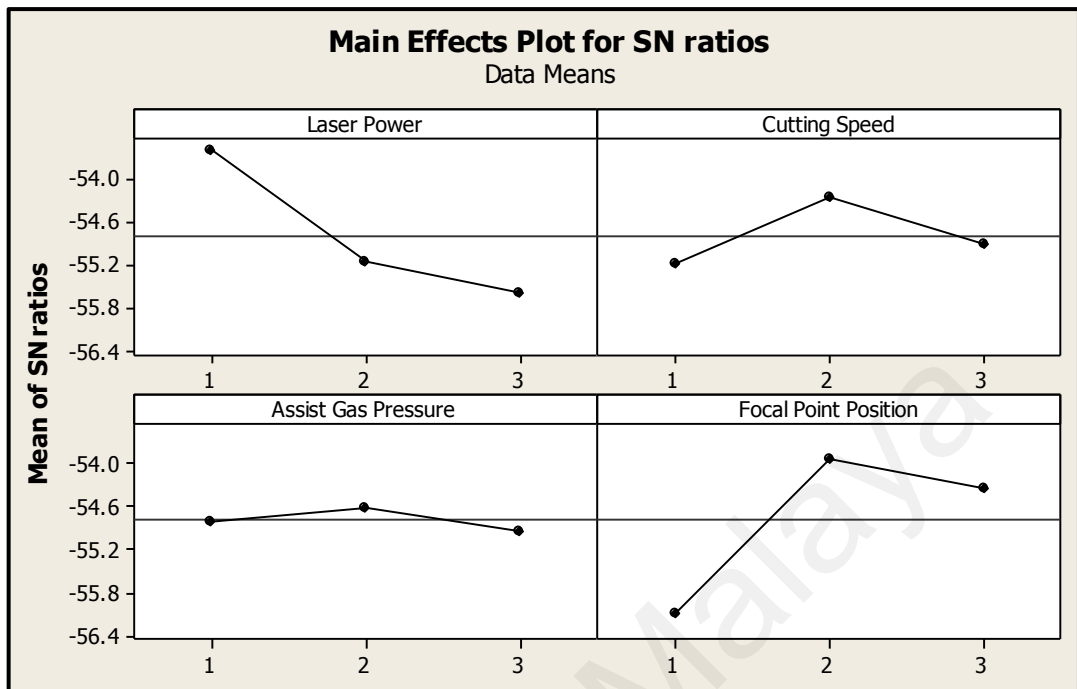
Figure 4.1: Control factor S/N factor response figure in NPM analysis
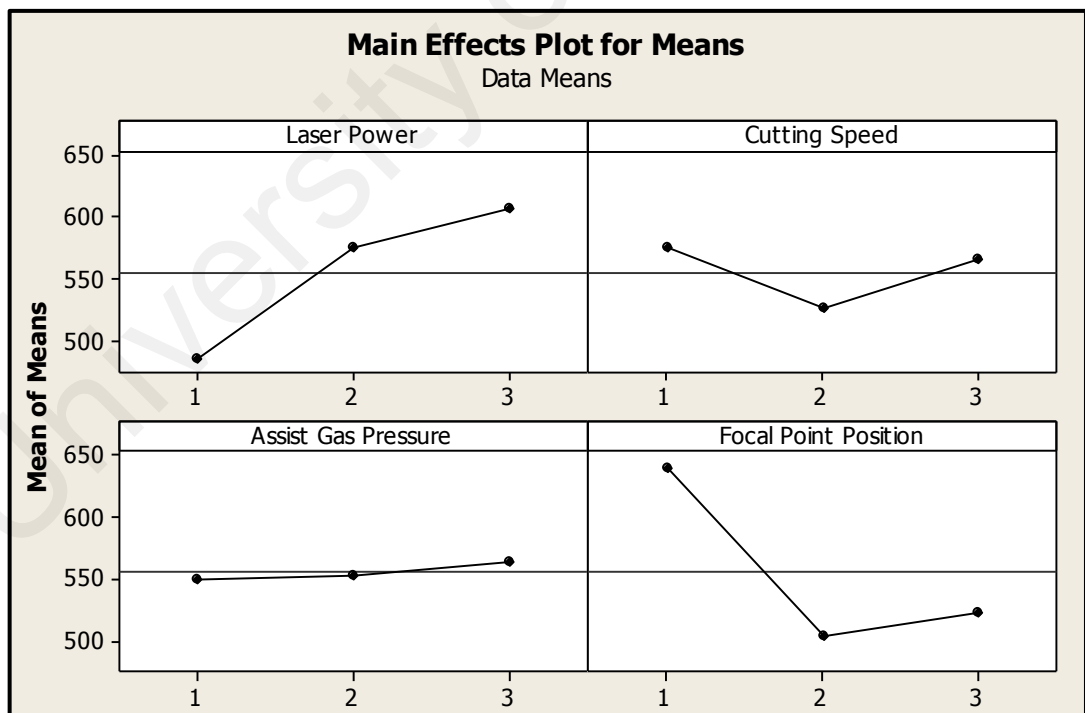
Figure 4.2: Control factor S/N factor response figure in TPM analysis

Response graph for each factor in each level using NPM and TPM analysis is shown in the figure 4.1 and figure 4.2 respectively. Based on the both response graph, upper kerf width increases as the laser power increases significantly. The upper kerf width increases when the cutting speed of 200 mm/min (level 1) was used. However, the upper kerf width decreases when cutting speed of 600 min/min (level 2) was used. This situation is also same for the focal point position. The upper kerf width is increased when the value of focal point -6 mm (level 1) was used, but the upper kerf width decreases when the value of focal point position is -3 mm (level 2). However, there are different in level of process characteristics for pressure of inert gas in NPM and TPM analysis. In NPM analysis, the upper kerf width increases when assist gas pressure of 50 psi (level 3) was used, but the upper kerf width decreases when assist gas pressure of 40 psi (level 2) was used while in TPM analysis, the upper kerf width increases as the pressure of inert gas increases significantly.

Analysis of variance (ANOVA) study was carried out to ascertain the main control factor which significantly affects the quality characteristics (Santhakumar, et al., 2009; Sayuti, Sarhan, Fadzil, & Hamdi, 2011). The contribution of each variable on the upper kerf width based on NPM and TPM analysis for Sample V is shown in Table 4.9 and Table 4.10, respectively.

Table 4.9: Pareto ANOVA for NPM analysis

Control Factor Levels	S/N Response Data (dB)			
	A Laser Power	B Cutting Speed	C Inert Gas Pressure	D Focal Point Position
Level 1	-53.60	-55.20	-54.81	-56.10
Level 2	-55.17	-54.27	-54.62	-53.94
Level 3	-55.61	-54.92	-54.95	-54.34
Sum of Square	6.6722	1.3727	0.1652	7.9342
Total Sum of Square	16.14			
Percentage of Contribution, %	41.33	8.50	1.02	49.15
Rank	2	3	4	1

Pareto Anova Analysis

Cumulative Contribution	49.15	90.48	98.98	100
Optimum Combination	D2	A1	B2	C2
Overall Optimum Condition for all Factors	A1 B2 C2 D2			

Table 4.10: Pareto ANOVA for TPM analysis

Control Factor Levels	TPM Response Data			
	Laser Power (A)	Cutting Speed (B)	Inert Gas Pressure (C)	Focal Point Position (D)
Level 1	484.6	575.5	550.4	640.0
Level 2	575.2	526.3	552.3	503.8
Level 3	606.8	564.9	564.0	522.8
Sum of Square	24134.70	4022.20	324.60	32672.30
Total Sum of Square	61153.8			
Percentage of Contribution, %	39.47	6.58	0.53	53.42
Rank	2	3	4	1

Cumulative Contribution	53.42	92.89	99.47	100
Optimum Combination	D2	A1	B2	C1
Overall Optimum Condition for all Factors	A1 B2 C1 D2			

Table 4.9 and table 4.10 represent the analysis of variance (ANOVA) for each factor of CO_2 laser cutting on Oil Palm Wood for Sample V based on NPM and TPM analysis. Significant factor that affect the upper kerf width can be found using the analysis of variance. From the analysis for both NPM and TPM analysis, focal point position has a very big effect on kerf width (49.15%) for NPM analysis and (53.42%) for TPM analysis. The second significant factor that affects the upper kerf width is laser power (41.33%) for NPM analysis and (39.47%) for TPM analysis, followed by cutting speed (8.50%) for NPM analysis and (6.58%) for TPM analysis while the least significant factor is pressure of inert gas (1.02%) for NPM analysis and (0.53%) for TPM analysis. Accordingly, the optimum level for NPM analysis is A1 B2 C2 D2 while the optimum level for TPM analysis is A1 B2 C1 D2.

4.3.2 Data Analysis for Sample W

The similar data analysis for Sample W was done in previous sub-section in this chapter and the result for the analysis in this Sample almost similar with the result of analysis in Sample V. The data analysis for Sample W is shown below.

Table 4.11: Control factor NPM / Signal to Noise Ratio (S/N) factor response table of the analysis of the Taguchi Design Experiment Method Analysis (Smaller is Better)

Level	Power	Speed	Pressure	Focal Point Position
1	-55.39	-56.85	-56.35	-57.47
2	-56.75	-56.01	-56.38	-55.70
3	-57.13	-56.41	-56.53	-56.09
Delta	1.74	0.84	0.18	1.77
Rank	2	3	4	1

Table 4.12: Control factor response table of the TPM analysis of the Taguchi Design Experiment Method Analysis

Level	Power	Speed	Pressure	Focal Point Position
1	592.6	695.7	657.5	748.9
2	689.8	639.0	670.8	614.8
3	720.9	668.6	675.2	639.8
Delta	128.3	56.7	17.7	134.1
Rank	2	3	4	1

The response of each factor on the kerf width in NPM and TPM analysis is shown in table 4.11 and table 4.12 respectively. The significant factor affecting on the upper kerf width in CO_2 laser cutting of oil palm wood in sample W is similar with the significant effect in Sample V. Based on the table 4.11 and 4.12, the most significant factor affecting on the upper kerf width in CO_2 laser cutting of oil palm wood is focal point position. The second significant factor affecting the upper kerf width is laser power. Cutting speed and pressure of inert gas are the third and fourth significant factor affecting the upper kerf width respectively. In order to obtain a good cut quality of an oil palm wood, the kerf width is preferably to be small. Thus, the smaller the better criterion is applied for the kerf width. The optimum level of parameter is the level which yields the smallest kerf width in the experiment and this optimum parameter for Sample W is similar with the optimum parameter for Sample V in NPM analysis because the similarity in pressure of inert gas. Therefore the optimum parameter level for Sample W, are laser power on level 1 (800 W), cutting speed on level 2 (600 mm/min), pressure of inert gas on level 1 (30 psi) and focal point position on level 2 (-3 mm).

The optimum cutting parameter level for upper kerf width using CO_2 laser cutting in NPM and TPM analysis is shown in table 4.13 and table 4.14 respectively.

Table 4.13 Optimum parameter level and its corresponding value for upper kerf width in NPM analysis

Parameter	Level	Value
Laser power	1	800 W
Cutting speed	2	600 mm/min
Inert gas pressure	1	30 psi
Focal Point Position	2	-3 mm

Table 4.14 Optimum parameter level and its corresponding value for upper kerf width in TPM analysis

Parameter	Level	Value
Laser power, (A)	1	800 W
Cutting speed , (B)	2	600 mm/min
Inert gas pressure, (C)	1	30 psi
Focal Point Position, (D)	2	-3 mm
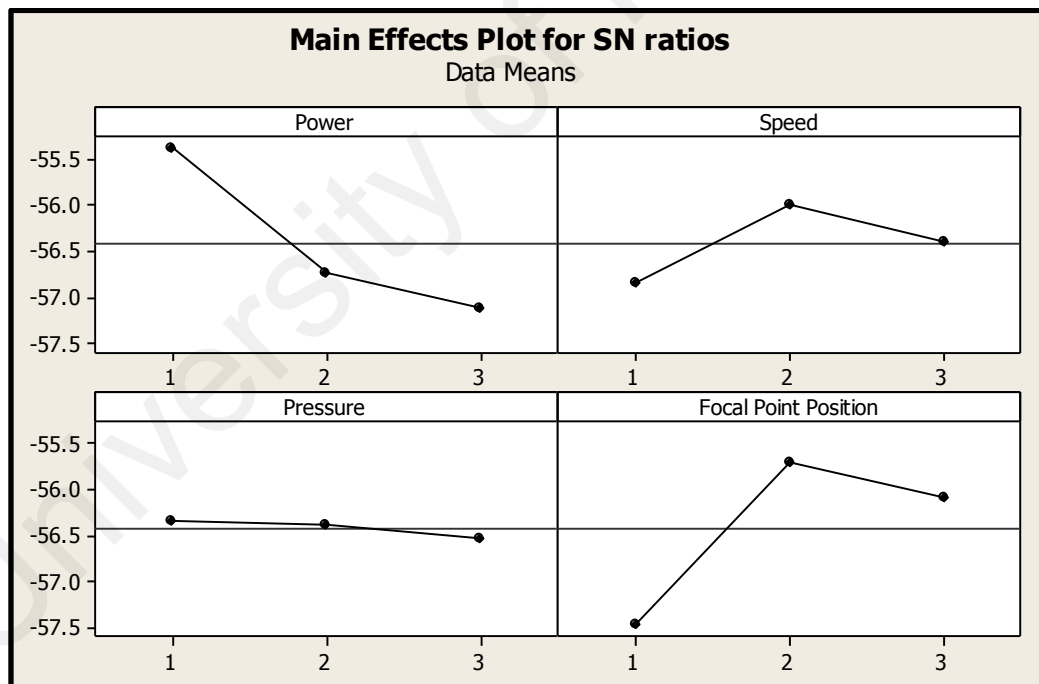
Figure 4.3: Control factor S/N factor response figure in NPM analysis
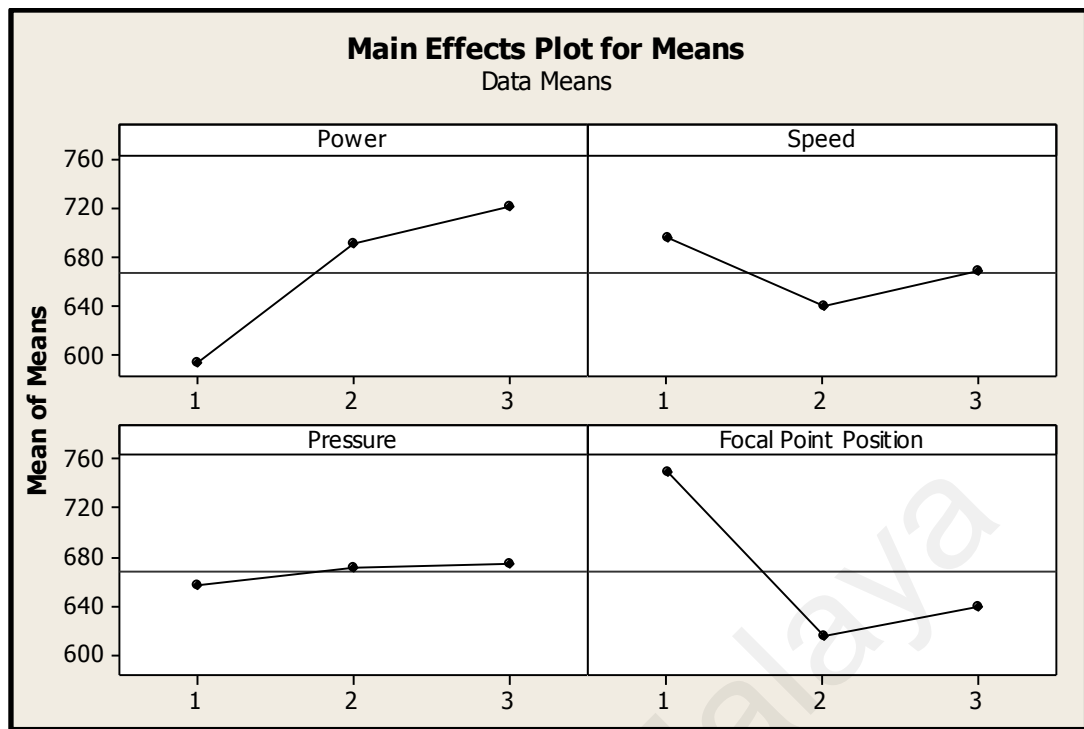
Figure 4.4: Control factor S/N factor response figure in TPM analysis

Response graph for each factor in each level using NPM and TPM analysis is shown in the figure 4.3 and figure 4.4 respectively. Based on the both response graph, the characteristic process for each level is similar characteristic process in Sample V in TPM analysis because the similarity characteristic process on pressure of inert gas. The upper kerf width increases as the laser power and pressure of inert gas increases significantly. The upper kerf width increases when the cutting speed of 200 mm/min (level 1) was used. However, the upper kerf width decreases when cutting speed of 600 min/min (level 2) was used. This situation is also same for the focal point position. The upper kerf width is increased when the value of focal point -6 mm (level 1) was used, but the upper kerf width decreases when the value of focal point position is -3 mm (level 2).

The same analysis (ANOVA analysis) done in previous sub-section is used to ascertain the main control factor which significantly affects the quality characteristics of upper kerf width. The contribution of each variable on the upper kerf width based on

NPM and TPM analysis for Sample W is shown in Table 4.15 and Table 4.16, respectively.

Table 4.15: Pareto ANOVA for NPM analysis

Control Factor Levels	S/N Response Data (dB)			
	A Laser Power	B Cutting Speed	C Inert Gas Pressure	D Focal Point Position
Level 1	-55.39	-56.85	-56.35	-57.47
Level 2	-56.75	-56.01	-56.38	-55.70
Level 3	-57.13	-56.41	-56.53	-56.09
Sum of Square	5.01	1.06	0.06	5.18
Total Sum of Square	11.31			
Percentage of Contribution, %	44.3	9.37	0.53	45.8
Rank	2	3	4	1

Cumulative Contribution	45.8	90.1	99.47	100
Optimum Combination	D2	A1	B2	C1
Overall Optimum Condition for all Factors	A1 B2 C1 D2			

Table 4.16: Pareto ANOVA for TPM analysis

Control Factor Levels	TPM Response Data			
	Laser Power (A)	Cutting Speed (B)	Inert Gas Pressure (C)	Focal Point Position (D)
Level 1	592.6	695.7	657.5	748.9
Level 2	689.8	639.0	670.8	614.8
Level 3	720.9	668.6	675.2	639.8
Sum of Square	23316.7	3879.9	381.6	33034.8
Total Sum of Square	62727.8			
Percentage of Contribution, %	42.86	7.69	0.81	48.64
Rank	2	3	4	1

Pareto Anova Analysis

Cumulative Contribution	48.64	91.5	99.19	100
Optimum Combination	D2	A1	B2	C1
Overall Optimum Condition for all Factors	A1 B2 C1 D2			

Table 4.15 and table 4.16 represent the analysis of variance (ANOVA) for each factor of CO_2 laser cutting on Oil Palm Wood for Sample W based on NPM and TPM analysis. The ranking of significant factor for this sample of oil palm wood (Sample W) is similar with the ranking in significant factor for Sample V from previous sub-section in this chapter. Significant factor that affect the upper kerf width can be found using the analysis of variance. From the analysis for both NPM and TPM analysis, focal point position has a very big effect on kerf width (45.80%) for NPM analysis and (48.64%) for TPM analysis. The second significant factor that affects the upper kerf width is laser power (44.30%) for NPM analysis and (42.86%) for TPM analysis, followed by cutting speed (9.37%) for NPM analysis and (7.69%) for TPM analysis while the least significant factor is pressure of inert gas (0.53%) for NPM analysis and (0.81%) for TPM analysis. Accordingly, the optimum level for both NPM and TPM analysis is A1 B2 C1 D2 and this optimum level is similar with optimum level for Sample V in TPM analysis.

4.3.3 Data Analysis for Sample X

The similar data analysis for Sample X was done in previous sub-section in this chapter and the result for the analysis in this Sample is different with the result of analysis in Sample V and W because the Sample X is dried sample while Sample V and W is fresh sample of oil palm wood. The data analysis for Sample X is shown below.

Table 4.17: Control factor NPM / Signal to Noise Ratio (S/N) factor response table of the analysis of the Taguchi Design Experiment Method Analysis (Smaller is Better)

Level	Power	Speed	Pressure	Focal Point Position
1	-62.19	-62.61	-62.32	-62.56
2	-62.40	-62.37	-62.41	-62.46
3	-62.61	-62.22	-62.46	-62.18
Delta	0.41	0.39	0.14	0.37
Rank	1	2	4	3

Table 4.18: Control factor response table of the TPM analysis of the Taguchi Design Experiment Method Analysis

Level	Power	Speed	Pressure	Focal Point Position
1	1288	1351	1307	1342
2	1319	1314	1321	1329
3	1350	1292	1330	1286
Delta	62	59	23	56
Rank	1	2	4	3

The response of each factor on the upper kerf width in NPM and TPM analysis is shown in table 4.17 and table 4.18 respectively. Both TPM and NPM analysis give similar result of the analysis. Based on the both table, the most significant factor affecting on the upper kerf width in CO_2 laser cutting of oil palm wood is laser power. The second significant factor affecting the upper kerf width is cutting speed. Focal point position and pressure of inert gas are the third and fourth significant factor affecting the upper kerf width respectively. In order to obtain a good cut quality of an oil palm wood, the kerf width is preferably to be small. Thus, the smaller the better criterion is applied for the upper kerf width value. The optimum level of parameter is the level which yields the smallest upper kerf width in the experiment. Therefore the optimum parameter level are laser power on level 1 (800 W), cutting speed on level 3 (1000 mm/min), pressure of assist gas on level 1 (30 psi) and focal point position on the top of the surface of the workpieces (0 mm at level 3).

The optimum cutting parameter level for upper kerf width using CO_2 laser cutting in NPM and TPM analysis is shown in table 4.19 and table 4.20 respectively.

Table 4.19: Optimum parameter level and its corresponding value for upper kerf width in NPM analysis

Parameter	Level	Value
Laser power	1	800 W
Cutting speed	3	1000 mm/min
Inert gas pressure	1	30 psi
Focal Point Position	3	0 mm

Table 4.20: Optimum parameter level and its corresponding value for upper kerf width in TPM analysis

Parameter	Level	Value
Laser power, (A)	1	800 W
Cutting speed , (B)	3	1000 mm/min
Inert gas pressure, (C)	1	30 psi
Focal Point Position, (D)	3	0 mm
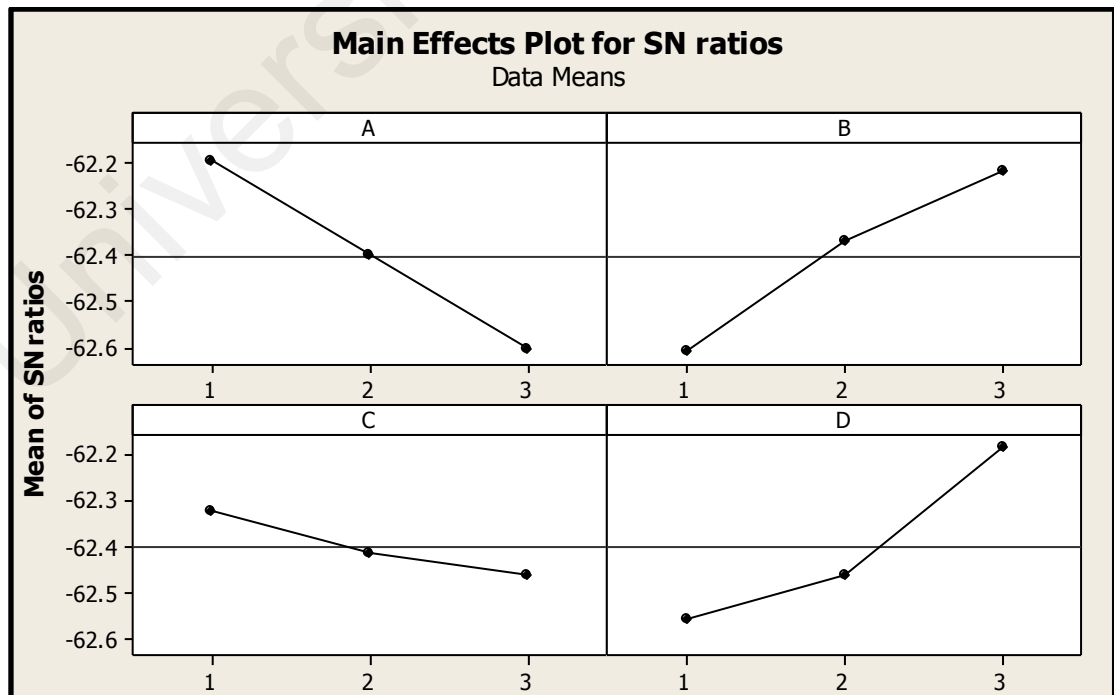
Figure 4.5: Control factor S/N factor response figure in NPM analysis
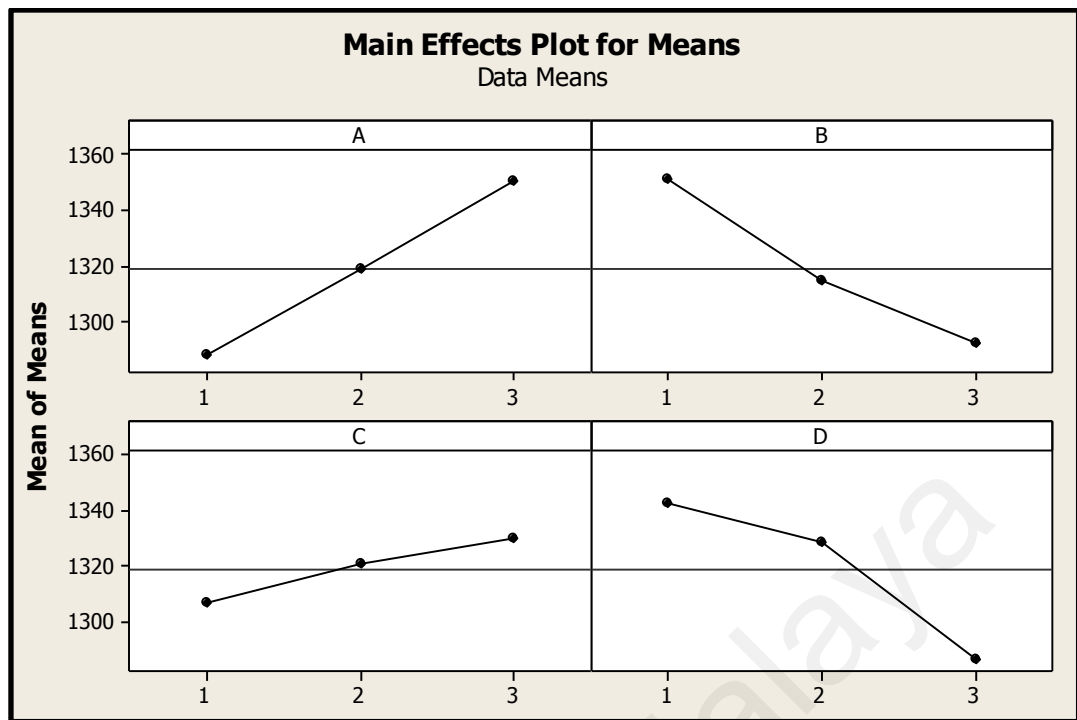
Figure 4.6: Control factor S/N factor response figure in TPM analysis

Response graph for each factor in each level using NPM and TPM analysis is shown in the figure 4.5 and figure 4.6 respectively. Based on the both response graph, the characteristic process for each level in NPM and TPM analysis is similar. The upper kerf width kerf width increases as the laser power increases significantly. However, the kerf width decreases as the cutting speed increases. The kerf width increases with the small changes when the pressure of assist gas increases. For focal point position, the kerf width is decreases when the value of focal point is increased.

The same analysis (ANOVA analysis) done in previous sub-section is used to ascertain the main control factor which significantly affects the quality characteristics of upper kerf width. The contribution of each variable on the upper kerf width based on NPM and TPM analysis for Sample X is shown in Table 4.21 and Table 4.22, respectively.

Table 4.21: Pareto ANOVA for NPM analysis

Control Factor Levels	S/N Response Data (dB)			
	A Laser Power	B Cutting Speed	C Inert Gas Pressure	D Focal Point Position
Level 1	-62.19	-62.61	-62.32	-62.56
Level 2	-62.40	-62.37	-62.41	-62.46
Level 3	-62.61	-62.22	-62.46	-62.18
Sum of Square	0.2531	0.2330	0.0301	0.2267
Total Sum of Square	0.7429			
Percentage of Contribution, %	34.08	31.36	4.04	30.52
Rank	1	2	4	3

Pareto Anova Analysis

Cumulative Contribution	34.08	65.44	95.96	100
Optimum Combination	A1	B3	D3	C1
Overall Optimum Condition for all Factors	A1 B3 C1 D3			

Table 4.22: Pareto ANOVA on TPM Analysis

Control Factor Levels	TPM Response Data			
	A Laser Power	B Cutting Speed	C Inert Gas Pressure	D Focal Point Position
Level 1	1288	1351	1307	1342
Level 2	1319	1314	1321	1329
Level 3	1350	1292	1330	1286
Sum of Square	5846.80	5357.10	792.10	5142.60
Total Sum of Square	17138.6			
Percentage of Contribution, %	34.11	31.26	4.62	30.01
Rank	1	2	4	3

Pareto Anova Analysis

Cumulative Contribution	34.11	65.37	95.38	100
Optimum Combination	A1	B3	D3	C1
Overall Optimum Condition for all Factors	A1 B3 C1 D3			

Table 4.21 and table 4.22 represent the analysis of variance (ANOVA) for each factor of CO_2 laser cutting on Oil Palm Wood for sample X based on NPM and TPM analysis. Significant factor that affect the upper kerf width can be found using the analysis of variance. From the analysis for both NPM and TPM analysis, laser power has a very big effect on kerf width (34.08%) for NPM analysis and (34.11%) for TPM analysis. The second significant factor that affects the upper kerf width is cutting speed (31.36%) for NPM analysis and (31.26%) for TPM analysis, followed by focal point position (30.52%) for NPM analysis and (30.01%) for TPM analysis while the least significant factor is pressure of inert gas (4.04%) for NPM analysis and (4.62%) for TPM analysis. Accordingly, the optimum level for both NPM and TPM analysis is similar and the optimum level is A1 B3 C1 D3.

4.3.4 Data Analysis for Sample Y

The similar data analysis for Sample Y was done in previous sub-section in this chapter and the result for the analysis in this Sample almost similar with the result of analysis in Sample X. The data analysis for Sample Y is shown below.

Table 4.23: Control factor NPM / Signal to Noise Ratio (S/N) factor response table of the analysis of the Taguchi Design Experiment Method Analysis (Smaller is Better)

Level	Power	Speed	Pressure	Focal Point Position
1	-61.56	-61.97	-61.68	-61.95
2	-61.77	-61.74	-61.84	-61.83
3	-62.01	-61.62	-61.81	-61.56
Delta	0.45	0.35	0.15	0.39
Rank	1	3	4	2

Table 4.24: Control factor response table of the TPM analysis of the Taguchi Design Experiment Method Analysis

Level	Power	Speed	Pressure	Focal Point Position
1	1197	1255	1214	1251
2	1226	1222	1236	1235
3	1260	1206	1234	1197
Delta	63	50	21	54
Rank	1	3	4	2

The response of each factor on the upper kerf width in NPM and TPM analysis is shown in table 4.23 and table 4.24 respectively. Both TPM and NPM analysis give similar result of the analysis and the result of this analysis is similar with the analysis done for Sample X . Based on the both table, the most significant factor affecting on the upper kerf width in CO_2 laser cutting of oil palm wood is laser power. The second significant factor affecting the upper kerf width is cutting speed. Focal point position and pressure of inert gas are the third and fourth significant factor affecting the upper kerf width respectively. In order to obtain a good cut quality of an oil palm wood, the kerf width is preferably to be small. Thus, the smaller the better criterion is applied for the upper kerf width value. The optimum level of parameter is the level which yields the smallest upper kerf width in the experiment. Therefore the optimum parameter level are laser power on level 1 (800 W), cutting speed on level 3 (1000 mm/min), pressure of assist gas on level 1 (30 psi) and focal point position on the top of the surface of the workpieces (0 mm at level 3).

The optimum cutting parameter level for upper kerf width using CO_2 laser cutting in NPM and TPM analysis is shown in table 4.25 and table 4.26 respectively.

Table 4.25 Optimum parameter level and its corresponding value for upper kerf width in NPM analysis

Parameter	Level	Value
Laser power	1	800 W
Cutting speed	3	1000 mm/min
Inert gas pressure	1	30 psi
Focal Point Position	3	0 mm

Table 4.26 Optimum parameter level and its corresponding value for upper kerf width in TPM analysis

Parameter	Level	Value
Laser power, (A)	1	800 W
Cutting speed , (B)	3	1000 mm/min
Inert gas pressure, (C)	1	30 psi
Focal Point Position, (D)	3	0 mm
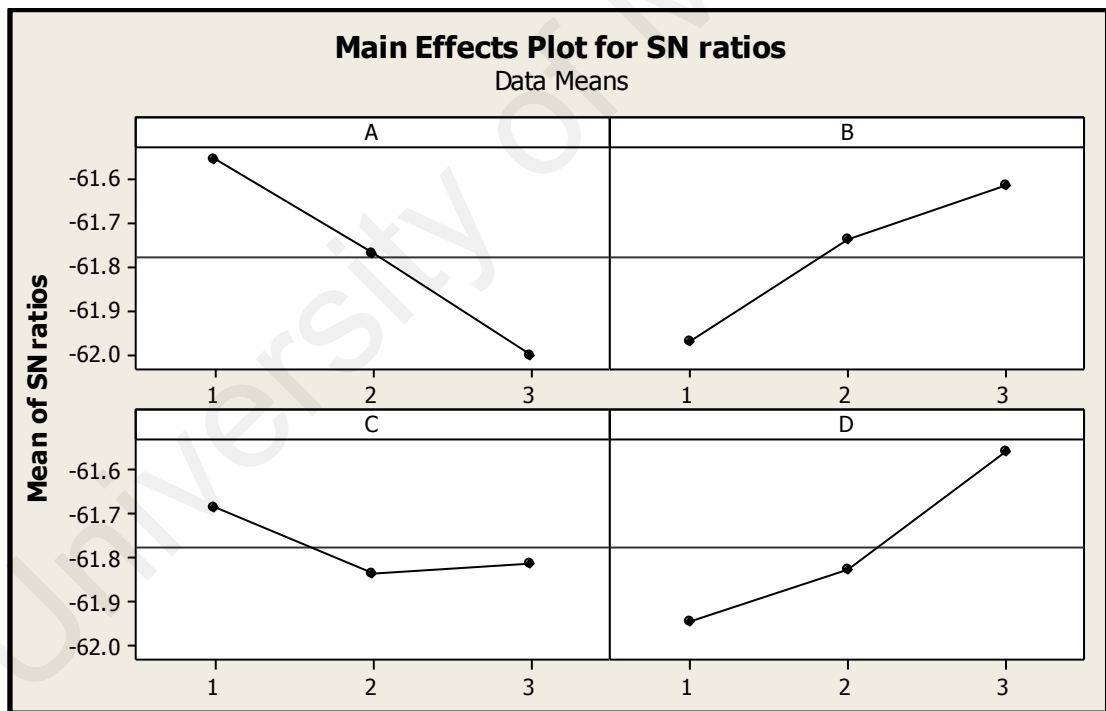
Figure 4.7: Control factor S/N factor response figure in NPM analysis
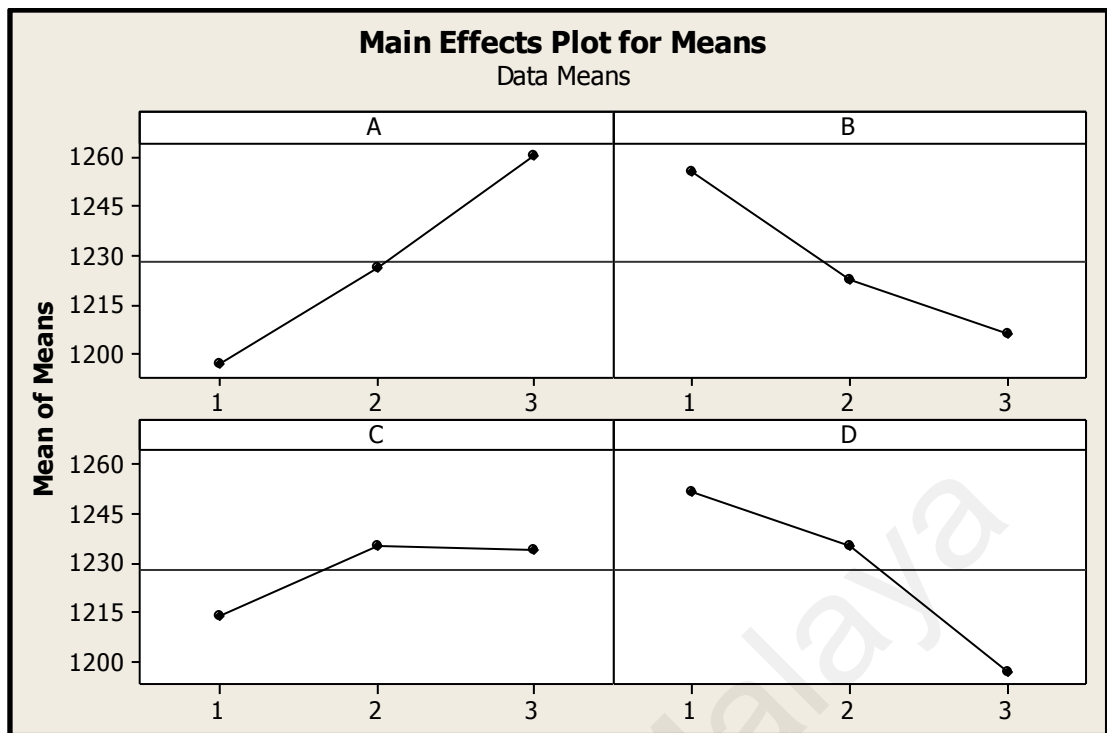
Figure 4.8: Control factor S/N factor response figure in TPM analysis

Response graph for each factor in each level using NPM and TPM analysis is shown in the figure 4.7 and figure 4.8 respectively. Based on the both response graph, the characteristic process for each level in NPM and TPM analysis is similar. This characteristic process for each level also similar with characteristic process for Sample X but have slightly different in characteristic process in pressure of inert gas. The upper kerf width kerf width increases as the laser power increases significantly. However, the kerf width decreases as the cutting speed increases. For focal point position, the kerf width is decreases when the value of focal point is increased. However, there is tendency of kerf width to increase from either ends towards gas pressure of 40 psi (level 2). Meanwhile, a much better kerf width is reported at lower pressure of 30 psi than that at higher pressure of 50 psi.

The same analysis (ANOVA analysis) done in previous sub-section is used to ascertain the main control factor which significantly affects the quality characteristics

of upper kerf width. The contribution of each variable on the upper kerf width based on NPM and TPM analysis for Sample Y is shown in Table 4.27 and Table 4.28, respectively.

Table 4.27: Pareto ANOVA for NPM Analysis

Control Factor Levels	S/N Response Data (dB)			
	A Laser Power	B Cutting Speed	C Inert Gas Pressure	D Focal Point Position
Level 1	-61.56	-61.97	-61.68	-61.95
Level 2	-61.77	-61.74	-61.84	-61.83
Level 3	-62.01	-61.62	-61.81	-61.56
Sum of Square	0.3018	0.1943	0.0398	0.2386
Total Sum of Square	0.7744			
Percentage of Contribution, %	38.97	25.08	5.14	30.81
Rank	1	3	4	2

Pareto ANOVA Analysis

Cumulative Contribution	38.97	69.78	94.86	100
Optimum Combination	A1	D3	B3	C1
Overall Optimum Condition for all Factors	A1 B3 C1 D3			

Table 4.28: Pareto ANOVA on TPM Analysis

Control Factor Levels	TPM Response Data			
	A Laser Power	B Cutting Speed	C Inert Gas Pressure	D Focal Point Position
Level 1	1197	1255	1214	1251
Level 2	1226	1222	1236	1235
Level 3	1260	1206	1234	1197
Sum of Square	6046	3832.30	850.30	4683.10
Total Sum of Square	15411.6			
Percentage of Contribution, %	39.23	24.87	5.52	30.38
Rank	1	3	4	2

Pareto Anova Analysis

Cumulative Contribution	39.23	69.61	94.48	100
Optimum Combination	A1	D3	B3	C1
Overall Optimum Condition for all Factors	A1 B3 C1 D3			

Table 4.27 and table 4.28 represent the analysis of variance (ANOVA) for each factor of CO_2 laser cutting on Oil Palm Wood for sample Y based on NPM and TPM analysis. The ranking of significant factor for this sample of oil palm wood (Sample Y) is similar with the ranking in significant factor for Sample X from previous sub-section in this chapter. Significant factor that affect the upper kerf width can be found using the analysis of variance. From the analysis for both NPM and TPM analysis, laser power has a very big effect on kerf width (38.97%) for NPM analysis and (39.23%) for TPM analysis. The second significant factor that affects the upper kerf width is cutting speed (30.81%) for NPM analysis and (30.38%) for TPM analysis, followed by focal point position (25.08%) for NPM analysis and (24.87%) for TPM analysis while the least significant factor is pressure of inert gas (5.14%) for NPM analysis and (5.52%) for TPM analysis. Accordingly, the optimum level for both NPM and TPM analysis is similar with optimum level for sample X and the optimum level is A1 B3 C1 D3.

4.3.5 Data Analysis to investigate the effect of material density

For this section, the effect of material density of oil palm wood is analysed. This analysis is conducted to ascertain the effect of material density on the upper kerf width and this blocking analysis is similar with analysis done by (I. A. Choudhury, ey al., 2012) . Having analyzed the data from Table 4.29, the contributions of four control factors along with the moisture content have been determined from ANOVA analysis and are presented in Tables 4.30 and Table 4.31. These tables show the contribution of all factors on upper kerf width base on Noise Performance Measures (NPM) and Target performance measure (TPM). Sample Y is in Level 1 while Sample X of oil palm wood is in Level 2 as shown in blue circle in Figure 4.9.
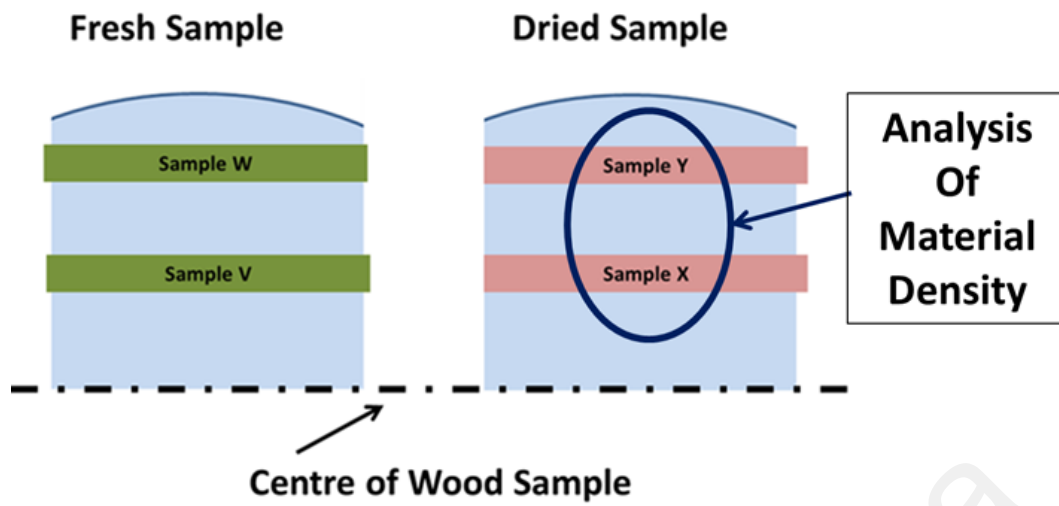
Figure 4.9: Sample X and Sample Y for analysis of material density

Table 4.29: Parameter level for blocking analysis

Run	Parameter					TPM	NPM
	Sample	Laser Power (level)	Cutting Speed (level)	Inert gas pressure (level)	Focal Point Position (level)		
1	Y	1	1	1	1	1234.40	-61.83
2	Y	1	2	2	2	1206.32	-61.63
3	Y	1	3	3	3	1150.15	-61.22
4	Y	2	1	2	3	1230.69	-61.80
5	Y	2	2	3	1	1250.49	-61.94
6	Y	2	3	1	2	1197.86	-61.57
7	Y	3	1	3	1	1301.34	-62.29
8	Y	3	2	1	3	1210.28	-61.66
9	Y	3	3	2	1	1269.53	-62.07
1	X	1	1	1	1	1331.02	-62.48
2	X	1	2	2	2	1294.50	-62.24
3	X	1	3	3	3	1238.55	-61.86
4	X	2	1	2	3	1319.46	-62.41
5	X	2	2	3	1	1347.64	-62.59
6	X	2	3	1	2	1288.99	-62.21
7	X	3	1	3	1	1402.72	-62.94
8	X	3	2	1	3	1300.50	-62.28
9	X	3	3	2	1	1348.15	-62.59

Table 4.30: Pareto ANOVA for NPM Analysis

Control Factor Levels	S/N Response Data (dB)					
	Sample	Laser Power (A)	Cutting Speed (B)	Inert Gas Pressure (C)	Focal Point Position (D)	Error
Level 1	-61.78	-61.88	-62.29	-62.00	-62.25	
Level 2	-62.40	-62.09	-62.06	-62.12	-62.15	
Level 3		-62.31	-61.92	-62.14	-61.87	
Sum of Square	1.7424	0.5537	0.4262	0.0658	0.4649	0.0069
Total Sum of Square	3.2598					
Percentage of Contribution, %	53.45	16.98	13.07	2.03	14.26	0.21
Rank	1	2	4	5	3	6

Pareto Anova Analysis

Cumulative Contribution	53.45	70.43	84.69	97.76	99.79	100
Optimum Combination	Sample Y	A1	B3	C1	D3	
Overall Optimum Condition for all Factors	Sample Y A1 B3 C1 D3					

Table 4.31: Pareto ANOVA on TPM Analysis

Control Factor Levels	NPM Response Data					
	Sample	Laser Power (A)	Cutting Speed (B)	Inert Gas Pressure (C)	Focal Point Position (D)	Error
Level 1	1228	1242	1303	1261	1297	
Level 2	1319	1273	1268	1278	1282	
Level 3		1305	1249	1282	1242	
Sum of Square	37399	11889	9120	1555	9811	175
Total Sum of Square	69949					
Percentage of Contribution, %	53.46	17	13.04	2.22	14.03	0.25
Rank	1	2	4	5	3	6

Pareto Anova Analysis

Cumulative Contribution	53.46	70.46	84.49	97.53	99.75	100
Optimum Combination	Sample Y	A1	D3	B3	C1	
Overall Optimum Condition for all Factors	Sample Y A1 B3 C1 D3					

Table 4.30 and Table 4.31 represent the analysis of variance (ANOVA) for each factor of CO_2 laser cutting on Oil Palm Wood based on NPM and TPM analysis. Significant factor that affect the kerf width can be found using the analysis of variance. From the analysis, material density namely Sample X and Sample Y of oil palm wood samples have a very big effect on kerf width (53.45%) for NPM analysis and (53.46%) for TPM analysis. The second significant factor that affects the kerf width is laser power, (16.98%) for NPM analysis and (17.00%) for TPM analysis. The third significant factor is focal point position (14.26%) for NPM analysis (14.03%) for TPM analysis followed by cutting speed (13.07%) for NPM analysis and (13.04%) for TPM analysis. The least significant factor is pressure of inert gas (2.03%) for NPM analysis and (2.22%) for TPM analysis. Accordingly, the optimum level for both NPM and TPM analysis is similar and the optimum level is material at Sample Y , Factor A1 B3 C1 D3.

4.3.6 Data Analysis to investigate the effect of moisture content

For this section, the effect of moisture content of oil palm wood is analysed. The same analysis known as blocking from previous sub-section in this chapter was used. The analysis known as blocking is conducted to ascertain the effect of moisture content on the upper kerf width. In this investigation the concept of blocking from design of experiment is combined with the orthogonal array. Having analysed the data from table 4.32, the contributions of four control factors along with the moisture content have been determined from ANOVA analysis and are presented in Tables 4.33 and Table 4.34. These tables show the contribution of all factors on upper kerf width base on Noise Performance Measures (NPM) and Target performance measure (TPM).

Fresh sample (Sample W) is in Level 1 while dried sample (Sample Y) of oil palm wood is in Level 2 as shown in Figure 4.10.
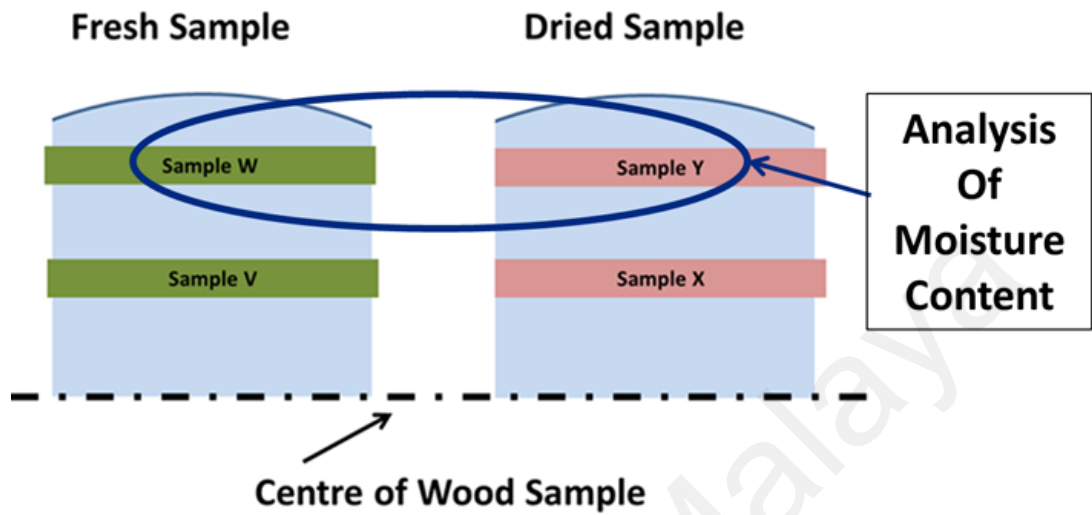
Figure 4.10: Sample W and Sample Y for Moisture Content Analysis

Table 4.32: Parameter level for blocking analysis of Moisture Content

Run	Parameter					TPM	NPM
	Sample	Laser Power (level)	Cutting Speed (level)	Inert gas pressure (level)	Focal Point Position (level)		
1	W	1	1	1	1	691.27	-56.79
2	W	1	2	2	2	513.79	-54.22
3	W	1	3	3	3	572.79	-55.16
4	W	2	1	2	3	692.74	-56.81
5	W	2	2	3	1	749.50	-57.50
6	W	2	3	1	2	627.30	-55.95
7	W	3	1	3	1	703.17	-56.94
8	W	3	2	1	3	653.85	-56.31
9	W	3	3	2	1	805.82	-58.12
1	Y	1	1	1	1	1234.40	-61.83
2	Y	1	2	2	2	1206.32	-61.63
3	Y	1	3	3	3	1150.15	-61.22
4	Y	2	1	2	3	1230.69	-61.80
5	Y	2	2	3	1	1250.49	-61.94
6	Y	2	3	1	2	1197.86	-61.57
7	Y	3	1	3	1	1301.34	-62.29
8	Y	3	2	1	3	1210.28	-61.66
9	Y	3	3	2	1	1269.53	-62.07

Table 4.33: Pareto ANOVA for NPM Analysis

Control Factor Levels	NPM Response Data					
	Sample	Laser Power (A)	Cutting Speed (B)	Inert Gas Pressure (C)	Focal Point Position (D)	Error
Level 1	-56.42	-58.47	-59.41	-59.02	-59.71	
Level 2	-61.78	-59.26	-58.87	-59.11	-58.77	
Level 3		-59.57	-59.02	-59.17	-58.83	
Sum of Square	129.09	3.81	0.93	0.07	3.35	3.92
Total Sum of Square	141.17					
Percentage of Contribution, %	91.44	2.7	0.66	0.05	2.37	2.78
Rank	1	3	5	6	4	2

Pareto Anova Analysis

Cumulative Contribution	91.44	94.22	96.92	99.29	99.95	100
Optimum Combination	Fresh		A1	D3	B2	C1
Overall Optimum Condition for all Factors	Fresh Sample, A1 B2 C1 D3					

Table 4.34: Pareto ANOVA on TPM Analysis

Control Factor Levels	NPM Response Data					
	Sample	Laser Power (A)	Cutting Speed (B)	Inert Gas Pressure (C)	Focal Point Position (D)	Error
Level 1	667.8	894.8	975.6	935.8	1000.2	
Level 2	1227.9	958.1	930.7	953.1	925.0	
Level 3		990.7	937.2	954.6	918.4	
Sum of Square	1411665	28523	7060	1307	24764	16485
Total Sum of Square	1489804					
Percentage of Contribution, %	94.76	1.91	0.47	0.09	1.66	1.11
Rank	1	2	5	6	3	4

Pareto Anova Analysis
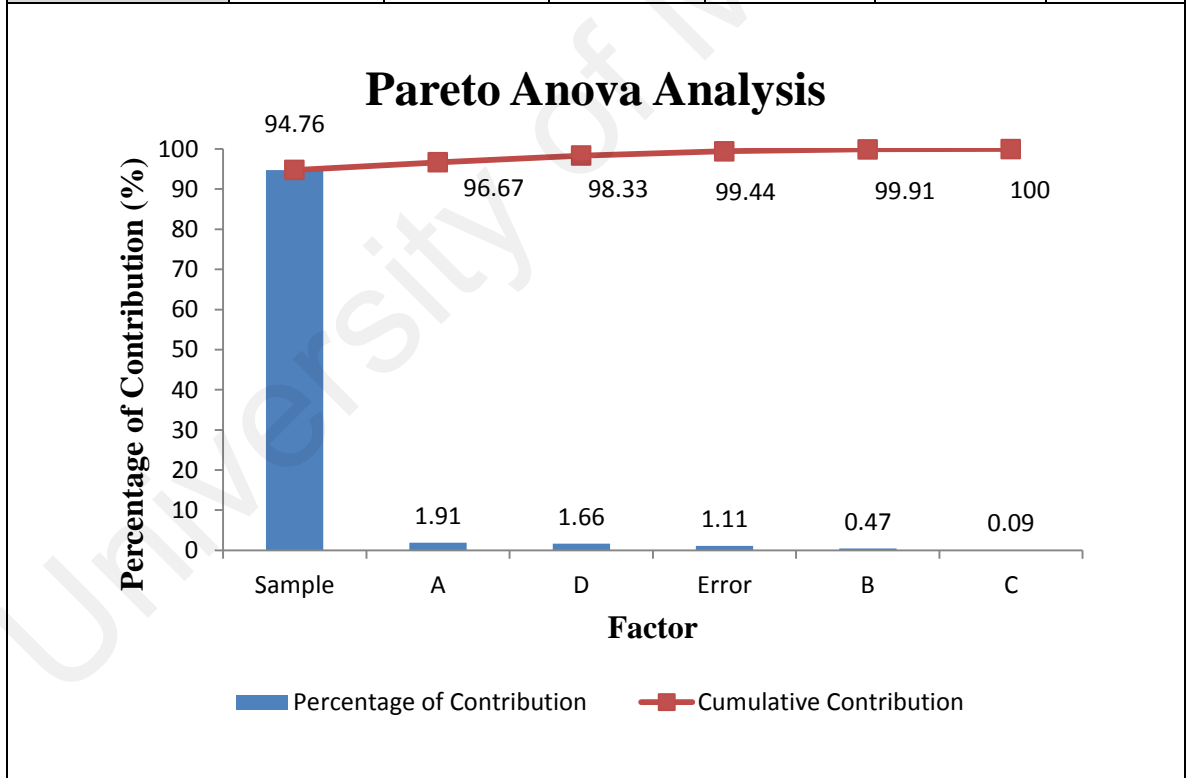
Cumulative Contribution	94.76	96.67	98.33	99.44	99.91	100
Optimum Combination	Fresh	A1	D3		B2	C1
Overall Optimum Condition for all Factors	Fresh Sample, A1 B2 C1 D3					

Table 4.33 and Table 4.34 represent the analysis of variance (ANOVA) for each factor of CO_2 laser cutting on Oil Palm Wood based on NPM and TPM analysis. Significant factor that affect the kerf width can be found using the analysis of variance. From the analysis, moisture content namely fresh and dried wood samples have a very big effect on kerf width (91.44%) for NPM analysis and (94.76%) for TPM analysis. The second significant factor that affects the kerf width is laser power, (2.70%) for NPM analysis and (1.91%) for TPM analysis. The third significant factor is focal point position (2.37%) for NPM analysis and (1.66%) for TPM analysis followed by cutting speed (0.66%) for NPM analysis and (0.47%) for TPM analysis. The least significant factor is pressure of inert gas (0.05%) for NPM analysis and (0.09%) for TPM analysis. Accordingly, the optimum level for both NPM and TPM analysis is similar and the optimum level is A1 B3 C1 D3.

4.4 Confirmation Experiment

From the response table of upper kerf width for all samples, the optimum level of parameter can be determined. Optimum parameters level combination used in order to obtain minimum upper kerf width based on TPM and NPM analysis is shown in table 4.35. In Sample V, the optimum level from NPM and TPM analysis is different in factor C (inert gas pressure). From ANOVA analysis as shown in Table 4.9 and 4.10, the percentage of contribution from NPM analysis for factor C is higher than percentage of contribution from TPM analysis. So, the selection of optimum level for factor C is obtained from the NPM analysis. The result of the experiments using these optimum parameter levels are shown in table 4.36.

Table 4.35: Optimum Parameter Level Combination For All Four Factor

Sample	Optimum Level in NPM analysis	Optimum Level in TPM analysis	Selection Level
Sample V	A1 B2 C2 D2	A1 B2 C1 D2	A1 B2 C2 D2
Sample W	A1 B2 C1 D2	A1 B2 C1 D2	A1 B2 C1 D2
Sample X	A1 B3 C1 D3	A1 B3 C1 D3	A1 B3 C1 D3
Sample Y	A1 B3 C1 D3	A1 B3 C1 D3	A1 B3 C1 D3

Table 4.36: Result For Upper Kerf Width Using Optimum Parameter Level Combination

Sample	Read 1 (μm)	Read 2 (μm)	Read 3 (μm)	Read 4 (μm)	Read 5 (μm)	Mean (μm)
Sample V	398.15	402.55	402.55	400.35	398.15	400.35
Sample W	463.23	468.98	463.23	468.55	468.55	466.508
Sample X	1165.72	1165.72	1165.72	1165.72	1165.72	1165.72
Sample Y	1051.88	1052.06	1052.06	1051.88	1052.06	1051.98

The confirmation experiment result indicates a reduction in quality characteristics compared with the one obtained when using the initial setting of the parameters level. However, the optimum parameter level for Sample V obtained is similar with experiment number 2 in Taguchi L9 parameter. The value of upper kerf width is reduced when the optimum parameter levels is used. Thus, it can be said that a considerable reduction in upper kerf width has been obtained using the optimum parameter level setting.

4.4 Prediction of Optimization

The first prediction used to predict the optimization result in this dissertation is by using Taguchi predicted value method. The predicted value (PV) of Taguchi method was obtained using the equation below.

$$\text{(PV)} = \bar{y} + \left(\overline{Ax} - \bar{y}\right) + \left(\overline{Bx} - \bar{y}\right) + \left(\overline{Cx} - \bar{y}\right) + \left(\overline{Dx} - \bar{y}\right) \tag{4.3}$$

Where the value of $\overline{Ax}$, $\overline{Bx}$, $\overline{Cx}$ and $\overline{Dx}$ is the value of optimum level for each factor in S/N ratio while the value of $\bar{y}$ is the average value of all S/N ratio value. Since the optimum level parameter of Sample V is similar in experiment number two in Taguchi L9 orthoganal array. So, only optimum parameter level for sample W, X and Y will predict. The result of prediction optimum level for each sample as shown in Table 4.37

Table 4.37: Prediction value of Optimum Level in CO_2 Laser Cutting of Oil palm Wood for each Sample

Sample	Optimum Level	Prediction Value, S/N	Prediction Value, mm
Sample W	A1 B2 C1 D2	-54.18	500.48
Sample X	A1 B3 C1 D3	-61.72	1215.74
Sample Y	A1 B3 C1 D3	-61.09	1130.33

The second prediction method to predict the optimization result is by using Artificial Neural Network (ANN). Levenberg Marquardt algorithm was selected since it is the best possible training algorithm. This technique is fast and gives minimum prediction errors. The name of this technique is called Taguchi ANN. The training was performed with four input and one output parameter S/R ratio of five replications of upper kerf width on orthogonal array as shown in figure 4.11 and figure 4.12. The training parameter for Taguchi ANN prediction of optimization is shown in Table 4.38
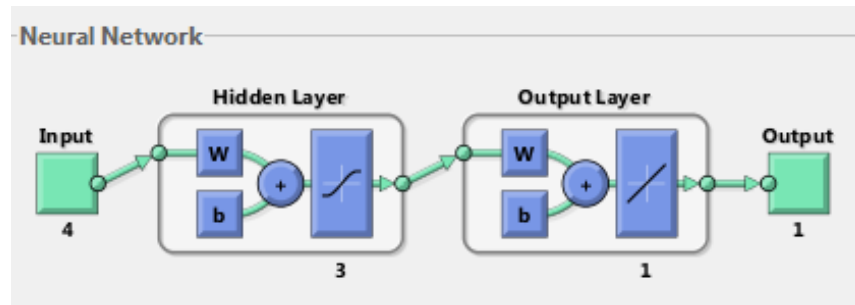
Figure 4.11: Levenberg Marquardt Algorithm Neural Network
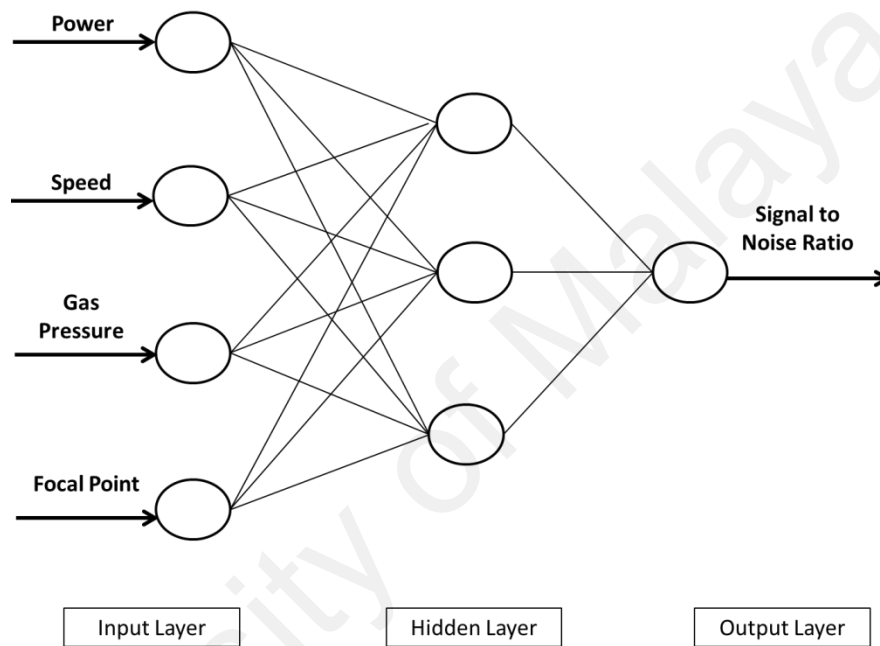
Figure 4.12: Architecture of Levenberg Marquardt algorithm model

Table 4.38: Parameter for ANN Training

Parameter	Value
Epoch	20 000
Learning Rate	0.1
Learning Momentum	0.1
Learning Time	Infinite

The training set needs validation and test datasets in Matlab neural networks toolbox. This training technique need to be obtained by normalization of input cutting parameters and output (signal to noise ratio). Table 4.39 shows the normalized input parameters and output by using the equation 2.3.

$$D_{nor} = D_{min} + \frac{V_{orig} - V_{min}}{V_{max} - V_{min}}(D_{max} - D_{min}) \qquad (2.3)$$

Where

$$D_{min} = 0.2$$

$$D_{max} = 0.8$$

Table 4.39: Normalised L9 orthoganal array data for the training samples of ANN model

Run	Control Factor				S/N Ratio For Sample		
	A	B	C	D	W	X	Y
1	0.2	0.2	0.2	0.2	0.60	0.55	0.54
2	0.2	0.5	0.5	0.5	0.20	0.41	0.43
3	0.2	0.8	0.8	0.8	0.34	0.20	0.20
4	0.5	0.2	0.5	0.8	0.60	0.51	0.53
5	0.5	0.5	0.8	0.2	0.70	0.61	0.61
6	0.5	0.8	0.2	0.5	0.47	0.39	0.40
7	0.8	0.2	0.8	0.5	0.62	0.80	0.80
8	0.8	0.5	0.2	0.8	0.52	0.44	0.45
9	0.8	0.8	0.5	0.2	0.80	0.61	0.68

The next prediction of optimization is called Hybrid Optimization. This Hybrid Optimization is combination of Artificial Neural Network and Genetic Algorithm. First, the L9 data is trained using Levenberg Marquardt algorithm. After the training is finished, genetic Algorithm will executed to find the optimum value of input and output for each parameter. Finally, by using the optimum input and output value obtained from execution of Genetic Algorithm, this data will train again using Levenberg Marquardt algorithm. The Genetic Algorithm parameter are as shown in Table 4.40.

Table 4.40: Parameter level for Genetic Alghorithm

Parameter	Value
Lower Boundary	0.2
Upper Boundary	0.8
Population	20
Generation	200
Number of variable	4

In the case of ANN simulation, the predicted values must be verified by experimental values. Table 4.41 shows a comparison of the predicted results of the Taguchi ANN and the hybrid model with experiments.

Table 4.41: Comparison of the predicted S/N kerf width obtained from Taguchi ANN, and Hybrid Model (GA+ Taguchi ANN)

Sample	Optimum Level	Predicted Value		Real experiment values
		Taguchi ANN	Hybrid Model	
Sample W	A1 B2 C1 D2	502.11	492.23	466.508
Sample X	A1 B3 C1 D3	1279.00	1230.99	1165.72
Sample Y	A1 B3 C1 D3	1253.85	1036.66	1051.98

The predicted percentage error is calculated as shown in equation 4.5. It is seen that the GA-Taguchi ANN model can provide better prediction results that are more precise than those for Taguchi ANN model as shown in Table 4.42. The GA-Taguchi ANN model has significant benefits in application to fabrication process because only 9 experiments should be performed to get the better prediction of optimization.

$$\text{error} = \frac{(\text{predicted value-experimental value})}{\text{experimental value}} \times 100 \qquad (4.5)$$

Table 4.44: Comparison of prediction of optimization with experiments value for each sample in percentage of error

Sample	Optimum Level	Predicted Percentage of Error %		
		Taguchi Prediction Value (PV)	Taguchi ANN	Hybrid Method
Sample W	A1 B2 C1 D2	7.28	7.63	5.51
Sample X	A1 B3 C1 D3	4.29	9.72	5.60
Sample Y	A1 B3 C1 D3	7.45	19.19	-1.46

4.5 Discussion

It was demonstrated that cutting using laser source produces better cut quality compared to conventional cutting method (M.Z.Harizam, et al., 2012; Nader, et al., 1999). The use of laser in materials processing has various benefits which include:

- No saw dust

- Narrow kerf

- Ease of manufacture

- No direct frictional force or mechanical stresses on the workpiece

- No tool wear

One of the most important effects of laser cutting on any materials is the kerf width. It is defined as the amount of material that have been melted and vaporized by the laser. From previous studies, many factors have been identified as the reasons behind the variation of the kerf width such as the laser power, cutting speed and type of assisting gas but there are no study is focusing on the effect that those factors have on

the kerf width of oil palm wood. Here, the discussion is based on the factor according the analysis done from previous.

4.5.1 Discussion on Laser Power

The radiation of CO_2 lasers is highly absorbed by cellulose of woods. Then, the main cutting mechanism is the chemical degradation of this organic constituent. In preliminary study, the through cut of the fresh workpiece that have moisture content is achieved when the laser power is higher than 800 W. This is because the material is too thick and need high power to achieve through cut and this situation is similar with the research done by (Quintero, et al., 2011) to cut 19.3 mm of phenolic resin board. From the analysis from Response Graph and Anova Table for each sample of oil palm wood, it found that that the significant of each factor are almost same. Furthermore, the optimum level for both fresh and dried sample also same. Here, laser power has highly significant effect for cut quality for all samples. With increasing the laser power, the value of upper kerf width increases and this is agree with the finding by (Lan, et al., 2011) in their research. The amount of laser power is proportional to the upper kerf width because of the heat subjected to the oil palm wood. Higher laser power will exert more heat at the oil palm wood and therefore would melt and vaporize the oil palm wood more which would widen the kerf width of the oil palm wood.

4.5.2 Discussion on Cutting Speed

Both dried sample shows that when cutting speed increases, the upper kerf width will decreases. This result could be because of the time period of oil palm wood being exposed to the laser for cut zone. Slower speed would result in longer exposure of laser at cut zone on the oil palm wood which would increase the amount of melted and vaporized area.

However, for both fresh wood samples required slower cutting speed. This is due to the process of vaporisation of water content will affect the absorption of heat on the material. Most of the intensity of heat will be used to dissipate the moisture and hence will required longer time to cut the material.

A higher laser power combine with low cutting speed will result in bigger kerf width. This is because there is more heat inserted in the cutting area per time, resulting in more material being burned while cutting. Thus, a greater kerf width will be produced. Laser power and cutting speed must be adjusted correctly in order to control the heat input to the cutting area per time. This will enable us to control the amount of material being burned away by the laser beam which in turn control the dimension of the kerf width produced. This variation of the laser power and cutting speed of laser cutting of oil palm wood is agrees with the findings made by H.A. Eltawahni, et al., (2011) in their research.

4.5.3 Discussion on Inert Gas Pressure

It also found that both fresh and dried samples have least contribution factor in inert gas pressure. The percentage of contribution for this factor is less than 10% for all samples. The variation of inert gas pressure does not yield any significant changes on the kerf width dimension. The changed of upper kerf width are small even increasing the pressure of inert gases and this finding is similar to the finding by (Lum, et al., 2000) when they investigate the surface roughness of laser cutting of MDF even using nitrogen gases as an inert gases. Since, the percentage of contribution of this factor is less than 10% for all samples of material; this factor can be neglected for manufacturing process.

4.5.4 Discussion on Focal Point Position

For focal point position, the upper kerf width is decreases when the focal point position is at the top of the workpieces so that a narrower cutting width can be obtained (H.A. Eltawahni, et al., 2011; L. Li & J.Mazumder, 1991). This will make the energy density of the laser beam to be more focused on the top of the workpiece, making it easier for the laser to cut through the material.

However, this result is contradicted with the both samples of fresh oil palm wood. The optimum focal point position for this fresh oil palm wood is inside the wood or in between the centre of workpieces and top of workpieces (-3mm below the surface). This result is similar with the finding by (Tayal, Barnekov, & Mukherjee, 1994) as they concluded that the maximum average laser power density is half of the

depth of focus and this finding is matches well with the depth of focus (7.0/2 = 3.5mm) for the optics used in our experiment

4.5.5 Discussion on Material Density

From the analysis, it's shown that the material density will give the greatest effect of laser cutting compared to the other four factors. The analysis shows that Samplex Y has smaller upper kerf width than that of Sample X. Although the two samples of one similar type of wood have the same thickness, the inner material properties at different sections of the trunk account for this discrepancy. Choo et al. (2010) found that the density of oil palm wood increases from the centre to the bark because the number of fibre shows a similar trend. This is because the number of fiber in the oil palm wood structure is increasing increases from the pitch to towards the bark and the remaining of its structure is cells of parenchymataous tissue (Balfas, 2006; Feng, et al., 2011). From the observation , fiber has high mechanical strength than this tissue. Since biological tissue can couple well with the CO_2 laser due to high absorption coefficient at that particular laser wavelength, sample with high tissue content would be relatively easy to cut. So this tissue is easily to have heat absorption by CO_2 laser and resulting easily to melt and vaporized that as might be expected taking into account, that the cutting mechanism for these materials is chemical degradation.

In our analysis, we have compared two different substrates X and Y of a similar material origin that were cut from two different sections. Optical image in Figure 4.13 shows that the fibre content in Y is higher than that of X after the drying process [at sample X-area, there have a porosity since the loss of tissue during drying process] and

this result matches well with the findings of (Kilmann & Lim, 1985) since the number of fibres increases from the pitch to the bark (Choo, et al., 2010). At section of low fibre content, parenchymataous tissue was found in greater quantity. As a result, the substrate density in Y is higher than that of X.
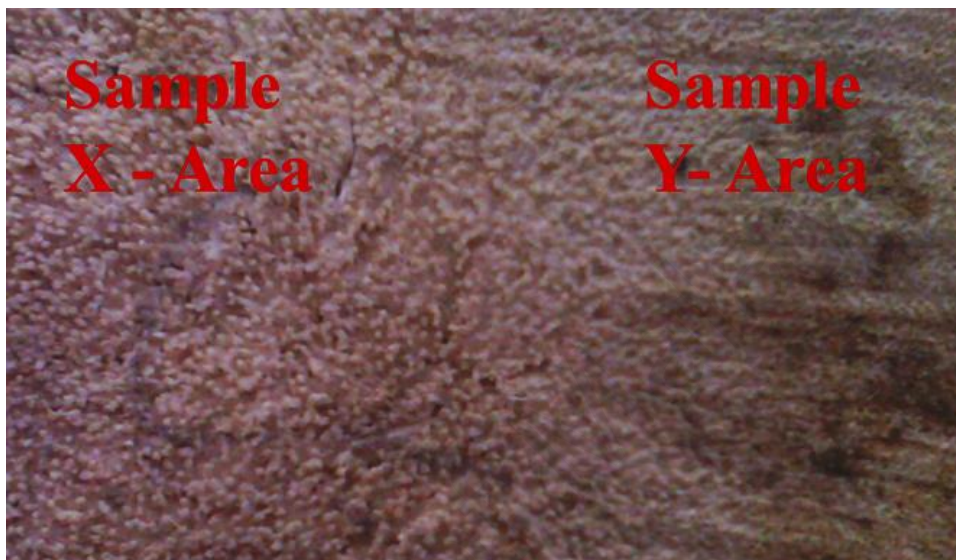
Figure 4.13: Optical Images of cross sectional of oil palm trunk

Our result also shows that as the density is decreasing the kerf width becomes larger. This is because the presence of tissue within the substrate enhances heat absorption since biological tissue couples well with the wavelength of a CO_2 laser than that of fibre.

4.5.6 Discussion on Moisture Content

From both the NPM and TPM Anova table in section 4.3.6, the percentage of contribution of moisture content of oil palm wood is larger than 90%. It means that, the moisture content gave the main effect of upper kerf width in laser cutting of oil palm

wood. The value of upper kerf width for dried sample is nearly two times larger than fresh sample oil palm wood and this is agree with the finding by (Carlos Hernández-Castañeda, Kursad Sezer, & Li, 2011) who investigated the effect of moisture content in laser cutting of pine wood. Since the CO_2 laser cutting is thermal processes, so the existence of water known as moisture content in oil palm wood will reduce the thermal energy from the laser and reducing the after burn effect.

4.5.7 Discussion on Confirmation Experiment

The confirmation experiment result indicates an improvement in quality characteristics for all samples compared with the one obtained when using the initial setting of the parameters level. Using the optimum parameter levels, the kerf width is reduced to 400.35 μm 451.55 μm 1165.88 μm and 1052.58 μm for samples V, W, X any Y respectively. Thus, it can be said that a considerable reduction in kerf width has been obtained using the optimum parameter level setting.

800 Watt of laser power used is enough for the laser beam to penetrate the through the workpiece at a given time while high cutting speed will control the heat input at the cutting area per unit time. This will result in complete cut of the material and reduction in burned and charred mark on the material. Nitrogen gas used as inert gas will make the carbon layer on the surface to be blown away effectively, leaving the fresh material exposed to the laser beam and reduces the after burn effect. All these contribute to the formation of a smaller kerf width. Thus applying the optimum level parameter combination will result in smaller kerf width than the initial setting of parameter.

4.5.8 Discussion on prediction of optimization

The objective of the Taguchi method is to identify the optimum settings of the controllable factors, not only to improve the product or process, but also to reduce the influence of the noise factors and make the prediction of optimization (Georgilakisa, Hatziargyrioub, Paparigasa, & Elefsiniotisa, 2001). Result obtained from Taguchi technique (NPM and TPM analysis) for optimum parameter setting in this research is closely matched well with ANOVA analysis and this technique also used by other researcher for optimization (Gopalsamy, et al, 2009).

In the process of laser cutting, Taguchi L9 and L9 +3 orthogonal array based experimental data was trained by ANN, using Levenberg Marquardt algorithm and the model was used to predict the upper kerf width. The prediction results show that Taguchi L9 (nine experiments) is not sufficient for prediction of upper kerf width within the engineering acceptable error. The errors in ANN and Taguchi ANN model simulations are still above 10% for some cutting conditions even with using the best training algorithm of Levenberg Marquardt. To overcome such limitation, a hybrid GA-Taguchi-ANN optimization model has been developed. It is constructed in such a way to realize mutual input output through ANN and GA. The trained ANN takes random machining parameters from GA and the output of ANN is again presented to the GA for error optimization. The results obtained from the hybrid model have confirmed that the GA-Taguchi ANN model can provide prediction results more precise than those for Taguchi ANN model and this is agree with the finding by another researcher who conduct the same study (Nukman, Hassan, & Harizam, 2013; Panneerselvam, S.Aravindan, & Haq, 2009; Yang, et al., 2011).

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this study, four variation of workpiece material was used. In order to enhance the result, two different values of moisture content (wet and dried) and two different material density from the same oil palm trunk are used. This was taken from two different location which two distance from the centre of trunk as shown in Figure 3.1. The result can be summarized as follow:

a. In laser cutting of fresh sample of oil palm wood, focal point position was found to be the biggest which influence the upper kerf width value. The second parameter is the laser power, followed by cutting speed. The least significant parameter is pressure of inert gas.

b. In laser cutting of dried sample of oil palm wood, laser power was found to the biggest which influence on upper kerf width value. The second parameter is the cutting speed, followed by focal point position. The least significant parameter is pressure of inert gas.

c. In laser cutting of fresh sample of oil palm wood, the upper kerf width increases when laser power increases. However, there is tendency of kerf width to increase from either ends towards cutting speed of 600 mm/min. Meanwhile, a much better kerf width is reported at high cutting speed of 1000 mm/min than that at lower cutting speed of 200 mm/min.

d. In laser cutting of dried sample of oil palm wood, the upper kerf width increases when laser power increases. However, the upper kerf width will decrease when the cutting speed increases. However if the cutting speed is too high, the through cut of the workpiece cannot achieved. For focal point position, the best cutting condition that give smaller value of upper kerf width is when the focal point position is at the top of the surface of the workpiece.

e. Material density of oil palm wood also affect the value of upper kerf width (53.45%). Samples at different location inside the trunk will give different material density because the number of fiber of vascular bundles varies from the center of the trunk towards the bark . Higher material density of oil palm wood will give smaller upper kerf width value than that of lower material density of oil palm wood

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f. Moisture content is one of the major factor affecting laser cutting of oil palm wood (91.44%). Upper kerf width value is decreases when the fresh samples is cut using CO_2 laser than using dried samples of oil palm wood. This is due the fact that water is highly absorptive to CO_2 laser radiation and this reduces the cutting efficiency.

g. The prediction of optimization results show that L9 (nine experiments) is not sufficient for predicting kerf width within the engineering acceptable error. Some of the errors in Taguchi ANN model simulations are still above

10% for some of the cutting conditions even when the best training algorithm of Levenberg Marquardt was used.

h. The results obtained from the hybrid model have confirmed that the GA-Taguchi ANN model can provide more precise prediction results and less experimental data than those for Taguchi ANN model and Taguchi ANN + 3 Data.

5.2 Recommendation

Since, there is neither time nor funding and facility to explore various investigations within the time frame; we recommend some future work as follow:

a. Further study may be required to determined the relationship between 2 sample dissimilar moisture content and material density in CO_2 laser cutting of oil palm wood as shown in Figure 5.1. This study is needed because both sample V and sample W have different moisture content and different material density.

b. It is suggested that for future analysis, Adaptive Fuzzy Logic shall be used since it was reported that it provides much improvement of optimization compared to ANOVA (Acilar & Arslan, 2011; Hassan, El-Sharief, Aboul-Kasem, Ramesh, & Purbolaksono, 2012; E. Zhou & Khotanzad, 2007).

Fresh Sample

Dried Sample

Analysis Of Material Density and Moisture Content

Sample W

Sample V

Sample Y

Sample X
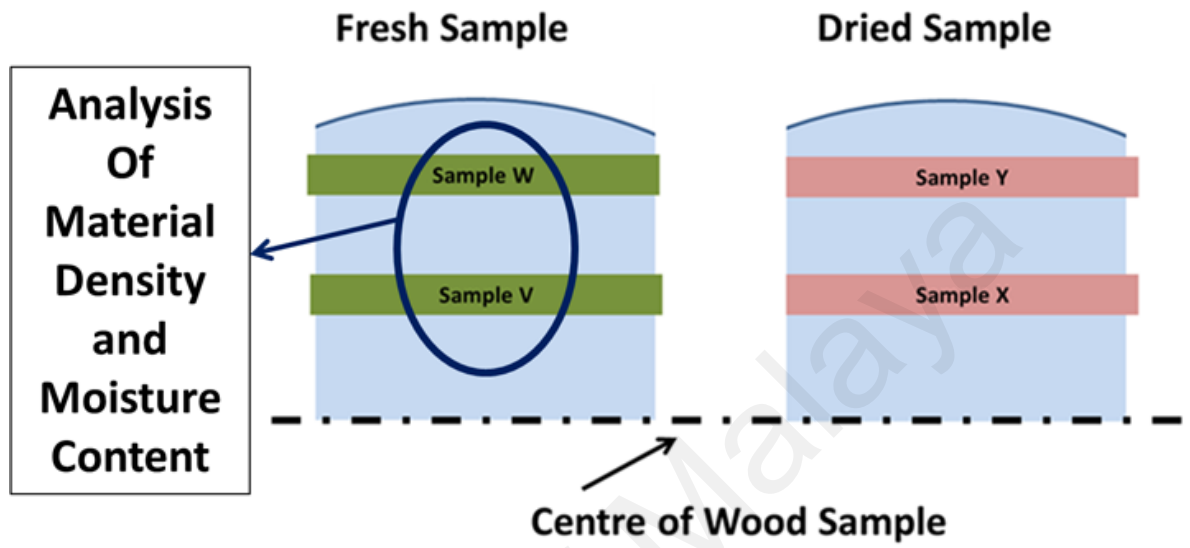
Centre of Wood Sample

Figure 5.1: Sample V and Sample W for analysis of dissimilar material Density and Moisture Content

BIBLIOGRAPHY

Acilar, A. M., & Arslan, A. (2011). Optimization of multiple input–output fuzzy membership functions using clonal selection algorithm. *Expert Systems with Applications, 38*(3), 1374-1381.

Agapie, A., Florin Fagarasan, & Stanciulescu, B. (1997). A Genetic Algorithm for a fitting problem. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 389*(1-2), 288–292.

Anand, T. J. S. (2010). DOE Based Statistical Approaches in Modeling of Laser Processing -- Review & Suggestion. *International Journal of Engineering & Technology, 10*(4), 1-8.

Anderson, B., & Donaldson, S. (1995). The Backpropagation Algorithm:Implications for the Biological Bases of Individual Differences in Intelligence. *Intelligence, 21*, 327-345.

Bachtiyar, C., Gultom, G., & Ginting, M. (2009). Optimization of Heating Characteristic and Energy Consumption at Bearing Heater U Model 220 Volt using Induction Electromagnetic Principle based on Taguchi Method.

Balfas, J. (2006). New Approach To Oil Palm Wood Utilization For WoodWorking Production Part 1: Basic Properties. *Journal of Forestry Research, 3*(1), 55-65.

Bamforth, P., Williams, K., & Jackson, M. R. (2006). Edge quality optimisation for CO2 laser cutting of nylon textiles. *Applied Thermal Engineering, 26*(4), 403-412.

Barnekorv, V. G., W.McMilin, C., & Huber, H. A. (1986). Factors Influencing Laser Cutting of Wood. *Forest Product Journal, 36*(1), 55-58.

Benyounis KY, O. A., Hashmi MSJ. (2008). Multi-response optimization of CO2 laser-welding process of austenitic stainless steel *Optics & Laser Technology, 40*(1), 76–87.

Caiazzo, F., Curcio, F., Daurelio, G., & Minutolo, F. M. C. (2005). Laser Cutting of Different Polymeric Plastics (PE, PP and PC) by A CO2 Laser Beam. *Journals of Materials Processing Technnology, 159*, 279-285.

Carlos Hernández-Castañeda, J., Kursad Sezer, H., & Li, L. (2011). The effect of moisture content in fibre laser cutting of pine wood. *Optics and Lasers in Engineering, 49*(9-10), 1139-1152.

Castaneda JCH, S. H., Li L. (2009). Statistical analysis of ytterbium-doped fiber laser cutting of dry pine wood. *Journal of Engineering Manufacture*, 775–789.

Choo, A. C. Y., Md. Tahir, P., Karimi, A., Bakar, E. S., Abdan, K., Ibrahim, A., et al. (2010). Density and humidity gradients in veneers of oil palm stems. *European Journal of Wood and Wood Products, 69*(3), 501-503.

Choudhury, I., & Shirley, S. (2010). Laser cutting of polymeric materials : An experimental investigation. *Optics & Laser Technology*, 503 - 508.

Choudhury, I. A., Chong, W. C., & Vahid, G. (2012). Hole qualities in laser trepanning of polymeric materials. *Optics and Lasers in Engineering, 50*(9), 1297-1305.

Datta, S., Bandyopadhyay, A., & Pal, P. K. (2006). Solving multi-criteria optimization problem in submerged arc welding consuming a mixture of fresh flux and fused slag. *The International Journal of Advanced Manufacturing Technology, 35*(9-10), 935-942.

Davim, J. P., Barricas, N., Conceic, M., & Oliveira, C. (2008). Some experimental studies on CO2 laser cutting quality of polymeric materials. *Journal of Materials Processing Technology*, 99 - 104.

Dubey, A. K., & Yadava, V. (2008a). Laser beam machining—A review. *International Journal of Machine Tools and Manufacture, 48*(6), 609-628.

Dubey, A. K., & Yadava, V. (2008b). Optimization of Kerf Quality During Pulsed Laser Cutting of Aluminium Alloy Sheet. *Journal of Materials Processing Technology, 204*, 412-418.

Eltawahni, H. A., Olabi, A. G., & Benyounis, K. Y. (2010). Effect of process parameters and optimization of CO2 laser cutting of ultra high-performance polyethylene. *Materials and Design, 31*, 4029–4038.

Eltawahni, H. A., Olabi, A. G., & K.Y. Benyounis. (2011). Investigating the CO2 laser cutting parameters of MDF wood composite material. *Optics & Laser Technology, 43*(3), 648-659.

Feng, L. Y., Tahir, P. M., & Hoong, Y. B. (2011). Density Distribution of Oil Palm Stem Veneer and Its Influence on Plywood Mechanical Properties. *Journal of Applied Sciences, 11*, 824-831.

Georgilakisa, P., Hatziargyrioub, N., Paparigasa, D., & Elefsiniotisa, S. (2001). Effective use of magnetic materials in transformer manufacturing. *Journal of Materials Processing Technology, 108* 209-212.

Ghany, K. A., & Newishy, M. (2005). Cutting of 1.2mm thick austenitic stainless steel sheet using pulsed and CW Nd:YAG laser. *Journal of Materials Processing Technology, 168*, 438–447.

Gopalsamy, B. M., Mondal, B., & Goal, S. (2009). taguchi method and ANOVA: An appoach of process optimization of hard machining while machining hardened steel. *Journal of Scientific & Industrial Research 68*, 686-695.

Guo-qiang, H., Dong-jie, X., & Ren-mu, H. (2004). *Genetic algorithm based design of power system stabilizers*. Paper presented at the 2004 EEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies.

Hasan, K. (2005). *Optimization of Product Quality by Fibre Calssification*: MPOB.

Hassan, M. A., El-Sharief, M. A., Aboul-Kasem, A., Ramesh, S., & Purbolaksono, J. (2012). A fuzzy model for evaluation and prediction of slurry erosion of 5127 steels. *Materials & Design, 39*, 186-191.

Oil Palm Plywood, (2003).

ISO 3130:1975. (1975). *Wood-Determination of Moisture Content for Physical and Mechanical Tests*.

ISO 3131:1975 (1975). *Wood-Determination of density for physical and mechanical tests*.

Jackson, M., Preston, M., & Tao, L. (1995). High speed cutting of patterned shapes from fabrics. *Mechatronics, 5*(2-3), 197-213.

K.M. Bhat, P. B. P., P.Rugmini. (2001). Characterization of Juvenile Wood in Teak. *Wood Science and Technology*, 517-532.

Kaebernick, H., Bicleanu, D., & Brandt, M. (1999). Theoretical and Experimental Investigation of Pulsed Laser Cutting. *Annals of the CIRP, 48*(1), 163-166.

Kaiser, M. (2007). Brain Architecture Design for Natural Computation. *Phil. Trans. R. Soc. A, 365*, 3033–3045.

Kamaruddin, H., Mohamad, H., Jalani, S., & Ariffin, D. (1997). *An estimated availability of oil palm biomass in Malaysia*. Paper presented at the PORIM Occasional.

Kamarulzaman Nordin, M. A. J., Mansur Ahmad, Hashim W. Samsi, Abdul Hamid Salleh, Zaihan Jalaludin. (2004). Minimizing the Environmental Burden of Oil Palm Trunk Residues Through the Development of Laminated Veneer Lumber Product. *Management of Environmental Quality: An International Journal, 15*(5), 484-490.

Karatas, C., Keles, O., Uslan, I., & Usta, Y. (2006). Laser cutting of steel sheets: Influence of workpiece thickness and beam waist position on kerf size and stria formation. *Journal of Materials Processing Technology, 172*(1), 22-29.

Kilmann, W., & Lim, S. C. (1985). *Anatomy and properties of oil palm stem.* Paper presented at the National Symposium on Oil Palm by-Products forAgro Based Industries, Kuala Lumpur.

Kizilkan.O. (2011). Thermodynamic analysis of variable speed refrigeration system using artificial neural networks. *Expert Systems with Applications 38*, 11686–11692.

Kuo, R. (1998). Intelligent Tool Wear System Through Artificial Neural Networks And Fuzzy Modeling. *Journal of Artificial Intelligence in Engineering, 5*, 229-242.

Kurt, M., Bagci, E., & Kaynak, Y. (2008). Application of Taguchi methods in the optimization of cutting parameters for surface finish and hole diameter accuracy in dry drilling processes. *The International Journal of Advanced Manufacturing Technology, 40*(5-6), 458-469.

Lan, H., Wang, W., Shangguan, Y., & Lin, S. (2011). *Fundamental Studies on High Power Fiber Laser Cutting Performance of 30 mm Thick Carbon Steel Plate*. Paper presented at the Strategic Technology (IFOST), 2011 6th International Forum on.

Li, L., & J.Mazumder. (1991). A study of mechanism of laser cutting of wood. *Forest Product journal, 41*(10), 53-59.

Li, Y., Y.B.Kim, Wang, L. S., M.J.Kim, M.S.Song, J.H.Yang, et al. (2000). Taguchi Parameter Design for the Fabrication Process of Anisotropic NdFeB Magnet by Single Stroke Hot Deformation. *Journal of Magnetics, 5*(3), 106-109.

Li, Z. L., Zheng, H. Y., Lim, G. C., Chua, P. L., & Li, L. (2010). Study On UV Laser Machining Quality Of Carbon Fibre Reinforced Composites.

Luger, G. F., & Stubblefield, W. A. (1998). *Artificial Intelligence (Structures and Strategies for Complex Problem Solving)* (Vol. Third ed). USA: Addion Wesley Longman.

Lum, K. C. P., Ng, S. L., & Black, I. (2000). CO2 Laser Cutting of MDF (medium-density fibreboard) – Determination of Process Parameter Setting. *Optics & Laser Technology, 32*, 67-76.

M.Z.Harizam, Y.Nukman, M.Anis, & K.F.Tamrin. (2012). *Investigation of Surface Roughness in Machining Oil Palm Wood.* Paper presented at the MPOB International oil palm Biomass Conference 2012, Istana Hotel, Kuala Lumpur.

Mahapatra, S. S., & Patnaik, A. (2006). Optimization of wire electrical discharge machining (WEDM) process parameters using Taguchi method. *The International Journal of Advanced Manufacturing Technology, 34*(9-10), 911-925.

Mathew, J., Goswami, G. L., Ramakrishnan, N., & Naik, N. K. (1999). Parametric Studies On Pulsed Nd:YAG Laser Cutting Of Carbon Fiber Reinforced Plastic Composites.

Montgomery, D. C. (2001). *Design and Analysis of Experiments*: Wiley.

Nader, N., Legacy, S., & L, C. S. (1999). preliminary investigations of ultrafast intense laser wood processing. *Forest Product Journal, 49*(6), 72-76.

Nukman, Y., Hassan, M. A., & Harizam, M. Z. (2013). Optimization of Prediction Error in CO2 Laser Cutting process by Taguchi Artificial Neural Network Hybrid with Genetic algorithm. *Applied Mathematics & Information Sciences, 7*(1), 363-370.

Öktem, H., Erzurumlu, T., & Çöl, M. (2005). A study of the Taguchi optimization method for surface roughness in finish milling of mold surfaces. *The International Journal of Advanced Manufacturing Technology, 28*(7-8), 694-700.

Panneerselvam, K., S.Aravindan, & Haq, A. N. (2009). Hybrid of ANN with genetic algorithm for optimization of frictional vibration joining process of plastics. *Int J Adv Manuf Technol, 42*, 669-677.

Powell, J. (1998). *CO2 laser cutting*: Springer Verlag.

Quintero, F., Riveiro, A., Lusquiños, F., Comesaña, R., & Pou, J. (2011). CO2 laser cutting of phenolic resin boards. *Journal of Materials Processing Technology, 211*(11), 1710-1718.

Ramle, S. F. M., Sulaiman, O., Hashim, R., Arai, T., Kosugi, A., Abe, H., et al. (2012). Characterization Of Parenchyma And Vascular Bundle Of Oil Palm Trunk As Function Of Storage Time. *Lignocellulose, 1*(1), 33-44.

Salem, H. G., Mansour, M. S., Badr, Y., & Abbas, W. A. (2008). CW Nd:YAG Laser Cutting of Ultra Low Carbon Steel Thin Sheets Using O2 Assist Gas. *Journal of Materials Processing Technology, 196*, 64-72.

Santhakumar, M., Asokan, T., & Sreeram, T. R. (2009). Analysis of Parameter Sensitivity Using Robust Design Techniques for a Flatfish Type Autonomous Underwater Vehicle. *International Journal of Quality, Statistics, and Reliability, 2009*, 1-10.

Sayuti, M., Sarhan, A. A. D., Fadzil, M., & Hamdi, M. (2011). Enhancement and verification of a machined surface quality for glass milling operation using CBN grinding tool—Taguchi approach. *The International Journal of Advanced Manufacturing Technology, 60*(9-12), 939-950.

Senthilkumar, Vaidyanathan, & Sivaraman. (2010). Thermal Analysis Of Heat Pipe Using Taguchi Method. *International Journal of Engineering Science and Technology, 2*(4), 564-569.

Shihani, N., Kumbhar, B. K., & Kulshreshtha, M. (2006). Modeling Of Extrusion Process Using Response Surface Methodology And Artificial Neural Networks. *Journal of Engineering Science and Technology, 1*, 31-40.

Shukla, A., Tiwari, R., & Kala, R. (2010). Artificial Neural Networks I *Real Life Applications of Soft Computing* (Vol. 1, pp. 41-73): CRC Press.

Sivarao, Brevern, P., El-Tayeb, N. S. M., & Vengkatesh, V. C. (2007). *Neural network multi layer perceptron modeling of surface quality in laser machining*. Paper presented at the Intelligent and Advanced Systems, 2007. ICIAS 2007.

Sulaiman, O., Awalludin, M. F., Hashim, R., & Mondal, M. I. H. (2012). The Effect Of Relative Humidity On The Physical And Mechanical Properties Of Oil Palm Trunk And Rubberwood. *Cellulose Chemistry And Technology, 46*(5-6), 401-407.

Sulaiman, O., Salim, N., Nordin, N. A., Hashim, R., Ibrahim, M., & Sato, M. (2012). The potential of Oil Palm Trunk Biomass as an alternative source for compressed wood. *BioResources, 7*(2), 2688-2706.

Tarng, Y. S., & Yang, W. H. (1998). Application of the Taguchi Method to the Optimization of the Submerged Arc Welding Process. *Materials and Manufacturing Processes, 13*(3), 455-467.

Tayal, M., Barnekov, V., & Mukherjee, K. (1994). Focal point location in laser machining of thick hard wood. *Journal of Materials Science Letters, 13*(9), 644-646.

Thanate Ratanawillai, T. C., Sittipon Kirdkong. (2006). An Investigation on the Mechanical Properties of Trunks of Palm Oil Trees for the Furniture Industry. *Journal of Oil Palm Research*, 114-121.

Trtik, P., Dual, J., Keunecke, D., Mannes, D., Niemz, P., Stahli, P., et al. (2007). 3D imaging of microstructure of spruce wood. *Journal of Structural Biology, 159*(1), 46-55.

Tsai, M.-J., Li, C.-H., & Chena, C.-C. (2008). Optimal Laser-Cutting Parameters For QFN Packages By Utilizing Artificial Neural Networks And Genetic Algorithm. *Journal Of Materials Processing Technology, 208*, 270–283.

Tsao, C. C., & Hocheng, H. (2004). Taguchi analysis of delamination associated with various drill bits in drilling of composite material. *International Journal of Machine Tools and Manufacture, 44*(10), 1085-1090.

Y. S. Tarng, & Yang, W. H. (1998). Optimisation of the weld bead geometry in gas tungsten arc welding by the Taguchi method. *The International Journal of Advanced Manufacturing Technology, 14*(8), 549-554.

Yang, C.-B., Deng, C.-S., & Chiang, H.-L. (2011). Combining the Taguchi method with artificial neural network to construct a prediction model of a CO2 laser cutting experiment. *Int J Adv Manuf Technol*

Yilbas, B. S. (1996). Experiment Investigation Into CO2 Laser Cutting Parameters. *Journal of Material Processing Technology, 58*, 323-330.

Yilbas, B. S., & A, S. S. (2011). Laser Cutting of Alloy Steel: Three-Dimensional Modeling of Temperature and Stress Fields. *Materials and Manufacturing Processes, 26*(1), 104 - 112

Yung, K. C., Mei, S. M., & Yue, T. M. (2001). A Study Of The Heat-Affected Zone In The UV YAG Laser Drilling Of GFRP Materials.

Yusoff, N., Ismail, S. R., Mamat, A., & Ahmad-Yazid, A. (2008). Selected Malaysian Wood CO2-Laser Cutting Parameters And Cut Quality. *American Journal of Applied Sciences, 5*(8), 990-996.

ZC, L., & CB, Y. (2010). Combining the Taguchi method with an artificial neural network to construct a prediction model of near field photolithography experiments. *Proc IME C J Mech Eng Sci, 224*(10), 2223–2233.

Zhou, B. H., & S.M.Mahdavian. (2004). Experimental and Theoretical Analyses of Cutting Nonmetallic Materials by Low Power CO2 Laser. *Journal of Material Processing Technology, 146*(2), 188-192.

Zhou, E., & Khotanzad, A. (2007). Fuzzy classifier design using genetic algorithms. *Pattern Recognition, 40*(12), 3401-3414.

APPENDIX

Appendix A: List of Publications

Nukman, Y., Hassan, M. A., & Harizam, M. Z. (2013). Optimization of Prediction Error in CO2 Laser Cutting process by Taguchi Artificial Neural Network Hybrid with Genetic algorithm. *Applied Mathematics & Information Sciences, 7*(1), 363-370.

Harizam, M. Z, Nukman, Y., Hassan, M. A., & Tamrin, K. F. The effect of Material Density in CO_2 Laser Cutting of oil palm wood.
[Ready to submit in *Journal of Advance Material Research*]

Harizam, M. Z, Nukman, Y., Anis, M., & Tamrin, K. F. Comparison of surface roughness in machining of oil palm wood.
[Ready to submit in *Journal of Oil Palm Research*]

Appendix B: List of Conferences

M.Z.Harizam, Y.Nukman, K.F.Tamrin. (2012). *Investigation of CO_2 Laser Cutting of Oil Palm Wood.* Paper presented at the 2012 Asia-Oceania Top University League in Engineering Conference, University of Malaya, Kuala Lumpur.

M.Z.Harizam, Y.Nukman, M.Anis, & K.F.Tamrin. (2012). *Investigation of Surface Roughness in Machining Oil Palm Wood.* Paper presented at the MPOB International oil palm Biomass Conference 2012, Istana Hotel, Kuala Lumpur.

M.Z.Harizam, Y.Nukman, & H.Khairuddin. (2011). *A study of the effect between the standoff distance and laser power by using laser power meter* Paper presented at the 2011 United Kigdom-Malaysia-Ireland conference, University of Malaya, Kuala Lumpur.