An Alternative Robust Design to Assist a Single-Objective Performance Optimization: Simulation Analysis of a Flexible Manufacturing System

Wa-Muzemba Anselm Tshibangu
Department of Industrial and Systems Engineering, Morgan State University, 1700 E. Cold Spring Lane, Baltimore, Maryland 21251, U.S.A.

Keywords: Flexible Manufacturing System (FMS), Discrete-Event Simulation, Taguchi, Design of Experiments (DOE), Robust Design, Single-Objective Optimization, ANOVA, T-Test, Normal Probability Plot.

Abstract: During the lockdowns following the Covid-19 pandemic many companies have become flexible by implementing new manufacturing technologies, such as group technology (GT), just-in-time (JIT) production systems, and flexible manufacturing systems (FMSs) that, hence, become among the solutions of the future. This paper uses the emergence of these systems to present an alternative robust design formulation to Taguchi methodology before proposing a single-objective optimization scheme to find the optimal operational settings of primary individual key performance indicators (KPIs). The study uses the Throughput Rate (TR) and the Mean Flow Time (MFT) as illustrative examples of KPIs, tracked over a range of AGV fleet sizes. Additional KPIs, e.g., Work-in-process (WIP), Machine utilization, and AGV utilization are also analyzed as secondary measures to validate and fine-tune the results of the procedure. The study deploys and uses in association multiple statistical tools for a proper analysis and validation of the technique. The effectiveness of the proposed model is validated by comparing the results to some other similar approaches. Although derived from simulation of manufacturing operations, the framework presented in this paper can be applied to various industries including food production, financial institutions, warehouse industry, and healthcare.

1 INTRODUCTION

The COVID-19 pandemic put forth the role of technology in everyday business, especially in the manufacturing operations. Products needed to be manufactured quicker without sacrificing quality standards. The situation raised the demand for rare production items such as ventilators, gloves, face shields, masks, paper towels, toilet papers, and sanitizers at a high rate (Cohen, 2020). Manufacturing giants such as General Motors and Ford Motor Company turned their production systems to support the need of society in terms of manufacturing ventilators (Aalok Kumar et al., 2020). Then, it became evident that a flexible manufacturing system (FMS) was inevitable to fulfil the requirement for such necessary items. Today, in the post pandemic era, national government institutions, health institutions, food processing industry, pharmaceutical manufacturing organizations, should be prepared in advance to tackle any situation to control the production of essential and nonessential items during a pandemic, and have sufficient buffer plans to address the availability of life saver stocks such as ventilators, vaccines, sanitizers, masks, and face shields (Aalok Kumar *et al*., 2020) and also, a variety of non-health related goods, e.g., food, tools, automobile parts, and other equipment.

The choice of performance measures in a processing system such an FMS depends highly on management policy and decision-making approach, especially under COVID-19-lke supply chain disruption conditions. Multiple objective measures, often referred to as Key Performance Indicators (KPIs) are needed to describe the dynamic nature of a manufacturing or production system such as an FMS.

A single performance measure is not enough to capture and characterize the overall performance of a system. Hence, optimizing a system with respect to one single objective only may lead to sacrificing other objective(s) of interest. For example, the objective of

Tshibangu, W.
An Alternative Robust Design to Assist a Single-Objective Performance Optimization: Simulation Analysis of a Flexible Manufacturing System.
DOI: 10.5220/0012392100003639

In *Proceedings of the 13th International Conference on Operations Research and Enterprise Systems (ICORES 2024)*, pages 309-316
ISBN: 978-989-758-681-1; ISSN: 2184-4372

minimizing in-process inventory might conflict with that of maximizing a production rate.

However, the author believes that during conditions of supply chain disruptions like the past pandemic era, it may become strategical to prioritize only one single performance to the detriment of others depending on the industry segment. Therefore, this paper presents a unique robust design scheme applied to an FMS with the objective of proposing a single-objective performance optimization procedure as well as all the statistical validation tools that support the scheme.

2 THE HYPOTHETICAL FMS

The paper analyzes a hypothetical flexible manufacturing system (FMS) using discrete-event simulation. The study proposes a unique and robust scheme in designing, modeling, and optimizing the system. The system is modeled with a total number of 9 workstations including a receiving and a shipping station. This 9-station flexible manufacturing system as schematically depicted in Figure 1 is served by a fleet of AGVs while processing fifteen-part types, each with a different processing time.

The study analyzes and proposes a single criteria "empirical" optimization scheme that is subsequently and separately applied to two most popular and conflicting performance measures indicators, namely, the Throughput Rate (TR) and the Mean Flow Time (MFT), over a range of AGV fleet sizes. The proposed optimization procedure also deploys a series of additional statistical tools intended to support the validation of the approach. Besides, three other metrics are tracked and analyzed as secondary measures or benchmarks to validate the selection of optimal values. The proposed optimization scheme is developed by studying an AGV-served FMS and evaluating its overall performance while considering 5 design parameters as controllable variables, designated by X_i $(i=1\ldots5)$, 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 variables have a direct impact on the performance of machines and material handling (AGVs), considered as the most expensive components of the overall system.

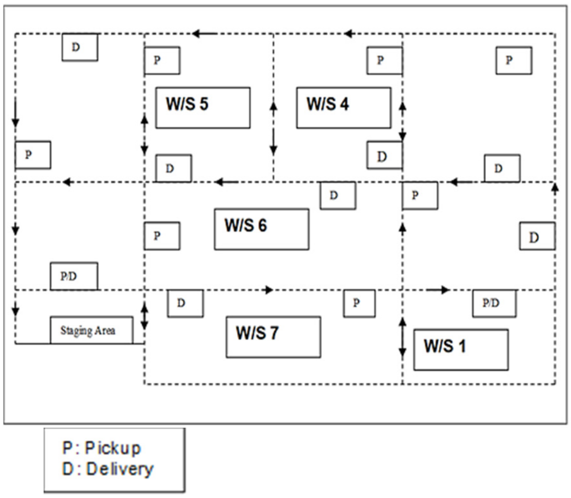

Figure 1: The Hypothetical Flexible Manufacturing System.

Table 1 depicts the shop configuration as studied in this paper.

Table 1: FMS – Shop Configuration.

Part Types Considered for Production	15
Arrival Time Between Parts	EXPO(5) and EXPO(15)
Machines (Workstations)	9 (including one loading and one unloading stations)
Queue Discipline (Machine Scheduling Rule)	FIFO, SPT
Material Handling System (AGV) - Size	Variable from 2 to 9
Speed of AGV	100-200ft/min
AGV Dispatching Rule	FCFS, STD
Buffer Capacity	8 to 40 for workstations 2 to 8
	Infinite for workstation 1
Loading/Receiving Stations	1 (workstation 1)
Unloading/Shipping Stations	1 (workstation 9)
Path Direction	Mixture of uni- and bi-directional paths

3 OVERVIEW

The COVID-19 pandemic has disrupted manufacturing and production operations around the world on a huge scale, challenging manufacturers, vendors, and suppliers to seek for innovative new ways to continue their operations safely while minimizing risks and disruptions (Cappelli et al., 2020).

Manufacturing becomes increasingly digital each day. This can be seen in the concept commonly referred to as "Industry 4.0." Essentially, Industry 4.0

refers to the digital automation of manufacturing capabilities. An FMS, by design, is part of Industry 4.0 as it is an integrated and automated system of numerically controlled (NC) machines, material handling systems (e.g., AGVs), and a system controller (i.e., a centralized/decentralized or computer system) designed to provide benefits of reduced WIP inventory and shortened production lead time (Park et al., 2001).

Because a characteristic of product demand in a modern economy is small quantity and high variety of products and or services, the effects of variations due to these uncontrollable factors can be drastic.

During the FMS operations, its components can fail due to several reasons. In such an integrated system the failure of a single component may force an extremely expensive machine to idle, and, because there is limited work-in-process (WIP) within the system boundary, the entire system can be brought to starvation and stoppage. In such a potentially disruptive environment, reliability-related issues and robustness become important because of their possible negative effect on the FMS performances. It has been demonstrated that reliability, and operating policies for the scheduling decisions affect the performance of an FMS (Tshibangu, 2016). Many analytical tools exist to address these issues, with simulation being a powerful strategic analysis tool, particularly for design (Ball and Love, 2009).

The natural values assigned to the robust design variables as applied in this research are displayed in Table 2. The controllable parameters X_1 through X_5 are set and tested at two setting levels (min and max). Table 3 displays the settings and values for the noise factors considered in this study, also the most investigated and documented in the reported literature (Montgomery 2013) are: i) the arrival rate between parts (or orders), (X_6), the mean time between failures of the machines (X_7) and the associated mean time to repair (X_8).

4 RESEARCH METHODOLGY AND ROBUST DESIGN

The various phases of the robust design methodology as applied in this paper are the same as proposed in most literature (Montgomery 2013, Taguchi 1987) except that in this study, after completing the simulation experiments and collecting all pertinent data the following additional steps are taken to accommodate any subsequent optimization procedures:

1. Calculate the mean and the variance with respect to noise factors $\sigma^2_{wrtnf(i)}$ for each treatment *i* (row of the inner array) and for each performance measure of interest; this variance measures the variation in performance when there is a change in noise factors.
2. Compute and use log $\sigma^2_{wrtnf(i)}$ of each performance measure to improve statistical properties of analysis.
3. Apply the normal probability plotting technique to the calculated mean and the log σ^2_{wrtnf} of each control factor setting to determine the significance of the main factors and their interaction effects on each measure of interest.
4. Develop and implement a four-step optimization procedure to predict the factors and their associated settings that will simultaneously minimize σ^2_{wrtnf} and optimize the mean of the performance measures. Adjust and fine-tune the settings to the most appropriate economical levels.
5. Apply the residual analysis to verify the results.
6. Run the confirmatory simulation tests.
7. Conclude on the optimization procedure.

These factors are also tested at two levels in combination with each control factor (X_1 through X_5) at each setting level. For both controllable and noise factors, the coded levels are (-1) and (+1) for the low and high level, respectively.

Table 2: Natural Values and Setting of Control Factor.

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

Table 3: Natural Values and Setting of Noise 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)

The general data collection plan (the *M* x *N* matrix) for the FMS under consideration in this research is displayed in Table 4. In this research the design matrix is constructed using a 2_v^{5-1} fractional factorial design while the noise factor is generated using a 2^3 full factorial design. The notation used in this table is defined as follows:

Let *Y* represent a performance measure of interest (e.g., throughput, flow time, machine utilization, work-in-process).

Let y^{IJ} represent a realization of this performance measure for system configuration or system design I =1, 2,…*M*, and noise set J = 1,2,…, *N*.

Let $\theta_i^{\ I}$ represent the setting of the ith controllable variable (i= 1, 2,…, *k*) for system configuration I (e.g., number of AGVs, AGV speed, AGV dispatching rule, machine queue discipline in force).

Let ω^J represent a set of noise conditions, J=1,2, ...*N*

Let $\omega_j^{\ J}$ represent the jth noise variable setting (j = 1, 2, …, *l*) for noise condition *J* (e.g., machine mean time between failure, mean time to repair, mean interarrival time).

Table 4: Data Collection Plan.

						ω^1	ω^2	. . .	ω^N	
						ω_1	ω_1^2	. . .	ω_1^N	
						ω_2	ω_2^2	. . .	ω_2^N	
						. .	. .	. . .	. .	
						ω_l	ω_l^2	. . .	ω_l^N	
θ^1	θ_1	θ_2	. .	. .	θ_k	y^{11}	y^{21}	. . .	y^{1N}	$Z^1(\theta)$
θ^2	θ_1^2	θ_2^2	. .	.	θ_k^2	y^{21}	y^{22}	. . .	y^{2N}	$Z^2(\theta$
θ^3	θ_1^3	θ_2^3	. .	. .	θ_k^2	y^{31}	y^{32}	. . .	y^{3N}	$Z^3(\theta)$
. .	. .	. .	. .	. .	. .	. .	. .	. . .	. .	. .
. .	. .	. .	. .	. .	. .	. .	. .	. . .	. .	. .
. .	. .	. .	. .	. .	. .	. .	.	. . .	. .	. .
θ^M	θ_1^M	θ_2^M	. .	. .	θ_k^M	y^{M1}	y^{M2}	. . .	y^{MN}	$Z^{MN}(\theta)$

Let $Z^I(\theta)$ represent a performance statistic for each design configuration (e.g., mean or variance of a performance measure such as throughput, flow time, machine utilization, work-in-process).

$Z^I(\theta)$ is a function or functions of all of the data that have been selected by the simulation analyst to examine one or more aspects of the performance of system configuration *i* over the noise conditions. By examining different choices for *Z,* the experimenter can examine various system performance aspects.

This research focuses on examining the mean system performance, the system variance with respect to noise ($\mathrm{Var}_{(\mathrm{wrtn})}$), the maximum and minimum system performance. Therefore, $Z^I(\theta)$ may represent a vector of values such as the row average, the row variance, and the row maximum or row minimum.

This simulation data collection plan described above represents a departure from the procedures discussed in the literature of experiments. The associated design of experiments strategy for robust design can facilitate detailed analysis. A robust system design is, then, one that performs desirably and consistently under all the noise conditions represented in the simulation experiments.

5 VARIANCES, MAIN AND INTERACATION FACTORS

A well-planned experiment makes it simple to subsequently analyze and predict the improved (optimal) parameter settings. In this study, for each of the simulated design configurations *i*, eight measurements (over the set of noise factor combinations) were taken for each performance measure of interest, and then, averaged across the replications to obtain $\overline{y}_i$ for each *i*th row of the inner array. Sixteen design configurations and five center-points (for a total of 21) designs were simulated over a set of eight noise factor combinations, leading to a total of 21 x 8 =128 simulation runs. The results of these various simulation experiments, too large to be displayed in this paper, but available upon request, were subsequently averaged up across the three replications.

This research intends to minimize the variances of the performance measures with respect to the noise factors for each run.

5.1 Determination of Main Effects on Means and Variances

The objective is to make the variances of the responses (performance measures) as small as possible while bringing the means to their optimum settings, i.e., minimum MFT and maximum for the TR. The study then computes the values of $\overline{y}_i$ and $log\ \sigma^2_{(wrtnf)i}$ at each design configuration.

Subsequently, the effects of each control factor on the overall mean and the variance (or $log\ \sigma^2_{wrtnf}$) are calculated using the normal probability method. The same procedure is applied to the complete set of controllable factors to assess the effects on the means of Throughput Rate (TR), Mean Flow Time (MFT), Work-in-Process (WIP), and Utilization (UT).

Table 5: Effects of Control Factors MFT Variance.

Control Factors	Effect on MFT log σ^2_{wrtnf} Level (+1)	Effect on log MFT $\sigma^2_{wrtnf\ at}$ Level (-1)	Absolute Value Difference
X_1	1.6159	1.657502	0.04155
X_2	1.6081	1.558286	0.04982
X_3	1.4921	1.781325	0.28920
X_4	1.6338	1.639566	0.00568
X_5	1.6032	1.670230	0.06701

The results, not all displayed in this paper, are available upon request. Then each controllable factor is tested at two levels and the magnitude of its effect on the mean measured.

Table 5 displays the effects of controllable factors on the MFT mean, just as an illustrative example.

Analysis of the results in Table 5 reveals that X_3 (queue discipline) has the most significant effect on the MFT variability as highlighted in bold, while the exam of other results shows that X_1 (number of AGVs) has the most significant effect not only on the MFT mean but as well as on the TR variability and mean. These results agree with previous findings Bardhan and Tshibangu, 2002, Tshibangu 2003).

Subsequently, the effect at high level is compared to the effect at low level, and the better setting of each control parameter is that gives the smaller average value of $log\ \sigma^2_{wrtnf}$. Results indicate that factor X_1 (the number of AGVs), when set at its high level, has the most significant effect on the mean value of MFT. Other results, not displayed here, but available upon request, indicate a high impact of X_1 (the number of AGVs) on TR.

Once identified, these significant factors for MFT and TR will be set at the settings (levels) that minimize $log\ \sigma^2_{wrtnf}$, i.e., X_1 and X_3 at high settings, and these, implemented. Note that a visual summary of the magnitude of each control factor's effect can also be used for analysis of various effects.

The relative importance of different main effects of control factors on the means and variances have been derived. Figure 2 displays a visual representation of the main effect on TR means for illustration purpose. Other graphs exist for the effects on variances and means of all other controllable factors. A quick glance at Figure 2 and others, not displayed here, reveals on one side, that control factor X_1 (fleet size) is a critical factor because it has a significant effect on the TR and MFT means and on TR Variance. On the other side, Factor X_3 (queue discipline) has the biggest effect on MFT variance. This agrees with the analytical results (Tshibangu 2003).

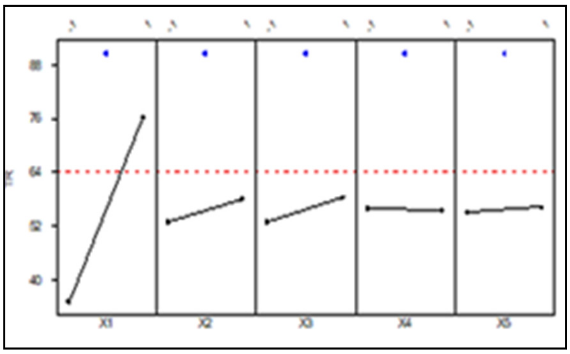

Figure 2: Main Effect Plot (data means) for TR.

5.2 Determination of 2-Way Interaction Effects

Effects due to interaction between factors are important in selecting an experimental design, because underestimating these effects may lead to incorrect conclusions whereas overestimating them may unnecessarily increase the experimental design size (Tshibangu 2003).

This research uses a resolution *V* design to allow an estimation of effects of two-way interactions. The effects of interactions between factors are determined using a Minitab software package for the estimation of main effects. As an example, and for illustration purposes, Figure 3 displays a 2-way interaction between mean values control factor TR.

To be certain that the samples collected through simulation and robust design of experiments approaches are statistically valid, all the necessary hypothesis and normal probability tests have been conducted at 95% confidence level.

Normal probability plots are useful in assessing the significance of effects from a fractional factorial, especially when several effects are to be estimated (Montgomery 2013).

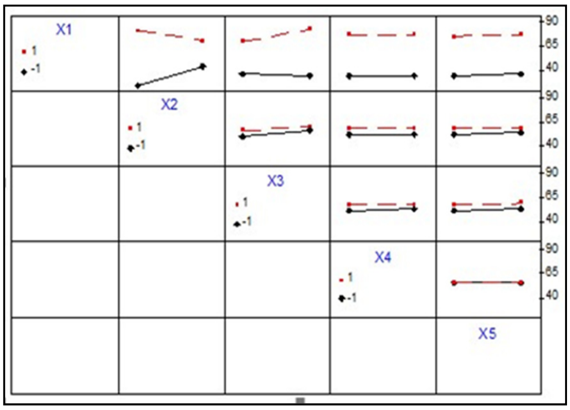

Figure 3: Interaction Plots (data means) for TR.

6 OPTIMIZATION SCHEME IMPLEMENTATION

In this section, a unique optimization procedure is developed and presented. The developed optimization procedure represents a departure from other approaches reported in the literature in the sense that this procedure is the first to include the effects of two-way interaction between controllable factors. The approach is inspired and motivated by Taguchi's strategy for improving product and/or process quality in manufacturing.

6.1 Four-Step Single-Response Optimization Approach for Robust Design

Because flexible manufacturing systems and any other process-oriented systems are subject to various uncontrollable factors that may adversely affect their performance, a robust design of such systems is crucial and unavoidable. The author has developed a four-step optimization procedure to be used simultaneously with the robust design as first step of the optimization scheme as proposed in this study:

Let $\overline{y}_i$ 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 treatment *i*. Kacker and Shoemaker, 1986 recommend using the logarithm of the variance to improve statistical properties of the analysis, and to 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:

Under the assumption that we have partitioned three categories of control vectors as non-empty sets X_v^T containing the factors that have a significant effect on the variances, X_m^T containing factors significant on the means (and their interactions), and X_0^T as the set of the factors that affect neither the mean nor the variance, respectively, then a four-step empirical optimization procedure may be implemented as follows:

Step 1
Identify the vector X_v^T and adjust the controllable factors members of this set to their values that minimize σ^2_{wrtnf} of the performance measure *y*.

Step 2
Identify vector $(X_m^T)_1$ of factors having a significant effect on the mean $\overline{y}$ and set the controllable factors members of this set to their level values that optimize the mean $\overline{y}$ of the objective performance y. Also, identify $(X_m^T)_2$ vector of factors having a significant effect on mean $\overline{y}$ and on the variance σ^2_{wrtnf} simultaneously and set the factor members of this set to their level values that optimize the mean $\overline{y}$ if this setting does not act in opposition with the minimization of the variance. Otherwise, find a compromise between minimizing the variance and optimizing the mean as suggested in *Step 4* where the final setting is to be decided.

Step 3
Identify the vector X_0^T and set the control factors members of this set to the values of their interaction with members of vector X_v^T that minimize the variance or *log* σ^2_{wrtnf} or the values of their interaction with members of X_m^T that optimize the mean $\overline{y}$. Otherwise, set the factors at their economic settings.

Step 4
Conduct a small follow-up experiment to find the trade-off between members of $(X_m^T)_2^B$ containing factors with effects on variance and mean acting in opposition and or the overall economical settings. A suggestion from this study is that in finding the overall economical setting, the step involves only those factors that have the greatest effect on either the variance σ^2_{wrtnf} or the mean $\overline{y}$.

6.2 Throughput Rate (TR) and Mean Flow Time (MFT) Optimization

When applying the above-described procedure the optima for TR (maximum) and MFT (minimum) are found using the associated plots and tables, the following result are obtained:

For Throughput Rate (TR)

X_v^T: [X_1(-1), X_2(-1)], *pending (X_1 and X_2 adjustment through follow-up and confirmatory runs).*

X_m^T: [X_5(-1)], *confirmed.*

X_0^T: [X_4 (-1), X_5(-1)], *confirmed.*

For Mean Flow Time (MFT)

X_v^T: X_3 (+1), *confirmed.*

(X_m^T): $(X_m^T)_1$: X_1(+1), X_2(+1)

$(Xm^T)_2$: $(X_m^T)_2^A$: X_3(+1), *confirmed.*

$(X_m^T)_2^B$: ϕ

(X_0^T): X_4 (-1), X_5(-1), *confirmed.*

6.3 Follow-up and Confirmatory Runs

Follow-up and confirmatory experiments are then be conducted under the above specified system conditions. For each configuration tested, besides the primary performance measures TR and/or MFT, other performance measures such as machine utilization, work-in-process (WIP), and AGV utilization are also recorded for benchmarking purposes. The results of the tuning and confirmatory runs at different settings for TR and MFT are displayed in Table 11 and 12, respectively.

At the completion follow-up/confirmatory, the most optimal and robust design to be implemented with respect to the performance measure of interest TR (used here as an example) is highlighted in bold in Table 6.

Table 6: TR Optimization follow-up/Confirmatory Runs Under Various #AGVs (X_1) & AGV Speed (X_2).

$X_2 \downarrow$ $\overrightarrow{X_1}$	4 AGVs	5 AGVs	6AGVs	7AGVs	8AGVs	9 AGVs	10AGVs	11 AGVs
TR_{100} (p/d)	*	*	*	2630	2992	2996	2997	2996
TR_{150} (p/d)	*	2627	**3000**	2996	3000	2996	2998	2997
TR_{200} (%)	2714	2994	2997	2995	2997	2996	2998	2998
MU_{100} (%)	*	*	*	79.47	89.55	89.77	89.79	89.76
MU_{150} (%)	*	79.7	**89.73**	89.76	89.78	89.77	89.8	89.76
MU_{200} (%)	81.99	89.71	89.79	89.77	89.76	89.76	90.52	89.76
WIP_{100} (p/d)	*	*	*	380	100	81	81	83
WIP_{150} (p/d)	*	377	**81**	79	78	80	81	82
WIP_{200} (p/d)	303	78	77	78	79	80	81	81
Ut_{100} (%)	*	*	*	*100	99.73	96.04	93.86	93.17
Ut_{150} (%)	*	*100	**97.87**	92.92	91.17	91.03	91.48	92.05
Ut_{200} (%)	*100	94.78	90.19	89.2	89.68	90.38	91.21	91.95

7 RESULTS AND COMPARATIVE ANALYSIS

In both TR and MFT cases, the results obtained are compared with those generated by similar procedures, such as Taguchi (using S/N ratio), Kacker and Schoemaker (1986), Wild and Pignatiello (1996), and Bulgak *et al*. (2000) approaches. Table 7 depicts one of the primary performance measures of optimal robust design configurations as achieved under various approaches. The reader is referred to Tshibangu 2003 for details and background about each procedure.

TR optimal design yields the highest throughput rate of (3000 parts/day), a fair machine utilization rate of (89.73%), an acceptable WIP (81 parts/day) and a relatively high AGV utilization (97.87%). Indices 100, 150, 200 refer to AGV speed in (ft/min). Using the natural values, the optimum of MFT is achieved with fleet of 6AGVs, at 200ft/min, SPT queue discipline, FCFS AGV dispatching rule, and a buffer capacity of 8 units, yielding MFT of 0.3666 min/part in coded units, machine utilization of (86.5%), a decent WIP of (77 parts/day) and an AGV utilization rate of (90.19%).

8 CONCLUSIONS AND FUTURE RESEARCH

The coronavirus crisis has dramatically increased risk for every business, with many, experiencing shocks in both supply and demand. Manufacturing plants are at the center of that uncertainty, and their continued operation through the crisis and beyond will depend in large part on the organization’s ability to navigate these wider risks (Vivek *et. al*. 2020).

In this study, a unique single-objective optimization procedure is developed and presented. Because of supply chain disruptions that have been experienced in the manufacturing and production industry, many organizations had to develop strategic approaches for survival by focusing on few key performance indicators, such as timely delivery of manufactured goods, or solely on the volume of products in need on the market.

Regardless of the selected KPI it was imperative to be the best in the market segment. This study has been motivated by the pandemic crisis to develop and propose a robust single-objective optimization procedure and apply it to a Flexible Manufacturing System (FMS) that has been designed and analyzed using a discrete-event simulation approach.

The developed approach is an approximation and empirical procedure that takes advantage of a unique robust design formulation to include the consideration of the two-way interaction factor effects. Although inspired and motivated by Taguchi’s strategy for improving product and/or process quality in manufacturing, the developed procedure, however, the intentionally departs from Taguchi’s and traditionally known approaches as it avoids the criticisms and insufficiencies thereof. Hence, a series of additional statistical tools is used to assist the procedure. These include main and interaction effects of control factors, t-test, ANOVA, normal probability plots, etc.

As further research pathway, the optimal values found in this single objective optimization procedure could then be used as target value in any subsequent multiple optimization scheme to be developed in future research studies.

Table 7: Comparison Optimal TR as Realized under Various Approaches.

Performance Measures	Taguchi	Wild and Pignatiello	Kacker and Shoemaker (D13)	This Research Approach
	[0,0,0,0,0]	[+1,-1,+1,-1,-1]	[+1,+1,+1-1,-1]	[+1,+1,+1-1,-1]
Design Simulated	(D20)		(D13)	
Throughput Rate TR (parts/month)	2980	2996	2996	**3000**
Machine Utilization (%)	89	89.77	89.76	89.73
WIP (parts/day)	68	81	80	81
AGV Utilization (%)	97.36 (6 AGVs)	96.04 (9 AGVs)	90.38 (AGVs) (9 AGVs)	97.87 (6 AGVs)

The procedure is developed and applied to the simulation outputs, focusing on optimizing TR (max) and MFT (min). These performance measures have been selected because they are extensively referred to as primary KPIs in the literature. Follow up/confirmatory runs are subsequently conducted as sensitive analysis to fine-tune and validate the settings initially uncovered through the first approximation.

There are three areas of focus can help plant managers and leaders navigate the transition from initial crisis: (i) *Protect the workforce:* standardize operating procedures and processes; (ii) *Manage risks to ensure business continuity:* anticipate potential changes and model the plant to react to fluctuations to enable rapid, fact-based actions. (iii) *Drive productivity at a distance:* Continue to effectively manage performance at the plant while physical distancing and remote working policies remain in place.

As future research, the single-objective optimal values can subsequently be used as targets for a more advanced analytical multiple-objective optimization scheme, using tools such as simulation metamodels. In addition, the multiple objective-optimization could include other KPIs such machine utilization, WIP, and AGV utilization as primary metrics instead of benchmarks or decision guides as used in this research (Abdessalem *et*. al, 2022).

REFERENCES

Abdessalem et. al., 2022. Multi-Objective Design Optimization of Flexible Manufacturing Systems Using Design of Simulation Experiments: A Comparative Study, *Machines 2022, 10, 247*.

Ball, P. and Love, D. (2009). Instructions in Certainty, Institute of Industrial Technology, 29-33.

Bardhan, T. K, and Tshibangu W. M. A. 2003. Analysis of an FMS with Considerations of Machine Reliability, P*roceedings of 8thAnnual IJIE Engineering Theory, Applications and Practice*, Las Vegas, Nevada.

Cappelli, A., Cini, E., (2020). Will the COVID-19 Pandemic Make us Reconsider the Relevance of Short Food Supply Chains and Local Productions? Trends Food Sci. Technol., doi: 10.1016/j.tifs.2020.03.041.

Cohen, M.J. (2020). Does the COVID-19 Outbreak Mark the Onset of a Sustainable Consumption Transition? Sustain. Sci. Pract. Policy,doi: 0.1080/15487733.2020.174047.

Kacker, R. N., Shoemaker, A. C., Robust Design, 1986. A Cost-Effective Method for Improving Manufacturing Processes., *AT&T Technical Journal*, Volume 65, 51-84

Kleijnen, J. P. C., Design and Analysis of Simulations, 1977. Practical Statistical Techniques, *SIMULATION*, Volume 28, no.3, 81-90.

Kumar, Aalok *et al*. (2020) COVID-19 impact on Sustainable Production and Operations Management. *Sustainable Operations and Computers*, Vol. 1, 1-7.

Montgomery, D. C., 2013, Design & Analysis of Experiments, (8th Edition, NY: John Wiley & Sons Inc.

Park et al., 2001, FMS design Model with Multiple Objectives Using Compromise Programming, International journal of Production Research, Volume 39, no. 15, 3513-3528.

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

Taguchi, G., 1986. Introduction to Quality Engineering-Designing Quality into Products and Processes, *Asian Productivity Organization,* Tokyo.

Tshibangu W. M. A., 2005. A Framework for Designing a Robust Material Handling Using Simulation and Experimental Design, *Proceedings of the 10th IJIE Conference* Florida.

Tshibangu, W. M. 2006, Robust Design of an FMS: S. M. Proceedings of the GCMM, COPEC, Council of Research in Education and Sciences November19-22, Santos, Brazil.

Vivek, et al., 2020, Managing a manufacturing plant through the corona virus crisis, McKinsey article, Apr 23.

Wild, R. H., and Pignatiello, J. J., Jr., 1991.An Experimental Design Strategy for Designing Robust Systems Using Discrete-Event Simulation, *SIMULATION,* Volume 57, no.6, 358-368.