CORRUGATED BOX PRODUCTION PROCESS OPTIMIZATION USING DIMENSIONAL ANALYSIS AND RESPONSE SURFACE METHODOLOGY

Sachin G Mahakalkar[1], Dr. Vivek H Tatwawadi[2], Jayant P Giri[3], Dr. J. P. Modak[4]

[1]Ph.D Research Scholar & Associate Professor Department of Mechanical Engineering YCCE (an autonomous institute), RTMNU Nagpur University (M.S) India 440011 **sachu_gm@yahoo.com**

[2] Principal & Professor DBACER, Wanadongri Hingna MIDC Road Nagpur (M.S) India 440011 **tatwawadi@yahoo.com**

[3]Ph.D Research Scholar & Assistant Professor Department of Mechanical Engineering YCCE (an autonomous institute), RTMNU Nagpur University (M.S) India 440011 **jayantpgiri@gmail.com**

[4] Dean (R&D), PCOE, Nagpur,(M.S),India,440019 **jpmodak@gmail.com**

Abstract

Response surface methodology (RSM) is a statistical method useful in the modeling and analysis of problems in which the response variable receives the influence of several independent variables, in order to determine which are the conditions under which should operate these variables to optimize a corrugated box production process. The purpose of this research is to create response surface models through regression on experimental data which has been reduced using DA to obtain optimal processing conditions. Studies carried out for corrugated sheet box manufacturing industries having man machine system revealed the contribution of many independent parameters on cycle time. The independent parameters include anthropometric data of workers, personal data, machine specification, workplace parameters, product specification, environmental conditions and mechanical properties of corrugated sheet. Their effect on response parameter cycle time is totally unknown. The developed model was simulated and optimized with the aid of MATLAB R2011a and the computed value for cycle time is obtained and compared with experimental value. The results obtained showed that the correlation R, adjusted R^2 and RMS error were valid.

Index Terms - *Response Surface Methodology (RSM), Dimensional Analysis (DA), Independent Variables, Response Variable, Correlations, Root Mean Square Error (RMS) and MATLAB*

---***---

1. INTRODUCTION

Cardboard packaging is one of the most widely used forms of packaging. The corrugated cardboard is stiff, strong and light in weight material made up of layers of brown craft paper. These brown craft paper rolls are transported to a corrugation machine where this paper gets crimped and glued to from corrugated cardboard called as single face corrugated board and then this single face corrugated board is cut according required dimension on the cutting machine. According to requirement by adding another corrugating medium and a third flat printed liner creates a double wall corrugated board or triple wall corrugated boards on gluing or bonding machine called as 3ply 5ply and 7ply.



Reel Inventory WS1 Printing WS2Corrugation



WS3 Gluing WS4 Creasing WS5 Creasing


WS6 Slotting WS7 Stitching

Figure-1: Snap Shot of Manufacturing Process of Corrugated Sheet Box

Then these cardboards are transferred to creasing and cutting machine where extra material is removed and creasing operation is performed (i.e., from where the box get folded). The next operation is slotting operation where the strip plate is slotted for stitching and finally with stitching operation corrugated box is manufactured. A in A. Sonin, M. E. Hossain introduces a generalization of dimensional analysis and its corollary, the Π-theorem, to the class of problems in which some of the quantities that define the problem have fixed values in all the cases that are of interest. The procedure can reduce the number of dimensionless similarity variables beyond the prediction of Buckingham's theorem. The generalized Π-theorem tells when and how large a reduction is attainable. Dimensional analysis is a method for reducing complex physical problems to their simplest forms prior to quantitative analysis or experimental investigation. Its use in science and engineering is ubiquitous. Applications are many, including astrophysics, electromagnetic theory, radiation, aerodynamics, ship design, heat and mass transfer, mechanics of elastic and plastic structures, explosions, chemical reactions, processing and Waterjet. G. A. Vignaux et al., Giovanni Miragliotta suggested Dimensional Analysis can make a contribution to model formation when some of the measurements in the problem are of physical factors. The analysis constructs a set of independent dimensionless factors that should be used as the variables of the regression in place of the original measurements. There are fewer of these than the originals and they often have a more appropriate interpretation. The technique is described briefly and its proposed role in regression discussed and illustrated with examples. We conclude that Dimensional Analysis can be effective in the preliminary stages of regression analysis when developing formulations involving continuous variables with several dimensions. Operations Research involves constructing models of human organizational systems in order to help in making the best decisions possible. DA can be applied to Operations Management (OM) topics and which benefits it can bring to researchers in this area. Stemming from this analysis, we applied the pi-theorem to the design of a Flexible Manufacturing System. A complex problem, requiring 13 dimensional quantities to be expressed, is first studied via simulation; then DA is applied, reducing the number of variables to 9 dimensionless ratios. The reduced problem has a suitable size to be analytically explored and a regression model is formulated which, compared with the simulation study, offers the same precision in analyzing the FMS behaviour, being more compact and powerful. This application shows the potential of DA in OM research, and will hopefully draw the attention of researches to this powerful, but unfamiliar and therefore neglected, methodology. (Montgomery, D.C, Jack P. C. Kleijnen) RSM is a collection of mathematical and statistical techniques used to determine the optimal levels of the independent variables of a production process, which involves estimating a regression model of first order by the method of least squares, with the coefficients of this model is set search direction by MMSD, subsequently, the step size on the ascent route is chosen until there is no further increase in the response, this method stops. (Box and Wilson in 1951) In statistics, response surface methodology (RSM) explores the relationships between several explanatory_variables and one or more response_variables. The main idea of RSM is to use a sequence of designed_experiments to obtain an optimal response suggest using a second-degree polynomial model to do this. They acknowledge that this model is only an approximation, but use it because such a model is easy to estimate and apply, even when little is known about the process. (Myers, R.H., Montgomery, D.C., Anderson and Box)Then we fit a new linear regression model, a new path of upward slope is determined and the procedure continues until it fits the regression model of first order. Finally, we start in the region where it was not possible to adjust the regression model of first order, a more detailed design is posed, as the central composite design (CCD), which is the kind of classic design to fit models of second order and find the optimal values of the independent variables analyzed, using methods of differential calculus. (A.K. Dubey and V. Yadava, S. Raissi and R. E. Farsani) Response surface methodology is a collection of statistical and mathematical methods that are useful for the modeling and analyzing engineering problems. The main objective is to optimize the response surface that is influenced by various process parameters. Response surface methodology also quantifies the relationship between the controllable input parameters and the obtained response surfaces. In this work, there are 43 independent variables and one response variable. These 43 independent variables are further reduced to 7 independent Pi terms using Dimension Analysis. The optimization of a cycle time as response variable for the corrugated sheet box manufacturing process is carried out with the aid of Response Surface Methodology and MATLAB 2011a taking the anthropometric data of operators, personal factors of an operator, workstation machine specification, workplace parameters, specification of the products, environmental conditions and mechanical properties of corrugated sheet boxes as the independent variables and the cycle time present at the bottom segment of the column as the dependent variable. The goal is to optimize the response variable cycle time, it is assumed that the independent variables are continuous and controllable by experiments with negligible errors. It is required to find a suitable approximation for the true functional relationship between independent variables and the response surface. (Christian Gogu, Raphael Haftka, Satish Bapanapalli, Bhavani Sankar) A response surface approximation (RSA) of this temperature was needed in order to reduce optimization computational time. The finite element model used to evaluate the maximum temperature at the design of experiment points involved a total of 15 parameters of interest for the design: 9 thermal material properties and 6 geometric parameters of the ITPS model. In order to reduce the dimensionality of the response surface approximation, dimensional analysis was utilized. A small number of assumptions simplified the equations of the transient thermal problem allowing easy nondimensionalization using classical techniques. The nondimensional equations together with a global sensitivity analysis showed that the maximum temperature mainly depends on only two nondimensional parameters which were selected to be the design variables for the RSA. It is important to note that the RSA was still constructed using the accurate finite element model which does not employ any of the simplifying assumptions used to determine the nondimensional parameters. The two variable RSA was checked for its accuracy in terms of geometric parameters and material properties variables at 855 additional test points using the finite element model. The error in the RSA was not due to the quality of the fit but mainly due to the reduction from 15 to only two variables.

2. REDUCTION OF INDEPENDENT VARIABLES USING DA

There are several quite simple ways in which a given test can be made compact in operating plan without loss in generality or control. The best known and the most powerful of these is dimensional analysis. In the past dimensional analysis was primarily used as an experimental tool whereby several experimental variables could be combined to form one. The field of fluid mechanics and heat transfer were greatly benefited from the application of this tool. Almost every major experiment in this area was planned with its help. Using this principle modern experiments can substantially improve their working techniques and be made shorter requiring less time without loss of control. Deducing the dimensional equation for a phenomenon reduces the number of independent variables in the experiments. The exact mathematical form of this dimensional equation is the targeted model. This is achieved by applying Buckingham's π theorem (Hilbert, 1961).When we apply this theorem to a system involving n independent variables, (n minus number of primary dimensions viz. L, M, T, and π) i.e. (n-4) numbers of π terms are formed. When n is large, even by applying this theorem number of π terms will not be reduced significantly than number of all independent variables. Thus much reduction in number of variables is not achieved. It is evident that, if we take the product of the terms it will also be dimensionless number and hence a π term. This property is used to achieve further reduction of the number of variables. Dimensional analysis is used to reduce the variables and following Pi terms were evolved out of it. David Randall, Mark C. Albrecht et al. suggested nondimensionalization is the first step of a scale analysis. The second step is to choose the numerical values of the scales. They are chosen so that the nondimensional dependent variables are of order one, for the problem of interest. Having settled on a reasonably short list of dimensional parameters, we then nondimensionalize, and the Buckingham Pi Theorem tells us that this will yield an even shorter list of nondimensional parameters. Dimensional reasoning is very common in atmospheric science and engineering. It is used in several different ways. Mass, length, time, and temperature suffice to describe the physical quantities used in most atmospheric science work. The Buckingham Pi Theorem tells us that a physical problem can be described most concisely if it is expressed using only nondimensional combinations. Dimensional analysis can be used to identify such combinations. Two powerful advantages associated with the method, relative to standard design of experiment (DOE) approaches are: (1) a priori dimension reduction, (2) scalability of results. The latter advantage permits the experimenter to effectively extrapolate results to similar experimental systems of differing scale. Unfortunately, DA experiments are underutilized because very few statisticians are familiar with them. In this paper, we first provide an overview of DA and give basic recommendations for designing DA experiments. Next we consider various risks associated with the DA approach, the foremost among them is the possibility that the analyst might omit a key explanatory variable, leading to an incorrect DA model. When this happens, the DA model will fail and experimentation will be largely wasted. To protect against this possibility, we develop a robust-DA design approach that combines the best of the standard empirical DOE approach with our suggested design strategy.

Table-1: Independent and Dependent Variables

Variables	Symbol
Arm span	X1
Foot breadth	X2
Height	X3
Arm reach	X4
Qualification grade	X5
BMI prime	X6
Age	X7
Experience	X8
Power HP	X9
Stroke/Seconds	X10
Age of Machine	X11
Machine Down Time	X12
Roller Speed	X13
Production rate of Machine	X14
Machine Width	X15
Weight of Machine	X16
Height of stool	X17
Height of work table	X18
Spatial distance between centroid of stool top and work table	X19
Area of tabletop	X20

Spatial distance between centroid of stool top and WIP table	X21
Thickness	X22
Length	X23
Breadth	X24
Part Weight	X25
Mc_criticality	X26
Volume	X27
Bursting Strength	X28
Bursting Factor	X29
Illumination sight range (Average)	X30
Noise level with Operation	X31
Dry bulb temperature	X32
Illumination at work table	X33
Noise level without Operation	X34
Wet bulb temperature	X35
Caliper	X36
Puncture Resistance Test	X37
Edge Crushing Test	X38
Flat Crushing Test	X39
Cobb	X40
Moisture (%)	X41
Box Compression Test Peak Load in Kg	X42
Box Compression Test Peak Load / Perimeter	X43
Cycle Time	Y1

Table-2: Pi Term Formulation for Independent and Dependent Variables using DA

Anthropomorphic Data	$\pi1 = (As \times Fb) \div (Ht \times Ar)$ In terms of MLT Indices $\Pi1 = \frac{(M^0L^1T^0 \ x M^0L^1T^0)}{(M^0L^1T^0 \ x M^0L^1T^0)}$
Personal factors of an Operator	$\pi2 = (Qgr \times BMI\ prime \times Ag) \div (Exp)$ In terms of MLT Indices $\Pi2 = \frac{(M^0L^0T^0 \ x M^0L^0T^0 \ x M^0L^0T^1)}{(M^0L^0T^1)}$
Machine Specification	$\pi3 = (P \times P_{rate}\ ofMc \times Aom \times Mc_{dt}) \div (Wt \times Sps \times Mc_{Wth} \times rps)$ In terms of MLT Indices $\Pi3 = \frac{(M^1L^2T^3 x M^0L^0T^{-1} \ x M^0L^0T^{-1} \ x M^0L^0T^1)}{(M^1L^0T^0 \ x M^0L^1T^1 \ x M^0L^1T^0 \ x M^0L^0T^1)}$
Workplace Parameters	$\pi4 = (Hos \times Htw \times Sd1) \div (Areattop \times Sd2)$ In terms of MLT Indices $\Pi4 = \frac{(M^0L^1T^0 \ x M^0L^1T^0 \ x M^0L^1T^0)}{(M^0L^2T^0 \ x M^0L^1T^0)}$
Specification of the Product	$\pi5 = (Bs \times Vol \times Bf \times t) \div (Part_{Wt} \times Mc_{criti} \times B \times L)$ In terms of MLT Indices $\Pi5 = \frac{(M^1L^{-2}T^0 x M^0L^3T^0 \ x M^0L^0T^0 x M^0L^1T^0)}{(M^1L^0T^0 \ x M^0L^0T^0 \ x M^0L^1T^0 \ x M^0L^1T^0)}$
Environmental Condition	$\pi6 = (Isr \times dBopr \times DBT) \div (lwt \times dB \times WBT)$ In terms of MLT Indices $\Pi6 = \frac{(M^1L^3T^{-1} \ x M^0L^0T^0 \ x M^0L^0T^0K^1)}{(M^1L^3T^{-1} \ x M^0L^0T^0 \ x M^0L^0T^0K^1)}$
Mechanical Properties of a Corrugated Box	$\pi7 = (Cal \times ECT \times FCT \times Mois \times PL) \div (PRT \times Cob \times PLP)$ In terms of MLT Indices $\Pi7 = \frac{(M^0L^1T^0 x M^1L^{-1}T^0 x M^1L^{-2}T^0 x M^0L^0T^0 \ x M^1L^0T^0)}{(M^1L^1T^0 \ x M^1L^{-2}T^0 \ x M^1L^{-1}T^0)}$
Cycle Time	$\pi8 = (cytime) \div (m/coptime)$ In terms of MLT Indices $\Pi8 = \frac{(M^0L^0T^1)}{(M^0L^0T^1)}$

3. RESPONSE SURFACE METHODOLOGY (*RSM*)

(Sundaram R.M) *RSM* is a collection of mathematical and statistical techniques for empirical model building by careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response. Originally, *RSM* was developed to model experimental responses and then migrated into the modeling of numerical experiments. The difference is in the type of error generated by the response. In physical experiments, inaccuracy can be due, for example, to measurement errors while, in computer experiments, numerical noise is a result of incomplete convergence of iterative processes, round-off errors or the discrete representation of continuous physical phenomena. In RSM, the errors are assumed to be random. The *RSM* is practical, economical and relatively easy for use and it was used by lot of researchers for modeling machining processes.

4. MODEL FORMULATION

A mathematical model, relating the relationships among the process dependent variable and the independent variables in a second-order equation is developed. The regression analysis was performed to estimate the response function as a second order polynomial.

$$Y_k = \beta_o + \sum_{i=1}^{n} \beta i \pi i + \sum_{i=1}^{n} \beta ii \pi i^2 + \sum_{i=1}^{n=1} \sum_{j=i+1}^{n} \beta ij \pi i \, \pi j + e \quad (1)$$

Where $Y_k = \pi8$ is the predicted response, k=cycle time, β_0, βi, βii, βij are constant coefficients estimated from regression and e is random error. They represent the linear, quadratic and interactive effects of πi, πi^2, $\pi i \pi j$ on response variable $\pi8$. Optimizing the response variable Y_k, it is assumed that the independent variables are continuous and controllable by the experimenter with negligible error. The response or the dependent variable is assumed to be a random variable. In corrugated sheet box manufacturing process, it is necessary to find a suitable combination of Pi terms X (Product of π2, π3, π5 pi term) and Y (Product of π1, π4, π6 and π7). The observed Response Z as a function of the X and Y can be written as

$$Y_k = f(X; Y) + e \qquad (2)$$

The quality of fit of the second order equation was expressed by the coefficient of determination R^2. Usually a best fit polynomial is fitted. The parameters of the polynomials are estimated by the method of least squares. A statistical software package Matlab2011a is used for regression analysis of the data obtained and to estimate the coefficient of the regression equation. The equations were validated by the statistical tests called the ANOVA analysis. Design-based experimental data were matched according to the second order polynomial equation. The independent variables were fitted to the second order model equation and examined for the goodness of fit. The quality of fit of the second order equation was expressed by the coefficient of determination R^2, and its statistical significance was determined by *F*-test. The significance of each term in the equation is to estimate the goodness of fit in each case.

The proposed relationship between the cycle time responses and independent variables for five products can be represented by the following:

Model 1 (*RSM1OCT*)

Linear model Polynomial21:

$$f(x, y) = p00 + p10*x + p01*y + p20*x^2 + p11*x*y \qquad (3)$$

Where *x* is normalized by mean 2.743 and std 2.361

And where *y* is normalized by mean 3.329 and std 8.045

Table-3: Coefficients obtained for Model RSM1OCT

Coefficients (with 95% confidence bounds)	
p00	2.238 (2.223, 2.253)
p10	-0.2215 (-0.2455, -0.1976)
p01	-0.2309 (-0.2481, -0.2137)
p20	0.09086 (0.08069, 0.101)
p11	0.03548 (0.023, 0.04796)

Putting the values of coefficients in equation 3, we get

$$Y_k = \pi 8 = 2.238 - 0.2215*(\pi 2*\pi 3*\pi 5) - 0.2309*(\pi 1*\pi 4*\pi 6*\pi 7) + 0.09086*(\pi 2*\pi 3*\pi 5)^2 + 0.03548*(\pi 2*\pi 3*\pi 5)*(\pi 1*\pi 4*\pi 6*\pi 7) \qquad (4)$$

Table-4: Result Analysis Model RSM1OCT

Analysis of RSM Model and Goodness of fit	
SSE	1.896
R-square	0.9595
Adjusted R-square	0.9591
RMSE	0.06759

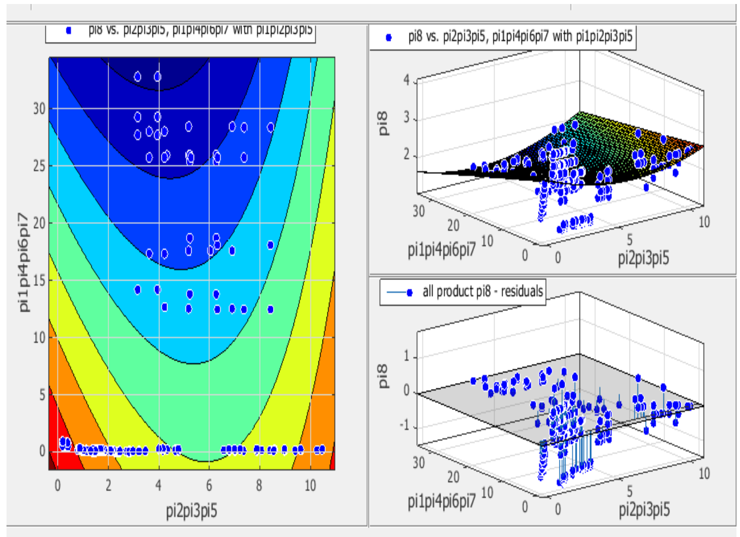


Figure-2: Showing Contour Plot, 3D Response Surface Plot and Residual Plot showing interactive effect of pi2pi3pi5 along X, pi1pi4pi6pi7 along Y on pi8(Response Variable) along Z for Model RSM1OCT.

Model 2 (*RSM11CT*)

Linear model Polynomial23:

$$f(x,y) = p00 + p10*x + p01*y + p20*x^2 + p11*x*y + p02*y^2 + p21*x^2*y + p12*x*y^2 + p03*y^3 \qquad (5)$$

Where *x* is normalized by mean 3.192 and std 7.763

And where *y* is normalized by mean 3.137 and std 2.53

Table-5: Coefficients obtained for Model RSM11CT

Coefficients (with 95% confidence bounds)	
p00	2.25 (2.119, 2.381)
p10	-0.04913 (-0.2612, 0.1629)
p01	-0.6638 (-0.9071, -0.4205)
p20	-0.03283(-0.1038, 0.0381)
p11	0.1666 (-0.07073, 0.4039)
P02	-0.3794 (-0.5212, -0.2376)
P21	0.04074 (-0.001487, 0.08296)
P12	-0.131 (-0.2454, -0.01664)
P03	0.3787 (0.2489, 0.5085)

Putting the values of coefficients in equation 5, we get

$$Y_k = \pi 8 = 2.25 - 0.04913*(\pi 2*\pi 3*\pi 5) - .6638*(\pi 1*\pi 4*\pi 6*\pi 7) - 0.03283*(\pi 2*\pi 3*\pi 5)^2 + 0.1666*(\pi 2*\pi 3*\pi 5)*(\pi 1*\pi 4*\pi 6*\pi 7) - 0.3794*(\pi 1*\pi 4*\pi 6*\pi 7)^2 + 0.04074*(\pi 2*\pi 3*\pi 5)^2*(\pi 1*\pi 4*\pi 6*\pi 7) - 0.131*(\pi 2*\pi 3*\pi 5)*(\pi 1*\pi 4*\pi 6*\pi 7)^2 + 0.3787*(\pi 1*\pi 4*\pi 6*\pi 7)^3 \qquad (6)$$

Table-6: Result Analysis Model RSM11CT

Analysis of RSM Model and Goodness of fit	
SSE	1.542
R-square	0.8266

Adjusted R-square	0.8081
RMSE	0.1434

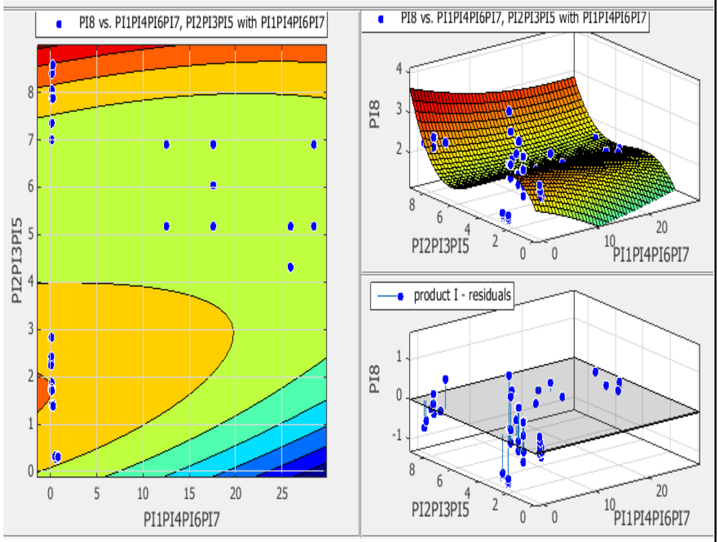


Figure-3: Showing Contour Plot, 3D Response Surface Plot and Residual Plot showing interactive effect of pi2pi3pi5 along X, pi1pi4pi6pi7 along Y on pi8(Response Variable) along Z for Model RSM11CT.

Model 3 (*RSM12CT*)

Linear model Polynomial22:

$f(x,y) = p00 + p10*x + p01*y + p20*x^2 + p11*x*y + p02*y^2$ (7)

Where x is normalized by mean 3.164 and std 7.681

And where y is normalized by mean 2.004 and std 1.58

Table-7: Coefficients obtained for Model RSM12CT

Coefficients (with 95% confidence bounds)	
p00	2.921 (2.789, 3.053)
p10	-0.9933 (-1.137, -0.8498)
p01	0.4021 (0.3005, 0.5036)
p20	0.1217 (0.09705, 0.1464)
p11	0.2438 (0.1739, 0.3136)
P02	-0.5708 (-0.6753, -0.4662)

Putting the values of coefficients in equation 7, we get

$Y_k = \pi 8 = 2.921 - 0.9933*(\pi 2*\pi 3*\pi 5) +.4021*(\pi 1*\pi 4*\pi 6*\pi 7) + 0.1217*(\pi 2*\pi 3*\pi 5)^2 + 0.2438*(\pi 2*\pi 3*\pi 5)*(\pi 1*\pi 4*\pi 6*\pi 7) - 0.5708*(\pi 1*\pi 4*\pi 6*\pi 7)^2$ (8)

Table-8: Result Analysis Model RSM12CT

Analysis of RSM Model and Goodness of fit	
SSE	1.54
R-square	0.8969
Adjusted R-square	0.8903
RMSE	0.1405

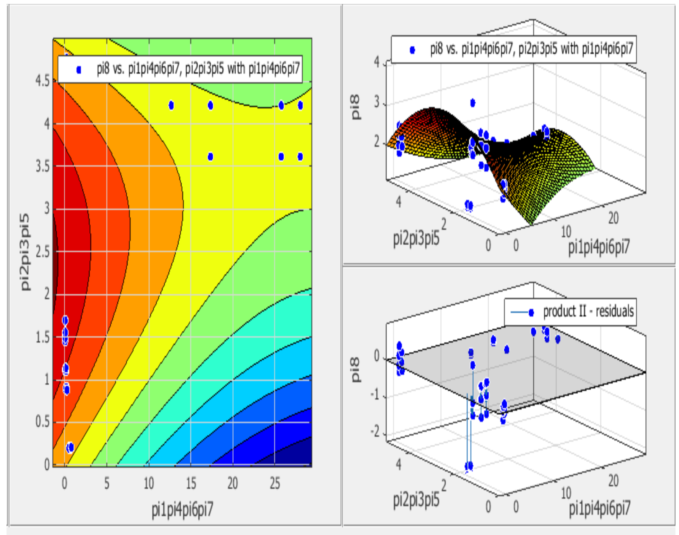


Figure-4: Showing Contour Plot, 3D Response Surface Plot and Residual Plot showing interactive effect of pi2pi3pi5 along X, pi1pi4pi6pi7 along Y on pi8(Response Variable) along Z for Model RSM12CT.

Model 4(*RSM13CT*)

Linear model Polynomial23:

$f(x,y) = p00 + p10*x + p01*y + p20*x^2 + p11*x*y + p02*y^2 + p21*x^2*y + p12*x*y^2 + p03*y^3$ (9)

Where x is normalized by mean 3.167 and std 7.56

And where y is normalized by mean 2.963 and std 2.236

Table-9: Coefficients obtained for Model RSM13CT

Coefficients (with 95% confidence bounds)	
p00	2.289 (1.34, 3.239)
p10	0.0272 (-2.046, 2.1)
p01	-0.674 (-2.099, 0.7514)
p20	-0.1173 (-0.2795, 0.04488)
p11	0.2452 (-3.15, 3.64)
P02	-0.4285 (-0.7321, -0.125)
P21	0.116 (0.01933, 0.2127)
P12	-0.2691 (-1.663, 1.125)
P03	0.4514 (0.1923, 0.7104)

Putting the values of coefficients in equation 9, we get

$Y_k = \pi 8 = 2.289 + 0.0272*(\pi 2*\pi 3*\pi 5) - 0.674*(\pi 1*\pi 4*\pi 6*\pi 7) - 0.1173*(\pi 2*\pi 3*\pi 5)^2 + 0.2452*(\pi 2*\pi 3*\pi 5)*(\pi 1*\pi 4*\pi 6*\pi 7) - 0.4285*(\pi 1*\pi 4*\pi 6*\pi 7)^2 + 0.116*(\pi 2*\pi 3*\pi 5)^2 *(\pi 1*\pi 4*\pi 6*\pi 7) - 0.2691*(\pi 2*\pi 3*\pi 5)*(\pi 1*\pi 4*\pi 6*\pi 7)^2 + 0.4514*(\pi 1*\pi 4*\pi 6*\pi 7)^3$ (10)

Table-10: Result Analysis Model RSM13CT

Analysis of RSM Model and Goodness of fit	
SSE	2.116
R-square	0.695

Adjusted R-square	0.6625
RMSE	0.168

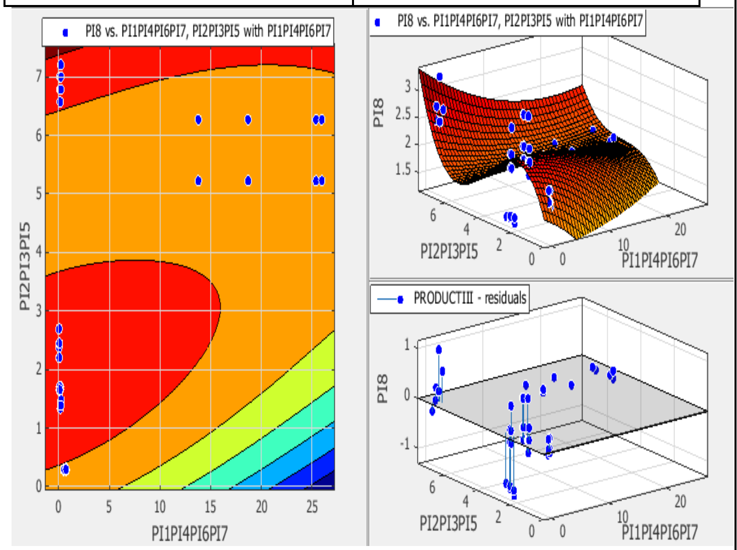


Figure-5: Showing Contour Plot, 3D Response Surface Plot and Residual Plot showing interactive effect of pi2pi3pi5 along X, pi1pi4pi6pi7 along Y on pi8(Response Variable) along Z for Model RSM13CT.

Model 5(*RSM14CT*)

Linear model Polynomial21:

$f(x,y) = p00 + p10*x + p01*y + p20*x^2 + p11*x*y$ (11)

Where x is normalized by mean 3.197 and std 7.764

And where y is normalized by mean 3.821 and std 3.07

Table-11: Coefficients obtained for Model RSM14CT

Coefficients (with 95% confidence bounds)	
p00	2.091 (2.056, 2.126)
p10	-0.5197 (-0.5661, -0.4733)
p01	0.07856 (0.04221, 0.1149)
p20	0.1304 (0.1165, 0.1442)
p11	-0.0242 (-0.04362, -0.004789)

Putting the values of coefficients in equation 11, we get

$Y_k = \pi 8 = 2.091 - .5197*(\pi 2*\pi 3*\pi 5) + 0.07856*(\pi 1*\pi 4*\pi 6*\pi 7) + 0.1304*(\pi 2*\pi 3*\pi 5)^2 - 0.0242*(\pi 2*\pi 3*\pi 5)*(\pi 1*\pi 4*\pi 6*\pi 7)$
(12)

Table-12: Result Analysis Model RSM14CT

Analysis of RSM Model and Goodness of fit	
SSE	0.6404
R-square	0.9204
Adjusted R-square	0.9164
RMSE	0.09004

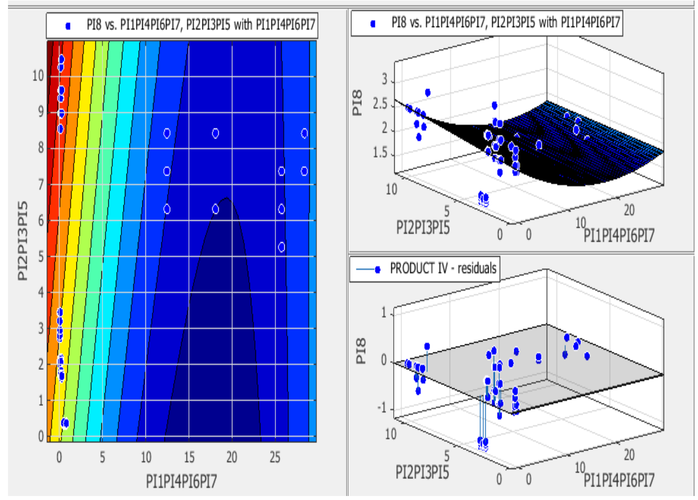


Figure-6: Showing Contour Plot, 3D Response Surface Plot and Residual Plot showing interactive effect of pi2pi3pi5 along X, pi1pi4pi6pi7 along Y on pi8(Response Variable) along Z for Model RSM14CT.

Model 6 (*RSM15CT*)

Linear model Polynomial22:

$f(x,y) = p00 + p10*x + p01*y + p20*x^2 + p11*x*y + p02*y^2$ (13)

Table- 13: Coefficients obtained for Model RSM15CT

Coefficients (with 95% confidence bounds)	
p00	1.777 (1.677, 1.876)
p10	-0.1935 (-0.2126, -0.1744)
p01	1.344 (1.167, 1.521)
p20	0.001609 (0.001328, 0.001889)
p11	0.03109 (0.02682, 0.03537)
P02	-0.3173 (-0.357, -0.2775)

Putting the values of coefficients in equation 13, we get

$Y_k = \pi 8 = 1.777 - 0.1935*(\pi 2*\pi 3*\pi 5) + 1.344*(\pi 1*\pi 4*\pi 6*\pi 7) + 0.001609*(\pi 2*\pi 3*\pi 5)^2 + 0.03109*(\pi 2*\pi 3*\pi 5)*(\pi 1*\pi 4*\pi 6*\pi 7) - 0.3173*(\pi 1*\pi 4*\pi 6*\pi 7)^2$ (14)

Table- 14: Result Analysis Model RSM15CT

Analysis of RSM Model and Goodness of fit	
SSE	1.424
R-square	0.8914
Adjusted R-square	0.8845
RMSE	0.1351

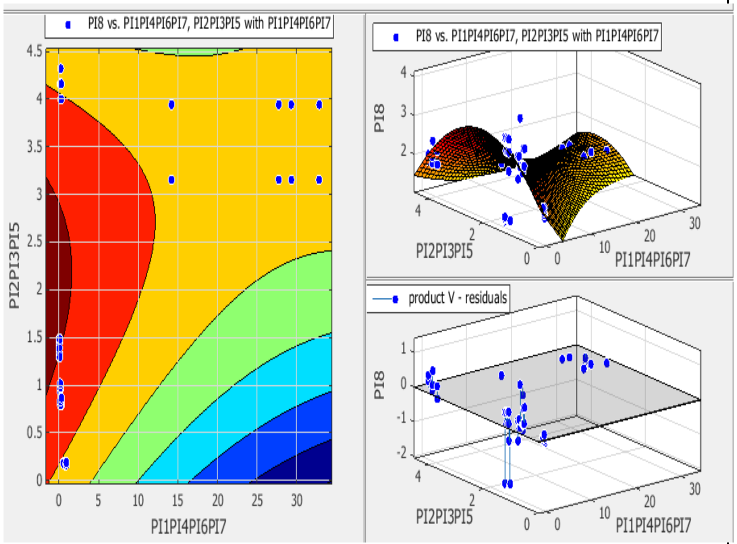


Figure-7: Showing Contour Plot, 3D Response Surface Plot and Residual Plot showing interactive effect of pi2pi3pi5 along X, pi1pi4pi6pi7 along Y on pi8(Response Variable) along Z for Model RSM15CT.

5. CONCLUSION

The present paper gave an illustration of how dimensional analysis (DA) can be applied to significantly reduce the number of independent variables used to optimize the cycle time as response variable using response surface methodology (RSM). Using DA 43 independent variables has been reduced to 07 dimensionless Pi terms. This can greatly help in constructing a response surface approximation function of fewer variables. These 07 Pi terms are further grouped in two X and Y and along Z the response variable Pi8 is placed as input in RSM.The second or cubic order response surface model for seven Pi terms and one response variables is developed from the experimental data gathered during experimentation. Six models equations were developed using RSM in MATLAB 2011a software. To test whether the data are well fitted in the model or not, the values of SSE, R, R^2, Adjusted R^2 and RMSE are observed. In general, the more appropriate Regression model is the higher the values of R^2 (R is correlation coefficient) and the smaller the values of RMSE (Root Mean Square Error). From the developed models, calculated RMSE value of the regression analysis on cycle time is well within 10% limits, which are smaller and R value for response variable(cycle time) are around 85-97% respectively. The closer the value of R (correlation coefficient) to 1, the better is the correlation between the experimental and predicted values. Here the value of R^2 being close to 1 indicated a close agreement between the experimental results and the theoretical values predicted by the model equation. This implies that the prediction of experimental data is quite satisfactory.

ACKNOWLEDGEMENT

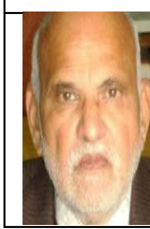
Authors are grateful to the authorities of Nagpur Carbon Pvt Ltd and Department of Mechanical Engineering, Yeshwantrao Chavan College of Engineering, an Autonomous Institute, at Nagpur, India for their support to carry out this work.

REFERENCES

1. Montgomery, D.C., Design and Analysis of Experiments, 6th edition, John Wiley & Sons, (2005).
2. Jack P. C. Kleijnen, Design and Analysis of Simulation Experiments. Springer. New York, p.p. 101-110, (2008).
3. Box, G.E.P., Statistics as a catalyst to learning by scientific method, part II-a discussion. Journal of Quality Technology 31 (1), p.p. 1-38, (1999).
4. Myers, R.H., Montgomery, D.C., Anderson-Cook, and C.M., Response surface methodology: process and product optimization using designed experiments, third edition, John Wiley & Sons, (2009).
5. Mathworks. 2012. MATLAB, the Language of Technical Computing. The Math Works, Inc., Natick.
6. A.K. Dubey and V. Yadava, Multi-objective optimization of laser beam cutting process, Optics & Laser Technology, 40 562-570 (2008).
7. S. Raissi and R. E. Farsani, Statistical process optimization through multi-response surface methodology, World Academy of Science, Engineering and Technology, 51 267-271(2009).
8. Sundaram R.M., An application of goal programming technique in metal cutting, Int. J. Prod. Res., 16, 375 382 (1978)
9. Theories of Engineering Experimentation Text Book by Hilbert Schenck Jr. Mc. Graw Hill Book Co. Ltd New York.
10. Jesus Everardo Olguín Tiznado, Rafael Garcia Martínez, Claudia Camargo Wilson, Juan Andres Lopez Barreras,Everardo Inzunza Gonzalez, Javier Ordorica Villalvazo, Effect of Size of the Step in the Response Surface Methodology using Nonlinear Test Functions, World Academy of Science, Engineering and Technology 66 pg(761-766) 2012
11. Christian Gogu, Raphael Haftka, Satish Bapanapalli, Bhavani Sankar, Applying dimensional analysis to response surface methodology to reduce the number of design variables, 7th World Congresses of Structural and Multidisciplinary Optimization COEX Seoul, Korea (2007)

12. Norasiah Muhammad, Yupiter HP Manurung, Mohammad Hafidzi, Sunhaji Kiyai Abas, Ghalib Tham and Esa Haruman, Optimization and modeling of spot welding parameters with simultaneous multiple response consideration using multi-objective Taguchi method and RSM†, Journal of Mechanical Science and Technology 26 (8) 2365~2370 (2012)
13. Ain A. Sonin, "A generalization of the Π-theorem and dimensional analysis", PNAS vol. 101 no. 23 pp 8525–8526 (2004)
14. M. E. Hossain, C. Ketata & M. R. Islam, "A Scaled Model Study of Waterjet Drilling", Petroleum Science and Technology, 27:12, pp 1261-1273 (2009)
15. Ain A. Sonin, "The Physical Basis of Dimensional Analysis", Department of Mechanical Engineering MIT Cambridge, MA (2001)
16. David Randall, "Dimensional Analysis, Scale Analysis, and Similarity Theories", Quick Studies in Atmospheric Science, (2012)
17. Mark C. Albrecht , Christopher J. Nachtsheim , Thomas A. Albrecht & R. Dennis Cook, "Experimental Design for Engineering Dimensional Analysis", Technometrics, DOI:10.1080/00401706.2012.746207 (2012)
18. 18.G A Vignaux and J L Scott, "Simplifying Regression Models Using Dimensional Analysis", September 12, (2001)
19. 19.G A Vignaux, "Some Examples of Dimensional Analysis in Operations Research and Statistics", School of Mathematical and Computing Sciences, Victoria University of Wellington, New Zealand (2005)
20. Giovanni Miragliotta, "The power of dimensional analysis in production systems design", Int. J. Production Economics 131 pp 175–182 (2011)

BIOGRAPHIES

	Sachin G Mahakalkar Ph.D Research Scholar & Associate Professor Department of Mechanical Engineering YCCE (an autonomous institute), RTMNU Nagpur University (M.S) India 440011 **sachu_gm@yahoo.com** Cell No.:+91-9850310196
	Dr. Vivek H Tatwawadi is working as Principal & Professor DBACER, Wanadongri Hingna MIDC Road Nagpur (M.S) India 440011 **tatwawadi@yahoo.com** Cell No.:+91-9765558909
	Jayant P Giri Ph.D Research Scholar & Assistant Professor Department of Mechanical Engineering YCCE (an autonomous institute), RTMNU Nagpur University (M.S) India 440011 **jayantpgiri@gmail.com** Cell No.:+91-9822929871
	Dr. J.P. Modak is working as Dean (R&D), PCOE, Nagpur,(M.S),India,440019 **jpmodak@gmail.com** Cell No.:+91-9890831037

Using DA Independent Pi Terms							**Z**	**X**	**Y**
Π_1	Π_2	Π_3	Π_4	Π_5	Π_6	Π_7	Π_8= Yexpt	$\Pi_2 \Pi_3 \Pi_5$	$\Pi_1 \Pi_4 \Pi_6 \Pi_7$
0.116107	31.08	0.001846	0.069998	39.12133	1.382881	1.845239	2.333333	2.244721502	0.020738463
0.116107	31.08	0.001938	0.069998	39.12133	1.382881	1.845239	2.666667	2.356957578	0.020738463
0.116107	31.08	0.001892	0.069998	39.12133	1.382881	1.845239	2.333333	2.30083954	0.020738463
0.116107	31.08	0.001892	0.069998	39.12133	1.342271	2.867886	2.666667	2.30083954	0.031285387
0.116107	31.08	0.001846	0.069998	39.12133	1.342271	2.867886	2.666667	2.244721502	0.031285387
0.116107	31.08	0.001846	0.069998	39.12133	1.342271	2.867886	3.5	2.244721502	0.031285387
0.116107	31.08	0.001846	0.069998	39.12133	1.367723	1.702743	2.333333	2.244721502	0.018927208
0.116107	31.08	0.001892	0.069998	39.12133	1.367723	1.702743	2.333333	2.30083954	0.018927208
0.116107	31.08	0.001938	0.069998	39.12133	1.367723	1.702743	4	2.356957578	0.018927208

0.116107	31.08	0.001892	0.069998	39.12133	1.410234	3.120132	2.333333	2.30083954	0.035760496
0.116107	31.08	0.001892	0.069998	39.12133	1.410234	3.120132	2.666667	2.30083954	0.035760496
0.116107	31.08	0.001846	0.069998	39.12133	1.410234	3.120132	2.333333	2.244721502	0.035760496
0.129645	24.75	0.000358	0.144643	273.8493	1.328125	1.845239	1.3	2.427741865	0.045956361
0.129645	24.75	0.000418	0.144643	273.8493	1.328125	1.845239	1.315789	2.832365509	0.045956361
0.129645	24.75	0.000358	0.144643	273.8493	1.328125	1.845239	1.3	2.427741865	0.045956361
0.129645	24.75	0.000418	0.144643	273.8493	1.4	2.867886	1.3	2.832365509	0.075291179
0.129645	24.75	0.000358	0.144643	273.8493	1.4	2.867886	1.3	2.427741865	0.075291179
0.129645	24.75	0.000358	0.144643	273.8493	1.4	2.867886	1.25	2.427741865	0.075291179
0.129645	24.75	0.000418	0.144643	273.8493	1.1945	1.702743	1.3	2.832365509	0.03814077
0.129645	24.75	0.000418	0.144643	273.8493	1.1945	1.702743	1.368421	2.832365509	0.03814077
0.129645	24.75	0.000358	0.144643	273.8493	1.1945	1.702743	1.3	2.427741865	0.03814077
0.129645	24.75	0.000418	0.144643	273.8493	1.346154	3.120132	1.25	2.832365509	0.078762911
0.129645	24.75	0.000358	0.144643	273.8493	1.346154	3.120132	1.368421	2.427741865	0.078762911
0.129645	24.75	0.000358	0.144643	273.8493	1.346154	3.120132	1.25	2.427741865	0.078762911
0.132669	68.26667	3.43E-05	0.886824	136.9246	2.172414	1.845239	2.125	0.320555173	0.471630133
0.132669	68.26667	3.29E-05	0.886824	136.9246	2.172414	1.845239	2	0.307732966	0.471630133
0.132669	68.26667	3.43E-05	0.886824	136.9246	2.172414	1.845239	2.428571	0.320555173	0.471630133
0.132669	68.26667	3.02E-05	0.886824	136.9246	2.274784	2.867886	2	0.282088552	0.767553301
0.132669	68.26667	3.43E-05	0.886824	136.9246	2.274784	2.867886	1.888889	0.320555173	0.767553301
0.132669	68.26667	3.43E-05	0.886824	136.9246	2.274784	2.867886	2	0.320555173	0.767553301
0.132669	68.26667	3.43E-05	0.886824	136.9246	2.434411	1.702743	2.125	0.320555173	0.487696351
0.132669	68.26667	3.02E-05	0.886824	136.9246	2.434411	1.702743	2.285714	0.282088552	0.487696351
0.132669	68.26667	3.43E-05	0.886824	136.9246	2.434411	1.702743	2.125	0.320555173	0.487696351
0.132669	68.26667	3.29E-05	0.886824	136.9246	2.153846	3.120132	2	0.307732966	0.790667797
0.132669	68.26667	3.43E-05	0.886824	136.9246	2.153846	3.120132	2.125	0.320555173	0.790667797
0.132669	68.26667	3.29E-05	0.886824	136.9246	2.153846	3.120132	2.125	0.307732966	0.790667797
0.136734	41.65	0.000449	0.266709	91.28309	1.067479	1.845239	2.5	1.707538356	0.071833579

Appendix: Prediction of Cycle Time as a Response Variable using RSM