# EFFECT OF DIMENSIONAL PARAMETERS ON WARPAGE OF INJECTION-MOLDED PLASTIC PART USING RESPONSE SURFACE METHODOLOGY

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# EFFECT OF DIMENSIONAL PARAMETERS ON WARPAGE OF INJECTION-MOLDED PLASTIC PART USING RESPONSE SURFACE METHODOLOGY

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Thesis submitted in fulfilment of the requirements
for the award of the degree of
Bachelor of Mechanical Engineering with Automotive Engineering

Faculty of Mechanical Engineering
UNIVERSITI MALAYSIA PAHANG

NOVEMBER 2009

## STUDENT’S DECLARATION

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

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## ACKNOWLEDGEMENTS

**In the name of Allah, the most Gracious and most Compassionate**

I would like to thank Allah Almighty for blessing and giving me strength to accomplish this thesis. A special thank to my supervisor, En Rosdi Daud who greatly helped me in every way I need to go through this study. I am very grateful to him for his patience constructive comments that enriched this research project. His time and efforts has been a great contribution during the preparation of this thesis that cannot be forgotten forever.

Many thank to all of the technicians in Mechanical Laboratory, Faculty of Mechanical Engineering, for their cooperation and assisting me in the various laboratory tasks. I would like to express my sincere appreciation to all of my friends and colleagues in Universiti Malaysia Pahang for coloring my daily live and helped me in one-way or another.

Deepest gratitude to my parents, who give me a real love, pray, support, and all they have. Finally, I am grateful to Universiti Malaysia Pahang for all of support during the period of this research work.

# ABSTRACT

This thesis discusses the effect of dimensional parameters on warpage of injection-molded plastic part using response surface method. The objectives of this thesis are to investigate the effect of dimensional parameter on warpage, to develop prediction first and second mathematical model for warpage of plastic part using response surface method. A thin plastic part model is used in the analysis. To achieve minimum warpage, optimum process condition dimensional parameters are determined. X dimension, Y dimension and Z dimension are used as variables. The most important input parameter in this experiment is Z dimension (wall thickness) which is affecting the warpage of the plastic part. The others input also must be considered. Use the different value of X dimension, Y dimension and Z dimension to determine different value of warpage. The design of experiment that use in this experiment is three level full factorial designs. Finite element analysis using MoldFlow is done to determine experimental value of warpage. Response surface methodology is used to predict the warpage value based on finite element result and suitable predictive model is selected based on percentage of error comparison then optimization process using response surface method is done and the optimum dimensional parameters with minimum warpage value is obtained.

# ABSTRAK

Tesis ini membincangkan kesan parameter dimensi pada warpage injeksi-bahagian plastik menggunakan kaedah permukaan respons. Objektif daripada tesis ini adalah untuk meneliti kesan daripada parameter pada warpage dimensi, untuk mengembangkan ramalan pertama dan kedua model matematik untuk warpage bahagian plastik menggunakan kaedah permukaan respons. Bahagian plastik tipis model yang digunakan dalam analisis. Untuk mencapai minimum warpage, kondisi muat yang optimum ditentukan parameter dimensi. Dimensi X, dimensi Y dan dimensi Z digunakan sebagai pembolehubah. Yang paling penting parameter masukan dalam percubaan ini adalah dimensi Z (ketebalan dinding) yang mempengaruhi warpage bahagian plastik. Masukan yang lain juga harus dipertimbangkan. Guna nilai yang berbeza dimensi X, Y dan Z dimensi dimensi untuk menentukan nilai yang berbeza warpage. Rancangan percubaan yang digunakan dalam percubaan ini adalah tiga peringkat rekabentuk faktorial lengkap. Analisis elemen hingga menggunakan MoldFlow dilakukan untuk menentukan nilai percubaan warpage. Permukaan respons metodologi yang digunakan untuk memprediksi nilai warpage berdasarkan keputusan elemen hingga dan model ramalan yang sesuai dipilih berdasarkan nisbah peratusan kesalahan maka proses pengoptimuman menggunakan kaedah respon permukaan dilakukan dan parameter dimensi yang optimum dengan nilai minimum yang diperolehi warpage.

**FACULTY OF MECHANICAL ENGINEERING**

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**REMARKS**

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF SYMBOLS

| | |
|---|---|
| $W$ | Warpage First RSM Model |
| $W''$ | Warpage Second RSM Model |
| $x$ | X dimension (mm) |
| $y$ | Y dimension (mm) |
| $z$ | Z dimension (mm) |
| $\beta$ | Model Parameter |

# LIST OF ABBREVIATIONS

| | |
|---|---|
| FE | Finite Element |
| RSM | Response Surface Method |
| MPI | MoldFlow Plastics Insight |
| CAD | Computer Aided Design |
| VS | Versus |
| ANN | Artificial Neural Network |
| GA | Genetic Algorithm |

# CHAPTER 1

# INTRODUCTION

## 1.1 BACKGROUND STUDY

Injection molding operation is the most cost-effective and agile processing technology for manufacturing when it comes to high demand for the components on a mass scale. The procedure of injection molding is described, such as plastication, injection, packing, cooling, ejection and process part/part quality control applications. When the interior of cavity has become stable, the product is ejected from the mold. Defects of the products, such as warpage, shrinkage, sink marks, and residual stress, are caused by many factors during the production process. These defects influence the quality and accuracy of the products. Dimensional stability is an important factor for the minimum warpage of name card holder part. Reducing warpage is one of the top priorities to improve the quality of injection-molded parts. During production of plastic parts, the quality problems arise from dimensional ratio of the parts designed. Designs of dimensional process parameters are investigated from several aspects in the literature. Several researches have been conducted on the warpage of name card holder parts. However, very few of them are devoted to the optimization of such parts. In this study, an efficient optimization method by coupling finite element analysis, response surface methodology and genetic algorithm is introduced to minimize warpage of name card holder parts. The developed optimization method is applied to a name card holder part model. During the optimization process, finite element (FE) analyses of the part model base are conducted for combination of process parameters organized based on statistical full factorial experimental design. X dimension, Y dimension, and Z dimension are considered as process conditions dimensional parameters influencing warpage. Other parameters of effecting minimum warpage are taken into consideration as constant, such as mold temperature, melt temperature, injection time, injection pressure, etc. A predictive model for warpage in terms of the critical process parameters is then created using response surface methodology. Response surface model is coupled with an effective genetic algorithm to find the optimum process parameter values. The following sections explain in detail the generation of predictive models for minimum warpage (Babur Ozcelik & Tuncay Erzurumlu).

## 1.2 OBJECTIVE

The objectives of the project are:

1. To develop prediction first and second mathematical model for warpage of thin shell plastic part using response surface method
2. To investigate the effect of dimensional parameter on warpage of thin shell plastic part
3. To investigate the optimum dimension for the thin shell plastic part with minimum warpage

## 1.3 PROBLEM STATEMENT

The plastic industry today is one of the most important industries in the manufacturing world. Many manufacturers are focusing in developing plastics parts for most of things in our daily life. For example, this news, Forte nanocomposite nears 2nd application By Frank Esposito GALVESTON, TEXAS --Posted October 4, 2004 Noble Polymers is gaining ground with its Forte-brand nanocomposites, aiming to have its second commercial application as well as an extrusion grade on the market by mid-2005. Forte, a polypropylene-based nanocomposite, is used in the interior trim console of a vehicle that will hit the road in June, Noble business unit leader Tim Patterson said at Flexpo 2004, held Sept. 15-17 in Galveston. Patterson declined to identify the vehicle, citing confidentiality agreements, but the console is noteworthy in that it is not being molded by Cascade Engineering Inc., the Grand Rapids, Mich.-based injection molded that owns Noble. The first commercial nano- composite use for Noble - which operates about 80 million pounds of compounding capacity and employs 23 in Grand Rapids - was a seat back molded by Cascade in September 2003. Cascade currently consumes about 95 percent of Noble's compounding output - mainly soft, flexible thermoplastic olefins - but Noble eventually hopes to sell more of its product to outside customers, Patterson said. The seat back commercialized last year had used 30 percent glass-filled PP, but had warpage issues, Cascade materials engineering director Taher Abujoudeh said. Forte eliminated warpage while offering better aesthetics and lower cost, he said. Other nanocomposite projects in the works for Noble include office furniture - where it can replace 20 percent glass-filled PP - as well as heavy-truck exterior trim and speaker housing parts. The nanocomposite business started out small for Noble, with modest sales of about 700,000 pounds in its just-completed fiscal year. But the firm already has new sales on the books equaling that amount, Patterson said. To date, Noble's nanocomposite work has centered on injection molding grades. Its first extrusion grade is set to debut in June, Abujoudeh said. Cascade placed 30th in a recent Plastics News ranking of North American injection molders, with annual sales of $200 million **(**http://www.plasticsnews.com/headlines2.html?id=04100401403&q=warpage 24/3/09 Tuesday).

## 1.4 PROBLEM SOLVING

From this study of effect of dimensional parameter on warpage, the problem encounter due to warpage of plastics part can be solved. Then the losses caused by rejected part due to warpage can be solved. The study of warpage optimization is one of the solutions to the problem faced by plastics industry.

## 1.5 PROJECT SCOPE

1. Using Finite Element (FE) (Moldflow) to get experimental warpage value
2. Using warpage value from MoldFlow to predict warpage using Respond Surface Method (RSM)
3. Compare result of FE analysis with predicted result from RSM (choose parameter with smallest predicted warpage value)

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 INTRODUCTION

Injection molding is one of the most important polymer processing methods for producing plastic parts. Process parameters in addition to molding material and part design are major factors affecting the quality of plastic parts produced by injection molding. Quality of these parts is often associated with warpage. Effects of process parameters on non-uniform shrinkage leading to warpage are investigated from several aspects in literature. In this study, the effect of dimensional parameter values for name card holder in minimizing warpage is investigated. Best values of process parameters in this study are obtained by exploiting advantages of finite element (FE) software MoldFlow, statistical design of experiments, integrated response surface method and genetic algorithm. FE analyses of the name card holder are conducted for dimensional parameters designed based on statistical full factorial experimental design. A predictive model for warpage is then created using integrated response surface method exploiting FE analysis results.

## 2.2 DIMENSIONAL INTEGRITY

The configuration (shape and dimensions) of a molded part is intimately related to the thermo-mechanical history of the material used during the process cycle, the cavity geometry, and the physical properties (compressibility and thermal expansion coefficient) of the material. The configuration of the molded part can be divided into two main contributions: (a) the “as-molded” configuration and (b) changes in configuration over time. The as-molded configuration is determined by the state of the material in the mold cavity at the instant just prior to mold opening, the abrupt changes in pressure and stress upon injection, and the subsequent unconstrained cooling of the solid part to ambient temperature after injection from the mold. The final configuration of as-molded part is controlled by several distinct, though strongly coupled, factors, including the pressure and temperature histories in the mold cavity, cooling (thermal) stress, warpage, and shrinkage. Warpage relates to the distortion induced by the inhomogeneous shrinkage and relaxation of residual stress in the part once outside the mold, while shrinkage simply expresses the overall dimensional change as the unconstrained part cool down to ambient temperature. (Jehuda Greener & Reinhold wimberger-Friedl)

## 2.3 INJECTION MOLDING HISTORY

The injection molding has seen steady growth since its beginnings in the late 1800's. The technique has evolved from the production of combs and buttons to major consumer, industrial, medical, and aerospace products. In 1868, perhaps in response to a request by billiard ball maker Phelan and Collander, John Wesley Hyatt invented a way to make billiard balls by injecting celluloid into a mould. By 1872, John and his brother Isaiah Hyatt patented the injection molding machine. The machine was primitive yet it was quite suitable for their purposes. It contained a basic plunger to inject the plastic into a mould through a heated cylinder. Revolutionizing the plastics industry in 1946, James Hendry built the first screw injection molding machine with an auger design to replace Hyatt's plunger. The auger is placed inside the cylinder and mixes the injection material before pushing forward and injecting the material into the mould. Now day, almost all injection molding machines use this same technique. ( http://www.plasticmoulding.ca/history.htm)

## 2.4 INJECTION MOLDING PROCESS PARAMETERS

Injection molding process have a few processing parameter. The processing parameter such as:

a) **Temperatures**

Typical temperature profiles are based on gradually increasing temperature during the compression phase with cooling at the nozzle.

b) **Injection**

A slow to moderate injection speed should be used if injection speed is too fast. The frictional heat can cause surface imperfections.

c) **Mold Temperature**

The recommend temperature for general molding for the mold is between 10°C to 40°C. However for certain grades and end applications a reduction below 10°C has been found to offer advantages with cycle time. When using temperatures below 10°C care must be taken to ensure cavities will consistently fill and no condensation appears on the mold face.

d) **Mold Cooling**

The purpose of mold cooling is to control the rate at which heat is removed from the molding. If there is no cooling on the mold then initially the mold will be cool and will heat up due to the heat transfer from the molded parts. This effect can result in varying shrinkage rates. Mold cooling is therefore recommended and the cooling channels should be evenly distributed in the mold. Unbalanced cooling will also have a detrimental effect on the quality and consistency of the product produced.

## 2.5 WARPAGE OF PLASTIC INJECTION MOLDING PART

Warpage is a distortion where the surfaces of the molded part do not follow the intended shape of the design. Part warpage results from molded-in residual stresses, which, in turn, is caused by differential shrinkage of material in the molded part. If the shrinkage throughout the part is uniform, the molding will not deform or warp, it simply becomes smaller. However, achieving low and uniform shrinkage is a complicated task due to the presence and interaction of many factors such as molecular and fiber orientations, mold cooling, part and mold designs, and process conditions.

**Influence of unfilled and filled materials**

For fiber reinforced thermoplastics, reinforcing fibers inhibit shrinkage due to their smaller thermal contraction and higher modulus. Therefore, fiber reinforced materials shrink less along the direction in which fibers align (typically the flow direction) compared to the shrinkage in the transverse direction. Similarly, particle-filled thermoplastics shrink less than unfilled grades, but exhibit a more isotropic nature. For non-reinforced materials warpage is generally influenced by wall thickness and mold temperature. If wall thickness and mold temperatures are not optimal the molding will most likely warp.

**Different of shrinkage between filled and unfilled materials.**

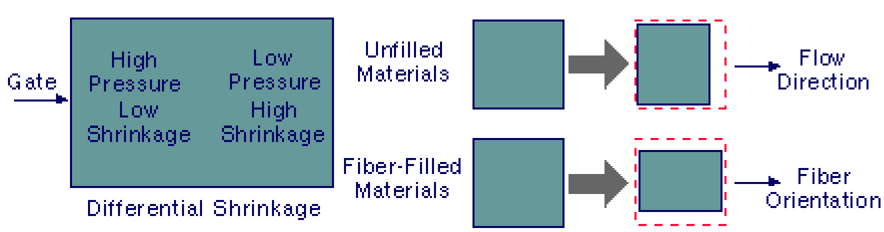


**Figure 2.1**: Shrinkage Differentials

Source: (http://www.dsm.com/en_US/html/dep/Warpage.htm 24/2/09 Tuesday)

For glass reinforced materials totally different characteristics are evident due to fiber orientation. If a non-reinforced and a fiber reinforced material are compared in the same design it is possible to see contary warpage in the same part.

**Unreinforced vs fiber reinforced materials.**

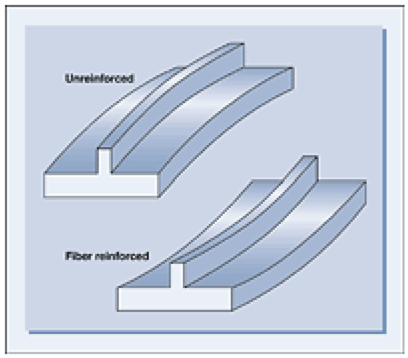


**Figure 2.2**: Unreinforced Vs Fiber Reinforced

Source: (http://www.dsm.com/en_US/html/dep/Warpage.htm 24/2/09 Tuesday)

**Influence of cooling**

Non-uniform cooling in the part and asymmetric cooling across the part thickness from the cavity and core can also induce differential shrinkage. The material cools and shrinks inconsistently from the wall to the center, causing warpage after ejection.

Part warpage due to:

(a) non-uniform cooling in the part

(b) asymmetric cooling across the part thickness

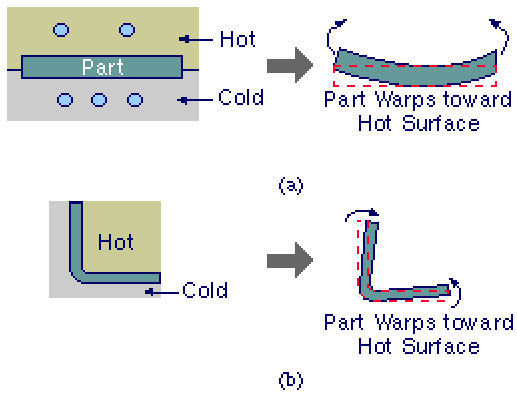


**Figure 2.3**: Cooling Influence

Source: (http://www.dsm.com/en_US/html/dep/Warpage.htm 24/2/09 Tuesday)

**Influence of wall thickness**

Shrinkage increases as the wall thickness increases. Differential shrinkage due to non-uniform wall thickness is a major cause of part warpage in unreinforced thermoplastics. More specifically, different cooling rates and crystallization levels generally arise within parts with wall sections of varying thickness. Larger volumetric shrinkage due to the high crystallization level in the slow cooling areas leads to differential shrinkage and thus part warpage.

**Diagram of high shrinkage/low cooling vs warped part.**

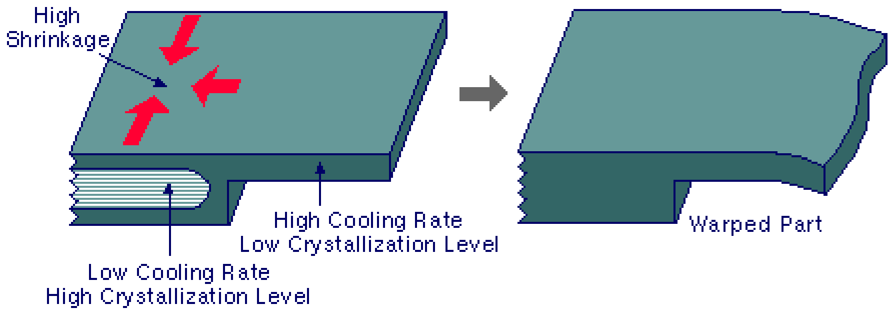


**Figure 2.4:** High Shrinkage/Low Cooling Vs Warped Part

Source: (http://www.dsm.com/en_US/html/dep/Warpage.htm 24/2/09 Tuesday)

**Influence of asymetric geometry**

Geometric asymmetry (e.g., a flat plate with a large number of ribs that are aligned in one direction or on one side of the part) will introduce non-uniform cooling and differential shrinkage that can lead to part warpage. The poor cooling of the wall on the ribbed side causes a slower cooling of the material on that one side, which can lead to part warpage.

**Poor design vs warped part.**

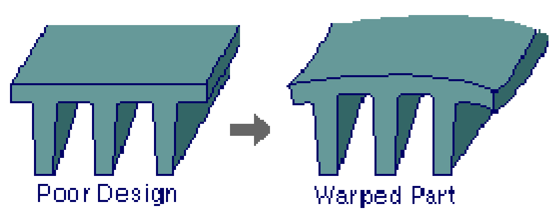


**Figure 2.5**: Poor Design Vs Warped Part

Source: (http://www.dsm.com/en_US/html/dep/Warpage.htm 24/2/09 Tuesday)

## 2.6 MOLDFLOW PLASTIC INSIGHTS

Moldflow Plastic Insight products are a complete suite of advanced plastics process simulation tools for predicting and eliminating potential manufacturing problems simulations tools for predicting and eliminating potential manufacturing problems and optimizing part design, mold design and the injection molding process. MPI products simulate the broadest range of manufacturing processes. With MPI, one can simulate the filling, packing and cooling stages of the thermoplastics injection molding process and also predict the resultant fiber orientations and take that into account when predicting part warpage. MPI users can also simulate other complex molding process such as gas assisted injection molding, co-injection molding, injection-compression molding, microcellular molding, reactive molding, and microchip encapsulation. MPI is being employed in both tooling design and simulation of molding. MPI used to simulate mold designs before the tool is actually built. The simulations helps user determine different gate designs and locations, placement of cooling lines, and melt overflows. The Moldflow Plastics Insight suite of software is the world leading product for the in-depth simulations to validate part and mold design. Companies around the world have chosen Moldflow's solution because they offer; Unique, Patented Fusion Technolgy. MPI/Fusion, which is based on Moldflow's patented Dual Domain™ Technology, allows you to analyze CAD solid models of thin-walled parts directly, resulting in a significant decrease in model preparation time. The time savings allow you to analyze more design iterations as well as perform more in depth analyzed.

## 2.7 RESPONSE SURFACE METHODOLOGY

The RSM is an empirical modeling approach for determining the relationship between various processing parameters and responses with the various desired criteria and searches for the significance of these process parameters in the coupled responses. It is a sequential experimentation strategy for building and optimizing the empirical model. Therefore, RSM is a collection of mathematical and statistical procedures, and is good for the modeling and analysis of problems in which the desired response is affected by several variables. The mathematical model of the desired response to several independent input variables is gained by using the experimental design and applying regression analysis.

The most extensive applications of RSM are in the particular situations where several input variables potentially influence some performance measure or quality characteristic of the process. Thus performance measure or quality characteristic is called the response. The input variables are sometimes called independent variables**,** and they are subject to the control of the scientist or engineer. The field of response surface methodology consists of the experimental strategy for exploring the space of the process or independent variables, empirical statistical modeling to develop an appropriate approximating relationship between the yield and the process variables, and optimization methods for finding the values of the process variables that produce desirable values of the response.

Computationally cost FE model is not suitable for large number of repetitive analyses which are often required in an optimization process. Therefore, in this study, the FE model for warpage is replaced by a simpler and more efficient predictive model created by response surface methodology (RSM). RSM is a model building technique based on statistical design of experiment and least square error fitting.

RSM is a collection of experimental strategies, mathematical methods, and statistical inference that enable an experimenter to make efficient empirical exploration of the system of interest. RSM can be defined as a statistical method that uses quantitative data from appropriate experiments to determine and simultaneously solve multi-variable equations. The work which initially generated interest in the package of techniques was a paper by Box and Wilson in year 1951. To solve such problems with conventional optimization, the RSM has been adopted. With RSM, optimization conditions are first set, and then a response surface is created between design variables and objective functions or constraint conditions (Amago. 19).

This method is now broadly used in many fields, such as chemistry, biology, and manufacturing. RSM can be used to determine the factor levels that will simultaneously satisfy a set of desired specifications and determine the optimum combination of factors that yields a desired response and describes the response near the optimum. Furthermore, it determines how a specific response is affected by changes in the level of the factors over the specified levels of interest it can achieve a quantitative understanding of the system behavior over the region tested. It could also predict product properties throughout the region even at factor combinations not actually run. In general, a second order regression model is developed because of first order models often give lack off fit (Montgomery, D.C. 1997).

In design optimization using RSM, the first task is to determine the optimization model, such as the identification of the interested system measure and the selection of the factors that influence the system measures significantly. To do this, understanding the physical meaning of the problem and some experience are both useful. After this, the important issues are the design of experiments and how to improve the fitting accuracy of the response surface models.RSM designs have the following properties such as predictions always have some degree of uncertainty but there is reasonable prediction throughout the experimental range, uniform prediction error is obtained by using a design the fills out the region of interest, the choice of experimental design is affected by the shape of the experimental region and in most cases, the region is determined by the ranges of the independent variable. Response surface methodology (RSM) is an optimization technique in the field of numerical analysis. For optimization, it uses a function called a response surface. A response surface is a function that approximates a problem with design variables and state quantities, using several analysis or experimental results. In general, design of experiments is used for analysis or experiment point parameter setting, and the least square method is used for function approximation. Response surface methodology is a combination of mathematical and statistical techniques useful for modeling and analyzing the problems in which several independent variables influence a dependent variable or response. The RSM technique attains convergence by repeating numerical and sensitivity analysis until the optimal solution as obtained. For problems with high non-linearity, and for multimodal problems, there may be cases in which no solution can be found because of problems such as inability to obtain sensitivities or a lapse into a local solution. The study uses the Box-Behnken design in the optimization of experiments using RSM to understand the effect of important parameters. Box-Behnken Design is normally used when performing non-sequential experiments. That is, performing the experiment only once. These designs allow efficient estimation of the first and second order coefficients. Because Box-Behnken design has fewer design points, they are less expensive to run than central composite designs with the same number of factors. Box-Behnken Design do not have axial points, thus we can be sure that all design points fall within the safe operating. Box-Behnken Design also ensures that all factors are never set at their high levels simultaneously (Draper, N.R. and H. Smith, 1981; Box, G.E.P. and N.R. Draper. 1987; Box, G.E.P. & Behnken, D.W. 1960).

RSM has been extensively used in the prediction of responses such tool life, surface roughness and cutting forces. The Box-Behnken design is based on the combination of the factorial with incomplete block designs. It does not require a large number of tests as it considers only three levels (-1, 0, 1) of each independent parameter (Hill, W.J. and Hunter, W.G. 1966). The application of experimental design and response surface methodology in fermentations process can result in improved product yields, reduced process variability and development time and overall costs (RAO, K. Jagannadha, KIM, Chul-Ho and RHEE, Sang-Ki. 2000). The Experimental design and response surface methodology were applied for the optimization of the nutrient concentration in the culture medium for the enzyme production in shaken flasks at 200 rpm and 30ºC. The statistical analysis of the results showed that, in the range studied, all the factors had a significant effect ($p < 0.05$) on glucosyltransferase production and the highest enzyme activity was observed in culture medium containing sugar cane molasses (160 g/L), bacteriological peptone (20 g/L) and yeast extract Prodex Lac SD® (15 g/L) (H. Y. Kawaguti, E. Manrich and H. H. Sato. 2006). Response surface methodology (RSM) to describe relationships between a combination of factors and an organism’s growth curve parameters (Devlieghere, F., Debevere, J. and Van Impe, J. 1998). In general application of the response surface methodology, the representative peak or average value is usually selected as a response to establish the relationship with the planned factors. For instance, a second-order polynomial equation was proposed to correlate the peak residual stress caused by the milling operation with the cutting conditions and the tensile strength of the material (M. M. EI-Khabeery and M. Fattouh. 1989). Response Surface Methodology used to predict the effects of cutting parameters on the variations of cutting forces during end milling operation of Al SiC metal matrix composite material by designing four factors, five level central composite rotatable design matrixes with full replication; for planning, conduction, execution and development of mathematical models (B. Ganesh babu, V. Selladurai and R. Shanmugam. 2008). RSM is a combination of mathematical and statistical techniques used in an empirical study of relationships and optimization, where several independent variables influence the process. The first and second order mathematical models, in terms of machining parameters, were developed for surface roughness prediction using RSM on the basis of experimental results.

# CHAPTER 3

# METHODOLOGY

## 3.1 INTRODUCTION

This chapter includes all overall process to determine the effect of dimensional parameter on warpage of name card holder plastic part. The first step is to determine other parameters that effecting warpage of plastic part.

Second step is to do simulation model of the name card holder part using CAD software. From the data obtain from the simulation; a RSM model will be created in order to improve the FE model due to inability of the model to do large number of repetitive analyses.

Then, from the RSM model, the warpage optimization will be done using the genetic algorithm method. From the result of genetic algorithm warpage optimization, the effect of dimensional parameter on warpage can be determined.

There are also example of table that can be used to analyze the data collected to determine the warpage optimization and then to determine the effect of dimensional parameter on warpage of plastic part.

## 3.2 PROJECT FLOW CHART

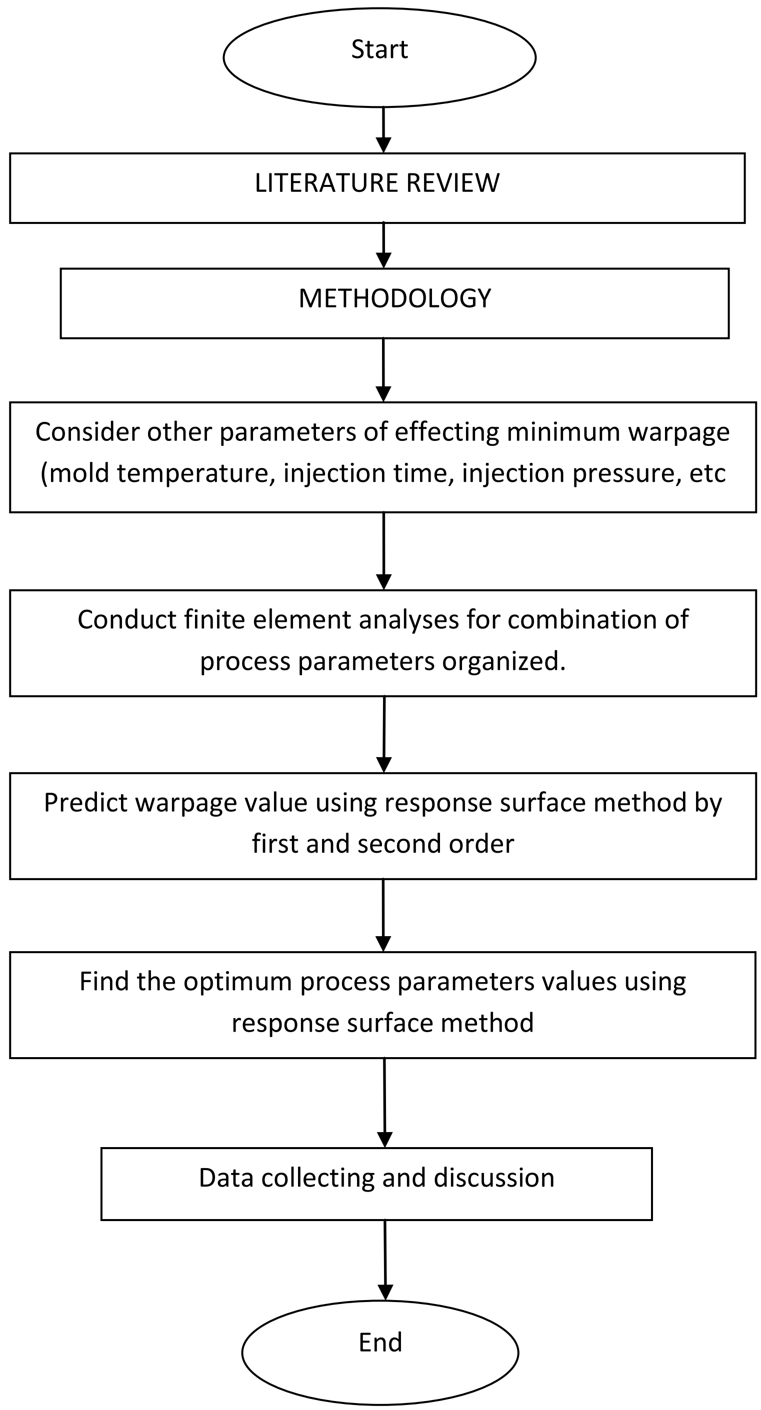


**Figure 3.1:** Project Flow Chart

## 3.3 DESIGN OF EXPERIMENT

Design of experiment (DOE) has been used to select process parameters that could result better quality of product. The DOE is an effective way to optimize various process parameters. Three independent variables consist of process parameters, each with three levels. For warpage were applied total of $3^3$ =27 experimental runs. In this study the three independent variables are X dimension, Y dimension, and Z dimension. These three variables had total of $3^3$=27 experiments. The model of plastics part is build using SOLIDWORKS software.

**Table 3.1**: Three Level Full Factorial Designs

| Factors | Level | | |
|---|---|---|---|
| | -1 | 0 | 1 |
| X dimension (mm) | 30 | 95 | 160 |
| Y dimension (mm) | 5 | 45 | 85 |
| Z dimension (mm) | 0.8 | 1.2 | 1.6 |

**Table 3.2**: Training Data Set According to Full Factorial Design

| Experiment number | X dimension (mm) | Y dimension (mm) | Z dimension (mm) |
|---|---|---|---|
| 1 | 95 | 5 | 0.8 |
| 2 | 30 | 5 | 1.6 |
| 3 | 160 | 45 | 0.8 |
| 4 | 30 | 85 | 0.8 |
| 5 | 95 | 45 | 1.6 |
| 6 | 160 | 85 | 1.6 |
| 7 | 160 | 5 | 1.2 |
| 8 | 95 | 85 | 1.6 |
| 9 | 160 | 85 | 0.8 |
| 10 | 30 | 5 | 0.8 |
| 11 | 160 | 45 | 1.6 |
| 12 | 30 | 85 | 1.6 |
| 13 | 30 | 5 | 1.2 |
| 14 | 95 | 5 | 1.6 |
| 15 | 30 | 85 | 1.2 |
| 16 | 160 | 85 | 1.2 |
| 17 | 95 | 5 | 1.2 |
| 18 | 160 | 5 | 0.8 |
| 19 | 30 | 45 | 1.2 |
| 20 | 30 | 45 | 1.6 |
| 21 | 95 | 45 | 1.2 |
| 22 | 95 | 85 | 0.8 |
| 23 | 95 | 45 | 0.8 |
| 24 | 30 | 45 | 0.8 |
| 25 | 160 | 5 | 1.6 |
| 26 | 160 | 45 | 1.2 |
| 27 | 95 | 85 | 1.2 |

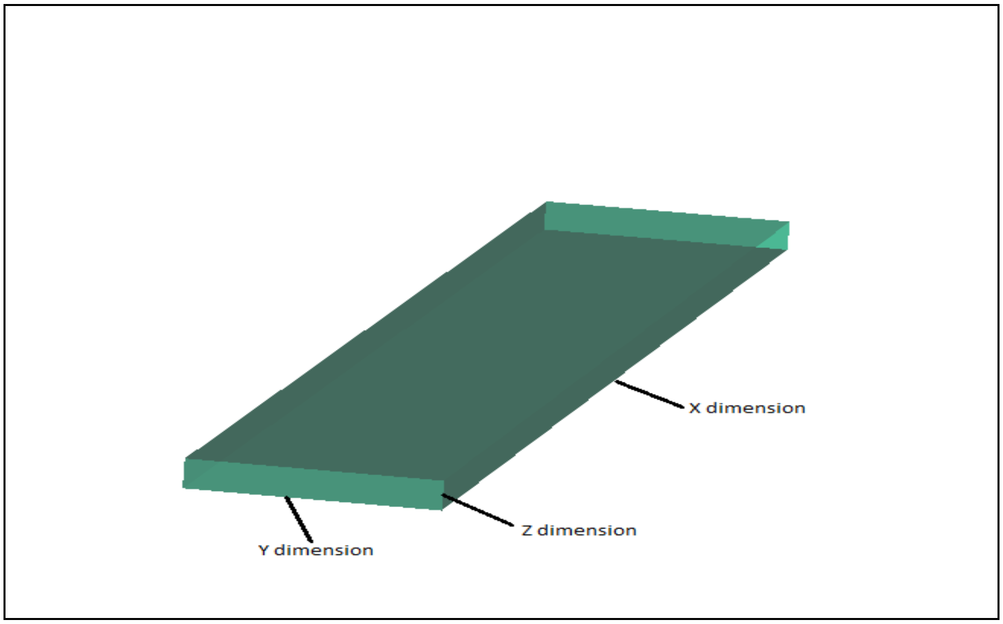


**Figure 3.2**: SOLIDWORKS model

## 3.4 FINITE ELEMENT ANALYSIS

The simulation model of the name card holder part was designed using CAD software. To develop a simulation model, the geometry of the name card holder part is executed using fusion mesh with MoldFlow. It is created by MoldFlow Plastic Insight 5.0 which is commercial software based on hybrid finite-element/finite-difference method for solving pressure, flow and temperature fields.

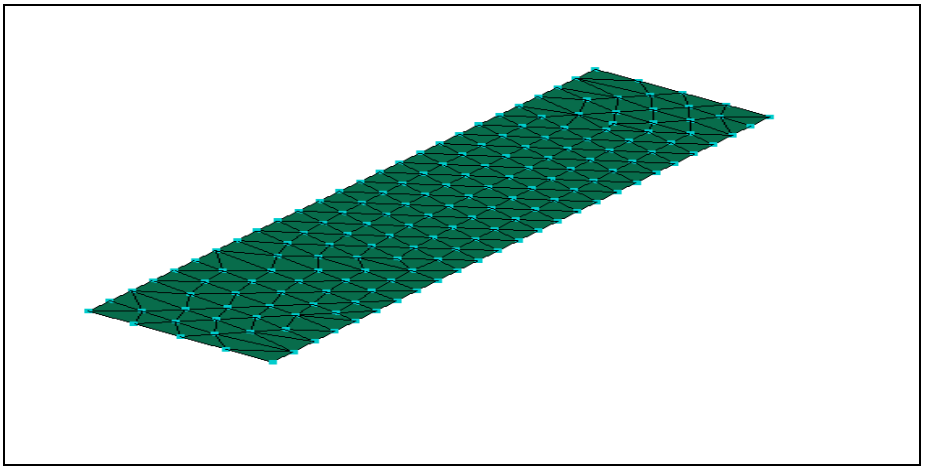

**Figure 3.3:** Plastic Models after Meshing In Moldflow Plastic Insight

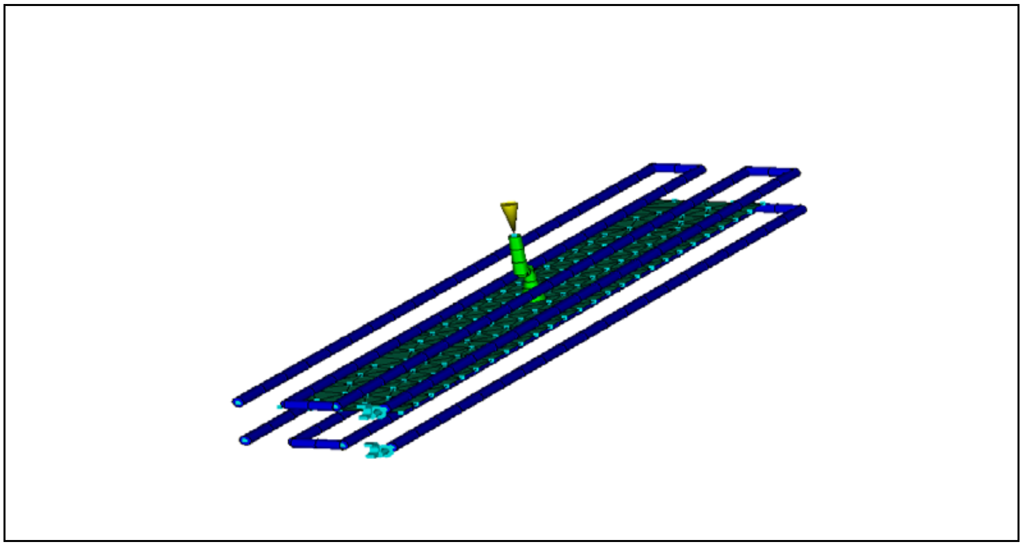

**Figure 3.4:** Plastic Models with Cooling Channel

## 3.5 RESPONSE SURFACE METHOD

FE model is not suitable for large number of repetitive analyses which are often required in an optimization process. Therefore, the FE model for warpage is replaced by a simpler and more efficient predictive model created by response surface methodology (RSM). RSM is a model building technique based on statistical design of experiment and least square error fitting. To create RS models, a computer program has been written in MATLAB language. The program has the capability of creating RS polynomials up to 10th order if sufficient data exist. All cross terms in the models can be taken into account. RS models can also be generated in terms of inverse of parameters. That is, xi can be replaced as 1/xi (i.e. inversely) in RS model if desired. RS models of varying orders from first order to third order are created and tested with the developed program. The data set consists of 33=27 analysis results and corresponds to the combination of three-dimensional parameters affecting the warpage. Therefore, RS models generated describe warpage in terms of the dimensional parameters (X dimension (Xd), Y dimension (Yd), and Z dimension (Zd)). The data set is divided into two parts; one part to create the model, other part to check the accuracy of the created model.

Steps in creating a response surface model by RSM.

1) Selection of Order of Polynomial Model
2) Selection of Analysis Points by Design of Experiment Method
3) Carrying out Analyses at Selected Points
4) Model Fitting for Analysis Results

Worksheet 1 ***

| ↓ | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|---|
| | x dimension (mm) | y dimension (mm) | z dimension (mm) | warpage (mm) | StdOrder | RunOrder | Blocks | PtType | |
| 1 | 30 | 5 | 0.8 | 0.0985 | 1 | 1 | 1 | 1 | |
| 2 | 30 | 5 | 1.2 | 0.1010 | 2 | 2 | 1 | 1 | |
| 3 | 30 | 5 | 1.6 | 0.1013 | 3 | 3 | 1 | 1 | |
| 4 | 30 | 45 | 0.8 | 0.1754 | 4 | 4 | 1 | 1 | |
| 5 | 30 | 45 | 1.2 | 0.1852 | 5 | 5 | 1 | 1 | |
| 6 | 30 | 45 | 1.6 | 0.1890 | 6 | 6 | 1 | 1 | |
| 7 | 30 | 85 | 0.8 | 0.2290 | 7 | 7 | 1 | 1 | |
| 8 | 30 | 85 | 1.2 | 0.2745 | 8 | 8 | 1 | 1 | |
| 9 | 30 | 85 | 1.6 | 0.2795 | 9 | 9 | 1 | 1 | |
| 10 | 85 | 5 | 0.8 | 0.1958 | 10 | 10 | 1 | 1 | |
| 11 | 85 | 5 | 1.2 | 0.2555 | 11 | 11 | 1 | 1 | |
| 12 | 85 | 5 | 1.6 | 0.2715 | 12 | 12 | 1 | 1 | |
| 13 | 85 | 45 | 0.8 | 0.2713 | 13 | 13 | 1 | 1 | |
| 14 | 85 | 45 | 1.2 | 0.3052 | 14 | 14 | 1 | 1 | |
| 15 | 85 | 45 | 1.6 | 0.3214 | 15 | 15 | 1 | 1 | |
| 16 | 85 | 85 | 0.8 | 0.3170 | 16 | 16 | 1 | 1 | |
| 17 | 85 | 85 | 1.2 | 0.3728 | 17 | 17 | 1 | 1 | |
| 18 | 85 | 85 | 1.6 | 0.4113 | 18 | 18 | 1 | 1 | |
| 19 | 160 | 5 | 0.8 | 0.2514 | 19 | 19 | 1 | 1 | |
| 20 | 160 | 5 | 1.2 | 0.3890 | 20 | 20 | 1 | 1 | |
| 21 | 160 | 5 | 1.6 | 0.4719 | 21 | 21 | 1 | 1 | |
| 22 | 160 | 45 | 0.8 | 0.3813 | 22 | 22 | 1 | 1 | |
| 23 | 160 | 45 | 1.2 | 0.4558 | 23 | 23 | 1 | 1 | |
| 24 | 160 | 45 | 1.6 | 0.4927 | 24 | 24 | 1 | 1 | |
| 25 | 160 | 85 | 0.8 | 0.5411 | 25 | 25 | 1 | 1 | |
| 26 | 160 | 85 | 1.2 | 0.5578 | 26 | 26 | 1 | 1 | |
| 27 | 160 | 85 | 1.6 | 0.5699 | 27 | 27 | 1 | 1 | |

**Figure 3.5** Data from Finite Element in Minitab 14

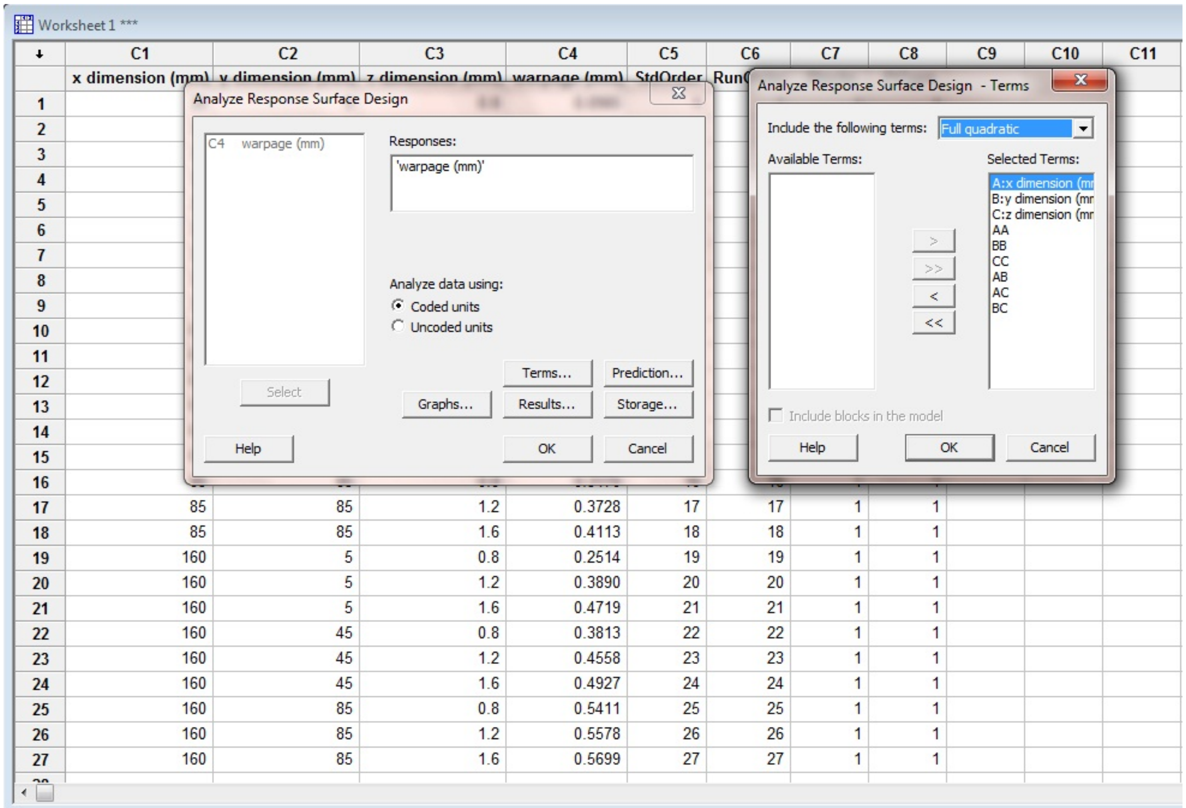


**Figure 3.6** Select Order of Polynomial

## 3.6 DATA COLLECTING

After all the process had been done, the data collected will then be studied and observed. So, comparison can be made to determine how the dimensional parameter effecting the warpage of plastic part. The data also can be described by plotting graph.

# CHAPTER 4

# RESULT AND DISCUSSION

## 4.1 INTRODUCTION

This chapter will discuss the whole of the project going on during analysis using MoldFlow and Response Surface Method. The final result of differential between warpage values from FE analysis will be compare with prediction values from Response Surface Method and then using optimization method from Response Surface Method, the smallest values of warpage will be determined and the parameter which produce the value also can be determine.

## 4.2 DATA PREPARATION

This project is to determine optimum value of warpage using Response Surface Method. By selecting the lowest value of warpage from optimization process using Response Surface Method, the optimum dimensional parameter for injection molding process is also determined.

For this project, the input data set is generating using statistical design of experiments (DOE) or experimental design method. Variable range is divided into levels/range between lowest and highest value in full factorial design method. A three-full factorial design creates $3^n$ input data, where $n$ is the number of variable or parameter that using in this project. Because of this project using three parameters

(X dimension, Y dimension, Z dimension), so $3^3$=27 input data are generated. Table 4.1 show the full factorial design that will be used for this project.

**Table 4.1:** Three Level Full Factorial Designs

| **Factor** | **Level** | | |
|---|---|---|---|
| | **1** | **2** | **3** |
| X dimension | 30 | 95 | 160 |
| Y dimension | 5 | 45 | 85 |
| Z dimension | 0.8 | 1.2 | 1.6 |

**Table 4.2:** Full Factorial Design Training Data

| **No of experiment** | **X dimension (mm)** | **Y dimension (mm)** | **Z dimension (mm)** |
|---|---|---|---|
| 1 | 95 | 5 | 0.8 |
| 2 | 30 | 5 | 1.6 |
| 3 | 160 | 45 | 0.8 |
| 4 | 30 | 85 | 0.8 |
| 5 | 95 | 45 | 1.6 |
| 6 | 160 | 85 | 1.6 |
| 7 | 160 | 5 | 1.2 |
| 8 | 95 | 85 | 1.6 |
| 9 | 160 | 85 | 0.8 |
| 10 | 30 | 5 | 0.8 |
| 11 | 160 | 45 | 1.6 |
| 12 | 30 | 85 | 1.6 |
| 13 | 30 | 5 | 1.2 |
| 14 | 95 | 5 | 1.6 |
| 15 | 30 | 85 | 1.2 |
| 16 | 160 | 85 | 1.2 |
| 17 | 95 | 5 | 1.2 |
| 18 | 160 | 5 | 0.8 |
| 19 | 30 | 45 | 1.2 |
| 20 | 30 | 45 | 1.6 |
| 21 | 95 | 45 | 1.2 |
| 22 | 95 | 85 | 0.8 |
| 23 | 95 | 45 | 0.8 |

**Table 4.2**: Continued

| No of experiment | X dimension (mm) | Y dimension (mm) | Z dimension (mm) |
|---|---|---|---|
| 24 | 30 | 45 | 0.8 |
| 25 | 160 | 5 | 1.6 |
| 26 | 160 | 45 | 1.2 |
| 27 | 95 | 85 | 1.2 |

## 4.3 FINITE ELEMENT ANALYSIS

Finite element analysis for the project is using MOLDFLOW Plastics Insight 5.0 (MPI). To create this model, there are few steps that need to consider in MPI. Started with import the model from Solidwork, following by generate the mesh, select the material, set gate location, create runner system, set cooling system and finally start with the warpage analysis. Using the data obtain from full factorial design, warpage analysis will be initialized.

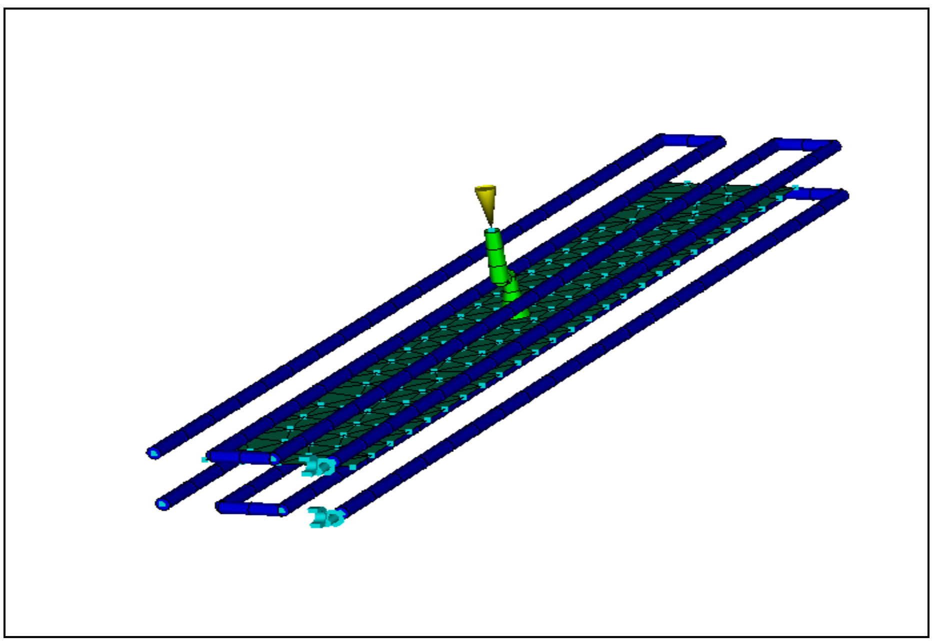

**Figure 4.1:** The Finite element model

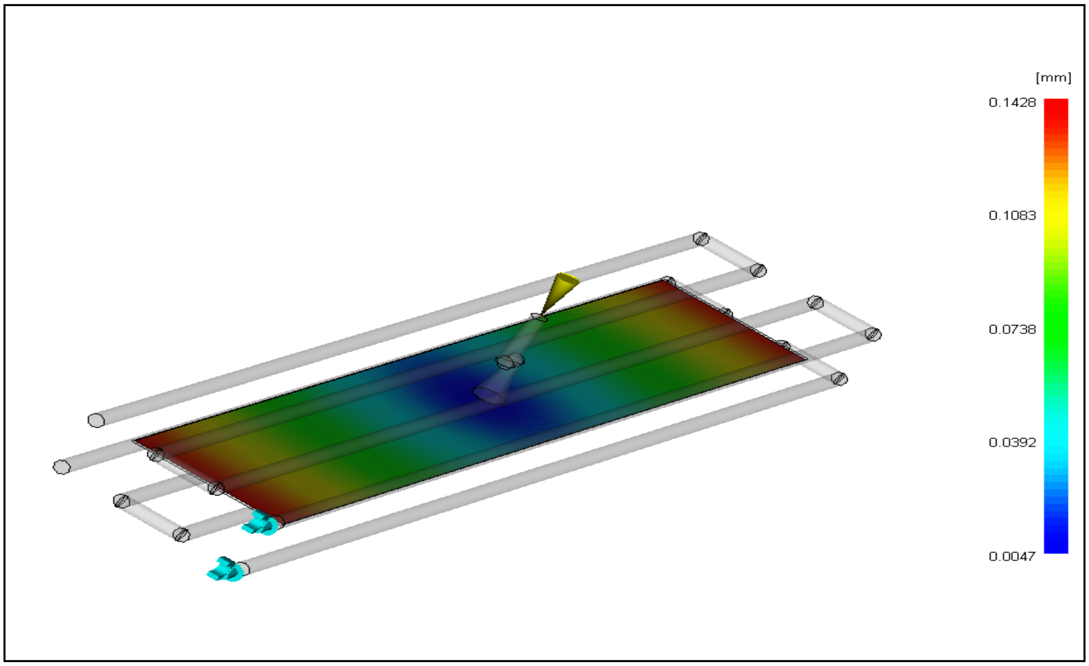


**Figure 4.2:** Finite element analyses

The area with blue color shows that warpage at the smallest value. While the red color shows warpage at the high value. From the figure 4.2 above, we can see that it starts to deflect at 0.0047 mm and end at 0.1428 mm.

**Table 4.3**: Finite element analysis result

| Experiment number | x dimension (mm) | y dimension (mm) | z dimension (mm) | FE warpage (mm) |
|---|---|---|---|---|
| 1 | 30 | 5 | 0.8 | 0.0985 |
| 2 | 30 | 5 | 1.2 | 0.1010 |
| 3 | 30 | 5 | 1.6 | 0.1013 |
| 4 | 30 | 45 | 0.8 | 0.1428 |
| 5 | 30 | 45 | 1.2 | 0.1852 |
| 6 | 30 | 45 | 1.6 | 0.1890 |
| 7 | 30 | 85 | 0.8 | 0.2290 |
| 8 | 30 | 85 | 1.2 | 0.2745 |
| 9 | 30 | 85 | 1.6 | 0.2795 |
| 10 | 95 | 5 | 0.8 | 0.1958 |

**Table 4.3**: Continued

| Experiment number | x dimension (mm) | y dimension (mm) | z dimension (mm) | FE warpage (mm) |
|---|---|---|---|---|
| 11 | 95 | 5 | 1.2 | 0.2555 |
| 12 | 95 | 5 | 1.6 | 0.2715 |
| 13 | 95 | 45 | 0.8 | 0.2713 |
| 14 | 95 | 45 | 1.2 | 0.3052 |
| 15 | 95 | 45 | 1.6 | 0.3214 |
| 16 | 95 | 85 | 0.8 | 0.3170 |
| 17 | 95 | 85 | 1.2 | 0.3728 |
| 18 | 95 | 85 | 1.6 | 0.4113 |
| 19 | 160 | 5 | 0.8 | 0.2514 |
| 20 | 160 | 5 | 1.2 | 0.3890 |
| 21 | 160 | 5 | 1.6 | 0.4719 |
| 22 | 160 | 45 | 0.8 | 0.3813 |
| 23 | 160 | 45 | 1.2 | 0.4558 |
| 24 | 160 | 45 | 1.6 | 0.4927 |
| 25 | 160 | 85 | 0.8 | 0.5411 |
| 26 | 160 | 85 | 1.2 | 0.5578 |
| 27 | 160 | 85 | 1.6 | 0.5699 |

The table above shows the warpage values from finite element analysis. From all experiments done the warpage value is all below 0.6 mm, these shows that for this particular plastics part, the warpage occur are small.

## 4.4 WARPAGE OPTIMIZATION USING RESPONSE SURFACE METHOD

Finite element method is not suitable to analyze a large number of repetitive analyses which are usually needed to perform an optimization process. In order to solve the problem, more efficient predictive model using response surface methodology (RSM) is used. RSM is a model building method based on statistical design of experiment and least square error fitting.

### 4.4.1 Prediction of Warpage Value Using Response Surface Method

In order to predict the warpage value using response surface method (RSM), the result from finite element is needed. From the result, the RSM model can be developed. Then from the model, the prediction of warpage value can be done.

## 4.5 MODEL FOR WARPAGE

With reference to the response surface method, where the response variable is the warpage in this study, the relationship between the investigated 3 dimension parameters and the response can be represented by the following linear equation such Equation 4.1 below.

$$\ln W = A \ln x + B \ln y + C \ln z \qquad (4.1)$$

where $W$ is the warpage (response), $A$, $B$, $C$, are constants, while $x$, $y$, and $z$ the x dimension (mm), y dimension (mm), and z dimension (mm), respectively.

Equation 4.1 can be written as Equation 4.2 below.

$$W = w - \varepsilon = \beta 0 x0 + \beta 1 x1 + \beta 2 x2 + \beta 3 x3 \qquad (4.2)$$

where $w$ is the warpage calculated value and $W$ is the predicted value, while $x0$, $x1$, $x2$, $x3$, $x4$ and $\varepsilon$ are dummy variable ($x0$ = 1), x dimension, y dimension, z dimension, and experimental error, respectively. $\beta 0$, $\beta 1$, $\beta 2$, and $\beta 3$ are the model parameters. In most cases, the response surface variables demonstrate some curvature in most ranges of the z dimension. Therefore, it would be useful to consider also the second order model in this study. The second order model helps understand the second order effect of each factor separately and the two-way interaction amongst these factors combined. This model can be represented by the following Equation 4.3.

$$W'' = \beta 0x0 + \beta 1x1 + \beta 2x2 + \beta 3x3 + \beta 11x^21 + \beta 22x^22 + \beta 33x^23 + \beta 12x1x2 + \beta 13x1x3 + \beta 23x2x3 \tag{4.3}$$

The parameters $\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$, $\beta 11$, $\beta 22$, $\beta 33$, $\beta 12$, $\beta 13$, and $\beta 23$ appearing in Equation 4.3, are determined using the method of least squares. The calculations are performed using MINITAB.

## 4.6 RESULT AND DISCUSSION

### 4.6.1 Development of First Order Warpage Model (RSM Linear Model)

To do the calculation of these parameters, the method of least squares is used with the aid of MINITAB. Table 4.4 shows estimated regression coefficients for warpage (mm) using data in uncoded units.

**Table 4.4:** Estimated Regression Coefficients for Warpage (mm) using data in uncoded units

| Term | Coefficient |
|---|---|
| Constant | -0.0767386 |
| X dimension (mm) | 0.00211402 |
| Y dimension (mm) | 0.00196806 |
| Z dimension (mm) | 0.0899583 |

Next, the first order equation (RSM linear model) for predicting the warpage can be expressed as Equation 4.4.

$$W = -0.0767386 + 0.00211402Xd + 0.00196806Yd + 0.0899583Zd \quad (4.4)$$

From this linear equation, one can easily notice that the response *W* (warpage) is affected significantly by the z dimension, x dimension and lastly, by y dimension. z dimension gives the most effect on the warpage because it has the largest coefficient value compared to others. Table 4.5 shows the warpage values from finite element analysis and the values predicted by the first order model (RSM linear model).

**Table 4.5:** Comparison between finite element alaysis and predicted results generated by first order model (RSM linear model)

| x dimension (mm) | y dimension (mm) | z dimension (mm) | FE warpage (mm) | Predicted warpage (mm) | Error (%) |
|---|---|---|---|---|---|
| 30 | 5 | 0.8 | 0.0985 | 0.0684889 | 30.46812183 |
| 30 | 5 | 1.2 | 0.101 | 0.1044722 | 3.437821782 |
| 30 | 5 | 1.6 | 0.1013 | 0.1404555 | 38.65301086 |
| 30 | 45 | 0.8 | 0.1754 | 0.1472113 | 16.07109464 |
| 30 | 45 | 1.2 | 0.1852 | 0.1831946 | 1.082829374 |
| 30 | 45 | 1.6 | 0.189 | 0.2191779 | 15.96714286 |
| 30 | 85 | 0.8 | 0.229 | 0.2259337 | 1.338995633 |
| 30 | 85 | 1.2 | 0.2745 | 0.261917 | 4.583970856 |
| 30 | 85 | 1.6 | 0.2795 | 0.2979003 | 6.583291592 |
| 95 | 5 | 0.8 | 0.1958 | 0.18476 | 5.638406537 |
| 95 | 5 | 1.2 | 0.2555 | 0.2207433 | 13.60340509 |
| 95 | 5 | 1.6 | 0.2715 | 0.2567266 | 5.441399632 |
| 95 | 45 | 0.8 | 0.2713 | 0.2634824 | 2.881533358 |
| 95 | 45 | 1.2 | 0.3052 | 0.2994657 | 1.878866317 |
| 95 | 45 | 1.6 | 0.3214 | 0.335449 | 4.37118855 |
| 95 | 85 | 0.8 | 0.317 | 0.3422048 | 7.951041009 |
| 95 | 85 | 1.2 | 0.3728 | 0.3781881 | 1.445305794 |
| 95 | 85 | 1.6 | 0.4113 | 0.4141714 | 0.698127887 |
| 160 | 5 | 0.8 | 0.2514 | 0.3433115 | 36.55986476 |
| 160 | 5 | 1.2 | 0.389 | 0.3792948 | 2.494910026 |

**Table 4.5**: Continued

| x dimension (mm) | y dimension (mm) | z dimension (mm) | FE warpage (mm) | Predicted warpage (mm) | Error (%) |
|---|---|---|---|---|---|
| 160 | 5 | 1.6 | 0.4719 | 0.4152781 | 11.99870735 |
| 160 | 45 | 0.8 | 0.3813 | 0.4220339 | 10.6829006 |
| 160 | 45 | 1.2 | 0.4558 | 0.4580172 | 0.486441422 |
| 160 | 45 | 1.6 | 0.4927 | 0.4940005 | 0.263953724 |
| 160 | 85 | 0.8 | 0.5411 | 0.5007563 | 7.455867677 |
| 160 | 85 | 1.2 | 0.5578 | 0.5367396 | 3.775618501 |
| 160 | 85 | 1.6 | 0.5699 | 0.5727229 | 0.495332514 |

It is clear that the predicted values are close to the calculated readings. This indicates that the obtained first order model (RSM linear model) is able to provide, to a great extent, accurate values of warpage.

### 4.6.2 Development of Second Order Warpage Model (RSM Quadratic Model)

The second order equation (RSM Quadratic Model) was established to describe the effect of the three dimension parameters that affect the value of warpage. Table 4.6 shows the estimated regression coefficients for warpage (mm) using data in uncoded unit.

**Table 4.6:** Estimated Regression Coefficients for Warpage (W) using data in uncoded units

| Term | Coefficient |
|---|---|
| Constant | -0.104205 |
| x dimension (mm) | 0.00107768 |
| y dimension (mm) | 0.00207367 |
| z dimension (mm) | 0.220810 |
| x dimension (mm)*x dimension (mm) | -1.08355E-06 |
| y dimension (mm)*y dimension (mm) | 4.65972E-06 |
| z dimension (mm)*z dimension (mm) | -0.0778819 |

**Table 4.6**: Continued

| Term | Coefficient |
|---|---|
| x dimension (mm)*y dimension (mm) | 2.82281E-06 |
| x dimension (mm)*y dimension (mm) | 0.000932241 |
| y dimension (mm)*z dimension (mm) | -6.53125E-04 |

Next, the model is obtained using the Box–Behnken design and the Equation 4.6 can be written as below.

$$W'' = -0.104205 + 0.00107768\ X + 0.00207367\ Y + 0.220810\ Z + (-1.08355E\text{-}06)\ X2 + 4.65972E\text{-}06\ Y^2 + (-0.0778819)\ Z^2 + 2.82281E\text{-}06\ XY + 0.000932241\ XZ + (-6.53125E04)\ YZ \quad (4.5)$$

Z dimension gives the most effect on the warpage because it has the largest coefficient value compared to others. Z dimension also refers to the wall thickness of the model. Warpage is greatly influenced by wall thickness and mould surface temperature. It follows that major differences in wall thickness and unsuitable mould temperatures will cause the moulding to warp (R. Wilkinson, E.A. Poppe, K. Leidig and K. Schirmer). The warpage value obtained from finite element analysis and predicted values by this equation are shown in Table 4.7.

**Table 4.7:** Comparison between finite element warpage value and predicted results generated by second order model (RSM Quadratic Model)

| x dimension (mm) | y dimension (mm) | z dimension (mm) | FE warpage (mm) | Predicted warpage (mm) | Error (%) |
|---|---|---|---|---|---|
| 30 | 5 | 0.8 | 0.0985 | 0.0846 | 14.087982 |
| 30 | 5 | 1.2 | 0.101 | 0.1205 | 19.329168 |
| 30 | 5 | 1.6 | 0.1013 | 0.1315 | 29.81182 |
| 30 | 45 | 0.8 | 0.1754 | 0.1594 | 9.1351485 |
| 30 | 45 | 1.2 | 0.1852 | 0.1848 | 0.2019052 |
| 30 | 45 | 1.6 | 0.189 | 0.1854 | 1.9296373 |
| 30 | 85 | 0.8 | 0.229 | 0.2490 | 8.751819 |
| 30 | 85 | 1.2 | 0.2745 | 0.2640 | 3.8102778 |
| 30 | 85 | 1.6 | 0.2795 | 0.2541 | 9.0813233 |
| 95 | 5 | 0.8 | 0.1958 | 0.1953 | 0.2744438 |
| 95 | 5 | 1.2 | 0.2555 | 0.2554 | 0.0391284 |
| 95 | 5 | 1.6 | 0.2715 | 0.2906 | 7.0405919 |
| 95 | 45 | 0.8 | 0.2713 | 0.2774 | 2.232052 |
| 95 | 45 | 1.2 | 0.3052 | 0.3270 | 7.1569282 |
| 95 | 45 | 1.6 | 0.3214 | 0.3518 | 9.4611465 |
| 95 | 85 | 0.8 | 0.317 | 0.3744 | 18.094504 |
| 95 | 85 | 1.2 | 0.3728 | 0.4136 | 10.943392 |
| 95 | 85 | 1.6 | 0.4113 | 0.4279 | 4.0389368 |
| 160 | 5 | 0.8 | 0.2514 | 0.2967 | 18.037368 |
| 160 | 5 | 1.2 | 0.389 | 0.3811 | 2.0252964 |
| 160 | 5 | 1.6 | 0.4719 | 0.4406 | 6.6380498 |
| 160 | 45 | 0.8 | 0.3813 | 0.3862 | 1.2793514 |
| 160 | 45 | 1.2 | 0.4558 | 0.4601 | 0.9442345 |
| 160 | 45 | 1.6 | 0.4927 | 0.5091 | 3.3300725 |
| 160 | 85 | 0.8 | 0.5411 | 0.4905 | 9.3473489 |
| 160 | 85 | 1.2 | 0.5578 | 0.5540 | 0.6817589 |
| 160 | 85 | 1.6 | 0.5699 | 0.5926 | 3.9744859 |

It can be concluded from the table that the equation can produce values close to finite element analysis. So, the second order polynomial model (RSM Quadratic Model) also can be used to predict the warpage value.

From both first and second order model (RSM Linear and Quadratic Model), warpage values can be predicted and the values are almost the same as the values from finite element analysis. So, comparison between both first and second order models (RSM Linear and Quadratic Model) result and finite element analysis result need to be done to determine which model is more significant to predict the warpage value. The comparison of error percentage of both first and secondary order (RSM Linear and Quadratic Model) can be done to select the less error percentage as the predictive model.

## 4.7 COMPARISON WARPAGE AND ERROR

The first and second order models (RSM Linear and Quadratic Model) were obtained from the effect of interaction between three dimension parameters x dimension, y dimension, z dimension and warpage response. Based on analysis before, it proves that the second order (RSM Quadratic Model) predicted result is very close to calculated result compared to first order (RSM Linear Model) predicted result as shown in Figure 4.3. Therefore in this thesis may conclude that second order model (RSM Quadratic Model) much accurate than first order model (RSM Linear Model).

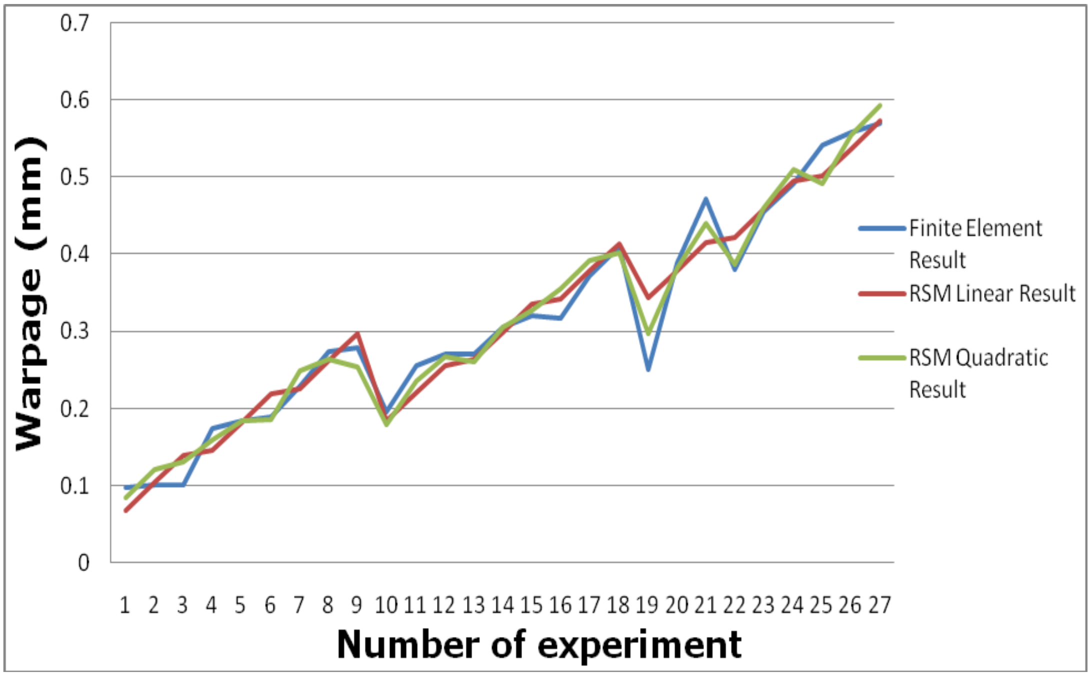


**Figure 4.3:** Comparison warpage between the calculated and predicted results

This situation happened because the average error for quadratic equation (RSM Quadratic Model) is 6.90% which is lower than linear equation to be 8.75% as shown in Table 4.8.

**Table 4.8:** Average error between linear equation and quadratic equation

| | **Model** | |
|---|---|---|
| | **Linear Equation** | **Quadratic Equation** |
| **Average error** (%) | 8.75 | 6.90 |

Therefore, we can conclude that second order model (RSM Quadratic Model) has a smooth pattern compare to first order model which it has rough pattern. To be clear, Figure 4.4 shows the error comparison between linear equation model and quadratic equation model (RSM Linear and Quadratic Model).

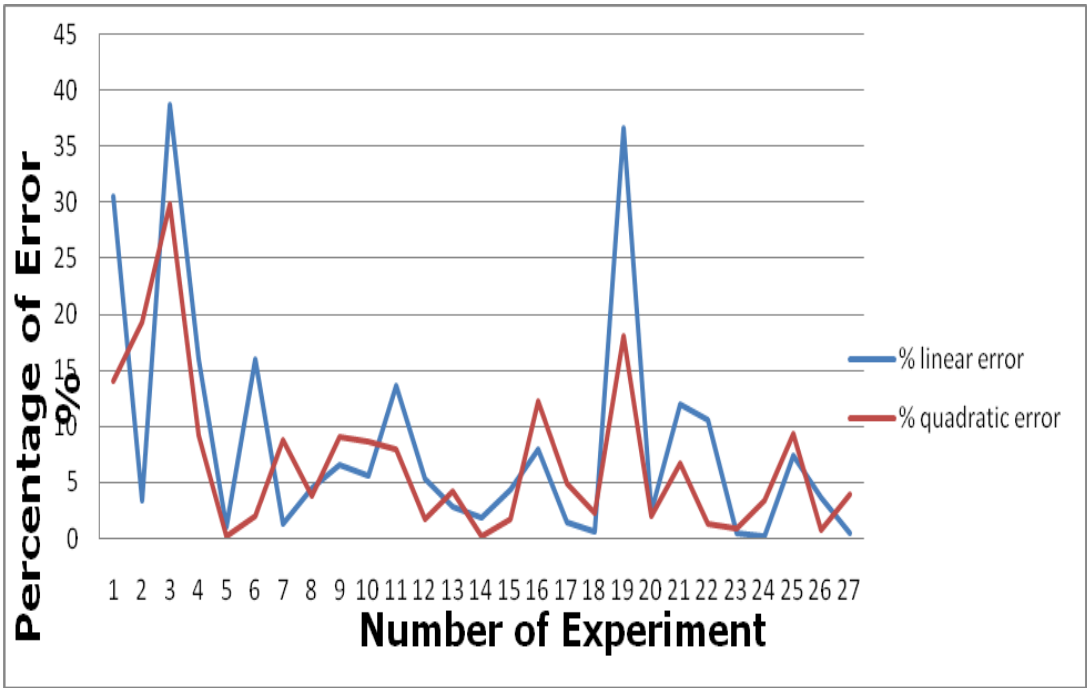


**Figure 4.4:** Error comparison between linear equation model and quadratic equation model

## 4.8 OPTIMIZATION USING RESPONSE SURFACE METHOD

The warpage optimization using RSM is done in Minitab 14. After select the minimum option, the low and top limit is set. Then the result show that the dimension parameters that provide the smallest value are X=30 mm Y=5 mm Z=0.8 mm with predicted warpage value of 0.0846mm.

# CHAPTER 5

# CONCLUSION AND RECOMMENDATIONS

## 5.1 CONCLUSION

In this study, an efficient optimization method using RSM was introduced in minimizing warpage of injection-molded plastic part. To minimize the warpage, the appropriate dimensional parameters were determined. X dimension, Y dimension and Z dimension were selected as dimensional parameters. Finite element analysis using MoldFlow was performed based on full factorial experimental design. Predictive model for warpage was created based on the three dimensional parameters selected earlier by using RSM. The second model (quadratic) of RSM is suitable to predict the warpage of thin shell plastic part based on the comparison graph and percentage error graph. The critical factor that effect the warpage of thin shell plastic part is the Z dimension (wall thickness) based on regression coefficient. Warpage is greatly influenced by wall thickness and mould surface temperature. It follows that major differences in wall thickness and unsuitable mould temperatures will cause the moulding to warp (R. Wilkinson, E.A. Poppe, K. Leidig and K. Schirmer). RSM was used to determine the optimum dimensional parameter that had minimum value of warpage. The dimensional parameters of the thin shell plastic part with the minimum warpage is X=30 mm Y=5 mm Z=0.8 mm with predicted warpage value of 0.0846mm.

## 5.2 RECOMMENDATIONS

1. The effect of dimension parameter on warpage can be explored more using different model of plastic part and different analysis approach such as Artificial Neural Network (ANN), Taguchi or etc.

2. Genetic Algorithm (GA) can be used as warpage optimization method in future study.

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# Appendix A

## Gant Chart

| PROJECT | | | | | | | WEEK | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ACTIVITIES | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| Project confirmation | ■ | | | | | | | | | | | | | |
| Introduction | | ■ | ■ | ■ | | | | | | | | | | |
| Literature review | | | | | ■ | ■ | ■ | | | | | | | |
| Methodology | | | | | | | | ■ | ■ | ■ | | | | |
| 3D structural modeling | | | | | | | | | | | ■ | | | |
| Make proposal | | | | | | | | | | | | ■ | ■ | |
| Presentation 1 | | | | | | | | | | | | | | ■ |

| PROJECT | | | | | | | WEEK | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ACTIVITIES | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| DOE | ■ | ■ | | | | | | | | | | | | |
| Review Literature Review | | | ■ | ■ | ■ | ■ | | | | | | | | |
| MOLDFLOW Analysis | | | | ■ | ■ | ■ | | | | | | | | |
| Data correlation | | | | | | ■ | ■ | ■ | ■ | | | | | |
| Result and discussion | | | | | | | | | | ■ | ■ | ■ | ■ | |
| Conclusion | | | | | | | | | | | | ■ | ■ | |
| Presentation 2 | | | | | | | | | | | | | ■ | ■ |
| Make final report | | | | | | | | | | | | | | ■ |

# Appendix B

## Response Surface Regression: warpage (mm) versus x dimension , y dimension , ..

The analysis was done using coded units.

Estimated Regression Coefficients for warpage (mm)

| Term | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 0.32061 | 0.006053 | 52.963 | 0.000 |
| x dimension (mm) | 0.13741 | 0.007370 | 18.644 | 0.000 |
| y dimension (mm) | 0.07872 | 0.007399 | 10.639 | 0.000 |
| z dimension (mm) | 0.03598 | 0.007399 | 4.863 | 0.000 |

S = 0.0313927  PRESS = 0.0344058
R-Sq = 95.47%  R-Sq(pred) = 93.12%  R-Sq(adj) = 94.88%

Analysis of Variance for warpage (mm)

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| Regression | 3 | 0.477412 | 0.477412 | 0.159137 | 161.48 | 0.000 |
| Linear | 3 | 0.477412 | 0.477412 | 0.159137 | 161.48 | 0.000 |
| Residual Error | 23 | 0.022667 | 0.022667 | 0.000986 | | |
| Total | 26 | 0.500078 | | | | |

Estimated Regression Coefficients for warpage (mm) using data in uncoded units

| Term | Coef |
|---|---|
| Constant | -0.0767386 |
| x dimension (mm) | 0.00211402 |
| y dimension (mm) | 0.00196806 |
| z dimension (mm) | 0.0899583 |

Predicted Response for New Design Points Using Model for warpage (mm)

| Point | Fit | SE Fit | 95% CI | 95% PI |
|---|---|---|---|---|
| 1 | 0.068489 | 0.0139604 | (0.039610, 0.097368) | (-0.002584, 0.139562) |
| 2 | 0.104472 | 0.0118382 | (0.079983, 0.128962) | ( 0.035068, 0.173877) |
| 3 | 0.140456 | 0.0139604 | (0.111576, 0.169335) | ( 0.069383, 0.211528) |
| 4 | 0.147211 | 0.0118382 | (0.122722, 0.171700) | ( 0.077806, 0.216616) |
| 5 | 0.183195 | 0.0092408 | (0.164078, 0.202311) | ( 0.115499, 0.250890) |
| 6 | 0.219178 | 0.0118382 | (0.194689, 0.243667) | ( 0.149773, 0.288583) |
| 7 | 0.225933 | 0.0139604 | (0.197054, 0.254813) | ( 0.154861, 0.297006) |
| 8 | 0.261917 | 0.0118382 | (0.237428, 0.286406) | ( 0.192512, 0.331322) |
| 9 | 0.297900 | 0.0139604 | (0.269021, 0.326779) | ( 0.226827, 0.368973) |
| 10 | 0.184760 | 0.0121067 | (0.159716, 0.209805) | ( 0.115158, 0.254363) |
| 11 | 0.220744 | 0.0095824 | (0.200921, 0.240566) | ( 0.152845, 0.288642) |
| 12 | 0.256727 | 0.0121067 | (0.231682, 0.281771) | ( 0.187124, 0.326330) |
| 13 | 0.263482 | 0.0095824 | (0.243660, 0.283305) | ( 0.195584, 0.331381) |

| | | | | |
|---|---|---|---|---|
| 14 | 0.299466 | 0.0060886 | (0.286870, 0.312061) | ( 0.233315, 0.365617) |
| 15 | 0.335449 | 0.0095824 | (0.315626, 0.355272) | ( 0.267550, 0.403348) |
| 16 | 0.342205 | 0.0121067 | (0.317160, 0.367249) | ( 0.272602, 0.411807) |
| 17 | 0.378188 | 0.0095824 | (0.358365, 0.398011) | ( 0.310289, 0.446087) |
| 18 | 0.414171 | 0.0121067 | (0.389127, 0.439216) | ( 0.344569, 0.483774) |
| 19 | 0.343312 | 0.0143540 | (0.313618, 0.373005) | ( 0.271905, 0.414719) |
| 20 | 0.379295 | 0.0122998 | (0.353851, 0.404739) | ( 0.309548, 0.449043) |
| 21 | 0.415279 | 0.0143540 | (0.385585, 0.444972) | ( 0.343871, 0.486686) |
| 22 | 0.422034 | 0.0122998 | (0.396590, 0.447478) | ( 0.352287, 0.491782) |
| 23 | 0.458017 | 0.0098253 | (0.437692, 0.478343) | ( 0.389970, 0.526065) |
| 24 | 0.494001 | 0.0122998 | (0.468557, 0.519445) | ( 0.424253, 0.563748) |
| 25 | 0.500756 | 0.0143540 | (0.471063, 0.530450) | ( 0.429349, 0.572164) |
| 26 | 0.536740 | 0.0122998 | (0.511296, 0.562184) | ( 0.466992, 0.606487) |
| 27 | 0.572723 | 0.0143540 | (0.543030, 0.602416) | ( 0.501316, 0.644130) |

### Normplot of Residuals for warpage (mm)

### Response Surface Regression: warpage (mm) versus x dimension , y dimension , ..

The analysis was done using coded units.

Estimated Regression Coefficients for warpage (mm)

| Term | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 0.327043 | 0.013828 | 23.651 | 0.000 |
| x dimension (mm) | 0.137639 | 0.006318 | 21.785 | 0.000 |
| y dimension (mm) | 0.079099 | 0.006330 | 12.495 | 0.000 |
| z dimension (mm) | 0.037226 | 0.006330 | 5.881 | 0.000 |
| x dimension (mm)*x dimension (mm) | -0.004578 | 0.011253 | -0.407 | 0.689 |
| y dimension (mm)*y dimension (mm) | 0.007456 | 0.010943 | 0.681 | 0.505 |
| z dimension (mm)*z dimension (mm) | -0.012461 | 0.010943 | -1.139 | 0.271 |
| x dimension (mm)*y dimension (mm) | 0.007339 | 0.007708 | 0.952 | 0.354 |
| x dimension (mm)*z dimension (mm) | 0.024238 | 0.007708 | 3.145 | 0.006 |
| y dimension (mm)*z dimension (mm) | -0.010450 | 0.007738 | -1.350 | 0.195 |

S = 0.0268054  PRESS = 0.0441275
R-Sq = 97.56%  R-Sq(pred) = 91.18%  R-Sq(adj) = 96.26%

Analysis of Variance for warpage (mm)

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| Regression | 9 | 0.487863 | 0.487863 | 0.054207 | 75.44 | 0.000 |
| Linear | 3 | 0.477412 | 0.478027 | 0.159342 | 221.76 | 0.000 |
| Square | 3 | 0.001384 | 0.001384 | 0.000461 | 0.64 | 0.598 |
| Interaction | 3 | 0.009067 | 0.009067 | 0.003022 | 4.21 | 0.021 |
| Residual Error | 17 | 0.012215 | 0.012215 | 0.000719 | | |
| Total | 26 | 0.500078 | | | | |

Estimated Regression Coefficients for warpage (mm) using data in uncoded units

| Term | Coef |
|---|---|
| Constant | -0.104205 |
| x dimension (mm) | 0.00107768 |
| y dimension (mm) | 0.00207367 |
| z dimension (mm) | 0.220810 |
| x dimension (mm)*x dimension (mm) | -1.08355E-06 |

```
y dimension (mm)*y dimension (mm)   4.65972E-06
z dimension (mm)*z dimension (mm)    -0.0778819
x dimension (mm)*y dimension (mm)   2.82281E-06
x dimension (mm)*z dimension (mm)   0.000932241
y dimension (mm)*z dimension (mm)  -6.53125E-04
```

Predicted Response for New Design Points Using Model for warpage (mm)

| Point | Fit | SE Fit | 95% CI | 95% PI |
|---|---|---|---|---|
| 1 | 0.084623 | 0.0187911 | (0.044977, 0.124269) | (0.015557, 0.153690) |
| 2 | 0.120522 | 0.0154841 | (0.087854, 0.153191) | (0.055210, 0.185834) |
| 3 | 0.131499 | 0.0187911 | (0.091853, 0.171145) | (0.062433, 0.200566) |
| 4 | 0.159377 | 0.0154841 | (0.126708, 0.192045) | (0.094065, 0.224689) |
| 5 | 0.184826 | 0.0136486 | (0.156030, 0.213622) | (0.121362, 0.248289) |
| 6 | 0.185353 | 0.0154841 | (0.152684, 0.218021) | (0.120041, 0.250665) |
| 7 | 0.249042 | 0.0187911 | (0.209396, 0.288687) | (0.179975, 0.318108) |
| 8 | 0.264041 | 0.0154841 | (0.231372, 0.296709) | (0.198729, 0.329353) |
| 9 | 0.254118 | 0.0187911 | (0.214472, 0.293763) | (0.185051, 0.323184) |
| 10 | 0.178837 | 0.0157293 | (0.145651, 0.212023) | (0.113265, 0.244409) |
| 11 | 0.235245 | 0.0136715 | (0.206401, 0.264090) | (0.171760, 0.298731) |
| 12 | 0.266732 | 0.0157293 | (0.233546, 0.299918) | (0.201159, 0.332304) |
| 13 | 0.259801 | 0.0136715 | (0.230956, 0.288645) | (0.196315, 0.323286) |
| 14 | 0.305759 | 0.0136486 | (0.276963, 0.334555) | (0.242296, 0.369223) |
| 15 | 0.326796 | 0.0136715 | (0.297951, 0.355640) | (0.263310, 0.390281) |
| 16 | 0.355676 | 0.0157293 | (0.322490, 0.388862) | (0.290104, 0.421248) |
| 17 | 0.391184 | 0.0136715 | (0.362340, 0.420029) | (0.327699, 0.454670) |
| 18 | 0.401771 | 0.0157293 | (0.368585, 0.434957) | (0.336198, 0.467343) |
| 19 | 0.296746 | 0.0194288 | (0.255754, 0.337737) | (0.226898, 0.366593) |
| 20 | 0.381121 | 0.0158727 | (0.347633, 0.414610) | (0.315396, 0.446847) |
| 21 | 0.440575 | 0.0194288 | (0.399584, 0.481566) | (0.370727, 0.510422) |
| 22 | 0.386178 | 0.0158727 | (0.352690, 0.419667) | (0.320452, 0.451904) |
| 23 | 0.460104 | 0.0136486 | (0.431308, 0.488900) | (0.396640, 0.523567) |
| 24 | 0.509107 | 0.0158727 | (0.475619, 0.542596) | (0.443381, 0.574833) |
| 25 | 0.490521 | 0.0194288 | (0.449530, 0.531513) | (0.420674, 0.560369) |
| 26 | 0.553997 | 0.0158727 | (0.520509, 0.587486) | (0.488271, 0.619723) |
| 27 | 0.592551 | 0.0194288 | (0.551559, 0.633542) | (0.522703, 0.662398) |

Normplot of Residuals for warpage (mm)

## Response Optimization

```
Parameters

               Goal     Lower  Target  Upper  Weight  Import
warpage (mm)   Minimum      0       0    0.5       1       1


Starting Point

x dimension    =    95
y dimension    =    45
z dimension    =   1.2


Global Solution

x dimension    =    30
y dimension    =     5
z dimension    =   0.8


Predicted Responses

warpage (mm)   =   0.0846230  ,   desirability =   0.830754


Composite Desirability = 0.830754
```