Taguchi Loss Function to Minimize Variance and Optimize a Flexible Manufacturing System (FMS): A Six Sigma Approach Framework

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Abstract: This paper analyzes a flexible manufacturing system (FMS) and presents a new scheme to find the optimal operational parameters settings of two of the mostly used performance measures in assessing manufacturing and production systems, namely the throughput rate (TR) and the mean flow time (MFT). The scheme uses an off-line model that combines discrete-event simulation, robust design principles and mathematical analysis to uncover the optimal settings. The research suggests a two-level optimization procedure that uses an empirical process followed by an analytical technique. In a first level, the empirical approach serves to derive the near-optimal values of the two individual performance measures of interest. These values are then used as targets in the second level of the optimization procedure in which, a Taguchi quality loss function (QLF) is applied to the FMS mathematical model derived through simulation-meta-modeling to find the optimal parameter settings. As advocated in Six Sigma Methodology the optimization of the modeled system is implemented and achieved through a minimization of the performance variation followed by an optimal adjustment of the performance's mean if necessary, in order to minimize the overall loss incurred due to the deviation of the mean from target.

1 INTRODUCTION

A high reliability is one of the most desired features in operating a production system in general and a Flexible Manufacturing System (FMS) in particular. For this reason, there has been a highly increasing need in the manufacturing sector to seek for both flexibility and robustness under optimal settings of main operating parameters.

The present research analyzes a hypothetical FMS and presents a unique scheme in designing, modeling and optimizing robust systems. The reader is referred to Tshibangu 2017 for a detailed description of the hypothetical FMS under study. A discrete-event simulation and typical data collection plan are used for the study. Data collected during simulation are subsequently fed into a non-linear regression model to generate meta-model that will characterize the FMS from the performance measures point of view. The optimization procedure as subsequently developed in this paper is performed at two levels. First an empirical technique is used to find near-to-optimal values for each individual performance criterion of interest. These values are subsequently used as target goals in the second level of the optimization procedure in which a Taguchi Quality Loss Function (QLF) is applied to the meta-models to uncover the optimal setting of the system parameters while minimizing the loss incurred to the overall systems for possibly missing the targets as set. Specifically, the analytical optimization is applied to a regression model equation (meta-model) derived from the simulation output results.

The approach used in this study takes advantage of a robust design methodology as it renders the system insensitive to uncontrollable factors (noise) and hence, guarantees the system stability required before any improvement and /or optimization attempt. The research is also motivated by both the Six Sigma governing principle, that seeks performance improvement through a reduction of variability and the Six Sigma methodology that advocates the use of DMAIC as roadmap to seek and implement the best solution while reducing defects, and thus, improving quality. The different steps in this study will identify the Six Sigma roadmap phases as well.

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2 LITERATURE REVIEW

The Six Sigma philosophy maintains that reducing 'variation' will help solve process and business problems (Pojasek, 2003). This quality management methodology is extensively used to improve processes, products and/or services by discovering and eliminating defects. The goal is to streamline quality control in manufacturing or business processes so there is little to no variance throughout. The strategic use of Six Sigma principles and practices ensures that process improvements generated in one area can be leveraged elsewhere to a maximum advantage, resulting in quantum increasing product quality, continuous process improvement resulting in corporate earnings performance (Sharma 2003).

There is still a limited number of reported flexible manufacturing system optimization using Six Sigma or a combination of both Lean principles and Six Sigma. Moreover, there is virtually no documentation on the merge of Six Sigma and Taguchi Quality Loss Function in attempt to optimize a process and or system. Sharma (2003) also mentions that there are many advantages of using strategic Six Sigma principles in tandem with lean enterprise techniques, which can lead to quick process improvement and/or optimization. More than 95% of plants closest to world-class indicated that they have an established improvement methodology in place, mainly translated into Lean, Six Sigma or the combination of both. Valles *et. al* 2009 use a Six Sigma methodology (variation reduction) to achieve a 50% reduction in the electrical failures in a semi-conductor company dedicated to the manufacturing of cartridges for ink jet printers. Han et al. 2008 also use Six Sigma technique to optimize the performance and improve quality in construction operations. Hansda *et. al* (2014) use a Taguchi QLF in a multi-characteristics optimization scheme to optimize the response in drilling of GFR composites. Tsui (1996) proposes a two-step procedure to identify optimal factor settings that minimize the variance and adjust to target using a robust design inspired from Taguchi methodology. Zhanga *et. al* (2013) use a QLF to adjust a process in an experimental silicon ingot growing process.

3 THE ROBUST DESIGN - (DEFINE)

Being part of what is known today as the Taguchi Methods, Robust Design includes both design of experiments concepts, and a particular philosophy for design in a more general sense (e.g. manufacturing design). Taguchi sought to improve the quality of manufactured goods, and advocated the notion that "quality" should correspond to low variance, which is also the backbone of the Six Sigma methodology today as it seeks a reduction of variance as a means to stabilize a process and, hence, improve "quality". The present study uses a robust design configuration inspired by Taguchi robust design methodology. However, because of the high amount of criticism against Taguchi's experimental design tools such as orthogonal arrays, linear graphs, and signal-to-noise ratios, the robust design formulation adopted here avoids the use of Taguchi's statistical methods and rather uses an empirical technique developed by Tshibangu (2003). Overall, implementing a robust design methodology or formulation requires the following steps:

- Define the performance measures of interest, the controllable factors, and the uncontrollable factors or source of noise.
- Plan the experiment by specifying how the control parameter settings will be varied and how the effect of noise will be measured.
- Carry out the experiment and use the results to predict improved control parameter settings (e.g., by using the optimization procedure developed in this study).
- Run a confirmation experiment to check the validity of the prediction.

In a robust design experiment, the settings of control parameters are varied simultaneously in few experimental runs, and for each run, multiple measurements of the main performance criteria are carried out in order to evaluate the system sensitivity to noise.

This study investigates the FMS performance with respect to the mean flow time (*MFT*) and throughput rate (*TR*) separately by considering 5 variables Xi as controllable parameters, namely: i) the number of AGVs (X_1), ii) the speed of AGV (X_2), iii) the queue discipline (X_3), iv) the AGV dispatching rule (X_4), v) and the buffer size (X_5). These parameters are not the only variables susceptible to affect the performance of the FMS under study. However, because one objective of the research is to design a robust FMS, the parameters considered here are those related to the performances of the most costly and vulnerable components of the system, also potential sources of disturbances, namely: machines and material handling (AGVs). The controllable parameters are tested at two settings (min and max) as displayed in Table 1.

The principal sources of noise tested in this study and commonly investigated and documented in the reported literature (Tshibangu 2014) are: i) the arrival rate between parts or orders in the manufacturing environment (X_6), ii) the mean time between failures of the machines (X_7), and iii) the associated mean time to repair (X_8).

These noise factors are also tested at two setting levels in combination with each control factor at all setting levels. Table 2 depicts settings and natural values for noise factors. For both controllable and noise factors, the coded levels are (-1) and (+1) for the low and high level, respectively.

3.1 Planning the Experiment

Planning the experiment is a two-part step that involves deciding how to vary the parameter settings and how to measure the effect of noise. In the case of a full factorial experimental design, with the 5 variables X_1, X_2, X_3, X_4, and X_5, identified as the control parameters to be evaluated at two settings, the experiment will require $2^5 = 32$ experimental runs. The research also investigates three noise factors X_6, X_7, and X_8, varied at two settings each, resulting in measuring a total of $2^3 = 8$ noise combination settings for each experimental run.

Therefore, the total number of experimental runs to be conducted in a full factorial configuration would therefore be equal to 32 x 8 = 256 simulation experiments.

Two-level, full factorial or fractional factorial designs are the most common structures used in constructing experimental design plans for system design variables. Tshibangu (2003) recommends appropriate fractional factorial designs of resolution *IV* or *V* in the design of robust manufacturing systems. This research decides to use a two-level fractional design of resolution *V*, denoted 2_V^{5-1} requiring only 16 runs, instead of the 32 needed for a full factorial design. Across the full set of noise factors, the design leads to a total of 16 x 8 =128 simulation runs (instead of 256 as required for a full factorial design). The study uses a design of resolution *V* to allow an estimation of both main factors and two-way interactions effects, necessary for the empirical optimization technique implemented in this research study.

Normally, a standard, statistical experimental design, also known as a data collection plan, should be used when conducting simulation experiments.

Table 1: Natural Values and Setting of Controllable Factors.

Designation	Noise Factor	Low Level (-1)	High Level(+1)
X_6	Inter-arrival	EXPO(15)	EXPO(5)
X_7	MTBF	EXPO(300)	EXPO(800)
X_8	MTTR	EXPO(50)	EXPO(90)

Table 2: Natural Values and Setting of Noise Factors.

Designation	Control Factor	Low Level (-1)	High Level(+1)
X_1	Number of AGVs	2	9
X_2	Speed of AGV	100	200
X_3	Queue Discipline	FIFO	SPT
X_4	AGV Dispatching Rule	FCFS	SDT
X_5	Buffer Size	8	40

The data collection plan used in this research is inspired from Genichi Taguchi's strategy for improving product and process quality in manufacturing. The proposed design strategy includes simultaneous changing of input parameter values. Therefore, the uncertainty (noise) associated with not knowing the effect of shifts in actual parameter values such as shifts in mean inter-arrival times, mean service times, or the effect of not knowing the accuracy of the estimates of the input parameter values, is introduced into the experimental design itself. Tshibangu (2003) gives detailed information about this specific data collection plan used in this study to run the simulation experiments and collect the statistics thereof.

3.2 Level 1 Optimization Procedure: Four-Step Single Response Optimization for Robust Design

Because flexible manufacturing systems are subject to various uncontrollable factors that may adversely affect their performance, a robust design of such systems is crucial and unavoidable. In order to improve the expected value of the function estimate or performance measure, Tshibangu (2003) has developed a four-step optimization procedure to be used simultaneously with the robust design in an empirical fashion as follows:

Let $\bar{y}_i$ represent the average performance measure across all the set of noise factors combination, averaged across all the simulation replications for each treatment combination (or design configuration) *i*. Let log $\sigma^2_{wrtnf(i)}$ be the associated logarithm of the variance with respect to noise for that particular treatment *i*. The author recommends to use the logarithm of the variance in order to improve statistical properties of the analysis.

Employ the effects values and or graphs in association with normal probability plots and or ANOVA procedures to identify and partition the following three categories of control factor vectors:

(i) X_v^T the vector of controllable factors that have a major (significant) effect on the variance with respect to noise factors σ^2_{wrtnf} (represented by log σ^2_{wrtnf}) of the performance measure of interest *y*.

(ii) X_m^T the vector of controllable factors that have a significant effect on the mean $\bar{y}$. The group X_m^T is further partitioned into two sub-groups:

a. $(X_m^T)_1$ including factors having a significant effect on the mean $\bar{y}$, with their main and interaction effects with members of X_v^T having no or less significance on the variance σ^2_{wrtnf}. The main idea here is: since these factors or any of their interaction with the controllable factors members of X_v^T do not have a significant effect on the variance, but have a large effect on the mean, they can be used as "tuning" factors to adjust the mean on the target without altering the variability.

b. $(X_m^T)_2$ including factors having a significant effect on mean $\bar{y}$ and on the variance σ^2_{wrtnf} simultaneously. That is, $(X_m^T)_2$ is a subset of X_v^T, or is totally confounded to the X_v^T set. $(X_m^T)_2$ is further categorized in $(X_m^T)_2^A$ that includes factors with effect on variance and mean acting in the same direction, and $(X_m^T)_2^B$ containing factors with effects on variance and mean acting in opposition. Because these settings affect inversely (in relation with the experiment's goal), there is a need for trade-off.

(iii) X_0^T the vector of controllable factors that affect neither the variance σ^2_{wrtnf} nor the mean $\bar{y}$, and whose interactions with members of set X_v^T has no effect on the variance σ^2_{wrtnf}.

Note that controllable factors members of set X_v^T may also affect the mean $\bar{y}$, i.e., they can also be members of X_m^T. Such factors affect both the variance σ^2_{wrtnf} and the mean $\bar{y}$. Thus, a compromise between variance and mean might be required if necessary. However, a controllable factor member of X_0^T cannot be simultaneously a member of X_v^T and or X_m^T. Also, the robust design configuration should have enough resolution (at least resolution *IV*) to allow identification of the two-way interaction effects.

This study assumes that X_v^T, X_m^T, and X_0^T, are not empty sets and subsequently implements the four-step optimization procedure as developed and proposed by the author (Tshibangu 2003). Using the related plots and tables, and applying it to the Mean Flow Time (*MFT*) and Throughput Rate (*TR*) performance measures, the following coded results are obtained: *MFT* = 0.3666 units time /part and *TR* = 3000 parts/month (100 parts/day). These values will be considered as the optimal target values to be achieved in the second level of the optimization procedure (multi-criteria optimization).

3.3 Simulation Meta-modeling - (Measure)

Kleijnen (1977) defines the purposes of meta-modeling as the method by which to measure the sensitivity of the simulation response to various factors that may be either decision (controllable) variables or environmental (non-controllable) variables. Meta-models are usually constructed by running a special RSM (Response Surface Methodology) experiment and fitting a regression equation that relates the responses to the independent variables or factors.

Let us assume that, for each objective performance of the FMS under study a model has been developed, representing the relationship between the system objective performances and the operating parameters $X_1, X_2, \dots, X_p$, in the form of:

$$\hat{y}_j = f(x_1, x_2, ..., x_p) \qquad (1)$$

where $\hat{y}_j$ is an estimate of the performance measure of interest obtained through regression meta-modeling, and $x_1, x_2, ..., x_p$ are the coded units of operating variables $X_1, X_2, \dots, X_P$. The FMS simulation statistics collected were subsequently fed into a non-linear regression meta-model. Applying the meta-modeling technique to the FMS under study leads to the estimate-equations $\hat{y}_{TR}$ and $\hat{y}_{MTF}$ for the responses of interest, i.e., for the throughput rate (*TR*), and for the mean flow time (*MFT*). The simulation results, not displayed here, but available upon request, yield the following equations for the performance measures of interest, $\hat{y}_{TR}$ and $\hat{y}_{MTF}$.

$$\begin{aligned}\hat{y}_{TR} = 90.7617 &+ 20.6726x_1 + 2.5357x_2 \\ &+ 2.6977x_3 + 3.8574x_4 + 0.5617x_5 \\ &- 4.712x_1^2 - 9.042x_2^2 - 8.732x_3^2 - 4.712x_4^2 \\ &- 7.923x_5^2 - 7.458x_1x_2 + +3.5513x_1x_3 \\ &- 0.5315x_2x_3 - 0.3304x_3x_4\end{aligned} \quad (2)$$

where x_1, x_2, x_3, x_4, x_5 are the coded units for the operating variables X_1, X_2, X_3, X_4, and X_5, respectively.

$$\begin{aligned}\hat{y}_{MFT} = 4.6503 &- 8.8338x_1 - 4.4760x_2 - 3.2451x_3 \\ &- 0.1345x_4 + 0.5054x_5 + 14.1731x_1^2 \\ &+ 1.5309x_2^2 - 1.3399x_3^2 - 0.4519x_4^2 \\ &- 1.4569x_5^2 + 5.3816x_1x_2 - 0.7952x_1x_3 \\ &- 0.0335x_1x_4 - 0.504x_1x_5 - 0.1457x_2x_3 \\ &- 0.3251x_2x_4 + 0.4863x_3x_5 - 0.7655x_4x_5\end{aligned} \quad (3)$$

3.4 Variance Metamodels – (Measure)

The same methodology used to derive the metamodels for the means of performance measures in equations (2) and (3) is applied to TR and MFT logarithmic variances to derive a regression model able to predict the variance with respect to noise at any treatment combination of the controllable factors (equations 4 and 5). Tables 3 displays an example of outputs from SPSS®, from which the metamodels of the TR log variances are generated as follows:

$$\begin{aligned}\hat{\sigma}_{TR}^2 = 97.2712 &+ 214.5807x_1 + 54.382x_2 \\ &- 91.435x_3 - 1.2502x_4 - 7.6521x_5 \\ &- 3700.923x_1^2 - 4586.6423x_2^2 \\ &+ 2396.3647x_3^2 + 5952.9562x_4^2 + 57.182x_5^2 \\ &+ 53.5783x_1x_2 - 91.90x_1x_3 - 1.3993x_1x_4 \\ &- 6.6974x_1x_5 - 13.2394x_23 + 1.1630x_2x_4 \\ &+ 7.08x_2x_5 + 7.6523x_3x_4 + 0.9297x_3x_5 \\ &- 13.633x_4x_5\end{aligned} \quad (4)$$

$$\begin{aligned}\hat{\sigma}_{MFT}^2 = 14.1221 &+ 11.3930x_1 - 0.3565x_2 \\ &- 18.207x_3 - 1.8633x_4 - 7.1266x_5 \\ &+ 24.7261x_1^2 + 1.7262x_2^2 + 6.3262x_3^2 \\ &+ 9.8262x_4^2 + 12.9262x_5^2 + 17.1912x_1x_2 \\ &- 51.0237x_1x_3 - 2.55724x_1x_4 \\ &+ 4.0895x_1x_5 - 15.3107x_2x_3 \\ &+ 6.4177x_2x_4 + 2.1228x_2x_5 + 1.1445x_3x_4 \\ &- 2.1945x_3x_5 - 1.35103x_4x_5\end{aligned} \quad (5)$$

For all the equations generated in this paper, i.e., (Equations 2, 3, 4 and 5) the R-squared values of all the prediction models are very high (e.g., 0.999+), indicating a good approximation of the prediction models. The accuracy of these prediction models have been verified and confirmed through simulation runs of all 21 designs followed by a subsequent residuals calculation and comparison of the observed values to the predicted values. The magnitude of residuals (not shown here) was less than 5% overall.

Table 3: Non Linear Regression Analysis and ANOVA for Var TR.

Nonlinear Regression	Summary Statistics		Dependent Variable VARTR
Source	DF	Sum of Squares	Mean Square
Regression	21	1903372.42116	90636.78196
Residual	0	525.76464	
Uncorrected Total	21	1903898.18580	
(Corrected Total)	20	1162541.93246	

R squared = 1 - Residual SS / Corrected SS = **.99955**

4 TAGUCHI QUALITY LOSS FUNCTION ANALYSIS – (ANALYZE)

This section overviews the basic features of the Quality Loss Function (QLF). Taguchi's approach in Quality Engineering is explained in the following steps:

- Each engineering output has an ideal target value.
- Any deviation from target incurs a loss. These losses include tolerance stack-up, performance degradation, and life reduction.
- The more the loss increases the more the output response deviates from the target.
- The goal of Robust Design (RD) is to reduce deviation of performance measure(s) from the target(s).

Performance begins to gradually deteriorate as the quality characteristic of interest and/or performance criterion deviates from its optimum value. Therefore, Taguchi proposed that the loss function be measured by the deviation from the ideal value.

A variety of loss functions have been discussed in the literature. However, a simple Quadratic Loss Function (QFL) may be appropriate in many situations (Tshibangu 2003). These quality loss functions, especially the nominal-the-best type function, are widely used in process adjustment. Most existing literature developed the algorithm by minimizing the expected mean sum of squared error, which is consistent with the nominal-the-best loss function (Tshibangu 2015).

In this research the Taguchi QLF is used to measure the loss of performance as compared to target value(s). The optimal values found during the implementation of the proposed empirical optimization procedure will be used as target values in the subsequent analytical optimization approach.

The two primary objective performances involved in separate and single optimization procedures as developed in this study are the Throughput Rate (TR) and the Mean Flow Time (MFT).

Tshibangu (2003) shows that Taguchi QLF for a single objective criterion can be extended to the case of multiple quality characteristics or objective performances, and then referred to as a "*multivariate quality loss function*". The purpose is to capture the overall system performance when addressing a set of performance objectives. This study addresses the single objective optimization for the MTF and TR using Taguchi QLF.

Let y_j, and T_j be the performance measures of interest ($j = 1$ to Q, where Q is the total number of performance measures), and the target for objective performance y_j respectively, and be denoted by y = $(y_1, y_2, \ldots, y_Q)^T$ and $T = (T_1, T_2, \ldots, T_Q)^T$ under the assumption that $L(y)$ is a twice-differentiable function in the neighborhood of T.

Assuming that each objective performance has a mean $\mu(x)_i$ and a variance $\sigma(x)_i^2$, then, after some mathematical developments and manipulations (Tshibangu 2003) the expected value of the quadratic loss function can be written as follows:

$$E\left[L(y)\right]=\sum_{i=1}^{Q}\theta_i\left[\left(\mu_i-T_i\right)^2+\sigma_i^2\right]+\sum_{i=2}^{Q}\sum_{j=1}^{i-1}\theta_{ij}\left[\sigma_{ij}+\left(\mu_i-T_i\right)\left(\mu_j-T_j\right)\right] \tag{6}$$

where $\theta_{ij}=\frac{1}{2}\left(\frac{\partial^2 L}{\partial y_i^2}\right)\forall i=j$ (7)

and $\theta_{ij}=\frac{1}{2}\left(\frac{\partial^2 L}{\partial y_i \partial y_j}\right)\forall i\neq j$ (8)

and σ_{ij} represents the covariance between yi and y_j.

Equation (6) reveals that several terms, such as the bias and variance generated by each objective performance, the covariance σ_{ij} between objective performance, and the cross products between biases, must be reduced in order to minimize the expected loss. Assuming that all the objective performances of interest are statistically independent, then, $\sigma_{ij}=0$ and equation (6) reduces to:

$$E\left[L(y)\right]=\sum_{i=1}^{Q}\theta_i\left[\left(\mu_i-T_i\right)^2+\sigma_i^{\,2}\right]+\sum_{i=2}^{Q}\sum_{j=1}^{i-1}\theta_{ij}\left(\mu_i-T_i\right)\left(\mu_j-T_j\right) \tag{9}$$

As pointed out in Tshibangu (2015), there are three aspects of interest in formulating robust design systems: (i) deviation from targets; (ii) robustness to noise; (iii) robustness to process parameters fluctuations. A weighted sum of mean squares is appropriate to capture (i) and (ii), while gradient information is necessary to capture (iii). This research is particularly interested in deviation from target and robustness to noise. Therefore, only the first term of Equation (9) is needed.

The next step consists of applying the derived QLF to the FMS meta-models obtained from simulation outputs and expressed in Equations (4) and (5). In order to determine the optimal input parameters, an objective function is developed from Equation (9) following a framework adopted by Tshibangu (2014).

Because of the robust design configuration adopted during the experiments and assuming a Six Sigma methodology is in use, it can be assumed that the variability of the system due to fluctuations of the operating parameters is negligible, then, for a given treatment, the loss incurred to a system as the result of a departure of the system performance from the target T_j can be estimated as:

$$L(i)=w_j\left[\left(\hat{y}_{j-}T^2\right)+\hat{\sigma}_{yj}^2\right] \tag{10}$$

where $L(i)$ is the loss at treatment i; w_j is a weight to take into account to consider the relative importance of an individual performance measure y_j ($j=1,2,\ldots Q$), especially in the case of a multiple optimization procedure; $\hat{y}_j, \sigma_{yj}$ are respectively the predicted (estimate) mean and standard deviation of the performance measures of interest y_j; T_j is the target for the system performance measure y_j. $L(i)$ is the objective function to be minimized. In this particular form, the objective function has two terms. The first term of the objective function, $\left(\hat{y}_j-T_j\right)^2$ accounts for deviations from target values. The second term, $\hat{\sigma}_{yj}{}^2$ accounts for the source of variability due to non-controllable (noise) factors.

Because this study is addressing a single criterion optimization separately for each performance measure and because the determination of goal's weights is beyond the scope of this research study, it has been assumed that both performance measures of interest are equally important, and most importantly, as the study is trying to set up a proof of concept by optimizing separately the performance measures before attempting any multivariate optimization procedure , a normalized weight value of 1 is applied to for both the throughput rate TR and the mean flow time *MFT*, respectively. Throughput Rate (TR) and Mean Flow Time (MFT) data means and their variances are also normalized.

It worth it to say that R-squared values should be associated to residual analysis to check if the assumption about the normality in the data is valid and therefore, to justify any valid statistical analysis and subsequent conclusions. When the effects of the various control factors have been computed, they can subsequently be plotted to normal probability paper by adjusting the probability *p* as:

$$p_k = 100 * (k - 0.5) / n \tag{11}$$

where k is the order number; $k = 1, 2, \ldots(n\text{-}1)$, n is the total number of runs, and p_k is the probability of k. Residual analysis is also conducted to verify the conclusion on predicted significant effects.

The residuals obtained from a fractional factorial design by the regression model should then be plotted against the predicted values, against the levels of the factors, and normal probability paper to assess the validity of the embedded model assumptions and gain additional insight into the experimental situation. The various residual plots required for this research are not displayed here for economy of space. These plots are used to check if the assumptions presumed embedded in the model are met.

The most common assumptions are that errors are (Normally, Independently Distributed) *NID* $(0, \sigma^2)$. When these assumptions are met, the residuals are normally distributed, have equal variances, and are not independent. The normal probability plots of TR residuals shown in Figure 1 for illustration purpose lie approximately along a straight line. As a result, there is no reason to suspect any severe non-normality in the data (p=0.15). Hence, residuals are *NID*$(0, \sigma^2)$. The same conclusion is also drawn for the MFT whose plots are not displayed here for economy of space.

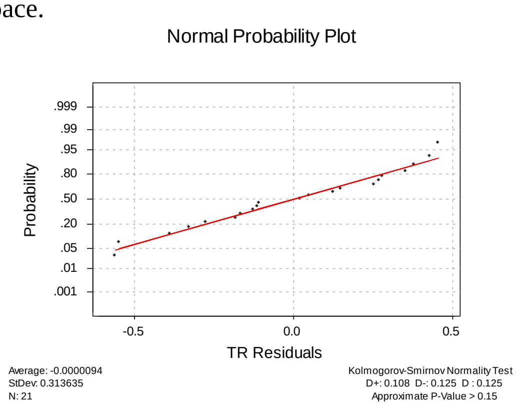

Figure 1: Normal Probability plots for TR Residuals.

5 LEVEL 2 OPTIMIZATION USING TAGUCHI QLF AND METAMODELS (IMPROVE-CONTROL)

Analysis of Equation (10) reveals that a minimal loss will be incurred to a performance measure when both terms of the equation are minimized. Let i_{min1} and i_{min2} be the treatment level with the lowest $(\hat{y}_j - T_j)^2$ and $\hat{\sigma}_{yj}^{\ 2}$ value, respectively among all 21 treatment combinations simulated. The minimization of the second term $\hat{\sigma}_{yj}^{\ 2}$ of Equation (10) is key to the proposed approach as it is most critical term for the quality of the product as it guarantees less variation among the various products delivered under a specific combination of operational parameters. Therefore, the second level of the proposed optimization scheme will first start with the minimization of the variance (second) term $\hat{\sigma}_{yj}^{\ 2}$ in Equation (10).

Step 1. A mathematical manipulation using basic Linear Programing, of the metamodels derived in Equation (4) and (5), expressed in the form of objective functions as illustrated in Tshibangu 2014 will lead to the determination of the treatment combination i_{min2} that yields the minimal value for the second term $\hat{\sigma}_{yj}^{\ 2}$.

Step 2. The minimum of the first term $(\hat{y}_j - T_j)^2$ is obtained by computing $(\hat{y}_j - T_j)^2$ for each treatment *(i)* of the 21 designs simulated across the noise level combination using TR and MFT metamodels found in Equations (2) and (3) in combination with the target values T_j derived from the empirical approach for both TR and MTF, respectively at each treatment level. The treatment combination yielding the minimum value is considered as the optimal combination for the first term of Equation (10). This treatment combination level will not necessarily be the same as the one derived through mathematical minimization of the second term $\hat{\sigma}_{yj}^{\ 2}$.

Also, it worth it to say that because this research has used a fractional design of experiments the treatment combinations i_{min1} and i_{min2} do not necessary have to be among the 21 simulated combinations. However, because one of the objectives of robust design is to reduce the performance measure variance, i_{min2} will be first consider as the basic optimal treatment combination level leading to the most robust (less variation) and optimal setting of operational parameters. Confirmatory runs will be carried out to validate the results while possible fine-tuning adjustments may be necessary to compensate for any possible mean loss.

6 RESULTS AND CONCLUSIONS

This research first addresses a robust design formulation and simulation data collection plan for a hypothetical FMS and implements in a first level, an empirical optimization procedure to use in order to avoid the controversial Taguchi statistical tools. Then the research derives a metamodel from the simulation outputs. The study also derives a QLF from the traditional Taguchi loss function in order to capture the loss incurred to the overall FMS when addressing a specific objective performance (*TR* or *MFT*). Next (second level of the optimization scheme), the QLF is analytically applied to the metamodels to optimize the FMS with respect to an objective performance. Target/optimum values of 100 parts/day and 0.3666 units time/part (in coded data) obtained in the first level of the empirical optimization procedure have been fixed for the TR, and MFT, respectively. This two-level optimization procedure leads to a solution that yields the least cost incurred to the overall FMS as a penalty for missing the objective targets. The values of 98 parts/day (-2% from target) and 0.3459 units time/part (+5.6% from target) are obtained as optima, for TR and MFT, respectively. Figure 2 is a Minitab output depicting the effects of control factors for TR. When using TR as performance measure the most robust and optimal FMS configuration would be at the following settings in natural values: Number of AGVs (X_1): 6; Speed of AGV (X_2): 150 feet/min; Queue discipline (machine rule) (X_3): SPT; AGV dispatching rule (X_4): STD; Buffer size: (X_5): 24.

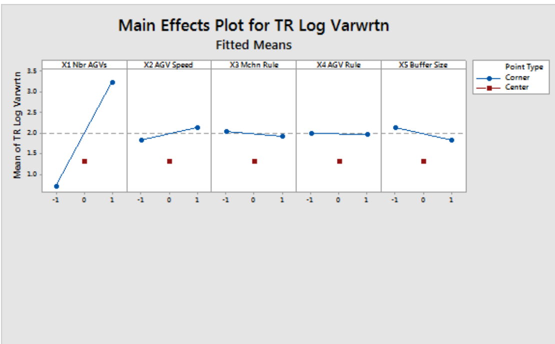

Figure 2: Effects of Control Factors on Log $\sigma^2_{(wrtnf)}$ TR.

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