Original Research Article

A Study of the Impacts of Measurement errors on Robust Parameter Design for Multi-response.

Abstract: *Robust parameter design is a principle in quality improvement methodologies that is directed towards reducing the effects of errors which are either poised by the noise factors or the control factors. Response surface methodology is an effective approach to robust parameter design. Previous studies discussedRobust parameter design based on response surface model by considering measurement errors in control variables for a single response variable. However, in process design, determining optimal levels of control variables is an important issue in some problems with different outputs. This study therefore investigates the impacts of measurement errors in the levels of control variables on processes with multiple quality characteristics (responses). Different variances of error were tested on the levels of control variables and the analysis of response surface modeling and optimization was performed. The result showed that as measurement errors in the levels of control variables increases, the coefficient of determinations for the multi-response and the expected quality lossdeviates from what is obtainable in the initial state. It can be concluded based on the result however, that measurement errors in the levels of control variables exert impacts on robust parameter design for multi-response.*

Keywords: Robust parameter design, Response surface model, multi-response, Measurement errors,Quality loss.

1. Introduction

Robust parameter design (RPD) is a technique used to improve average quality in products and processes through proper setting of levels of controllable variables. The technique was introduced by [1,2] and it seeks to cut the effect of noise variables on the control variables (parameters in Taguchi's terminology). To make the product or process robust, is to organize the levels of control variables to make the response (outcome) variables insensitive to the variability posed by noise variables. Taguchi suggested the signal-to-noise ratio statistics that provides information about the mean and variance and had been employed hugely to the characteristic analysis of systems in different aspects of the manufacturing industries with testimonies of good performance. He described the system to consist of two categories of input variables – the controllable factors called the control factors denoted as X and the noise factors denoted as Z [3]. It is assumed that the majority of variability around the target Y (response variable), is generated by the presence of this second set of factors – the noise factors. Noise factors cannot be control in the design of a product or in the normal operation of the process and as a result, transmits variability to the target (response variable Y). [4] studied confounding of the mean and variance in the signal-to-noise (a kind of summary statistic used to evaluate the performance of a system relative to variation caused by the noise) analysis, which weakened Taguchi's approach.[5] further incorporated the idea of response surfaces each for the process mean and process variance to minimize variations and optimize performance and improve quality.

One major glitch with Taguchi's approach, is in the inability to accommodates interactions which in its very essence, have a very large contribution to product or process performance. An approach that readily incorporates and handle interaction problem, is the response surface approach proposed by [6], which defines the relationship between response variable and candidates of inputs variables to includes control variables, noise variables and the interaction between control variables and noise variables.

Over the years, researchers have proposed various approaches to address the issues of RPD. [7] studied the performances of processes with asymmetric tolerances in the presence of gauge measurement error (GME). [8] presented that poor estimation of the response model can be caused by errors in the noise variables and hitherto, affect optimal setting of the control factors. [9] offered an adjustment to the dual response surface modeling, which incorporates the option of stochastically simulating some of the noise factors when their probabilistic behavior is known. The method applied to design of high-precision optical profilometer as it was suitable for designing complex measurement systems. [10] gives an idea of mean square error (MSE) that allows for some gap from the mean of the target value and as well minimizes the variance. [11] adopted MSE reduction technique and joint optimization of the mean and variance. [12] presented that some measurement errors might appear during product or process execution stage, notwithstanding, measurement errors which are negligible only show up during product or process designing stage and by this postulation, response model gotten from the experimental results is unaffected by measurement errors. [13] issues that errors in measurements, would happen unavoidably as a result of various events like human errors and equipment imprecision. [14] put forward that error in the measurements introduces noise into predictions, affects parameter estimations, making it difficult to discover new phenomena. Generally notwithstanding, they consider errors due to noise variables only.

Concurrently, multi-response optimization in RPD became much necessary following the recognition of dimensionality in quality characteristics. [15] proposed the idea of desirability function to optimize multi-responses. [16] applied artificial neural network to the problem of multi-response optimization in RPD. [17] presented using multiple regression and the Taguchi signal-to-noise ratio to robust parameter design the event of dynamic characteristics. [18] studied the analysis of fatigue in truck cabins with respect to multi-response optimization based robust parameter design. [19] applied RPD and multi-response optimization technique in the analysis of a railway vehicle trajectory. [20] also studied RPD and economical multi-objective optimization on characterizing rubber for shoe soles. However, the works do not consider the implication of measurement errors in the levels of control variables on RPD.

[21] presented robust parameter design considering measurement errors in the control variables and pointed out that errors in control variables affects parameter estimations and predictions. However, the work only considered the effect of measurement errors on modeling for a single response situation.

In some problems with different outputs, determining optimal level of control variables is an important issue in a process design. This type of problem is called multi-objective response optimization problem and given the expanded nature of threats posed by measurement errors associated to processes and/or systems as a whole, it becomes imperative to study the influence of error multi-dimensionally.

This paper therefore presents the impacts of measurement errors in the control variables on robust parameter design for multi-response using response surface model.

2. Materials and Methods

2.1 Data Used for the Study

The data used for the study was from a case study of the vulcanization process of rubber shoe sole experiment provided in [20] involving three control factors- pressure, time, mold temperature and one noise factor- the environmental temperature. Each of the input factors are set at low, medium and high levels respectively and coded as +1, 0, -1. The experiment was carried out using Box-Behnken design.

Table 1: Factors with their Ranges (levels)

Parameter	Lower level (-1)	Middle level (0)	Higher level 1
Pressure (psi)	1200	1250	1300
Time (min)	2.50	3.00	3.50
Mold temperature (℃)	145	150	155
Environmental temperature (℃)	20	25	30

Source; [20]

Table 2: Experimental data of the design matrix

Run	Pressure (psi) x_1	Time (min) x_2	Mold temperature (°C) x_3	Environmental Temperature (°C) z	Maximum Load (kN) Y_1	Hardness (Shore A) Y_2
1	-1	-1	0	0	0.42	68.0
2	1	-1	0	0	0.34	66.0
3	-1	1	0	0	0.40	65.7
4	1	1	0	0	0.32	67.2
5	0	0	-1	-1	0.36	68.7
6	0	0	1	-1	0.36	69.0
7	0	0	-1	1	0.30	66.8
8	0	0	1	1	0.30	69.2
9	-1	0	0	-1	0.42	68.8
10	1	0	0	-1	0.38	64.2
11	-1	0	0	1	0.38	69.5
12	1	0	0	1	0.42	66.5
13	0	-1	-1	0	0.36	67.2
14	0	1	-1	0	0.38	67.3
15	0	-1	1	0	0.40	69.3
16	0	1	1	0	0.36	68.0
17	-1	0	-1	0	0.44	68.2
18	1	0	-1	0	0.36	68.7
19	-1	0	1	0	0.40	67.5
20	1	0	1	0	0.34	68.7
21	0	-1	0	-1	0.38	66.7
22	0	1	0	-1	0.38	68.2
23	0	-1	0	1	0.32	68.2
24	0	1	0	1	0.38	67.3
25	0	0	0	0	0.40	67.0
25	0	0	0	0	0.36	66.2
27	0	0	0	0	0.32	66.5

Source; [20]

The target for the maximum load is $t_1 = 0.35kN$ with a tolerance limit between 0.25kN to 0.45kN and the target for the hardness is $t_2 = 67.5$ Shore A, with a tolerance limit between 64.5Shore A to 70.5Shore A. and it is assumed that measurement errors exist in the design process and that the involved design variables are independently and identically distributed (iid) random variables with variance of measurement errors as 0, 0.06, 0.07, 0.08, 0.09, 0.1.

2.2 Model Fitting

The second-degree response surface model for the responses- maximum load and hardness each is given by;

$$y = f(x,z) = \eta_0 + \beta' X + \gamma' Z + X' C_1 X + X' C_2 Z + \varepsilon \qquad (2.1)$$

Where η_0 is a constant term, X = $(X_{1,} X_2 \ldots . X_k)^{'}$ is a vector of controllable variable k, Z = $(Z_1, Z_2 \ldots \ldots Z_q)^{'}$ is a vector of the noise variable q, $\beta^{'} = (\beta_1, \beta_2, \ldots \ldots \beta_k)$ and $\gamma^{'} = (\gamma_1, \gamma_2, \ldots \ldots \gamma_q)$ are the coefficient vectors for x and z, $C_1 = (\beta_{11}, \beta_{12}, \ldots . \beta_{k1}, \beta_{1k}, \beta_{k2}, \ldots . \beta_{kk})$ and $C_2 = (b_{11}, b_{12}, . \, . \, . . b_{1q}, b_{q1}, \ b_{k1}, b_{k2}, \ldots \ldots b_{kq})$ are respectively the coefficient matrix for the quadratic and interaction terms. The error is assumed to be normally distributed with zero mean and constant variance i.e$\varepsilon \sim N(0, \sigma_\varepsilon^2)$. Additionally, it is assumed that $E(z) = 0$, and $var(z) = \sigma_z^2$ implying that the noise variable is uncorrelated with known variance.

So that $\hat{\theta}$ is represented as a px1 vector of intercept η_0 and the coefficients $\beta^{'}$,$\gamma^{'}$, C_1, $C_2$and are determined using

$$\hat{\theta} = (X^{'} X)^{-1} X^{'} y$$

i.e$\hat{\theta} = c(\eta_0, \beta_1, \beta_2, \beta_3, \gamma_1, \beta_{12}, \beta_{13}, b_{11}, \beta_{23}, b_{12}, b_{13} \beta_{11}, \beta_{22}, \ \beta_{33})$

X is a nxp model matrix consisting of the levels of the independent variables expanded to model form, y is a nx1 vector of responses.

The expectation of Equation 2.1 with respect to the noise variable z, is given thus;

$$\hat{y}_r = \mu_y = E_z(y) = \eta_0 + \beta' X + X' C_1 X \qquad 2.2$$

$\hat{y}_r, \mu_y$ is the estimated response

This means that the process mean, denoted as $E_z(y)$, is equal to the terms involving only the control variables

2.2.1 Adequacy checks

Coefficient of multiple determination: this is defined as

$$R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_E}{SS_T} \qquad (2.3)$$

Where $SS_R = b' X' y - \frac{(\sum_{i=1}^{n} y)}{n}$ with k degree of freedom $SS_T = y' y - \frac{(\sum_{i=1}^{n} y)}{n}$ with n-1 degree of freedom and $SS_E = y' y - b' X' y$ with n-k-1 degree of freedom.

2.3 Optimization Technique

Given $L = k_0(y-t)^2$ as the quality loss function,one of the viable Optimization methods is the mean square error (MSE) loss function for the dual objective single response approach proposed by [10] and defined as:

$$MSE(\hat{y}) = E(L) = (\mu_{\hat{y}} - t)^2 + \sigma^2_{\hat{y}} \qquad (2.4)$$

Where $\mu_{\hat{y}}$ and $\sigma^2_{\hat{y}}$ are the estimated mean and variance, and t is the target value of the responsefor $k_0 = 1$ and therefore to optimize, we minimize the expected loss function as the objective function.

$$Min\ E(L)$$

$$subject\ to$$

$$x \epsilon R^k$$

Where R^k is the imposed range.

An extended multiple response optimization using loss function was introduced by [23]. The expected loss function is giving by

$$E(L) = [\hat{y}_r - T_r]' C[\hat{y}_r - T_r] + Trace[C\Sigma_{\hat{y}_r}] \qquad (2.5)$$

$r = 1, 2, ...$ is the number of response variables.

Where $[\hat{y}_r - T_r]' C[\hat{y}_r - T_r]$ is the loss associated to any predicted value away from the target.

$Trace[C\Sigma_{\hat{y}_r}]$ is the loss generated from the quality of the prediction.

$\Sigma_{\hat{y}_r}$ is the variance covariance matrix for the estimated responses.

The prediction variance-covariance matrix for the estimated responses is;

$$\Sigma_{\hat{y}_r} = x^{(m)'}(X'X)^{-1} x^{(m)} \Sigma$$

Where X is the model matrix for the response, the vector $x^{(m)}$ is a function of location in the design variables at which to predict the response, (m) reflect the model as does X .

The loss of quality cost is determined by the cost coefficient $C = K\hat{\Sigma}^{-1}$, where K is a matrix with the diagonal elements reflecting the economic importance of each response and the offdiagonal element measuring the correlation of the responses. The estimated expected loss function is then;

$$\hat{E}(L) = [\hat{y}_r - T_r]' C [\hat{y}_r - T_r] + Trace[K x^{(m)'} (X'X)^{-1} x^{(m)}] \qquad (2.6)$$

The object of the optimization is to find the nominal values (optimal operating condition) which minimizes the expected loss function $E(L)$. It can be solved through non-linear programming method in the following form using the genetic algorithm in R-software;

$Min(\hat{E}(L))$

Subject to

$x \in R^k$

Where R^k is the imposed range of factor x.

2.4 Response Surface Measurement Errors model

When there are errors in setting the levels of control variables, the values of those variables become uncertain and can be considered random. If we denote the vector of the intended values for the control variables as x, the actual observed value denoted as x^*, may deviate from the intended value due to these errors such that

$$x^* = x + e \qquad (2.7)$$

Where e represents the vector of the measurement errors associated with the control variables. It is assumed that the measurement error system is unbiased, meaning that on the average, the measurement errors do not systematically overestimate or underestimate the true values. The covariance of the measurement error system is denoted as Σ_e, indicating the degree of variability or dispersion of the measurement errors [21]. Additionally, it is assumed that the measurement errors for each control variables are independent of each other, implying that the error in one variable does not influence the errors in other variables. i.e

$$e \sim N(0, \Sigma_e)$$

Where $\Sigma_e = diag(\sigma_{e1}^2, \sigma_{e2}^2, \dots \dots \dots \sigma_{ep}^2)$

From eqn 2.1 above, the response surface measurement error model becomes

$$y_{e,z} = \eta_0 + \beta' x^* + \gamma' z + x^{*\prime} C_1 x^* + x^* C_2 z + \varepsilon \qquad (2.8)$$

So that the expectation of y taken over the distribution of random variables$e$ and z, is computed as follows; [21]

$$\hat{y}_r = E(y_{e,z}) = \eta_0 + \beta' x + tr(C_1 \Sigma_e) + x' C_1 x \qquad (2.9)$$

From the above,the objective function (expected quality loss function) for the multiple responses given nominal-the-best quality characteristic, can be determinedusing Equation 2.6.

So that

$Min(E(L))$

Subject to

$$x \epsilon R^k$$

3. Results and Discussion

Second order response surface model is fitted for Maximum load and hardness at the initial error magnitude of zero. ($i.e\ \sigma_e^2 = 0$)

Such that

$$y_{\max\_load} = 0.36 - 0.025x_1 - 0.0033x_3 - 0.015z + 0.005x_1x_3 + 0.02x_1z - 0.015x_2x_3 + 0.015x_2z + 0.0267x_1^2 + 0.0042x_2^2 - 0.0058x_3^2 \quad (4.1)$$

Equation 4.1, is a response surface model with $R^2 = 0.5344$, which means that about 53.44% of the variability in the response is explained by the control variables.

$$y_{hardness} = 66.5667 - 0.5333x_1 - 0.1417x_2 + 0.4x_3 + 0.1583z + 0.875x_1x_2 + 0.175x_1x_3 + 0.4x_1z - 0.35x_2x_3 - 0.6x_2z + 0.525x_3z + 0.1375x_1^2 + 0.15x_2^2 + 1.3375x_3^2 \quad (4.2)$$

Equation 4.2, is the second order response surface model for the Hardness. The model gives $R^2 = 0.5692$, which means that about 56.92% of the variability in the response is explained by the control variables.

The optimization carried out consider the two quality characteristics simultaneously so that as one quality characteristic stay on or near the target, the other also remain on or closer to the target.

The mean of the maximum load and hardness are thus;

$$y_1 = E_z(y_{\max\_load}) = 0.36 - 0.025x_1 - 0.0033x_3 + 0.005x_1x_3 - 0.015x_2x_3 + 0.0267x_1^2 + 0.0042x_2^2 - 0.0058x_3^2 \quad (4.3)$$

$$y_2 = E_z(y_{hardness}) = 66.5667 - 0.5333x_1 - 0.1417x_2 + 0.4x_3 + 0.875x_1x_2 + 0.175x_1x_3 - 0.35x_2x_3 + 0.1375x_1^2 + 0.15x_2^2 + 1.3375x_3^2 \quad (4.4)$$

Using Equation 2.10, with

$T_1 = 0.35KN$ and $T_2 = 67.5shoreA$, $C = K\Sigma^{-1}$ for $K = \begin{pmatrix} 1 & -0.0018 \\ -0.0018 & 1 \end{pmatrix}$

$$\Sigma^{-1} = \begin{pmatrix} 1542.1693 & 2.3136 \\ 2.3136 & 1.4437 \end{pmatrix}, \quad C = K\Sigma^{-1} = \begin{pmatrix} 1542.1651 & 2.311 \\ -0.4623 & 1.4396 \end{pmatrix}$$

From where we

$$Min(E(L))$$

Subject to the constraints

$$-1 \le x_1, x_2, x_3 \le 1$$

From the above, we have that the expected quality loss is 11.1712 for the target-the-best quality characteristics using the multi-response optimization. The optimal operating conditions of the control variables obtained are $x_1 = -0.9871$, $x_2 = 0.9511$, and $x_3 = -0.9930$ while the average responses at the optimal levels are $\hat{y}_{\max\_load} = 0.4311$ and $\hat{y}_{Hardness} = 67.8304$ It is observed that the estimated values of each response are within the customer tolerance gap.

Table 3 Coefficient of determination (R^2) for Maximum load and Hardness at various magnitude of measurement errors.

Error variance	Coefficient of determination	(R square)
	$\hat{y}_{\max\_load}$	$\hat{y}_{Hardness}$
0	53.44%	56.92%
0.06	52.6%	59.29%
0.07	52.51%	59.67%
0.08	52.44%	60.03%
0.09	52.37%	60.39%
0.1	52.31%	60.74%

Table 3 above, show the coefficient of determination for each model of maximum load and hardness as error variances changes and it is observed that as error variance increases from zero for maximum load, the adequacy of the model in terms of coefficient of determination was diminishing while in the case of hardness, the adequacy of the model in terms of coefficient of determination was growing higher.

Table 4 optimal operating conditions and responses with the expected quality loss

Error variance	Optimal	operating	Condition	Expected quality loss	$\hat{y}_{\max\_load}$	$\hat{y}_{Hardness}$
	x_1	x_2	x_3			
0	-0.9871	0.9511	-0.9930	11.1712	0.4311	67.8303
0.06	-0.9837	0.9536	-0.9930	13.7592	0.4421	67.7848
0.07	-0.9859	0.9236	-0.9930	13.9622	0.4430	67.7824
0.08	-0.9855	0.9805	-0.9930	15.5752	0.4482	67.7386
0.09	-0.9842	0.9677	-0.9930	15.3555	0.4482	67.7230
0.1	-0.9895	0.9301	-0.9666	15.6384	0.4485	67.6505

Table 4, displays the optimal values of the control variables and their respective responses. It can be observed that the responses for both quality characteristics as error magnitudes changes, fall within the specification. However, as the error variance increase for maximum load, the average responses at the optimal values also further away from the target while for the hardness, the increase in error variance, results to the average responses at the optimal values drawing closer to the target. For the expected quality loss, as the variances of error deviates from initial status of zero, the loss in the system/process grow bigger.

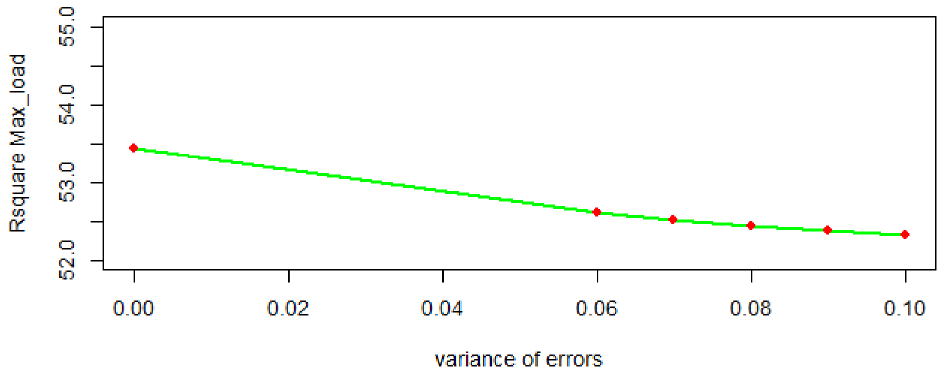

Figure 1: graph of R-square values against error variances for the maximum load

Figure 1 show that as errors infects the levels of the control variables, the R-square values diminishes. When error in the levels of control variables was zero, the R-square was 53.44% and dropped to 52.6% at the error of 0.06. it is observed that the R-square value keep dropping up to the error variance of 0.1 with a value of 52.31%.

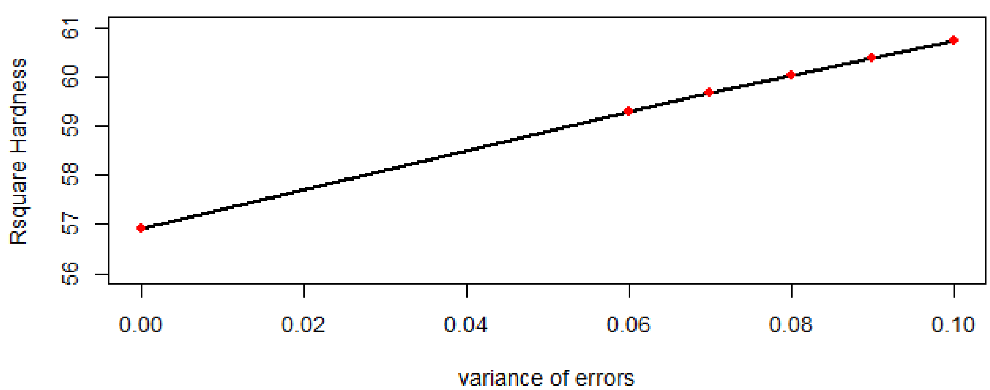

Figure 2: Graph of R-square against error variances for hardness

Conversely, Figure 2 display the values of R-square increasing as measurement errors in the levels of the control variables increases. Initially, with the error of zero, R-square was 56.92% and increases to 59.29% as error variance increases to 0.06. and continuously up to the error of 0.1, where the R-square value was 60.74%.

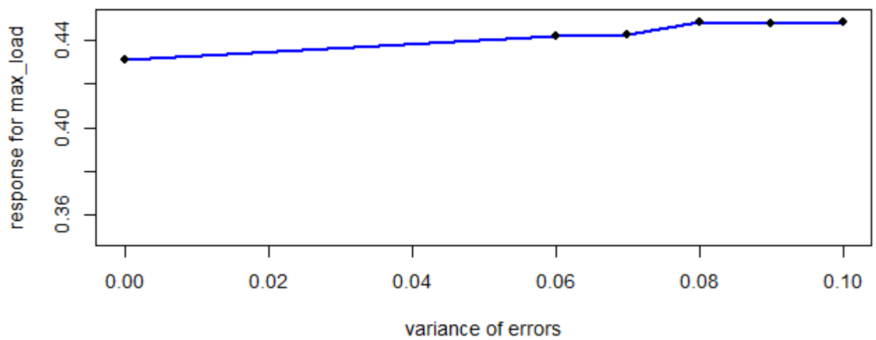

Figure 3: A graph of responses at the optimal condition against error variances for maximum load.

Figure 3 show average values of maximum load at the optimal values of the control variables for different magnitudes of errors. For zero error, the response was 0.4311kN and continue to raise up to 0.4485kN with 0.1 error variance in the levels of the control variables.

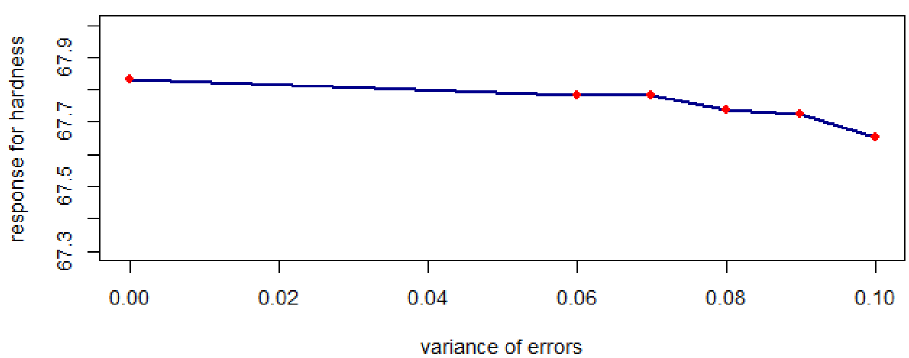

Figure 4: A graph of responses at the optimal condition against error variances for hardness.

The Figure 4 above, is a graph of responses for hardness at the optimal operating condition across various variances of error. It shows that as error increases, the average response values drop downward from what was earlier obtained. i.e from 67.8303Shore A. on an error magnitude of zero, to 67.6505Shore A. on an error magnitude of 0.1

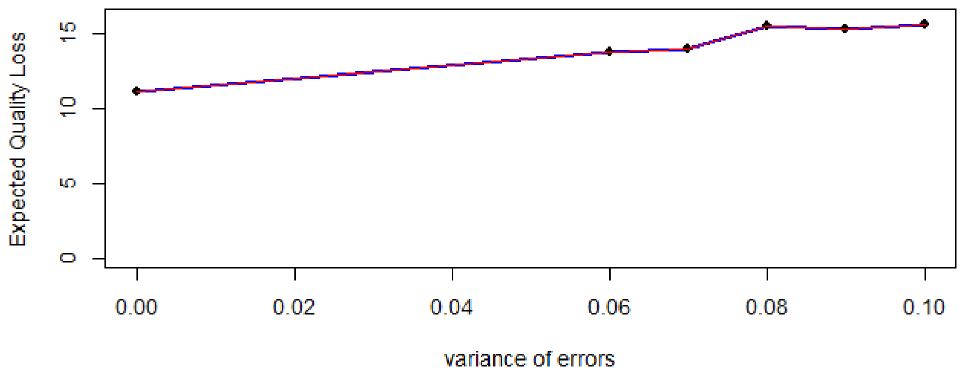

Figure 5: A graph of expected quality loss against error variances.

The Figure 5 is a graph showing the expected quality loss at each variance of error. At the error of zero, the expected quality loss was 11.1712. it continues to increase across error magnitudes, and was 15.6384 when the error was 0.1.

3.1 Discussion of Results

Overall, five different ranges of measurement errors were used and second order response surface models are fitted across theseerror variancesfor each of Maximum load and Hardness. The coefficients of determination contained in Table 4, were respectively measured,indicating the amount of variability explained by the control variables (pressure, time, and mold temperature). It is observed therein that as magnitudes of measurement errors changes from the initial state of zero for each of the response surface model, the coefficient of determination (R-square) values for the maximum load deflateswhile for the hardness, the values continue to inflates.

Similarly, from the result of multi-response optimization, optimal operating condition of the control variables were obtained all across the magnitudes of errors considered.The average responses for maximum load and hardness were also computed as given in Table 4 and were such that all values fall within the tolerance limit.Though, the values for the maximum load were gradually moving away from the target value and that of hardness were drawing towards the target value,it is noticed however, that as error expands, both values will fall outside the tolerance limit at the either ends on the long run.

In respect of the expected quality loss at the optimal condition of the control variables across error variances,the respectivevalues of the expected quality loss are displayed inTable 4. It is observed that as magnitudes of measurement errors changes from the initial state, the loss continue to deviates and increasing higher indicating that impact of error is playing on the system. Figures 1 to 5 graphically presents the information on Tables 3 and4 respectively.Comparatively, as with the case of [21], where single quality characteristic was studied, the case of multi-response optimization of the two responses in this research, presents that the impacts of measurement errors in the levels of the control variables, in terms of the coefficient of determinations is not moving towards same direction for all the response. Both the coefficients of determination and the expected quality loss is however, established to deviates from what was obtained when the magnitude of measurement errors was zero.

4. Conclusion

The main interest of this research is to study the influence of measurement errors in the levels of the control variables on robust parameter design for a system/process that contains multiple responses, using response surface modeling and optimization. Based on the result obtained from the analysis, the following conclusion can be made:

1. The response surface models across error variances show that the coefficient of determination is not stable and not in the same direction for both responses. This means that errors in the levels of the control variables can underestimate and overestimate performance of quality characteristics all together.
2. Average responses of the two quality characteristics at the optimal operating condition of the control variables for different error variances, all presents values that falls within the tolerance limits but it is observed that as error in control variables increases, the values are moving towards the limits in opposing directions.
3. Lastly, the expected quality loss when there were no measurement errors in the levels of the control variables was smaller while as error variances infects the control variables, the expected quality loss raises higher and the higher the loss of quality, the greater the implication to the system.

Given the above, it is observed that the presence of errors in the levels of the control variables impacts on robust parameter design for multi-response using response surface modeling and optimization, whatever the unit in measurements and must be taken into cognizance, to avoid poor estimation and predictions.

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