

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

STATISTICAL APPROACH IN RESPONSE PREDICTION

This report submitted in accordance with requirement of the Universiti Teknikal Malaysia Melaka (UTeM) for the Bachelor Degree of Manufacturing Engineering (Manufacturing Process) with Honours.

By

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This report is submitted to the Faculty of Manufacturing Engineering of UTeM as a partial fulfillment of the requirements for a degree of Bachelor of Manufacturing Engineering (Manufacturing Process) with Honours. The member of the supervisory committee is as follow:

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ABSTRACT

Statistics is a branch of mathematics used extensively in natural science and also in the engineering field as well as in social science, physics and computing. The title of this study is "Statistical Approach in Response Prediction". The machining process selected for this study is the laser cutting process. In this study, an empirical model is developed through design of experiment and the effect of selected parameters i.e. cutting speed, frequency and duty cycle on the responses i.e. surface roughness and kerf width are investigated. This work shows that for the surface roughness, cutting speed and duty cycle is of a major concern whilst the frequency has no visible effect. The duty cycle and frequency are directly proportional in their effect on kerft width while high cutting speed value is always preferred for a good kerf width. The model developed shows good error upon validation suggesting a good predictability.

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ABSTRAK

Statistik adalah salah satu daripada cawangan matematik yang digunakan secara meluas di bidang sains tulen. Selain itu, statistik juga digunakan secara mendalam dalam bidang kejuruteraan, sains social, fizik dan juga komputeran. Tajuk kajian ini ialah "Statistic Approach in Response Prediction". Proses memesinan yang dipilih untuk dikaji ialah proses laser. Dalam projek ini, satu model matematik telah dijana melalui "Design of Experiment" dan cara ini juga telah digunakan untuk mengunkai kaitan di antara parameter eskperimen (halaju potong, frequensi dan "duty cycle") dengan response (kekasaran permukaan dan "kerf width"). Ujikaji ini menunjukkan bahawa halaju potong dan "duty cycle" amat penting untuk mendapatkan kekasaran permukaan yang baik manakala frequensi tidak memnujukkan pengaruh yang berkesan. Untuk "kerf width" pula halaju potong adalah tetap di mana halaju yang tinggi selalu member kesan yang baik manakala "duty cycle" dan frequensi saling berkait bagi mendapatkan nilai "kerf width" yang bagus. Modal matematik yang telah dianalisa juga memberi ralat yang bagus mencadangkan bahawa modal ini boleh digunakan untuk meneliti "response" bagi suatu proses memesinan laser.

DEDICATION

To my mum and dad. You are my everything.

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LIST OF ABBREVATIONS, SYMBOLS AND NOMENCLATURES

LBM	-	Laser Beam Machining	
EDM	-	Electric Discharge Machining	
WEDM	-	Wire Electric Discharge Machining	
RSM	-	Response Surface Methodology	
CCD	-	Central Composite Design	
ANN	-	Artificial Neural Network	
MRSN	-	Multi-Response Signal-to-Noise	
CPNN	-	Counter Propagation Neural Network model	
FEA	-	Finite Element Analysis	
RBFN	-	Radian Basis Function Network	
SAO	-	Sequential Approximation Optimization	
ANOVA	-	Analysis Of Variance	
MRR	-	Material Removal Rate	
QFN	-	Quad Flat No – lead	
HAZ	-	Heat Affected Zone	
PP	-	Polypropylene	
PC	-	Polycarbonate	
PMMA	-	Polymethyl Methacrylate	
CD	-	Compact Disk	
CO_2	-	Carbon Dioxide	
Nd:YAG	-	Neodymium-doped Yttrium Aluminium Garnet	
Nd:Glass	-	Neodymium-doped Glass	
He	-	Helium	
Ne	-	Neon	
N_2	-	Nitrogen	
kg/cm ²	-	Kilogram per Centimeter squared	
ms	-	Milliseconds	
μs	-	Microseconds	
Hz	-	Hertz	

kHz	-	KiloHertz
mm/min	-	Millimeter per Minute
mm/rev	-	Millimeter per Revolution
mm	-	Millimeter
А	-	Ampere
Rpm	-	Rotations per Minutes
N/mm ²	-	Newton per millimeter squared
kW	-	Kilowatt
mJ	-	Mill Joule
J/mm ²	-	Joule per millimeter squared
mm/s	-	Millimeter per Second
J	-	Joule
%	-	Percentage
0	-	Degree
ε	-	Error

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- A Gantt Chart for PSM I
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CHAPTER 1 INTRODUCTION

1.1 PROJECT BACKGROUND

The quality of the manufacturing industry has become a critical criterion where a slightest error in manufacturing and processing can cause tremendous lost in terms of financial value of the industry or company or worse still, lost of customers" trust on the product all together. Once the customers do not trust the quality of a company"s products, it will be very hard to convince them other vice.

When it comes to product manufacturing and processing, the quality of the parts produced is directly related to the quality of the process outputs. In other words here, process outputs are also referred to as the process responses. The title of this research is "*Statistical Approach in Response Prediction*". As such, the primary focus of this study will be on predicting the responses of a process by statistical means. Statistical approach here refers to an empirical method of describing the relationship between the input factors (parameters) as to how far their influence ranges on the output (responses). It is a mathematical evaluation of signifying the relationship of the parameters to the responses.

Primarily, there are two concepts need to be understood; parameters and responses. Process parameters refers to the input factors of a machining process such as cutting speed, power and type of material. Responses refer to the quality of the machining process such as surface roughness, accuracy of cut and micro-hardness.

1.2 PROBLEM STATEMENT

Just as for other machining processes, laser beam machining also causes defects on the machined surface. These defects can either be a macro defect or micro defect. Defects such as rough surface cut, deviation in kerf width, HAZ and other can be avoided through research by correlating the effect of the parameters to the outcome of the cut.

In laser machining, various studies have been conducted in associating the responses to the parameters. Such studies were on average conducted with only one responses being studied by using mathematical modeling. However, the problem arises when one request the effect that the parameters have on two or more responses.

With the cost for machining being high and the stringent availability of time and technician services, trial and error method to obtain the best parametric settings for a good cut is unacceptable. Therefore, it is best if an empirical model is developed to investigate the relationship between the selected parameters and the responses.

1.3 OBJECTIVES

The objectives of this project are to:

- I. Develop an empirical model for kerf width and surface roughness by adjusting the design parameters.
- II. To be able to predict the output of the responses based on the parametric values.
- III. Validate the empirical model prediction with experimentation.

1.4 SCOPE

In a typical machining process, the input parameters are significant in determining the quality of the output and on the process performance. Among the output that will be affected by the setting of the input parameters are material removal rate, machined geometry, surface roughness, kerf conditions and mechanical properties. Here, laser machining is used as a primary machining process under investigation.

In this experimental study, mathematical modeling and prediction is done for process observation. The study focuses primarily on developing an empirical model and run validation for the predicted results. The relationship between the kerf width and surface roughness with the controlled parameters will also be analyzed.

1.5 THEORY

In a book by Arce R. G. (2005) part of statistical branch revolves around deriving information about the properties of random processes from sets of observed samples. A general objective for a statistical study is to investigate causality especially to correlate the effect of changes in the parametric values to the responses. As mentioned by Chatfield C. (1995), it is most helpful to construct a model which provides a mathematical representation of the given situation for most of the statistical based investigation. The model should provide an adequate description of the given data in order to enable prediction and other inferences to be made.

In other words, for statistical approach of response prediction, statistical analysis is used, where a model is developed and relates the parameters to the response in mathematical terms and thus giving us the advantages of predicting the possible output for a set of parametric values.

In general, the statistical approach can be divided into three categories:

- a) Statistical model
- b) Empirical model
- c) Mathematical model

1.5.1 STATISTICAL MODEL

Chatfield C. (1995) described that a statistical model normally contains one or more systematic components as well as a random (or stochastic) element. The random element is sometimes referred to as noise. This element arises for various reasons and it is sometimes helpful to differentiate between:

- a) Measurement error
- b) Natural random variability

The natural random variability occurs due to the difference between experimental units and from changes in experimental circumstances that cannot be controlled. As for the systematic components, it is sometimes refers to as signal. In the engineering point of view, statistical analysis can be regarded as extracting information about the signal in the presence of noise.

1.5.2 EMPIRICAL MODEL

An empirical model can also be referred to as a regression or ANOVA model. In Chatfield C. (1995) book, the mentioned this model aims to capture some sort of smooth average behavior in the long run. The advantage of this model (or in some cases seen as the disadvantage) is that it is not based on highly specific subjectmatter consideration.

In general, empirical model can be summarized as building a model then using experimentation data to test the model. Thompson J.R. (1989) stated that a scientist"s empirical model is simply his current best guest as the underlying mechanism at hand. In other, an empirical model is developed to understand the factors that contribute to a process and how they affect each other as well as the output.

An empirical model can be built to explain the existing situation by using the existing data related to it. The empirical model consists of a function that fits the data. A matter to note here is that empirical model cannot be used to explain the

system. It can only be used to predict and estimate behavior where data does not exist.

1.5.3 MATHEMATICAL MODEL

A mathematical model can be described as a theoretical model that uses mathematical language to explain the behavior of a system. Among the forms of a mathematical model are game theory model, differential equation and dynamic system. However, mathematical model are not just limited these alone.

Mathematical model is able to overlap with other models involving an array of abstract structure. In a mathematical model, there are six basic groups of variables:

- a) Decision variables
- b) Input variables
- c) State variables
- d) Exogenous variables
- e) Random variables
- f) Output variables

A mathematical model can be categorized into a black-box model and a white box model. A black-box model is a system where there is no prior information of the system is available. A system with prior information is called a white-box system.

(Retrieved from http://www.sciencedaily.com/articles/m/mathematical_model.htm at 9.30pm)

CHAPTER 2 LITERATURE REVIEW

This chapter primary revolves around the literature review done in order to assist the course of the experimental study. The literature review here generally discusses and summarizes previously done experiments that were published in renowned journals with regards to the title undertaken. Therefore, this chapter dwells in the findings, results and data gathered from previous experimentation in the field of laser machining and response surface methodology.

2.1 INTRODUCTION

The main theme of this research is to use statistical approach to predict and also optimize the responses in laser beam machining process. Before we blindly rush into the experiment, it outmost vital that we understand the concept of response surface methodology, RSM. According to R. H. Myers *et al* RSM refers to the utilization of statistical and mathematical technique for developing, improving and optimizing a process. It also includes in design, development and formulation of new products as well as improvement of existing products.

RSM is most advantages in a situation to analyze the relationship of several input parameters to the output responses. The output responses can also be categorized as process performances or quality characteristics of the process. The input parameters are sometimes referred to as independent variable where it is manipulated and controlled by the engineers either according to the process performance or the process setting. The most commonly used RSM techniques are central composite design (CCD), Box – Behnken and Taguchi method. MINITAB and Design Expert are the few examples of software where RSM modeling can be done.

Asides from the mentioned RSM methods above, there are also other techniques and methods that can be used for optimizing a machining process. Among these methods are ANN, MRSN, CPNN and FEA. Although they each differ in the techniques used, the finding from the experiments can be used to attain the optimum parametric value settings.

2.2 RESPONSE SURFACE METHODOLOGY

According to Avanish Kumar Dubey and Vinod Yadava (2007), the CCD technique the most commonly used experimental design technique in mathematical modeling for laser machining process optimization. In addition, they also stated that the most common research done in laser machining is experimental studies, modeling and optimization studies. In this case, the latter is used where statistical design experiment is used to show the relationship between input parameters and responses