Taguchi Method or Compromise Programming as Robust Design Optimization Tool: The Case of a Flexible Manufacturing System

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Abstract: Competitive advantage of a firm is usually reflected through its superiority in production resources and performance outcomes. In order to achieve high performance (e.g., productivity) and significantly improve product quality, major US industries have promoted and implemented Robust Design (RD) techniques during the last decade. RD is a cost-effective procedure for determining the optimal settings of the control factors that make the product performance insensitive to the influence of noise factors. In this research, we employ and compare two RD optimum-seeking methods to optimize a flexible manufacturing system (FMS). Taguchi Method (TM), which uses robust design concept, i.e., Signal-To-Noise Ratio (S/N) to reduce the output variation, is applied first. Taguchi's approach to robust design drawn much criticism because it relies on the signal-to-noise (S/N) ratio for the optimization procedure. Because of this paramount criticism, a second method known as the Compromise Programming (CP) approach, i.e., the weighted Tchebycheff, is also used. This method formulates the robust design as a bi-objective robust design (BORD) problem by taking into account the two aspects of the RD problem, i.e. minimize the variation and optimize the mean. This approach seeks to determine the RD solution which is guaranteed to belong to the set of efficient solutions (Pareto points). Both methods use a RD formulation to determine an optimal and robust configuration of the system under study. The results gained through simulations and analytical formulations show that the current ways of handling the multiple aspects of the RD problem by using Taguchi's S/N ratio may not be adequate.

1 INTRODUCTION

A variety of approaches has been proposed for the design, control and optimization of manufacturing systems in order to find the best parameter settings for an optimal operation. These techniques include mathematical programming, queuing networks, computer simulation, Artificial Intelligence (AI). It has been noticed that the usefulness of any of these tools depends on the nature of the problem.

Computer-aided and automated production and manufacturing systems can be described or characterized as a group of processing centers connected by an automated material handling system under computer control. Selecting the optimal setting in such an environment is critically important since it affects the manufacturing performance measures, production cost and the loss due to a plant performance deviation from the company-identified target value. The selection of the appropriate setting of input factors in order to attain the required process target (mean) is of major interest in various manufacturing optimization models including Robust Design models. Material handling system is the back-bone of a Flexible Manufacturing System (FMS). It connects various production functions and regulates movement of parts through the facility. Automated guided vehicles (AGVs) have been the most popular choice among the several types of material handlers available and used in FMSs. Achievement of high performance from an Automated Guided Vehicle System (AGVS) is influenced by several "D*esign*" and "*Operational Control"* issues. These include specifying the type and number of vehicles to be employed, specifying appropriate guide path configuration together with locating load transfer stations, locating vehicle buffering areas and specifying their loading capacity, specifying vehicle dispatching and routing strategies, managing traffic, specifying unit load sizes, specifying central and/or local work-in-

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process storage capacity, specifying the machine queue discipline, etc.

2 OPTIMIZATION OF FMSS

Most of the contemporary manufacturing firms, typically flexible manufacturing systems possess a certain randomness that invites complexity. As the degree of complexity increases, it becomes difficult if not impossible to use analytical models to study the manufacturing system behaviors. Therefore, simulation is widely used to study manufacturing systems' performances (Tshibangu, 2004). But, although a significant amount of simulation studies has been conducted for design and analysis of FMSs, especially to construct performance models, this technique does not provide optimal solutions.

The present study analyzes an hypothetical Flexible Manufacturing System and aims to maximize the Throughput Rate (TR) of such a system while making the system robust, i.e., insensitive to uncontrollable factors otherwise known as noise. To achieve this, the research uses the well-known Robust Design (RD) methodology. Typically, when implemented by optimization, robust design is achieved by optimizing the mean of performance and minimizing the variation of performance.

3 APPROACH IN THIS STUDY

This study employs one of the well-known robust design methodologies, namely the Taguchi Method (TM), to find the optimal combination of input factor settings (levels) that would optimize (i.e., maximize) the throughput rate (TR) of the selected hypothetical Flexible Manufacturing System. In particular, the research uses the two-part orthogonal array for experimental design and the signal-to-noise-ratio (S/N-ratio) as the robust optimization criterion.

Although Taguchi's Methods (TM) are widely accepted in the industry, and although the inclusion of noise factors for the purpose of design optimization has been considered as an innovative concept by several researchers, others have severely criticized its statistical methods. Taguchi's approach to robust design has particularly drawn a high amount of criticism because it relies on the signal-to-noise (S/N) ratio for the optimization procedure (Pignatiello and Ramberg, 1991; Tshibangu, 2004). Because of the various criticisms formulated in disfavor of using the signal-to-noise ratio as optimization criterion following Taguchi robust design approach, this research paper has decided to address the multiple aspects of the robust design problem by exploring a different approach known as the Compromise Programming (CP), specifically the Tchebycheff method. Compromise Programming (CP) was first proposed by Zeleny (1974) and subsequently used by many researchers (Randhir, 2000, Gorantiwar *et. al*., 2010, Gharis, 2012).

CP identifies the best compromise solution as the one that has the shortest distance to an ideal point where the multiple objectives/responses as formulated in the optimization objective function problem simultaneously reach their optimal values. The ideal point is not practically achievable but may subsequently be used as a base point or target.

This study uses "Simulation" as an approach to modeling an hypothetical FMS and applies the two above mentioned methods, namely TM and CP separately while using the Throughput Rate (TR) as the unique and single performance measure. The results of both methods are subsequently compared before drawing conclusions in terms of advantages and disadvantages of one method over another. The paper focuses on the determination of the best combination of design- and operational-related parameters to optimize the hypothetical FMS with respect to the throughput rate (TR). The reason being that a high TR would result into the realization of a higher productivity, under the assumption that the use of specific queue discipline rules such as FIFO (First-In-first-Out) or Shortest Processing Time (SPT) would generally yield a lower Mean-Flow-Time (MFT) as demonstrated by several researchers (Shang, 1995; Tshibangu, 2004, 2013)

4 TAGUCHI ROBUST DESIGN

RD is a cost effective methodology for determining the optimal setting of the control factors that would make the product performance insensitive to the influence of noise factors (Cho *et al*., 2000). Taguchi proposed a three-step approach to product and process design. These are system design, parameter design, and tolerance design. In this study, the philosophy and experimental design principles developed by Taguchi (1986) will be applied.

The reader is referred to Taguchi (1986), Pignatiello *et. al*. (1991), Tshibangu (2004, 2013) for details about Taguchi Method and RD implementation steps. The main advantage of using

Taguchi Method (TM) is that products and processes become *robust* to uncertain conditions.

The common meaning of "*robust*" is that product functions are insensitive to variations in real application environment. Taguchi (1985) first suggested the use of the so-called orthogonal arrays using inner array for control factors and an outer array for the uncontrollable (noise) factors and Signal-To-Noise (S/N) ratios as optimization tool.

4.1 Orthogonal Array

The goal of this research is to study the effects of the noise factors on the performance criterion and optimize such effects. Thus, designs that enable this research to study these effects in an economical way must be favored. Consequently, it is logical to choose the orthogonal arrays or fractional factorial designs that allow to study the effects of noise factors as well as the interaction effects by running the minimum (economical) number of experiments. The matrix that designates the settings of controllable factors for each run is called inner array. The matrix that designates the setting of uncontrollable factors is called an outer array.

The nomenclature of the orthogonal array is $L_a(X^b)$, where "X" represents the number of levels to be explored, "a"represents the number of experimental runs and "b" represents the number of factors that are studied. After the appropriate designs for both control and noise factors are chosen, they are assigned to the inner and outer arrays, respectively. The inner-outer array design is the main strategy for robust design. The noise factors are assigned to the outer array to find some level of a control factor that does not result in much variation in spite of noise factors definitely being present.

4.2 Signal-to-Noise Ratio (S/N)

An adequate performance measure should incorporate both the desirable and the undesirable aspects of the output characteristics. A metric developed by Taguchi in order to optimize a design is the Signal-to-Noise ratio (S/N) using the ratio of the variation in output response resulting from control factors to that resulting from unpredictable or noise factors. In the Taguchi method, the term signal represents the desirable component. The term noise represents the undesirable component and is a measure of the variability of the output characteristic, which preferably should be as small as possible. The Signal-to-Noise Ratio is defined as:

$$S / N = -10 \log(MSD) \quad (1)$$

The Mean Squared Deviation (MSD) is defined for different quality characteristics. For Smaller-The-Better (STB):

$$MSD = (y_1^2 + y_2^2 + y_3^2 + \ldots + y_n^2)/n \quad (2)$$

For Nominal-The-Best (NTB):

$$MSD = (y_1 - T)^2 + (y_2 - T)^2 + (y_3 - T)^2 + \ldots (y_n - T)^2 / n \quad (3)$$

For Bigger-The-Better (BTB):

$$MSD = (1/y_1^2 + 1/y_2^2 + 1/y_3^2 + \ldots 1/y_n^2)/n \quad (4)$$

where

y_i =The results of experiments in each row

T = Target value of results

n = Number of noise combinations

4.3 Quality Loss Function (QLF)

Taguchi also uses the Quality Loss Function (QLF) as a metric for robust optimization. The main idea is that a loss is always incurred when a product/process performance deviates from its target value, regardless of how small the deviation is. The QLF is given by:

$$L(Y) = K(Y - T)^2 \quad (5)$$

where K is the (positive) loss function coefficient, Y is the random variable of quality characteristic y, T is the target or desired value of the quality characteristic of interest.

The reader is referred to the extensive discussions in the literature on various Loss Functions (Berger 1985, Pignatiello 1991). An interesting and desirable characteristic of the QLF is that it was proven (Ribeiro 1995, Tshibangu 2004, 2013): that for the Nominal-the- Better (NTB) type problem, the expected loss is given by:

$$E[L(Y,T)] = K[\sigma^2 + (T - \mu)^2] \quad (6)$$

where σ and σ^2 represent the mean and variance of Y, respectively. It is interesting to note that minimizing the quality loss can be achieved by minimizing both the variance (σ^2) and the bias $(|\mu - T|)$ or difference between the mean and the target $(T - \mu)$.

Chen *et al.* (1998) found that one issue that has not been adequately addressed in the previous investigations is the multiple aspects of the objective in robust design. They suggest for the robust design problem a formulation that would consider "*optimizing the performance*" and "*minimizing the variance*" as two objective functions to be optimized separately. Their approach is used in the present study.

Therefore, to address the multiple aspects of robust design, it is necessary to treat it as a multi-objective optimization problem. Since the performance variation is often minimized at the cost of scarifying the best performance, a tradeoff between the aforementioned aspects should necessarily take place. There are several ways of dealing with the tradeoff between multiple objectives. Chen *et al*. (1998) used a combination of the rigorous multi-objective mathematical programming method and the principles of decision analysis to address the multiple aspects of the objective in robust design.

They proposed the use of Compromise Programming approach (CP), i.e., the Tchebycheff method in place of the traditional WS method. For details on the Compromise Programming (CP) method, the reader is referred to Park *et. al*. (2001).

5 COMPROMISE PROGRAMMING

The CP was developed by Zeleny (1974), under the motivation of looking for a more powerful method in generating a Pareto set.

Let $F(x) = [f_1(x),..., f_m(x)]$ and $f_i(x), i = 1,...,m$, be real-valued continuous functions defined in R^m. Let X denotes the design space that is formed by both the design constraints and the range of design variables x, and $Y = F(x) \subset R^m$ be the objective space, in a multi-objective problem formulated as:

$$\text{minimize } F(x) \text{ subject to } x \in X \subset R^m \quad (7)$$

A point x_0 is called a *Pareto solution* of the multi-objective optimization problem if there is no other feasible point x, such that $f_i(x) \le f_i(x_0)$, $i = 1,...,m$, with strict inequality for at least one index i. The image $F(x_0)$) of a Pareto solution in the objective space is called the *efficient solution*.

The common practice for finding Pareto solutions has been the Weighted Sum (WS) method that performs the minimization of a linear combination of the objective functions. The corresponding weighted-sum problem $(WSP\ (w))$ is:

$$\text{minimize } \sum_{i=1}^{m} w_i f_i(x)$$

$$\text{subject to } x \in X \subset R^m \quad (8)$$

$$\text{where } w_i \ge 0, i = 1,...,m \text{ and } \sum_{i=1} w_i = 1$$

Scalars w_i are referred to as the weights assigned to the objective $f_i, i = 1,...,m$, and determine the importance of each objective. It is well recognized in the literature that an optimal solution of the $((WSP\ (w)))$ for any positive weights is always a Pareto solution of the original problem, which consists of minimizing each objective function individually over the design space (Gorantiwar *et. al*. 2010, Anita *et. al*., 2012, Gharis 2012).

The basic idea of the CP method is to identify an ideal solution (*utopia point*) where each attribute under consideration achieves its optimum value. In the case of conflict among the different attributes, the designer seeks a solution, which is the closest possible to the ideal solution. In Chen *et al*.1998, the authors review and compare two approaches to finding its Pareto set: the WS approach and the CP method. They show the limitations of the former and the advantages of the latter. Typically, the advantages of the $CP(\infty, w)$ approach over the WS method in locating the efficient multi-objective robust design solutions (Pareto points) are illustrated. The $CP(\infty, w)$ also known as the *weighted Tchebycheff approach* is very useful in generating Pareto solutions.

In this paper, beside the Taguchi's approach (TM), the Compromise Programming $CP(\infty, w)$ which guarantees that all efficient solutions of the problem are generated, is also used to solve a bi-objective robust design problem (BORD). The results of both methods are further analyzed and compared.

6 ROBUST DESIGN USING CP

Based on the principles of the CP approach, a robust design procedure has been proposed by Chen *et al*. 1998 to address the multiple aspects of robust design. The first step is to transform the traditional optimization problem into a RD formulation, that is, an engineering design problem is stated using the conventional optimization model as follows:

$$\text{minimize } f(x))$$

subject to $g_j(x) \le 0,\ j = 1,2,...,J$

$$x_L \le x \le x_U \qquad (9)$$

where x, x_L and x_U are vectors of design variables, their lower bounds and upper bounds, respectively; $f(x)$ is the objective function and $g_j(x)$ is the $j-th$ constraint function. The RD design model can therefore be stated as a bi-objective robust design (BORD) problem as follows (Gharis, 2012):

minimize $\lfloor \mu_f, \sigma_f \rfloor$

subject to $g_j(x) + k_j \sum_{i=1}^{m} \left| \frac{\partial g_j}{\partial x_i} \right| \Delta x_i \le 0$, $j = 1,2,...,J$

$$x_L + \Delta_x \le x \le x_U - \Delta x \qquad (10)$$

where μ_f and σ_f are the mean and standard deviation of the researched objective function, $f(x)$ respectively.

The next step once the problem is transformed into a BORD is to seek for the ideal solution (*utopia point*) by optimizing μ_f and σ_f individually, using the model as stated in Equation (9). μ_f can be optimized by using either the "Smaller-the-Better", the "Nominal-the-Best" and the "Larger-the-Better". But it is always desired to minimize σ_f. The utopia point found through the abovementioned process is denoted $\lfloor \mu_f^*, \sigma_f^* \rfloor$.

Knowing the ideal solution of the robust design problem, the designer needs to specify a preference structure by assigning weights w_1 and w_2 to represent the relative importance of the two objectives. The process stops only when a satisfactory solution is reached. Details on technique relating utility function optimization to CP is extensively provided in *Chen et al*. 1998.

7 EXPERIMENTS + METHODOLOGY

The steps used for the robust design methodology applied in this study can be summarized as follows:

1) Choose the levels of the control factors and noise factors.
2) Chose the appropriate design for both control and noise factors.
3) Assign the control factor to the inner array and noise factor to the outer array.
4) Conduct the experiments using discrete-event simulation program (ARENA is used in this study).
5) Calculate the mean and the variance of the Throughput Rate (TR).
6) Apply Taguchi's Robust Design method to optimize the throughput mean and minimize the variation in the Throughput Rate, and predict the control factors that optimize the manufacturing system under study.
7) Apply the CP approach to Robust Design for the same purpose as in 6.
8) Apply confirmation methods such as residual analysis.
9) Run the confirmatory experiments for each case (i.e., Taguchi and CP).
10) Compare results and make final conclusions.

7.1 Shop Conditions and Simulation Model

The manufacturing system analyzed in this research is composed of 5 workstations, one loading and one unloading station, as illustrated in Tshibangu (2003). Each workstation is constituted of one machine. The control factors explored in this research are the number of AGVs, the number of pallets, the buffer size per machine, the machine dispatching rule, the AGV dispatching rule, the interarrival time and the AGV speed. Uncontrollable factors considered are the MTBF (Mean Time Between Failure) and MTTR (Mean Time To Repair). Taguchi experimental design principles and simulation were used to measure the Throughput Rate, the single performance measure criterion considered in the present study. Table 1 gives the factors and their associated levels for the simulation of the FMS under study.

Consider a system involving a response Y (i.e., throughput) which depends on the level of k control factors $(x_1, x_2, ..., x_k)$. Suppose that m replicates are taken at each of the design points.

Finding the true functional relationship between the dependent variable Y (Throughput Rate) and the independent variables x_k will lead, when using regression analysis, to an approximating function of the form:

$$\widehat{Y} = \beta_0 + \sum_{1}^{k} \beta_i x_i \qquad (11)$$

Table 1: Factors and their levels for simulation.

Designation	Controllable Factors	Level 1	Level 2	Level 3
X_1	Number of AGVs	2	5	8
X_2	Number of Pallets	80	90	100
X_3	Buffer Size per Machine	4	8	12
X_4	Machine Dispatching Rule	TPT	SPT.TOT	SPT
X_5	AGV Dispatching Rule	FCFS	STD	LQS
X_6	Interarrival Time	30 min.	20	10
X_7	AGV Speed	60 f/min	80	100

	Uncontrollable Factors	Level 1	Level 2
X_8	Mean Time Between Failure (MTBF)	300 (Low)	700 (High)
X_9	Mean Time to Repair (MTTR)	50 (Low)	90 (High)

Table 2: Parameter design results.

Inner Array								Outer Array				Response	
n	A	B	C	D	E	F	G	H1 I1	H1 I2	H2 I1	H2 I2	Y	S/N
1	1	1	1	1	1	1	1	149	133	233	161	169	44.018
2	2	2	1	1	2	2	2	194	140	348	241	230.75	45.889
3	3	3	1	1	3	3	3	279	145	352	242	254.5	46.698
4	2	2	1	2	1	3	3	224	121	399	232	244	45.486
5	3	3	1	2	2	1	1	219	121	369	293	250.5	45.681
6	1	1	1	2	3	2	2	276	207	373	268	281	48.418
7	3	3	1	3	1	2	2	241	187	385	303	279	47.996
8	1	1	1	3	2	3	3	257	195	328	272	263	47.942
9	2	2	1	3	3	1	1	285	215	361	265	281.5	48.55
10	2	3	2	1	1	2	3	318	217	416	305	314	49.24
11	3	1	2	1	2	3	1	240	169	385	255	262.25	47.299
12	1	2	2	1	3	1	2	202	193	265	212	218	46.583
13	3	1	2	2	1	1	2	184	141	375	244	236	45.861
14	1	2	2	2	2	2	3	251	218	352	263	271	48.28
15	2	3	2	2	3	3	1	298	198	415	274	296.25	48.547
16	1	2	2	3	1	3	1	233	190	281	231	233.75	47.126
17	2	3	2	3	2	1	2	269	212	354	241	269	48.148
18	3	1	2	3	3	2	3	376	223	415	346	340	49.857
19	3	2	3	1	1	3	2	353	268	380	328	332.25	50.204
20	1	3	3	1	2	1	3	236	149	316	220	230.25	46.304
21	2	1	3	1	3	2	1	247	196	371	283	274.25	48.085
22	1	3	3	2	1	2	1	243	157	326	207	233.25	46.466
23	2	1	3	2	2	3	2	309	263	389	328	322.25	49.91
24	3	2	3	2	3	1	3	271	220	416	289	299	48.858
25	2	1	3	3	1	1	3	258	214	346	265	270.75	48.279
26	3	2	3	3	2	2	1	241	219	396	318	293.5	48.67
27	1	3	3	3	3	3	2	267	206	377	298	284	48.547

If there is a curvature in the system, then a polynomial of higher degree must be used, such as the second-order model:

$$\hat{Y} = \beta_0 + \sum_{1}^{k} \beta_i x_i + \sum_{1}^{k} \beta_{ii} x_i + \sum_{i} \sum_{j} \beta_{ij} x_i x_j \quad (12)$$

Equations 11 and 12 will be used in the CP approach. The Taguchi Method experimental design as carried out in this study results into 27 design configurations to be run using simulation package ARENA^{TM}. The coded experimental results for the 27 runs under the four uncontrollable factor combination levels are given in Table 2.

7.2 Taguchi Method Results an Analysis

For the Taguchi approach, analysis of data will first involve calculation of $\overline{Y}$ and the S/N ratio. In this research, Throughput Rate has the "Bigger-the-Better" characteristic, because it desired to be maximized. Therefore, Equation 4 has to be used for the S/N calculations.

The ANOVA (not represented here) for the regression model including all the variables has confirmed what is already known from previous studies (Tshibangu, 2003), namely that the number of pallets is not a significant factor. Although AGV and machine dispatching rules have shown a slight significance, they are considered as insignificant factors in this study. Therefore, the number of AGVs (X_a), the buffer size (X_b), the interarrival time (X_c) and the speed of AGV (X_d) as renamed variables will be considered as the only factors of interest in this study. The confidence interval level used in this study is 95%. After analyzing the main and interaction effect plots as suggested by Taguchi, the factors (and their levels) recommended by the Taguchi Method and confirming the regression analysis conclusions, study are found to be : $X_a = 5$, $X_b = 12$, $X_c = 20$, and $X_d = 80$, leading to a maximum throughput of 253 units in coded data. Table 3 displays the regression analysis coefficients.

Table 3: Regression analysis coefficient and R^2.

Predictor	Coeff.	StDev	T	p
Constant	-36.667	6.023	-6.09	0.000
AGV	7.667	1.475	5.20	0.000
Buffer	6.35	1.475	4.32	0.000
InterArr	6.333	1.475	4.29	0.000
SpeedAgv	5.667	1.475	3.84	0.001

S = 6.260 R-Sq = 78.1% R-Sq(adj) = 74.2%

A first-order model to these data by least squares gives, for the best subset, in coded variables the following equation:

$$\hat{Y} = 7.67 \text{ AGV} + 6.33 \text{ Buffer} + 6.33 \text{ InterArr} + 5.67 \text{ SpeedAgv} - 36.7 \quad (13)$$

Using now X_a, X_b, X_c , and X_d for number of AGVs, Buffer size, Interrarrival time and AGV speed, respectively, Equation 13 is written as follows:

$$\hat{Y} = 7.67\, X_a + 6.35\, X_b + 6.33\, X_c + 5.67\, X_d - 36.7 \quad (14)$$

The ANOVA Table for the model is displayed in Table 4. It shows all the four factors significant as confirmed by the F-test results for the overall regression and the regression coefficients. All the interactions between factors are considered to be insignificant.

Table 4: ANOVA Best subsets regression model.

Source	DF	SS	MS	F	p
Regression	4	3080	770	19.65	0.0
Residual Error	22	862	39.18		
Total	26	3942			

7.3 CP Method Results and Analysis

The BORD problem for the FMS configuration under study is formulated as follows:

$$\text{Minimize} \left[\frac{\mu_f}{\mu_f{}^*}, \frac{\sigma_f}{\sigma^*{}_f} \right]$$

Subject to
$$2 + \Delta X_1 \le X_1 \le 8 - \Delta X_1$$
$$4 + \Delta X_2 \le X_2 \le 12 - \Delta X_2$$
$$-30 + \Delta X_3 \le X_3 \le -10 - \Delta X_3$$
$$60 + \Delta X_4 \le X_4 \le 80 - \Delta X_4 \quad (15)$$

where the mean function and standard deviation can be derived from the following equations:

$$\mu_f = E[Y(x_i)] = 7.67\, E[X_a] + 6.35\, E[X_b] + 6.33\, E[Xc] + 5.67\, E[X_d] - 36.7 \quad (16)$$

$$\sigma_f = Var((Y(x_i)) \quad (17)$$
$$= \sqrt{7.67^2 Var(X_1) + 6.35^2 Var(X_2) + 6.33^2 Var(X_3) + 5.67^2 Var(X_4)}$$

It worth it to note that if the function was non-linear, the mean function and the standard deviation could have been derived using first-order Taylor expansion series. To seek the ideal solutions, μ_f^*, σ_f^*, the above optimization problem formulated in (17) is solved separately as the design objective. Note that in Equation (15), in order to study the variation of the constraints, the original constraints are modified by adding a penalty term to each of them. The penalty factors are to be determined by the designer. The bounds of design variable vector (x) are also modified to ensure feasibility under deviation. When the size of the variation is considered as $\Delta X = 0$ ($\Delta X_a = \Delta X_b = \Delta X_c = \Delta X_4 = 0$) and, and the penalty factor k is taken as 1.0 (in this example ($g_j = 0$, the ideal solution under the assumption of equal density functions, are obtained in coded values, as $X^*_{\mu_f}(4.95, 7.92, 19.8, 79.2)$ for $\mu_f^* = 258$ units, and $X^*_{\sigma_f}(2.0, 4.0, 22.0, 88.2)$ for $\sigma_f^* = 109.22$.

8 CONCLUSIONS

The primary objective of this paper is to propose an enhanced optimization strategy by formulating the robust design procedure using the recent development on mathematical programming methods and decision analysis principles. The multiple aspects of the objective in RD are addressed explicitly and designers are allowed to select their preferred structure among a set of candidate optimal solutions.

The study presents two methods for FMS design and optimization, particularly for AGVs and machines (work stations). Because it is almost impossible to predict the response (Throughput Rate in this case) as mathematical functions of the factors, an empirical (simulation) approach has been adopted.

First, Taguchi Method is used to act as a screening process and to quickly identify the optimal area. This is important, because no more experimental effort has to be spent on the non-significant factors, and the designer can quickly concentrate on the important (significant) factors that have been identified. Taguchi Method also helps to reduce the noise factors rather than eliminating them (which is neither practical nor feasible). Furthermore, Taguchi Method provides a unique fashion for optimization when qualitative factors are concerned.

Because there is still some controversy about optimization tools used by Taguchi Method such as orthogonal arrays, signal-to-noise ratios, and linear graphs, a second optimization approach known as the Compromise Programming is proposed and applied. The basic idea of CP is to identify an ideal solution (*utopia point*) where each attribute under consideration achieves its optimum value (Adeyeye *et. al*., 2010, Anita *et. al.* , 2012).

This enhanced optimization model in robust design considers both the product/process bias and the variance. It was numerically demonstrated that this proposed model might provide a better solution in terms of control factor settings in an FMS or other environments. Many of the previous studies have concentrated on the minimization of the variance while keeping the bias at zero. But, it has been shown (Cho *et al*, 2000) that there are situations where the minimum variance with a zero bias may not provide the minimum expected loss.

When compared to the existing methods for robust optimization such as Taguchi's S/N ratio, the proposed approach has many advantages (Chen *et al*. 1998), namely: capability of generating the efficient solutions, interactive robust design procedure, significance of the multi-objective approach to robust design, etc. As a research strategy however, we suggest that these two methods be used together, especially when there are qualitative factors involved. We propose that the region of investigation be determined by the TM before using CP. When TM is used alone, the interaction factors cannot be fully taken into account due to the limit of the linear graph in the orthogonal array.

On one hand, the optimization is only done over the points (three levels in this study) considered in the design. These points (factor levels) may not lead the true optimum when continuous variable are involved. On the other hand the CP approach is unable to handle qualitative variables. Using the two methods combined will help designers to determine what level of the input factors and AGV and machine dispatching rules will maximize the Throughput Rate for a specific FMS. Simulation, Taguchi and CP approaches to RD are powerful tools to improve the design and performance in the FMS environment. Further research may consider multiple performances measures instead of one used in this study.

REFERENCES

Adeyeye *et. al.*, 2012. Multi-objective methods for welding flux performance Optimization, *RMZ – Materials and Geoenvironment,* Vol. 57, No. 2, pp. 251-270.

Anita *et. al*. 2012, A Mathematical Analysis of Compromising Programming Techniques. IOSR Journal of Mathematics ISSN: 2278-5728. Vol. 3.

Berger, J.O., 1985,.Statistical Decision Theory and Bayesian Analysis (New York: Springer-Verlag).

Chen, W., Wiecek, M.M., Zhang, J., 1998, Quality Utility- A Compromise Programming Approach to Robust Design, *ASME Design Technical Conference*, paper no. DAC5601, Atlanta, GA.

Cho, B.-R, Kim, Y.J., Kimbler, D.L., and Philips, M.D, 2000. An Integrated Joint Optimization Procedure for Robust and Tolerance Design. *International Journal of Production Research*, Vol. 38, N°10, 2309-2325

Pignatiello, J. and Ramberg, J.S., 1991, Top Ten Triumphs and Tragedies of Genichi Taguchi. *Quality Engineering*, Vol. 4, N°2, 221-225.

Gharis, 2012. A Compromise Programming Approach to Effectively Value and Integrate Forest Carbon Sequestration into Climate Change Policy. Dissertation, Carolina State University, *Department of Forestry and Environmental Resources* , Raleigh, NC.

Gorantiwar *et. al*., 2010, Multicriteria Decision Making (Compromise Programming) for Integrated Water Resources Management in an Irrigation Scheme, *Future State of Water Resources & the Environment, EWRI-ASCE,* Chennai.

Park, T., Lee, H., and Lee H., 2001. FMS Design model with multiple objectives using compromise programming, *International Journal of Production Research*, Vol.39, N°15, 3513-28.

Randhir T. O., Lee, J. G., Engel, B., 2000. Multiple Criteria Dynamic Spatial Optimization to Manage Water Quality on a Watershed Scale. *Transactions of* the ASAE, VOL. 43(2): 291-299 © 2000.

Ribeiro, J.L., and Elsayed, E.A., 1995. A Case Study on Process Optimization Using the Gradient Loss Function, *International Journal of Production Research*, Vol. 33, no. 12, 3233-48.

Shang, J.S., 1995. Robust design and optimization of material handling in an FMS, *International Journal of production Research*, Vol.33, N°9, 2437-2454.

Taguchi, G., 1985. Introduction to Quality Engineering (MI: American Supplier Institute); 1987, System of Experimental Design, edited by Don Clausing, Vol.1 and 2 (New York: *UNIPUB/Kraus International Publications*).

Tshibangu, WM Anselm, 2013. A Two-Step Empirical-Analytical Optimization Scheme, A DOE-Simulation Meta-Modeling Approach, 10th International Conference on Informatics in Controls, Automation and Robotics.

Tshibangu, WM. Anselm, 2004, Multiple Optimization of a FMS Using a Multivariate Quadratic Loss Function, International Journal of Industrial Engineering Proceedings of the 9th Annual International Conference on Industrial Engineering Theory, Applications and Practice, Auckland, New Zealand.

Zeleny, M., 1974, A Concept of compromise solutions and the method of displaced ideal. *Computer and Operations Research*, Vol. 1, 479-496.