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Editorial Board

About ICRQE 2013

This conference was initiated in year 2011 and it is usually conducted by the Quality Engineering Society (QES) in Japan. However, for 2013, UTM Razak School of Engineering and Advanced Technology is given the opportunity to organize the conference. Therefore, this 1st International Conference on Robust Quality Engineering (ICRQE 2013) is the first conference on Taguchi Method to be organized outside Japan, and Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia is honoured to be the first organization to host the conference. Apart from UTM Razak School of Engineering and Advanced Technology (UTM Kuala Lumpur), ICRQE 2013 is jointly organized with the, American Supplier Institute of United States of America (ASI USA), Quality Engineering Society (QES) and MEIJI University, Japan.

This conference is held in Malaysia as proposed by Mr Shin Taguchi, President of ASI USA, son of the founder of Taguchi Method. This is due to the popular application of Taguchi Method in research, academic and industry, particularly those involving product and process development, optimization, recognition, and predictions. The conference also aim to attract other industry sectors that could benefit from its concepts, in particular in minimizing loss when there is no variability and the best response is achieved in various areas of product design. In conjunction with ICRQE 2013, the first two days is the Taguchi Method Workshop to give added value to the participants. The workshop will be delivered by Mr Shin Taguchi himself. The following two days of ICRQE 2013 is expected to serve as a catalyst and platform of knowledge-sharing onTaguchi method practices and researches.

In emphasizing the importance of robust quality engineering, especially in current engineering practices, ICRQE 2013 aims to:

- Inculcate the importance of quality engineering for the betterment of technology development in Malaysia
- Provide practical understanding of robust engineering to Malaysian industries and researchers
- Present industrial experiences and case studies in industry, emphasizing the applications of Taguchi Method
- Identify new areas of knowledge and research extracted from the experience of the private companies and public institutions

Quality engineering is applied regardless of the field; engineering, science, technology, and services. Thus, ICRQE 2013 is one of the platforms to educate our society towards a developed nation. Lastly the Organizing Committee of this conference would like remind all delegates that the objective of Robust Engineering is to minimize the loss to society for a better world. Poor quality goods and services will cause loss to society. To minimize it, we need to optimize "FUNCTION" for robustness!!!

Welcome to ICRQE 2013.

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OPTIMIZATION OF CUTTING PARAMETERS USING TAGUCHI METHOD ON TURNING PROCESS

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***Abstract*— Surface roughness an indicator of surface quality is one of the prime customer requirements for machined parts. Surface roughness plays a major role in the selection of material in industries. For efficient use of machine tools, optimum cutting parameters are required. The turning process parameter optimization is highly complex and time consuming. In this paper Taguchi parameter optimization methodology is applied to optimize cutting parameters in turning process. The turning parameters evaluated are cutting velocity, feed rate, depth of cut, length of the tool from tool holder and coolant each at three levels of the operations. MINITAB and MATLAB are the two software's used for the analysis of this experiment. The results of analysis show that depth of cut and length of the tool from tool holder have significant contribution on the surface roughness and cutting velocity, feed rate and coolant have less significant contribution on the surface roughness.**

***Keywords*---Optimisation, orthogonal array, surface roughness, Taguchi method, turning parameters, ANOVA method, chi square test**

I. INTRODUCTION

Optimization of machining operation is one of the greatest concerns in the manufacturing industry. Surface roughness has formulated an important design features. It imposes one of the most critical constraints for the selection of machine tools and cutting parameters in process planning. Different procedures have been used by researchers from time to time for the process of optimization for example linear programming, quadratic programming, lagrangian multiplier, geometric program-Ming, particle swarm optimization, genetic algorithm, taguchi method etc [1]. Taguchi method is an experimental method. It is effective methodology to find out the effective performance and machining conditions. Taguchi parameter design offers a simple, systematic approach and can reduce number of experiment to optimize design for performance, quality and manufacturing cost. Signal to noise ratio and orthogonal array are two major tools used in robust design. The process of optimization may be based on various parameters like best possible surface finish, maximum production rate; minimum production cost etc. in machining operations this is possible by suitable representation of the parameters in terms of objective function and constraints. It has long been recognized that conditions during cutting, such as feed rate, cutting speed and diameter of cut, should be selected to optimize the economics of machining operations. The objective of this research is to study the effect of cutting speed, feed, depth of cut, length of the tool from tool holder and coolant in an experimental approach. Robust design is a methodology for obtaining product and process condition which are minimally sensitive to the various causes of variation, and which produce high quality products with low development and manufacturing costs.

Taguchi ideas can be distilled into two fundamental concepts
(i) Quality losses must be defined as deviations from targets, not conformance to arbitrary specifications.
(ii) Achieving high system-quality levels economically requires quality to be designed into the product. Quality is designed, not into the product.

The machinability of materials is determined by surface finish. Surface roughness and dimensional accuracy are the important factors required to predict machining parameters of any machining operations, optimization of machining parameters not only increases the utility for machining economics, but also the product quality increases to a great extent. In this context, an effort has been made to estimate the surface roughness using experimental data. Since turning is the primary operation in most of the production process in the industry, surface finish of turned components has greater influence on the quality of the product. Surface finish in turning has been found to be influenced in varying amounts by a number of factors such as feed rate, work material characteristics, work hardness, unstable built up edge, cutting speed, depth of cut, cutting time, tool nose radius and tool cutting edge angles, stability of machine tool and work piece setup, and chatter, and use of cutting fluids [2]. Taguchi method consists of a plan of experiments with the objective of acquiring data in a controlled way, executing these experiments and analyzing data, in order to obtain information about the behaviour of a given process. It uses orthogonal arrays to define the experimental plans and the treatment of the experimental results is based on the analysis of variance (ANOVA)[2].

II. LITERATURE SURVEY

Traditionally, the selection of cutting conditions for metal cutting is left to the machine operator. In such cases, the experience of the operator plays a major role, but even for a skilled operator it is very difficult to attain the optimum values each time. Machining parameters in metal turning are cutting speed, feed rate and depth of cut. The setting of these parameters determines the quality characteristics of turned parts. Following the pioneering work of Taylor (1907) and his famous tool life equation, different analytical and experimental approaches for the optimization of machining parameters have been investigated. J.paulo davim (2001) this paper presents a study of the influence of cutting conditions(cutting velocity and feed) and cutting time on turning metal matrix composites. A plan of experiments, based on the techniques of Taguchi, was performed machining with cutting conditions prefixed in work pieces .M. Nalbant, H. Go¨kkaya, G. Sur (2006) investigated the orthogonal array, the signal-to-noise ratio, and analysis of variance which are employed to study the performance characteristics in turning operations of AISI 1030 steel bars using Tin coated tools. V.N. Gaitonde, S.R. Karnik, J. Paulo Davim (2007) reported the Minimum quantity of lubrication (MQL) in machining is established alternative to completely dry or flood lubricating system from the viewpoint of cost, ecology and human health issues. Hence, it is necessary to select proper MQL and cutting conditions in order to enhance machinability for a given work material. The work aims at determining the optimum amount of MQL and the most appropriate cutting speed and feed rate during turning of brass using K10 carbide tool. Chorng-Jyh Tzeng, Yu-Hsin Lin, Yung-Kuang Yang, Ming-Chang Jeng (2008) investigated the optimization of CNC turning operation parameters for SKD11 (JIS)using the Grey relational analysis method. Nine experimental runs based on an orthogonal array of Taguchi method were performed. Yung-Tien Liu , Wei-Che Chang , Yutaka Yamagata (2010) in this research, the optimization of compensation cutting for eliminating the residual form error of an aspheric surface using the Taguchi method was performed. Ilhan Asilturk, Harun Akkus (2011) they conducted experiments on hard turning operations in lathe by the orthogonal array of L9 method. Ilhan Asiltürk,Süleyman Neseli (2011) introduced a new method of mathematic models for surface roughness (Ra and Rz) on a CNC turning. LB Abhang and Hameedullah (2012) carried out the experiment on a steel turning operation on the basis of taguchi method. For analyzing significance of each parameter they used analysis of variance method known as the ANOVA method in their experiment. Ali R. Yildiz (2012) he proposed the optimization approach can be applied to two case studies for multi-pass turning operations to illustrate the effectiveness and robustness of the proposed algorithm in machining operations. Fabrício José Pontes, Anderson Paulo de Paiva, Pedro Paulo Balestrassi, João Roberto Ferreira,Messias Borges da Silva (2012) discussed the study on the applicability of radial base function (RBF) neural networks for prediction of Roughness Average (Ra) in the turning process of SAE 52100 hardened steel, with the use of Taguchi's orthogonal arrays as a tool to design parameters of the network. Nanaji Kshirsagar, Awneesh Yadav, Srinivas Athreya, Sahil Pati, Rizwan Hassan, , Vineeth Menon proposed the procedures and strengths of the Taguchi method in Lathe facing operation. The orthogonal array, the signal-to-noise ratio, and analysis of variance are employed to study the performance characteristics in facing operation.

III. EXPERIMENTAL CONCEPT

Traditional method of doing experiments are too complex and a large number of experiments must be carried out in it. When we consider a large number of parameters the number of experiment increases and a lot of time is consumed for doing that work. To solve this problem, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with only a small number of experiments [6]. The experiments were carried out with five independent factors (cutting speed, feed rate, depth of cut, length of the tool from the tool holder and coolants at three levels each. Here a standard L27 orthogonal array is used. The various factors and their levels are shown in table I.

Table I: Different parameters and levels

Levels / factors	1	2	3
Cutting speed(m/mm)	12.75	24.492	30.63
Feed rate (mm/rev)	0.130	0.260	0.520
Length of thr tool from tool holder (mm)	15	20	25
Depth of cut (mm)	1	1.5	2
Coolant	No	Soap sol	kerosene

Using minitab15 software orthogonal array required for the experiment is calculated. Experiment is conducted on the level based values from the orthogonal array and it is mentioned in the table II.

Table II: Orthogonal array using MINITAB

Sl no	Cutting speed (v)	Feed rate (f)	Length of the tool from tool holder (L)	Depth of cut (d)	Coolant (C)
1	1	1	1	1	1
2	1	1	1	1	2
3	1	1	1	1	3
4	1	2	2	2	1
5	1	2	2	2	2
6	1	2	2	2	3
7	1	3	3	3	1
8	1	3	3	3	2
9	1	3	3	3	3
10	2	1	2	3	1
11	2	1	2	3	2
12	2	1	2	3	3
13	2	2	3	1	1
14	2	2	3	1	2
15	2	2	3	1	3
16	2	3	1	2	1
17	2	3	1	2	2
18	2	3	1	2	3
19	3	1	3	2	1
20	3	1	3	2	2
21	3	1	3	2	3
22	3	2	1	3	1
23	3	2	1	3	2
24	3	2	1	3	3
25	3	3	2	1	1
26	3	3	2	1	1
27	3	3	2	1	3

A. Work piece material

The work piece material used in the study was aluminium 2011 t3. They were in the form of cylindrical bar of diameter 30mm and length 150mm.

B. Cutting tool material

The cutting tool used in the study was HSS with round nose at tip.

C. Machine tool

The turning operation is carried out on a rigid lathe with 2.25kw (spindle speed 54-1200 rpm) motor drive.

D. Surface roughness tester (fig I)

Test principle: Inductance type
Measurement range: 160 μ m
Stylus tip radius: 2 μ m
Stylus tip material: Diamond
Measuring force: 4 MN (0.4 gf)

E. Constraints

Range of depth of cut (1 to 2mm).
Range of cutting speed (10-20m/min for HSS).
Range of feed rate (0.130-.520mm/rev).

Table III: Experimental design using l27 orthogonal array

Sl no	V m/ mm	F mm /rev	L mm	D mm	c	Ra1	Ra2	Ra avg
1	1	1	1	1	1	4.255	4.010	4.132
2	1	1	1	1	2	3.252	3.562	3.407
3	1	1	1	1	3	3.433	3.476	3.454
4	1	2	2	2	1	5.354	5.684	5.519
5	1	2	2	2	2	6.023	6.285	6.156
6	1	2	2	2	3	4.049	3.692	3.870
7	1	3	3	3	1	3.084	3.225	3.170
8	1	3	3	3	2	3.492	4.001	3.746
9	1	3	3	3	3	5.282	5.381	5.331
10	2	1	2	3	1	4.621	4.731	4.677
11	2	1	2	3	2	4.811	4.962	4.886
12	2	1	2	3	3	3.926	3.611	3.768
13	2	2	3	1	1	4.212	4.614	4.413
14	2	2	3	1	2	3.962	3.172	3.492
15	2	2	3	1	3	4.212	4.610	4.410
16	2	3	1	2	1	3.812	4.962	4.683
17	2	3	1	2	2	2.928	3.018	2.973
18	2	3	1	2	3	3.182	3.678	3.430
19	3	1	3	2	1	4.281	4.619	4.450
20	3	1	3	2	2	4.384	4.998	4.691
21	3	1	3	2	3	6.623	5.092	5.857
22	3	2	1	3	1	6.293	6.087	6.910
23	3	2	1	3	2	5.431	5.230	5.330
24	3	2	1	3	3	5.031	5.781	5.406
25	3	3	2	1	1	5.281	5.087	5.184
26	3	3	2	1	2	4.281	4.671	4.476
27	3	3	2	1	3	3.981	3.991	3.986

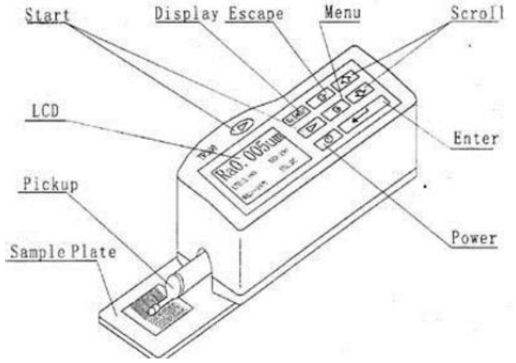

Fig 1: Surface roughness testing machine

IV. RESULTS AND DISCUSSIONS

Experiments are conducted according to the standard orthogonal array of L27 with the help of MINITAB16. The surface roughness of each work piece is measured using a surface roughness measuring instrument. Roughness value is initially measured twice and after that mean of that value is considered. The results obtained are tabulated in table III and analysis of variance of the data with the surface roughness with the objective of the analyzing the influence of each variables on the total variance of the results is performed and the results obtained are tabulated in table IV. It shows percentage contribution of each parameter towards be surface roughness.

From the above table, it is observed that the cutting velocity (20%), length of the tool from tool holder (26.92%) and depth of cut (26.92%) have great influence on surface roughness .But the factor feed rate (18%) and coolant (14.32%) have present less significant contribution on the surface roughness. Since this is a parameter based optimization design, from the above values it is clear that length of the tool from tool holder and depth of cut is the prime factor to be effectively selected to get the good surface finish.

Table IV: Anova table for surface roughness

Factor	Sum of squares	Percentage Contribution
Cutting speed	12.835	20%
Feed rate	11.486	18%
Length of the tool from the tool holder	13.653	26.92%
Depth of cut	13.653	26.92%
Coolant	10.652	14.32%

V. REGRESSION ANALYSIS

The correlations between different factors (cutting speed, feed rate, depth of cut, length of the tool from tool holder and coolant) and surface roughness were obtained by regression analysis (running a program in mat lab).

$$\mathbf{Ra=4.27\ f^{0.00528}\ L^{0.0013}\ v^{-0.0848}\ d^{-0.0586}\ c^{-0.0903}}$$

where Ra is the surface roughness.

VI. CHI-SQUARE TEST

Chi square test is conducted to check the feasibility of the test conducted. Here the expected value (E) is calculated using correlation obtained by regression analysis and it is shown in table V, table VI and table VII

Table V

Observed Value (O)	Expected Value (E)	$(O-E)^2/E$
4.132	3.416	0.1500
3.407	3.637	0.0145
3.454	3.416	4.22e-03
5.519	3.349	1.406
6.156	3.566	1.881
3.870	3.349	0.810
3.170	3.307	5.67e-03
3.746	3.52	0.0145
5.331	3.307	1.238

Table VI

Observed Value (O)	Expected Value (E)	$(O-E)^2/E$
4.676	3.116	0.781
4.886	3.317	0.742
3.768	3.318	0.136
4.413	3.245	0.420
3.492	3.454	4.180e-04
4.41.	3.245	0.418
2.973	3.38	0.502
3.430	2.179	6.70e-04
4.450	3.38	0.0262

Table VII

Observed Value (O)	Expected Value (E)	$(O-E)^2/E$
4.691	3.099	0.588
5.857	3.299	0.587
6.190	3.099	2.454
5.330	3.126	3.003
5.406	3.328	1.087
5.184	3.126	2.254
4.476	3.195	10238
4.782	3.402	0.338
3.986	3.195	0.195

$\chi^2 = \sum(O-E)^2/E = 20.29038$
Here degrees of freedom = n-1 = 26.
Taking a level of significance α =0.01.
$\chi^2_{\alpha,n-1}$=36.473 (table value)

Since $\chi^2 < \chi^2_{\alpha,n-1}$ the sample is having goodness of fit

VII. CONCLUSION

For solving machining optimization problems, various conventional techniques had been used so far, but they are not robust and have problems when applied to the turning process, which involves a number Of variables and constraints. To overcome the above problems, Taguchi method is used in this work. Since Taguchi method is experimental method it is realistic in nature. According to this study the prime factor affecting surface finish are length of the tool from the tool holder and depth of cut.

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Optimization of Cutting Parameters on Tool life and Surface Roughness in End Milling of AlSi/AlN MMC - Taguchi Method and Grey Relational Analysis

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Abstract – **The highly abrasive of ceramic particles reinforcement and irregular nature of the particles along the matrix material are the main problems leading to the difficulties in machining of Metal matrix composites (MMCs). Therefore, the experimental investigation was made on machinability of newly developed of MMC with reinforcement of smaller particles. End milling of AlSi/AlN MMC with various volume fraction of particles reinforcement (10%, 15% and 20%) under dry cutting condition was performed using two types of cutting tool (uncoated & PVD TiAlN coated carbide). In order to obtain better surface finish and at the same time longer tool life, the optimization of cutting parameters were conducted using Taguchi method and Grey Relational Analysis (GRA). Eighteen experiments (L18) orthogonal array with five factors (type of tool, cutting speed, feed rate, depth of cut, and volume fraction of particles reinforcement) were implemented. The analysis of optimization using GRA concludes that the better results for the combination of lower surface roughness and longer tool life could be achieved when using uncoated carbide with cutting speed 240m/min, feed 0.4mm/tooth, depth of cut 0.3mm and 15% volume fraction of AlN particles reinforcement. The study confirmed that with a minimum number of experiments, Taguchi method is capable to determine the optimum cutting parameters for the surface roughness and tool life using GRA for this newly develop material under investigation.**

Keywords - **AlSi/AlN MMC, uncoated carbide, coated carbide, surface roughness, tool life, Taguchi method, Grey relational analysis**

I. INTRODUCTION

Metal matrix composites has many potential in engineering application such as in automotive and aerospace due to their superior mechanical properties including high strength, high hardness, good wear resistance and excellent strength to weight ratio [1]. However, the highly abrasive and irregular nature of the reinforcement causes the machinability of MMCs facing difficulties. Diamond tools are considered the most significantly for the machining of MMCs [2, 3]. Polycrystalline diamond (PCD) also shows better wear resistance and produced better surface finish than carbide or alumina tools when machining of MMCs [2, 4, 5]. However, the innovation of coated carbide shows that the kind of tools be able to be used in machining of MMCs with a good quality of products.

Nowadays, most of manufacturing industries are facing great challenges in achieving high quality products with maximum productivity and economically. Though the engineering components made from MMCs are primarily manufactured in near-net-shape, the finishing process of components is always essential for the better quality of product. The quality of product surfaces is one of the great importances for product quality and its function [6]. For example Toyota has developed a metal matrix composite (MMC) diesel engine piston but they still need secondary machining operations for finishing purposes [7, 8]. In meantime, longer tool life will ensure the higher productivity in terms of production rate and cost [9]. In end milling, optimization of cutting parameters is a must to ensure the lower surface roughness (Ra) and longer tool life. Cutting speed (V), feed rate (f), axial depth of cut (DOC) and volume fraction of reinforcement are the examples of cutting parameters will effects the surface roughness value and tool life.

Design of experiment (DOE) methods is widely used in experimental approaches such as full factorial, response surface methodology (RSM) and Taguchi method. Taguchi method or robust design is an engineering methodology, appropriate for improving productivity during research and development [10]. High quality products can be produced in a short time and at low cost by using a matrix experiment. Ghani et al. [11] determined the optimum cutting parameters in end milling when machining hardened steel AISI H13 with a TiN coated P10 carbide insert tool under semi-finishing and finishing conditions of high cutting speed. They found that the optimization of the combination for the low resultant cutting force and a good surface finish are high cutting speed, low feed rate and low depth of cut. Oktem et al. [12] developed a Taguchi optimization method for low surface roughness in terms of process parameters when milling the mould surfaces of 7075-T6 aluminium material. They concluded that the Taguchi method is very suitable in solving the surface quality problem of mould surfaces. Shetty et al. [13] analyzed the influence of speed, feed, depth of cut, nozzle diameter and steam pressure in the turning of age hardened Al6061-15% vol. SiC 25 µm particle size MMC with cubic boron nitride inserts, CBN. They determined the multi-performance of the machining characteristics and indicated that, among the parameters, steam pressure is the most significant parameter. Nalbant et al. [14] analyzed the optimum of three cutting parameters; insert radius, feed rate, and depth of cut in machining of AISI 1030 steel bars. They demonstrated that the radius of insert and feed rate are the main parameters that influence the surface roughness of machined material. Ramanujam et al. [15] determined the optimum cutting parameters for turning Al-SiC(10p) MMC using ANOVA and grey relational analysis. They concluded that the performance characteristics of the Al-SiC (10p) MMC machining process, such as surface roughness and specific power, are improved by using the Taguchi method.

Grey relational analysis has been introduced in optimizing the control parameters which having multi-responses through grey relational grade by Deng in 1989 [16]. Grey relational analysis was applied in this experiment to find the most influential factor among the end milling cutting parameters that affects the surface roughness, and tool life. Data preprocessing was employed based on 'smaller-the-better' for Ra and 'larger-the better' for tool life. To obtain the grey relational coefficients, the deviation sequences were calculated. In addition, the grey relational coefficients were averaged using equal weighting to obtain grey relational grade.

The main objective of this paper is to investigate and optimize the cutting parameters on surface roughness and tool life. Taguchi method with orthogonal array [10] was utilized as DOE for experimental investigation during end milling of AlSi/AlN MMC. Grey relational analysis (GRA) was employed for optimization purposes by measuring the degree of relationship between machining characteristics with specific steps [17]. This new material is under investigation in terms of its machinability and the effects of the cutting parameters.

II. METHODOLOGY

The work material used for the experiment was a 100 mm × 150 mm × 50 mm block of age treated AlSi/AlN MMC. The chemical composition of the AlSi alloy, as shown in Table I, was determined by a glow discharge profiler (Model-Horiba Jobin Yyon). The mean size of the reinforcement particles is <10 µm and the purity >98%. The AlSi/AlN MMC work material passed through a double ageing process, was hardened at 540 °C for 6 hours, which was followed by water solution treatment. It was then reheated for another 4 hours at 180 °C, immediately cooled in open air at room temperature. The purpose of the heat treatment process is to increase the mechanical properties such as strength and hardness.

TABLE I
CHEMICAL COMPOSITION OF AL-SI ALLOY

Elements	Fe	Si	Zn	Mg	Cu	Ni
Wt%	0.42	11.1	0.02	0.01	0.02	0.001
Elements	Sn	Co	Ti	Cr	Al	
Wt%	0.016	0.004	0.0085	0.008	Balance	

The milling test was conducted using uncoated carbide inserts (Catalogue no: R390-11 T3 02E-KM H13A and R390-11 T3 02E-PM 1030) for PVD TiAlN coated carbide under dry cutting conditions. Cutting inserts were mounted on a tool body with a diameter of 20mm. Fig. 1 shows an illustration of the cutting tool geometry and the specification of the cutting tool is shown in Table II. The wear progression on the cutting edge will be measured using a two-axis toolmaker's microscope with a digital micrometer for the x-axis and y-axis with 0.001 mm resolution. For these experiments, 0.3mm flank wear (VB) will be taken as the tool life criteria in milling according to ISO 8688-2. While the surface roughness value (Ra) was measured using a contact-type stylus profilometer: Mahr Perthometer M1.

There are five factors to be investigated. The first factor is considered at two levels, and a further four factors are considered at three levels. Table III shows the experimental factors or cutting parameters to be designed and their levels.

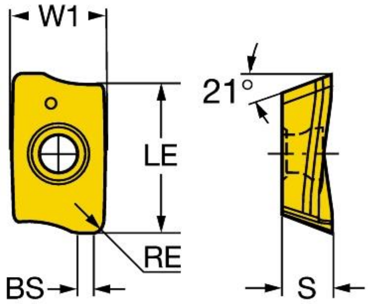

Fig. 1. Geometry of cutting insert

TABLE II
CUTTING TOOL SPECIFICATION

Tool type	Uncoated and PVD TiAlN coated carbide (2.2 µm coating thickness)
Manufacturer	Sandvik
Rake	Positive
Nose radius	0.2mm
W1	6.8 mm
BS	0.7 mm
LE	11.0 mm
S	3.59 mm
Lead angle	90°
Base Material	EH520, fine-grained carbide, WC-10%CO

TABLE III
CUTTING PARAMETERS AND LEVELS

Parameter	Factor	level 1	2	3
coating of insert	A	uncoated	coated	
cutting speed (m/min)	B	240	320	400
feed rate (mm/tooth)	C	0.3	0.4	0.5
Axial depth of cut (mm)	D	0.3	0.4	0.5
Volume fraction of reinforcement (%)	E	10	15	20

III. RESULTS AND DISCUSSION

Taguchi methods were applied in this experiment. Table IV shows the data for surface roughness (Ra) and tool life which taken according to the cutting parameters designated via orthogonal array L18.

TABLE IV
EXPERIMENTAL RESULTS FOR SURFACE ROUGHNESS (RA) AND MATERIAL REMOVAL RATE (MRR)

Exp no.	A	B	C	D	E	Ra (µm)	Tool life (min)
1	1	1	1	1	1	0.405	72
2	1	1	2	2	2	0.3825	60
3	1	1	3	3	3	0.6075	70
4	1	2	1	1	2	0.5125	66
5	1	2	2	2	3	0.437	50
6	1	2	3	3	1	0.51	23
7	1	3	1	2	1	0.425	17
8	1	3	2	3	2	0.355	28
9	1	3	3	1	3	0.565	38
10	2	1	1	3	3	0.745	45
11	2	1	2	1	1	0.655	64
12	2	1	3	2	2	0.56	53
13	2	2	1	2	3	0.5375	48
14	2	2	2	3	1	0.47	25
15	2	2	3	1	2	0.6725	48
16	2	3	1	3	2	0.6325	27
17	2	3	2	1	3	0.744	44
18	2	3	3	2	1	0.4975	13

Grey relational analysis (GRA) will be used for the optimization analysis. The calculation started with the calculation of data pre-processing. For surface roughness, the data will be pre-processed as 'smaller-the-better'. The equation used as follow;

$$xi * (j) = \frac{\max\ xi(0)(j) - xi(0)(j)}{max\ xi(0)(j) - min\ xi(0)(j)} \qquad (1)$$

For the tool life, the data will be pre-processed as 'larger-the-better'. The equation used was different compared to the previous equation. The equation stated as follows;

$$xi * (j) = \frac{xi(0)(j) - min\ xi(0)(j)}{max\ xi(0)(j) - min\ xi(0)(j)} \qquad (2)$$

All the calculations results is summarized and shown in table V.

TABLE V
PERFORMANCE CHARACTERISTIC AFTER DATA PRE-PROCESSING SEQUENCES AND DEVIATION SEQUENCES

Exp no.	Data pre-processing sequences results		Deviation sequences	
	Ra	Tool life	Ra	Tool life
1	0.872	1.000	0.128	0.000
2	0.929	0.797	0.071	0.203
3	0.353	0.966	0.647	0.034
4	0.596	0.898	0.404	0.102
5	0.790	0.627	0.210	0.373
6	0.603	0.169	0.397	0.831
7	0.821	0.068	0.179	0.932
8	1.000	0.254	0.000	0.746
9	0.462	0.424	0.538	0.576
10	0.000	0.542	1.000	0.458
11	0.231	0.864	0.769	0.136
12	0.474	0.678	0.526	0.322
13	0.532	0.593	0.468	0.407
14	0.705	0.203	0.295	0.797
15	0.186	0.593	0.814	0.407
16	0.288	0.237	0.712	0.763
17	0.003	0.525	0.997	0.475
18	0.635	0.000	0.365	1.000

Table VI shows the grey relational coefficient, grey relational grade and grade order. From the table, it shows that experiment 1 indicated the higher grey relational grade, means the cutting parameters in experiment 1 is said to be close to the optimal. It also could be seen clearly in Fig. 2.

TABLE VI
PERFORMANCE CHARACTERISTIC AFTER CALCULATION OF GREY RELATIONAL COEFFICIENT & GREY RELATIONAL GRADE

Exp no.	Grey relational coefficient		Grey relational grade	Grade order
	Ra	MRR		
1	**0.796**	**1.000**	**0.898**	**1**
2	0.876	0.711	0.794	2
3	0.436	0.937	0.686	5
4	0.553	0.831	0.692	4
5	0.704	0.573	0.638	6
6	0.557	0.376	0.466	14
7	0.736	0.349	0.542	9
8	1.000	0.401	0.701	3
9	0.481	0.465	0.473	12
10	0.333	0.522	0.428	16
11	0.394	0.787	0.590	7
12	0.488	0.608	0.548	8
13	0.517	0.551	0.534	10
14	0.629	0.386	0.507	11
15	0.380	0.551	0.466	13
16	0.413	0.396	0.404	18
17	0.334	0.513	0.423	17
18	0.578	0.333	0.456	15

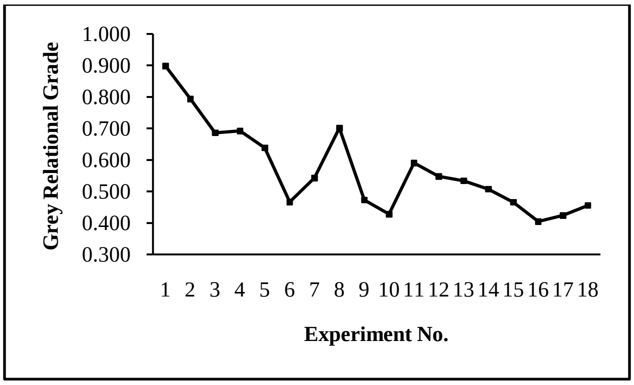

Fig. 2. Grey relational grade (the higher grade the better)

The mean response table for overall grey relational grade is shown in Table VII and also shown in fig. 3 graphically. From the response tables and response graph, the optimal parameter combination has been determined as A1, B1, C2, D1, and E2.

TABLE VII
MEAN RESPONSE TABLE FOR GREY RELATIONAL GRADE

Response table for grey relational grade					
Level/Factor	A	B	C	D	E
1	*0.655	*0.657	0.583	*0.590	0.577
2	0.484	0.551	*0.609	0.585	*0.601
3		0.624	0.564	0.570	0.468
diff Δ	0.170	0.157	0.093	0.058	0.070

From Fig. 3, the optimum levels for minimum surface roughness and longer tool life are the higher value of mean response were; A_1 (uncoated carbide insert), B_1 (cutting speed: 240m/min), C_2 (feed rate: 0.4mm/tooth), D_1 (axial depth: 0.3mm) and E_2 (15% volume fraction of reinforcement).

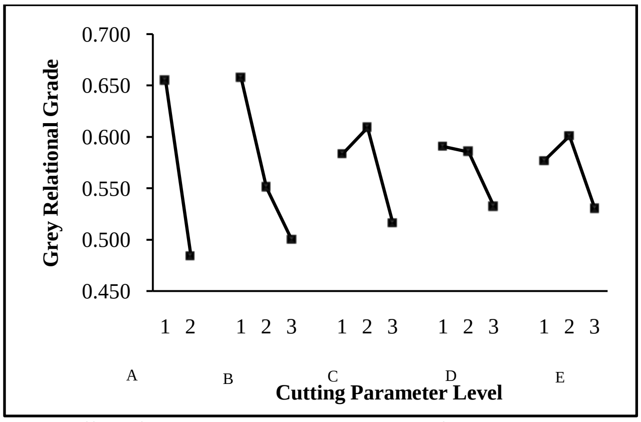

Fig. 3. Effect of cutting parameter levels to the surface roughness and tool life

IV. CONCLUSION

Taguchi method and Grey relational analysis was applied in this experimental investigation. The aim of this paper is to determine the optimum cutting parameters for surface roughness and tool life while milling AlSi/AlN MMC. The following observations were made:

1. Based on the Grey Relational Analysis (GRA), the mean response for GRA as shown in Table V11 and Fig. 3 shows the effect of cutting parameter levels to the surface roughness and tool life respectively. Therefore these parameters $A_1B_1C_2D_1E_2$ with uncoated carbide insert, cutting speed of 240m/min, feed rate of 0.4mm/tooth, axial depth of 0.3mm, and 15% volume fraction of AlN reinforcement are the optimum combination of cutting parameters for the designated experiment.

2. The Taguchi method is suitable not only for the optimization of cutting parameters in a milling operation, so it can also be used for other operations; turning, grinding etc.

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Authentication Based on Seating Pressure Distribution Using the MT System

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Abstract - **This paper proposes a system for authentication based on seating pressure distribution, using the MT system as a new method of biometric authentication that is difficult to forge and does not inconvenience users. The main characteristic is that the only action required of the user is to sit down. Feature values were extracted based on the pressure distribution when individuals sat down in the seat, and individual users were distinguished from other persons by means of the Mahalanobis-Taguchi (MT) system used in quality engineering. The result of the experiment was a False Rejection Rate of 2.2% and a False Acceptance Rate of 1.1%.**

Keywords – **Quality engineering, Mahalanobis-Taguchi (MT) system, Authentication, Seating pressure**

I. INTRODUCTION

The need for identity authentication has been growing in recent years. The methods of authentication are broadly classified into the three categories listed in Table 1. Authentication by something you know and authentication by something you have provide a high level of certainty, but these methods are beset by the risk of memory lapse, loss, theft and forgery. The third method, authentication by something you are (biometric authentication), includes authentication using physical characteristics and authentication using behavioral characteristics. Physical characteristics include, for example, fingerprints, veins, or irises, and the accuracy of authentication is generally high because of their unique and permanent qualities. However, identity fraud using artificial fingers or artificial irises to forge physical characteristics has recently become a problem. In addition, fingerprint authentication inconveniences the user with the need for extra action, such as scanning fingerprints. Authentication by facial image is hardly stress-free because having your face photographed poses a psychological burden. Authentication by keystroke patterns when using a keyboard has also been proposed as a form of authentication using behavioral characteristics [1]. The advantage of methods using such behavioral characteristics is that they are tough to forge or imitate, so identity fraud would be difficult, but since the reproducibility of behavioral characteristics is low, the disadvantage is alower authentication accuracy.

Table 1: Authentication methods

Authentication types	Examples
Something You Know	Password, Code number
Something You Have	Magnetic card, IC card, Key
Something You Are	Fingerprints, Veins, Irises

The search is still on for a highly accurate authentication method that places no burden on the user.

II. PROPOSAL FOR A SYSTEM OF AUTHENTICATION BY SEATING PRESSURE

Therefore, this paper proposes a system of authentication by seating pressure distribution using the MT (Mahalanobis-Taguchi) system [2] as an authentication method that would be difficult to forge, and that would not inconvenience the user. The main characteristic of the system for authentication by seating pressure distribution is that it verifies identity based on the distribution of pressure when an individual sits on a chair, or in the driver's seat of a vehicle, and there is no need for the user to take any other action than to sit down.

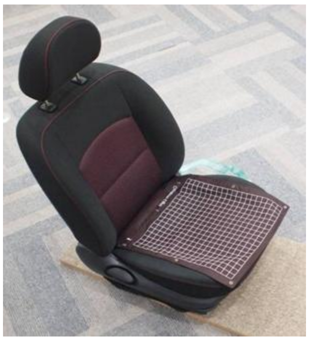
III. SEATING PRESSURE DISTRIBUTION AND FEATURE VALUES

A. Measuring Seating Pressure Distribution

As indicated in Fig. 1, the driver's seat of a vehicle is fitted with a pressure sensor sheet (Conform-Light by NITTA Corporation), and when the individual sits in the seat, it is possible to obtain the kind of pressure distribution measurements shown in Fig. 2. The pressure sensor sheet has a grid of 18 by 20 pressure sensor cells measuring about 1 cm in diameter with each cell outputting the pressure on a 256-point scale. Fig. 2 (a) shows an example of a two-dimensional measurement, while Fig. 2 (b) shows a three-dimensional example. Pressure distribution data can be obtained at a maximum speed of 80 frames per second. The data can be processed in the same way as image data and runs on many image processing technologies.

B. Extracting Feature Values

Fig. 2 shows the results of measuring pressure distribution in the seat, but the pattern characteristics vary with the individual. For authentication purposes, the differences in the patterns are digitized in the form of feature values. For example, the feature values used here include maximum pressure value, average pressure value, hip print area, and so on. Needless to say, it is important to figure out which feature values are highly effective for distinguishing between individuals. In the present example, we devised a total of 39 feature values and used the MT recognition technique used in quality engineering to distinguish between individuals.



(a) Driver's seat in vehicle

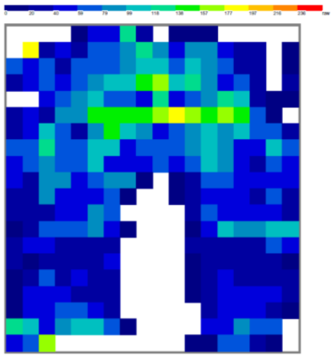
(b) Pressure sensor sheet

(c) Measuring seating pressure distribution

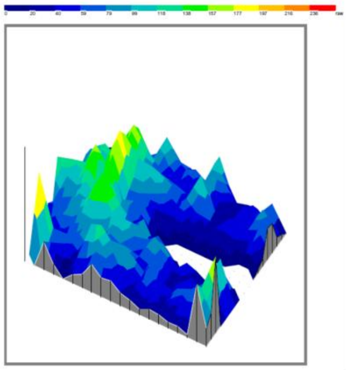
Fig. 1 The experimental device

IV. IDENTIFICATION BY USINGTHE MT METHODFOR QUALITY ENGINEERING

We use the MT method of quality engineering developed by Dr. Taguchi for the user authentication. With the MT method, we create a unit space based on the feature values for a particular individual, and then we calculate the distance from there (the Mahalanobis distance). If the value is small, the system recognizes the person as a particular individual; if the value is large, the system recognizes that the person is someone else. That is, multiple feature values are converted into a single evaluation indicator referred to as the Mahalanobis distance, and based on this value, the system distinguishes between a particular individual and other persons.



(a) Seating pressure distribution (2D display)



(b)Seating pressure distribution (3D display)

Fig. 2 Measurement example of seating pressure distribution

The method for calculating the Mahalanobis distance D is explained below. To start with, before creating the unit space, we standardize the mean for each feature value as 0, and standard deviation as 1. Then, if the number of standardized feature values u is k, and the number of measured data is n, the square value of the Mahalanobis distance D for p-th data is given in the following equation. Below, we refer to the square value of the Mahalanobis distance as the MD value. Then, u_{ip} is the standardized feature value, and r_{ij} is the correlation coefficient for the feature value $u_i$and the feature value u_j. The matrix for the correlation coefficient is referred to as the correlation matrix.

$$D^2 = u_{1p}, u_{2p}, \cdots, u_{kp} \begin{bmatrix} 1 & r_{12} & \cdots & r_{1k} \\ r_{21} & 1 & \cdots & r_{2k} \\ \vdots & \vdots & & \vdots \\ r_{k1} & r_{k2} & \cdots & 1 \end{bmatrix}^{-1} \begin{bmatrix} u_{1p} \\ u_{2p} \\ \vdots \\ u_{kp} \end{bmatrix}$$

In addition, with the MT method, the MD value is divided by the number of feature values k, so that the mean value of the Mahalanobis distance, calculated by using the individual's unit space sample data, is 1. If the feature value matches the mean value for the unit space data, the MD value is 0. Consequently, when calculating the MD value using feature value data for the individual, the MD value should be near to the data recorded for that unit space, so the expectation is for a small MD value near to 0. Conversely, when the feature value of another person is concerned, the MD value will be high if it is calculated using the individual's correlation matrix when the unit space was created because the feature value for the other person has a different pattern than that of the individual. Consequently, if it is possible to set a threshold value between the MD value for the individual and the MD value for someone else, the individual can be distinguished from other persons.

V. AUTHENTICATION BASED ONTHEMAHALANOBIS DIATANCE

For this research, we identified the authentication by calculating a single MD value based on 39 feature values and using the value as the indicator. For example, we created a unit space with individual data for the owner of a vehicle, and then we calculated the MD value based on unit space for unidentified data (the individual or other persons). In this instance, the smaller the MD value compared to the predetermined threshold value, the likelier that the person was the owner of the vehicle. Conversely, if the MD value was high compared to the threshold value, the person was identified as someone else.

Six subjects (Mr. A to Mr. F) collaborated with the present experiment where we calculated the MD value for the unit space of Mr. A. The result is shown in Fig. 3. The MD value for Mr. A is the smallest and the only one below 10, while the Mahalanobis distance for Mr. B to Mr. F is large and far exceeds the threshold value of 100. In this case, it is easy to distinguish between the individual and other persons using the MD value as the indicator.

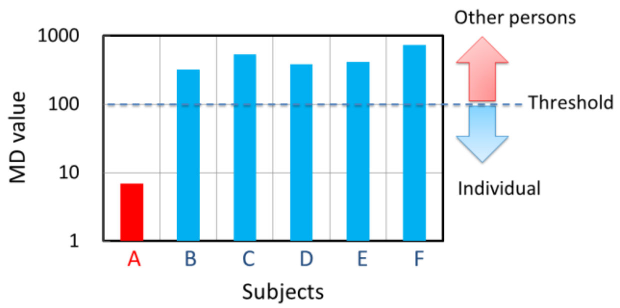


Fig. 3 Distinguishing between the individual and other persons based on the Mahalanobis distance (MD value)

VI. RESULTS OF AUTHENTICATION EXPERIMENT

Next, we discuss the results of the experiment since we conducted the experiment for the identification rate for authentication based on seating pressure distribution. Authentication is always beset by two error rates. Namely, the False Rejection Rate when the individual is not recognized, and the False Acceptance Rate when someone else is accepted as the individual. We made an experimental study of these two error rates.

For each of the six subjects (Mr. A to Mr. F), we conducted two experiments. In one of the experiments the individual sat down 15 times to see whether he was correctly identified or not, and for the other experiment, we brought in another 25 persons, who sat down three times each for a total of 75 times, to see whether or not they were mistakenly identified as the individual in question. In the experiments, the threshold value for the Mahalanobis distance was set to 100 for identification. The results are shown in Table 2.

Table 2: Identification rates for authentication by seating pressure distribution

Subjects	False Rejection Rate	False Acceptance Rate
A	0.0%	0.0%
B	6.7%	1.3%
C	0.0%	0.0%
D	0.0%	5.3%
E	6.7%	0.0%
F	0.0%	0.0%
Average	2.2%	1.1%

According to Table 2, the average value for the False Rejection Rate is 2.2%, while the average value for the False Acceptance Rate is 1.1%. That is, the identification success rate for particular individuals is 97.8%, while the identification success rate for other persons is 98.9%. In addition, in Table 2, the False Rejection Rate is 6.7% because there was one case of misidentification in 15 events. When recognizing an individual, there is a high likelihood that even if there is one failure, the individual will be correctly identified if the identification is attempted again. The False Acceptance Rate of 1.3% is due to one failure in 75 events, and the False Acceptance Rate of 5.3% represents a ratio of 4 failures in 75 events.

VII. USESFOR AUTHENTICATION BYSEATING PRESSURE DISTRIBUTION

To start with, there are practical applications for the driver's seats in vehicles. For example, to stop thefts by preventing the engine from starting unless the individual is authenticated, or to automatically set the seat position or tilt the angle of the steering wheel once the driver has been authenticated. It would also be possible to develop a range of services such as automatically setting the air conditioning, car audio and car navigation systems.

In the future, another effective application might be in offices. These days many offices use hot desking where employees no longer have assigned desks. One might imagine applications in the field of office security where employees are automatically identified and logged into a PC when they arrive at the workplace and sit down in a chair.

VIII. CONCLUSION

This paper proposes a system for authentication based on seating pressure distribution, using the MT system as a new method of biometric authentication that is difficult to forge and does not inconvenience users. The main characteristic is that the only action required of the user is to sit down. Feature values were extracted based on the pressure distribution when individuals sat down in the seat, and individual users were distinguished from other persons by means of the Mahalanobis-Taguchi (MT) system used in quality engineering. The result of the experiment was a False Rejection Rate of 2.2% and a False Acceptance Rate of 1.1%. Adopting this technology in the driver's seats of vehicles would serve to prevent automobile theft.

ACKNOWLEDGMENT

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Taguchi Method in Research

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Abstract – **Taguchi Method has been extensively used for over 60 years in making industrial processes and products robust against noisy environmental conditions and noisy process inputs. Standard Orthogonal Arrays (OA's) are used for planning the experiments when control factors are required to be orthogonal. Over the last decade, the focus is shifting towards use of Taguchi Method for research problems, wherein study of interactions becomes important. Taguchi developed a graphic tool, called linear graphs, which allows study of a few specific interactions using standard OA's. This paper postulates goals of research and criteria for suitably modifying linear graphs of L54 and L81 to achieve the research goals.**

Keywords – **Taguchi Method, Linear graphs**

INTRODUCTION

Taguchi Method is probably the best known method for developing ROBUST processes and products [1-2]. Taguchi proposed several path breaking concepts, and derived statistical expressions for, Quality Loss Function, use of noisy inputs, Signal-to-Noise Ratios (SN Ratio or SNR), use of Orthogonal Arrays (OA's) and Linear Graphs [3]. The concept of introducing noisy inputs in controlled experiments and use of Signal-to-Noise Ratios as objective function was the corner stone in making the industrial processes or products ROBUST against the selected noises. The control factors are orthogonal to each other so that OA's could be used for planning and conducting the experiments. Taguchi proposed and developed a graphic tool, called Linear Graphs, to assist in study of interactions between selected control factors and, yet, simultaneously achieve the objective of developing a ROBUST process.

Research, however, requires more thorough study of the processes and thus has more varied goals. This paper postulates the goals of research and obtains suitable modifications of standard OA's to achieve these goals.

METHODOLOGY

Taguchi Method consists of performing OA based experiments using control factors and noise factors so that the process or product becomes ROBUST with respect to the selected noise and identifies the "best settings" of control factors which will improve the mean and reduce the variance in the desired output. Taguchi method is the only method that encourages use of noisy inputs during the experiments to achieve a "ROBUST" process or product. Taguchi defined "Quality Loss Function" and derived special objective functions called "Signal to Noise Ratios (SNRs)" such that maximizing SNRs resulted in reduced quality loss. Taguchi used a specific set of "Design of Experiments" called the "Orthogonal Arrays (OA's)" for planning the experiments with control factors having 2, 3, 4 or 5 levels and collecting data which captured the effect of noise factors. Analysis of Mean (ANOM) and Analysis of Variance (ANOVA) are used to determine the factor effects for each level of control factors and to determine the Significance or Rank of each control factor. Furthermore, the analysis predicts the output when control factors are used at their best settings. Confirmation or verification experiments are then performed and output is compared with the predicted results. A good match indicates that the process has been optimized and also that it has become ROBUST with respect to the selected noise factors.

Research usually begins by studying an existing process and then improving it by introducing a "new" idea to give one or more of the following good results,

a) Substantially improve an existing feature or property
b) Obtain/achieve an additional desirable feature
c) Eliminate (not reduce!) an undesirable effect
d) Reduce resources required, namely, materials and time or effort
e) Eliminate a component from the system, thus making the system cheaper (low cost) and simpler (and hence more reliable)
f) Eliminate an operation, thus making the process shorter (in time) and hence improve productivity
g) Make the process or product 'insensitive' to uncontrollable noisy inputs (materials, humans and environment factors like temperature, humidity, dust etc)
h) Exploit non-linearities between "R", process control factors and noise factors, to attain better features and ROBUST performance
i) Eliminate the conflict between two response (output) parameters say, A and B. The conflict is stated as "if A improves, then B degrades"

or "if B improves, then A degrades". Eliminating conflict means achieving "A improves as well as B improves" or simply "BOTH A and B improve"

j) Take the system to its "natural" limits that is very close to its "ideal" result

k) Determine a mathematical model that gives response "y" as a function of research parameter "R" as well as other control factors, say A, B, C, D etc. The dependence of "y" on "R" and "A", "B" etc. could be linear, quadratic or cubic.

***"R" the research Parameter*:** If we introduce "R" as the "new" or "additional" control factor in any existing experiment, we would like to do it in following 4 ways,

(1) Use "R" as the "new" Multilevel Control Factor:
(2) Use "R" as a Blocking Factor
(3) Use OA of strength 3, 4 or more
(4) Develop a model for factor effects for "R"

(1) Use "R" as the "new" Multilevel Control Factor:

The existing process may have several control factors, say A, B, C, D etc. and we wish to add a new control factor to study its effect on output. While the existing control factors (A, B, C, D etc) may be taken at 3-levels each, the new research control factor, called "R" for Research, may be taken as a multilevel factor, with 6, 8, or 9 levels. This will allow us to determine the effect of the new factor "R" with finer details or more accuracy.

The above requirement translates into the new task of constructing an OA which has mixed levels, say one 6-level or 9-level column and other columns of 2 or 3-levels. Mixed level arrays can be easily obtained from linear graphs of a suitable OA that has adequate degrees of freedom to determine factor effects and interactions. Examples of suitable OA's (having 3-levels) for this purpose are L9, L18, L27, L54 and L81.

Combining columns 1 and 2 in L18 results in a modified L18 OA with one 6-level factor and six 3-level factors (see Fig 1a). Similarly, L27 with columns 1 and 2 combined (and keeping columns 3 and 4 unassigned or empty) result in a modified L27 OA with one 9-level factor and nine 3-level factors (see Fig 1b).

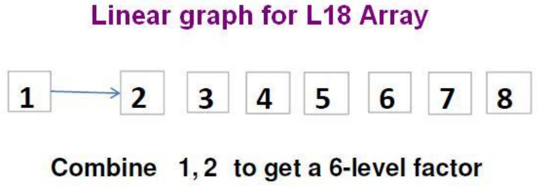

Fig 1a Combine 1, 2 columns to get a 6-level factor

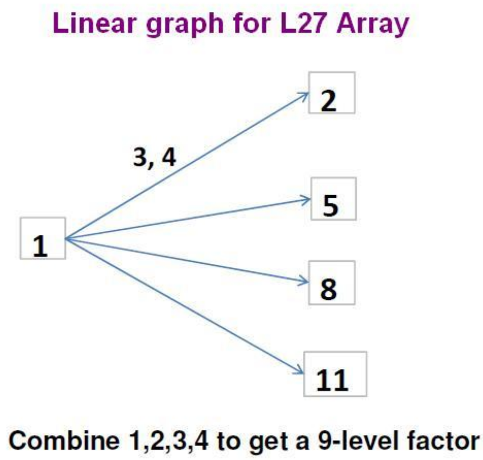

Fig 1b Combine 1,2,3,4 columns to get a 9-level factor

Experiments can be performed using these mixed level modified L18 arrays and data analysed using ANOM and ANOVA to find the best levels of control factors and predict the best result (using the best levels of control factors)

(2) Use "R" as a Blocking Factor:

We can use the research factor "R" as a blocking factor with an OA of a size that was suitable for performing the existing experiment. As an example, let us take L9 with four control factors of 3-levels each as the starting OA. Now, we create an extra column for "R" and assign level 1 in column for "R" in each of the 9 rows of the L9 array. This is called block 1. Now add a copy of L9 below the 9th row, thus adding rows 10 to 18. This is called block 2. Assign level 2 to column for "R" in each of the rows 10 to 18. We may continue adding more blocks of L9 and assigning levels 3, 4 etc till we get the desired count of levels for "R", say 6-levels or 9-levels. The blocking procedure is shown in Fig 2.

L9 as Starting Array					Blocking Factor
Expt No.	A	B	C	D	R
1	1	1	1	1	1
2	1	2	2	2	1
3	1	3	3	3	1
4	2	1	2	3	1
5	2	2	3	1	1
6	2	3	1	2	1
7	3	1	3	2	1
8	3	2	1	3	1
9	3	3	2	1	1
10	1	1	1	1	2
11	1	2	2	2	2
12	1	3	3	3	2
13	2	1	2	3	2
14	2	2	3	1	2
15	2	3	1	2	2
16	3	1	3	2	2
17	3	2	1	3	2
18	3	3	2	1	2
19	1	1	1	1	3
20	1	2	2	2	3
21	1	3	3	3	3
22	2	1	2	3	3
23	2	2	3	1	3
24	2	3	1	2	3
25	3	1	3	2	3
26	3	2	1	3	3
27	3	3	2	1	3
	.	.	.	.	
36	and so on	.	.	.	4
. . .	.	.	.	.	
45	and so on				5
. . .					
54	and so on				6
. . .					
63	and so on				7
. . .					
72	and so on				8
. . .					
81	and so on				9

Fig 2 R as blocking factor with L9 as Starting Array

Creation of OA using blocking with research factor "R" has the useful property that it would allow study interactions of "R" with all control factors of the starting array. Thus, we can study interactions RxA, RxB, RxC, RxD, etc. The starting arrays are usually small and could be L4(2^3), L8(2^7), L9(3^4) or L12(2^11).

The blocking technique allows us to create an OA with a new research factor "R" that has multilevels (say 6 or 9) along with existing control factors with 2 or 3 levels. The resulting array, using above construction, allows us to study factor effects of A, B, C, D etc and R as well as study interactions RxA, RxB, RxC, RxD etc.

Another important property is that analysis is possible at every stage of construction. At the starting stage, L9 array allows determination of factor effects of A, B, C, and D. After adding L9 at the second stage, the resulting array is L18 with "R" with 2 levels and A, B, C, D with 3 levels. We can determine factor effects of A, B, C, D at 3 levels and "R" at 2 levels and also determine interactions RxA, RxB, RxC and RxD. On adding L9 at stage 3, results in L27 array wherein interactions RxA, RxB, RxC and RxD can be determined. The progressive block additions can be depicted precisely by construction of linear graphs as shown in Fig 3.

Addition of blocks of starting array can be continued till we get a set of arrays viz., "R" with 4 levels gives L36, "R" with 5 levels gives L45, "R" with 6 levels gives L54, "R" with 7 levels gives L63, "R" with 8 levels gives L72, and "R" with 9 levels gives L81.

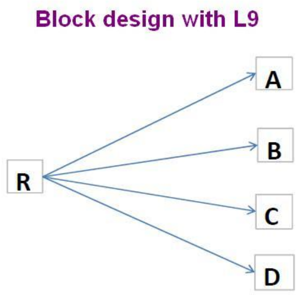

Fig 3 R as blocking factor with L9 as Starting Array

Thus, addition of starting array at every stage allows us to determine the factor effects and interactions. On the other hand, in the normal use of a bigger array, say L27, L36, L45, L54, and L81, would need output in all rows before any analysis can be done.

(3) Use OA's with Strength of 3 or 4:
Normal OA's have the default strength of 2, which implies that any 2 columns will have all combinations equal number of times. So, we can define the property that an OA should possess strength of 't' is that any 't' columns will have all combinations equal number of times.

Obviously, as strength increases the size of the array (number of rows) increases linearly with strength. Some examples of OA's with higher strength are given below,

L16 (15 columns, strength 2), 2-levels
L16 (8 columns, strength 3), 2-levels
L64 (63 columns, strength 2), 2-levels
L64 (7 columns, strength 6), 2-levels
L54 (25 columns, strength 2), 3-levels
L54 (5 columns, strength 3), 3-levels
L81 (40 columns, strength 2), 3-levels
L81 (12 columns, strength 3), 3-levels
L64 (21 columns, strength 2), 4-levels
L64 (6 columns, strength 3), 4-levels
L125 (31 columns, strength 2), 5-levels
L125 (6 columns, strength 3), 5-levels
L625 (156 columns, strength 2), 5-levels
L625 (6 columns, strength 4), 5-levels

Example 1: L54 with strength 3
We will have 3x3x3=27 combinations in any 3 columns and each combination will occur 2 times.

Example 2: L81 with strength 3
We will have 3x3x3=27 combinations in any 3 columns and each combination will occur 3 times.

Example 1 and 2 give us an interesting and novel idea

"new idea" : If we use only 5 control factors but decide to use either L54 or L81, and assume that only 3 of the 5 control factors are dominant (quite a reasonable assumption), then 'all' combinations of the 'dominant' factors occur exactly 2 times in L54 and exactly 3 times in L81.

From the L54 experiments, the best result (decided mostly by dominant factors) will already appear in 2 rows of L54. The ANOM and ANOVA will point out the 3 dominant factors, their best levels and predict the best result. Since all combinations of any 3 factors occur 2 times in L54, the best result is already available in these 2 rows. There is no need to perform confirmation experiment. The L81 array does it even better; the best result appears in 3 rows.

Thus, use of OA's with strength of 3 or more is extremely useful when the experimental facilities are either unavailable later or are likely to get modified after completion of the main OA based experiments.

Apart from the advantages of not having to perform confirmation experiments, use of bigger array has the advantage of a large repeat number, defined as the number of times a factor level repeats in the full experiments, for example L54 has repeat number of 18 and L81 has a repeat number of 27! The larger the repeat number, the better will be the prediction, implying smaller error bars.

(4) Develop a Model for Factor Effects of "R"

The ANOM and ANOVA analysis of an OA experiment is founded on an "additive model" that describes how the sum of independent functions of the control factors can be added to obtain the objective functions called as the Signal-to-Noise ratios (S/N Ratios). The interactions between control factors, if any, have separate terms in the additive model to maintain the additive nature of the "additive model".

While the existing process having control factors A, B, C, D etc. may implicitly satisfy the "additive model", the introduction of a new research factor "R" will add one more term, for its own factor effect, in the additive model as well as add several additional terms if interactions RxA, RxB etc have been explicitly included in the OA used for the experiments.

We may need a set of models for the factor effects of "R" on the S/N Ratio of the output response. If "y" is the S/N ratio, and the factor effect is "r" then

(i) Linear model: $y = a_0 + a_1 (r)$

(ii) Quadratic model: $y = a_0 + a_1 (r) + a_2 (r^2)$

(iii) Cubic model: $y = a_0 + a_1 (r) + a_2 (r^2) + + a_3 (r^3)$

And so on.

The number of levels of the control factor decides the number of points in the factor effect plots and the degree of freedom for a control factor is one less than the number of levels. Both point towards the fact that number levels of the control factor decides the "order of the polynomial" that can be fitted in the "additivity model".

For example,
2-level factor "R" will give "Linear model"
3-level factor "R" will give "quadratic model"
4-level factor "R" will give "cubic model"
5-level factor "R" will give "4th order polynomial model"
And so on . . .

For the task of construction of a suitable OA with following requirements on "R",

(i) "R" as a multilevel factor,
(ii) Allow interactions RxA, RxB etc to be studied
(iii) "R" has at least the quadratic model

We can adopt the following strategy,
Using "R" as a blocking factor and a suitable starting OA that is adequate to describe the existing process, create the required number of levels for "R", say 6 levels or 9 levels. This construction will implicitly satisfy the above 3 requirements. Take an example of starting array as L9 with 4 control factors A, B, C, D of 3 levels each. Now use L9 as the starting OA and "R" as a blocking factor to create 9 levels for "R". So we have thus created an 81 row OA, call it as L81(R=9, A=3, B=3, C=3, D=3). Experiments can be conducted in blocks of 9 experiments with a single value of "R" for the 9 experiments, but the "R" value changes in every block.

Now, the only desirable property that remains to be achieved is the strength of 3 or 4. This paper describes below the procedure adopted to obtain all 4 properties from the original L81 array that has 40 factors of 3-levels.

MODIFIED L81, L54 ARRAYS FOR RESEARCH

From Taguchi's linear graphs for L81 we have a graph wherein all 2-way interactions between columns 1, 2, 5, 14, 27 can be studied and we still have 15 more factors (10, 12, 13, 19, 21, 22, 25, 29, 31, 33, 34, 35, 37, 38, 39) that can be used (see Fig 4a). Furthermore, out of these 15 factors, only 31, 37 and 39 satisfy conditions for strength 3 with 1, 2, 5, 14, 27. Taking the union between the above two lists we get (1, 2, 5, 14, 27, 31, 37, 39). The linear graph is shown in Fig 4b.

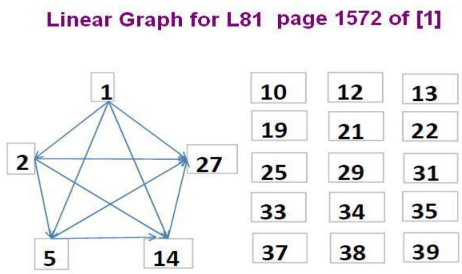

Fig 4a Linear graph for L81 (from page 1572 of [1])

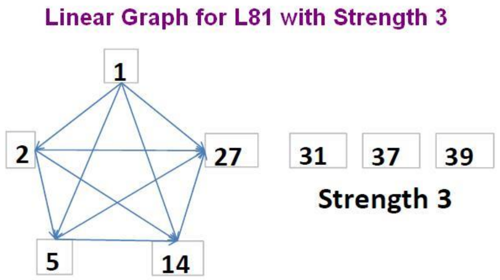

Fig 4b Modified Linear graph for L81 with Strength 3

Continuing, we combine columns 1,2,3,4 to obtain a 9-level factor "R" and then we have the new list as (x1x2, 5, 14, 27, 31, 37, 39) where x1x2 is the new research factor "R" of 9 levels and all other factors are 3 levels. We checked for interactions between x1x2 or "R" and 5, 14, 27, 31, 37, 39 and found 2 interesting results.

(i) Interactions Rx5, Rx14, Rx27 can be studied keeping 37, 39 as separate control factors. We call this OA as L81(9^1, 3^5) (see Fig 5a)

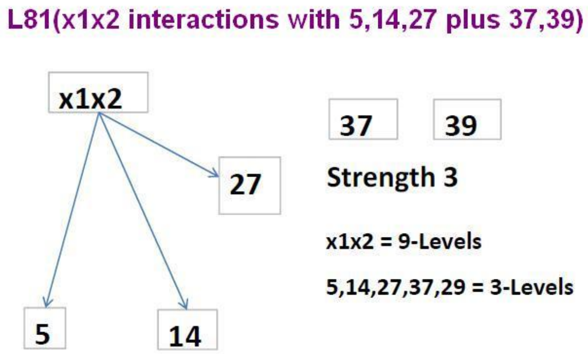

Fig 5a Interactions of R with 5, 14, 27 can be studied and 37, 39 can be used as separate control factors

or

(ii) Interactions Rx5, Rx14, Rx27 and Rx37 can be studied by keeping 39 unassigned. We call this OA as L81(9^1, 3^4) (see Fig 5b)

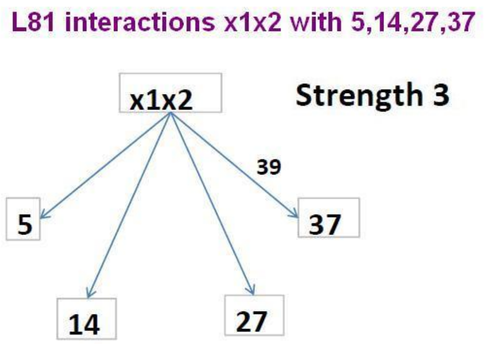

Fig 5b Interactions of R with 5, 14, 27, 37 can be studied by keeping column 39 unassigned or empty

Similarly, beginning with L54 (2^1, 3^25) that has one 2-level factor and twenty-five 3-level factors, we have combined the 2-level column and 3-level column 1 to get a 6-level factor designated as the research factor "R". Of the remaining 24 factors of 3-levels, two way interactions which can be studied were found to be Rx2, Rx8, Rx16 and Rx19 (see Fig 6a). Interactions between the 3 level factors that could be studied are 2x8, 2x16, 2x19, 8x16 and 8x19. Only interaction that cannot be studied is 16x19 (see Fig 6b). This implies that all combinations of R and any 2 of (2, 8, 16, 19) occur exactly once. Furthermore, all combinations of any 3 of (2, 8, 16, 19) occur exactly twice (except those involving pair 16, 19).

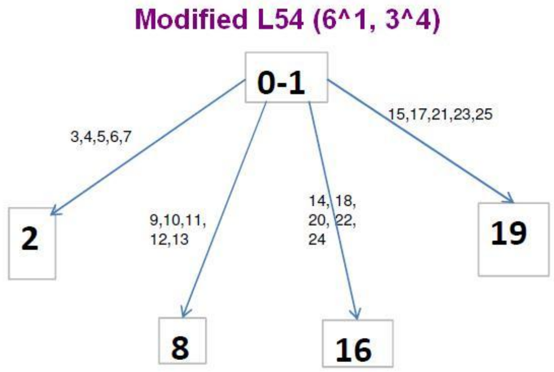

Fig 6a Interactions Rx2, Rx8, Rx16, Rx19 can be studied

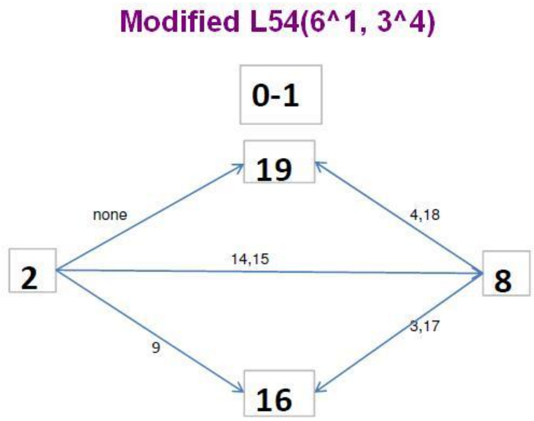

Fig 6b Interactions 2x8, 2x16, 2x19, 8x16, 8x19 can be studied

The modified OA's L81(9^1, 3^5), L81(9^1, 3^4) and L54(6^1, 3^4) have all the 4 properties that we stated earlier for the study with new research factor "R"

(1) "R" as the "new" Multilevel Control Factor
(2) "R" as a Blocking Factor so that interactions RxA, RxB, RxC, etc. can be studied
(3) OA has strength 3 (R and any 2 of A, B, C, D)
(4) Develop a model for factor effects for "R"

CONCLUSION

This paper has proposed effective use of Taguchi Method in research for achieving 4 goals,

(1) Using research parameter R as a multilevel factor
(2) Using research parameter R as a Blocking factor so that interactions RxA, RxB, RxC, RxD etc can be studied
(3) Construct OA's with strength 3 or 4
(4) Develop linear or higher order polynomial model for the effects of R

The application of "Taguchi Method in Research" has been demonstrated by constructing modified L54 and L81 arrays which inherently incorporate the essence of the 4 research goals highlighted in this paper.

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Dynamic Response Optimization for Cemented Carbide Injection Molding

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Abstract – **The need to optimize the injection molding parameters for producing cemented carbide parts via Metal Injection Molding process is crucial to ensure the system's robustness towards manufacturer and customer's satisfactions. Defect free product with best density can be produced while reducing time and cost in manufacturing. In this work, the feedstock consisting of WC-Co powders, mixed with palm stearin and polyethylene binder system was injection molded to produce green parts. Several processing variables, namely powder loading, injection temperature, holding pressure and injection rate, were optimized towards the density of the green body, as the response factor. By considering humidity level at morning and evening conditions as the noise factor, the results show the optimum combination of injection molding parameters that produces best green density.**

Keywords – **Cemented carbide, Metal Injection Molding, optimization.**

I. INTRODUCTION

Cemented carbide injection molding has been widely accepted as a promising technology in producing small and complex shape with high performance and good surface finish in mass production [1, 2]. The process consists of four sequential steps – mixing, injection molding, debinding and sintering – all of each step has an effect on the characteristic of the final parts. A homogeneous feedstock from deagglomerated powders produced from the mixing step was injection molded to produce green parts, followed by removing the binder system by undergoing the debinding step and finally, sintering the brown parts to produce final parts with high sintered density. The handling of specimen between the interval times of processing step must be made in full caution since the specimen is fragile and any mishandling can lead to the broken parts easily. Thus, a part with high density, which reflects its strength, is required to ensure the successful production for the whole system.

Several researchers have conducted optimization process for the injection molding step for various feedstock. Focusing on Taguchi Method, the optimum injection molding parameters have been found for stainless steel SS 316L [3,4], and titanium [5] powders. Each of them uses classical approach of static experimental design, without considering the power input signal into their consideration. Thus, to overcome this research gap, the aim of this study is to optimize injection molding parameters for WC-Co feedstock with dynamic response approach. This work is done by varying the power input, which can stimulate the energy transformation to the output function based on its ideal function. The best green density produced is expected to give best properties in the final sintered parts.

II. METHODOLOGY

2.1 Materials and sample preparation methods

WC (D_{50} of 8.6μm) and Co (D_{50} of 1.6μm) powders used in this study were supplied by *Eurotungstene. com* and *Inframat Advanced Materials, LLC.*, respectively. The WC-9Co alloy was then formed by wet milling the elemental powders in ethanol media. Then, the powder was mixed with palm stearin and polyethylene binder system with the ratio of 60:40. The mixing process is conducted by using sigma blade mixer at a speed of 40 rpm and at temperature of 150 ^{o}C for 1.5 hours. The powder loading is varied at 59, 61 and 63% vol.

The feedstock was then injection-molded into a tensile shape part by using a Battenfeld 250 CDC injection molding machine with various injection molding parameters. Table 1 summarizes all the control factors and their levels, noise factor and the response factor for the injection molding step.

TABLE 1:
FACTORS AND LEVELS FOR ANALYSIS

Factor \ Level			1	2	3
Control factors	A	Injection rate (ccm/s)	10	20	--
	B	Powder loading (%vol)	59	61	63
	C	Injection temperature (^{o}C)	140	150	160
	D	Holding pressure (bar)	700	1800	1900
Noise factor	E	Humidity level	Morning	Evening	--
Response factor	y	Green density	Level on operating condition		
Energy input	M	Injection pressure (bar)	1400	1500	1600

Then, the density of the tensile shape of the green part was tested based on the Archimedes Method, according to MPIF 42 Standard.

2.2 Taguchi Methods

Based on Table 1, L_{18} orthogonal array was used in this study. Figure 1 represents the P diagram for the system, associated with its ideal function.

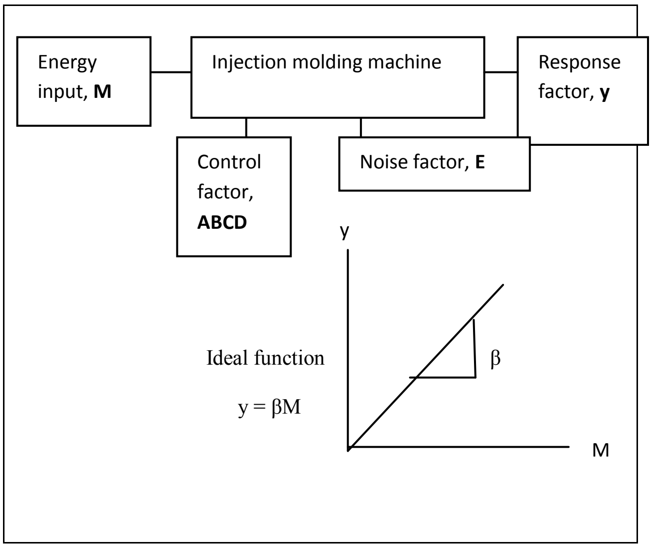
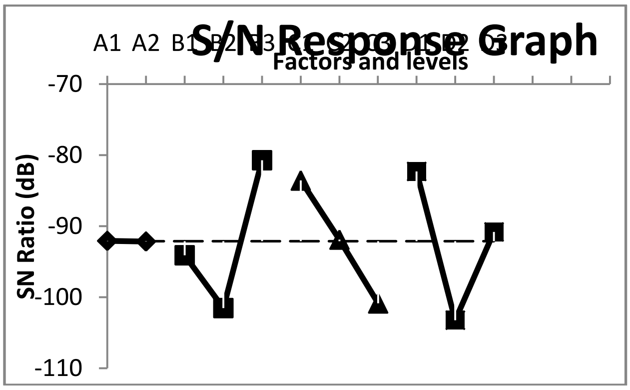


Figure 1: P diagram and ideal function

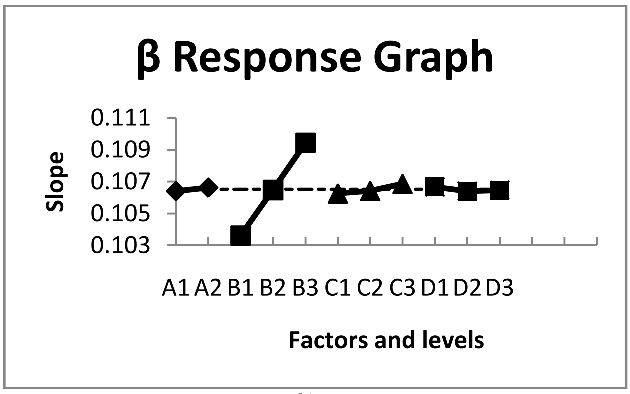
III. RESULTS AND DISCUSSIONS

Figure 2 represents the S/N ratioand β response graph for the system. Based on the two step optimization method, for higher efficiency, higher sensitivity is desirable [6]. Once higher efficiency is established, the opportunities to reduce cost, size and weight of the subsystem will exist [7].

The first step is to maximize S/N. According to Figure 2(a), the maximum point lies at point B3C1D1, while for point A, the line is quite horizontal and significantly hard to determine the maximum point. Thus, the second step is to adjust the β slope, to see which A point gives more significant effect. From Figure 2 (b), the maximum point for signal line lies at point A2, making the overall optimum combination for injection molding step became A2B3C1D1.



(a)



(b)

Figure 2: (a) S/N and (b) β Response Graph

The following Table 2 represents the optimum condition associated with their actual values for each processing parameters. Next, is to see the significance of each variables to the performance of response function, which is green density. This step involves creating Response Tables for S/N and β slope (sensitivity), as can be seen inTable 3.

TABLE 2:
THE OPTIMUM CONDITION FOR INJECTION MOLDING STEP

Factor		Parameter
Injection rate	A2	20 ccm/s
Powder loading	B3	63% vol.
Injection temperature	C1	140 ^{o}C
Holding pressure	D1	1700 bar

TABLE 3:
RESPONS TABLE FOR S/N VALUES

	A	B	C	D
	-92.04	-94.08	-83.56	-82.27
	-92.15	-101.5	-91.87	-103.23
		-80.70	-100.85	-90.78
Δ	0.11	20.81	17.29	20.96
Rank	4	2	3	1

As seen in Table 3, the significance for each factor is determined by looking at the rank Δ numbered accordingly. The difference (Δ) is detected between the highest and lowest point for S/N values. The largest contribution is factor D (holding pressure). This is by the fact that the holding pressure compresses the melt and fills the cavity, and has an effect until the gate solidifies. Holding pressure makes density uniformity in the cavity, whereas if the holding pressure is not enough sufficiently, slumps can occur on the surface [8]. On the other hand, if too high holding pressure is applied, sticking of the molded part to the cavity could happen. Thus, a moderate holding pressure could lead to the highest density of the green part.The second largest contribution is factor B (powder loading). The higher the powder loading, the bonding between powder particles increased within the feedstock and make the green part to pack more densely due to the less void created [9]. Hence, the density of the green parts increases. This finding is quite similar with work [3], which also got powder loading as the second most influencing factor after optimization process done on stainless steel based feedstock. Injection temperature (factor C) is still important since the temperature of materials has an effect on the viscosity of the melt, and consequently on the ability of the melt to fill up the cavity [9]. The parts will be unfilled if the viscosity of the melt is too high. Meanwhile for factor A (injection injection rate), the significance is too low and the effect can be neglected. This is because the injection rate only controls the time and amount of melt to fill up uniformly into the die cavity.

TABLE 4:
PREDICTION VALUES FOR S/N AND β

Predictions	S/N (dB)	β (%)
Initial	-75.68	0.103
Optimum	-62.39	0.109
Gain	13.28	5.84

According to the prediction values for S/N and β as seen in Table 4, it shows the positive increment of 13.28 dB for the S/N value and 5.84% gain for β value, between the initial condition (before optimization) and optimum condition (after optimization). The positive increment proves the significance or successful optimization done on the process. Next, a confirmation run is needed in order to validate the prediction values made beforehand. The confirmation result is shown in the following Table 5.

TABLE 5:
COMPARISON OF S/N AND β VALUES BETWEEN PREDICTIONS AND CONFIRMATION RUNS

	Predictions		Confirmation	
	S/N	β	S/N	β
Initial design	-75.6679	0.103403	-75.6679	0.103403
Optimum design	-62.3888	0.109443	-71.115	0.108521
Gain	13.28 dB	5.84 %	4.55 dB	4.95 %

From Table 5, it can be seen that there is a positive increment at the S/N values as much as 4.55 dB and 4.95% gain for β value for confirmation run. Although there is a difference between the predictions and confirmation values, but it can still be accepted since there exist positive increment for the S/N value and lies within ±0.5% for the β value. Thus, the optimized system is proven to be better, and more robust to the surrounding, despite having best green density amongst all.

IV. CONCLUSION

Taguchi method, with dynamic response optimization has been carried out to develop optimum processing parameter for injection molding cemented carbide parts. Based on the two step optimization result, it has been demonstrated that the most influencing factor to the green density is holding pressure, followed by powder loading, injection temperature and lastly injection rate, which is very less significant and can be neglected. The green part exhibited best density by following this optimum processing parameters, A2B3C1D1, that are flowrate 20 ccm/s, powder loading at 63% vol., injection temperature at 140 ^{o}C, and holding pressure at 1700 bar. Based on the confirmation run, it is proven that the increment has a gain as much as 4.95%, compared to the initial design. Thus, the result is acceptable and believed to be robust to the ambient's humidity level at all energy input variations (injection pressure). Future efforts will involve debinding and sintering of green parts with this optimum condition to get the best sintered parts with desired properties.

ACKNOWLEDGMENT

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Effect of Tool Geometry on Dimensional Accuracy and Surface Finish of Turned Parts

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Abstract - **This paper investigates, experimentally and analytically, the influence of tool geometry on two major dimensional accuracy characteristics of a turned part—diameter error and circularity—and the surface finish characteristic arithmetic average. Data were analysed via two methods: Pareto ANOVA and Taguchi method. The findings indicate that the two selected tool geometry parameters—insert shape and nose radius—have a considerable effect on diameter error (total contribution 67.0%) and minor effects on surface finish (total contribution 11.6%) and circularity (total contribution 7.5%). The major contributor to surface finish is feed rate, whereas circularity is dominated by interaction effects.**

Keywords - **Diameter error, circularity, surface roughness, Pareto ANOVA, Taguchi method**

I. INTRODUCTION

Machining operations are influenced by several input variables, of which cutting tool is the most critical one [1]. The cutting tool affects almost all aspects of machining, such as chip formation, heat generation, tool wear, dimensional accuracy, and surface finish. The influence of the cutting tool, especially its geometry, on the dimensional accuracy and surface finish of machined parts is more obvious, as the final shape, dimensions, finish, and special geometric details are created by direct contact between the cutting tool and the work piece. Research on cutting tools concentrates on its two major aspects: material and geometry. This paper is limited to a study on the influence of tool geometry.

Investigations of the effect of tool geometry on machining operation have received notable attention in the literature. However, these studies primarily focus on machinability characteristics such as cutting force [2,3], residual stress [4,5], chip formation [6,7], heat generation [8,9], and tool wear [10,11]. A review of the effect of tool geometry on finish turning can be found in Dorga et al. [12]. A number of papers [13-15] have reported on dimensional accuracy and surface finish, but they typically considered the effect of major cutting parameters—cutting speed, feed rate, and depth of cut. It appears that there is a lack of research on the effect of tool geometry on technical characteristics, such as dimensional accuracy and surface finish of finished component parts. The objective of this research is to fill this gap.

II. SCOPE

Single-point cutting tools used in turning operations are available in three major types: (a) solid tool, (b) brazed insert, and (c) mechanically clamped insert. The mechanically clamped type insert tool is the most popular choice and is the topic of our investigation. Tool inserts are available in a number of shapes, such as triangle, square, diamond, and round. The strength of the cutting edge of an insert depends on its shape. The larger the included angle, the higher the strength of the edge; however, it requires more power and has a higher tendency for vibration [16]. Therefore, it is anticipated that the shape of the insert might influence the dimensional accuracy and surface finish of the finished part, and it was selected as an input variable in this study. Insert nose radius is another variable know to influence surface finish, chip breaking, and insert strength. As such, it was also selected as an input variable. The third selected input variable is feed rate, which is known to have a great influence on surface roughness.

The two most important dimensional accuracy characteristics of turned component parts are diameter error and circularity, and they were selected for the present study. Surface finish can be expressed through a number of parameters, such as the arithmetic average, root-mean-square roughness, peak-to-valley height, and ten-point height. The arithmetic average is the most commonly used roughness parameter because of its simplicity. In this study, arithmetic average was adopted to represent surface roughness.

The results were analysed applying two techniques—Pareto analysis of variation (ANOVA), and Taguchi's signal-to-noise (S/N) ratio analysis. Pareto ANOVA is an excellent tool for determining the contribution of each input parameter and its interactions on the output parameters. It is a simplified ANOVA analysis method that does not require an ANOVA table and does not use *F*-tests. Therefore, it does not require detailed knowledge about the ANOVA method. Further details on Pareto ANOVA are available in Park [17]. The Taguchi method is another popular tool for parameter design. It applies signal-to-noise (S/N) ratio as a quantitative analysis tool for optimizing the outcome of a manufacturing process. The S/N ratiocan be calculated using the following formula [18]:

$$S/N = -10\log\frac{1}{n}\left(\sum_{i=1}^{n} y_i^2\right) \qquad (1)$$

where n is the number of observations and y is the observed data.

The above formula is suitable for quality characteristics in which the adage 'the smaller the better' holds true. All three quality characteristics considered fall in this category. The higher the value of the S/N ratio, the better the result is, because it guarantees the highest quality with minimum variance. A thorough treatment of the Taguchi method can be found in Ross [18].

III. EXPERIMENTAL WORK

The experiments were planned using Taguchi's orthogonal array; a three-level, three-parameter L_{27} orthogonal array was selected for our experiments. A copy of $L_{27}(3^{13})$ array is available in Taguchi [19]. The details of the input parameters are given in Table 1. A total of 27 experimental runs were conducted; they were carried out in nine parts, each of which was divided into three segments. Each part was turned with a new insert, shape, and nose radius, which were determined by the design of experiment (DoE). The inserts used were manufactured by Stellram (USA). AISI-4340 steel was chosen as the work material, as it is readily available and widely used in the industry. The nominal size of each part was 170 mm length and 40 mm diameter. The experiment was carried out on a Harrison conventional lathe, with 330 mm swing, under dry condition. The depth of cut (1 mm) and cutting speed (212 m/min) were maintained constant. The diameter error and circularity were measured by a Discovery Model D-8 coordinate measuring machine (CMM), manufactured by Sheffield (UK). The surface roughness parameter, arithmetic average (R_a), for each turned surface was measured with a Surftest SJ-201P, manufactured by Mitutoyo (Japan).

IV. RESULTS AND ANALYSIS

A. *Diameter Error*

The Pareto ANOVA analysis for diameter error is given in Table 2. It shows that nose radius (B) has the most significant effect on diameter error, with a contribution ratio P ≅ 50%, followed by insert shape (A) (P ≅ 16%). The interactions between insert shape and feed rate (A×C) and between insert shape and nose radius (A×B) also played roles, with a contribution of 8.7% and 8.4%, respectively. Feed rate (C) showed a small effect (P ≅ 4%). It is worth pointing out that the total contribution of the main effects was about 71%, compared to the total contribution of the interaction effects of 29%. As such, it is moderately difficult to optimize diameter error by selecting input parameters. The response graph for the mean S/N ratio is shown in Fig. 1. The results show that parameter B (nose radius) has the most significant effect on diameter error. Fig. 1 also shows that as the included angle increases, the diameter error increases, and the worst diameter error is achieved by the square-shaped insert, which has a 90º included angle. The most likely cause is the more elastic deformation of the workpiece, caused by increased cutting force due to the increase in the included angle.

In selecting the optimum combination of parameters, both the Pareto ANOVA analysis (Table 2) and the response for the mean S/N ratio (Fig. 1) confirm that the largest nose radius (B2) provides the lowest diameter error. A two-way table of A×C interactions showed that A2C0 achieved the lowest diameter error; i.e., triangular-shaped insert and lowest feed rate (0.11 mm/rev). The two-way table is not included in this paper due to space constraints. The best combination is A2B2C0.

B. *Circularity*

The Pareto ANOVA analysis for circularity is given in Table 3. It shows that among the input variables, feed rate (C) has the most significant effect on circularity, with a contribution ratio P ≅ 11%, followed by nose radius (B) (P ≅ 6%) and insert shape (A) (P ≅ 1%). In this Pareto graph, the dominance of the interaction effects is noteworthy. The interaction between insert shape and feed rate (A×C) has the highest influence (P ≅ 26%), followed by interaction of nose radius and feed rate (B×C) (P ≅ 23%). The total contribution of the interaction effects is about 82%, compared to the total contribution of the main effects of 18%, thus making it highly difficult to optimise the circularity error by selecting the input parameters.
The response graph for the mean S/N ratio for circularity is shown in Fig. 2. The best circularity can be achieved by the A1B1C1 combination; i.e., turning with a diamond-shaped insert with medium nose radius (0.8 mm), at a medium feed rate (0.22 mm/rev).

C. *Surface Roughness*

The Pareto ANOVA analysis for surface roughness is given in Table 3. It shows that feed (C) has the most significant effect on surface (P ≅ 76%), followed by nose radius (B) (P ≅ 7%). The interactions between insert shape and nose radius (A×B) also played a role, with a contributing ratio of P ≅ 6%. Insert shape (A) showed a small effect (P ≅ 4%). In this case, the high influence of feed rate (C) is noteworthy. The total contribution of the main effects is about 88%, compared to the total contribution of the interaction effects of 12%. Therefore, it is relatively easy to optimize the surface finish by selecting the input parameters, especially through proper selection of feed rate. The results obtained from the Pareto ANOVA analysis, shown in Table 4, are verified by the response graph for the mean S/N ratio, shown in Fig. 3. The results show that parameter C (feed rate) has the most significant effect on surface roughness, represented by the highest slope on the response graph. The findings shown in Fig. 3 support the results obtained from the Pareto ANOVA analysis, shown in Table 2.

In selecting the optimum combination of parameters, both the Pareto ANOVA analysis (Table 4) and the response for the mean S/N ratio (Fig. 3) confirm that the lowest feed rate (C0) provides the best surface finish. A two-way table of A×B interactions showed that A0B2 achieved the best surface roughness; i.e., diamond-shaped insert and largest nose radius (1.2 mm). The two-way table is not included in this paper due to space constraints. The best surface roughness can be achieved by the A0B2C0 combination. The influence of feed rate and nose radius on surface roughness is well known, and most of the geometric models for surface roughness include these two parameters. As expected, surface roughness improved as nose radius increased, and deteriorated as feed rate increased.

V. CONCLUSION

From the experimental work conducted and the subsequent analysis, the following conclusions can be drawn:

- Tool geometry parameters—insert shape and nose radius—have considerable effects on diameter error (total contribution 67.0%). The effect of feed rate is minor (contribution 3.7%).
- No single parameter contributes significantly to circularity, and the interaction effected is dominant (total contribution 71.6%).
- Surface roughness is mainly affected by feed rate (contribution 76%). Tool nose radius has a minor effect (contribution 7%).

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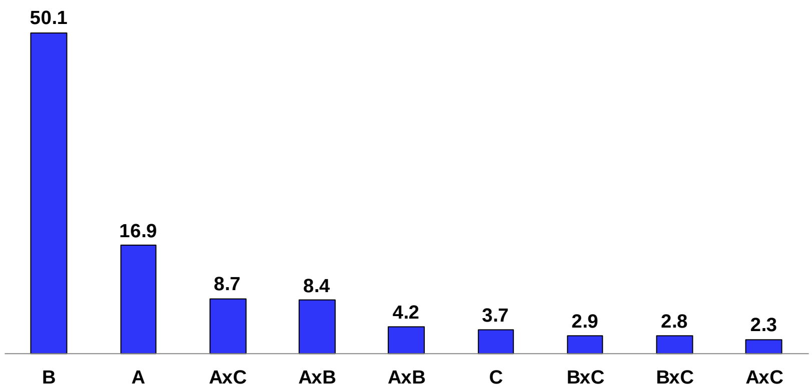
TABLE 1
INPUT VARIABLE

Input parameters	Unit	Symbol	Levels		
			Level 0	Level 1	Level 2
Insert shape		A	 Square	 Diamond	 Triangle
Nose radius	mm	B	0.4	0.8	1.2
Feed rate	mm/rev	C	0.11	0.22	0.33

TABLE 2
PARETO ANOVA ANALYSIS OF DIAMETER ERROR

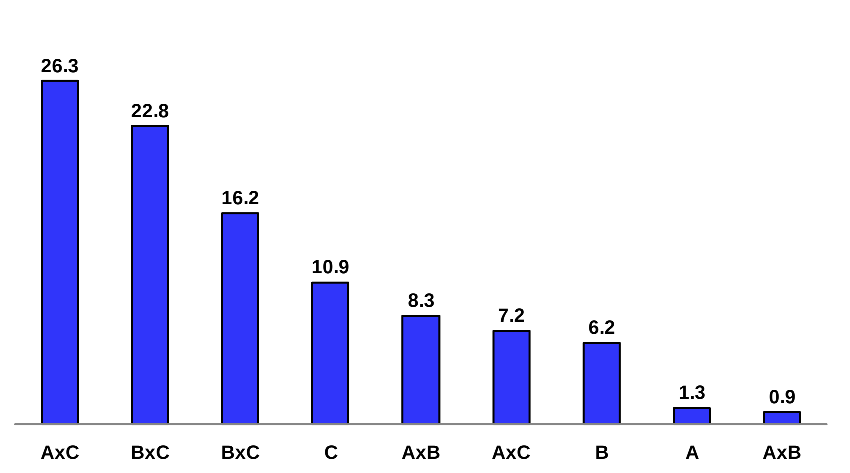
Sum at factor level	Factor and interaction								
	A	B	AxB	AxB	C	AxC	AxC	BxC	BxC
0	106.07	121.05	118.39	110.64	119.08	115.09	121.93	119.18	112.56
1	118.32	99.17	108.71	117.95	115.99	118.71	114.28	114.73	114.57
2	121.99	126.16	119.28	117.79	111.31	112.58	110.17	112.47	119.24
Sum of squares of difference (S)	416.89	1233.05	206.25	104.38	91.71	56.96	213.76	70.01	70.46
Contribution ratio (%)	16.92	50.05	8.37	4.24	3.72	2.31	8.68	2.84	2.86



Cumulative contribution	50.05	66.97	75.65	84.02	88.26	91.98	94.84	97.68	100.00
Check on significant interaction		AxC two-way table (not included)							
Optimum combination of significant factor level		A2B2C0							

TABLE 3
PARETO ANOVA ANALYSIS OF CIRCULARITY

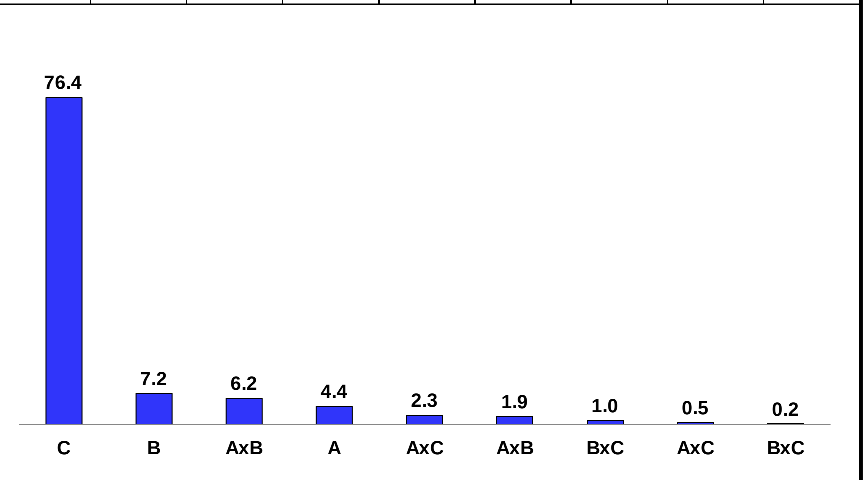
Sum at factor level	Factor and interaction								
	A	B	AxB	AxB	C	AxC	AxC	BxC	BxC
0	377.07	389.14	388.21	389.89	393.01	385.52	400.99	387.22	359.86
1	389.55	394.21	385.10	395.92	395.74	397.76	399.67	355.32	404.76
2	384.55	367.81	377.86	365.35	362.41	367.89	350.51	408.62	386.54
Sum of squares of difference (S)	236.43	1177.45	169.23	1573.68	2054.87	1353.24	4967.88	4316.72	3059.81
Contribution ratio (%)	1.25	6.23	0.89	8.32	10.87	7.16	26.27	22.83	16.18



Cumulative contribution	26.27	49.10	65.28	76.15	84.47	91.63	97.86	99.11	100.00
Check on significant interaction	AxC two-way table (not included)								
Optimum combination of significant factor level	A1B1C1								

TABLE 4
PARETO ANOVA ANALYSIS OF SURFACE ROUGHNESS

Sum at factor level	Factor and interaction								
	A	B	AxB	AxB	C	AxC	AxC	BxC	BxC
0	-25.69	-70.38	-33.10	-21.41	31.70	-51.32	-59.00	-54.07	-45.93
1	-60.79	-35.02	-44.21	-62.62	-49.57	-41.89	-39.36	-39.62	-40.71
2	-47.03	-28.10	-56.20	-49.47	-115.65	-40.29	-35.14	-39.82	-46.87
Sum of squares of difference (S)	1876.56	3085.53	801.30	2658.61	32683.30	213.12	972.54	411.58	66.18
Contribution ratio (%)	4.39	7.21	1.87	6.22	76.42	0.50	2.27	0.96	0.15



Cumulative contribution	76.42	83.63	89.85	94.24	96.51	98.38	99.34	99.84	100.00
Check on significant interaction	AxB two-way table (not included)								
Optimum combination of significant factor level	A0B2C0								

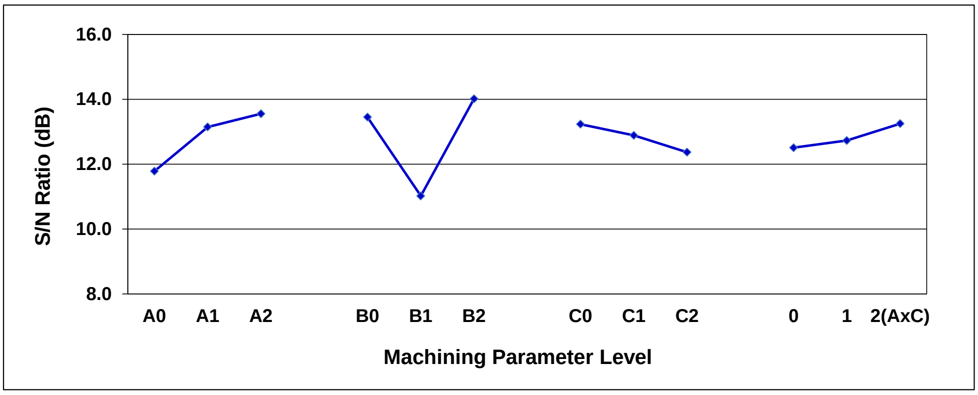


Fig. 1 Response graph for diameter error

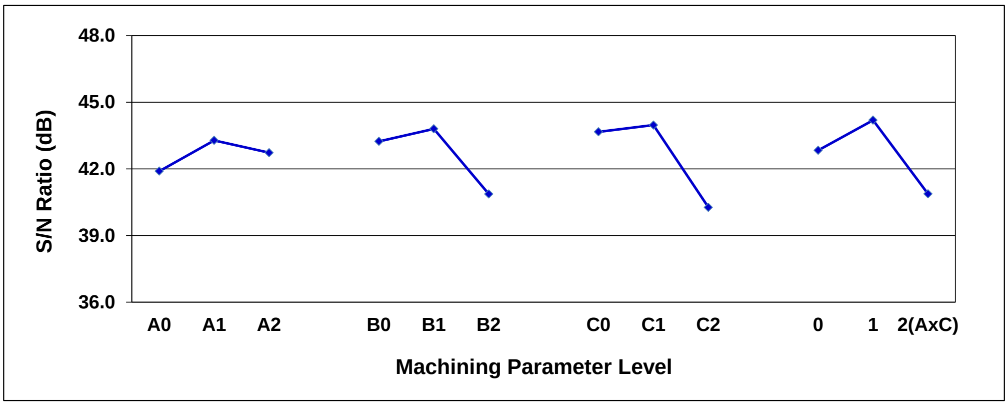


Fig. 2 Response graph for circularity

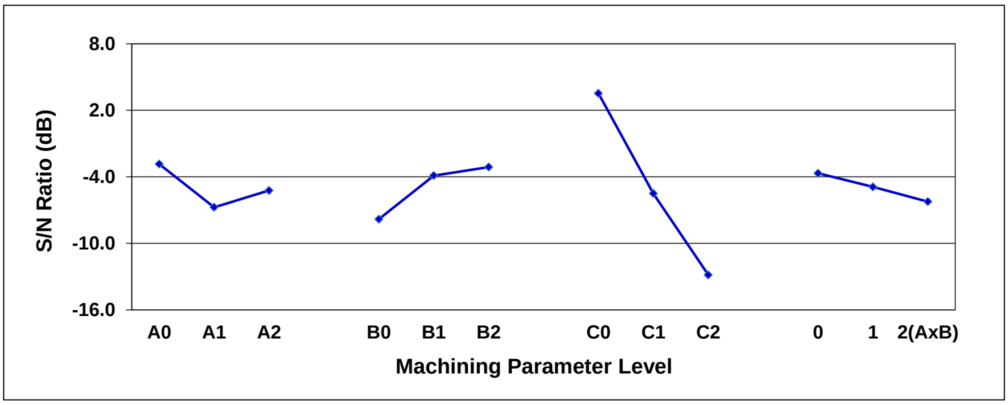


Fig. 3 Response graph for surface roughness

Examples of the MT System Application

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Abstract **-The Mahalanobis-Taguchi (MT) System is one of the best pattern recognition technologies. And, Dr. Genichi Taguchi proposed "feature extraction techniques from wave form pattern" in 1995. This technique can be applied to the problems of the image as well as the problems of the wave pattern. Two actual examples are shown in this article.**

Keywords **- feature extraction, inspection, Mahalanobis distance, monitoring, MT System, pattern recognition, Quality Engineering, Taguchi Methods, waveform pattern**

1. INTRODUCTION

The Mahalanobis-Taguchi(MT) System is one of the strong theories for pattern recognition. In this paper, we introduce two representative applications of the MT System. One is “appearance inspection of industrial commodity” and the other is “monitoring of machine conditions.” The feature extraction technique from wave form pattern is explained before those examples because the technique is applied to those different applications commonly.

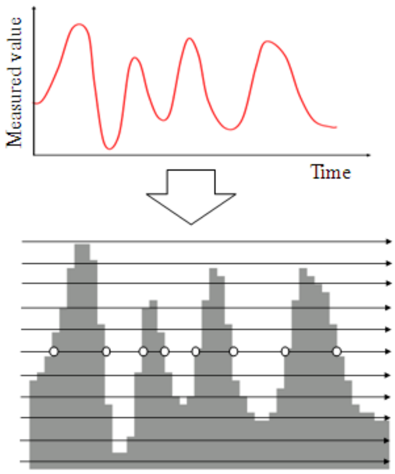
2. FEATURE EXTRACTION TECHNIQUE FROM WAVEFORM PATTERN

2.1 Past Waveform Features

The features of waveforms include frequency and amplitude. Frequency analysis, wavelet, etc. has also been common. Frequency analysis and wavelet are excellent methods of explaining the characteristics of waveforms. Nonetheless, it cannot quite be said that both convey sufficient information on the characteristics of the given waveform pattern. For instance, frequency analysis is not adept at capturing waveform changes that may be occurring within short time spans.

2.2 Extraction of Variation and Abundance Information from Waveform Patterns

The variation and abundance information extraction method was proposed by Dr. Genichi Taguchi [1] [2] as a means of expressing the characteristics of image patterns and waveform patterns in more accurately quantified terms. The method is explained below.



Variation value	Abundance value
0	0
2	6
6	20
8	28
8	38
8	47
8	65
8	78
6	88
3	95
1	100

Fig. 1 Waveform Pattern; Variation and Abundance Values

Let us suppose we are given a wave form as shown in Fig.1.Ifwe fill in the body of a waveform with gray, we obtain a graph appearing in the bottom.

Next, we define multiple, horizontal straight lines as reference lines. In the example at hand, 11 reference lines are defined and numbered 1 to 11 in ascending order, starting from the bottom. We then count the points at which each of the reference lines cross the contour of the waveform. Focusing on the sixth reference line (line No. 6), we encircle the points at which the graph waveform intersects it. We count eight circles. We will refer to this number of intersections as the “variation value.” The sum of those segments of a given reference line that are covered by the shaded areas of the graph will be referred to as the *abundance value*. Note in passing that, in this example, the width of the domain is set at 100 so that the abundance value for the first reference line is 100.

Reading the variation values and abundance values from all the reference lines, we tabulate the result as shown in the table on the right side. The numbers in the rows in the table reflect their corresponding reference line readings; waveform and numbers can be easily checked. There are 11 reference lines, and with two feature values, the variation value and the abundance value is collected for each and a total of 22 quantified feature values are acquired. These 22 numerical values together provide the feature value set of the waveform.

3. APPEARANCE INSPECTION OF INDUSTRIAL COMMODITY

3.1 Purpose that the Inspection System Serves

In many cases, the inspection of the appearance of products is conducted as part of industrial product assembly line activity. Over long hours, inspection workers perform their massive, detailed, nerve-wracking duties. There has, therefore, been an earnest call for the automation of appearance inspection, but much of the task continues to depend on human beings to this day. This is because it is difficult to extract defect data from a given image with reliable certainty, making it all but impracticable to apply a *typical* inspection standard.

The automotive clutch disk (called “disk” hereafter) is a concrete example that illustrates the difficulty of automating appearance inspection. The difficulty comes from the following points:

The disk and the defect are of similar coloring, so it is not easy to tell one from the other on the image data. Telling the two apart is made all the more difficult by a slit pattern on the disk surface.

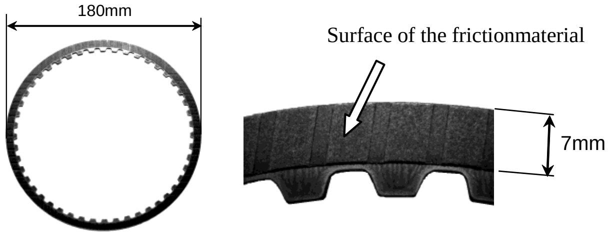
The inspection time required per piece is less than several seconds, but the image processing, which is of slower speed, falls behind. The defects are all unique and of infinite variety, making it difficult to usefully apply a typical inspection standard.

The disk, as shown in Fig. 2 (a), has an outer diameter of 180 mm and is discus-shaped with friction material adhering to either side of the sheet metal part. Fig. 2 (b) is an enlarged view of the friction material surface. The width of the friction material is 7 mm.Defects such as dab of adhesive, misaligned pattern may occur during production.

We proceeded, then, to develop an appearance inspection system on the basis of the following lines of thinking:

(a)Make a Unit Space of the image of a normal disk, and use the MT Method to find any pattern differing from it.

(b)In order to make the most of the image’s light-and-shade distribution information, regard the image data as an aggregation of waveform data from which to extract features. If there are defects, it is expected that it should be possible to detect them in the form of waveform pattern differences.



(a) (b)

Fig. 2 Appearance of the Clutch Disk

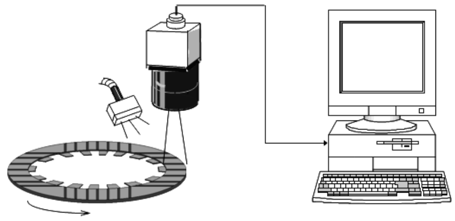


Fig. 3 Composition of the Image Capturing Unit

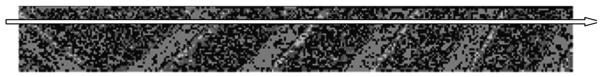
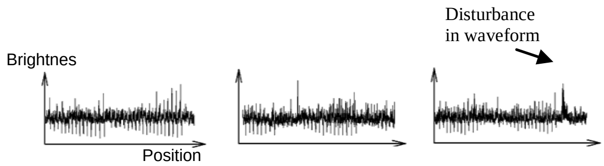


Fig. 4 Image of the Disk Surface and the Waveform Extraction Line



(a) (b) (c)

Fig. 5 Waveform Patterns Extracted from Image Data

3.2 Composition of Image Capturing Unit

As shown in Fig. 3, the disk is rotated at a chosen speed, and the disk surface is photographed with a line camera. This method makes it possible to photograph the friction surface with the exposure limited to a single rotation of the disk.

3.3 Conversion of Image Data into Waveform Patterns

A partial view of the image of a disk’s friction surface is shown in Fig.4. This image shows that the shapes of the slits on the friction surface are captured as well. The pixel count for the image at this time is 35 in the direction of the disk width and 6,000 in the direction of the circumference of the disk.

Note the arrow traversing the image in the horizontal direction in Fig. 4. The brightness information carried by this arrow, when extracted, produces the waveform data shown in Fig. 5. In this figure, the horizontal axis represents the disk’s position in the direction of the circumference, and the vertical axis, the brightness. Since there are 35 pixels in the vertical direction of the image, the image of the disk can be treated as an aggregation of 35 waveforms.

Some examples of the waveforms are shown in Fig. 5. (a), which is the waveform reflecting the absence of any defect on the disk; (b) is the waveform indicating the presence of some defects; and (c) shows evidence of some clearly identifiable disturbances, which the arrow points to. In the case of (b), however, it is not terribly clear whether it deviates from the norm or not.

3.4 Feature Extraction

As discussed in Chapter2, several reference lines for feature extraction are defined in relation to the waveform. For purposes of discussion in this context, the following four feature values are included in addition to the variation (change) and abundance (existing) values. Those are, Greatest length of stretch where waveform exists, Smallest length of stretch where waveform exists, Greatest length of stretch where no waveform exists and Smallest length of stretch where no waveform exists.

These are feature values that we judged anew to be necessary for the purpose of capturing the characteristics of the waveform patterns shown in Fig. 5. Forty reference lines were defined, and six feature values were defined per reference line, which will mean that 240 feature values will be extracted from one waveform.

3.5 Creation of a Unit Space

400 samples of normal disks ascertained beforehand to be defect-free were collected, and a Unit Space was created from them. Next, from each of them, 240 feature values were extracted. This means that the samples populating the Unit Space amounted to 240 variables x 400. Some portions of the population are described in Table 1.

Table1 Samples of Unit Data

	Future No.								
	1	2	3	4	5		238	239	240
Sample No.	Ref. Line 1					. . .			
	Vr	Ab	El	Es	Nl	. . .	Es	Nl	Ns
1	18	5989	1318	13	74	. . .	1	3447	2552
2	18	5994	1341	15	81	. . .	6	3449	2561
3	24	5992	1344	17	79	. . .	6	3456	2559
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
400	18	5993	1342	18	79	. . .	4	3451	2556

3.6 Computation of the Mahalanobis Distance (MD) and Judgment Processing

Feature values were likewise extracted from the inspection object disks and their Mahalanobis Distances (MD) were measured. The result of the measurements is shown in Fig. 6. Of the four graphs in the figure, (a) and (b) are MD measurements for defect-free disks, (c) for a disk with small amounts of an adhesive agent still attached; and (d) for a disk with portions of friction material peeled off. In each graph, the horizontal axis represents position in the direction of the disk's radius (for 35 pixels), and the vertical axis, the MD.

The figure makes it clear that defect-free disks yield smaller MD values while defect-riddled disks yield larger MD values. These findings have been confirmed to be consistent with the condition of actual disks.

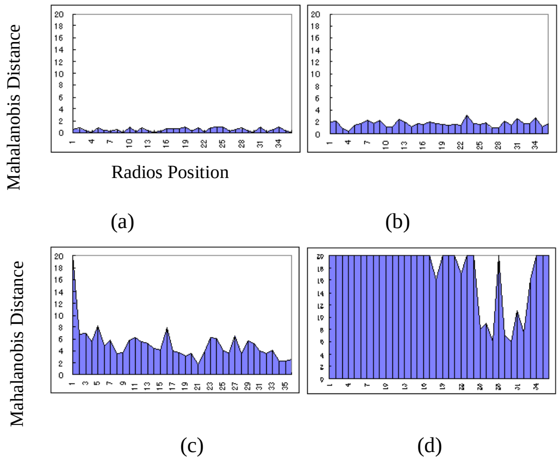


Fig. 6 Results of Inspection of Object Disks

4. MONITORING OF MACHINE CONDITIONS

This chapter introduces a case in which remote monitoring is used to determine whether or not a machine is in a normally functioning state based upon multiple measured values collected from the machine. Conventionally, "control charts" have been in extensive use for monitoring purposes, but use of the MT Method has made it possible to widen the scope of effectiveness of monitoring.

4.1 Purpose of Machine Monitoring and Measured Values

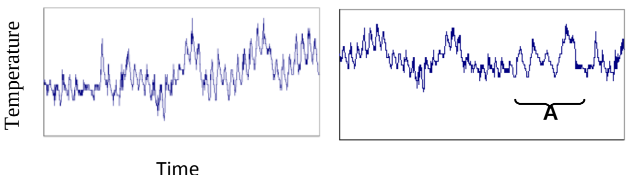
Because of the purpose it serves, the machine involved in this case is not allowed to get out of order in an emergency situation. The state of the machine therefore needs to be monitored on a full-time, ongoing basis; and the measured values are transmitted online to the monitoring center every ten minutes. The measured values carry information pertaining to temperature, state of liquid components, etc. If any abnormality or early indicators of trouble are detected, inspection personnel are required without delay to stand by for instructions or proceed to procure and deliver designated parts.

Control charts have been widely used historically for monitoring machines in similar situations, but there has been a call for a more accurate method of scrutiny to become available that could also detect early symptoms of abnormality. For this reason, we have decided to try extracting the variation patterns of measured time-series data for monitoring with the MT Method.

4.2 Definition of the Unit Space

The state in which the machine functions normally was defined as the Unit Space. Note, however, that the Unit Space in this particular case is defined as the normal state the subject machine is in both prior to and after factory shipment. This is because the machine undergoes long hours of operation tests before it ships out, and the actual on-site operation starts only upon judgment that the data collected following the machine's placement at its ultimate destination is identical to the data collected before shipment.

From the five measured values, the one that carries temperature data is shown as the example in Fig. 7(a). The horizontal axis represents time. In the segment of the pattern shown here, data is measured every ten minutes.



(a) (b)

Fig. 7 Temperature Variation Pattern in Normal Time

4.3 Problems Left Unresolved with the Conventional Control Format

A look at Fig. 7(a) makes it clear that the temperature consists of a large surge and a waveform varying periodically in a recurring, characteristic pattern. The waveform that appears in the monitoring object is shown in Fig. 7(b). In this figure, the temperature variation pattern in the graph segment marked A is not found in the waveform in (b), namely the normal waveform.

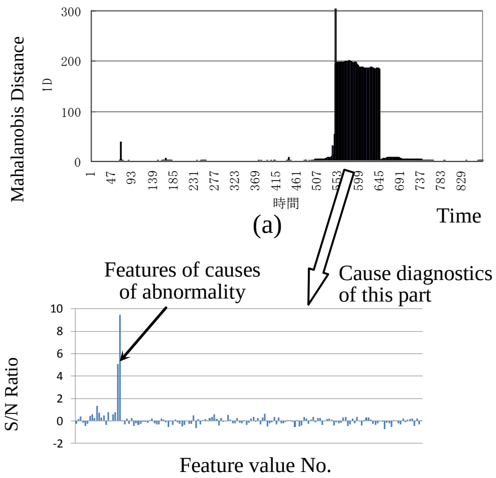
A monitoring attendant would sense that "something is not right" and look at it closely. But the measured values themselves cannot be regarded as abnormal when compared with other segments. In other words, it is not the case here that the values as displayed are too high or too low. The old control chart would judge based on whether the object data was within the upper and lower limits or not, and therefore would not have been able to detect anything abnormal about the segment marked A.

Patterns that would cause experienced workers to wonder if something were wrong are not always straightforward situations; they may appear as combinations of a variety of values and measured readings. In dealing with machines and equipment requiring sophisticated monitoring, it is important to equip the monitoring system with more heightened sensitivity to patterns that deviate from normal patterns.

4.4 Mahalanobis Distance and Cause Diagnostics

The Mahalanobis Distances (MDs) that have been found for the unknown data are displayed in Fig.8 (a). As can be understood from the figure, time segments with large MD values correspond to the segment of the graph marked "A" in Fig. 7(b). A diagnostic made of the same segment for causes has yielded the results displayed in (b) of the same figure. In Fig.8(b), the horizontal axis displays feature value numbers.; the feature values centering on No. 20 are seen showing large values (SN ratios). Given that these are feature values extracted from the temperature, it can be deduced that, of the five types of measured values, these are the ones where "temperatures are in an "abnormal state."

In this way, it has become possible, with the use of feature extraction technology and the MT Method, to detect abnormalities that conventional methodology could not handle and diagnose for causes of trouble.



(b)

Fig. 8 Results of MD Measurements and Cause Diagnostics

5. CONCLUSION

The necessary elements for Pattern Recognition are: (1) measurement technology, (2) feature extraction technique, and (3) recognition processing. The MT System is software technology that fulfills (2) and (3) at an extremely advanced level. Not only that, but the MT System also has the capability of determining whether or not the (1) measurement technology being employed is sufficient.

The author has developed and continues to produce a wide variety of practical technology.

For a more detailed explanation of the MT System, please refer to the literature[3] referenced.

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An Analysis of Forecasting Techniques in Detecting The Future Financial Crisis in Malaysia: The Mahalanobis Taguchi System

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ABSTRACT – **The Asian Financial Crisis (AFC) that hit Malaysia in the late 1990s appears to have a bad impact on economic growth at that time as a result of the collapse of the currency in Thailand bath. Although Malaysia has experienced many economic crises since the early 1970s, but this financial crisis is the worst crisis ever recorded. Then, after 10 years later, Malaysia once again attacked by the Global Financial Crisis in 2008 as a result of the subprime mortgage system failure in the United States. It showed that without proper precautionary plan and actions, the economy can collapse harshly. So that, it is important for Malaysia to develop a forecasting and detection model in the shape of an Early Warning System (EWS) to prevent similar consequences. Therefore, the aim of this study is to predict the Malaysian financial crisis in the future using the model of Mahalanobis-Taguchi System (MTS). The finding shows that the accuracy of MTS in 1998, 1999, and 2000 is obtained at 98 percent, 96 percent and 98 percent. The result in this study also reported that MTS shows a good performance compared to neural network in the aspect of data size, efficiency and time**.

Keywords: ***Financial Crisis, Mahalanobis***

I. INTRODUCTION

The Asian Financial Crisis was a period of financial turmoil that gripped much of Asia beginning in July 1997, and raised fears of a worldwide economic meltdown due to financial globalization. Some of the countries that were significantly affected by this crisis were primarily Thailand, Malaysia, Korea, Hong Kong, and Indonesia. The crisis began in Thailand with the collapse of the Thai *baht* caused by the decision of the Thai government to float the *baht*, cutting its peg to the USD after exhaustive efforts to support it in the face of significant financial over-extension. At that time, Thailand had acquired a foreign debt burden, which ultimately led to a high deficit in their balance of payments.

As the crisis spread, most of the Southeast Asia and Japan saw slumping currencies, devalued stock markets and asset prices, along-side a precipitous rise in private debt. Indeed, at that moment Malaysia also faced the same crisis following the depreciation of the *ringgit* and its floatation that followed nearly two weeks after the floating of the Thai *baht*. From July to September of 1997, the Malaysian *ringgit* gradually declined from RM2.61 to RM3.00 relative to the dollar. On January 7, 1998, the *ringgit* declined further to RM4.88 to the dollar, as the regional contagion worsened resulting from decline in the value of Indonesian's *rupiah*. The AFC was the worst crisis ever recorded by Malaysia. When the crisis occurred, the most significant effect was immediately apparent in the rate of economic growth, which declined from 7.3 per cent in 1997 to -7.4 percent in 1998.

Regardless of the 1997 Financial Crisis, Malaysia learned a lesson to be more aware about the harsh reality that the crisis had on the economy. It showed that without proper precautionary planning and actions, the economy can be significantly adversely affected. It is important for Malaysia to develop a forecasting and detection model in the shape of an Early Warning System (EWS) to prevent similar occurrences. Therefore, it is appropriate that the State properly manages and supervises the monetary and financial system, since monetary and financial management is an important factor in the economy of a country. The failure to see early signs of a decline in the linkages within the domestic financial market could result in a local economic downturn within the global economy if a country is dominated by the main economy in the world such as the United States [1].

Based on the statement above, the main objective of this research is to study the need of Malaysia to develop a financial crisis detector, through an appropriate model in order to detect a future financial crisis. Thus, in order to predict a future financial crisis in Malaysia, the Mahalanobis-Taguchi method has been used. This method can then be compared with other methods, such as the Artificial Neural Network (ANN), to determine which method is the best in detecting a future financial crisis.

II. LITERATURE REVIEW

Forecasting financial crises has always been one of the most controversial topics in modern finance, especially in recent years. Predicting an economic crisis is both a challenging task and also a risk worth taking. There are economists in history whom have correctly predicted such crises. Based on the previous studies, most domestic and overseas researchers have tended to use multivariate discriminate analysis, a linear probability model, logistic regression, probit analysis, and neural network to construct a corporate financial crisis early-warning model. Of all the methods, logistic regression and neural network are more commonly used and their forecasting performance is relatively better [10].

In making prediction of a financial crisis, in the early 1980s, a study conducted by Ohlson [11] initiated the logistic regression to build up the forecasting model and changed the difference in sample numbers between experiment groups and control groups. The study used nine financial variables to create three forecasting models and proved that four items out of these financial data showed statistical significance towards the probability of bankruptcy, with greater forecasting capability of 96 percent, 95 percent, and 93 percent of discriminate accuracy, respectively. Since Ohlson proved logistic regression generated greater forecasting capability, more researchers on financial crisis switched to logistic regression, a linear probability model, or probit analysis.

Similar to the study by Ohlson, (1980), Cipollini and Kapetanios (2009) employed the component analysis to obtain a measurement that can predict the financial crisis in the future, by analyzing the external debt data from 1983 until 2004 from the Bank of International Settlements. A high debt implied a deficit existing in the balance of payment, and the government would be more aware of a possibility that the economy would be adversely affected by an ensuing financial crisis. The results of this study showed that, the combination between dynamic factor analysis and the logit model can explicate the likelihood of a future crisis.

In contrast to the Cipollini and Kapetanios (2009) and Ohlson (1980) studies, Lee and Teng (2009) stated that to predict a potential financial crisis for companies in Taiwan, they introduced a scientific model to the economy involving a prediction method. The model is known as Mahalanobis-Taguchi System (MTS). This study has applied the data ranging from 2005 to 2006. This research intended to study the ability of the MTS to predict the financial crisis in Taiwan in the future. The results of this study showed that, 96 percent accuracy rate of prediction were successfully explained. The results also showed that the accuracy rate of financial crisis early-warning system established by logistic regression and neural network are 92.3 percent, and 96.1percent, respectively. This indicates that the model of MTS provides a greater application effect in order to predict a financial crisis.

Other studies by [6] also stressed the importance of the need for the prediction model in preventing excessive losses resulting from a future financial crisis. They evaluated the warnings made by the Early Warning System and assessed the overall banking crisis. In addition, this study used secondary data obtained from the World Development Bank and the Early Warning System. The data was then analyzed by the Multivariate Longit Model and the Extraction Warning Model. The results of this study showed that the logit model actually predicts the highest possibility of a banking crisis in 2001 at almost 2 percent (linked to the peak of the equity bubble and the start of the bear market). On the other hand, the second tier logit model is able to detect an increase in crisis probability during the years 2000 to 2005, although the probability declines during 2006 and 2007.

III. METHODOLOGY

This study will be using the model of Mahalanobis-Taguchi System (MTS) as the main method to predict the Malaysian financial crisis in the future. MTS involves a new collection of methods used for diagnosis and forecasting method for multivariate data (Taguchi and Jugulum, 2002). The main method of MTS is to make accurate predictions in multidimensional systems by constructing a measurement scale (Yu-Cheng and Hsiao-Lin, 2009; Taguchi and Jugulum, 2002).

Through the MTS, there are some steps that need to be implemented in order to determine whether the selected variables are significant and accurate in predicting future crises. They are:

First step: Defining the normal group is a critical step in this method since the Mahalanobis Space (MS) is the reference point and base of the measurement scale. The normal group is identified with the mean and standard deviation of each company, calculated on data for each variable as the function below (Cudney et al., 2007 and Taguchi et al, 2001):

$$Mi = 1/n\ (X_i1 + X_i2 + \ldots\ldots\ldots\ldots\ldots\ldots + X_in \qquad (1)$$

$$\sigma i = \sqrt{[1/(n-1)]}\ [(X_i1 - mi)2 + \ldots. + (X_in - mi)2] \qquad (2)$$

The other group is called abnormal group. We also should be able to identify the abnormal group, so that we can compare these two groups in terms of their finance situation. This abnormal group refers to troubled companies in Malaysia, which are being listed in the PN4 list – companies that fail to meet the financial requirements for continued trading on Bursa Malaysia. As with the normal group, the mean and standard deviation of each abnormal group company, calculated on data for each of the variables selected.

***Second steps*:** Then the data will be standardized using the function (3). This standardization is to develop the relationship between the variables taken on the next step of the correlation coefficient of the function (4). Then, a reverse matrix is applied on the results of the correlation coefficient.

$$X_i l = X_i l \text{ - mi / σi} \quad (3)$$

$$\text{rij} = 1/n\ [\ (X_i l \text{ - mi /σi}) \times (X_j l \text{ - mj /σj}) + \ldots\ldots\ldots + (X_i n - \text{mi/σi}) \times (X_j n - \text{mj/σj})\ ] \quad (4)$$

***Third steps*:** The Mahalanobis Distance (D^2) is then calculated using the data of normal and abnormal group. D^2 is calculated to prove that the selected variables are good measures to predict future crisis as in function (5), which is, a low D^2 value indicates high significance of the variables analyzed.

$$D^2 = 1/k\ \Sigma \text{ aij } [\ (X_i \text{ - mi/σi}) \times (X_j \text{ - mj/σj})\ ] \quad (5)$$

***Fourth steps*:**The next step is to optimize the discriminating ability of the MTS system using orthogonal arrays (OA) and the signal-to-noise (S/N) ratio. In this step, the purpose is to reduce the dimensionality of a multivariate system but still obtain meaningful results. The S/N ratio, obtained from the test D^2, is used as the response for each combination of OA. Based on the S/N ratios calculated using the runs in the OA, analysis of means (ANOM) tables are constructed to determine the useful variables and identify the candidate variables for elimination. The larger the S/N ratio value of a company, the more accurate the forecast of a future financial crisis, indicating a low error in the forecast. The S/N ratio is calculated by using functions (6) to (12).

$$y_i = \sqrt{\text{Di}^2} \quad (6)$$

$$\text{St} = y_1{}^2 + y_2{}^2 + \ldots\ldots\ldots\ y_i{}^2 \quad (7)$$

$$\text{S}\beta = 1/r\ (\text{M1 } y_1 + \text{M2 } y_2 + \ldots\ldots \text{ Ml yl})^2 \quad (8)$$

$$\text{R} = \text{Mi}^2 + \text{M2}^2 + \ldots\ldots\ldots\ldots + \text{Ml}^2 \quad (9)$$

$$\text{Se} = \text{St} - \text{S}\beta \quad (10)$$

$$\text{Ve} = \text{Se / l -1} \quad (11)$$

$$\eta = 10\log\ [1/r\ (\text{S}\beta - \text{Ve}) / \text{Ve}] \quad (12)$$

Moreover, with the S/N ratio, the larger the number in the positive direction indicates a greater impact of the corresponding variable on the system.

IV. SOURCES OF DATA

To predict a future Malaysian financial crisis, this study will use the secondary data obtained from Bank Negara Malaysia, Bursa Malaysia and the Department of Statistics. The data was collected from annual reports of the companies involved from 1998 until 2000. This study used 52 samples of companies listed in Bursa Malaysia as the parameters to predict a financial crisis. The selected indicators are revenue (X_1), profit loss before tax (X_2), depreciation (X_3), fixed asset (X_4), total long-term assets (X_5), total assets (X_6), total liabilities (X_7), total reserves (X_8) and shareholders' funds (X_9). The selected variables are similar with the study by Yu-Cheng and Hsiao-Lin (2009). All of these selected indicators will then be analyzed by the Mahalanobis-Taguchi System, as the main research method, using a Microsoft Excel spreadsheet. In line with the findings of Beaver (1966), Altman (1968), Ohlson (1980), Yu-Cheng and Hsiao-Lin, 2009, and Cudney et al. (2007), comparisons of the financial ratios used in this study are expected to highlight differences in the average mean values for healthy firms and those of distressed firms.

V. EMPIRICAL RESULTS

A. Mahalanobis Taguchi System (MTS)

In order to compute the MTS, firstly we have to divide the listed companies in Bursa Malaysia into the two groups, specifically, the normal group and the abnormal group. A normal group is defined as companies that listed on the Main Board of Bursa Malaysia, which do not have a problem or crisis in the financial management of the company. In this study, we used 39 samples of normal companies in year 1998 till 2000 (Table I). While, the abnormal group refers to troubled companies listed on Bursa Malaysia, and a total of 13 distressed companies have been selected for this study (Table I). The selected companies are companies that have been classified as PN4, being companies that fail to meet the financial conditions for continued trading and listing on Bursa Malaysia.

TABLE I
NORMAL AND ABNORMAL GROUP

GROUP	NORMAL	ABNORMAL	TOTAL
1998	39	13	52
1999	39	13	52
2000	39	13	52

TABLE II
THE MEAN VALUE AND STANDARD DEVIATION (SD) FOR ABNORMAL GROUP 1998-2000

YEAR	TITLE	X_1	X_2	X_3	X_4	X_5
	MEAN	99,548.60	-82,672.30	3,207.50	83,067.80	168,266.40
1998	STDEV	224,304.70	160,164.20	7,528.60	259,561.80	413,485.90
	MEAN	50,070.20	-80,697.60	3,336.20	99,515.10	161,264.80
1999	STDEV	108,041.30	161,177.40	7,823.10	407,388.20	498,134.90
	MEAN	43,851.30	-26,718.20	2,446.10	98,499.50	141,653.50
2000	STDEV	82,494.80	57,396.60	5,521.60	408,516.20	463,982.40

YEAR	TITLE	X_6	X_7	X_8	X_9
1998	MEAN	284,146.10	253,521.30	-52,585.10	14,149.80
	STDEV	611,477.50	490,472.20	216,994.80	165,746.30
1999	MEAN	251,161.90	286,225.80	-123,313.60	-56,526.50
	STDEV	682,218.50	609,294.10	274,812.00	187,391.30
2000	MEAN	205,054.60	270,574.00	-147,651.70	-80,711.10
	STDEV	587,650.90	564,593.30	314,859.00	207,891.50

As we can see, for the abnormal group, the ratios are positive throughout with the mean value being stable with no noticeable upward or downward trend (Table II). The results also show that the D^2 for the abnormal group was higher than the D^2 for the normal groups and show a positive sign rather than the normal group coded a negative sign values. According to Taguchi & Jugulum (2002) the lower the D^2 the more significant the variables used, which is why, the D^2 is taken as a measure in determining the first level and second level in the step to determine Orthogonal Arrays (OA). Besides that, we also analyzed the value of the S/N ratio (Table III) to calculate the benefits that determine the significant of the variables.

The analysis of the S/N ratio shows that the interest by all indicators are positive in 1998, this result shows that nine variables is reliability and validity to be used for forecasting the financial crisis in the near future. The same results as shown by the year 1999 and 2000 also resulted positive value for all variables. In order to calculate the accuracy of the MTS model, we again used the data in the normal group and selected all 9 key variables to re-establish Mahalannobis Space. Our determination is also based on minimizing type I and type II error to calculate its accuracy rate (Lee and Teng, 2009; Wang, 2004; and Bovas and Mulayath, 2003). By using all the variables in this study, the accuracy of classification in 1998, 1999, and 2000 is obtained at 98 percent, 96 percent and 98 percent.

B. Artificial Neural Network (ANN)

When comparing the MTS with the model of neural network, the study showed a different result. A neural network model is a powerful parallel computation consisting of an extremely large number of simple processors with manyinterconnections and it is useful method for pattern recognition, learning, classification, generalization and interpretation ofnoisy input. A structure is composed of interconnected artificial neurons. Each neuron has an input and output characteristic andimplements a local computation or function. The output of any neuron is determined by its input output characteristic and itsinterconnection to other neurons and external inputs [4][12]. In this study, about 7 data sets from the abnormal group were used as training data and 1 data set for validation testing (after running the neural network command in MATLAB software). Then, the results turn into a different accuracy classification of the neural network. As we can observe in Table IV, the higher accuracy was shown in the year of 2000.

TABLE IV
NEURAL NETWORK CLASSIFICATION OF TRAINING SET

YEAR	GROUP	MSE	R^2	ACCURACY
1998	Normal	0.0098	0.99	97%
	Abnormal	0.0043	0.97	
1999	Normal	0.000296	0.97	92%
	Abnormal	0.00342	0.92	
2000	Normal	0.00118	0.84	98%
	Abnormal	0.00125	0.98	

TABLE V
COMPARISON OF THE CLASSIFICATION ACCURACY FOR NEURAL NETWORK AND MTS

YEAR	ACCURACY	
	Neural Network	MTS
1998	97%	98%
1999	92%	96%
2000	98%	98%

TABLE III
SIGNAL OF NOISE (SN) RATIO FOR THE ABNORMAL GROUP

		X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
	Level 1	20.001	15.614	18.457	18.792	17.939	17.939	18.274	18.153	18.488
1998	**Level 2**	-3.926	1.160	-2.382	-2.717	-2.382	-2.828	-2.524	-2.382	-2.413
	Interest	23.927	14.454	20.839	21.509	20.321	20.767	20.799	20.535	20.902
		X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
	Level 1	23.850	23.879	23.752	23.752	24.159	22.388	24.379	23.585	23.443
1999	**Level 2**	-0.249	-0.278	-0.151	-0.472	-0.151	-0.562	-0.562	0.158	0.158
	Interest	24.099	24.156	23.902	24.224	24.309	22.950	24.941	23.427	23.285
		X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
	Level 1	24.895	24.511	24.577	24.895	21.778	22.877	22.877	24.267	24.267
2000	**Level 2**	-2.068	-1.675	-1.750	-2.068	-1.674	-0.050	-0.353	-1.440	-1.440
	Interest	26.964	26.186	26.326	26.964	23.452	22.928	23.230	25.708	25.708

According to the empirical results in Table V of MTS and neural network, the accuracy rate of MTS shows the higher values than the neural network. Hence, a high accuracy rate recorded by troubled companies (abnormal group) enables them to be classified into a potential financial crisis group. It show that the forecasting effect delivered by the MTS model is better than that neural network, a result that is in line with most of the viewpoints in research papers by Lee and Teng (2009).

VI. CONCLUSION

In conclusion, the results obtained in this study is in line with findings from the previous studies [10], which stated that the model of MTS is able to prove the accuracy of the variables involved in determining a future financial crisis. The result in this study also reported that MTS shows a good performance compared to neural network in the aspect of data size, efficiency and time. Compared to the neural network, we could only calculate the overall output of MSE, R2 and the accuracy rate. In addition, by applying the MTS model the empirical results from this study have also shown that the nine variables used, confirm their ability to predict a future financial crisis (using the S/N ratio step). Variables involved are the revenue (X_1), profit loss before tax (X_2), depreciation (X_3), total fixed assets (X_4), total long-term assets (X_5), total assets (X_6), total liabilities (X_7), total reserves (X_8) and total shareholders' funds (X_9). The study has also demonstrated that the MTS is a better method to predict a future financial crisis rather than the neural network.

Predicting an economic crisis is both a challenging task. However, as a way for the government to avoid experiencing a severe economic recession in the future as a result of a financial crisis, then predictive techniques should be implemented. Whilst we do not know what will happen in the future, a financial crisis may well be derived from the present, so it is important for stakeholders to be prepared and become aware of future crises, by conducting a prediction model involving an early warning system, whereupon it is hoped that society would be better positioned to understand and assess potential financial instability.

ACKNOWLEDGMENT

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Outliers Effect in Measurement Data for T-peel Adhesion Test Using Robust Parameter Design

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***Abstract* - As many researches focused on application of robust design engineering in practical case study, very less concerned on the criticality to data measurement system in parameter design. This paper will emphasize on the importance to be critical to data. The existance of outliers is often ignored and the impact is overlooked, thus endanger the experiment by producing false alarm and giving completely wrong parameter setting. The optimum condition from the data that contains outliers is compared with the corrected data measurement. The finding presents the indication procedure on how to confirm whether the data is reliable or not for evaluation. The data is unreliable when two main indicators are detected. Firstly, the measurement data plot detects outlier through linear regression analysis as it does not belong on the linear line. Secondly, dB gain difference from reproducibility examination of signal-to-noise ratio (SNR) between estimation and confirmation run is more than 30% shows that the experiment is a failure. This failure affects the experimental design and lead to wrong optimum condition. T-peel test optimization using orthogonal array L9 is done as a case study to elucidate the detection of outlier and outlier effect on optimum condition.**

Keywords – Robust parameter design method, Al-CPP flexible film, outliers, linear regression, dynamic Signal-to-Noiseratio, T-peel test, peel strength

I. INTRODUCTION

Robust design engineering is an engineering optimization strategy ideally used for the development of new technologies in product and process design [1]. One of its component focused in this paper is parameter design which defined as a systematic way to make a design robust against noise factors which takes place in improvement stage of the product development process [2]. However, the methodology of conducting robust design usually started with data analysis of sum and mean, deviation, variation and variance [3]. None emphasizes on the measurement data before the data can proceed to be analyzed. Data which being affected by extraneous sources of variation other than variation studied in outer array could lead to wrong decision. Investigation has to be made whenever anomalies are found, and outlier analysis is one kind of investigation analysis. In this paper, the criticality to measurement data is discussed on a case study performed in T-peel adhesion test to find an optimum condition of a peel strength measurement system. There are many methods to evaluate peel strength of laminated packaging film such as 90^o peel, 180^o peel, T-peel test and climbing drum peel test [4]. The packaging film is flexible material and consists of several layers of flexible films. Therefore, T-peel test is the most suitable peel test to measure the peel strength. The peel strength of multilayer film is one of an important property as practical use for the packaging product. In this paper, T-peel test has been used to measure peel strength on flexible packaging film using new T-peel test apparatus [5]. Thus, it is crucial to establish an optimum testing condition using robust parameter design L9 which has minimum variation in peel strength. For reducing variation, noise factor is taken into consideration. In order to observe the effect of outliers on optimum condition, two L9s are constructed; one with outlier data (L9A) and another one with no outliers (L9B). Experiments were then carried out to detect outlier and its effect on signal-to-noise ratio (SNR). The importance to be critical to data is presented in outlier detection procedure. This paper is organized in the following manner. Firstly, the case methodology of T-peel adhesion test optimization is described as a case study for its measurement process. Next, the measurement data is evaluated for outlier detection through regression plot and reproducibility of experiment. Finally, the paper concludes with a summary of this study.

II. CASE METHODOLOGY

TEST SPECIMEN

The specimen used in this experiment is a four-layer packaging film. Full lamination consists of polyethylene terephthalate(PET), polyamide, aluminum foil and cast polypropylene (CPP) is shown in Fig. 1:

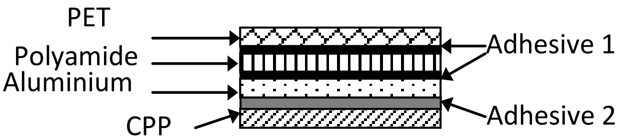

Fig. 1. Test specimen

Peel strength is determined in Newton (*N*) measured by the strength required to peel away between the interlayer of cast CPP and aluminium. Peel angle is read from aluminum side of packaging film [5]. Standardized testing method for T-peel test by ASTM D1876 and Japanese Industrial Standard (JIS K 6854-3) are used to measure the peel strength of the flexible composite materials. However, this method is fit for rigid materials and not suitable on flexible film.Big variation occurred due to specimen failure to sustain the peel angle [6]. New testing apparatus had been established toovercome this problem and suit flexible film peel testing.

NEW TEST APPARATUS

As shown in Fig. 2, angle adjuster is used to changed the peel angle according to orthogonal array setting. Specimen is attached at the bottom of the drum, and a weight (paper clip) is fixed on the free-end of the film to keep the specimen in T-shape. When the specimen started to peel, parallel spring is pulled by pulley wire attached on the rotating drum along peeling process. The spring displacement is detected by a laser displacement sensor.

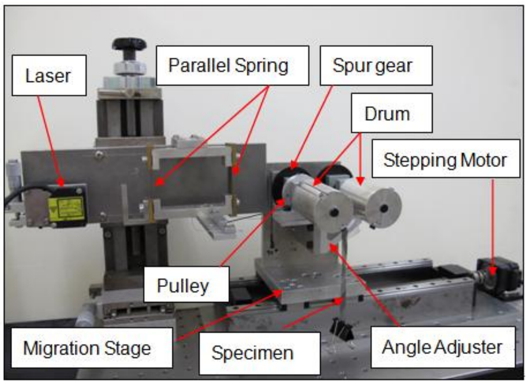

Fig.2. New apparatus for T-Peel test

IDEAL FUNCTION AND P-DIAGRAM

A dynamic ideal function is used, based on wide range of specimen width. The response, Y; is peel strength, the output from the measurement process with as small unwanted variation as possible. M is the input of signal factor from various range of specimen width for peel strength linearity. Beta,β, is the measurement sensitivity to different inputs, thus the slope must be steep. Therefore, the dynamic ideal function is zero-point proportional equation [3], Y=βM.P-diagram is described in Fig. 3:

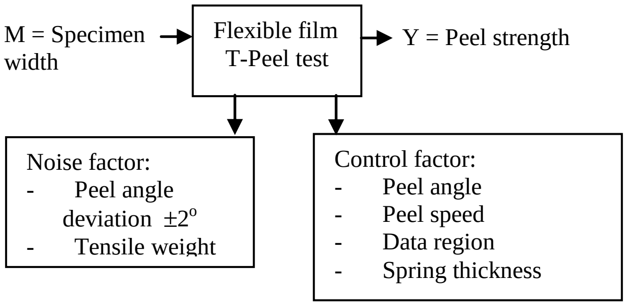

Fig. 3. P-diagram of T-peel test

CONTROL FACTOR

The control factors are set in inner array chosen based on testing and design condition. Peel angle, peel speed, peeling curve data region, and spring thickness are controllable factors considered based on testing condition and apparatus design.

ORTHOGONAL ARRAY SELECTION

Orthogonal array is a balanced set of experimentation runs to explore the design space with small number of experiments[3]. 54 experiments in one L9 is implied for this study (9 x 3 signal level x 2 noise level). Table I summarized the factors used in L9. Two L9s are constructed, one with outliers data and another L9 is repeated without outliers.

TABLE I FACTORS AND THEIR LEVELS IN L9

Control Factor	***Unit***	***Level 1***	***Level 2***	***Level 3***
A: Peel angle	°	60	90	120
B: Peel speed	mm/s	6	9	12
C: Data region	%	30	50	70
D: Spring thickness	mm	0.3	0.4	0.5
Signal Factor				
M: Specimen width	mm	5	10	15
Noise Factor		***N1***	***N2***	
Tensile weight	g	8	4	
Peel angle deviation	°	+2	-2	

SIGNAL FACTOR

In the ideal function, the energy transformation occurs for three different specimen width that are 5mm, 10mm and 15mm. Signal factor is a controllable variable to actualize the intention to achieve robust condition regardless of various width condition. A dynamic signal-to-noise ratio (SNR) has been used in this study, where the specimen width as the signal factor with 3 levels that are 5mm, 10mm and 15mm is used to measure the peel strength linearity. Hence, signal-to-noise ratio (SNR), η, for dynamic response is used in this study to measure various range of input to ensure robustness.

η= 10 log [(1/(r_o. r)) (S_β - V_e) / V_N] (1)

NOISE FACTOR

Noise factor is a factor that cause variation in measurement system. For noise factor, peel angle deviation of $\pm$2 degrees is chosen as shown in Fig. 4. Peel angle is adjusted in three levels that are 60^o, 90^o and 120^o. The angle would vary during exchanging the peel angle and along peeling process. Therefore, noise in peel angle is defined as deterioration in $\pm$ 2^o for each level. Tensile weight of 4g and 8g is also considered as noise factor because a weight is loaded at the end of specimen to sustain the T-shape.

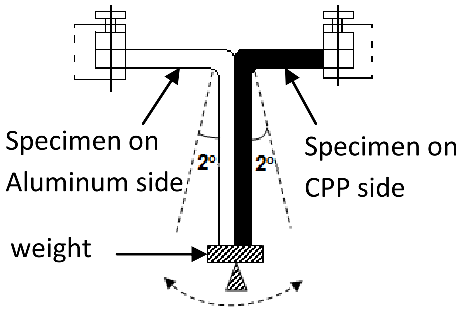

Fig.4. Deviation in peel angle during T-peel

Noise 1 is the higher level ($N1$ = +2^o and 8g) and Noise 2is the lower level for ($N2$ = -2^o and 4g). N1 and N2 are arranged in outer array to study the variation effect when combine with control factors and signal factors. Table II summarized the noise factor:

TABLEII NOISE FACTOR FORL9

N1	N2
62^o, 8g	58^o, 4g
92^o, 8g	88^o, 4g
122^o, 8g	118^o, 4g

III. MEASUREMENT RESULTS

Peel strength result is taken for SNR calculation. First measurement result is labelled as L9A and shown in Table III. The data, Yij, is assumed independent and in normal distribution.

TABLE IIIL9ARESULT

Run	Specimen width (mm)						SNR
	5		10		15		η(dB)
1	9.07	8.44	16.21	16.88	25.25	26.13	10.03
2	7.92	7.85	14.95	15.19	22.22	21.75	11.20
3	9.61	9.45	19.01	20.93	27.72	30.47	4.87
4	8.04	8.44	19.57	20.32	27.62	30.07	3.55
5	8.52	8.21	16.84	17.21	26.05	25.68	16.27
6	7.57	8.17	15.77	15.55	21.72	22.44	7.69
7	6.39	6.49	13.52	13.71	20.14	20.58	14.18
8	12.88	8.21	20.86	20.52	29.60	30.22	2.20
9	7.69	7.08	17.30	16.50	24.87	23.75	6.37

SNR, η = 10 log (1/r) [(S_β - V_e) / V_N] (1)

S_β = $\frac{((9.07+8.44)5+(16.21+16.88)10+(25.25+26.13)15)^2}{2(5^2+10^2+15^2)}$

$V_e = S_e/f_e = (S_T - S_\beta - S_{Nx\beta}) / 4$ (2)

S_T = $9.07^2+8.44^2+16.21^2+16.88^2+25.25^2+26.13^2$

$S_{Nx\beta}$=$((9.07)5+(16.21)10+(25.25)15)^2+((8.44)5+(16.88)10+(26.13)15)^2) / (5^2+10^2+15^2) - S_\beta$

$V_N = S_e' / f_e' = (S_T - S_\beta) / 5$ = 0.29 (3)

η = 10 $\log_{10}(1/2(5^2+10^2+15^2))[(S_\beta - V_e) / V_N]$ = 10.03dB

IV. DISCUSSION

Once the result is obtained, it is important to be critical to data before proceeding to further analysis. Otherwise, the analysis of improper data will endanger the experiment and lead to improper conclusion. Linear regression plot is one alternative to investigate the existance of outliers. Measurement data for L9A is shown in Fig. 5. In 5mm, one outlier is detected as it does not belong to its population group. Peel strength of that one point is abnormally different, that is 12.88N. The investigation is continued by plotting the regression plot for 5mm as in Fig. 6 to investigate the problem. N1 and N2 are assumed as two variables and the correlation coefficient, r, is used to measure the linear relationship between two variables. The squared coefficient of correlation, R^2, gives the proportion of common variance between two variables, also called coefficient of determination [7]. The closer the value of R^2 is to 1, the stronger the linear association

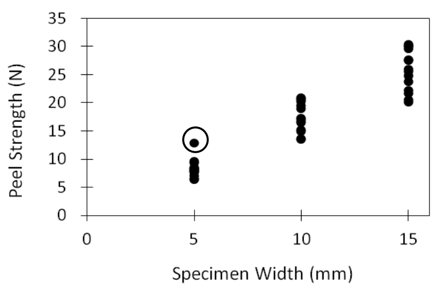

Fig. 5. L9A measurement data

between the variables. One extremely deviant observation, so-called outlier, can dramatically influence the value of R^2 [7]. In Fig. 6, R^2 without outlier is 0.766, but when the outlier is added to the set, the correlation is equal to -1.935. R^2 can never be negative as it is the square of r. The value of R^2 is bounded by 0 < R^2< 1. The existance of outlier presents a suspicious observation and the result need to be repeated to confirm the cause or else it might lead to wrong conclusion. In L9A, the outlier data is 12.88N in run 8 for specimen 5mm under N1. Outlier is not observed in specimen 10mm and 15mm as R^2 for specimen 10mm and 15mm is 0.910 and 0.895

respectively. Then, mean SNR so-called process average is calculated to find the effect of each control factor. The process average is used to calculate the optimum condition based on SNR factorial effect plot.

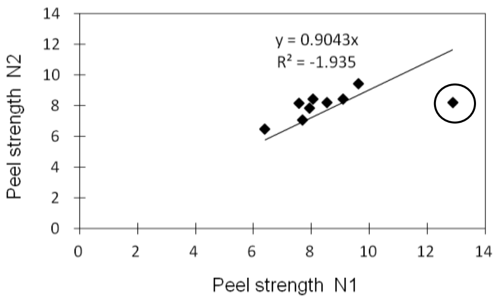

Fig. 6. Specimen 5mm measurement result

Optimum condition for L9A derived from SNR formula in (1) is A2 B2 C3 and D2. The detection procedure is proceed by checking the experiment reproducibility through comparison of SNR estimation and confirmation dB gain. Estimation SNR for optimum condition is calculated by:

= A2+B2+C3+D2 – (DOF n-1)($\Sigma\eta$ / n) (4)

= (A2+B2+C3+D2) – (4 factor–1)(average SNR in L9A)

= 41.84dB – 3(8.48dB) = 16.39dB

Estimation SNR for worst condition is calculated to get the dB gain. The effect of the optimum condition is shown by the dB gain size.

= (A3+B3+C1+D3) – (4 factor–1)(average SNR in L9A)

= 24.07dB – 3(8.48dB) = - 1.38dB

Thus, estimated db gain is 17.77dB. Confirmation run is done to ensure the reproducibility of optimum condition. However, the confirmation dB gain is 9.75dB, which is 45.1% different from estimation dB gain. The result of experiment is considered not satisfactory. This indicates the possibility of wrong optimum condition resulted from outlier data. The dB gain difference should not exceed 30% difference from estimation dB gain [8]. From the anomaly of R^2 and dB gain difference, second L9 which is called L9B in Table IV is employed as to repeat the experiment and confirmed the outlier reproducibility. All 9 runs are conducted again to reduce extraneuos sources of variation.

TABLE IVL9B RESULT (REPEATEDEXPERIMENT)

Run	Specimen width (mm)						SNR η
	5		10		15		(dB)
1	8.70	8.37	16.62	16.78	24.96	24.09	12.40
2	8.04	8.12	15.28	16.21	23.91	24.52	11.77
3	8.72	8.09	16.59	16.39	24.49	24.30	15.15
4	7.79	8.04	15.68	15.86	23.87	24.38	15.97
5	8.45	8.41	16.49	16.20	24.12	23.99	14.85
6	8.26	8.18	15.51	15.80	24.43	24.32	13.28
7	7.59	7.74	14.77	15.15	22.16	22.20	16.76
8	7.46	7.69	15.03	15.83	22.68	23.58	11.76
9	8.49	8.27	15.87	16.29	23.76	24.09	14.43

Measurement data of L9B is plotted to observe any outlier. R^2 for 5mm, 10mm, and 15mm are 0.729, 0.676, and 0.645 respectively. No outlier is observed. The outlier in L9A is a special cause, due to environment noise or measurement mistake that cause the 12.88N as outlier data. SNR as in (1), SNR process average and effect plot, and estimation SNR as in (4) are calculated as same as L9A. The optimum condition for L9B is A2 B1 C3 D3 as shown in Fig. 7. The estimated db gain is 7.31dB and confirmation db gain is 6.53dB. Table V summarized only 10.7% difference, thus L9B is considered a success:

TABLE VREPRODUCIBILITYEXAMINATIONFORL9A AND L9B

Type	Condition	Estimated	Confirmation
L9A A2 B2 C3 D2	Optimum	16.39	15.10
	Worst	-1.38	5.35
	SNR dB gain	17.77	9.75
	Gain difference	8.02 dB (45.1% difference)	
L9B A2 B1 C3 D3	Optimum	17.49	16.45
	Worst	10.18	9.92
	SNR dB gain	7.31	6.53
	Gain difference	0.78 dB (10.7% difference)	

Notice that there are some deviations between condition L9A and L9B. SNR for L9B is higher than L9A due to repetition error since L9B is done after realizing the outlier existing, which took some time gap between both experiment. The variation is also due to extraneous factors which inevitably vary during experiment such as temperature and humidity. As the paper focused on the effect of outlier from response data and its influence on optimum condition, the difference in optimum condition level between separated data set is assumed has no effect in outlier examination.

V. CONCLUSION

The importance of making thorough analysis of assumptions and possible existance of outliers have become obvious from the case study in this paper. Even

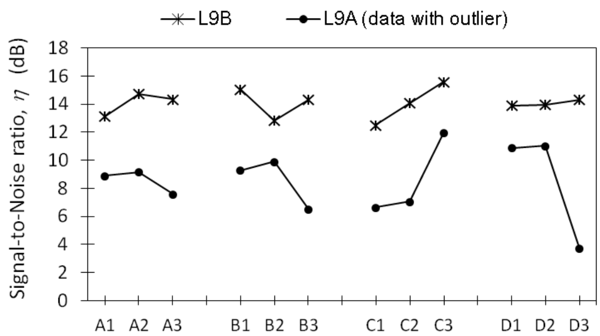

Fig. 7. SNR factorial effect plot for L9B and L9A

though the confirmation test indicated the problem and thus trigger suspicious to data, a thorough investigation of possible anomalies in measurement data should be performed. Thus, it is very important to ensure that the data is reliable enough to draw a conclusion at the end of the experiment. Two ways to examine on data reliability:

a) Outliers examination - by observing the linear relationship in regression plot. R^2 changed dramatically when deviant observation is found.
b) Reproducibility examination – Estimation and confirmation in dB gain difference should not deviates too much or exceeds 30%. The similar the value between estimation and confirmation SNR, thus more reliable the optimum condition is.

Measurement data should be examined immediately once the experiment is performed to prevent perils.

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Visible Penetration Testing Of Defects in Similar and Dissimilar Metal Butt Joint TIG Welding

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Abstract - The aim of this research is to determine the optimum visible penetrant parameter significantly with quality characteristic “the smallest the better. The optimum parameters drive to appropriate setting of variable method and techniques in visible penetration testing to gain better developer dwell time and total cycle time of the penetration testing operation. This research paper is focused on dissimilar and similar metal. Taguchi design experiment has shown that the type of butt joint material has significant role in producing the proper way for defect indication and interpretation. This results obtained by this method will be useful for manufacturer create routing for production activities and further research on mathematical modeling of visible penetration testing for dissimilar metal.

Keywords - **Non-destructive testing, visible penetration testing, Taguchi method and butt joint welded sample**

I. INTRODUCTION

Non-destructive testing has been in high demand lately due to the increased customer demand on the good functionality, durable, consistency, reliability, efficiency and safety product. Non-destructive testing or NDT is an inspection practice that utilizes different method. It performs examination and evaluation to verify the structural integrity of part without compromising the mechanical or chemical properties of the material. It also can be used for inspect dissimilar metal [1]. The non-destructive testing (NDT) can be applied to evaluate the quality of a weld. It is necessary to examine weld characteristics covers the magnitude of the weld and the presence of discontinuities. Inspection of weld structure is essential to ensure quality of the materials and for safety and reliable operations [2].The NDT methods involve ultrasonic, magnetic-particle, liquid penetrant, radiographic, remote visual inspection (RVI) and eddy-current testing [3]. Liquid penetrant testing is one of the NDT methods. It is an inspection for examine, interpretation, evaluate and indication surface open defect of the good surface condition tested metallic and non-metallic material that coated penetrant with a visible or fluorescent dye for prevent product, component and structure failure caused performance of erosion, wear ,fatigue crack, shrinkage crack, shrinkage porosity ,corrosion and creep. The liquid penetration testing is inexpensive compared to radiography, eddy current and ultrasonic testing. It’s relative easy, quick and simple operation based on the lesser amount of testing material, reduced setup and training required to carry out the test. For almost important reflect to it’s concern about the highly sensitive to detect small discontinuities and appropriate for part with large area and complex shapes. This research provides a clear understanding on the method and technique in penetration relating to a few independent variables approach to be made in the attempt to overcome the cost saving, reliable, high-sensitive non-destructive method to detect surface discontinuities in objects .The optimization of all technological stages of PT and the search for additional possibilities to increase the efficiency of PT, are of principal importance [4].

Design of experiment (DOE) is an organized arrangement and method for data collection desirable to motivation valid and defensible data. There are typical model design of experiment such as full factorial, Taguchi method, surface response methodology and others. Therefore, the Taguchi method was selected due systematic and inspiration technique to find the optimal process parameters condition in the visible penetration testing. Optimization of process parameters is the key step in the Taguchi method to achieving high quality without increasing cost. This is because optimization of process parameters can improve quality [5].Amazingly; it formed the lesser number of experiments. Each process parameter is assigned to a column and each row corresponds to one experimental run [6].Taguchi method capable to standardized form of design of experiment with special principle and suitable technique for study several effect of factors [7].Quality characteristic observed in this study was “the smallest the better" due to the fact that smallest developer dwell time represents less inspection time for flaws detection and indication. This researcher recommended the quality characteristics deviating from desired value can be measure using S/N ratio which S/N analysis can calculated the S/N ratio. In addition, they seen the relationship in term a greater S/N ratio corresponds to better quality characteristics and agreed with the optimal level of the process parameters is the level with the greatest S/N ratio [7].

II. EXPERIMENTAL SET UP

The materials studied in this research were carbon steel, stainless steel and aluminum. Two dissimilar test samples were observed in this study included a test specimen of dissimilar ferrous material metal such as carbon steel joint stainless steel and a test specimen ferrous with nonferrous dissimilar materials is carbon steel joint aluminum. And encounter a test specimen of similar metal is aluminum joint aluminum were prepared by supplier using TIG welding machine for produced butt joint test samples. Therefore, three test samples were examined in this research work. In this study, stainless steel, carbon steel and aluminum sheets which have 150 mm in length, 106 mm in width and 3mm thicknesses were welded in type butt joint configuration. All section stainless steel samples were TIG welded with sectioned carbon steel samples as shown in Figure.1 followed by carbon steel welded with aluminum as illustrates in Figure.2. Subsequently, Figure.3 shows aluminum joint with aluminum. An L27 orthogonal array is designated for experimentation with five-three level visible penetrant process parameters such as dry time, dye penetration angle, dye penetration layer, penetration dwell time and type of butt joint material are deliberated in Table I.

Fig 1.Carbon steel joint stainless steel

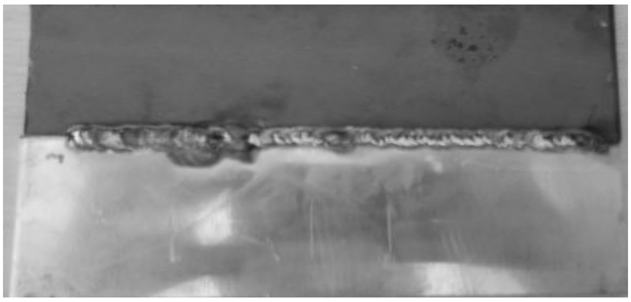

Fig 2: Carbon steel joint aluminum

Fig 3: Aluminum joint aluminum

Three different levels value of visible penetration testing parameters are applied. On the other hand, there are three factors that are believed to influence the variation of the response. Body position, humidity and temperature factors were selected as the noise factor in this experiment. Dye penetration testing was performed on these surface materials. In dye penetration testing, primarily with visual inspection was performed on the surface welded material and applied penetrant application with different angle setting such as 35 degree,40 degree and 45 degree and consequently with typical number of layer dye penetrant included 1 layer,2 layer and 3 layer. Then the penetrant permitted remaining for a certain time called penetration dwell time in different setting time cover 5 minutes, 6 minutes and 7 minutes. Continue with removal of excess penetrant and then the drying process was performed on the different dry time level was set 1 minutes, two minutes and three minutes in exposure environment. Next, stage of developer application and inspection The Inspection was performed using visible eye and magnifying glass to detect indications from any flaws present .Finally, post cleaning is performed where the surface is brushed and cleaned thoroughly with remover.

TABLE I
L27 ORTHOGONAL ARRAY AFTER ASSINGMENT OF PARAMETERS

Run	dry time (minutes)	dye penetration angle (degree)	dye penetration layer (number of layer)	penetration dwell time (minutes)	Type of butt joint material
1	1	35	1	5	CS joint SS
2	1	35	1	5	CS joint AL
3	1	35	1	5	AL joint AL
4	1	40	2	6	CS joint SS
5	1	40	2	6	CS joint AL
6	1	40	2	6	AL joint AL
7	1	45	3	7	CS joint SS
8	1	45	3	7	CS joint AL
9	1	45	3	7	AL joint AL
10	2	35	2	7	CS joint SS
11	2	35	2	7	CS joint AL
12	2	35	2	7	AL joint AL
13	2	40	3	5	CS joint SS
14	2	40	3	5	CS joint AL
15	2	40	3	5	AL joint AL
16	2	45	1	6	CS joint SS
17	2	45	1	6	CS joint AL
18	2	45	1	6	AL joint AL
19	3	35	3	6	CS joint SS
20	3	35	3	6	CS joint AL
21	3	35	3	6	AL joint AL
22	3	40	1	7	CS joint SS
23	3	40	1	7	CS joint AL
24	3	40	1	7	AL joint AL
25	3	45	2	5	CS joint SS
26	3	45	2	5	CS joint AL
27	3	45	2	5	AL joint AL

III. RESULTS AND DISCUSSIONS

TABLE II
RESPONSE TABLE FOR SIGNAL TO NOISE RATIOS SMALLER IS BETTER (DYE PENETRATION TESTING).

Factor	Level 1	Level 2	Level 3	Delta	Ranking
Dry Time	-36.2	-35.86	-36.66	0.8	5
Dye Penetration angle	-35.51	-36.99	-36.23	1.49	2
Dye Penetration Layer	-35.69	-36.77	-36.26	1.08	4
Penetration Dwell Time	-36.68	-35.38	-36.67	1.3	3
Types Of butt joint material	-37.37	-36.02	-35.34	2.03	1

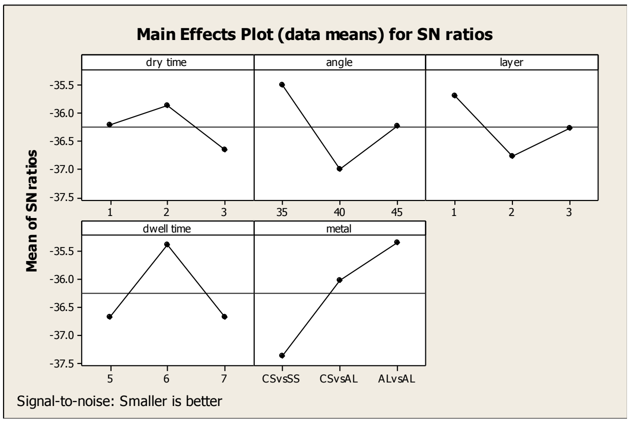

Fig 4 : Mean S/N graph for dye penetration testing

IV. DISCUSSION

Fortunately, thru experiment observation seems that all work piece sample were fully covered with dye penetration when applied different dye penetration angle. Consequently, applied dye penetration, remover and developer from aerosol cans entail providing a prodigious attention to shield personal safety and health. The results were analyzed by employing main effects and the signal-to-noise ratio (S/N) analyses.Furthermore, a confirmation test was performed to compare the experimental results with the estimated results.Expressively,the designed S/N ratio for five factors on the dye penetration testing for each level is exposed in Fig.4.Subsequently,as shown in Table II and Figure.4 type of butt joint material is a leading parameter on the dye penetartion testing followed by dye penetration angle.

Accentuate,the dry time had a lower effect on the dye penetration testing process.Lower developer dwell time and total cycle time of dye penetration testing is always ideal.The quality characteristic measured in the investigation is smaller the better characteristics. Despite the fact that smaller developer dwell time in dye penetration testing represents less inspection time .In the present investigation, when the dye penetration angle is set at 35° is applied the developer dwell time is minimized. The study indicated that the optimum conditions for the dye penetration testing can be recognized at, Dry time (A): 2 minutes, Dye penetration angle (B): 35° degree, Dye penetration layer (C): 1 layer, (D) Penetration dwell time: 6 minutes, (E) type of butt joint material: Aluminum joint aluminum.

V. CONCLUSION

Dye penetration inspection was successfully conducted on butt joint dissimilar and similar metal at different parameter condition. It can be emphasized that dye penetration testing is portable inexpensive system and economically for weld inspection. This paper has presented an exploration on the optimization parameters on dye penetration testing process.Based on the experimental and analytical results, the following conclusions are drawn:

- The effect of control parameters on the dye penetration testing has been evaluated with the adopt of Taguchi method and optimal parameter conditions to minimize the developer dwell time and total cycle time of dye penetration testing have been determined.
- The type of butt joint material is the dominant parameter for dye penetration testing followed by the dye penetration angle. Dry time shows minimal effect on dye penetration testing process compared to other parameters.
- For achieving good inspection time on the butt joint work piece, high dry time , high

penetration dwell time ,lower dye penetration angle and lower penetration layer are preferred.The exsisting optimum contol parameter is as a part of method and technqiue in dye penetration inspection line and can be simply adopted for industrial applications.

- Butt joint similar and dissimilar material inspection is a medium complex activity dependent upon method and technqiue of dye penetration testing and human visuability and reliability especially in decision making process whether accept or reject.

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Optimization of Sintering Parameters of Titanium Alloy Foams Using Taguchi Method for Improved Electrical Conductivity

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Abstract ; **Titanium Alloy powder was used to prepare titanium foam using the slurry method. The electrical conductivity is the most important parameter to be considered in the production of good bipolar plates. To achieve a high conductivity of the titanium alloy foam, the effects of various parameters of sintering including temperature, time profile and composition have to be characterised and optimised. This paper reports the use of the Taguchi method in optimising the sintering parameters of titanium alloy foams. The effects of four sintering factors, namely, composition, sintering temperature, heating rate and soaking time on the electrical conductivity has been studied. The titanium slurry was prepared by mixing titanium alloy powder, polyethylene glycol (PEG), methylcellulose and water. Polyurethane (PU) foams were then impregnated into the slurry and later dried at room temperature. These were next sintered in a high temperature vacuum furnace. The various factors were assigned to an L_9 orthogonal array. From the Analysis of Variance (ANOVA), the composition of titanium powder has the highest percentage of contribution (66.04) to the electrical conductivity followed by the soaking time (1.59). The optimum electrical conductivity was found to be 843.6011 ± 126.54 S/cm^{-1} for this titanium foam. It was achieved with a 70% composition of titanium alloy, sintering temperature of 1300^{o}C, a heating rate of 1.0^{o}C/min and 150 minutes of soaking time. Confirmatory experiments have produced results that lay within the 90% confidence interval.**

Keywords**; PEMFC; Slurry Method; Metal Foam; Sintering**

I. INTRODUCTION

The polymer electrolyte membrane fuel cell (PEMFC) is a cell of choice for future automotive propulsion applications, in part because of its modestly low operation temperature (< 100°C) (1). Hydrogen and oxygen were used in PEMFC system to generate electricity with water as the only byproduct. The advantage of this system is very environmental friendly. The components in this system are MEAs (membrane electrode assemblies), anode and cathode. We can also call anode and cathode as bipolar plate. This bipolar plate are designed to accomplish many functions, such as to distribute reactants uniformly over the active areas, remove heat from the active areas, carry current from cell to cell and prevent leakage of reactants and coolant (2).

Conventionally, carbon based materials have been selected to make the bipolar plate. These carbons are chemically steady in a fuel cell environment and produce the highest electrochemical power output. However, the lack of mechanical strength with is natural with carbon, limits the size of the bipolar plate can be produced, as well same as the volumetric power density (3). Because of these disadvantages, many researchers have studied the alternative material to replace carbon as a bipolar plate. The alternative materials are carbon-carbon composite, carbon-polymer composite and metals (4). This study, focused mainly on the possibility of adopting titanium (Ti) foam as bipolar plate.

The traditional approach to experimental work is to vary one factor at a time, holding all other factors fixed. This method does not produce satisfactory result in a wide range of experiment settings (5). In this study, the Design Of Experiment (DOE) method which is called Taguchi method is adopted to determine and optimize the sintering parameters. In recent years, the Taguchi method has become a powerful tool for improving productivity during research and development (6). The effect of four factors: composition of titanium alloy, sintering temperature, heating rate and soaking time on the electrical conductivity were investigated. The optimum sintering condition was proposed and confirmation experiments were conducted.

II. METHODOLOGY

A. Sample preparation

Titanium powder was purchased from Sumitomo Titanium Corporation of Japan. The particles are spherical in shape with the diameters less than 45µm. The density of the titanium powder was 4540 kg/m^3 and the melting point was 1670^{o}C. Polyethylene glycol (PEG) and methylcellulose (CMC) were used as binders. PEG and methylcellulose are water soluble materials (7).

Firstly, PEG and CMC were stirred in distilled water for one hour. Pure titanium powder was subsequently added to the solution and stirred for two hours. The titanium slurry was used to impregnate polyurethane (PU) foam. The PU foams were dipped into the slurry and the dipping and drying processes were repeated until the struts of the foam were completely coated with titanium slurry. The excess slurry was then removed by pressing the foam under a roller. Lastly sintering process will be carried out for these samples followed the orthogonal array of Taguchi method (7).

B. Design of Experiment (DOE).

There are many sintering parameters that can affect the mechanical and physical properties of titanium foam. A design of experiment (DOE) methods is necessary for the experimental work which involving many inputs to minimise the number of experiments need to be performed. The most frequently used methods are partial or full factorial and the Taguchi approach. The Taguchi approach is mostly used for scientific research. The method is based on balanced orthogonal arrays (8). In this work, L_9 (3^4) orthogonal array consisting of 9 experiment trials and 4 column is used followed by ANOVA (ANalysis Of VAriance) to determine the significant level and contribution of each variables to the electrical conductivity. The main variables involved in this study are shown in Table 1. Three levels for each variable refer to the maximum and minimum limit that influences electrical conductivity.

Table 1: Factor level in the experiment and Orthogonal array

Experiment no.	Factor				Experimental value			
	A	B	C	D	Composition	sintering Temperature (^{o}C)	Heating rate (^{o}C min^{-1})	Soaking time (min)
1	0	0	0	0	60	1200	1.5	60
2	0	1	1	1	60	1250	1	90
3	0	2	2	2	60	1300	0.5	120
4	1	0	1	2	65	1200	1	120
5	1	1	2	0	65	1250	0.5	60
6	1	2	0	1	65	1300	1.5	90
7	2	0	2	1	70	1200	0.5	90
8	2	1	0	2	70	1250	1.5	120
9	2	2	1	0	70	1300	1	60

III. RESULT AND ANALYSIS

The electrical conductivity was calculated using resistivityfrom the sample after the sintering process. Three replications were recorded for each experiment as shown in Table 2. The ANOVA technique was used to establish the relative significance of the factors. As shown in Table 2, a combination of A_2 B_2 C_1 D_2 gives a maximum electrical conductivity (876.92 S/cm). While, a combination of A_0 B_0 C_0 D_0 produced a minimum electrical conductivity for titanium alloy foam (300.76 S/cm). These values are much higher compare to carbon fibre epoxy composite (300 S/cm) and carbon based polypropylene composite (36.4 S/cm) (10, 11). Overall, the value for electrical conductivity of the samples was much higher than the requirement electrical conductivity for bipolar plate PEMFC. From the previous research, the requirement for electrical conductivity should be over 10 S/cm (9).

Table 2 Result Electrical Conductivity of titanium alloy foams

Experiment	Replication, conductivity (S/cm^{-1})			Average
	R1	R2	R3	
1	324.12	232.75	345.42	300.76
2	205.94	414.54	630.93	417.14
3	301.51	530.63	685.2	505.78
4	545.79	590.96	409.78	515.51
5	329.13	358.02	319.66	335.60
6	407.68	455.6	366.63	409.97
7	1006.22	750.83	644.6	800.55
8	692.91	945.38	921.7	853.33
9	1095.47	835.47	699.83	876.92

Besides that, the analysis of variance (ANOVA) was used to establish the relative significance of the factors. ANOVA is a table of information that displays relative influences of factor and interactions assigned to the column of an OA. Table 3 shows the results of the ANOVA after "pooling" with "at least 99% confidence". From the ANOVA table, the effects of sintering factors on the electrical conductivity were determined.

The composition of the titanium powder has significant effect on the electrical conductivity at the 99% significance level or $\alpha = 0.005$. On the other hand, the sintering temperature and heating rate factors did not have any contribution for this experiment. For the soaking time factor, F ratio did not exceed 90% of significant level (2.6239) but it still gave 1.59% contribution for this experiment.

Table 3 ANOVA for electrical conductivity of titanium alloy foam at $\alpha = 0.005$

Variable	Degrees of Freedom, f_n	Sum squared, S_n	Variance, V_n	Pure Sum squared, S_n	Varience ratio, F_n	Critical F value	Contribution, P_n
A	2	1107386	553693	1064787	25.996	$F_{0.005,2,18}$=7.2148	66.04
B	2	21953.22	10976.6		0.515		
C	2	31479.77	15739.9		0.739		
D	2	68209.997	34105	25611.12	1.601		1.59
error	18	383389.9	21299.4				32.38
Total	26	1612418.9					100.00

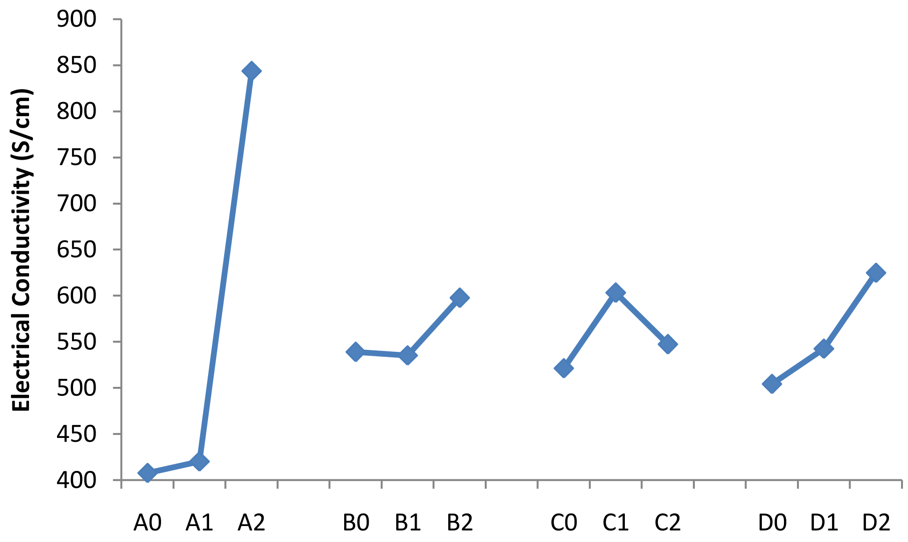

Figure 2 Response graphs of electrical conductivity against various factors

Based on the ANOVA, the main effect of the experiments is calculated based on the highest average value as shown in Figure 2. As shown by the response plot in Figure 2, a combination of A_2 B_2 C_1 D_2 is the highest yield, i.e., composition 70% of titanium powder, sintering temperature 1300°C, heating rate 1.0°C/min and soaking time 180 minutes.

The expected result at optimum performance is as shown in Table 4. The optimum performance is as high as 843.6011 S/cm while the range of the optimum performance based on 90% confidence level is 717.0631 S/cm <μ< 970.1391 S/cm of the electrical conductivity. The optimum parameter has been proven in the confirmation experiment that is conducted at the combined setting of A_2 B_2 C_1 D_2 and the result fell within the predicted 90% confidence interval as shown in Table 4.

Table 4 Optimum sintering parameter, optimum performance and confirmation experiment

Optimum parameter: A2 B2 C1 D2 (Composition, 70% of titanium powder; sintering temperature, 1300°C; Heating rate, 1.0°C/min; soaking time, 180 minute)				
Optimum performance: 843.6011 S/cm Confident interval: ± 126.54 at 90% confident level (α = 0.1) Range of optimum performance: 717.0631 S/cm <μ< 970.1391 S/cm				
	Confirmation experiment			
Repeat	1	2	3	Average
S/cm	750.7	808.05	739.68	766.14

IV. DISCUSSION

From the analysis of the experimental results using the Taguchi method, the composition of titanium has the most significant effect on the electrical conductivity.

Among the three compositions, 70% of titanium has the highest electrical conductivity. When more particle of titanium in the sample, more connection among of particle is obtained and more current (I) pass through in the sample. From the Ohm's law theory, if current

(I) was increases so the resistance (R) is also increases, therefore the electrical conductivity will be increased.

The second factor which has a significant influence to the electrical conductivity is the soaking time. When the soaking time is increase, the porosity will be decreased and the grains become finer (5). As porosity decrease, the sample will shrink further, and there will reduce the area of the sample. As the area of the sample decreases, the resistivity (ρ) will also decreases and the electrical conductivity will be increased [12].

V. CONCLUSION

Electrical conductivity of the titanium foams was optimised using the Taguchi method. An L_9 orthogonal array was used to vary the experiment variables. ANOVA showed that the composition of titanium powder and the soaking time as the most significant that influence the electrical conductivity of the titanium alloy foams produced. The optimum sintering parameter were found to be A_2 B_2 C_1 D_2 corresponding to 70% of composition titanium powder, 1250°C of sintering temperature, 1.0°C/min of heating rate and 180 minutes of soaking time. Confirmation experiments indicated that when sintering titanium foam was performed at the optimum condition, an electrical conductivity of 766.14 S/cm can be achieved.

VI. ACKNOWLEDGMENT

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Educational case studies for engineers and students to learn the parameter design

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Abstract - **In this paper, we will analyze a simple transistor circuit using Texas Instruments' TINA-TI and discuss methods to optimize the elements in the circuit using parameter design. We will use this case study to learn about parameter design processes and features that should be noted.**

Keywords - parameter design, simulation, electrical circuit, TINA-TI, Taguchi Methods

Ⅰ. Introduction

Parameter design is one of many techniques for the Taguchi Methods and is powerful for engineers. Engineers can solve practical issues and improve their technical skills by mastering this technique. However, to apply parameter design in practical situations would require a lot of time and significant costs. In addition, applying parameter design in a real-world environment does not necessarily mean that a technical issue can be solved. It is for these reasons that some engineers will hesitate to apply parameter design in real-world environments.

In this paper, we encourage engineers and students studying parameter design to use simulations. Although simulations cannot always be utilized in a practical scenario, students can avoid the risk of system failure by using a simulation when first learning about parameter design.

In this paper, we will introduce a case study where parameter design is used to optimize element constants of a simple transistor circuit. This transistor circuit is analyzed using TINA-TI, which is free software provided by Texas Instruments. We will use this case study to demonstrate parameter design processes and at the same time, to discuss the points to be noted when applying simulations in parameter design.

Ⅱ.The Objectives of this Case Study

The objective of this case study is to understand the processes of parameter design through optimizing grounded emitter amplifier circuit element constants using simulations. At the same time, the case study will be used to discuss the points that should be noted when applying parameter design in simulations.

Ⅲ.Parameter Design study objects and the free software used in our simulations

The circuit simulator we will use is called TINA-TI. This is free software provided by Texas Instruments (TI)

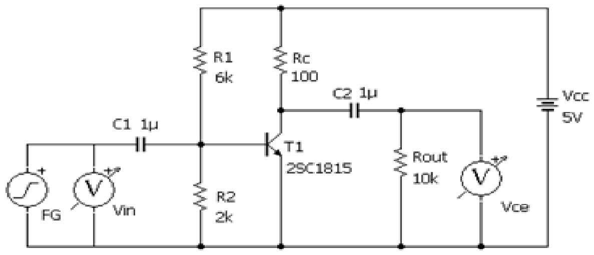


Figure 1 Grounded emitter amplifier circuit for parameter design

and can be downloaded from http://www.ti.com/tool/tina-ti. TINA-TI determines the constants for grounded emitter amplifier circuit elements, like the example shown in Figure 1. The program can also be used to display an output waveform and the text data from the simulation of the circuit, as shown in Figure 2. This is obtained by simulating an input sine waveform of 1 MHz in FG of Figure 1, and using TINA-TI's oscilloscope function to plot the resulting output.

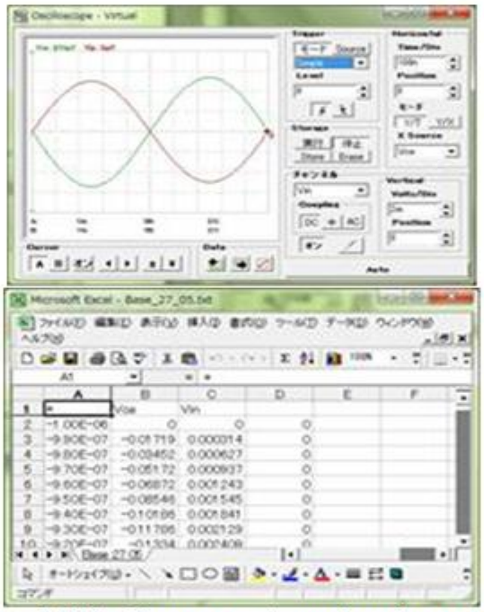


Figure 2 TINA-TI output result sample and output text data

Ⅳ.Using Parameter Design

Step1：Parameter Design Objectives

The objective of this parameter design is to determine the element constants for the transistor circuit shown in Figure 1 so as to minimize the impact of noise on the output from this circuit.

Step2：Basic Function Definitions

A signal that is entered in the transistor circuit shown in Figure 1 is amplified and output. It is desired that the input signal voltage and output voltage are proportional to one another. Therefore, the function of this transistor circuit is defined as

$$y = \beta M, \qquad (1)$$

where M is the input signal voltage and y is the voltage obtained from the amplifier circuit's output port.

Step3：Noise Factor Selection

The ambient temperature in the simulation is initially set at 27°C resulting in Figure 2. Since it is preferable for the output from the transistor circuit to remain unchanged even when the ambient temperature is changed, the ambient temperature of the transistor circuit is considered to be a noise factor. The ambient temperatures were set at 27°C, the initial temperature, and at 125°C, an estimated high temperature. When the simulation was performed at the ambient temperature of 125°C, the results are as shown in Figure 3, and clearly demonstrate distortion in the output waveform. Therefore, the maximum positive and negative amplitudes are also considered to be noise factors. The noise factors in this simulation are summarized in Table 1.

Table 1　Combination of noise factors

Combination	Ambient temperature (°C)	Amplitude directions
1	27	Positive
2		Negative
3	125	Positive
4		Negative

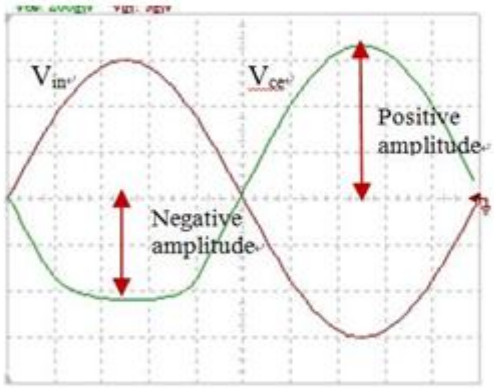


Figure 3 Noise factor (Amplitude)

Step4：Signal Factor Selection and Output Characteristic Values

The signal factor that controls the output values of the transistor circuit is the input voltage (M). It is set at three levels: 5 mV, 10 mV, and 15 mV. Further, we take the absolute values of the maximum and minimum Vce from the data shown in Figure 2 to be the output characteristic values of the transistor circuit.

Step5：Simulation and Calculation Methods for the S/N Ratio and the Sensitivity based on the Initial Data

Table 2 and Figure 4 show the results for a simulation conducted under the conditions stipulated above. The S/Nratio and sensitivity are calculated using the results from Table 2 and the process shown below.

Effective number of replication

$$r=5^2+10^2+15^2=350 \qquad (1)$$

Linear equation 1

$$L_1=5\times0.2763+10\times0.5493+15\times0.8192=19.16 \qquad (2)$$

Linear equation 2

$$L_2=5\times0.2772+10\times0.5550+15\times0.8108=19.10 \qquad (3)$$

Linear equation 3

$$L_3=5\times0.2123+10\times0.4281+15\times0.6637=15.30 \qquad (4)$$

Linear equation 4

$$L_4=5\times0.2113+10\times0.3865+15\times0.4409=11.54 \qquad (5)$$

Total variation

$$S_T=0.2763^2+0.5493^2+\cdots+0.4409^2=3.149 \qquad (6)$$

Table 2 Simulation results for the initial design

			Vin (mV)		
			5	10	15
Vce (V)	27°C	max	0.2763	0.5493	0.8192
		min	0.2772	0.555	0.8108
	125°C	max	0.2123	0.4281	0.6637
		min	0.2113	0.3865	0.4409

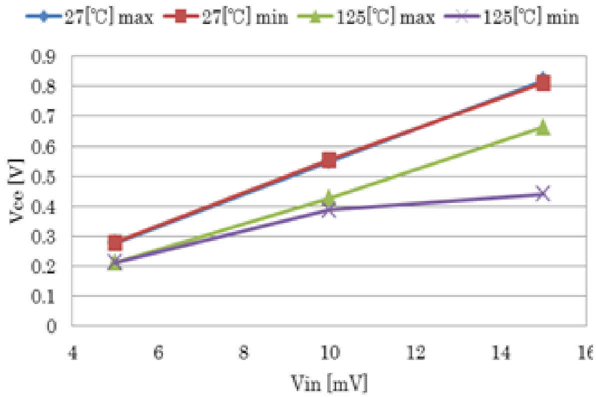


Figure 4 The relationship between the input voltage and output voltage in the initial design

Linear term difference

$S_\beta=(L_1+L_2+L_3+L_4)^2/(4\times r)=3.027$ (7)

Variation of temperature due to noise

$S_{t\times\beta}=\{(L_1+L_2)^2+(L_3+L_4)^2\}/(2\times r)-S_\beta=0.09328$(8)

Variation of vibration due to noise

$S_{N\times\beta}=\{(L_1+L_3)^2+(L_2+L_4)^2\}/(2\times r)-S_\beta=0.01046$ (9)

Variance of noise

$Se=S_T-S_\beta-S_{N\times\beta}=0.01826$(10)

Total error variation

$S_N=S_{N\times\beta}+Se=0.1220$ (11)

Equations (7) and (11) are then used to calculate the S/N ratio η, and sensitivity S as

$\eta=10\log(S_\beta/S_N)=13.95$ db (12)

$S=10\log(S_\beta)=4.81$ db (13)

Step6 : Control Factor Selection

Table 3 Control factors

Source		First level	Second level	Third level
B	R_1	5 KΩ	6 KΩ	7 KΩ
C	R_2	1.8 KΩ	2 KΩ	2.2 KΩ
D	C_1	0.5 μF	1 μF	1.5 μF
E	C_2	0.5 μF	1 μF	1.5 μF
F	R_C	10 Ω	100 Ω	200 Ω

There are seven circuit elements in the grounded emitter amplifier transistor circuit shown in Figure 1. However, only five elements are set as control factors (R_c, R_1, R_2, C_1 and C_2), excluding the transistor's output stage R_{out} (external resistance). The values for control factors R_1, R_2, C_1 and C_2, are shown in Table 3. Further, the values in Table 3 are assigned as an orthogonal array L_{18}, as shown in Table 4.

Table 4 Control factor orthogonal array L_{18} assignment

No.	e	R_1	R_2	C_1	C_2	R_C	e	e
1	-	5	1.8	0.5	0.5	10	-	-
2	-	5	2	1	1	100	-	-
3	-	5	2.2	1.5	1.5	200	-	-
4	-	6	1.8	0.5	1	100	-	-
5	-	6	2	1	1.5	200	-	-
6	-	6	2.2	1.5	0.5	10	-	-
7	-	7	1.8	1	0.5	200	-	-
8	-	7	2	1.5	1	10	-	-
9	-	7	2.2	0.5	1.5	100	-	-
10	-	5	1.8	1.5	1.5	100	-	-
11	-	5	2	0.5	0.5	200	-	-
12	-	5	2.2	1	1	10	-	-
13	-	6	1.8	1	1.5	10	-	-
14	-	6	2	1.5	0.5	100	-	-
15	-	6	2.2	0.5	1	200	-	-
16	-	7	1.8	1.5	1	200	-	-
17	-	7	2	0.5	1.5	10	-	-
18	-	7	2.2	1	0.5	100	-	-

Table 5 S/N ratio and sensitivity calculation results

No.	η	S	No.	η	S
1	17.74	-5.77	10	7.40	3.33
2	5.45	2.97	11	0.93	1.57
3	1.13	0.48	12	17.12	-5.17
4	16.62	5.05	13	18.19	-7.21
5	1.45	1.46	14	13.91	4.79
6	17.38	-6.33	15	1.16	1.98
7	2.91	2.38	16	3.02	2.16
8	18.32	-8.05	17	18.50	-8.05
9	17.78	5.12	18	17.76	5.11
			Ave	10.93	-0.23

η : S/N ratio (db) S: Sensitivity (db)

Step7 : Performing the Parameter Design

The simulation was executed according to the circuit element combination conditions shown in Table 4.

Step8 : Calculating the S/N Ratio and Sensitivity

The S/N ratio and sensitivity for these 18 conditions are calculated using the simulation results and the calculation process shown in step 5. Table 5 shows the result of this calculation.

Step9 : Control Factor Average by Level and Factorial Effect Diagram

Table 6 shows the average values for the S/N ratio and sensitivity for each control factor. This is calculated from the result in Table 5. Figure 5 and Figure 6 are the graphical representation of Table 6. This diagram is called the Factorial Effect Diagram for the S/N ratio and sensitivity.

Step10 : Estimating the Optimum Conditions and Gain

We can assume that the transistor circuit's output is stable against the noise factors by adopting the level of the control factors circled in red in Figure 5. These conditions are set as optimum conditions. In other words, the combinations of B_3, C_3, D_1, E_1, and F_2 (R_1=7 kΩ, R_2=2.2 kΩ, C_1=0.5 μF, C_2=0.5 μF, and R_C=100 Ω) are optimum. In addition, the combination for the initial design factor is B_2, C_2, D_2, E_2, and F_2. Estimating the S/N ratios for the initial design and optimum design from the average value per control factor level and total average, yields the following results:

Under optimum conditions,

$\eta_{opt} = 13.05 + 12.06 + 12.12 + 11.77 + 13.15 - 4 \times 10.93$

$= 18.43$ db, (14)

under the initial design,

$\eta_{ini} = 11.45 + 9.76 + 10.48 + 10.28 + 13.15 - 4 \times 10.93$

$= 11.40$ db. (15)

The variance between the S/N ratio under optimum conditions and the S/N ratio of the initial design, in other words, the gain, is 7.03 db.

Table 6 Average values for S/N ratio and sensitivity by lev

S/N ratio average by level					Sensitivity average by level				
source		1	2	3	source		1	2	3
A	e	10.98	10.89	-	A	e	-0.30	-0.17	-
B	R1	8.29	11.45	13.05	B	R1	-0.43	-0.05	-0.
C	R2	10.98	9.76	12.06	C	R2	-0.01	-0.88	0.
D	C1	12.12	10.48	10.19	D	C1	-0.02	-0.08	-0.
E	C2	11.77	10.28	10.74	E	C2	0.29	-0.18	-0.
F	Rc	17.88	13.15	1.77	F	Rc	-6.76	4.39	1.
G	e	11.84	8.80	12.16	G	e	0.43	-0.62	-0.
H	e	10.64	10.46	11.70	H	e	-0.32	-0.29	-0.

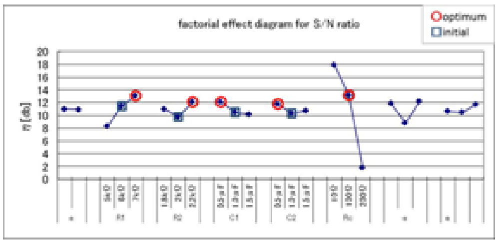


Figure 5 Factorial effect diagram for the S/N ratio

Sensitivity was not used in determining the optimum conditions even though the control factors showed some impact on the size of the output voltage.

Step11 : Confirmation calculation

The S/N ratio and sensitivity are calculated by creating and running a simulation of a model using optimum conditions and the initial designed values. The calculation results are summarized in Table 7. Although the variance in gain between the estimated and confirmed values is significant, the calculation results confirm that there are improvements in stability against noise factors.

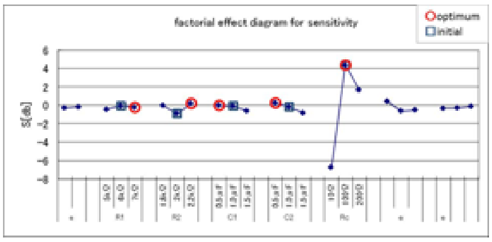


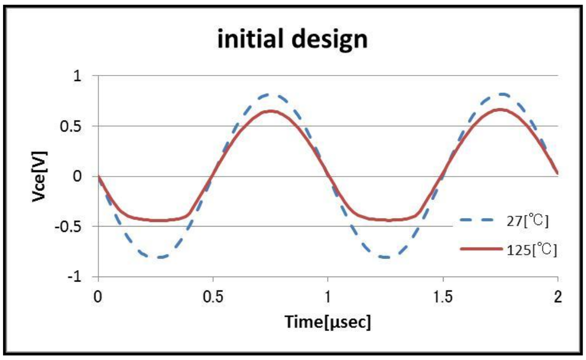
Figure 6 Factorial effect diagram for the sensitivity

Table 7 Confirmation

	S/N ratio (db)		Sensitivity (db)	
	Estimated	Confirmed	Estimated	Confirmed
Initial design	11.40	13.94	4.14	4.81
Optimum condition	18.43	17.78	5.37	5.12
Gain	7.03	3.84	1.22	0.31

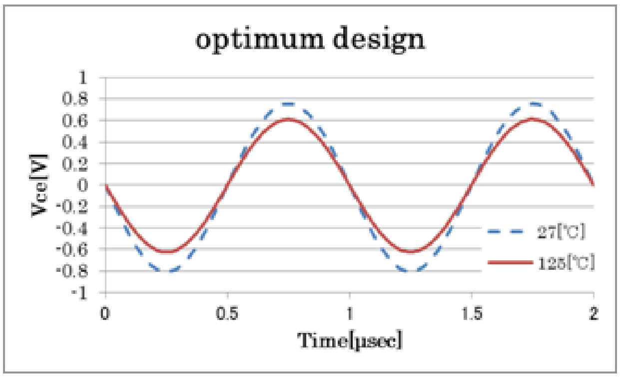
V. Live Data Confirmation

Figure 7 shows the comparison of the initial design data with the optimum design data. It is seen that the output voltage for optimum design has not dropped and the negative waveform distortion at 125°C has been reduced. Figure 8 also confirms that the relationship between the input voltage and output voltage in the optimum design is more stable than in the initial design.



The negative output waveform at 125°C is warped

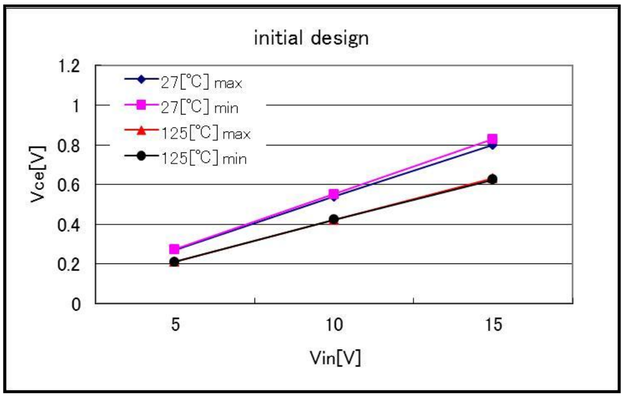
(a) Initial design



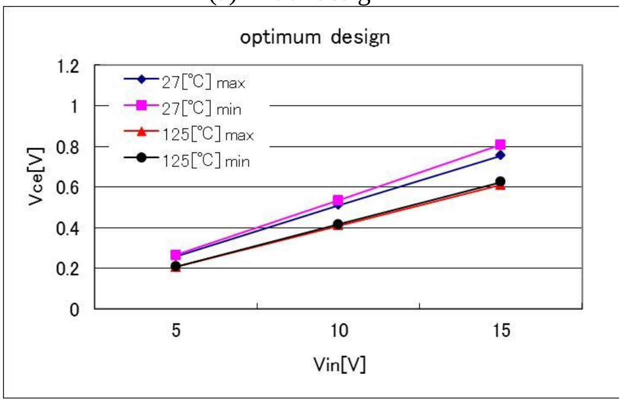
No visible warp in waveform

(b) Optimum design

Figure 7 Waveform data for 15 mV input at 27°C



(a) Initial design



(b) Optimum design

Figure 8 The relationship between input and output peaks

Ⅵ. Techniques for the Application of Simulations in Parameter Design

The approach to parameter design with either experiments or simulations is identical. Nevertheless, there are a few points that should be taken in to consideration.

(a) Defining Basic Functions

When simulations are applied in parameter design, the relationship between input and output cannot always be expressed using a function due to the characteristics of the simulator. In such cases, a 'nominal-is-best' S/N ratio can be determined.

(b) Noise Factors

There are many simulators that cannot adopt environmental conditions as noise factors. In such cases, it is normal to adopt a method that varies the noise factor value. In this case, careful attention should be taken since the combination of the orthogonal array of control factors with the orthogonal array of noise factors will be a direct product, causing the volume of the calculation to increase.

(c) Control Factors

Using simulations is different from experiments, since simulations allow us to select many control factors. Therefore, the orthogonal array used are not fixed to the recommended L_{18}, and using other large scale orthogonal arrays such as L_{27} and L_{36} is also recommended. However using a three level orthogonal array is preferable.

Ⅶ. Conclusion

This case study demonstrated the processes for parameter design through a case study optimizing grounded emitter amplifier circuit element constants using simulations. At the same time, this case study also discussed the points that should be noted when applying parameter design while using simulations.

1) We have attempted to optimize the constants for the grounded emitter amplifier circuit elements. As a result, optimization is achieved, as determined from the adequate size of the gain obtained, yet the gain repeatability is not always good.

2) We were able to show the processes in parameter design through a simulation case study. It is preferable to follow the processes shown in this case study since there are many in parameter design.

3) We were able to elucidate the points that should be noted when combining simulations with parameter design.

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Comparison between Taguchi Method and Response Surface Methodology (RSM) In Optimizing Machining Condition

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Abstract - **The application of Taguchi method and RSM to optimize the milling parameters when machining Aluminum silicon alloy (AlSic) matrix composite reinforced with aluminum nitride (AlN) with three types of carbide inserts is presented. Experiments were conducted at various cutting speeds, feed rates, and depth of cut according to Taguchi method using a standard orthogonal array L_9 (3^4) and RSM historical data. The effects of cutting speeds, feed rates, depth of cut and types of tool on the surface roughness in milling operation were evaluated using Taguchi optimization methodology by utilizing the signal-to-noise (S/N) ratio and RSM optimization. Surface finish produced is very important in determining the quality of the machined part is within the specification and permissible tolerance limit. The analysis of results using S/N ratio concludes that the combination of low feed rate, low depth of cut, medium cutting speed and uncoated tool give a remarkable surface finish. Desirability criterion in RSM shows the optimum condition is at combination of high feed rate, high depth of cut, medium cutting speed and uncoated tool. In this case, the optimum condition obtained using Taguchi method is more accurate than RSM. Therefore it can be concluded that Taguchi method requires less number of experiment than RSM to determine an accurate optimum machining condition.**

Keywords - **Taguchi method, Response Surface Methodology, Machining process, Surface roughness.**

I. INTRODUCTION

Design of experiment (DOE) is very important tool to significantly reduce the time required for experimental investigation, as it is effective in investigating the effects of multiple factors on performance as well as to study the influence of individual factors to determine which factor has more influence, which less [1,2]. The most important stage in the design of an experiment lies in the selection of control factors. Robust design is an engineering methodology for obtaining product and process conditions, which are minimally sensitive to the various causes of variation to produce high-quality products with low development and manufacturing costs [1]. Taguchi's parameter design is an important tool for robust design. It offers a simple and systematic approach to optimize design for performance, quality and cost. Two major tools used in robust design are [1, 3-4]:

- Signal to noise ratio, which measures quality with emphasis on variation, and
- Orthogonal arrays, which accommodate many design factors simultaneously.

Taguchi's approach is totally based on statistical design of experiments [1], and this can economically satisfy the needs of problem solving and product or process design optimization [2]. Some of the previous works that used the Taguchi method as tool for design of experiment in various areas including metal cutting are listed in the references [5-6].

As many factors as possible should be included, so that it would be possible to identify non-significant variables at the earliest opportunity. Taguchi creates a standard orthogonal array to accommodate this requirement. Depending on the number of factors, interactions and levels needed, the choice is left to the user to select either the standard or column-merging method or idle-column method, or etc. Two of the applications in which the concept of S/N ratio is useful are the improvement of quality through variability reduction and the improvement of measurement. The S/N ratio characteristics can be divided into three categories when the characteristic is continuous [1]:

Nominal is the best characteristic; S/N $= 10\log\frac{\bar{y}}{s_y^2}$

Smaller the better characteristics; S/N $= -10\log\frac{1}{n}\left(\sum y^2\right)$

Larger the better characteristics; S/N $= -10\log\frac{1}{n}\left(\sum\frac{1}{y^2}\right)$.

Where, $\bar{y}$ is the average of observed data, s_y^2 is variance of *y*, *n* is number of observations, and *y* is the observed data. For each type of the characteristics, with the above S/N ratio transformation, the higher the S/N ratio the better is the result.

RSM can be defined as a statistical method that uses quantitative data from appropriate experiments to determine and simultaneously solve multivariate equations, it is a collection of mathematical and statistical techniques for empirical model building whose objective is to optimise the responses [7]. Initially, RSM was developed to model experimental responses, and then migrated into the modelling of numerical experiments [8]. The application of RSM in design optimisation is aimed at reducing the cost of expensive methods of analysis.

Surface roughness is generally known to be highly affected by feed rate, followed by cutting speed and axial depth of cut [9-10]. The geometrical shape of the insert is another factor considered in studies on surface roughness [11-12]. According to Iqbal, et al. [13], who conducted a study on tool steel, material inclination angle, followed by radial depth of cut, was found to be parameter that most significantly affects surface finish after machining.

II. EXPERIMENTAL DETAILS

Taguchi Method

In this experiment with three factors at three levels each, the fractional factorial design used was a standard L_9 (3^4) orthogonal array [14]. This orthogonal array was chosen because of its minimum number of required experimental trials. Each row of the matrix represented one trial. However, the sequence in which those trials were carried out was random. The three levels of each factor were represented by a '0' or a '1' or a '2' in the matrix.

The factors and levels were assigned in L_9 (3^4) orthogonal array as in Table I according to roughing and semi-finishing conditions for the said material.

TABLE I
FACTORS AND LEVELS USED IN THE EXPERIMENT

Experiment No.	Cutting speed *V*(m/min)	Feed rate *f* (mm/gigi)	Depth of cut *d*(mm)	Type of insert
1	230	0.4	0.3	Uncoated
2	230	0.6	0.4	TiN
3	230	0.8	0.5	TiB2
4	300	0.4	0.4	TiB2
5	300	0.6	0.5	Uncoated
6	300	0.8	0.3	TiN
7	370	0.4	0.5	TiN
8	370	0.6	0.3	TiB2
9	370	0.8	0.4	Uncoated

Factors A, B, C and D are arranged in column 1, 2, 3 and 4 respectively in the standard L_9 (3^4) orthogonal array.

Response Surface Methodology (RSM)

In RSM the experiment were run according to the sequence in Table II as suggested in the Design expert software. The technique used was RSM historical data.

TABLE II
EXPERIMENTAL SEQUENCE USING CODING

Std	Run	Block	A:Vc m/min	B:fz mm/tooth	C:DOC mm	D:Tool
3	1	{ 1 }	-1	-1	-1	{ 1 0 }
6	2	{ 1 }	-1	0	0	{ 0 1 }
2	3	{ 1 }	-1	1	1	{ -1 -1 }
4	4	{ 1 }	0	-1	0	{ -1 -1 }
1	5	{ 1 }	0	0	1	{ 1 0 }
9	6	{ 1 }	0	1	-1	{ 0 1 }
5	7	{ 1 }	1	-1	1	{ 0 1 }
8	8	{ 1 }	1	0	-1	{ -1 -1 }
7	9	{ 1 }	1	1	0	{ 1 0 }

Materials and Milling Process

AlN reinforced Al-Si alloy matrix composite was fabricated by the method of stir casting which Al-Si alloy ingot, called matrix material, was reinforced with AlN particles of 10wt % reinforcement. The chemical chemical composition of Al-Si alloy was determined by Glow Discharge Profiler (Model-Horiba Jobin Yyon) as shown in Table III. The mean size of the reinforcement particles is <10 μm and the purity of >98%.

TABLE III
CHEMICAL COMPOSITION OF ALSi ALLOY

Elements	Fe	Si	Zn	Mg	Cu	Ni
Wt%	0.42	11.1	0.02	0.01	0.02	0.001
Elements	Sn	Co	Ti	Cr	Al	
Wt%	0.016	0.004	0.0085	0.008	Balance	

The experimental study was carried out in a DMC635V eco DMGECOLINE vertical milling machine fitted. Cutting inserts was attached in the tool body diameter ∅12mm. The surface roughness of the machined surface was observed using Roughness Tester Mpi Mahr Perthometer.

The surface roughness of the workpiece was measured at several locations along the length of the cut using a portable surface roughness tester model Mpi Mahr Perthometer. The length of each cutting path was 0.103 m.

III. RESULTS AND DISCUSSION

Experimental Results

Table IV shows the result of surface roughness. It is shown that, uncoated tool combined with high feed rate and medium depth of cut will produce high Ra i.e. rough machined surface. Previous study [15] also found that the feed rate was the most significant factor in controlling the surface finish. Martelotti [15] describes the chip thickness model as follows:

$t = s$ Sin b, where s and b represent feed per tooth and tool angular position, respectively. Whereas the height of the tooth mark is given by the following:

$$h = \frac{s^2}{8[R + (sxN/\pi)]} \quad (1)$$

Where h is the height of tooth mark above point of lowest level, mm; s the feed per tooth, mm; R the radius of cutter, mm; N the number of teeth in cutter. The height of tooth mark can be reduced by increasing the radius of the cutter and by decreasing the feed per tooth until the tooth mark becomes scarcely distinguishable, particularly at the lower feed rates.

Coated tool normally will produce better Ra, since the coating material acts as dry lubrication. Similar results were found by previous researchers [16-17].

TABLE IV

RESULT OF SURFACE ROUGHNESS

No.	Cutting speed V(m/min)	Feed rate f (mm/ tooth)	Depth of cut d(mm)	Type of insert	Surface Roughness, (μm)		Ra
1	230	0.4	0.3	Uncoated	0.57	0.74	0.5
2	230	0.6	0.4	TiN	1.13	1.05	1.05
3	230	0.8	0.5	TiB2	1.33	1.28	1.43
4	300	0.4	0.4	TiB2	0.35	0.33	0.39
5	300	0.6	0.5	Uncoated	1.28	1.59	1.26
6	300	0.8	0.3	TiN	1.5	1.47	1.48
7	370	0.4	0.5	TiN	0.75	1.09	0.93
8	370	0.6	0.3	TiB2	0.34	0.46	0.45
9	370	0.8	0.4	Uncoated	2.31	2.18	2.93

Optimization of Machining Condition Using Taguchi method

The objective of this study is to find the optimum condition for surface roughness when cutting AlSi/AlN using three types of cutting tools. One of the methods to analyze data for process optimization is the use SN ratio. Figure 1 shows the mean of SN ratio for smaller the better characteristic of surface roughness obtained using Minitab 14. From the slope of the graphs, it is observed that the feed rate is the most significant factor, followed by the type of coating material, depth of cut and cutting speed. Similar result is obtained from the Response Table for Signal to Noise Ratios Smaller is better in Table V The optimum condition is determined by the highest means SN values, and therefore the optimum condition is A1 (300 m/min), B0 (0.4 mm/rev), C0 (0.3 mm) and uncoated tool.

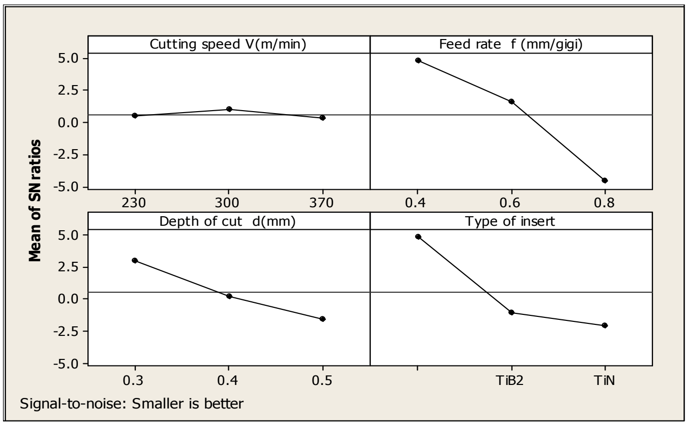

Fig 1 Mean of SN ratio for smaller the better characteristic of surface roughness

level	Cutting speed V(m/min) cut	Feed rate f (mm/tooth)	Depth of cut d(mm)	Type of insert
1	0.4357	4.7600	2.9968	4.8451
2	0.9930	1.5456	0.2257	-1.0896
3	0.2764	-4.6004	-1.5174	-2.0505
Rank	4	1	3	2

TABLE V

RESPONSE TABLE FOR SIGNAL TO NOISE RATIOS SMALLER IS BETTER

Optimization of Machining Condition Using RSM

ANOVA was performed as shown in Table VI. R squared for this ANOVA and equation (2) is 0.98. This indicates that the mathematical model is significant, and factor A (cutting speed) is not significant on the surface roughness model.

TABLE VI

ANOVA TABLE FOR SURFACE ROUGHNESS

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Model	1.023840091	5	0.204768	31.481656	0.0085	significant
A	0.003192256	1	0.0031923	0.4907871	0.5340	
B	0.482645742	1	0.4826457	74.203419	0.0033	
C	0.145184167	1	0.1451842	22.321054	0.0180	
D	0.392817925	2	0.196409	30.196509	0.0103	
Residual	0.01951308	3	0.0065044			
Cor Total	1.04335317	8				

SQRT 1/Ra = 1.083 + 0.023 A - 0.283 B - 0.156 C - 0.156 D1 - 0.139 D2 (2)

Table VII shows the value of actual and predicted using equation (2), and the error was found less than 9%.

TABLE VII

VALUES OF ACTUAL AND PREDICTED SURFACE ROUGHNESS

No.	*V*(m/min)	*F*(mm/tth)	*d* (mm)	Type of insert	Average *Ra* (*μm*)	Predicted Ra (*μm*)
1	230	0.4	0.3	Uncoated	0.6	0.55
2	230	0.6	0.4	TiN	1.07	1.18
3	230	0.8	0.5	TiB2	1.34	1.19
4	300	0.4	0.4	TiB2	0.35	0.36
5	300	0.6	0.5	Uncoated	1.37	1.68
6	300	0.8	0.3	TiN	1.48	1.5
7	370	0.4	0.5	TiN	0.92	0.83
8	370	0.6	0.3	TiB2	0.4	0.41
9	370	0.8	0.4	Uncoated	2.47	2.25

Optimization is carried out by finding the desirability value using Design Expert software. Table VIII shows a part of the result generated. The optimum condition is when Ra equal 0.56 µmthat can be achieved when machining at cutting speed of 326 m/min, feed rate of 0.8, depth of cut of 0.47, and using uncoated tool. This optimum condition is not similar with the one obtained using Taguchi method. This may be due to a small number of data that caused the misleading of the result. Therefore it is recommended to use RSM CCD and Box Behkin to obtain an accurate optimization condition.

TABLE VIII

OPTIMIZATION USING DESIRABILITY CRITERION

No	Vc	fz	DOC	Tool	Ra	Desirability	
1	326.80	0.7	0.47	Uncoated	0.56	1	Selected
11	301.82	0.80	0.46	TiN	0.57	1	
21	308.03	0.80	0.50	TiB2	0.94	0.71	

IV. CONCLUSION

Two techniques of DOE has been compared i.e. Taguchi method and RSM. From the result obtained, the following can be concluded:

1. Taguchi method is found giving a better graphic visualization to determine the optimum condition by calculating SN ratio. But how big is the contribution of each factor need further investigated using ANOVA.
2. In RSM, the equation and ANOVA are the important elements to analyze the result. Therefore from this information, one can easily determine the degree of significant of each factor.
3. The desirability criterion available in the software for RSM will easily help user to determine the optimum condition. In order to avoid misleading result, user should ensure have enough data such as in CCD or Box Behkin arrays.
4. If user wants to use RSM, the steepest accent concept must be visualized to ensure the optimum condition is accurately determined, which requires more data.
5. Taguchi method requires less data to find the optimum condition than RSM. Therefore it is recommended to use Taguchi method if the experimental run is time consuming and costly.

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Optimization of 67% Powder Loading Co-30Cr-6Mo µMIM Part by Taguchi Method

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Abstract - **This study study the effect of injection moulding parameters on the density of green body of Cobalt-30Chromium-6Molybdenum (Co-30Cr-6Mo) for powder injection moulding (PIM) feedstock. In this paper 20 micron Co-Cr-Mo powder was mixed with a palm stearin and polyethylene binder system. L_{18} orthogonal array by Taguchi Method was used to optimize and predict the future performance. Several injection parameters were optimized such as injection temperature, holding pressure, injection temperature, mould temperature and injection time. The result shows that the optimum combination of these parameters will produce higher density micro parts. The optimum parameters for 67% powder loading of 20µm Co-30Cr-6Mo powder is 180 ^{o}C injection temperature, while injection pressure, mold temperature, packing time and injection time are 10 bar, 100 ^{o}C, 5s and 7s respectively.**

Keywords - **Taguchi method, optimization, injection moulding, green density**

I. INTRODUCTION

Metal injection moulding is favourable in producing small intricate part and cost effective for mass production [1]. The high quality injected part is a must for achieving high quality final sintered part. However, there are few factors that need to be optimized in achieving good quality of injected part such as the density, strength, defect and etc. One of challenges in micro injection molding is the ability to completely fill in the micro-scale cavity [2].

Therefore to minimize cost, defect and time, DOE techniques has been applied. Taguchi method is one of well known optimization tool among researchers. For example, Ji et. al. [3] studied on the sintering of 316L stainless steel metal injection moulding parts and Ahmad et. al [4] determined the optimised sintering parameters of titanium alloy foam by Taguchi method. Besides optimization, Taguchi focuses on determining the effects of the control factors on them robustness of the product’s function [5].

Nevertheless, this study will focused on the optimization of injection moulding parameters such as injection pressure, injection temperature, mould temperature, packing time and injection time of Co-30Cr-6Mo to produce high density green part. Powder with 67% powder loading were chosen based Critical Powder volume percentage (CPCP) done previously.

II. METHODOLOGY

The feedstock consists of Co-Cr-Mo powder with palm stearin (PS) and Polyethylene (PE) binder. The characteristic of powder (Co-30Cr-6Mo) is shown in Table 1 and the morphology of the powder under 2000 magnification is shown in figure 1.

Table 1: Co-30Cr-6Mo characteristics

Characteristic	Details
Tap density, g/cm^3	5.20
Pycnometer density, g/cm^3	6.44
Powder size, µm	20

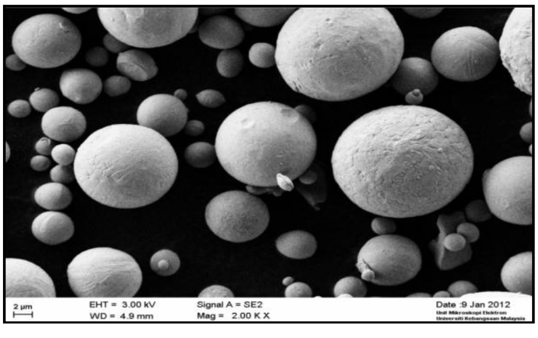

Figure 1: Spherical shape of Co-30Cr-6Mo powder

The densities of the parts were determined using a mass balance Sartorius model BSA224S-CW based on Archimedes method. Three level designs of experiment with 5 parameters are consider in the injection moulding where basically all of them were chosen based on screening test. The screening test or injection is done prior to find the upper and lower value for injection parameters. In this work, design of experiment (DOE) method is necessary to minimize the number of experiments to be performed. The parameters that involved in the design were injection pressure, injection temperature, mould temperature, injection time and holding time. Table 2 shows the orthogonal array which allocates the level of each parameter. Three levels for each parameter refer to maximum and minimum limit that influence the density result.

Table 2: Injection parameters for three level Taguchi designs

Level	Injection Pressure (bar) **A**	Injection Temp. (^oc) **B**	Mold Temp. (^oc) **C**	Injection Time (s) **D**	Holding Time (s) **E**
0	9	160	100	6	6
1	10	170	110	7	7
2	11	180	120	8	8

III. RESULTS

The optimization of control parameters to obtain best results is achieved by the Taguchi Method. Orthogonal arrays (OA) provide a set of well balanced (minimum) experiments and signal to noise ratio (S/N), which are log functions of desired output by data analysis and prediction of optimum result. The known or targeted density value of Co-30Cr-6Mo density is 8.28 g/cm^3. Thus in this work, the characteristics needed are the 'nominal the best'' in order to optimize the density:

$$S/N= 10 \text{ Log } \{y/ (\sigma_{n-1})^2\}$$

Where y is value of mean density and n is number of replication, while:

$$(\sigma_{n-1})^2 =\sum_1^n \frac{(y_i-\overline{y})^2}{n-1} \quad \text{------------------ (1)}$$

The values are recorded in Table 3 using Taguchi orthogonal array. The density results were repeated for three times.

Table 3: Taguchi L$_{18}$ orthogonal array demonstrates the value of the experimental density

Experiment No.	Parameters 1 e	2 A	3 B	4 C	5 D	6 E	7 e	8 e	Green Density (g/cm^3) Repeat 1	Repeat 2	repeat 3	S/N (dB)
1	1	1	1	1	1	1	1	1	5.146	4.856	5.509	11.1998
2	1	1	2	2	2	2	2	2	4.864	5.002	5.490	11.4441
3	1	1	3	3	3	3	3	3	4.817	5.127	4.817	14.1828
4	1	2	1	1	2	2	3	3	4.492	4.730	5.156	9.1112
5	1	2	2	2	3	3	1	1	4.891	4.515	5.104	12.4140
6	1	2	3	3	1	1	2	2	4.946	4.336	4.944	11.2739
7	1	3	1	2	1	3	2	3	5.169	5.235	5.546	10.8540
8	1	3	2	3	2	1	3	1	4.944	4.961	5.065	19.3533
9	1	3	3	1	3	2	1	2	4.876	4.908	4.889	26.8546
10	2	1	1	3	3	2	2	1	4.917	4.915	3.874	8.7203
11	2	1	2	1	1	3	3	2	5.035	5.044	5.210	16.2328
12	2	1	3	2	2	1	1	3	4.592	4.592	4.907	11.8735

13	2	2	1	2	3	1	3	2	4.684	5.179	5.072	7.3809
14	2	2	2	3	1	2	1	3	5.085	5.069	4.739	10.8445
15	2	2	3	1	2	3	2	1	4.681	5.246	5.095	14.5736
16	2	3	1	3	2	3	1	2	5.276	4.644	4.739	11.2721
17	2	3	2	1	3	1	2	3	5.244	5.06	5.233	27.5925
18	2	3	3	2	1	2	3	1	4.714	4.866	5.227	18.1974

Table 4: ANOVA table showing the percentage contribution of the parameters studied

Factors		Degree of Freedom f_n	Sum squared, s_n	Variance	Ratio F_n	Contribution P_n, (%)
A	Injection Temperature	2	112.7144	56.3572	1.4263	20.3734
B	Injection Pressure	2	84.0298	42.0149	1.0633	15.1886
C	Mould Temperature	2	56.1892	28.0946	0.7110	10.1563
D	Packing Time	2	20.1625	10.0812	0.2551	3.6444
E	Injection Time	2	3.5472	1.7736	0.0449	0.6412
Error, e		7	276.5997	39.51424		49.9961
Total		17	553.2429	177.8357		100

Table 4 shows the ANOVA table showing the degrees of freedom, the sum of squares, Mean square, F ratio and the percentage contribution of the parameters studied of green density. Injection temperature (A) is found shall have the greatest influence on the green density followed by injection pressure (B), mold temperature (C), packing time (D) and injection time (E).

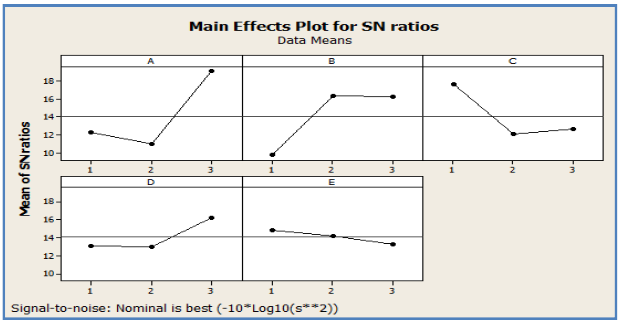

Figure 2: Main effects plot for S/N ratios

IV. DISCUSSION

Based on calculated S/N ratio using equation (1), the main effects plot is developed as shown inFigure 2. Figure 1 shows the main effects plot for S/N ratio from the density result. The optimum parameters were summarized in table 5. The optimum temperature for injection is 180 ^{o}C while injection pressure, mold temperature, packing time and injection time were 10 bar, 100 ^{o}C, 5s and 7s respectively. Based on the optimized result, the injection process need the highest injection temperature which is 180 ^{o} C in order to achieved the nominal density. According to Attia and Alcock, in order to achieve complete filling into the tiniest cavities in the mould; temperatures and pressures of melt flow is usually adjusted [5].

Table 5: Optimum parameter for 67% powder loading Co-Cr-Mo

Factors	Level	Optimmum Parameter
Injection temperature	3	180^{o}C
Injection Pressure	2	10 bar
Mould Temperature	1	100^{o}C
Packing Time	3	7 s
Injection Time	1	5 s

V. CONCLUSION

According to the Taguchi result, the optimum injection molding parameter that fulfils the optimum green part density is A3 B2 C1 D3 E1. The most important factor that needs to be taken into consideration is injection temperature, followed by injection pressure and mold temperature. However packing time and injection time is less significant in optimizing the green density. The packing time and injection time can be reduced to decrease the manufacturing time, and increase the parts production.

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The Volvo Robust Engineering System: An industrial approach to robust design

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Abstract - **Volvo Robust Engineering System (VRES) is a pragmatic approach to introduce robust design as a normal way of working for product development engineers. VRES consists of 5 principles as a basic value system and 8 practices which contribute to System, Parameter and Tolerance Design. VRES was developed through a learning alliance between Volvo and Chalmers University of Technology.**

Keywords - **robust design principles, robust design practices, Taguchi Methods, RDM, learning alliance, industrial application, product development**

I. INTRODUCTION

Robust design in early phases of Product Development (PD) has been the subject of much research and many industrial applications. Initial efforts focused on utilization of tools like the Taguchi Methods [1, 2], but did not reach its potential in terms of industrial results [3]. Instead of being tool-focused, later approaches like Robust Design Methodology (RDM) [4] have more emphasized the integration of the underlying principles of robust design in daily product development work. There are also literature-based studies on how to apply RDM in practice, so called robust design practices [5], but there seems to be a lack of academic studies discussing practices of robust design based on learning from industrial applications.

Developing robust products is a priority for the truck companies within the Volvo Group [1]. Volvo 3P [2] therefore launched an initiative in 2004 to implement Taguchi Methods in selected pilot projects. This first trial was relatively unsuccessful in that the utilized tools did not gain acceptance as natural practices in daily product development work [6]. A new and improved initiative, the Volvo Robust Engineering System (VRES), was therefore launched in 2006-2009 to develop and implement new local robust design practices. VRES contributed to, that by the end of 2009, the company's fault frequency had fallen by 70 % in comparison to 2006.

VRES was run as a joint action research program with the Division of Quality Sciences at Chalmers University of Technology in Gothenburg, Sweden (from now on called Chalmers). This paper describes and discusses the robust design principles and practices developed at Volvo 3P through this program.

II. METHODOLOGY

The methodology in this paper follows the approach of the research program, action research. Lewin [7] argued that in order to "understand and change certain social practices, social scientists have to include practitioners from the real social world in all phases of inquiry". This is possible through the continuity between action and learning, so called learning processes which mutually reinforce change implementation and scientific knowledge generation [8].

The action research program presented below utilized a specific approach to create learning processes referred to as a "learning alliance" [9, 10], which is built upon the fact that learning mainly takes place in joint relationship between actors due to their mutual need. Since learning is a key factor for organizational change as well as action research, a learning alliance between an industrial firm and a university can be a great opportunity for both – for the firm to learn in order to stimulate change, and for the university to learn in order to generate scientific knowledge.

During the course of 2,5 years of the action research program, a total of 22 international master students from Chalmers did their theses work on development and implementation of robust design practices at Volvo 3P. They worked with Product Development (PD) engineers on a daily basis. In this learning relationship, the master students provided state-of-the-art tools and practices of robust design while the PD engineers contributed practical technical knowledge of product development. Through this mutual learning the students

[1] www.volvo.com
[2] Volvo 3P was until the end of 2011 the name of the truck PD organization in the Volvo Group.

and the PD engineers together developed products while utilizing and adapting robust design practices.

III. ROBUST DESIGN METHODOLOGY (RDM)

RDM represents any effort (statistical or non-statistical) to achieve insensitivity to the sources of variation in product or service performance [4]. This perspective is what makes RDM different from the concept that Taguchi pioneered. RDM includes principles and practices. Principles are tackling the mind-sets of individuals and practices are to bridge the gap between the principles and application of the tools in industry. Arvidsson et al. [11] introduced three RDM principles and Hasenkamp et al. [5] have elaborated upon six linked RDM practices, based on a literature review.

Table 1: RDM principles and practices (Source: Hasenkamp et al. [5])

Principles	Practices
Variation Awareness	Focus on the customer
	Identifying and understanding noise factor
	Checking the assumption
Insensitivity to noise factors	Exploiting nonlinearities and interaction
	Designing the insensitivity to noise factors
	Using the conventional design rules
Continuous applicability	No practice defined

IV. VOLVO ROBUST ENGINEERING SYSTEM

An important learning from the first trial at Volvo 3P during 2004 was that in the Volvo context, an initiative with ‘tool-pushing’ and a predefined solution did not work [6]. Therefore in the second initiative the focus was on ‘practice-pulling’ through local learning processes in the organization [10], facilitated by learning alliances between PD engineers and master students. As a result of this, five principles of VRES (2006-2009) were developed and exemplified through eight different robust design practices [12].

VRES Principles

In VRES, the principles are ‘systems of values’ which the PD employees should consider in their daily work, not limited to a part of a process or part of an organization, but principles that address essential aspects in the general PD working culture.

1. Customer focus: One of the findings from the first initiative (2004) was lack of customer orientation in PD processes. One explicit example of such problems was found in the requirement management process. Not all requirements were clearly described and transparent in PD processes, from end-customers’ point of view. The focus was instead on internal stakeholders and mainly on ‘second-hand’ translations of customer needs. The same problem also existed in the verification and validation process. Therefore, in the new initiative, the first robust design principle was identified as customer focus, emphasizing that it is not enough to deliver a robust product to the market; it should also behave as the customer wants. To do so, there is a need to be customer focused in every activity starting from early phases of the PD.

2. Transparency and Communication: Another finding from the first initiative was a lack of transparency and communication in PD processes. The information flow in the processes was very slow. Therefore, the right input at the right time, could not always be secured for many processes and tools which caused them to be ineffective in application. Lack of transparency in what everybody do in the company impedes shared understanding of problems and affects synchronization of activities and decisions, and it therefore hinders the development of robust products in the most efficient way. In the new initiative, transparency and communication was identified as the second robust design principle, to secure right input and prompt information flow in the processes, contributing to shared understanding of problems, and synchronization of activities and decisions.

3. Variation awareness: One learning from the first trial was that most of the PD engineers involved could not see any reason for applying the introduced robust design tools. Some engineers highlighted other issues which they believed had higher priority than robust design. Some claimed that they did not have time to follow the new tools; other engineers claimed that their current way of working was very well handling the robustness, partly rightfully and partly not. To be able to highlight the reasoning and importance of robust design, it was crucial to increase the level of awareness concerning variation and its sources, as well as its consequences on the results. Therefore the third robust design principle was defined as variation awareness which refers to conscious consideration of variation and its consequences during the development process. In this sense, variation does not only refer to sources that exist in manufacturing or during the usage period but also to those that exist in all PD processes, which might affect the robustness of processes and therefore robustness of products. This is the context in which robust design can be most valuable, emphasizing creating a culture of thinking and acting in terms of variation and robustness for both processes and products.

4. Insensitivity to variation sources: In the first trial, it was also realized that the most important objective should have been to develop products which are less sensitive to the sources of variation, instead of focusing on tools. Without criticizing the power of the statistical tools, yet it was found that there was a need for a more basic approach to design for insensitivity. To support engineers with a more pragmatic approach there was a need to change from looking at robust design in a more narrow way, as a statistical tool, to a broader view of robust design that focuses on how to act in terms of variation and robustness. Therefore in the new initiative insensitivity to variation sources was identified as the fourth principle of VRES, emphasizing "the culture of developing for robustness in all we do in the daily development work" to eliminate sensitivity of products to noise factors rather than eliminating or controlling the factors. This also emphasizes insensitivity to variation sources in PD processes, referring to continuous improvement of the PD processes making them less sensitive to different situations and therefore more stable. In such a context, focusing on variation and on understanding its consequences, the engineers could build, test and learn new ways of working and consciously improve their practices towards robustness of products.

5. Knowledge sharing and documentation: In the first trial some engineers claimed that their current way of working is very well handling the robustness, or at least they had been involved in projects that had worked very well with respect to robustness. Investigating the cases they referred to revealed that there had quite a number of good practices of investigating sources of variation for products, developing robust products and also many types of experimentation with respect to variation. However, in most of the cases, the practice was limited in application, it was very difficult to retrieve the knowledge and the practices were not shared. Therefore the fifth principle of robust design in the new initiative was knowledge sharing and documentation. This emphasizes the necessity of sharing even simple documentation of the generated knowledge and applied practices, specifically with respect to variation and robustness. In this context knowledge sharing could also happen through networks or different knowledge sharing forums.

VRES Practices

In the VRES context a practice is described as a particular set of activities (description of how to do things) including an intention (why to do them) and finally, a description of the main deliverables expected from each single practice (deliverable to convey) explaining in a clearer way what to deliver towards the gates in the PD process[3]. Guidelines on how to develop those deliverables have also been developed based on the learning from cases and collected good examples.

The VRES initiative developed in total eight practices for the three steps of robust design outlined by Taguchi; system, parameter and tolerance design (Figure 2) [2].

[3]Global Development Process (GDP)

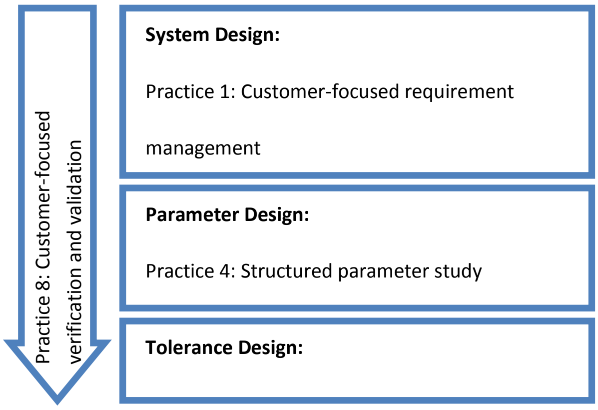

Figure 2: VRES practices in connection to system, parameter and tolerance design

There are also several quality tools proposed for each practice, although the intentions and deliverables are independent of the tools employed. Knowledge managers at the company have the role to support the selection of the right tools in each project. They are very well trained in robust design, most of them having six sigma black belt and they also continuously receive internal and external training. They also have the role to cascade the training in the organization. A summary of the eight practices is presented below.

Practice 1: Customer-Focused Requirement Management

The intention with this practice is visualization, communication and commitment of project requirements among all stakeholders. The main requested deliverables for this practice are: a) translated "Voice-of-Customer" and other "stakeholder requirements" into Design Characteristics [4], b) transparency of the whole chain of requirement translations for all project members, and c) progress follow-up of projects based on the maturity of the designs with respect to the requirements. This will create better customer focus in all project activities. This practice could be applied using tools like Quality Function Deployment (QFD), requirement reviews, brainstorming, or other systems engineering tools, e.g. Requirement Specification (RS).

Practice 2: Functional Approach

The intention with this practice is to establish a common understanding of the desired functions by customers through detailed description at different levels of systems. This will create a more functional view over products rather than a physical parts and components view. It will also improve customer focus as customers are interested more in the functions of physical products rather than in the products themselves. Such a practice also supports a more innovative PD

[4] Design Characteristics are measurable functional, non-functional or technical requirements at sub-system level.

which provides a greater space for thinking of many different innovative ways to provide a function, rather than being stuck within more physical boundaries. The main deliverables for this practice are: a) visualized system architectures, and b) functional specification and detailed functional description of systems. There are several potential tools for functional approach which can support this practice, such as External Functional Analysis, Functional Analysis System Techniques (FAST)[5], Structured Analysis and Design Techniques (SADT) [6] , Detailed Functional and Architectural Description, and Boundary Diagram.

Practice 3: Systematic Concept Evaluation & Selection

The intention with this practiceis to establish a cross-functional decision-making for concept evaluation and selection which better secures that the concepts are balanced against requirements and also robust in their performance. Such a decision should also be fact-based, transparent and anchored to make it easier for projects to progress and avoid late loops. This practice might be utilized at different levels of concepts, both at a high level of project concept selection and at a more detailed level of product system and sub-system concept selection. The main deliverables for this practice are: a) evaluation of several alternative concepts, b) the facts and data in the evaluation and selection process, and c) transparency and commitment with stakeholders through the whole process. Tools like Pugh matrix, morphologic matrix, and set-based engineering tools such as trade-off curves are introduced for performing this practice.

Practice 4: Structured Parameter Study

The intention with this practice is to provide a deeper understanding of the factors which influence the function by gathering and visualizing the knowledge of variations and sources of variation, as well as control factors (design parameters) for different systems and subsystems. This will help both to create better variation awareness and documentation of the variation knowledge. In order to complete such a practice, engineers also need to better understand customers and how they use products. The main deliverables for this practice are: a) identified signal and noise factors in all phases of the product lifecycle, b) identified control factors, and c) described expected functions and corresponding potential errors. Tools like P-diagram, Noise Factor Management Table (NFMT), and Variation Mode and Effect Analysis (VMEA) can be used. This practice could be utilized both for analysis of a product system or other system of processes in the company.

Practice 5: Proactive Risk Management

The intention with this practice is to secure preventive action for potential failure causes in order to minimize the risk of severe undesirable customer effects due to variation in performance. The main deliverables for this practice are: a) identified risks and graded undesirable customer effects, b) identified critical to quality (CTQ) and safety (CTS), c) proposed design modifications to mitigate risks for variation, d) implemented downgraded modes, and finally d) the residual risks. Tools like Failure Mode and Effect Analysis (FMEA), Variation Mode and Effect Analysis (VMEA), Noise Factors Management Table (NFMT) and Dependability Analysis can be applied for this practice. This practice is valid both for product or project risk analysis; however the tools might be slightly different depending on application.

Practice 6: Robust Parameter Design

The intention with this practice is to gain knowledge of parameter interactions and influences on the functions through systematic experimentation. Therefore this practice will enhance operational efficiency by increasing the capability of the organization to develop more robust products for customers in a more efficient way. It also helps to create more flexibility to adapt products for different applications. The main deliverables for this practice are: a) identified most efficient test plan (for knowledge building and optimization) with high coverage area, b) identified interaction between noise factors and control factors, c) identified worse case scenarios of the application, d) the optimized functionality, and e) documentation of generated knowledge. Tools like statistical Design of Experiment (DoE), Response Surface Methodology, Taguchi Methods for parameter design, tools and test plans can be employed. Also many new simulation and calculation software programs have such statistical tools integrated in the software.

Practice 7: Robust Tolerance Design

The intention with this practice is to have cost-efficient and performance-efficient tolerances to avoid tightening-up tolerances where the target could be met through parameter-mean-value setting instead. The main deliverable for this practice is the optimized tolerances based on quality and cost trade-off. Tools like simulation software, Taguchi Methods for tolerance design, and Robust Design and Tolerancing (RD&T) are introduced for performing this practice.

[5] It challenges the assumptions of "How" and "Why" a function accomplishes the need. In this way it is possible to understand what is necessary to accomplish the function. FAST is the analysis of functions independent of any alternative system as a solution for providing functions.

[6] It is a tool to describe a system in a hierarchy of functions. See http://en.wikipedia.org/wiki/Structured_Analysis_and_Design_Technique for further references.

Practice 8: Customer-focused Verification & Validation

The intention with this practiceis to attain a holistic view over all verification and validation activities. These activities refer to all virtual or physical tests as well as other subjective methods (e.g. cliniques) with the intention of verification (for a system or a sub-system) and validation (for complete product). The practice is to verify and validate that the result meets requirements. This is done by breaking down the requirements to the level where solutions can be created and verification can be performed using the V-model as the framework. Verification and validation activities are performed at all levels of projects and in all phases. The main deliverables for this practice are: a) verified requirements specification at system level and validated for complete offer level, b) written test reports in connection to each test activity, and c) and action plans for deviations. Tools like the V-model, Verification and Validation plan, Product Delivery Plan (PDP) support this practice.

V. DISCUSSION

Comparing the VRES approach with the RDM that Arvidsson et al. [11] and Hasenkamp et al. [5] developed, it can be concluded that both the result of the VRES in terms of the definition of a principle and a practice, as well as content of the principles and practices, are different from their approach. VRES has provided a broader definition for principles. In VRES principles are 'a system of values' which employees should consider in every-day work. A principle is not limited to a part of a process or part of an organization. In RDM [5] principles are mainly referring to "efforts", not to the system of values, which makes it more simple to analyze from the academic point of view but has its limitations in achieving results from the industrial point of view. Hasenkamp et al. also connected the practices to specified RDM principles. But in VRES principles are 'a system of values' and prerequisite to be in place in order to be able to get operational result from practices. Therefore, connecting a specific principle to specific practices is somehow meaningless.

VRES has been utilized not only in Sweden, but at other Volvo 3P sites as well, e.g. France and Brazil. However, a single VRES practice is still partly context related. Most of the value of VRES was not only in its single practice but also in the process of developing practices in a system. Hence, for other companies it could be valuable to start with the VRES practices to test and learn, but there is a need for further development and adaptation to each company's own context. This process of developing practices also supports the ability of using them in application.

In order to spread the learning from the initiative some training programs were developed and several experience sharing sessions were arranged, involving PD engineers telling about their experiences. However, still the importance of 'sharing practices' to achieve stable result and culture shift was underestimated in the 2006-2009 VRES initiative.

VI. CONCLUSION

One contribution of this paper is the extended view achieved in practice concerning the robust design concept. The view has changed from looking at robust design in a more narrow way, as a statistical tool, to a broader view of robust design that focuses also on the systems of values and practices to act in terms of variation and robustness and produce products, which are satisfying customers. This view also encompasses the necessity of thinking about variation, which goes along both products and processes.

Another contribution of this paper concerns the concept of 'robust design practices'. Previous research contributions concerning 'robust design practices' have had an abstract view of the 'practices' based on literature [5]. However, in VRES the ambition was to use a pragmatic view concerning robust design practices. This view perceives robust design practices as natural activities and ways of doing product development, growing the practices locally in the context, while the 'robust design practices' based in literature could be perceived more as general guidelines.

Furthermore, Hasenkamp et al. [5] in their literature review could not conceptualize any specific practice for the "continuous applicability" principle of RDM. The continuous application of robust design depends on whether the organization has learnt to keep, reinforce and spread the approach or not. Here another contribution of this paper emerges: the positive influence of everybody's engagement in an iterative learning process, for development, implementation and sharing of robust design practices and therefore "continuous applicability" of it. Learning refers to an iterative process of studying existing practices, thinking, reflecting upon, and using new practices.

As mentioned later, in VRES the importance of knowledge and practice sharing, both tacit and explicit, was under-estimated and not tackled enough. In the later Lean Product Development initiative (2009) at AB Volvo, the experiences from VRES served as a foundation. This has also been a new research subject for students at Chalmers in collaboration with Volvo.

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Application of Design of Experiments to Homemade Yogurt Production Process

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Abstract- **Design of experiments (DOE) is a necessary component of product development and improvement, and prepares a scientific approach to evaluation and optimization of experimental factors. This study presents the application of DOE to homemade yogurt production process in order to detect the critical process factors which influence PH values of homemade yogurt and identify the optimal setting for these effective factors. Homemade yogurt were made by changing two different levels of skim milk powder, inoculation temperature, incubation temperature, incubation time, and fat percentage to investigate main and interactions effects on PH of the fermented milk and achieve the optimal PH value from customer prospective in the range of 4.2 to 4.6. The results demonstrated that incubation time and fat percentage are the most effective factors on PH development and the optimal settings for these factors should be 11.31 hours for the incubation time and 1.5 per cent for the fatpercentage.**

Keywords - **Design of experiments; homemade yogurt; PH; response optimizer; case study**

I. INTRODUCTION

DOE is a systematic powerful technique in order to analyze and determine crucial process factors which are influential in the responses or quality characteristics of the processes and thereby specifying the optimum settings for these factors so as to improve performance of the processes. DOE was created by Sir R.A.Fisher, at the Rothamsted Agricultural Field Research in London, UK in the early of 1920s. At that time, Fisher utilized DOE to determine the best crop by varying and optimizing some parameters such as sunshine, water, amount of fertilizer and soil. Nowadays, DOE is considered a significant advanced method within the optimization phase of Six Sigma and Design for Six Sigma (DFSS). The main purposes of implementation of DOE in systems and processes include determination of factors which are most impressive on the outputs, determination of influential process factor settings to achieve the best response, and the reduction of variability.

While the application of DOE becomes widespread in many production processes and systems, there are a few studies which have been performed in diverse yogurt production processes by employing DOE to determine key factors influencing improvement of the quality characteristics of various yogurts [1],[2]. Although response surface methodology has been utilized to achieve optimum level of predetermined factors in yogurt studies, diagnosing critical factors which are most effective on quality characteristics of yogurt is still controversial [3],[4],[5],[6].Accordingly, identification of crucial factors which conclude acceptable and qualified commercial yogurts from customer prospective is significant and also it is regarded as an appropriate prerequisite for response surface methodology. In this study, the application of DOE to homemade yogurt production process was analyzed by utilizing fractional factorial designs which is exerted to specify the most important process factors by executing fewer set of runs than set of runs in full factorial designs. The purpose of application of DOE to homemade yogurt production process in this paper was summarized into two-fold. The first objective was to diagnose and determine the key factors which were most effective on the quality characteristic of homemade yogurt, PH value, and the second objective was to gain the optimal settings of critical factors based on customer perspective.

II. CASE STUDY

Nowadays, yogurt represents a significant dairy product all over the world. Yogurt is made by mixing a starter of active yogurt including two types of cultures, Lactobacillus bulgaricus and Streptococcus thermophiles into heated milk. The bacteria convert the milk's sugar, lactose, to lactic acid during fermentation. The lactic acid decreases the pH and makes it slightly sour. Diverse types of yogurt have been produced because of market forces, consumer demands and preference, changing lifestyles, and dietary adjustments. Flavored yogurts were the first and major evolution of yogurt market and inserted a large quantity of types of yogurt to the markets such as fruit flavored [7]. In this study, homemade yogurt which the process of production is somehow similar to manufacturing plain yogurt in factories was utilized.

All quality characteristics in yogurt include texture, color, PH, flavor, viscosity, and composition. Lactic acid produced by fermentation process has an important role in the process of yogurt productions and quality characteristics of final yogurt. Hence, quality control programs in yogurt plants usually include measurements of the rate of the acidity in most of the process. Importance of the acidity increases when acidity of the finished yogurt becomes characterizing criteria for consumers because acidity affects flavors of the yogurt by making it tart. The rate of acidity is measured by titratable acidity tests, but more reliable and prompt tests for acidity measurement are PH measurement by PH Meter [7].

In the present research, five factors at two levels are selected for application of DOE to homemade yogurt production process. The list of process factors together with their levels which are used for experiments summarized in Table I. In addition, it was decided to perform experiments in order to determine significant process factors and interactions between them to PH level of homemade yogurt after fermentation as a response. According to studies, consumers prefer to use yogurt with moderate acidity (4.2 to 4.6) [7]. This acceptable range is considered for finished or cooled yogurt; also, cooling yogurt after fermentation of the milk influence to reduce the PH of fermented milk about 2 degrees. Therefore, the range of optimal PH, PH of fermented milk after fermenting and before cooling stage, is designated to be 4.4 to 4.6 as an optimal target for responses in DOE.

III MATERIALS AND METHODS

A. *Preparation of homemade yogurt*

Low-fat milk with 1.5 percent of fat and high-fat milk with 3.5 percent of fat were prepared from Dutch Lady Plant and were homogenized. The samples were provided by blending appropriate amounts of milk with 0.5 g/100g and 4.5 g/100g skim milk powder. The mixtures were heated at 85°C for 10 min. Starter culture was provided from commercial, unflavored yogurt, Nestle plant. For making homemade yogurt, plain yogurt can be used for starter culture [8]. Milk samples were cooled at two levels of inoculation temperatures, 50°C and 55°C, by storing in the refrigerator. Samples of 950 ml of specified milk compositions were inoculated with 50 ml of the starter culture at aforementioned inoculation temperatures. The inoculated milk samples were incubated at 40°C and 44°C until 4 hours and 12 hours by microwave.

B. *PH Measurement*

The PH values of the yogurt samples at the end of incubation time was measured by dipping the glass electrode of the pH meter (Sartorious AG, PB-10) into the milk. The pH meter was cleaned between measurements by water and was calibrated with buffers before measuring the next sample. All experiments were made with 450 ml of yogurt in a glass beaker.

C. *Experimental design and statistical analysis*

A $2^{(5-1)}$ fractional factorial design with resolution V at two replicates was used to investigate main and interactions effects on PH of the yogurt. The experiments were performed in two replicates, totally 32 runs. Furthermore, each replicate were carried out in one block, that is the first replicate were run on one day and second replicate on another day. The Minitab, version 15, was used to present all statistical analysis.

IV. RESULTS AND DISCUSSION

A. *Design of PH experiment and identification of significant process factors*

The design and the results of experiments, which are the PH values of fermented milk as a response, are shown in table II. The design generator is E = ±ABCD and the defining relation is I = ABCDE. In this fractional factorial design, the effects and interaction effects which are confounded with each other, that are called aliases, are given in table III.

TABLE I
List of process factors used for the experiment

	Process Factor	label	Low setting	High setting
1	Skim milk powder (g/100g)	A	0.5	4.5
2	Incubation Temperature (°c)	B	50	55
3	Incubation Time (Hour)	C	40	44
4	Incubation Temperature (°c)	D	4	12
5	Fat Percentage (%)	E	1.5	3.5

TABLE II
$2^{(5-1)}$ design for the PH experiments

run	A	B	C	D	E=ABCD	PH replicate1	PH replicate2
1	0.5	50	40	4	3.5	5.04	4.98
2	4.5	50	40	4	1.5	4.96	5.01
3	0.5	55	40	4	1.5	4.92	4.87
4	4,5	55	40	4	3.5	5.35	4.91
5	0.5	50	44	4	1.5	4.89	5.07
6	4.5	50	44	4	3.5	4.95	4.89
7	0.5	55	44	4	3.5	4.98	4.92
8	4.5	55	44	4	1.5	5.01	5.07
9	0.5	50	40	12	1.5	4.41	4.69
10	4.5	50	40	12	3.5	4.71	4.85
11	0.5	55	40	12	3.5	4.66	4.81
12	4.5	55	40	12	1.5	4.51	4.65
13	0.5	50	44	12	3.5	4.47	4.85
14	4.5	50	44	12	1.5	4.49	4.55
15	0.5	55	44	12	1.5	4.53	4.44
16	4.5	55	44	12	3.5	4.96	4.85

TABLE III
List of process factors used for the experiment

Process Factor	label	Low-level setting
A = BCDE	AB = CDE	BD = ACE
B = ACDE	AC = BDE	BE = ACD
C = ABDE	AD = BCE	CD = ABE
D = ABCE	AE = BCD	CE = ABD
E = ABCD	BC = ADE	DE = ABC

TABLE IV
Analysis of variance output from minitab for PH experiments

Fractional Factorial Design

Estimated Effects and Coefficients for Response(PH) (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		4.8203	0.02357	204.50	0.000
Block		-0.0178	0.02357	-0.76	0.462
A	0.0744	0.0372	0.02357	1.58	0.136
B	0.0394	0.0197	0.02357	0.84	0.417
C	-0.0256	-0.0128	0.02357	-0.54	0.595
D	-0.3369	-0.1684	0.02357	-7.15	0.000
E	0.1319	0.0659	0.02357	2.80	0.014
A*B	0.0731	0.0366	0.02357	1.55	0.142
A*C	0.0031	0.0016	0.02357	0.07	0.948
A*D	0.0144	0.0072	0.02357	0.30	0.765
A*E	0.0206	0.0103	0.02357	0.44	0.668
B*C	0.0356	0.0178	0.02357	0.76	0.462
B*D	0.0094	0.0047	0.02357	0.20	0.845
B*E	0.0481	0.0241	0.02357	1.02	0.324
C*D	0.0069	0.0034	0.02357	0.15	0.886
C*E	-0.0294	-0.0147	0.02357	-0.62	0.543
D*E	0.1044	0.0522	0.02357	2.21	0.043

Analysis of Variance for Response(PH) (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Blocks	1	0.01015	0.01015	0.01015	0.57	0.462
Main Effects	5	1.10892	1.10892	0.22178	12.47	0.000
2-Way Interactions	10	0.17173	0.17173	0.01717	0.97	0.508
Residual Error	15	0.26670	0.26670	0.01778		
Total	31	1.55750				

The analysis of variance for this experiment which is obtained from Minitab is presented in Table IV. It was decided to choose the significance level (α) 5 per cent to determine significant factors and interactions. In Analysis of Variance table, if the p-value becomes less than the significance level (α), the factor or the interaction effect is then regarded to be statistically significant, on the other hand, if the p-value becomes greater than α, it is concluded that the factor or interaction effect are not significant. For the PH experiment, main effects D and E and the interaction effect D×E are significant because the p-values are less than 0.05 (as shown in right highlighted figures in table IV). From evaluating the effects of significant factors and interactions in Table IV (as shown in left highlighted figures), it is indicated that incubation time (D) has highest effect on PH value in proportion to other effects. In addition, changing incubation time from low to high level reduces PH value because of negative effect. Fat percentage (E) has second highest effect on PH value; also changing fat percentage from low to high level increases PH value due to positive effect. Finally, the effect of D×E interaction is smallest and has p-value of 0.043. It means that this interaction is significant at the 0.05 α-level

B. *Analysis of main effects and interactions trends*

From comparison among main effects plot which is shown in fig 1, it is inferred that when fat percentage raise from low level to high level, the PH of yogurt increases. In addition, shifting from low level of incubation time to high level causes PH of yogurt to be decreased. The strong interaction between incubation time (D) and fat percentage (E) is shown in fig 2. This plot indicates that, see lower interaction plot in fig 2, the decrease in PH by moving from the low to the high level of incubation time is greater when the fat percentage is low (solid line) than when it is high (dash line). In other words, the slope of reducing PH is further at low level of fat percentage while moving from low level of incubation time to high level. In this experiment 3-ways and 4 ways interaction are considered negligible in this experiment.

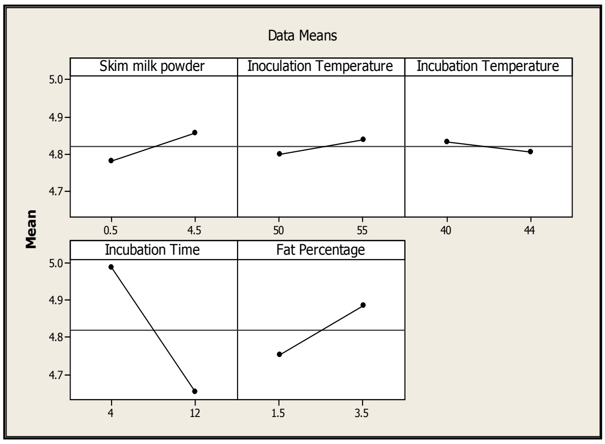

Fig. 1. Main Effects Plot

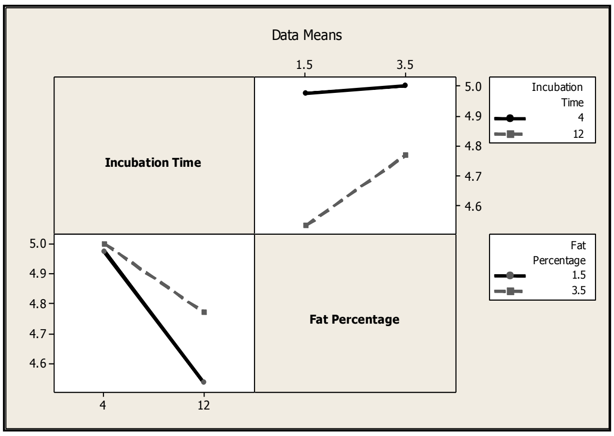

Fig. 2. Interaction Plot

C. *Calculation of optimal process factor settings*

The determination of optimal process factor settings which influence PH value, in order to be located in the range of 4.4 to 4.6, was decided to conduct by Minitab

Response Optimizer. The objective for PH values is to achieve a quantity at or next to the target value of 4.5. Therefore, the PH values in the range of the specification limits, 4.4 to 4.6, are satisfactory and the PH values less than 4.4 or higher than 4.6 are not acceptable. By using response optimizer of Minitab, it is concluded that the optimal process factor settings are achieved in relatively high level of incubation time (D), 11.31 hours, and low level of fat percentage (E), 1.5%. Furthermore, results in table V shows that the desirability of this optimal arrangement is equal to one; it indicates that the predicted response, y, by the value of 4.5, is completely close to the target requirements.

After specification of level of process factors for reaching to optimal target of PH value, it was decided to execute five more experiments for confirmation of findings. The methodology which applied for performing more experiments was completely corresponding to aforesaid methods in section 2; however, the factors of incubation time (D) and fat percentage (E) were selected in relatively high level, 11.31 hours, and low level, 1.5 per cent, correspondingly. The PH values of fermented milk were 4.53, 4.51, 4.49, 4.51, and 4.53. These results indicate that the significant controllable factors, which are most effective on PH values, are incubation time and fat percentage. Moreover, for reaching to the optimal range and target of the PH values, the high level of incubation time and the low level of fat percentage should be considered.

TABLE V
Response Optimization output from Minitab for PH experiments

Response Optimization

Parameters

	Goal	Lower	Target	Upper	Weight	Import
PH	Target	4.4	4.5	4.6	1	1

Global Solution

Skim milk Powder = 1.07440
Incubation Time = 11.3178
Inoculation Temperature = 55
Incubation Time = 11.3178
Incubation Temperature = 40
Fat Percentage = 1.5

Predicted Responses
PH = 4.5 , desirability = 1.000000
Composite Desirability = 1.000000

D. *Model development*

Reduced regression model based on significant factors and interactions, incubation time (D), fat percentage (E) and D×E interaction is (1)

$$y = \beta 0 + \beta 4\, x4 + \beta 5\, x5 + \beta 45\, x4\, x5 \qquad (1)$$

where y is response (PH), x4 is incubation temperature (D), x5 is fat percentage (E), and x4x5 is D×E interaction. Also, the coefficients β0, β4, β5, and β45 are identified the regression coefficients. The regression coefficients β4, β5, and β45 are estimated from one-half of the corresponding effects and β0 from the grand average of all 32 observations. The estimation of response or predicted value for PH is (2)

$$\begin{aligned} \hat{y} &= 4.8203 - 0.1684\, x4 + 0.0659\, x5 + 0.0522\, x4\, x5 \\ &= 4.8203 - 0.1684\,(+1) + 0.0659\,(-1) + 0.0522\,(+1)(1) \\ &= 4.5338 \end{aligned} \qquad (2)$$

It is clear that this value of PH is in the range of desirable PH value, 4.4 to 4.6, and is close to the optimal target of PH, 4.5.

V. CONCLUSION

Two objectives of this study were determination of significant process factors in homemade yogurt production process and specification of optimal settings for these factors. The crucial factors which are most effective on PH values of homemade yogurt were incubation time and fat percentage. Moreover, in order to achieve the optimal range of PH value in homemade yogurt, 4.4 to 4.6, the optimal settings for these factors should be 11.31 hours for the incubation time and 1.5 per cent for the fat percentage. The results of the study can direct researchers to apply response surface methodology and other optimization techniques for future researches.

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Determining the Factor Affecting the Chip Formation of Machining Mild Steel Using Taguchi Method

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Abstract - **This paper outline the application of Taguchi method in optimizing the machining condition for obtaining desirable chip shape and color. An L8 standard orthogonal array of Taguchi method was used to sequence the experiments factors and levels. Six factors were identified that may influenced the chips shape and color. The factors were type of lubrication, depth of cut, RPM, type of material and depth of cut. These factors were varied at two level each. The results show that the depth of cut, RPM and material were the most influential factors that determine the chips shape, whereas other factors such as type of cutting tool and feed rate were insignificant. For color of chips, RPM was identified the most influential factors, followed by material, cutting tool, lubrication, depth of cut and feed rate. Taguchi method with SN ratio graphing effect which requires minimal time is found suitable to analyze the problem and withdrawn a valid conclusion.**

Keywords - **Taguchi method, SN ratio graphing effect**

I. INTRODUCTION

The chip formation is a result of tearing or pulling rather than cutting, which will affect tool life, surface finish, and workpiece accuracy. The mechanism of chip formation is of fundamental importance, because it relates the properties of the material to surface integrity, machinability and other machining characteristics. At a low speed, chips curled slightly and the curling became more severe with increasing cutting speed [1].

Earlier findings reviewed by Zorev [2], indicated that high speeds and heavy loads caused large changes in chip and cutting temperatures during machining. However, direct influence of the depth of cut on the chip formation process is insignificant, as well as at low cutting speeds. From the point of view of tribology, increasing the load leads directly to higher stresses, and this will result in more severe damage [3]. Furthermore, the interface temperature will depend on the load and sliding velocity, and control of power dissipated at the interface. Therefore, the tool-chip interface temperature is directly dependent on the feed rate, the depth of cut and the cutting speed.

When machining hardened steels, workpiece material microstructure and thermal properties affect chip flow. It is common to observe that different thermal properties of the tool material may result in lower cutting forces [4].The color of the chips is caused by oxidation, which is temperature dependent, and according to Nelson *et al.* [5], it does not provide a good indication of the temperatures involved during the cutting tests. One can refer to the color of the steel chips which indicate the temperatures involved during the chip formation as given by Ning *et al.*[6]. The lack of color for light brown color chip is due to intimate contact between the chips and tool that prevent oxidation [7]. This experiment revealed that the higher the feed rate, the depth of cut and the cutting speed used, the darker is the color of the chips, which means a higher extent of oxidation due to a higher temperature. The temperature rises monotonously with the increase of the cutting speed and the cutting depth [6-8] also shows that the cutting edge temperature increased with the increase in depth of cut, and Dewes *et al*. [7] proved that smaller depths of cut gave significantly lower temperatures.

When machining hardened materials, continuous chip formation is observed at a conventional to high cutting speeds and low to moderate feed rates [4]. At higher feed rates 'saw tooth' chips are produced [9]. The later type of chip formation can cause cyclic variations of both cutting and thrust forces and can result in high frequency vibration that affect tool life and tool failure. Fallbohmer *et al.* [4] recent studies show that the formation of 'saw-tooth' chips is due to periodic formation of cracks at the head of the tool. The fracture on the surface of the workpiece propagates inside the chips until the stress state is altered from a low to high compressive stress region. According to recent observations, the frequency of shear localized saw-tooth shape chips is very high. The cutting edge is subjected to a high frequency force variation. The chip formation certainly affects the cutting force. Segmented chips are produced by plastic instability and they are responsible for reducing the cutting force [8].

This study will utilizes the Taguchi method in determining the optimum condition for obtaining desirable chip shape and size in machining mild steel.

II. METHODOLOGY

The machining tests were carried out using Lathe Pinacho S90/180 to investigate the effect of various factors on the chip formation process as shown in Table 1. Table 1 is an L8 standard orthogonal array of Taguchi method that used to sequence the experiments and factors and levels. Two types of mild steel known as red and blue were tested and assigned as factor D.

TABLE I
FACTORS AND LEVELS USED FOR MACHINING TESTS

Experiment no	A: Lubrication	B: DOC (mm)	C: Cutting tool	D: RPM (rev/min)	E: Material	F: Feed rate (mm/rev)
1	Dry	0.1	HSS	860	red	0.05
2	Dry	0.1	HSS	1000	blue	0.2
3	Dry	0.3	Carbide	860	red	0.2
4	Dry	0.3	Carbide	1000	blue	0.05
5	Wet	0.1	Carbide	860	blue	0.05
6	Wet	0.1	Carbide	1000	red	0.2
7	Wet	0.3	HSS	860	blue	0.2
8	Wet	0.3	HSS	1000	red	0.05

The chip formation criteria will be evaluated based on the type of chips form and color of the chips produced as shown in Table II. Therefore, parameter design of discrete data was selected based on Multi-Class Discrete Data: Scoring Method. In this method, fixed marginal discrete data such as excellent, good, fair, and poor with weights 0,1,2,…*k* are assigned to the respective class [10]. The SN ratio is calculated as [10]:

$$SN = -10 \log [\sum w^2_i n_i/n] \qquad (1)$$

TABLE II
THE MARGINAL DISCRETE OF THE CHIPS SHAPE AND COLOUR

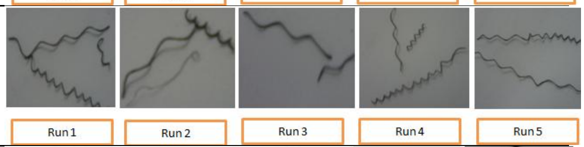
Chips shape	Marginal discrete	Chips color	Marginal discrete
Elemental	excellent	Blue	Excellent
Continuous and short	Good	Brown	Good
Continuous and long	Poor	Silver	Poor

After computing the SN ratio, the SN ratio graphs were plotted. From these graphs, the significant and insignificant factors that affecting the chips color and shapes will be identified. Later from these graph, the optimum conditons for both desired chips color and shape will be determined. By using the SN graphing effect, the important factors and optimum conditions can be easily determined without performing ANOVA.

III. RESULTS AND DISCUSSION

The chips form from the experimental can be observed varied from elemental, discontinuous and short, and continuous and long shapes. Table 3 shows every shape of chips produced for the eight experimental runs.

TABLE III
CHIPS SHAPE FOR EVERY EXPERIMENTAL RUN

Expt no	Chip shape
1	
2	
3	
4	
5	
6	
7	
8	

SN ratio using the Multi-Class Discrete Data: Scoring Method was computed as shown in Table 4. Table 4 shows result for color and shape of chips and the coressponding SN ratio at various cutting condition. It is shown that the blue color of chips were obtained when machining using experiments number 1,2 and 8 conditions, and in experiment 8, the silver color chips were also produced. Therefore by referring to these observations, the decision to come out with the optimum condition to obtain preferred chips color is very difficult. This problem is solved by constructing a SN graph as shown in Figure 1 and 2 respectively for chip shape and chip color.

TABLE IV
COMPUTATION OF SN RATIO FOR CHIPS SHAPE AND COLOUR

Experiment Number	Data (n=5) Chips shape Weights 0 Elemental	1 Discontinuous	2 Continuous	$SN = -10\log[\sum w_i^2 n_i / n]$	Data (n=5) Chips color Weights 0 Blue	1 Brown	2 Silver	$SN = -10\log[\sum w_i^2 n_i / n]$
1	3	2	0	-5.57	0	4	1	-5.38
2	5	0	0	-6.99	0	1	4	-4.51
3	0	5	0	-6.99	5	0	0	-6.39
4	0	0	5	-3.49	5	0	0	-6.39
5	0	0	5	-3.49	1	4	0	-6.05
6	0	5	0	-6.99	3	2	0	-4.65
7	0	0	5	-3.49	5	0	0	-6.39
8	0	5	0	-6.99	2	0	3	-3.48

The observation of all the chips shapes formed in this experiment showed that physically the shape and structure of the chip is independent with the type of cutting tool and feed rate. But, it will depend on the depth of cut, RPM and material, because these factors will determine the amount of heat generated. This result was similarly found by Sahin *et al.* [11] when machining of the alloy matrix that cutting speed was the main factors.

From the investigation, it is found that. The colors and sizes of the chip formed could also give a good indication to select the cutting conditions in our machining operation. Generally for machining of steel, small and dark blue colored chips are preferred since they indicate that all the heat generated during the cutting process has been dissipated and taken away by the chip, leaving only a small amount of heat on the machined surface, and consequently unaltered and good quality of machined surfaces are obtained. The acceleration of chips leaving the machined surface is helped at high cutting speed. But too high of cutting speed will encourage more heat generation and lead to catastrophic failure of the cutting edge.

Analysis of chip shape using SN graph

Figure 1 shows the SN graph for chip shape during the machining tests. The SN ratio graph is easily visualize to determine the optimum condition and the significant factors. The desired chip shape can be achieved by having machining conditions of A1B1C1D1E0F0. But the ranking in Table 5 shows that factors B, D, and E have the same weightage effect on the chips shape, therefore depth of cut, RPM and material were the important factors in determining the chip shape in the machining process, compared to others factors of lubrication, cutting tool, and feed rate. Prvious study [9] found that feed rate has a significant effect to the chip shape when machining hardened steel. This may be due to the values of feed rate used in this study will not cause any changes in the shape of the chips produced.

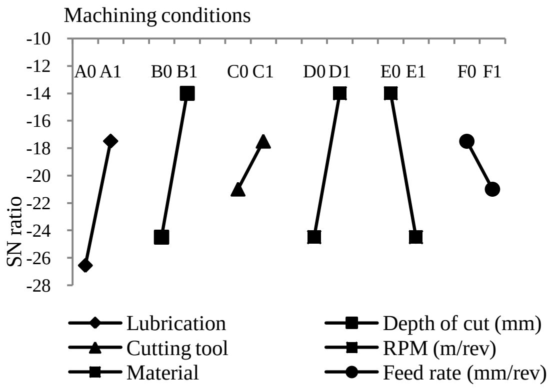


Figure 1 SN ratio graph vs. machining conditions for chips shape

TABLE V
RANKING OF FACTORS THAT INFLUENCE THE CHIPS SHAPE

	A	B	C	D	E	F
Δ	-9.06	-10.48	-3.49	-10.48	10.48	3.49
Ranking	2	1	3	1	1	3

Analysis of color of chips using SN graph

Figure 2 shows the SN ratio graph vs. machining conditions for determining the optimum machining conditions for obtaining desirable chips color. From Figure 2, the optimum machining conditions is A1B0C0D1E0F0 with ranking as shown in Table 5. From Table 6, the factors that influenced the chips color is found to be the RPM, followed by material, cutting tool, lubrication, depth of cut and feed rate. RPM will determine the cutting temperature generated and therefore caused color changes of the chips produced. Previous study [6-8] found that the temperature rises monotonously with the increase of the cutting speed and the cutting depth, and smaller depths of cut gave significantly lower temperatures [7].

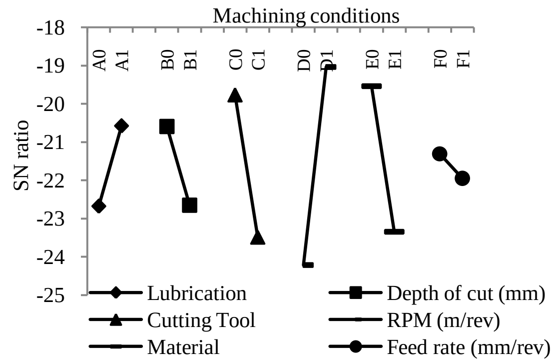


Figure 2 SN ratio graph vs. machining conditions for chips color

TABLE VI
RANKING OF FACTORS THAT INFLUENCE THE CHIPS COLOUR

	A	B	C	D	E	F
Δ	-2.10	2.06	3.72	-5.17	3.81	0.65
Ranking	4	5	3	1	2	6

II. CONCLUSION

From the result obtained the following can be concluded:

1. The graphing effect of SN ratio in Taguchi method can easily help to determine the important factors that affecting the chip color and shape in machining process without computing ANOVA.
2. The depth of cut, RPM and material were identify the most influential factors that determine the chips shape, whereas other factors such as type of cutting tool and feed rate were insignificant. The optimum condition for desirable chips shape was at A1B1C1D1E0F0
3. For color of chips, RPM was identified the most influential factors, followed by material, cutting tool, lubrication, depth of cut and feed rate. The optimum condition for desirable chips color was at A1B0C0D1E0F0.

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The Potential Application of Robust Engineering Principle to Capture Building Maintainability Requirements at Design Stage

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Abstract— **Building performance is often criticised for not meeting users' expectation for maintenance related consideration. Low maintenance related consideration will lead to costly maintenance. The aim of this paper is to identify the potential of Robust Engineering (RE) principle in building design to capture the maintenance related consideration. RE acts as a tool in guiding building designers to focus on users' expectation. It is important to understand how to adapt this method so that the designers in the construction industry are able to assimilate the principle in construction towards developing new design approaches to capture maintenance needs in building design. The primary data collection method in this research is an expert panel interview. The interviewees consist of professional design engineers and building operators who have experience in building design and maintenance. Currently there is no specific tool used to identify maintenance related consideration in building design. Current building designs rely on the experience of the designers. Building design uses an intuitive procedure to fulfil the authorities' approval condition. An approach such as the RE has the potential to help the decision making in building design and identify maintenance related consideration at the design stage. It also helps the clients to make balance decisions when selecting a design solution.**

Keywords **- building design process, maintenance related consideration, Robust Engineering in construction**

I. INTRODUCTION

Constructing a building does not only involve considering the design, construction time, capital cost and expected quality. It also involves the commitment to long-term use of budget. Throughout a building's life cycle, the building maintenance must be constantly performed to ensure its safety, liveability and sustainability. Evidence shows that even if a building was designed according to the needed term of reference, it still has a high maintenance cost. This reflects the low attention of maintenance related consideration during the design. The impact of low maintenance related consideration is only felt by the occupiers and building owners and not the designers and builders. Costly maintenance works are exhausting the available budget and lessening the capacity to perform the maintenance tasks. It is critical to identify the maintenance related consideration to produce high maintainability building designs.

II. RESEARCH OBJECTIVES

The aim of this paper is to identify the potential application of Robust Engineering (RE) principle adaptation in the building design. RE is proven to be an effective method in manufacturing product development and design. It has the capacity to capture end-users' needs and meet the wanted engineering quality. It acts as a tool for guiding building designers in producing better building designs. This will help designers to assimilate the method to construction design in developing new design methods to capture maintenance needs in building design.

III. METHODOLOGY

The primary data collection method in this research is an expert panel interview using a prepared semi structured interview questions. The respondents of the interview are professional design engineers and building operators who have experience in building design and building maintenance. Table 1 describes the workflow of data collection and analysis.

TABLE 1.SUMMARY OF ACTIVITIES AND TASKS IN DATA COLLECTION

Main activities	Tasks
Data instrument development	• Development of interview questions and protocol • Identification of respondents
Data collection	• Interview respondent • Transcribe interview
Data analysis	• Coding • Development of themes based on the content analysis • Triangulation of result with current literature

Adapted from [1]

IV. LITERATURE REVIEW

Building maintainability was introduced by the military services in the United Stated since 1954 [2]. However building performance is often criticized for not meeting users' expectation in terms of maintenance related consideration. Reports [3–5] aiming to improve the industry productivity promote the need to improve construction design to meet users' expectation. As reported in [5], nearly £1 billion was spent to correct a building because of low consideration of maintenance related need. Further investigation suggests that these corrections can be identified at the design stage.

A. The need to incorporate maintenance related consideration in building design

Maintainability is a simplicity where a system can be maintained to optimise the use of space and equipment with minimum interruption to users of the building [6]. The major drawback of building design is the failure to make use of lessons learned from maintenance experience of building and not considering the whole life cycle of the building. A design with low maintenance related consideration has a significant effect on the building performance. As the need becomes more complex, the building design approach also needs to change its focus. Table 2 describes the comparison between current building design approach and the change needed to enable better building design based on extensive literature review done by authors. Current building designs rely on the experience of the designers and previous project lesson learned [7–9]. To improve designs, a structured approach that focuses on meeting the users' expectation in terms of maintenance related consideration is being highlighted.

As for the Malaysian's construction industry, the important and proper strategies to address the building maintainability issue is far lacking compared to our neighbouring countries. In a competitive economy where budget for development becomes limited, clients are now asking for more where they do not only want a functional design as in their need statement but they also desire a predictable cost of ownership.

TABLE 2. CURRENT BUILDING DESIGN APPROACH AND CHANGE NEEDED FOR BETTER BUILDING DESIGN

Element	Current approach	Change of approach
View as	Conversion of needs and requirements, flow of processes and value generation	Ownership of operational processes
Input of designer	Until handover	Extended to facility in use
Tools used	Modelling Based Design	Outcome Based Design
Perspective of designer	Lesson learned from previous projects	The downstream operational requirement
Output of design tasks	How to incorporate this based on our past experience	Performance in use integration/Product Based Strategies
Emphasis on solution	Translation of needs and requirement	How to achieve Product Based Strategies
Focus	How to achieve sustainability	Avoidance of loss to users

Source : [10]

It is important to develop a tool and the strategies of adaptation in building design which are able to capture the users' expectation in term of maintenance related consideration in the design stage.

B. Construction product development as a manufacturing process

Manufacturing improvement in terms of product design, make and assembly, has been realised through the adaptation of a better production philosophy. Recent researches suggest that the manufacturing product development approach significantly influences the construction industry in terms of integration and meeting the client's satisfaction [11–15]. Adaptating and mirroring the manufacturing to construction industry is with the assumption that it will produce the same benefits to the construction industry as it has done to the manufacturing industry. The similarities between the manufacturing and construction industries are [14], [13], [16]:

- Both industries produce physical engineering products and used by the users;
- Both industries use raw materials and assembly of parts to produce final products;
- Both industries involve repetition of tasks in their design and construction stages;
- They have high cost of reworks; and
- They have large data management between the organisation and disciplines.

The likeness of building construction and manufacturing is not in the product, but the linkages of tasks involved through repeated tasks in design and production of products [17]. Construction involves on-site production of large product where else manufacturing produces products in mass production.

C. RE application and core elements

RE is an effective optimisation strategy in the design of engineered products [18] before the product is released to users to avoid loss to the society. RE is an approach that evaluates and fulfills improvements of products, materials and equipment [18–27]. These improvements aim at improvising the needed characteristics and simultaneously reducing the number of defects by studying the key variable controlling the procedures or design to yield the best results. The method is applicable over a wide range of engineering fields that include the production of raw materials, subsystems, products for professional and consumer markets. The main elements of RE [18] are:

- Represents the application of the Taguchi Method at the start of research and development or advanced product and process

development activities to optimise performance;
- Concentrates on identifying the "ideal function (s)" for a specific technology or product/process design; and,
- Concentrates on selectively choosing the best nominal values of design parameters that optimised performance reliability (even in the presence of factors causing variability) at the lowest cost.

V. DISCUSSION

Data were collected from the expert panel interview using a prepared semi structured interview questions. The respondents are professional design engineers and building operators who have experience in building design and maintenance. The responses to the interview questions asked in the interviews are recorded and transcribed verbatim. The interview starts by first presenting the aims of the research, followed by questions and a discussion of the responses from the design engineers of both organisations.

A. *Maintenance related consideration in current design practices*

Table 3 shows the summary of interview answers while Table 4 tabulates the potential application of RE in building design. There is a general agreement by the expert panel that there is no specific tools or method used to measure maintainability of a building project. Building design has assumed that the current code of practice has considered the maintenance needed. The code of practice incorporates maintenance related consideration based from experience and presents the consideration as a specification and manual.

The expert panel suggested that the building operators must be a part of the design team. Its main role is to review and suggest maintenance related consideration in the design and contribute their experience in terms of managing day-to-day of housekeeping, planned maintenance and unplanned maintenance. The collaborative design efforts are a better approach which is similar to manufacturing philosophy such as concurrent engineering. The method acts as a design optimisation strategy in building design which defines specification boundary for product performance in the production or assembly stage.

TABLE 3. SUMMARY OF INTERVIEW ANSWER OF CURRENT DESIGN PRACTICE

Statement	Agreed/ Disagreed
No formal procedure for designers to incorporate maintenance requirement in the design	Agreed
No formal procedure used to translate the maintenance needs into design specifications	Agreed
The maintenance needs are incorporated in design based on the experience of the designers	Agreed
There are standard guidelines for the integration of needs in the design stage	Disagreed
There are standard guidelines for material and equipment selection criteria in the design stage	Disagreed
There is a method used to analyse the maintenance need of the building	Disagreed
Incorporating maintenance need is not satisfactory and can be improved	Agreed
Building operators' involvement is able to identify maintenance related consideration at design stage	Agreed

Note : Extracted from the expert panel interview

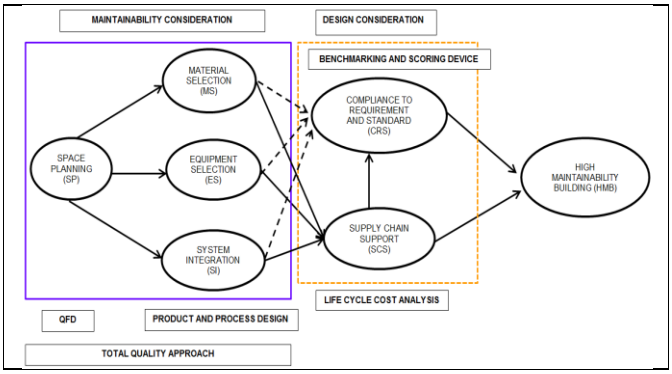
TABLE 4. POTENTIAL APPLICATION OF RE IN BUILDING DESIGN

Focus	RE in building design process	Desire improvement
Ownership of operational processes	As an enabler for production and related tools to integrate the design processes	Provides implementation strategies and the ability to capture the maintenance consideration during design
The downstream operational requirement	Basis for parameter and acceptable tolerance of product and specification	The integration of information between stages and design team members
Operational focus of built structure	Reduce variation and enhance engineering quality	Quality and goal attainment

Source : Authors

B. *RE principles in capturing maintenance related consideration in building design*

The expert panel in this interview agreed that design consideration in producing building design is sufficient for safety (meeting rule and statutory needs, constructability and functionality) and cost (maintainability and engineered quality). Design is a complex decision making. There are many factors to consider and some trade offs made to suit the limition of cost. Figure 1 shows the factors that are considered by the designers during the interview. The main concerns consist of space planning, material selection, equipment selection and integration. Building design uses an intuitive procedure to suit the authorities' approval. An approach such as the RE is a better tool to complement the decision making in building designs. The main emphasis that reflects the RE aim is to ensure minimal or no loss to the users and society in terms of reducing defective product. The efficient simulation and confirmation test reduce the possibility of failure during building use. It also helps the clients to make more accurate decisions when selecting a design solution.



Source : Authors

FIGURE 1. FOCUS OF BUILDING DESIGN ELEMENT

For effective application of RE in building design, some guiding principles to incorporate RE principles in building design are needed. The proposed guiding principles are as follows:

- Collaborative design effort in sharing and translating design information;
- Efficient use of information and effective analysis method;
- Focus on product performance in users' environment; and
- Sustainable use of resources as an integrated system with low waste generation.

VI. Conclusion

To meet building users' expectation, the building design must have a high degree of engineered quality buildings and they are free from any problems which the building users do not want. Adapting construction as manufacturing is assuming that it produces positive impacts to the construction industry as it has done to the manufacturing industry. Current building designs rely on the experience of the designers and competency of the team delivering the design. To ensure maintainability,both parties must support an approach to produce building design solution. Collaborative design efforts is a better approach. RE with end-users' focus acts as an effective tool in building design to capture maintenance related needs.

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Effect of Temperature Related Parameters in Plastic and Metal Injection Molding Process using Taguchi Method

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Abstract - **Injection molding has been emerged as a promising manufacturing process because of several advantages. Conventional injection molding was dominated by plastic as raw material, but for better engineering properties feasibility, injection molding with metal powder as raw material has been given special attention and known as Metal Injection Molding (MIM). However, because of different properties and rheology, processing parameters for both processes must be treated accordingly. In this paper, significant process parameter is justified for both processes using the state of the art Taguchi method of designing experiment. Simulation using Moldflow software is conducted with various process settings. In this paper, it is proven that due to rheological behaviour, all the input parameter give effect in MIM process while only one parameter is dominating during the injection molding of polypropylene.**

Keywords – **Metal Injection Molding, simulation, Taguchi,**

I. INTRODUCTION

In recent years, there has been an increasing interest in Plastic Injection Molding (PIM) because of the advantages of precision, wide range of plastic material selection and ability to produce complex geometry. With the purpose of taking the benefit of the process, MIM was inspired as the material properties are over polymers. In conventional injection molding, the raw material is thermoplastic pellet, but in MIM, feedstocks which comprised mixture of selected metal powder and set of thermoplastic material as temporary binder are used. Basically, ini MIM, there are four sub processes involved: mixing of metal powder and thermoplastic binders. Then the feedstocks will undergo injection molding process to shape the green part. After injection molding, green part needs debinding process to remove some of the binder before undergo the final step, which is sintering.

The process setting in plastic injection molding cannot be applied directly to MIM [1] as we are actually dealing with different type of material. Therefore, process settings play very important roles in influencing the quality of final product. In optimizing the parameters, researchers all over the world use various approach such as Taguchi method [1, 2] and simulation [3].

Modelling and simulation are widely utilized in optimization to avoid wasting cost and time as there is no necessity to conduct real process. Simulation tools for PIM are maturely established and easily available. Simulation software that able to handle peculiar rheology of feedstock in MIM though is hardly found. Thus, MIM process always been simulated by software tools that purposely developed for other similar manufacturing processes such as casting and PIM [4].

Dealing with the process setting to determine the quality of final product, causal relationship between input and output parameters is often not straightforward [3]. Ahn et al. [5] used a classification of output parameter into three main categories which are pressure, temperature and velocity (flow) dependent parameter for systematic analysis of the process design. Temperature has been identified as major contributing factors in both MIM and PIM process. This paper will focus only on the temperature dependent output parameter which consist of Melt Front Temperature Difference (MFTD), Cooling Time (t_{cool}) and Packing Time (t_{pack}) [2,5].

The main objective of this paper is to investigate whether only MIM is significantly affected by temperature variable, as the existence of metal powder in the feedstocks. To achieve this objective, Taguchi method is employed by means of determining the percent of influence of every identified factors.

II. METHODOLOGY

A. *Material Properties*

For plastic material, polypropylene was chosen to represent thermoplastic material. This is the similar type of material employed by [1] in their comparison study. In this study, the material is selected from the MoldFlow material library and the details of the plastic properties are as stated in Table 1.

TABLE 1
PROPERTIES OF PLASTIC MATERIAL

Family name	Polypropylenes (PP)
Identification	Lupol TE-5007B
Manufacturer	LG Chemical
Density	928 kg.m^3
Specific heat capacity	2931 J/kg.C
Thermal conductivity	0.118 W/m.C

For MIM, material testing has been done to the feedstocks prepared, and the properties are used in this study to represent metal material. The feedstocks is mixture of Stainless Steel SS316L powder, and of (in weight percentage) 73% PEG, 25% PMMA and 2% Stearic Acid as the binder system. The stainless steel powder is water atomized and manufactured by Atmix Corporation Japan, with average particle size of 5µm. In the binder system, PEG acts as the main component, PMMA as the backbone polymer while Stearic Acid works as surfactant. The best powder loading 61.5% as claimed by [6] is used. The properties of the stainless steel powder material are simplified in Table 2.

TABLE 2
MATERIAL PROPERTIES OF SS316L STAINLESS STEEL POWDER

Identification	SUS316L powder
Manufacturer	Epson Atmix Corp., Japan.
Particle shape	Irregular
Grade	PF-10F
Density - Tap - Pycnometer	4.06 g/cm^3 8.0471 g/cm^3
Average particle size	D_{10} = 2.87µm D_{50} = 5.96µm D_{90} = 10.65µm

B. Process Setting

All the process setting used in this study are according to the investigation reported by [1]. Three different process setting levels are varied as depicted in Table 3 in both PIM and MIM to observe their respond to the temperature dependent output parameters.

TABLE 3
PROCESS PARAMETERS FOR PIM AND MIM

Factors		Levels		
Filling time (t_f)		1.0 (s)	1.25 (s)	1.5 (s)
Switch Over (*SO*)		99%	98%	97%
Melt temperature (T_m)	PIM	210°C	230°C	250°C
	MIM	150°C	160°C	170°C
Wall temperature (T_w)	PIM	45°C	60°C	75°C
	MIM	30°C	40°C	50°C

In laboratory experiment, these parameters are usually fed into the machine control setting. However in this paper, data were gathered from multiple series of simulation procedures by employing the conditions as depicted in Table 3. The conditions range was decided as the best and common by literatures and experience.

C. Simulation Procedure

Simulation was conducted using Autodesk Moldflow Plastic Insight 2010. Tensile bar shaped sample as given in Fig. 1 was used in the simulation. The meshed geometry of the sprue, runner, gate and the tensile bar sample are with 1218 elements and 655 nodes. The feeding system consisted of one cold tapered sprue, one cold runner with circular section and one gate with semi-circular section. The gate was positioned about the middle of the part to reduce the polymer flow length during mould filling step [7].

For both materials, Moldflow described the feedstock viscosity by using Cross-WLF viscosity model. This model described viscosity as a function of temperature, shear rate and pressure.

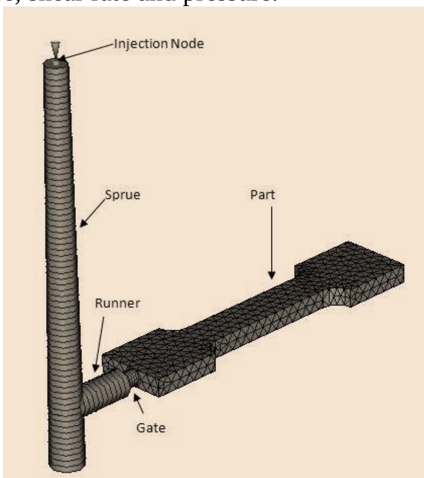

Fig. 1. The design of the tensile bar and feeding system

D. Design of Experiments

The Taguchi Method also known as robust design method was used for process optimizing and main effect detection. The simulation runs were executed based on L_9 orthogonal array designs on each material. Optimised characterisation was done by taking four input processing parameters as control factor and three output parameters. In this paper, the smaller the better characteristic of S/N ratio was chosen for all three output parameters; MFTD, t_{pack} and t_{cool}. The data gathered then analysed using analysis of variance (ANOVA) to evaluate the most influencing and significant parameters.

III. RESULTS

From nine runs of MoldFlow simulation, the result for three output parameters for both materials was summarised in Table 4.

TABLE 4
THE OUTPUT VALUES FROM SIMULATION RESULTS

Run	PIM			MIM		
	MFTD (°C)	t_{cool} (s)	t_{pack} (s)	MFTD (°C)	t_{cool} (s)	t_{pack} (s)
1	0.2	51	30.49	6.1	11.25	9.99
2	0.1	84.5	50.82	7.8	31	11.98
3	0.1	64.25	37.8	7.1	18.5	9.97
4	0.1	66.75	39.99	18.1	18.25	9.99
5	0.1	53.75	31.96	16.9	11.25	9.98
6	0.2	76.5	48.49	12.6	30.5	11.44
7	0.1	80.75	50.74	10.8	30.75	11.74
8	0.2	60.25	36.06	9.7	18	9.97
9	0.1	56.75	33.5	13.9	13	9.96

Figure 2, 3 and 4 show Signal to Noise ratio plots for both PP and MIM materials for different responses; MFTD, Cooling Time and Packing Time respectively.

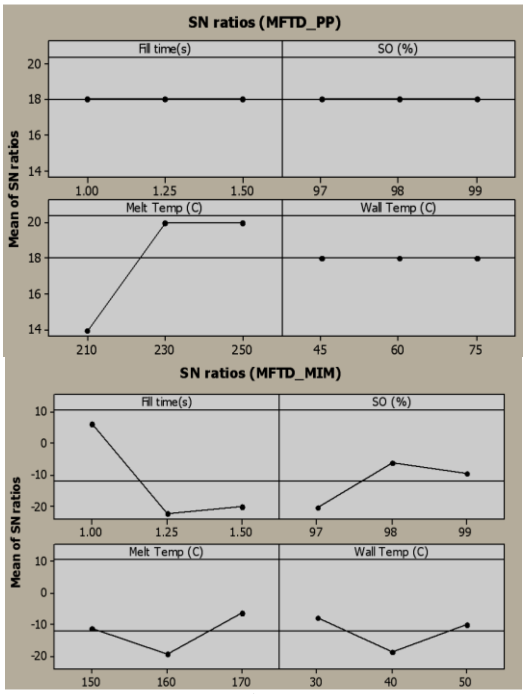

Fig. 2. S/N plots for MFTD response

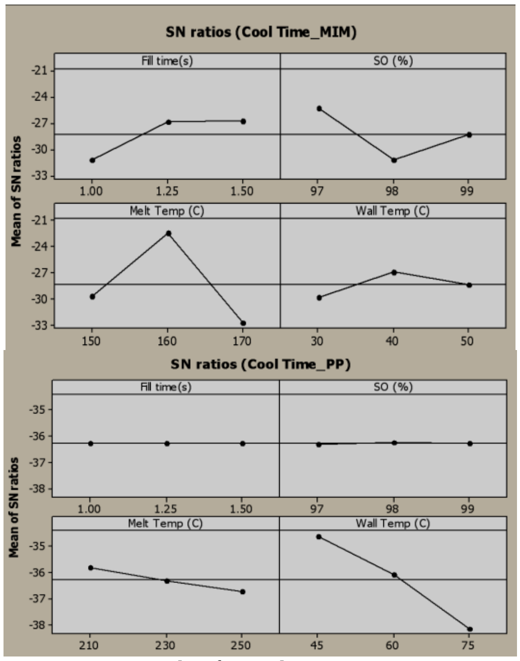

Fig.3. S/N plots for Cooling Time response

Statistical results from ANOVA for instance the S/N ratio at three levels were then summarized in Table 5 for Polypropylene and Table 6 for MIM materials. Note that due to redundancy, the similar analysis has been conducted for all factors but only sample of data shown in Table 5 and Table 6 for the purpose of giving calculation example. R indicates the sum of squares in ANOVA while P_i(%) represents the percent of influence of each factors.

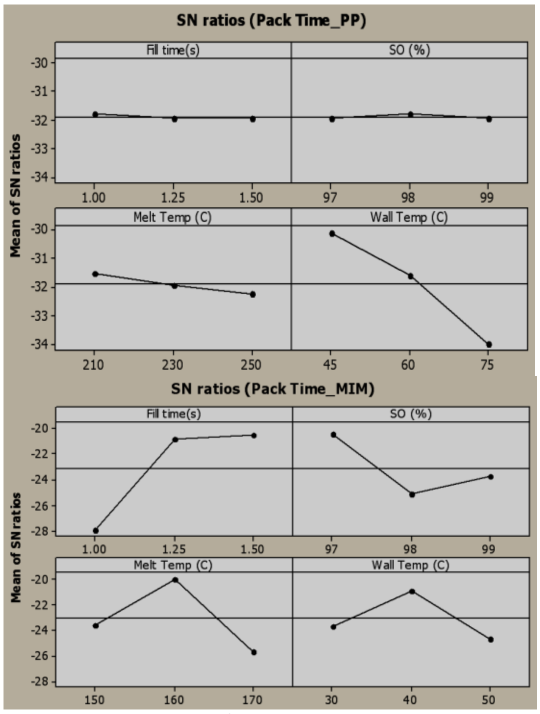

Fig.4. S/N plots for Packing Time response

TABLE 5
SUM OF S/NRATIOS AND INFLUENCE PERCENT FOR PACK TIME RESPONSE FOR POLYPROPYLENE MATERIALS

PP (Pack Time)		Fill time	SO	Melt Temp	Mold Temp
S/N	Level 1	31.78	31.92	31.51	29.89
	Level 2	31.92	31.78	31.92	31.31
	Level 3	31.95	31.94	32.22	33.98
Average		31.883	31.880	31.883	31.727
R		0.016	0.015	0.254	8.624
P_i (%)		0.185	0.171	2.851	96.793

TABLE 6
SUMOF S/NRATIOS AND INFLUENCE PERCENT FOR COOL TIME RESPONSE FOR MIM MATERIALS

MIM (Cool Time)		Fill time	SO	Melt Temp	Mold Temp
S/N	Level 1	-31.24	-25.34	-29.69	-29.75
	Level 2	-26.82	-31.19	-22.46	-26.85
	Level 3	-26.80	-28.33	-32.71	-28.26
Average		-28.287	-28.287	-28.287	-28.287
R		13.083	17.114	55.485	4.206
P_i (%)		14.555	19.039	61.727	4.679

From all the data collected, the comparison of influence on each factor was simplified and shown in Fig. 5,6 and 7.

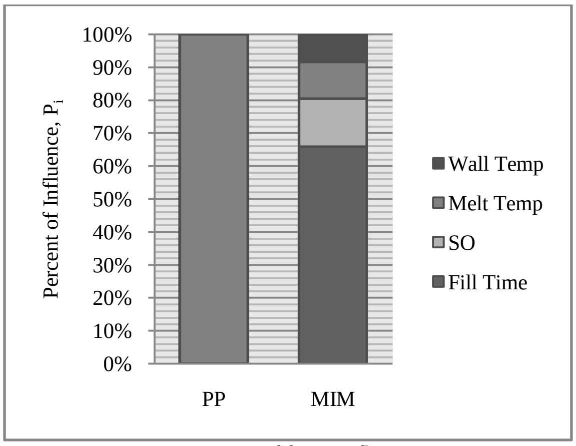

Fig. 5. Comparison of factor influence on MFTD

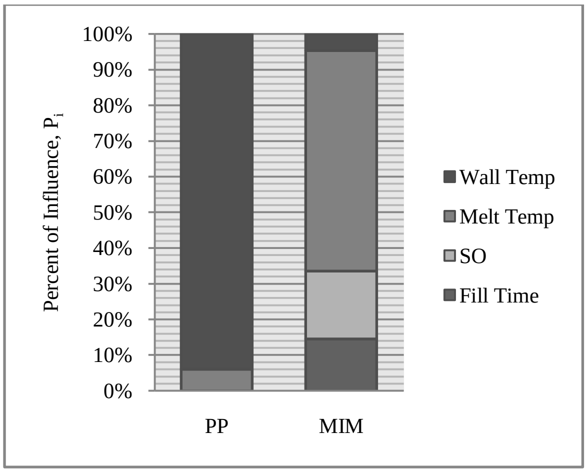

Fig.6. Comparison of factor influence on Cooling Time

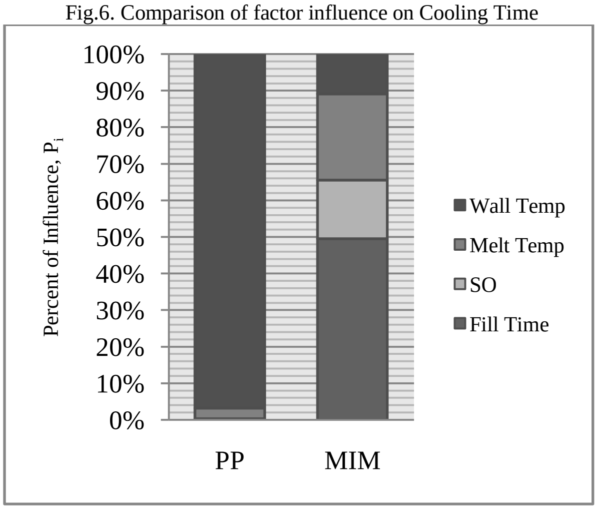

Fig.7. Comparison of factor influence on Packing Time

IV. DISCUSSION

A. Effect of MFTD output

Fig. 5 clearly depicted that pallet melt temperature dominated the result of MFTD on polypropylene however to minimize the difference of melt front temperature in the MIM part, the filling time parameter must be given special attention. Surprisingly, the ANOVA showed that the other controlled parameter give no influence on MFTD output in polymer injection molding. Discussing on temperature related parameter for both material, metal powder in MIM contribute higher heat capacity and small difference on filling time may cause uneven temperature distribution over the part.

B. Effect on cooling time output

For cooling time effect, as we can see the trend is similar where only one parameter dominating the polypropylene injection molding which is in this study, wall temperature setting. Contrary, MIM with its peculiar rheology behaviour influenced by all controlled parameter, but the most manipulating factor among them is the feedstocks melt temperature. The observed correlation between cooling time and melt temperature might be due to energy relevant properties such as feedstocks density, specific heat capacity and thermal conductivity that significantly contributed by the existence of metal powder. It is encouraging to compare this finding with the finding of Ahn et al. [5] that melt temperature is more significant during MIM process as compared to plastic injection molding.

C. Effect on packing time output

Polypropylene shows comparable trend as on MFTD and cooling time effect where it was only dominated by single parameter, this time is also by mold wall temperature. This finding has important implication for designing the mold and be more cautious for setting the machine when dealing with polymer injection molding. In MIM however, packing time is affected most by filling time selection. This verified by the significant shorter cycle time taken by MIM as compared to plastic injection molding as founded by [1]. This is due to thermal diffusivity of MIM that roughly seven times larger than of plastic injection molding. Thus, the ratio between the packing time of MIM to polypropylene is comparably small and consequently small changes on this filling time may cause fluctuation in packing time for MIM. From the ANOVA analysis, we also found out that complex behaviour of MIM has been a factor that every parameter being responsive in order to compensate the volume shrinkage during packing time.

V. CONCLUSION

In summary, this paper laid down the idea that Taguchi Robust Design method is more than able to determine significant parameter in injection molding for both metal and polymer materials. This study has found that in every factor influence studied, polymer only affected by single parameter dominantly. On the other hand, all input parameters influenced all the output readings although only one parameter is significant at every run. Switch over position did not contibute significant effect at this study, probably because this parameter commonly associated with pressure related parameter. In the future, it would be interesting to assess the effect of pressure dependant and velocity dependent parameter

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DOE in Learning Application: Comparison Analysis of Taguchi Method and Factorial Designs in verification of the effectiveness of learning kit.

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Abstract - **Learning design of experiment is very much important to ensure experiment is successfully executed. There are several design of experiment (Doex) techniques recently used to enhance in analysis of factors and their effects. To certain extent optimization is desired and could be achieved through the application of these analysis techniques. This study focused on designing a training kit for learning the Doex. A model has been established to provide a platform and facilities to conduct design of experiment. A system of ball rolling on a designated track has been made to fulfill this objective. Several factors could be set up to conduct real experiments repetitively. To verify the feasibility of this training kit, four different kinds of experiment have been used to test the reliability of the factors levels and their response quality characteristics. Taguchi L8 and L9 matrices are used to find the optimum response time for a ball to complete the full travelling cycle, with quality objective of smaller the better, experiments conducted have revealed a correspond result between Taguchi and Factorial designs that were used to confirm the experiments.**

Keywords - **Training Kit, Feasibility, Factorial design, Taguchi Method.**

I. INTRODUCTION

Learning design of experiment for practical and actual application is the crucial part of any preparation of design or process optimization. The ability to perceive and evaluate result of any experiment is much important to unfold the content of design analysis and the depth exploration of any process and system. Since there are various kinds of design experiment types and approaches, the best and user friendly tools will attract practitioners and affects its wide and extensive application of design of experiment.

The applications of Doex were then noted for several key criteria such as for research and design, product and process optimization, screening and problem solving. Hence, product and process optimization is the main criteria where Doex is highly used for improving such level of quality performance. It is very important to understand noise factors before conducting an experiment, Taguchi method emphasizes this to be explored and known. Noise will affect the accuracy of results obtained from any experiment. The approach confined its scope of experiment within a possible controlled situation after knowing the noise factors. In optimization of products or processes, improvement are expected to be achieved when results produce better quality performance; reduce processing cost, increase output quantity and sustain desired product performance. Typical example in machining process, the optimization is assessed by productivity, total manufacturing cost and other relevant criteria [1]. Taguchi method is leading the application area in the optimization, it has been reported that Taguchi method has simplified the analysis method and reduce the experimental time and as a result, cost saving could be achieved by optimizing many quality characteristics with very few numbers of experiments [2].

Significantly, many Taguchi successful experiments have improved a lot of industrial works, designs and processes. The strength of Taguchi method is conclusively for an experiment conducted without interaction analysis of factors in its responsive effect, this is apparent when noise factors are known and experiment is run under controlled. Noise factors are run or tested as replications [3]. The robustness of the experiment in product or process design has created insensitiveness to uncontrollable environmental condition [4]. To clarify the effectiveness, two experiments were conducted for same factors and response variable to compare the results between the result from Taguchi method and central composite design are found to be similar [1]. Next significant use and application of Taguchi method is in multi-response variables which is much more complicated than optimization of single quality characteristic [5]. Knowledge and experiences of relevant engineering matter is required to decide optimum decision making in relation to cost, productivity and performance when response variables are interconnected with each other. In design of experiments factors are chosen because they displayed great degree of uncertainty and variability to output responses [6].

The step in conducting the Taguchi method is explained in sequence from recognition of problem until conducting a confirmatory experiment [7]. Verification of the optimum setting obtained from the result of experiment is the vital step to confirm the Taguchi experiment is accurate and reliable for next decision making. Results of the confirmatory test shall be within the plus minus 90% confidence interval, as suggested by practitioner [8].

Since design of experiments are widely used not only for optimization purpose, such application are in research, developing control variables and understanding attributes factors and its phenomenon. In industry, factorial designs are widely used in experiment [9]. However there are many occasions in experiment that interaction effects are of the interest in the study. These concerns are influenced by the degree of criticality of the responses and the sensitivity of the factors effects which was scientifically determined from past records. An option to this, factorial design of experiments are commonly used to explore and screen a large number of potential factors effect, how far it could affect changes to the output response are possible to be studied. It was reported that key factors and noise factors are experimented together using fractional factorial in a combined arrays in screening experiment [10]. As the objective of an experiment is to know the effect of factors to subject under study, factorial approach has its own diversified methodology from step to step to higher order of the design of experiments. The design has complimentary approach to consider every single facet of factors to be analysed, from lower order resolution to higher order, from factorial to star point of design cube and from selective range to computed selection of testing range. However it was found that higher order interaction in fractional factorial design was assumed insignificant in comparison with the main effect and as a result, relatively clear main effects will be obtained from the experiment [6]. The most economical factorial design in screening experiment is the fractional factorial of resolution III, an experiment conducted with no interaction study [11]. Resolution IV of factorial designs is used extensively in screening experiment [12]. Further analysis in selected and significant factors is enhanced through the application of more detail design, for example, for non-linear responses, central composite design approach is highly recommended [11]. In addition, full factorial with few number of determined factors are often used to analyse factors and optimum effects. Both are applicable to the surface response methodology.

And some important points to an experimenter are the intentions to conduct experiments, and followed by selection of the appropriate type of these experiments to suit their objectives. These could only be achieved with profound understanding on how experiment is configured, planned, executed and visually being employed in analyzing factor effects. As experiment shall be planned for obtaining appropriate data for statistical analysis, this is important to attain valid and objective conclusion [1]. Nevertheless, when using Doex as improvement tools such awareness of potential issues that could arise during the journey shall be highly considered, prior knowledge of any possible problem will prevent wrongdoing and abandoned of the great effort [13]. Therefore, the studied in design of experiment requires repeated observations and experiences. This quality is expected to be acquired prior to positioning in the work place, research and improvement activities.

There are many design of experiments conducted in regards to academic researches as well as huge application in industrial environment, nevertheless less are focusing on developing the skills, fundamental ability and practical usages of the design of experiment. As reported, the basic problem in experimental designs, are the establishment of appropriate and reliable design criteria followed by selection of the corresponding designs [14]. In facts there is no established standard to verify the competency of learner on its ability to perform the Doex. This has indicated that knowing the right Doex and its application is still not a major concerned in several organization and institution. There are several kits and software that could assist these short-comings but it was not focused on teaching for fundamental in real applications. Such details information is expensive to be obtained by a beginner. Furthermore, many learning package was developed and intended for commercial purpose, and where it is permissible for reference, some limitations are imposed, typically for the trial version. At the end, cost factor has become the main reason to upbringing the learning curve. This phenomenon need to be resolved if the ability of the young learners, engineers, anyone who is designated with the tasks, beginners and early researchers are expected to have minimum capability to do the design of experiment in their respective field. For instance, by realistic numerical contribution, engineers can estimate the magnitude and direction of the effect of factors [15].

Therefore, conducive and repetitive learning in design of experiment is necessary to support the learning to be more effectives. Effectives learning will trigger creativity in further applications. The success to the effective learning could be complemented by establishing a standard for assessing the capability or competency of any learner.

II. METHODOLOGY

The process of this evaluation is made on the observation of a ball rolling on a designated path at several heights of gravitational effect. The learning kits are developed similarly to system of roller coaster, using thin sphere ball rolling from the heights determined at certain angles. The ball is released at a point where kinetic energy is applied; the starting point which is pre-determined is spotted by a first proximity sensor linked to an electronics timer. The ball will roll along the designated path of rail with support at several points. The height of each support is set based on the purpose of study. At the end of each cycle, a proximity sensor is installed to detect the final contact of travelling time. The objective of this study is to evaluate the feasibility of the training kit in repetitive learning of design of experiment (Doex). The quality characteristic set for the experiment is the smaller the better, to obtain the smallest travelling time within the selected ranges of each factor levels. This target is set for both Taguchi and factorial design of experiments. Prior to optimization of factor levels, screening experiments will be conducted to identify significant factors. This input will be used in Taguchi and Factorial optimization experiments. Figure 1 is showing the complete system for the experimental testing.

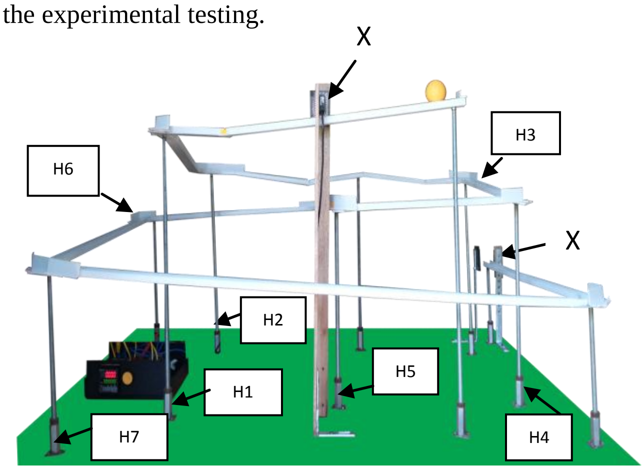

Figure 1: Complete ball and track system applied in the experimental kits.

There are seven factors selected to be experimented with one single response variable as detailed in Table I. The response variable is the time taken for the ball to travel from point X1 to point X2. Table I depicted the factors and their levels set for the experiments. Such factors are determined in a manner that the ball will be able to roll from one level to another level to complete the whole cycle. Predetermined or test is required to confirm this setting applicability. The ball weight is 2 grams and is set as a constant factor.

Table I: Factors and levels of experiment.

Factors	level1	level 2	Scale unit
1- Height 1	47	50	mm
2- Height 2	44	47	mm
3- Height 3	40	43	mm
4- Height 4	38	40	mm
5- Height 5	35	38	mm
6- Height 6	32	35	mm
7- Height 7	28	31	mm

Two types of design of experiments are selected for this case study; Taguchi method and fractional factorial design. The first experiment will be the Taguchi method. It will be conducted in matrix of L8. The second method will be the fractional factorial. The reason being to use this fractional factorial is its reduction in number of experiments and its similarity to the Taguchi method. As known, fractional factorial is tightly connected with the notion of orthogonal arrays [9]. In order to justify the effectiveness of the designed kit in teaching the Doex, comparison analysis of the two different types of experiments will be conducted. Table II is showing the experimental L8 matrix in Taguchi method and Table III is for the fractional factorial 2^{7-3} experimental matrix.

The Taguchi method of experiment is conducted base on the designed excel templates with reference to Taguchi techniques employed and written by several experts [16].The fractional factorials and full factorial are conducted base on trial version of the Design Expert 8 software .

The L9 matrix is used to determine the optimum condition and factors setting. The levels are set within the range of previous L8 experiment setting. From the L9 the magnitude of factor effect is plotted to determine the optimum setting, this will be confirmed by the ANOVA. Four repetitive readings are taken for each run to represent the possible noise factors. And the output is finally calculated in the form of S/N ratio.

Information obtained from the screening experiments will be an input to decide number of factors used for the second stage of optimization experiment. Results from full factorial experiment will be compared with the result obtained from the Taguchi L9 experiment.

All experiments are run in a confined room to avoid significant wind or air resistance effects.
There are two criteria that will be tested for comparison: level of the significant of each factor and the optimum setting for the expected output performance. The magnitude, significant of each factor effect and the optimum parameter setting for the same desired objectives suggested by each different type of the design of experiments will be evaluated and analyzed.

III. RESULTS AND DISCUSSION

Result of L8 is recorded in Table II, it has revealed four significant factors that are influencing the travelling time. Figure 4 of the main effect graph of S/N ratio has shown that, Factor H1, H2, H6 and H7 are significant to affect the travelling time.

Table II: Result of L8 experiment in S/N ratio

	FACTORS							NOISE FACTORS		
RUN	H1	H2	H3	H4	H5	H6	H7	R1	R2	SN ratio (larger the better) N
1	47	44	40	38	35	32	28	11.16	11.24	-20.98
2	47	44	40	40	38	35	31	12.01	12.18	-21.65
3	47	47	43	38	35	35	31	11.37	11.80	-21.28
4	47	47	43	40	38	32	28	10.79	10.89	-20.70
5	50	44	43	38	38	32	31	11.78	11.71	-21.40
6	50	44	43	40	35	35	28	11.79	11.87	-21.46
7	50	47	40	38	38	35	28	11.96	12.24	-21.66
8	50	47	40	40	35	32	31	11.48	11.37	-21.16

The main effect graph for each factor is shown Figure 2. H6 is major contributor followed by H1.

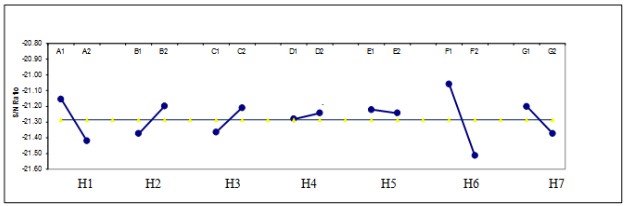

Figure 2: The main effects graph for L8

The ANOVA result from Table III has confirmed the finding from the main effect graph. H6 is major contributor followed by H1, H2 and H7 respectively. Factor H4 is pooled since the contribution is less than 1%. This provides values of the mean square ratio for each remaining factor.

Table III: ANOVA contribution of Factor Effects for L8 experiment

RUN	Factor/Source	Degree of Freedom	Sum of Squares	Mean Squares	Mean Square Ratio – F	Percent Contribution %
1	Height-H1	1	0.069	0.07	0.178	9.0793
2	Height-H2	1	0.031	0.03	0.079	4.0082
3	Height-H3	1	0.024	0.02	0.060	3.0772
4	Height-H4		Pooled	----	---	--
5	Height-H5	1	0.017	0.02	0.044	2.2598
6	Height-H6	1	0.204	0.20	0.524	26.7513
7	Height-H7	1	0.029	0.03	0.075	3.8378
	Error	0	0.39	0.389		50.99
	Total	7	0.76			100
	Effective DOF Factors	6				

Result of the experiment from Fractional Factorial is shown in Table IV.

Table IV: Result for Fractional Factorial Experiment 2^{7-3}

		FACTORS							NOISE FACTORS
STD	RUN	H1	H2	H3	H4	H5	H6	H7	R1
15	1	47	47	43	40	35	35	28	11.26
4	2	50	47	40	38	35	35	31	11.88
12	3	50	47	40	40	35	32	28	11.19
7	4	47	47	43	38	35	32	31	11.14
16	5	50	47	43	40	38	35	31	11.39
6	6	50	47	43	38	35	35	28	11.98
2	7	50	44	40	38	38	32	31	11.87
1	8	47	44	40	38	35	32	28	11.26
13	9	47	44	43	40	38	32	31	11.98
11	10	47	47	40	40	38	32	28	11.15
8	11	50	47	43	38	38	32	28	11.26
3	12	47	47	40	38	38	35	28	11.49
9	13	47	44	40	40	35	35	31	11.89
10	14	50	44	40	40	38	35	28	11.68
14	15	50	44	43	40	35	32	31	11.71
5	16	47	44	43	38	38	35	31	12.84
18	17	50	44	40	38	38	32	31	11.80
25	18	47	44	40	40	35	35	31	11.98
32	19	50	47	43	40	38	35	31	11.36
23	20	47	47	43	38	35	32	31	11.37
17	21	47	44	40	38	35	32	28	11.14
19	22	47	47	40	38	38	35	28	11.42
28	23	50	47	40	40	35	32	28	11.40
20	24	50	47	40	38	35	35	31	12.15
24	25	50	47	43	38	38	32	28	11.43
27	26	47	47	40	40	38	32	31	11.51
21	27	47	44	43	38	38	35	31	12.31
30	28	50	44	43	40	35	32	31	11.64
26	29	50	44	40	40	38	35	28	11.66
31	30	47	47	43	40	35	35	28	11.49
22	31	50	44	43	38	35	35	28	12.14
29	32	47	44	43	40	38	32	28	12.17

The ANOVA results from Table V has shown that height 2(H2) and Height 6 (H6) and height 7(H7) are significant, the significant of height 1 (H1) lies under the interaction effects in AE and AD. Thus, we consider factor height 1(H1) also a significant factor. Significant level is determined when the probability value is more than 0.05, according to calculation made in Design expert software version 8. Table VI is showing the comparison result of L8 and fractional factorial of 2^{7-3}.

Table V: ANOVA for Fractional Factorial 27^{-3} experiment

Source	Sum of Squares	Df	Mean Square	F - Value	p-value Prob > F	
Block	0.031	1	0.031			
Model	4.28	14	0.31	6.79	0.0002	Significant
A-H1	6.15E-004	1	6.125E-004	0.014	0.9086	
B-H2	1.60	1	1.60	35.61	< 0.0001	
C-H3	0.12	1	0.12	2.78	0.1150	
D-H4	0.13	1	0.13	2.83	0.1117	
E-H5	0.090	1	0.090	2.01	0.1757	
F-H6	0.75	1	0.75	16.68	0.0009	
G-H7	0.29	1	0.29	6.42	0.0221	
AB	0.17	1	0.17	3.74	0.0710	
AD	0.27	1	0.27	6.00	0.0262	
AE	0.78	1	0.78	17.23	0.0008	
AF	0.033	1	0.033	0.72	0.4078	
AG	0.026	1	0.026	0.59	0.4544	
BD	0.018	1	0.018	0.40	0.5354	
ABD	1.25E-003	1	1.25E-003	0.028	0.8697	
Residual	0.72	16	0.045			
Cor Total	5.03	31				

Table VI: Summary of results between L8 and Fractional Factorial 2^{7-3} for factor effects.

Code	Source	Ranking in L8		Ranking in 27-3		Remarks
H1	Height 1	2	Significant	7	Significant	In interaction of AE &AD
H2	Height 2	3	Significant	1	Significant	Agreed
H3	Height 3	5		5		
H4	Height 4	7		4		
H5	Height 5	6		6		
H6	Height 6	1	Significant	2	Significant	Agreed
H7	Height 7	4	Significant	3	significant	Agreed

It is noted that both experiment agreed on which factors are significant and this are further tested with Taguchi L9 and full factorial design of 2^4. Four factors are selected for these two experiments; height 7, height 6, height 2 and height1.

Experimental data is reported in Table VII. Data plotted for the main effect has significantly shown H6 is most dominant factor and followed by factor H2. Non-significant factors in this experiment were pooled as described in the ANOVA as depicted in Table VIII.

Table VII: Result of L9 experiment in S/N ratio.

	FACTORS				NOISE FACTORS				
RUN	H6	H2	H7	H1	R1	R2	R2	R2	SN ratio (larger the better) N
1	32	44	28	47	11.72	11.58	11.61	11.66	-21.32
2	32	46	30	49	11.03	11.31	11.18	11.23	-20.98
3	32	47	31	50	11.54	11.49	11.44	11.66	-21.24
4	34	44	30	50	11.77	11.73	11.63	11.65	-21.36
5	34	46	31	47	11.36	11.50	11.44	11.70	-21.21
6	34	47	28	49	11.16	11.20	11.34	11.24	-21.01
7	35	44	31	49	12.16	12.12	11.90	11.92	-21.60
8	35	46	28	50	11.92	11.59	12.04	12.08	-21.52
9	35	47	30	47	1162	12.04	11.75	11.86	-21.45

The pooled ANOVA has provided absolute main factor effects calculation to determine the optimum experimental output condition. Factor H7 and H1 were pooled as they were not significant. However factor H2 is remained since its contribution is moderately high at 11.68% despite the low F value.

Table VIII: The Pooled ANOVA for Taguchi L9 experiment.

RUN	Factor/ Source (Height)	Degree of Freedom	Sum of Squares	Mean Squares	Mean Square Ratio – F	X = not in used or Pooled variance	Pure sum of square	Percent Contribution %
A	H6	2	0.23	0.11	7.15		0.20	53.522
B	H2	2	0.07	0.04	2.34		0.04	11.689
C	H7					X		
D	H1					X		
	Error	4	0.06	0.0159			0.127	34.789
	Total (error)	8	0.37					100.00
	Effective DOF Factors	4						

Below is the simplified and determined equation for optimum result [17];

Optimum Response: Mean + (MH6- Mean) + (MH2- Mean)

Optimum Response = -21.30 db +0.121db+ 0.065db = 21.11db. Optimum factor setting is H6 = 32mm, H2 = 47mm, H7= 46 mm, H1 = 49mm. Result of confirmatory run has fallen within the 90% (-20.91db until -21.31db) confidence level when its S/N ratio is -21.03db and in scale value is11.25 seconds. The 90% confidence interval range in scale value is from 11.1 Seconds until 11.6 Seconds. Experiment is validated.

Experiment was continued with full factorial 2^4 and results obtained are shown in Table IX. ANOVA table has revealed the significant level of factor H6 and factor H2 this is correspond to the result obtained from Taguchi L9. The ANOVA table for 2^4 experiments is shown in Table X.

Table IX: The result of 2^4 full factorial experiments

STD	RUN	H6	H2	H7	H1	R1
27	1	35	44	31	50	11.27
31	2	35	47	31	50	11.64
15	3	35	47	31	47	11.35
29	4	32	47	31	50	11.52
25	5	32	44	31	50	11.34
23	6	35	47	28	50	11.49
19	7	35	44	28	50	11.44
17	8	32	44	28	50	11.51
3	9	35	44	28	47	11.19
13	10	32	47	31	47	11.86
5	11	32	47	28	47	11.77
1	12	32	44	28	47	11.44
21	13	32	47	28	50	11.87
11	14	35	44	31	47	11.36
9	15	32	44	31	47	11.44
7	16	35	47	28	47	11.54
20	17	35	44	28	50	11.59
16	18	35	47	31	47	12.09
8	19	35	47	28	47	11.88
10	20	32	44	31	47	12.16
32	21	35	47	31	50	11.64
2	22	32	44	28	47	12.08
14	23	32	47	31	47	12.62
26	24	32	44	31	50	11.66
28	25	35	44	31	50	11.99
30	26	32	47	31	50	12.17
22	27	35	47	28	50	12.03
12	28	35	44	31	47	11.58
24	29	35	47	28	50	12.16
6	30	32	47	28	47	11.95
4	31	35	44	28	47	11.69
18	32	32	44	28	50	12.13

Table X: ANOVA for 2^4 factorial experiment.

Source	Sum of Squares	Df	Mean Square	F –Value	p-value Prob > F	
Block	1.71	1	1.71			
Model	0.86	4	0.21	6.11	0.0013	Significant
A-H6	0.42	1	0.42	11.88	0.0019	
B-H2	0.43	1	0.43	12.27	0.0017	
C-H7	1.531E-004	1	1.531E-004	4.369E-003	0.9478	
D-H1	9.453E-003	1	9.453-003	0.27	0.6079	
Residual	0.91	26	0.035			
Cor Total	3.47	31				

The optimum condition obtained from the experimental solution is 11.43 sec with combination of factors at H6=35 mm, H2=44 mm, H7=28 mm and H1=47 mm. Even the setting for the full factorial 2^4 experiment are different in levels selection, the objective and quality characteristic value from this optimum setting has fallen within the projected scale value of 90% confidence intervals from L9 experimental result.

IV. CONCLUSION

Results have shown that Taguchi experiment has been successfully conducted through this training kit and the tested factorial designs in principle agreed with information obtained from Taguchi method. There are however differences in factor level settings and amount of the magnitudes of each factor due to statistical inference made when interaction is considered and used in the calculation of the optimum output. The selection of appropriate factorial design in experimental study requires careful and objectively selected as some interaction effects could not be captured in the optimization process. But this could be overcome by Taguchi method as the actual confirmation result is always matching against the expected confidence levels. The model made for learning design of experiment are proven feasible with easy and fast experimental preparation as well its adequacy to represent a mechanism in understanding between factors and effect. The study could also be done for other type of Doex techniques and the training kit need further upgrade to reduce several noise factors.

The significant outcome of this experimental unit is its ability to provide repeated learning of Doex, learners could repeat the experiment to understand possible errors and how they will affect their experimental results.

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Study on Parameter Design of Nozzle Device Using Small Screw in Fused Deposition Modeling

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Abstract - Additive Manufacturing technology is the technology of manufacturing three-dimensional shape, by adding material little by little and laminating it. Since complicated shape is also feasible in a simple process, it has been used by part manufacture of rapid trial production technology and limited production with a wide variety. In this report, Fused Deposition Modeling (FDM) which is one of the Additive Manufacturing technologies is studied.

Functional evaluation of the discharging performance of the nozzle device with high viscous material for the purpose of the improvement in performance of a Fused Deposition Modeling was studied. Furthermore, the optimal structure of the nozzle device using a small screw was examined using the parameter design of quality engineering.

Keywords - FDM, Additive Manufacturing, Parameter Design

I. INTRODUCTION

FDM is one of the Additive Manufacturing technologies which manufacture a three-dimensional part shape. A thermoplastic resin is sent out from the tip of a nozzle, and material is added little by little and laminated. Three-dimensional parts are realized by repeating this process.

In recent years, the application to product production from a trial production is required increasingly, and it is expected that the mechanical property of parts strength and precision will reach the one produced by injection molding. Moreover, the application with new materials, such as metal, is also required.

Nancharaiah et al. [1] is investigating the influence by dimensional accuracy and surface finish on building parameter conditions, using Taguchi Methods as a development research of an FDM device. Finke et al. [2] makes the metal of a semi molten state send out by an FDM device, and is evaluating the material characteristics and microstructure. Zhang et al. [3] is devising the method to build three-dimensional shape, witha reactive resin to build up three dimensional object to convert the reactive prepolymer to a higher molecular weight thermoplastic resin. In order to raise the discharging performance in a dispenser, Maruyama et al. [4] devises a new dispenser nozzle device, and shows the structural analyses, response of device and experimental result.

With the existing device shown in Fig. 1, it tends to poor building, which resin is not fulfilled within layer, when complicated shape with many curvilinear portions is requested. The cause is that control of a discharge is insufficient. In this study, the method of controlling the discharge which extrudes material by a screw revolution is proposed.This study examines the evaluation method of a discharge function. Then, the optimum shape of a nozzle device is examined based on the parameter design of quality engineering.

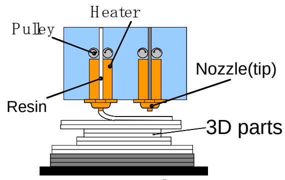


Fig.1. FDM device

II. METHODOLOGY

A. Functional evaluation experiment of a nozzle device

Functionality is examined about the nozzle device to develop. A nozzle device makes material send out using the power of rotating a screw by a motor. Material is sent to a nozzle entrance hole by rotational power. And material is extruded in a nozzle exit hole.

In the case of the idea based on energy loss, the rotational energy of a screw is transformed into the kinetic energy of the material at the time of discharge. The rotational energy of a screw can be denoted by the following equation[5]:

$$E = \frac{1}{2} I\omega^2 \tag{1}$$

It is dependent on a moment of inertia and angular velocity (speed of rotation). Unless screw shape changes, since the moment of inertia is constant, speed of rotation is considered as an input. On the other hand, the kinetic energy of material can be denoted by the following equation:

$$E = \frac{1}{2} mv^2 \tag{2}$$

It is dependent on discharge mass and discharge velocity. Discharge mass and discharge velocity are considered as an output. The system chart of the system can be expressed as shown in Fig.2.

As a noise factor, an ideal functionality of the nozzle device should work properly independent of the property value of various materials. Therefore, the viscosity coefficient which affects the output of a nozzle device is set to a noise factor. Functional evaluation examines what kind of input-output relation is suitable as a measuring characteristic. The signal factor of an input is speed of rotation or rotational energy, and an output is discharge mass, discharge velocity, or kinetic energy respectively. An SN ratio and contributions are used for a performance index.

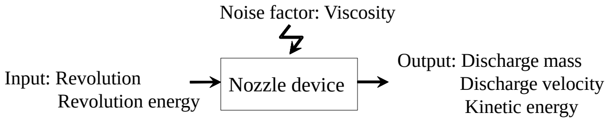


Fig.2. System chart

Laboratory equipment is shown in Fig.3. Laboratory equipment consists of a screw, a nozzle and a motor, and a controller (Musashi engineering co. ltd.). As shown in theFig. 3, material enters from material input, the screw rotates, and material is sent out from nozzle tip.

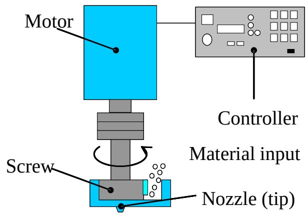


Fig.3. Laboratory equipment

The screw and the nozzle were designed with CAD software, and built using FDM machine, Dimension768 (STRATASYS co. ltd.). Screw shape is shown in Fig. 4 and nozzle sizes are shown in Fig. 5 (a). The bore diameter of a nozzle is set to 0.5 mm.

The change of discharge mass is measured with different speed of rotation. With a high speed camera,discharge velocity is measured.

Material is the mixture of polyvinyl alcohol and a borax water solution, i.e. slime. In order to consider only the influence of shape, without considering the influence of temperature, the slime, which can adjust various viscosity coefficients at room temperature, is used. The viscosity coefficient of resin as a noise factor was set to N1=0.1 [Pa-s] and N2=100 [Pa-s]. As a reason for having set up this range, it is because the epoxy resin for Additive Fabrications is at least 0.3 [Pa-s]. The maximum viscosity coefficient of slime is set as N2 in this experiment.

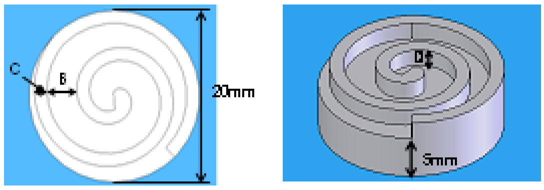


Fig. 4 Screw shape

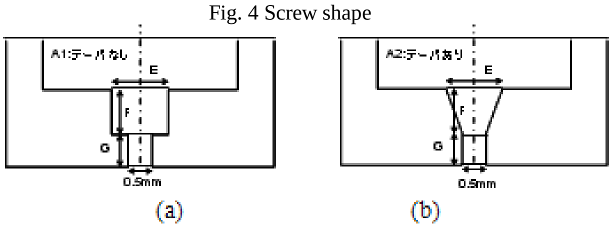


Fig. 5 Nozzle dimensions

B. The parameter design experiment of a nozzle device

A screw and a nozzle are fabricated and prepared; discharge experiments are conducted using the laboratory equipment of Fig. 3.

L18 orthogonal array is called an orthogonal mixed-level design, and there is the feature that an interaction effect does not appear in a specific column. Since an interaction effect is distributed by each column in an orthogonal mixed-level designs, even if a certain amount of interaction effect occurs, it is said that it is easy to find a factor with main effect[6].For this reason, since the scale of an experiment and the number of control factors are suitable, L18 orthogonal array is chosen in this experiment. Each parameter A-G of a screw and nozzle dimensions, which is a control factor, is shown in Fig. 4 and Fig. 5.This level value is assigned to L18 orthogonal array, and screw and nozzle are fabricated by 18 patterns.

In consideration of the maximum capacity of laboratory equipment, the level of the signal factor was set up at equal intervals. The speed of rotation of a screw is given on three levels of 120,240,360 [rpm].A control factor and a level value are shown in Table 1.Optimum condition is estimated from the factorial effect diagram of an SN ratio. After estimating the optimum conditions, reproducibility is checked. The identification of reproducibility is judged by the difference (profit) of the SN ratio of the optimum conditions and an initial condition. The profit of an estimated value and the profit of the confirmation value by experiment are calculated, and the difference of this profit is computed. Reproducibility shall be acquired, if the difference of this profit is small.

TABLE 1
CONTROL FACTOR AND LEVELS FOR PARAMETER DESIGN

	Control factor (parameter)	1st level	2nd level	3rd level
A	The taper of a nozzle hole	without	with	-
B	Flute width [mm]	3	4	5
C	Wall width [mm]	0.5	1	1.5
D	Groove depth [mm]	2	3	4
E	Entrance bore diameter [mm]	2	3	4
F	The upper part hole depth [mm]	1	2	3
G	The lower part hole depth [mm]	1	3	5

III. RESULTS

A. *The experimental result of functional evaluation*

The result of relation of the speed of rotation and the discharge mass is shown in Fig. 6. Discharge mass increased as the speed of rotation increased. The SN ratio was -44.5[db] and the contribution was 99%. From this result, the relation between speed of rotation and discharge mass showed proportional with small variation.

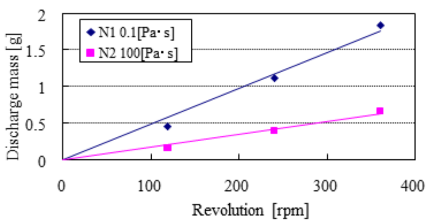


Fig. 6 Speed of rotation and discharge mass

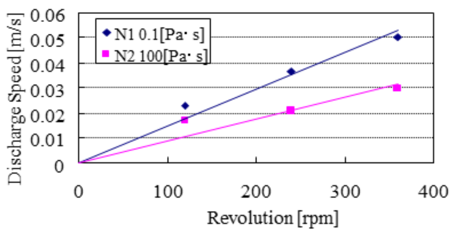


Fig. 7 Speed of rotation and rotating speed

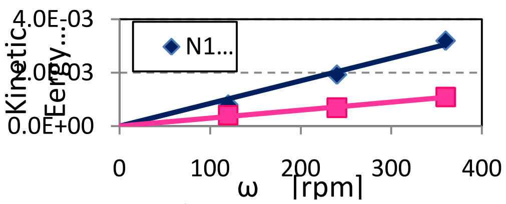


Fig. 8 Square root of rotational energy and kinetic energy

The result of the speed of rotation and discharge velocity of a screw is shown in Fig. 7. The SN ratio was -54.5[db] and the contribution was 70%.

The result of the rotational energy of a screw and the kinetic energy of the material at the time of discharge is shown in Fig. 8. The SN ratio was -52.5[db] and the contribution was 88%.

These results showed that the contribution in the relation between speed of rotation and discharge mass was the highest, and it was suitable as measuring characteristics.

B. *The experimental result of a parameter design*

Experiment was performed based on the L18 orthogonal table, and the SN ratio in each combination of nozzle and screw were computed. The factorial effect diagram of an SN ratio is shown in Fig. 9 about each parameter of a screw and nozzle sizes. The optimum conditions are examined from this factorial effect diagram. Since the parameter of a value with a high SN ratio has an effect in the variation in discharge, A2 B1 C2 D2 E3 F3 G1 gets the optimum conditions. An initial condition is set to A1 B1 C2 D1E1 F2 G2.

The optimum shape is produced and reproducibility is checked. The difference of the estimated value of the SN ratio on the optimum conditions and an initial condition, an identification value, and a profit is shown in Table 2. The difference of the profit was -2.225 [db]. Since the difference of the profit is less than ±3 [db], it is judged that reproducibility has been attained. Moreover, the optimum condition of SN ratio was higher than an initial condition. The confirmation experiment result of an initial condition and the optimum conditions is shown in Fig.10 – Fig.11. It turns out that discharge is promoted from Fig. 12 that the shape of optimum conditions cannot be easily influenced by the difference in viscosity.

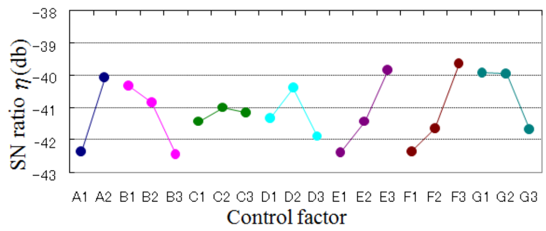
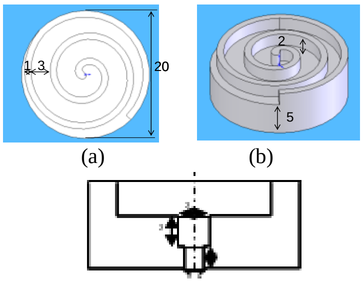


Fig. 9Factorial effect diagram

TABLE 2
ESTIMATED VALUE AND CONFIRMATION VALUE

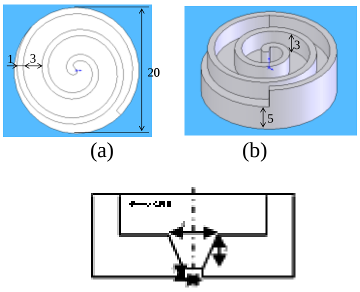
Conditions	SN ratio [db]	
	Estimated value	Confirmation value
Optimum conditons	-36.00	-34.83
Initital condition	-41.74	-42.79
Difference (profit)	5.74	7.96
Estimated value – confirmation value		-2.22



(a) (b)

(c)

Fig. 10Initial shape of Nozzle device



(a) (b)

(c)

Fig. 11Optimum shape of Nozzle device

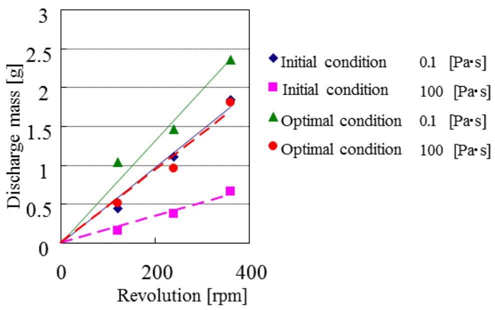


Fig. 12Confirmation results

IV. DISCUSSION

In quality engineering, it is said that it is better to think a fundamental functionality based on energy loss. However, in this functional evaluation experiment, the result (input: rotational energy, output: kinetic energy) of energy conversion had the low contribution. The reason is that kinetic energy depends not only on discharge mass but also on discharge velocity. It is necessary to measure velocity and mass to compute kinetic energy this time, and if a measurement error is included, the calculating result will be affected. Rather than an independent numerical value, when multiplying by observed values, an effective digit number will follow the one where precision is lower. Since the contribution of speed of rotation and discharge velocity was as low as 70%, an error is included in an energy calculating result and a contribution is considered to have got the value lower than discharge mass.

TABLE 3
ANOVA OF CONTROL FACTOR E3

E3	Optimum			
Source	f	S	V	ρ (%)
β	1	18.95	18.95	-
N×β	1	1.99	1.99	8.47
e	34	1.952	0.057	8.53
T	36	22.89		

TABLE 4
ANOVA OF CONTROL FACTOR E1

E1	Initial			
Source	f	S	V	ρ (%)
β	1	27.36	27.36	-
N×β	1	6.23	6.23	16.43
e	34	3.68	0.11	9.87
T	36	37.28		

TABLE 5
ANOVA OF CONTROL FACTOR F3

F3	Optimum			
Source	f	S	V	ρ (%)
β	1	18.32	18.32	-
N×β	1	1.62	1.62	7.71
e	34	0.78	0.02	3.74
T	36	20.72		

TABLE 6
ANOVA OF CONTROL FACTOR F2

F2	Initial			
Source	f	S	V	ρ (%)
β	1	17.29	17.29	-
N×β	1	3.09	3.09	13.53
e	34	2.01	0.06	8.96
T	36	22.39		

Next, the effect of each parameter in a parameter design is considered. ANOVA is conducted by a factorial effect diagram about the parameter E F whose effect was large, and the contribution of a viscosity coefficient is computed. It means that if a contribution is smaller, it is little influenced on the factor.

In the entrance bore diameter (E3) of the optimum conditions, the contribution to the viscosity coefficient was 8.47%, and the contribution to variation was 8.53%. In initial shape, the contribution to the viscosity coefficient was 16.43%, and the contribution to variation was 9.87%. As for the optimum conditions E3, the differences of contribution of a variation and a viscosity coefficient from optimum to initial condition were1.34% and 7.96% respectively. We can read from the data that the entrance bore diameter E has high influence on a viscosity coefficient rather than variation.

In the bore depth (F3) of the optimum-shaped nozzle upper part, the contribution to the viscosity coefficient was 7.71%, and the contribution to variation was 3.74%. In the bore depth (F2) of the initial-shaped nozzle upper part, the contribution to the viscosity coefficient was 13.53%, and the contribution to variation was 8.96%. It turns out that the optimum conditions F3 lessened influence on a viscosity coefficient 5.82% rather than initial condition F2, and variation was lessened 5.22%. We can read from the results thatbore depth F of the nozzle upper part has an effect in both the influence of a viscosity coefficient, and variation.

V. CONCLUSION

The following conclusions were obtained, as a result of performing the parameter design of a nozzle device and confirming reproducibility.

- The relation between speed of rotation and discharge mass was suitable as measuring characteristics in this experiment.
- The factorial effect diagram showed that the parameters of A2 B1 C2 D2 E3 F3 G1 were the optimum conditions.
- In the nozzle device of the optimum conditions, the difference of the profit of an estimated value and a confirmation value was -2.225 [db], and reproducibility was obtained.

ACKNOWLEDGMENT

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Robust Optimization of planar High-k/Metal Gate NMOS Device with 22nm gate length

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Abstract - **Robust optimization using Taguchi's orthogonal arrays is becoming a necessity as a means to optimize device parameter designs prior to the actual fabrication in an effort to reduce fabrication costs. In this paper, Taguchi method was applied in the design of a 22 nm gate length planar NMOS transistor to study the leakage current (I_{LEAK}) of the device. This is a continuation of our previous work where the best combination of device design parameters was obtained in an effort to optimize the threshold voltage (V_{th}) values since the V_{th} is one of the key factors in determining the functionality of the device. In the current device design, titanium dioxide (TiO_2) was used as the high permittivity (high-k) material instead of silicon dioxide (SiO_2) dielectric whereas tungsten silicide (WSi_x) as a metal gate was deposited on top of the high-k dielectric layer. The device's fabrication, characterization and optimization were executed using an industrial-based numerical simulator. The L9 orthogonal array consisting of 36 simulation runs was utilized where four control factors and two noise factors were identified. The functional objective is to obtain I_{LEAK} values using Smaller-the-Better (STB) signal-to-noise ratio (SNR). The optimization results in the attainment of the I_{LEAK} mean value of $3.2537e^{-10}$ A/µm. This value is in accordance to the predicted value given in the International Technology Roadmap for Semiconductors (ITRS) 2011.**

Keywords- **Taguchi Method, 22 nm gate length NMOS, high-k/metal gate, leakage current.**

I. INTRODUCTION

The downsizing of the complementary metal-oxide-semiconductor (CMOS) devices brings lot of improvements in the performance of devices and circuits. Smaller devices can be implemented in a smaller area of integrated circuits and this leads to increasing the number of transistor-per-wafer and in the same time increases the performance of these products.But the aggressive downsizing dimensions of transistors require the reduction of the gate dielectric thicknesses since the silicon dioxide (SiO_2) layer has been used as an efficient gate dielectric material over decades in electronics products. The need in reducing the equivalent oxide thicknesses (EOT) until 1nm makes it impossible for SiO_2 to be fabricated since this thickness causes an increase in the gate leakage current leading to enormous, current densities and high power dissipation [1, 2].Downscaling the device causes the drain to be much closer to the source thereby introducing short channel effects which leads to the potential to increase the leakage current [3].Gate leakage current problems can be solved by the introduction of high permittivity (high-k) gate dielectrics [4].Therefore, by replacing high-k dielectrics to replace SiO_2 as a CMOS gate is one of the major challenges for further downscale in order to keep planar CMOS devices still on track [5]. There are a number of high-k materials being proposed and analyzed as the replacement of SiO_2 in the next generation of MOSFETs. The device characteristic prediction made by the International Technology Roadmap for Semiconductors (ITRS) gives a good reference to researchers as a guidance in scaling down the size of the MOSFET transistor.

In our previous work, we successfully optimized the threshold voltage (V_{th}) in designing a 22nm gate length NMOS transistor using a combination of TiO_2 as the high-k material and metal gate [6]. With this motivation, in this paper we continue our optimizing process in order to obtain the minimum leakage current or I_{LEAK}. The optimization of the fabrication process parameters was performed using Taguchi's Robust Design [7]. In the Robust Design signal-to-noise ratio (SNR) is used where it measures the quality of the orthogonal arrays. Many design parameters are studied simultaneously using only a small number of experiments with added noise factors in order to get the optimal process parameters [8].

In this experiment, we implemented an L9 orthogonal array that consist of four process parameters which are the Halo implantation, Source/Drain (S/D) implantation, the compensation implantation and the V_{th}

adjust implantation. The Sacrificial Oxide Layer (PSG) temperature and the P-well implantation temperature were selected as the noise factors. The aim of the current work is to minimize the I_{LEAK} of the device to minimize it as small as possible in reference to the ITRS 2011 prediction for 22 nm gate length NMOS transistor where the accepted maximum value for I_{LEAK} is 100 nA/µm [9].

II. MATERIALS AND METHODS

The fabrication process steps are as follows. A p-type silicon substrate with <100> orientation is used and P-well region using Boron as a dopant with a dose of $3.75\text{x}10^{12}$ ions/cm^2 is produced. The silicon wafer is then annealed at 900°C in a Nitrogen environment followed by dry oxygen in order to ensure that the boron atoms are being spread properly in the wafer. The 130 Å thickness of Shallow Trench Isolator (STI) was produced by oxidized in dry oxygen for 25 minutes followed by a low pressure chemical vapour deposition process (LPCVD) to produce a 1000Å nitride layer [10]. Then a photo resist deposition took place and the trench depth of 3200 Å was achieved. Thereafter, a sacrificial oxide layer was grown and then etched followed by a sacrificial nitride layer whereby the trench is then completed.

The next step was to implant the N well active area, with boron dose of $6.98\text{x}10^{12}$ ions/cm^2. Later on, a halo implantation took place in order to get an optimum performance for the NMOS device where indium was implanted with a dose of $12.75\text{x}10^{12}$ ions/cm^2. The dosage was varied in order to get the optimum value [11,12]. Then the high-k material, TiO_2 (dielectric permittivity, ε_{opt} = 5.4) was deposited for a final thickness of 2 nm [13] and this is followed by etching to get the desired thickness and was adjusted to produce a 22 nm gate length. Tungsten silicide (WSi_x) as a metal gate was then deposited on the top of the bulk device with a thickness of 6 nm and etched accordingly to produce the gate contact point as desired [14].

Then, side wall spacers were formed at each of the source and drain regions respectively where it functions as a mask for the source and drain implantation [15]. Then, there are source-drain implantations where Arsenic was firstly implanted with a dose of $5.15\text{x}10^{13}$ ions/cm^2, followed by phosphorous with a dosage of $1.75\text{x}10^{12}$ ions/cm^2. The next process was the development of 0.5 µm Borophosphosilicate Glass (BPSG) layer that acts as a pre metal dielectric (PMD) [16].

After Borophosphosilicate Glass (BPSG) deposition, the wafer undergoes annealing process at a temperature of 850°C [17]. The next process was compensation implantation by phosphorous, with a dose of $3.65\text{x}10^{13}$ ions/cm^2 [17]. Then lastly, aluminium layer was deposited on top of the structure and then it was etched accordingly to form the metal contact for the source and drain. Then, the transistor undergoes electrical characteristic measurement using ATLAS simulation module in order to study the leakage current of the device with reference to ITRS 2011 [9].

A. *Taguchi L9 Orthogonal Array Method*

Taguchi method is used to optimize the device design in order to get the best process parameter combination to achieve high device performance with a reduced number of experiments. Since a minimum I_{LEAK} value is needed, the Taguchi L9 (3^4) orthogonal array consist of different parametric combination of 4 process parameters at 3 different levels. Two noise factors were also added to make the process parameters insensitive. Therefore, a total of 36 runs are needed to optimize the developed device design. All the values of the process parameters and noise factors are listed in Table 1 and Table 2 respectively.

TABLE 1
PROCESS PARAMETERS AND THEIR LEVELS

Symbol	Process Parameter	Level 1	Level 2	Level 3
		(atom/cm^3)		
A	Halo Implantation	$1.270e^{13}$ (A1)	$1.275\ e^{13}$ (A2)	$1.280\ e^{13}$ (A3)
B	S/D Implantation	$5.100e^{13}$ (B1)	$5.150\ e^{13}$ (B2)	$5.200\ e^{13}$ (B3)
C	Compensation Implantation	$3.650\ e^{13}$ (C1)	$3.700\ e^{13}$ (C2)	$3.750\ e^{13}$ (C3)
D	V_{th} Adjust Implantation	$6.940\ e^{12}$ (D1)	$6.960\ e^{12}$ (D2)	$6.980\ e^{12}$ (D3)

TABLE 2
NOISE FACTORS AND THEIR LEVELS

Symbol	Noise Factor	Level 1	Level 2
		°C	
X	Sacrificial Oxide Layer	900 (X1)	902 (X2)
Y	P-well Implantation Temperature	850 (Y1)	852 (Y2)

III. RESULTS AND DISCUSSION

The results of the I_{LEAK} were analyzed and processed using Taguchi method in order to get the smallest possible value in designing the NMOS device.

A. *Analysis for 22nm NMOS Device*

The L9 orthogonal array analysis for I_{LEAK} which is specified in the orthogonal array table was simulated and listed in Table 3 for different noise factor combinations.

TABLE 3
I_{LEAK} VALUES FOR NMOS DEVICE FOR DIFFERENT NOISE FACTOR COMBINATIONS

Exp. No	Leakage current (A/µm) X1Y1	X1Y2	X2Y1	X2Y2
1	5.33880e-10	5.51814e-10	5.34654e-10	5.52611e-10
2	9.11650e-10	9.42631e-10	9.12968e-10	9.43993e-10
3	15.5757e-10	16.112e-10	15.5983e-10	16.1353e-10
4	6.22079e-10	6.43277e-10	6.22978e-10	6.44207e-10
5	12.2233e-10	12.6440e-10	12.2410e-10	12.6623e-10
6	7.32308e-10	7.57583e-10	7.33364e-10	7.58674e-10
7	5.31337e-10	5.50089e-10	5.32094e-10	5.50872e-10
8	3.19473e-10	3.30798e-10	3.19926e-10	3.31267e-10
9	6.24670e-10	6.46984e-10	6.25563e-10	6.47902e-10

Since the target in this experiment is to get a minimum leakage current, therefore the leakage current is optimized using signal-to-noise ratio (SNR) of Smaller-the-Better [18]. The SNR (Smaller-the-Better), η_{STB} can be expressed as

$$\eta_{STB} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \qquad (1)$$

where n is number of tests and y_i is the experimental value of the leakage current. By applying the formula given in Eq. (1) the η_{STB} for the device was calculated and given as in Table 4. The parameteric combination level of the process and noise factors is also listed in Table 4.

The performance of the device characteristic is evaluated by the SNR value. Generally, in smaller-the-better SNR analysis, the best performance of the device is when the SNR has the highest value. Therefore, the optimal level of the process parameters is the level with the highest SNR [6].

TABLE 4
SNR FOR THE LEAKAGE CURRENT AND THEIR MAIN EFFECTS

Exp No.	SNR (dB)	Process Parameter Level			
		Halo Implant (A)	S/D Implant (B)	Compensation Implant (C)	V_{th} Adjust Implant (D)
1	185.30	1	1	1	1
2	180.65	1	2	2	2
3	176.00	1	3	3	3
4	183.97	2	1	2	3
5	178.10	2	2	3	1
6	182.55	2	3	1	2
7	185.33	3	1	3	2
8	189.75	3	2	1	3
9	183.93	3	3	2	1

Referring to Table 4, row 8 has the highest SNR value of 189.75 dB. The high value indicates that the process parameter in this row gives the best insensitivity for the response characteristics. Since the experimental design is orthogonal, the effect of each process parameter on the SNR at different levels can be separated out.

The SNR (Smaller-the-Better) for each level of the process parameters with total mean of the SNR for the experiments is summarized in Table 5.

TABLE 5
S/N RESPONSE FOR THE LEAKAGE CURRENT

	Process Parameter	SNR (Smaller-the-Better)			Total Mean SNR
		Level 1	Level 2	Level 3	
A	Halo Implantation	180.65	181.54	186.34	182.84
B	S/D Implantation	182.83	184.87	180.82	
C	Compensation Implantation	185.87	182.85	179.81	
D	V_{th} Adjust Implantation	182.44	182.84	183.24	

The factor effect graph for the SNR (Smaller-the-Better) of the experiment is shown in Figure 1. The dashed horizontal lines in the graph represent the values of the overall-mean of the SNR (Smaller-the-Better).Referring to the graphs, from the left, the slopes correspond to the Halo Implantation (Factor A), followed by S/D implantation (Factor B), Compensation Implantation (Factor C) and lastly V_{th} Adjust Implantation (Factor D) respectively.

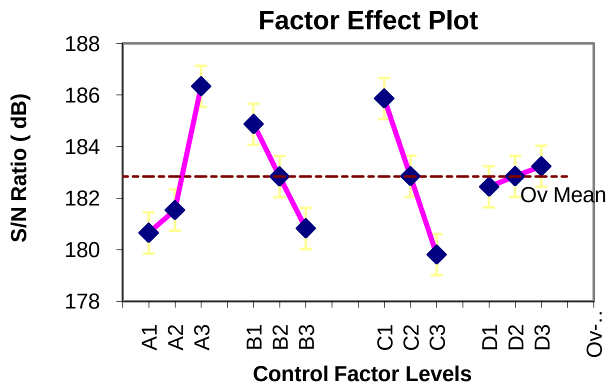

Figure 1 SNR (Smaller-the-Better) graph

B. Analysis of Variance (ANOVA)

The priority of the process parameters with respect to the I_{LEAK} values was investigated to determine the accuracy of the optimum combinations. The result of ANOVA for the device is presented in Table 6. The factor effect percentage on SNR indicates the priority of a factor (process parameter) to reduce variation. The high percentage of a factor effect on SNR contributes to the greatest influence on the I_{LEAK} with respect to the noise parameters.

TABLE 6
RESULTS OF ANOVA

	Process Parameter	Degree of Freedom	Sum of Square	Mean square	Factor Effect on SNR (%)
A	Halo Implantation	2	56	28	41
B	S/D Implantation	2	25	12	18
C	Compensation Implantation	2	55	28	40
D	V_{th} Adjust Implantation	2	1	0	1

The results of the factor effect on the SNR clearly shows that the Halo implantation dose with 41% has the greatest influence in minimizing the leakage current of the NMOS device, while the Compensation Implantation is ranked second at 40%. The percentage effect for the SNR for the S/D Implantation and V_{th} Adjust Implantation were much lower, being 18% and 1% respectively.

IV. CONFIRMATION OF OPTIMUM RUN

Based on the results in Table 4 we can clearly see that the highest SNR value is experiment 8 with SNR value of 189.75 dB Table 5 shows the highest SNR value of each process parameter level to achieve minimum I_{LEAK} where for the Halo Implantation, it is level 3 with SNR of 186.34 dB, S/D Implantation at level 2 with SNR of 184.87 dB, while Compensation Implantation at level 1 with SNR of 185.87 dB and last but not least is V_{th} Adjust Implantation at level 3 with SNR value of 183.24 dB. The best setting of the process parameters for a NMOS device that affects the I_{LEAK} which is suggested by Taguchi method is A_3, B_2, C_1, D_3 and this is summarized in Table 7. These final parameters were then simulated with the noise factors to get the final I_{LEAK} results as noted in Table 8.

TABLE 7
BEST SETTING OF THE PROCESS PARAMETERS

Symbol	Process Parameter	Level	Best Value (atom/cm^3)
A	Halo Implantation	3	$1.28e^{13}$
B	S/D Implantation	2	$5.15e^{13}$
C	Compensation Implantation	1	$3.65e^{13}$
D	V_{th} Adjust Implantation	3	$6.98e^{12}$

TABLE 8
RESULT S OF BEST SETTING PARAMETER WITH ADDED NOISES

LEAKAGE CURRENT (A/µm)					SNR (STB)
I_{LEAK} 1 (X1,Y1)	I_{LEAK} 2 (X1,Y2)	I_{LEAK} 3 (X2,Y1)	I_{LEAK} 4 (X2,Y2)	I_{LEAK} (Mean)	
$3.1947e^{-10}$	$3.3080e^{-10}$	$3.1993e^{-10}$	$3.3127e^{-10}$	$3.2537e^{-10}$	189.75

After the optimization approach, the value of SNR (Smaller-the-Better) of the I_{LEAK} for the developed NMOS device shows that it is in range of the predicted SNR (Smaller-the-Better) where the range is between 190.94 until 187.77. The lowest I_{LEAK} value obtained is 3.194 nA/ µm which is much lower that the value of 100 nA/um predicted in ITRS 2011.

V. CONCLUSION

As a conclusion, the Taguchi method is a reliable technique in optimizing the process parameters of a planar NMOS transistor utilizing high-k/metal gate technology in order to achieve the optimum solution in fabricating a 22nm gate length device with reference to the ITRS 2011. Leakage current was kept as minimum as possible to increase the speed of the device and minimizing the time for the transistor to function. The best process parameter value that gives the minimum I_{LEAK} for Halo Implantation, S/D Implantation, Compensation Implantation and V_{th} Adjust implant are 1.28×10^{13} atom/cm^3, 5.15×10^{13}atom/cm^3 and 3.65×10^{13} atom/cm^3 and 6.98×10^{12}respectively. While the noise parameter values for Sacrificial Oxide Layer and P-well Implantation Temperature are 900 °C and 850 °C respectively. The lowest I_{LEAK} value of 3.194 nA/µm was attained upon Taguchi optimization.

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Optimization of the Paper Permeability Tester Using Robust Design

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Abstract – **This paper is using practical case study of robust design engineering. Effect of control factors and optimum condition is studied to design a more robustness of Paper Permeability Tester. In this study, robustness means decreasing uncertainty that is validity of measurement results with the Tester. Robustness is required to keep a guarantee of the measurement results in the field of the measurement tester. Thus, orthogonal array L_{18} is employed and the optimum condition was obtained for decreasing the measurement dispersion. Experiment reproducibility of Signal-to-Noise Ratio (SNR) and sensitivity were confirmed within 20%. SNR value is linearly depends on air permeance value. When the value of air permeance is small, it tends to provide small SNR. Flow rate in nozzle was considered as a major cause. Sensitivity with nozzle diameter was dramatically large. Nozzle specification tolerance was found to have strong influence on measurement result.**

Keywords – **Permeability tester, permeance, Robust Parameter Design, Signal-to-Noise Ratio, tolerance design**

I. INTRODUCTION

Air permeance of paper is assessed as related printing characteristic. Recently, demand for the Paper Permeability Tester is increased due to its variety of functional materials which are high quality paper and porous films. Although the Paper Permeability Tester is standardized by Japanese Industrial Standards (JIS)[1] and ISO [2], the reliability in the test results is pointed out as necessary,parallel with the demand of Paper Permeability Tester. The Tester has an uncertainty in its test result. Reducing uncertainty in the result will increase the accuracy of Tester. Therefore, the main purpose of this study is optimizing the Tester to ensure the reliability in test results usingrobust parameter design.

II. METHODOLOGY

Paper Permeance

Paper Permeability and its test are standardized by JIS. Value of paper permeability, air permeance, is defined by taking the time at which constant air volume passed through the specimen [2]. The permeability is evaluated as one of alternative characteristics of printability. Ifthere are many holes passing the air in the specimen, value of paper permeance is low.

Tester

Oken type Paper Permeability Tester which is better than Gurley Type Paper Permeability Tester [2] was used in this study. Fig.1 shows a schematic diagram of the Oken Tester. Air is pushed out from the compressor goes into a chamber where air is kept at static pressure, 4.903kPa (500mmAq), by a water column. The air coming from unit pressure chamber goes into a measurement chamber through an inlet nozzle which is called reference nozzle, and constant air is passed through the specimen. Measurement nozzle is used as a specimen instead of paper [3] to calibrate the Permeability Tester. Measurement nozzle length and reference nozzle are referring to the same nozzle part. However, the location of the nozzle is at different part of the system, thus serving different function and label. Measurement nozzle is installed outside the pressure chamber (factor *M*,*D*) and reference nozzle is installed inside the pressure chamber (factor *B*,*C*). Flow rate of the reference nozzle, Q_r, and measurement nozzle, Q_m, are determined by means of the following equation.

$$Q_m = \frac{\pi}{8\mu}\left(P_C - P\right)\frac{R^4}{L} \tag{1}$$

$$Q_r = \frac{\pi}{8\mu} P \frac{r^4}{l} \tag{2}$$

$$T = \frac{1.28 \times 10^4 \mu L}{\pi P_C D^4} \tag{3}$$

where μ is the viscosity coefficient of air; P_c is value of unit pressure in the chamber; P is value of pressure in the measurement chamber; r is the inside radius of the reference nozzle; l is the length of the reference nozzle; R is the inside radius of the measurement nozzle; L is the length of the measurement nozzle; Permeance, T, is determined by the ratio between Q_r and Q_m.

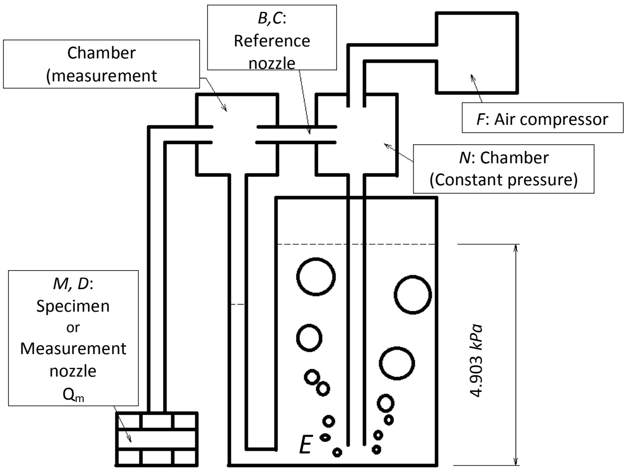

Fig.1 Paper Permeability Tester

P-diagram and Factors

P-diagram was obtained by (1), (2), (3), and Fig.1. Measurement nozzle length is related to the measurement result in linear relation between nozzle length and Permeance. Therefore, measurement nozzle length which is the input signal is related linearly to Permeance which is the output, Y, by a function in Permeability Tester, (3). Fig.2 shows the relation between Measurement Nozzle Length and Air permeance. The condition of flow was considered only for laminar flow, depicted as a solid line in Fig. 2. Meanwhile, turbulent area where measurement nozzle length is shorter than 30 mm is ignored. Therefore, a Linear Equation method [4] was used to calculate SNR and sensitivity with dynamic response, (4) and (5). M is distance from an average of input signal levels. Reference point which is the average of input signal level is 50mm. The reason why Linear Equation method is used is because of the unknown whether the zero intercepts is reached when the turbulent area is ignored since only laminar flow is taken into measurement.

Constant pressure in the chamber always fluctuate, therefore, noise factor was determined.

$$\eta = 10\log\frac{(1/r_0 r)(S_\beta - V_e)}{V_e} \tag{4}$$

$$S = 10\log\frac{S_\beta - V_e}{r_0 r} \tag{5}$$

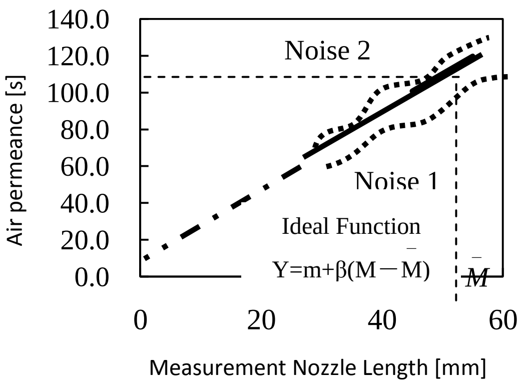

Fig.2 Ideal function for the Tester

Six control factors were determined from the principal of Oken Tester. Level of input signal, noise factor, and each factor were summarized in Table I, II, and III. Factor A; Value of water has not been defined in detail. Effect of value of water need to be found if the Tester should weight saving. Factor B, C, and D; Value of permeance depends on Reference Nozzle Length, Reference Nozzle Diameter, and Measurement Nozzle Diameter. Effects of these factors and optimum condition should be investigated to design a more robustness Tester using Taguchi Method with L_{18}.

Level of Reference Nozzle Length, Reference Nozzle Diameter, and Measurement Nozzle Diameter was determined under laminar flow where nozzle length is assumed in optimum condition around 40-55mm. Factor E; bubble reducer is a plastic material to reduce amount of bubble inside of the Tester. The installed position of the bubble reducer is changed in three levels; that are upper, middle, and lower position from standard point set in this study. The different position will affect the length of the metallic pipe, thus, the pressure is kept constant.

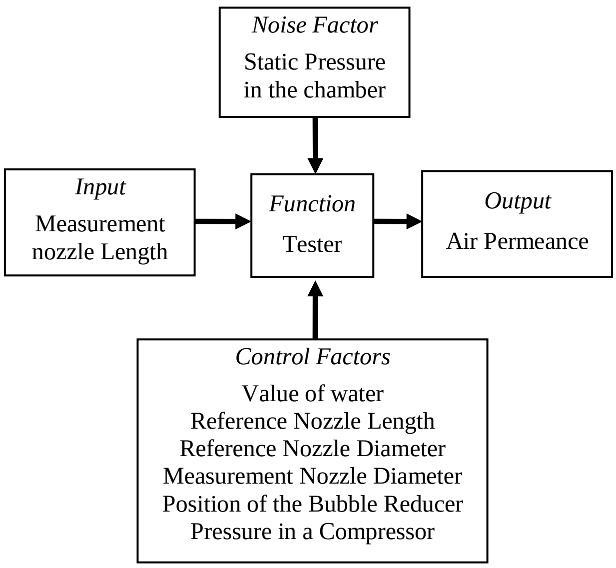

Fig.3 P-diagram

TABLE I
LEVEL of Input Signal

Signal Factor	Level 1	Level 2	Level 3	
Measurement Nozzle Length	45	50	55	mm
M (Distances from an Average)	-5	0	5	

TABLE II
LEVEL of Noise Factor

Noise Factor	Level 1	Level 2	
Pressure	498	502	mmAq

TABLE III
LEVEL of Control Factors

	Control Factors	Level 1	Level 2	Level 3	
A	Water Volume	Nomal	-55		cm^3
B	Reference Nozzle Length	45	50	55	mm
C	Reference Nozzle Diameter	0.33	0.41	0.51	mm
D	Measurement Nozzle Diameter	0.33	0.41	0.51	mm
E	Position of Bubble Reducer	2	0	-2	mm
F	Pressure in Compressor	0.005	0.01	0.02	MPa

III. RESULTS& DISCUSSION

Signal-to-Noise Ratio, SNR, and sensitivity were calculated by using data below. For instance, SNR and sensitivity calculation for run 1 is shown in the following equation.

TABLE IV
DATA of run 1

M 1		M 2		M 3	
N1	N2	N1	N2	N1	N2
101.0	100.7	109.8	109.0	120.0	119.0

$S_T$is the total sum of square of air permeance measurement data to calculate the total variation around the mean in run 1:

$S_T = y^2_{11}+y^2_{12}+ \quad y^2_{21}+y^2_{22}+ \quad y^2_{31}+y^2_{32} - S_m$ (6)

$= 101.0^2+100.7^2+109.8^2+109.0^2+120.0^2+119.0^2 - 72490$

$= 72840$

S_m is the mean of run 1:

$$S_m = \frac{(\sum y_{ij})}{kr_0} = 72490 \quad (7)$$

$S_\beta$is the variation caused by the linear effect of signal:

$$S_\beta = \frac{1}{r_0 r}\left[y_1(M_1-\bar{M})+y_2(M_2-\bar{M})+\ldots+y_k(M_k-\bar{M})\right]^2 \quad (8)$$

$$= \frac{1}{100}\left[101.0\times(45-50)+\ldots+119.0\times(55-50)\right]^2$$

$$= 347.82$$

S_e is the error variation:

$S_e = S_T - S_\beta - S_m$ (9)

$= 1.67$

$V_e$is the error variance:

$$V_e = \frac{S_e}{4} \quad (10)$$

$$= 0.42$$

Thus, SNR is calculated as:

$$\eta = 10\log\frac{(1/100)(347.82-1.67)}{1.67}$$

$$= 9.21 \quad \text{dB}$$

The sensitivity is calculated as:

$$S = 10\log\frac{347.82-1.67}{100}$$

$$= 5.41 \quad \text{dB}$$

Fig. 4 shows an example of the ideal function graph of run 1:

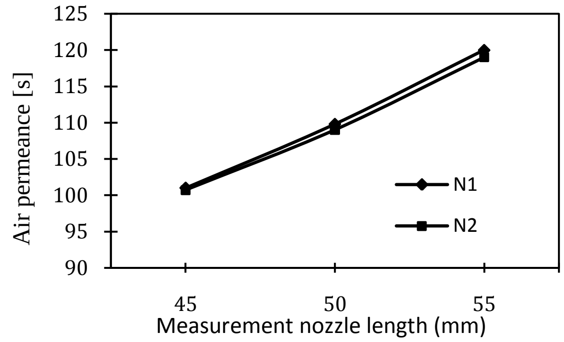

Fig. 4 Ideal function graph for Run 1

Fig.5 shows the value of SNR, and Fig.6 shows the value of sensitivity obtained by L_{18}. Although initial condition is $A_1B_1C_2D_2E_2F_2$, optimum condition was obtained at $A_1B_1C_2D_1E_3F_1$, as circled in Fig. 4.

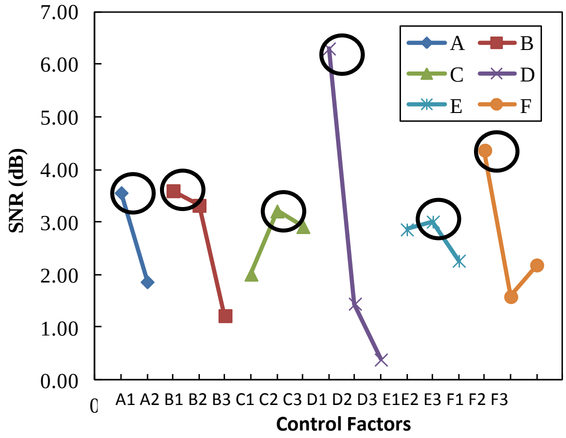

Fig.5 Factor effect plot for SNR

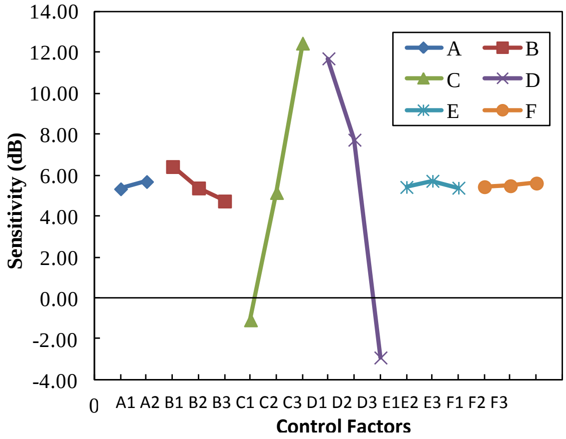

Fig.6 Factor effect plot for Sensitivity

Table IV andV show a comparison of SNR and sensitivity. Both of SNR and sensitivity in estimation and confirmation have good reproducibility. Db gain difference in reproducibility of SNR was about 20% and sensitivity was about 10%. However, sensitivity of *C* and *D* is remarkable. There are two reasons why factor *C* and *D* sensitivity is large.

Firstly, tolerance of nozzle diameter is wide approximately 10% from specification. Flow in a nozzle was greatlyinfluenced by this wide tolerance of nozzle diameter. Robust design for tolerance diameter should be established for nozzle flow robustness. Secondly, SNR depends onrange of measurement. Air permeance is takenfrom the ratio of flow rate.Thus, related factors to the datum nozzle flow rate, *B* and *C*, are affecting other factors. When the value of air permeance is small, SNR tendsto be small. An ideal condition of measurement is in same range, for instance around 100s.

TABLE IV
SNR Comparison

SNR	Estimation	Confirmation	
Optimum condition	9.69	8.08	
Initial condition	2.05	2.07	
Gain	7.64	6.02	[dB]

TABLE V
Sensitivity Comparison

Sensitivity	Estimation	Confirmation	
Optimum condition	11.10	12.76	
Initial condition	7.17	8.45	
Gain	3.93	4.31	[dB]

Fig. 7.a and 7.b shows the ideal function graph for confirmation experiment which consists of initial and optimum condition respectively. Good improvement is shown in optimum condition $A_1B_1C_2D_1E_3F_1$ with SNR 8.08dB and 20% reproducibility.

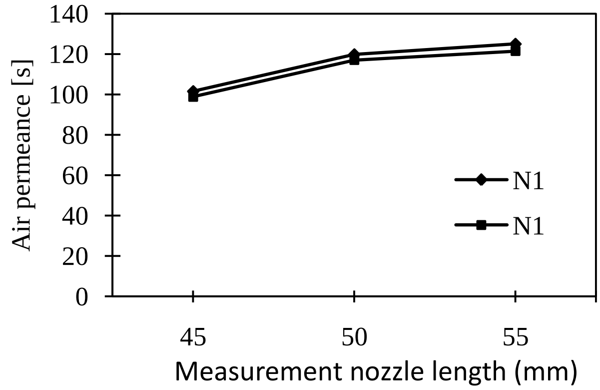

Fig. 7.a Ideal function graph of initial condition

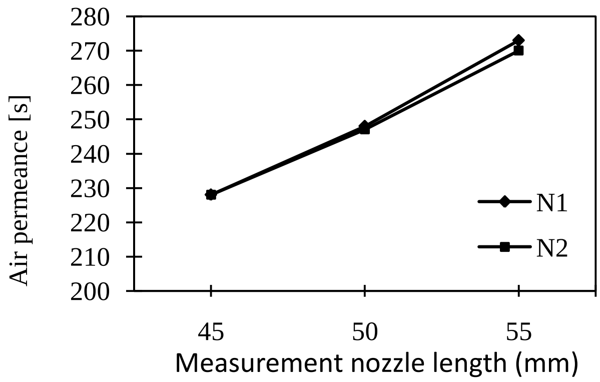

Fig. 7.b Ideal function graph of optimum condition

IV. CONCLUSION

Optimum condition for the Paper Permeability Tester was obtained by using orthogonal array L_{18}. Reproducibility of gain with SNR and sensitivity was confirmed. Difference of SNR db gain was 20% between estimation and confirmation. According to Fig.6, factor *C* and *D* are the most sensitive factor and best to adjust to desired value. Tolerance of nozzle diameter had influenced the result of measurement. Tolerance for specification of nozzle diameter and nozzle length is required to make the paper permeability tester more robust.

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Taguchi Method-Based Optimization in Plastic Injection Moulding: A Novel Literature Review-Based Classification and Analysis

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Abstract - **Injection moulding is the most common technique of plastic forming. The industry is usually referred to as a MIMO (multi-input-multi-output) process that is basically involved with several input parameters (control factors) yielding almost inconsistent results on output variables (response factors). As a result of this, product quality is a major challenge in such unstable manufacturing environment. Taguchi methods (TMs) are commonly used in plastic injection molding industry (PIMI) as a robust optimization technique to serve for a wide range application from product design optimization to mould design and from optimal material selection to processing parameter optimization. This paper primarily aims at providing a comprehensive chronological review and classification on different applications of TMs in PIMI to serve for the following two purposes: first to present an evolutionary trend of TMs in PIMI and second for a comparative capability analysis of TMs in selected industrial-based case studies. Major pros and cons of TMs in will also be highlighted as compared to other optimization techniques rather than Taguchi Method.**

Keywords - **Taguchi, Optimization, Process, Design, PIMI, MIMO**

I. INTRODUCTION

Taguchi method is technically classified as one of a group of optimization techniques commonly known as the umbrella term, design of experiments (DOE). It was originally pioneered in 1948 by Japanese statistician and Deming prize winner; Dr. Genichi Taguchi to improve quality through Robust Design of products and production processes. The method was primarily based on traditional concepts of DOE such as full and fractional factorial design and orthogonal arrays but later in the 1980s and parallel to its introduction in the United States, new features such as signal-to-noise ratios (S/N ratio) and tolerance design were also added to the traditional technique.

On the other hand, plastic industry (PI) is recognized as one of a few worlds' billion-dollar industries which is moulding. However, to survive as a competitive industry, it strongly needs to focus on 3 important factors as quality, time and cost which can be achieved through the concept of robust quality engineering [1].

Taguchi method is considered as a technique that in fact has gained much of its credit from statistical analysis of robust design. The main objective of this method is to achieve economical quality design based on a very limited number of experimental runs. This salient feature is most applicable in cases where quality is a multi-variable function such as in plastic injection moulding [2]. Therefore in plastic injection moulding (PIM), number of experimental needs to be reduced to a minimum possible level to save for the quality-related time and costs [3]. In this regard, Taguchi's DOE employs Taguchi loss function (TLF) to investigate both product parameters and key environmental factors by setting variation reduction as the primary goal of quality improvement.

II. TAGUCHI LOSS FUNCTION (TLS)

TLF is strongly focused on minimizing losses or cost. Such quality philosophy is named as an "enlightened approach" by W. H. Moore which is based on the following triple assumptions: (a) - in TLF, the smallest loss is obtained by the target value for each product quality characteristics (b) - total loss increases with an increase in process variation and finally (c) - loss should be measured in monetary units [4].

As it is illustrated in Fig. 1, TLF states a nonlinear relationship for loss fluctuation as being deviated from target value (T), which is in contrast with the traditional view of zero point loss for the interval between lower specification limit (LSL) and upper specification limit (USL).

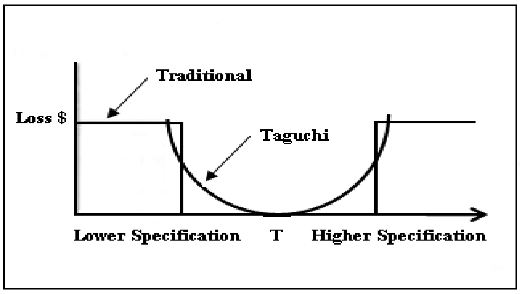

Fig. 1. Taguchi Loss Function vs. Traditional view [4]

The TLF shown in Fig. 1 can be mathematically modeled as a simple quadratic equation that compares the measured value of a unit of output X to the target T as given by equation (1) in which L(X) is the expected loss associated with any value of X variable representing an specific quality characteristic :

$$L(X) = (X - T)^2 \tag{1}$$

Equation (1) can be operated to set quality performance measures that allow for the optimization of any product's quality characteristic. For any single quality characteristic, as a response variable, it is important to know both values of its average and variation.

III. SIGNAL-TO-NOISE RATIO (S/N)

Equation (1) suggests that these two values can be combined as a single measure known as "signal-to-noise ratio(S/N)". Taguchi method is then used to select the appropriate levels of design parameters that will maximize the relevant S/N ratio. Such S/N ratios are then used as a criterion to get as close as possible to the target value or to reduce the amount of variation in product's quality characteristics. S/N ratio (α) is generally calculation based on the following 3 concepts summarized as: 1.NOB (nominal-the-best), 2. LOB (Lower-the-better), 3-HIB (Higher-the-better).with this classification, the highest S/N ratio will determine the optimal parameter combination. NOB type of problem attempts to minimize mean square error (MSE) around a specific target value and is calculated by equation (2) in which μ and σ is the mean and standard deviation respectively.

$$\text{S/N ratio } (\alpha_{NOB}) = -10 \log10 (\mu^2/\sigma^2) \tag{2}$$

LOB S/N ratio is calculated as the equation (3), with i ranging from 1-n and X as the observed value of the measured variable. This type of S/N ratio is used where the objective is solely to minimize the value of a certain quality characteristic.

$$\text{S/N ratio } (\alpha_{LOB}) -10 \log_{10} (1/n\Sigma X_i^2) \tag{3}$$

And finally HOB type of S/N ratio is used when the intention is to maximize the selected quality characteristic and is calculate by equation (4) in which "n" is the number of replication and I ranges from 1-n [5].

$$\text{S/N ratio } (\alpha_{HOB}) = -10 \log_{10} (1/n\Sigma 1/x_i^2) \tag{4}$$

IV. ANALYTIC LITRATURE REVIEW

Taguchi methods have been used in plastic injection moulding either individually or in combination with other methods since it emergence in 1950s.

In this section the evolutionary process of Taguchi method from birth to present will be comprehensively reviewed with respect to its application in PIMI.

Table I is aimed at providing an overall view of the primary information of each paper, while Table II reviews the research objective, materials & methods used in the paper as well as salient remarks. Table 3 illustrates control factors and response variables and finally in Table IV, a triple analysis of scope, S/N ratio and DOE will be presented.

TABLE I
A GLANCE LITRATURE REVIEW

Ref	Researcher (Year)	Application	Ref	Country
1	Erzurumlu (2005)	Production of mould parts for PIM	[6]	Turkey
2	Rajesh et al. (2011)	Polymer Nano-composites	[7]	France
3	J.C. Lin et al. (2005)	Injection molding process optimization	[8]	Taiwan
4	Shen et al. (2008)	Scaffold of tissue engineering	[9]	Taiwan
5	Wu and Liang(2005)	Weld-line characteristics of structures with different cross-sections	[10]	Taiwan
6	Liet al.(2007)	Improving appearance quality	[11]	China
7	Ohmori et al. (2005)	Improving surface profile of optical lenses	[12]	Japan
8	Akbarzadeh & Sadeghi (2011)	Minimization of PP and PS shrinkage and dimensional changes	[13]	Iran
9	Huang & Lin (2007)	Control effect environmental noise when setting results & limits are very close	[14]	Taiwan
10	Chung-Feng (2006)	Injection molding for Polyether Ether Ketone (PEEK)	[15]	Taiwan

TABLE II
IN DEPTH LITRATURE REVIEW OF TABLE 1

REF	Research Objective	Material / Methods	Remarks
1	Prediction of mould low surface roughness	Al 7075-T6	Artificial neural Network is by 2.05 % to 1.48% difference in error more accurate than RSM
		FFD , RSM, ANN	
2	Effect analysis of PIM on Nano-platelets dispersion degree	Metal mixed PP/clay	Injection flow rate and back pressure to be the first 2 dominant single factors
		Dynamic rheological measurement & orthogonal array	Interaction between back pressure and screw rotation speed was also significant

TABLE II-Continued

3	Minimizing of wrappage temperature difference and the total injection time	Hybrid Taguchi, FEM,ANN, abductive Design & simulated annealing	FEM-based simulation & simulated annealing-based optimization approach Applicable to parts with free-form geometry
4	Analysis of 3-D biodegradable polymeric scaffold on precision injection molding	Polylactic acid (PLA 7000D) FEM combined Taguchi	Providing a reference data for the processing window of biodegradable polymeric scaffold 3-D numerical simulation for flow situation on precision injection molding of biodegradable polymeric
5	Analysis of process parameters and cross-sectional dimensions on tensile strength	polypropylene (PP) & high density polyethylene (HDPE) Taguchi's orthogonal arrays	- Melt temperature, mold temperature, injection speed, and packing pressure are the most influential factors - Microinjection molding in not compatible e with the result of a standard test foe weld line strength
6	Study the effect of weld line of plastic parts appearance quality	Taguchi experimental design	-Calculation of hue values of sample products using digital camera & Minitab -Weld line appearance is mostly influenced by melt temperature, injection velocity & injection pressure
7	To restrain porosity creation and minimizing thickness reduction.	Hybrid neural network algorithm-3D Timon simulation and Taguchi	Eliminating the need for experiments by using a numerical simulation software named Timon-3D™
8	Investigation the effect of PIPM on minimizing shrinkage and wrappage for PP and PS	polypropylene & polystyrene Regression & ANOVA Analysis	-Use of Invasive Weed Optimization (IWO) algorithm in mathematical modeling - Packing pressure and injection pressure as the most and least important factors for PP and melting temperature as the most influential factor for PS based on ANOVA -Reducing shrinkage up to 1 % as compared to previous studies
9	An innovative search method for robust process parameters	PMMA Taguchi orthogonal arrays L18	- Reducing the effect of environmental noise on part quality - Low order and few experimental runs -Using steepest ascent method as the search engine -Deficient rate of the new model is 0 to 21 per 100 items as compared to Taguchi
10	Improve the drawbacks of the Taguchi	PEEK DOE, Orthogonal arrays, ANOVA	Based on actual experimental work and determination of optimum conditions using statistical tools

TABLE III
CONTROL-RESPONSE FACTOR LITRATURE REVIEW

REF	MIMO Fact Sheet	
	Critical Control Factors (CCF)	Response(s)
1	feed, cutting speed, axial–radial depth of cut,& machining tolerance	Mould surface roughness
2	screw rotational speed, back pressure, injection flow rate and holding pressure	storage modulus
3	Runner diameter ,Runner length ,Gate diameter Gate length, Material thickness	Warp, temperature, time
4	Melt temperature ,mold temperature, injection pressure, packing time	deflection
5	mold temperature, packing pressure, melt temperature, injection speed, injection acceleration, and packing time	tensile strength
6	melt temperature, injection velocity, and injection pressure	Weldline appearance
7	injection time, injection temperature, mold temperature and holding/cooling time	thickness reduction, volumetric distortion
8	melting temperature, packing pressure, packing time and injection pressure	shrinkage
9	Injection temperature , Back pressure, Mold temperature	replication
10	mold temperature, pre-plasticity amount, injection pressure, injection speed, screw speed, packing pressure, packing time and cooling time	Screw outer diameter, tensile strength and twisting strength.

TABLE IV
M2P2, S/N RATIO & DOE ANALYTIC LITRATURE REVIEW

REF	**M2P2** Analysis	S/N Ratio Analysis			DOE Analysis [a]			
	M2P2(material, mould, product, parameter)	NOB	LOB	HIB	N_{CF}	N_{RV}	N_{LE}	N_{EX}
1	Mould design	1	0	0	5	1	3	243
2	Process parameter Nano composites	0	1	0	4	1	2	16
3	Mould Design-runner dimension	1	0	0	5	3	3	27
4	Process parameter Precision injection	0	1	0	4	1	3	9
5	Process parameter Micro injection	1	0	0	6	1	2	16
6	Process parameter	0	1	0	3	1	3	27
7	High-precision injection molding	0	0	1	4	2	3	-
8	Mold parameters	0	1	0	4	1	3	27
9	Process parameter	1	0	0	3	2	2	8
10	Process parameter	0	1	0	7	3	3	$2*7^3$

[a] $\mathbf{N_{CF}}$refers to the number of control factors, $\mathbf{N_{RV}}$is thenumber of response variables, $\mathbf{N_{CF}}$is the number of experiment levels and $\mathbf{N_{CF}}$representstotalnumber of experimental runs

V. DISCUSSION

Based on a chronological analysis as shown in Fig. 2, starting 2004 onwards, the number of papers on Taguchi application in PIMI has almost steadily increased. Geographical distributions also show that most of the papers are published in Asia with the maximum number of papers coming from China/ Taiwan. Table II clearly reveals that in most cases Taguchi is used as a hybrid quality optimization technique. The average number of control factors is more than 4, with the min and max runs to be 8 and $2*3^7$ respectively as shown in Tables III & IV.

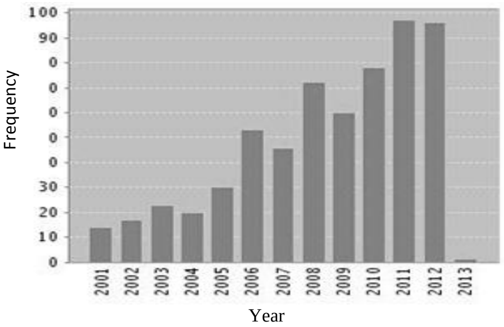

Fig. 2. Distribution of Taguchi-PIMI based papers (retrieved from Web of Science Citation Reports, dated 12 Dec 2012)

VI.CONCLUSION

Taguchi method is the most practical and efficient optimization technique for plastic injection moulding as it is highly compatible with the inconsistent nature of such MIMO process. On the other hand, TMs as combined with other heuristic methods such has Artificial Neural Networks and Genetic Algorithm proves to be a better optimization tool especially for material selection and mould design. All in all, Taguchi method is most useful in PIM process optimization where different set of parameters need to be optimized simultaneously.

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Productivity Improvement of Manufacturing System Using Design of Experiment and Computer Simulation

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Abstract – **Manufacturing companies are seeking to achieve higher productivity such as high resource utilization and high throughput. In order to evaluate the system's performance based on these they must deal with difficulties in the manufacturing system. Therefore, managers and engineers define the planning horizon for these aims. In the operative aims one of the most challenging is the bottlenecks. Indeed they try to identify and eliminate the bottlenecks in the production line. This paper shows a continuous and discrete event simulation of a color manufacturing industry. The constructed model was used to bottleneck analysis to improve the system productivity. To achieve this goal design of experiment was conducted in order to find the combination of factors that have the most significant effect on the process productivity.**

Keywords – **Computer Simulation, Design of Experiment, Manufacturing System, Productivity Improvement**

I. INTRODUCTION

In the manufacturing industry, managers and engineers are seeking to find methods in order to eliminate the common problems in manufacturing systems such as bottlenecks and waiting times. This is because that all of these kinds of problems impose extra cost to the companies. In addition, manufacturing companies are striving to sustain their competitiveness by improving productivity, efficiency and quality of manufacturing industry for instance high throughput and high resource utilization. So it can be acquired by finding ways to deal with various industrial problems which have affected the productivity of manufacturing systems such as high lead time and WIP and etc. [1].This thesis paper concentrates on the application of design of experiment and computer simulation to recognize and to weight the significance of different factors in the production line.

Simulation modeling is an empirical method and used methodology which is selected to analyze system behavior, to construct hypothesizes or theories that explain behavior, and to apply these theories for predicting future activities or effects from changes in operational input [2].In general simulation is applied for different issues such as model the manufacturing systems, process improvement, production control, programming and scheduling and etc. Simulation represents the dynamic real system by using a simulation model that behaves the same condition as the systems itself [3]. There are many advantages of using manufacturing simulation in the manufacturing systems viz saving the money investment, enhance the resource utilization, reducing the process cycle time, increment of throughput [3].

It is obvious that the statistical methods such as Design of Experiment technique can aid researchers recognize the main factors affecting the process improvement and to offer alternatives to deal with the problems.In order to deal with these problems engineers would apply design of experiment to recognize the important factors which have affected system performance. In fact, by using the design of experiment we are able to estimate how changes in input variables influence on the result of response of the experiment [4]. Reference [5] used the design of experiment and simulation study of flexible manufacturing systems in order to evaluate the system performance. Reference [6] applied the design of experiment and computer simulation for estimating the highest number of demand increase in an emergency room in hospital. Reference [7] constructed a discrete event simulation model of sawmill industry in Chile. In order to increase the productivity of wood process a simulation model of manufacturing system was developed for analysing bottlenecks and proposing alternatives that would yield to an improvement in the system productivity.The advantage of the design of experiment along with the computer simulation is mostly a great help to improve the performance of the simulation process, decreasing the trial and error to seek solutions [8]. Reference [9] used the DOE as a framework to optimize the system. A problem of microsatellite system was proposed to shows the productivity of cited framework. In order to solve the optimization problems of satellite system they simulate the system then by using DOE they get a complicatedly designed plan. Finally the effect of each factor on the system performance was analyzed.

Reference[10] reported on tutorial about the experimental design approach in order to apply the simulation runs to reveal the effect of system design factors on simulation output productivity.

II. METHODOLOGY

The main goal of this paper is improving the productivity of manufacturing system by integrating design of experiment and computer simulation. DOE technique is used to develop the experimental plan required for determining the significant factors that affect process productivity and the optimum resource level combination that will result in the best process productivity.

A. Design of Experiment

In order to determine the significance of factors in the production line, a design of experiment was conducted. The factors chosen in this study have been selected in the below table. The variation range or level of factors is indicated in Table 2. As can be seen, each factor has a high (+) and low (-) level.

Table I.FACOTRS AND LEVELS

Factor	level	
	-1	+1
Number of labor	3	5
Number of Big Mixer	1	2
Number of DELPAK Mixer	1	2
Number of Lifter	1	2

B. Calculating the Performance Measurement (Response Variable)

In a manufacturing system the output variables of the simulation modeling are considered as system performance assessed in throughput, cycle time and resource utilization. These measures can be integrated into one performance measure that shows all these values. This measure named process productivity that can be defined as:

$$\text{Process Productivity} = \frac{output}{input} * (100)$$

C. Case Study

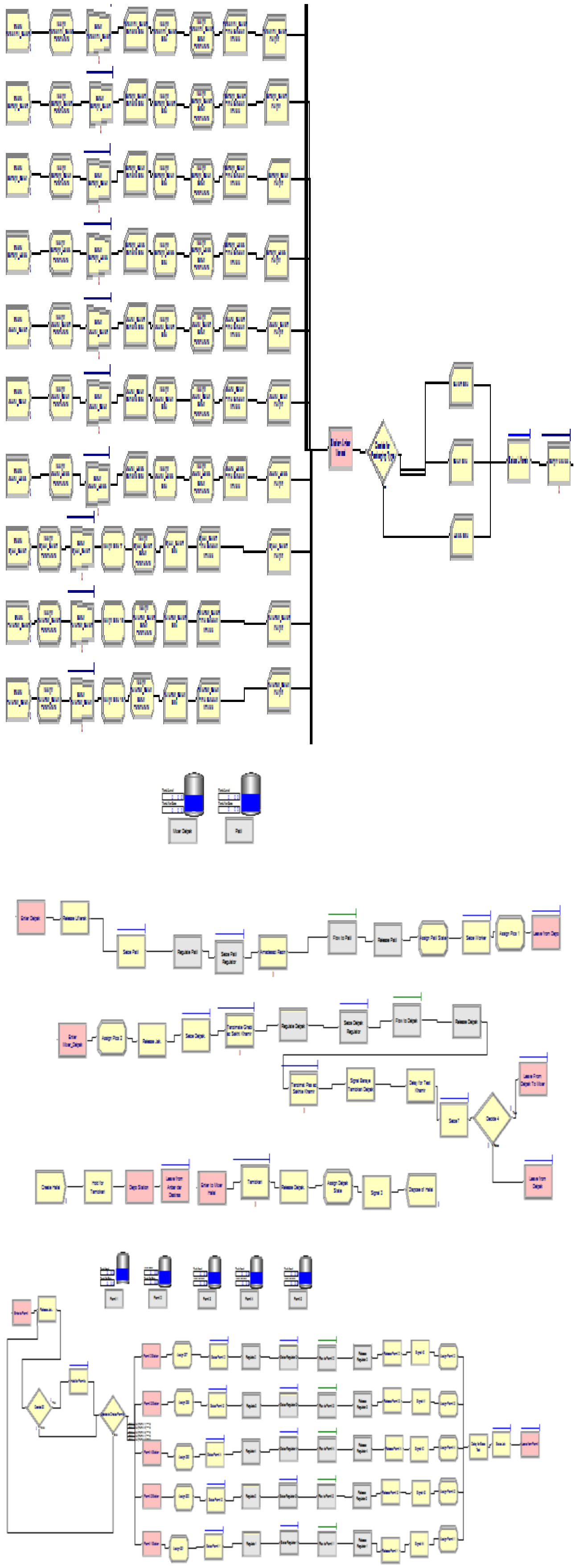
A Color Factory is selected as a case study in this thesis. The production line of this manufacturing system is considered to be simulated and then improve the productivity of production line through implementation of design of experiment. This company is a leading manufacturer of industrial and building paint. Since the products are produced according to the customer order, the layout of the factory is based on job shop system. The production line of different products (such as industrial paint, plastic paint, stone putty, and thinner) is located separately as well as the packaging section and laboratory. The production line of industrial paint has the largest number of machines. Other product lines are plastic paint and its mixer, the production line of stone putty (a small room), and production line of thinner each of which is located in a different and separate position. The laboratory is also located in a separate unit.

D. Production System Description

For production of industrial paints at first, raw material is moved from the inventory part and resin is added to the cauldron and then carried to the mixer by jack pallets. At this level, the paint paste is produced. After that the base paint should be made which can be done by 5 available gloss mills. Note that wood paints skip this level. When the base paint is ready, it is brought to the big mixer and some solvents (according to the type of product) are added to the mixer as well. When the paint is produced, samples are taken for the laboratory tests. If the product does not meet the standards it is mixed again and other necessary material are added to the paint. Finally, when the quality of the product is approved, it is carried to the bascule for weighting and then, moved to the packaging area by the big lift (can carry up to 3 cauldrons). The paints are packaged in three categories: quart, gallon, and barrel. Quart paints are packaged with the fully automated machine, while the other categories are packaged manually or by air cap closer. Each 12 quarts are put together, as well as each 4 gallons, while the barrels skip this level.

D. The Simulation Model

In order to construct the simulation model, simulation software, Arena 13.9 is selected. Fig 1 shows the logic simulation model of production line.



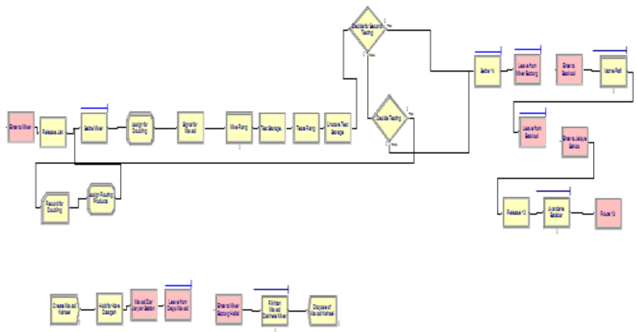


Fig. 1.Simulation model of manufacturing system

III. RESULTS

Table V shows the result of the 16 experiments which have done. Each scenario was simulated for 720 days and 2 replications.

Table VI. Result Of Simulation Experiment

	A	B	C	D	Response	
1	-	-	-	-	0.1826	0.1810
2	+	-	-	-	0.1627	0.1557
3	-	+	-	-	0.1680	0.1670
4	+	+	-	-	0.1505	0.1486
5	-	-	+	-	0.1649	0.1650
6	+	-	+	-	0.1483	0.1491
7	-	+	+	-	0.1519	0.1521
8	+	+	+	-	0.1423	0.1412
9	-	-	-	+	0.1615	0.1601
10	+	-	-	+	0.1540	0.1512
11	-	+	-	+	0.1497	0.1484
12	+	+	-	+	0.1470	0.1476
13	-	-	+	+	0.1501	0.1503
14	+	-	+	+	0.2017	0.2006
15	-	+	+	+	0.1404	0.1398
16	+	+	+	+	0.1829	0.1894

Having done the experiments the significant factors which have influence the manufacturing system productivity are determined. The normal probability of these effects is shown in the Fig. 2. The effects which lie along the line are negligible, whereas the significant effects are far from the line. The significant effects that emerge from this analysis are the main effects of A, B, C, D, and etc.

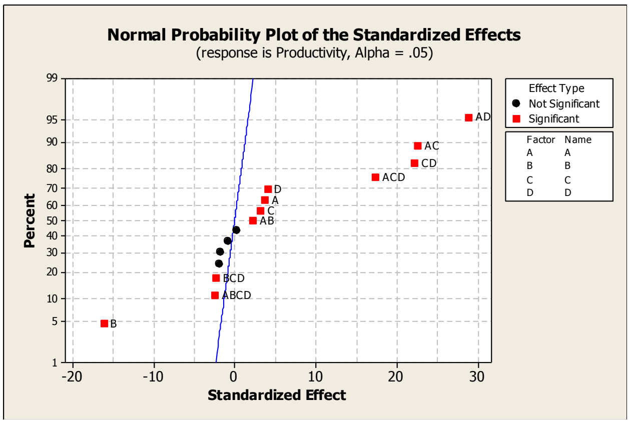


Fig. 2. Normal probability

According to the analysis it is concluded that the factors C and D should be set in the high position.so it is significant to analyze how the factors A and B must be set to maximize the manufacturing system productivity. The Fig. 3 shows that the effect of factors A and B when the factors C and D fixed in high level.

The main effects of A, B, C and D have plotted in Fig.4. The figure illustrate that all of the significant effects except are positive, so if we considered only these important factors, we would run all these two factors at the high level to maximize the flight time. However it should be noted that main effects do not have much meaning when they are also involved in significant interactions.

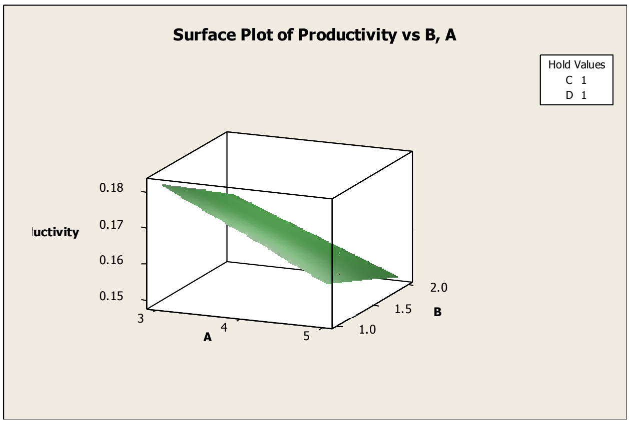


Fig. 3. Response surface plot of factors A and B

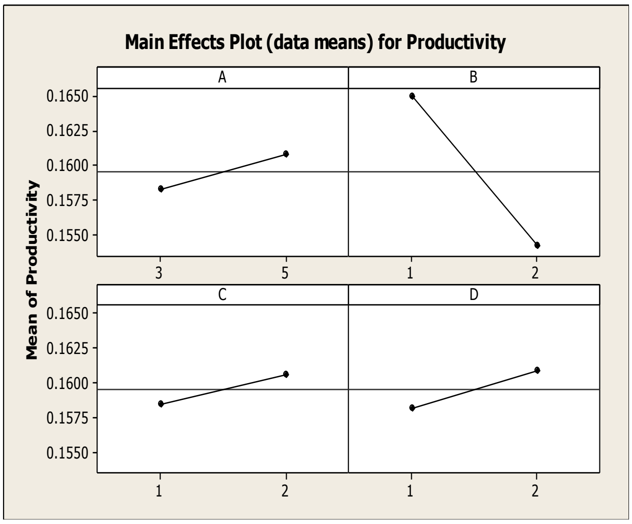


Fig. 4. Main effect plots

The response surface plot shows that in order to maximize the production line productivity it is necessary to set the two factors in a low level, 3 labors and 1 number of Big mixer.as can be seen the plot presents that the maximum productivity is reached after the level of three labor. Fig.5 can describe better this issue.

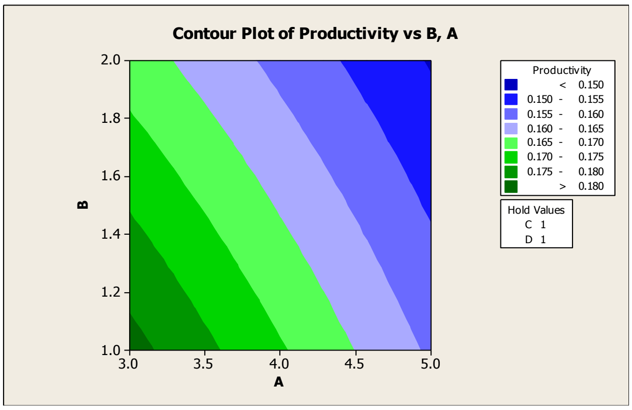


Fig. 5. Contour map

The contour lines show the level of resources needed to reach more than 0.18 productivity improvements. It can be concluded that the number of labors is close to 3.2 people. Therefore, it can be interpreted as a requirement of three full time labors and one part time labor.

V. CONCLUSION

This paper presents how computer simulation and design of experiment can be applied in order to analyze productivity improvement of manufacturing system. The analysis shows that the all of the factors have an significant factors on the productivity of production rate. The result presents that the resources needed to reach high level of productivity. The most significant conclusion of this study is that 3.2 labors are required to reach maximum productivity.

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Closer to Customers

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Most of the arrogant product or service providers design & develop new products & services and force it on the customer using the so called dynamic sales force. The customers are taken for granted: "I have made it for you and you should like it". At times, they do analyse customer preferences using Quality Function Deployment, however, they use the attributes of the products /Services in isolation and not in a comprehensive manner. Conjoint analysis helps the organizations to research customers to know how they make a series of trade-offs. Analysis of these trade-offs reveals the relative importance or utilities of the component attributes. To improve the predictive ability of this analysis, research participants are grouped into similar segments based on objectives, values and/or other factors. The exercise was administered to survey respondents in a rating exercise (where the respondent awards each trade-off scenario a score indicating appeal), and each alternative in the trade-off is the description a real product or service).

Analysis is carried out with some form of modeling using Design of Experiment using signal to noise ratio.

Key words:

Conjoint Analysis, Conjoint Card, Attributes, Tradeoffs, Orthogonal Array, Market Segmentation Signal-To-Noise Ratio, Taguchi Optimisation, Utilities

1. INTRODUCTION

Statistical experimental methods have emerged as a powerful method for analyzing cause and effect relationships among factors for over more than seven decades. Design of Experiments (DoE) methods is used in industry for process improvement and optimization purposes. Orthogonal Arrays (OAs) are very important mathematical arrangements not only because they can be utilised in a number of fields in engineering for the optimisation because Of experiment design. OAs were first introduced by C.R.Rao in a series of papers during the 1940's (K.R.Nair; C.R.Rao (1948), "Confounding in Asymmetrical Factorial Experiment"), Where certain combinatorial arrangements were presented. However, the idea of utilising Such arrangements for the optimisation of engineering processes belongs to Genichi Taguchi (G.Taguchi, "On Robust Technology Development").

Dr. Genichi Taguchi simplified and modified DoE approach, which has been widely adopted in industry. More recently, the power of Taguchi's approach is that it is quite generally applicable to a broad range of experimental situations in which the robustness of process is ensured using the concept of interaction of the controllable factors with un-controllable external & internal variations, called noise.

It has been used in diverse applications as designing the product, processes and services, as well as engineering and science in general While Taguchi methods have been used widely in all sorts of applications, their use in marketing is relatively limited. As a matter of fact, as has been seen in the Review, the literature on the use of experimental method in Marketing, particularly Taguchi's method, is relatively sparse. The conjoint analysis combined with Taguchi methods could provide sound marketing strategy aiding in determination of product features.

This project provided a convenient opportunity to demonstrate the use of Taguchi methods in marketing analysis aiding a new product design.

2. REVIEW

In the late 1940s and early 1950s experimentation received another very large benefit when it began to merge with the quality movement that began taking root in Japan. In 1956 work, Taguchi published the original version of his revolutionary work on experimental method. Although many other Japanese scientists have made many substantial contributions to the field of experimental method, it is Taguchi, more than any other, who has advanced this area of science, and after whom the field has been named as "Taguchi Methods."

3. METHODOLOGY

A Machine Tools designing, manufacturing &marketing company decided to introduce Vertical Turning Machine (VTM). The VTM is used for different machining operations by engineering organizations. The companies could be segregated into different sectors like automotive, tooling, pumps & valves, and machine tools... Before finalising the design of this new product, the company decided to capture the customer requirements and to understand the features that are very critical to customer. So a Cross Functional Team (CFT) is formed under the leadership of Sales function including the representation from Sales, Marketing, Design, Procurement, Manufacturing and Application departments. The objective of this project was to finalise the design features, which are critical to customer, translate these features into Machine characteristics and come out with the design acceptable to most of the customers. If the design is not acceptable to develop variants depending on customer sectors. To get an idea about the market share segment wise along with the preference rating of the design attributes customer the optimization using signal to noise ratio was found to be very useful. The belief was that whole is always better than evaluation of parts in isolation.

In applying this methodology to marketing analysis, it was first necessary to decide which product features for a Vertical Turbine Machine, would be selected to be sampled with the respondents. Product features were determined through exploratory research survey by benchmarking similar products including review of secondary data, a focus group and interviews with

4. APPLICATION OF METHODOLOGY

As per the concept of Full Factorial experiment, the total number of factor-level combinations become 2^{11} ie 2048 experimental combinations. But if the feedback on the most preferred combination, it is very difficult as customer needs to compare the merits and demerits of the each combination against other combinations and give his rating for the combination under consideration. So it was decided to use Orthogonal Array for minimising the total number of combinations.

self described early sporadic /heavy users with two different market segments, namely Automotive part manufacturers and other engineering product manufacturers. Along with those features to be tested, it was also necessary to determine the number to be included in the analysis at one time. In an actual product development application, more features might have been chosen for consumer testing. The team members sat together and listed down all the features for the proposed machine. During this brainstorming, the team has listed around 35 to 40 features. A customer survey using basic Quality Function Deployment technique brought down this huge list of features to top ten characteristics/features which act as a value driver in designing a vertical turning machine. These parameters are prioritised based on the application and delivery requirements which are the basic expectations of the customer for any product. Each of these parameters is pegged at 2 levels for incorporating it in the final design of the product. However, this would have meant that more feature interactions would have to have been investigated. , the set of factors or attributes, shown below in Table 1, was selected for designing the product and subsequently collection of responses from the focussed group of customers.

Table 1

Attribute	Level1	Level2
TurningLength	800mm	600mm
MaximumTurningDiam	850mm	700mm
Power	22/30 KW	18.5/22
GearBox	Without	With
Turret	Electro-	Servo
Rapids	20m/min	12m/min
SpindleRigidity	NNK&Thru	TaperRoll
System	Fanuc	Mitsubish
DeliveryLead-Time	5Months	3Months
SafetyFeature	Fullscale	Limited
Price	High	Low

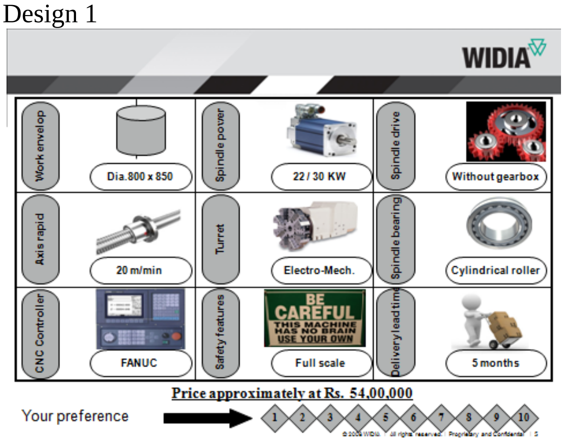
The result of these operations is shown in Table 2 using the special orthogonal array developed by Dr. Taguchi. Further, in order to facilitate assignment of the above features to the orthogonal array, factor identification, along with column identifications for each factor, was made for each of the above features as shown in Table 2.

Each row of the design table indicates a product and offer design, which coceptually was done by product designer. So theere were 12 Designs of Product. Table 3 shows the basic design no 1 pictorially, which was outlined in a structured 3D design layout.

Table 2

Turning Length	Maximum Turning Diameter	Power	Gear Box	Turret	Rapids	Spindle Rigidity	System	Delivery Lead-Time	Safety Feature	Price
800mm	850mm	22/30KW	Without	Electro-mechanical	20m/min	NNK&Thrust-More	Fanuc	5Months	Fullscale	High
800mm	850mm	22/30KW	Without	Electro-mechanical	12m/min	TaperRoller-Les	Mitsubishi	3Months	Limited	Low
800mm	850mm	18.5/22KW	With	Servo	20m/min	NNK&Thrust-More	Fanuc	3Months	Limited	Low
800mm	700mm	22/30KW	With	Servo	20m/min	TaperRoller-Les	Mitsubishi	5Months	Fullscale	Low
800mm	700mm	18.5/22KW	Without	Servo	12m/min	NNK&Thrust-More	Mitsubishi	5Months	Limited	High
800mm	700mm	18.5/22KW	With	Electro-mechanical	12m/min	TaperRoller-Les	Fanuc	3Months	Fullscale	High
600mm	850mm	18.5/22KW	With	Electro-mechanical	20m/min	TaperRoller-Les	Mitsubishi	5Months	Limited	High
600mm	850mm	18.5/22KW	Without	Servo	12m/min	TaperRoller-Les	Fanuc	5Months	Fullscale	Low
600mm	850mm	22/30KW	With	Servo	12m/min	NNK&Thrust-More	Mitsubishi	3Months	Fullscale	High
600mm	700mm	18.5/22KW	Without	Electro-mechanical	20m/min	NNK&Thrust-More	Mitsubishi	3Months	Fullscale	Low
600mm	700mm	22/30KW	With	Electro-mechanical	12m/min	NNK&Thrust-More	Fanuc	5Months	Limited	Low
600mm	700mm	22/30KW	Without	Servo	20m/min	TaperRoller-Les	Fanuc	3Months	Limited	High

Design 1



5. RESPONSE

Since the Vertical Turning Machine is used in Automobile as well as in General engineering sectors, we have to collect the customer choice from both the sectors. 308 customers were the mixture of Automobile as well as General Engineering. The representative from Sales Team conducted this survey. The Sales Person approached the customer individually and explained the whole concept of the Design.

Convincing of customer to give the feedback regarding his choice was a difficult task, as unless customer is convinced about how this study would benefit him, he might not give the right feedback. In the absence of right feedback from customer, the whole purpose of Conjoint Survey gets defeated and the features that are provided in the design of final machine may not serve the customer and there is high amount of risk that the new product may become failure. By explaining about the features and creating the awareness about the VTM as well the conjoint analysis, the customer is convinced that he has been considered and involved in designing new product. With this, getting right feedback became an easy task. Each customer is handed over the booklet of 12 conjoint cards and is asked to rate each choice from 1 to 10 scales, 10 being most preferred choice and 1 being the least preferred choice.

6. ANALYSIS OF RESULTS

As might have been expected at the onset of the analysis, the six features to be included in a final design and marketing strategy for the VTL Machine could be classified as System, Power, Price, Rapids, Delivery Lead-Time, Spindle

Rigidity proved to receive the strongest response from thecustomers. Also, features like Turning Length, Max. Turning Diameter, Type of Gear Box, Turret, and Safety features, received weak participant response, and were not therefore significant at the 95% level of significance. Although it was anticipated initially some of these features would be highly significant, it was retained from the possible cost reduction purpose.

The result of the analysis is shown in Table 4, and the corresponding graph.

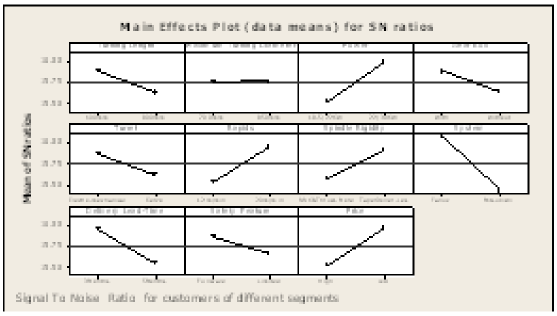
Table 4: Utility of The attributes

Response Table for Signal to Noise Ratios (For Avg effect two categories): Larger is better

Alternatives	*Length*	*Maximum Turning Diameter*	*Power*	*Gear Box*	*Turret*	*Rapids*
Delta	*0.25*	*0.01*	*0.46*	*0.23*	*0.25*	*0.42*
Utility	*7*	*11*	*2*	*9*	*8*	*4*
Significant	*No*	*No*	*Yes*	*No*	*No*	*Yes*

Alternatives	*Spindle Rigidity*	*System*	*Lead-Time*	*Safety Feature*	*Price*
Delta	*0.33*	*0.63*	*0.40*	*0.20*	*0.44*
Utility	*6*	*1*	*5*	*10*	*3*
Significant	Yes	Yes	Yes	No	Yes

Graph 1



7. CONCLUSIONS

The purpose of this project was to develop a new machine as per customer preferences, segment wise as a method using Taguchi methods of experimental analysis to determine which of several possible features might best be made available in a VTL Machine Launch in order to maximize market share for the product. The method advanced in this paper enables a firm contemplating a new product not only to identify those features that should be included in the product design, but also to measure the strength of he preference for those features. Thus, this approach affords the very important advantage of including or excluding features in the product design based upon computing the actual strength of user preference for one or another of the possible features.

Finally, in this phase, Taguchi methods might be used to optimize the measure of each feature as a function of customer preferences. This approach, it would be possible to estimate profits as a function of feature measures. Thus, although relatively new and little used, there is a very powerful and useful ynergism to be realized through the use of Taguchi Methods in Marketing. It is needless to say that the optimised VTL Machine design coupled with marketing strategy to-day enjoys about 45% market share in the focussed market segment.

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