Flexible Manufacturing System Optimization by Variance Minimization: A Six Sigma Approach Framework

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Abstract: From the performance view point, manufacturing strategy relates to the decision about where to focus concentration among quality, speed, dependability, flexibility and cost. This study analyzes a hypothetical flexible manufacturing system (FMS) and aims to illustrate an optimization procedure based on a variance reduction applied on two strategic performance measures, namely the Throughput Rate (TR) and the Mean Flow Time (MFT). The study uses a Taguchi robust design of experiments (DOE) methodology to model and simulate the hypothetical FMS, analyzes the output of the simulations, then proposes a unique and hybrid (empirical-analytical) methodology to quickly uncover the optimal setting of operating parameters. The robust design is used to guarantee the system stability necessary to improve the system and validate the outcomes. Using the key principle of the Six Sigma methodology that advocates a reduction of variability to improve quality and processes the proposed methodology quickly reaches a near optimum by considering both the main and interaction effects of the control factors that will minimize the variability of the performances. Fine-tuned follow-up runs may be necessary to compromise and uncover the true optimum.

1 INTRODUCTION

Accomplishing excellence, global competition, and catching up with the rapid technological changes and advances in manufacturing and information technology, are forcing manufacturers to optimize all possible manufacturing processes and operations for the purpose of delivering high quality products in a short period of time. Achieving the above requires a strategic decision-making at the corporate level that involves the coordination of additional sub-strategies for marketing, engineering, manufacturing, research and development.

At the tactical and operation levels a variety of approaches, including mathematical programming, queuing networks, computer simulation, Artificial Intelligence (AI), and others, are among the most proposed techniques for the design and control of production and manufacturing systems. When it comes to find the best and optimal setting of the operational parameters Lean Six Sigma is emerging nowadays as one of the most rapid and powerful techniques for process and/or system continuous improvement. It has been noticed however, that the usefulness and appropriateness of any of these techniques depend on the nature of the problem and systems under consideration.

The drastic reduction of product life cycles has lead manufacturing flexibility to become a competitive weapon in many industries, increasing the popularity of Flexible Manufacturing Systems (FMS). The performance of an FMS is influenced by several complex "*design*" and "*operational control"* issues requiring an optimal setting of operational parameters. Thus, the problem of identifying the most optimal configuration of FMSs is gaining importance in today's operation and production management strategies. For that reason this study simulates a flexible manufacturing system. The selection of a poor, non-suitable or inappropriate combination of an FMS's

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design variables and control measures may consequently lead the system to exhibit counterproductive behaviors in the form of work-in-process storage queues, vehicle blocking due to path contention, and even a shop locking phenomenon. The proposed model used in this study results in smooth materials and vehicles flow, high productivity environment free of adverse behaviors.

The research is motivated by both the Six Sigma governing principle, that seeks performance improvement through a reduction of variability and the Six Sigma methodology that uses the DMAIC roadmap to seek and implement the best solution.

Lean and Six Sigma principles based on Little's law and reduction of variance, respectively recommend a stable system or process before implementing an improvement/optimization scheme. Robust DOE is used to render the system insensitive to uncontrollable factors (noise) and guaranty system stability. Simulation is used because it becomes difficult if not impossible to apply strict analytical models to study manufacturing systems behaviors.

The optimization of the modeled system is subsequently implemented and achieved through a minimization of the performance variation followed by an optimal adjustment of the performance's mean.

2 LITERATURE REVIEW

There is still a limited number of reported system optimization using Lean, Six Sigma or both combined. Sharma (2003) mentions that there are many advantages of using strategic Six Sigma principles in tandem with lean enterprise techniques, which can lead to quick process improvements. 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. "Lean" is an integrated system of principles, practices, tools and techniques that are focused on reducing waste, synchronizing workflows, and managing production flows (de Koning and de Mast 2006). Shihata (2014) applies "Lean" technique to optimize the flow of solutions in a refrigerator assembly line. David Forgaty (2015) uses Lean Six Sigma to optimize the process of bid data extraction in manufacturing. 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.

The pursuit of optimization has intensified the demand for higher process/product development speed, manufacturing flexibility, waste elimination, better process control, and efficient manpower utilization to gain competitive advantages (Karim *et al*.2010). The Six Sigma philosophy maintains that reducing 'variation' will help solve process and business problems (Pojasek, 2003). 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).

3 SYSTEM CONSIDERATIONS

There are 9 machines (workstations) in the system to process 15 different part types (jobs). Seven of these workstations are typical machining centers, such as turning, milling, drilling, etc. The two remaining stations are used as a receiving station for loading when jobs enter the system, and a shipping station for unloading when the jobs exit the system.

The throughput rate (TR) and the mean flow time (MFT) are used to track the performance of the simulated system. Note that these indicators also give a measure of a third one, the work-in-process (WIP) through Little's law, considered as the backbone equation governing Lean principles. The two indicators have been selected to serve the purpose of this research while additional measures such as Machine Utilization (MU) and AGV Utilization (AU) are also used in this study, more as benchmarks to evaluate the goodness of the developed model.

The research considers a sequence of machine visitation with a number of operations uniformly distributed between 2 and 8. The corresponding processing times range from 5 to 30 minutes. Table 1 illustrates the shop conditions. The processing of jobs within the FMS is modeled, following the basic assumptions (Tshibangu 2013).

Table 1: 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	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 Sations	1 (workstation 1)
Unloading/Shipping Stations	1 (workstation 9)
Path Direction	Mixture of uni- and bi-directional paths

4 THE ROBUST DESIGN

A robust system immune to the noise factors during the actual operations will secure a valid optimization procedure as the Six Sigma technique assumes a stable and predictable system. Lean Six Sigma also advocates the use of a roadmap methodology known as DMAIC (Define- Measure-Analyze-Improve and Control). This study follows a similar procedure. In the following sections each one of these steps will be referred to with the initial letter, e.g., D, M, A, I, C.

4.1 Formulating the RD Problem - (D)

The objective in formulating a robust design problem is to find those control factor settings for which noise has a minimal effect on the performance measures. Three concepts are needed to define in a precise manner the robust design problem): (i) functional characteristics, (ii) control parameters, (iii) and sources of noise.

4.1.1 Functional Characteristics

These are basic, measurable quantities that determine (from the management or the experimenter perception) how well and how smoothly the manufacturing system operates. The functional characteristics of this study are the performance measures. Five measures are computed but only two (TR and MFT) will be used in the illustration of the single optimization formulation model. The other three (machine utilization, material handling system utilization and work-in-process) are monitored and used as guideline or benchmarks to evaluate the goodness of the developed model.

4.1.2 Control Factors

Also referred to as controllable inputs or process variables, their operating values are fixed by the engineering management team and/or by the top management of the firm. This research considers five input variables: fleet size (number of AGVs), vehicle speed (speed of AGVs), queue discipline (machine scheduling rule), AGV dispatching policy, and buffer size. Control parameters can be controlled both in the real world and during the simulation runs.

4.1.3 Sources of Noise

Sources of noise in contrast are identified as the variables that are impossible or expensive to control in the real world but can be controlled during the simulation experiments. This research study considers interarrival rate and machine reliability as source of noise. They will be varied at two different levels during simulation. Machine reliability is considered through the Mean Time Between Failure (MTBF) and Mean Time To Repair (MTTR).

4.2 Operational Steps for RD

Implementing the robust design formulation as applied throughout the next sections of the study requires the following steps:

1. Define the performance measures of interest, the controllable and uncontrollable factors.

2. Plan the experiment by specifying how the control parameter settings will be varied and how the effect of noise will be measured.
3. Carry out the experiment and use the results to predict improved control parameter settings (optimization).
4. Run a confirmation experiment to check the validity of the prediction.

4.3 Experimental Conditions

Knowing that material handling dynamic introduces a lot of randomness in an FMS and because one of the objectives is to design a robust system, this research considers mainly those parameters that are directly related to the material handling system performance.

It should be noted that the machine utilization (MU) is not directly taken into account as a performance criterion because an FMS is a highly capital intensive system. Thus, it must operate at a high machine utilization of 85% or above.

The WIP is not considered as a direct objective performance but rather is monitored as a benchmark as it is directly related to the two performance measures studied through Little's law. This law, also known as the Lean methodology governing equation and first principle of manufacturing systems, states that the work-in-process (WIP) is directly proportional to the flow time (lead time), the proportionality constant being production exit rate (TR).

AGV utilization is not included in the developed model as a primary objective function either. However, it is used as secondary objective function and indicator of the system congestion. An AGV system utilization rate of 100% suggests that the system is highly congested while an utilization in the range of 80-90% indicates rather a highly smooth flow of material in the system. AGV utilization values less than 70% suggest a poorly used vehicle fleet.

Also, although the research is particularized only to two functional characteristics, the developed and proposed model is a generalized model that can accommodate as many characteristics as needed for a specific experiment, research and/or application.

4.4 Simulation Experiments - (M)

To formulate the robust design and be able to subsequently (in a further research study) construct a metamodel for the simulated FMS, a 2_v^{5-1} experimental design augmented with five center points is used. It should be noted that adding a center point to a 2^k factorial design is a method that will provide some protection against pure quadratic effects that can be easily captured by a 3^k because to fit a quadratic model, all factors must be run at least at three levels. Since a 2^k design will support main effects plus interactions model, some protection against curvature is already inherent in the design (Tshibangu 2013). One can test to determine if the quadratic terms are necessary. Table 2 and Table 3 depict the experimental values for the control and noise factors, respectively.The center points consist of n_c (n_c = 5 in this study) replicates run at the point $x_i = 0$ ($i = 1,2,\dots, k$).

The experimental design under this study resulted into 21 various configurations across all eight noise factor combination.

Table 2: Settings of the Control Factors.

Factor	Control Factor	Low Level (-1)	High Level (+1)	Center Point (0)
X_1	Number of AGVs	2	9	(6)
X_2	Speed of AGV	100	200	(150)
X_3	Queue Discipline	FIFO	SPT	(SPT)
X_4	AGV Dispatching Rule	FCFS	SDT	(SDT)
X_5	Buffer Size	8	40	24

After the robust design process was completed, the experimental runs were carried out accordingly. The output results of the various simulation experiments are partially displayed in Tables 4 and 5 just for illustration purpose. These results are the average of the three replications used in this research study.

Table 3: Settings of the Noise Factors.

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

A well-planned experiment makes simple the analysis needed to predict the improved or optimal parameter settings. In this research, 8 measurements (over the set of noise factor combinations) are taken for each performance measure of interest, i.e., throughput rate, mean flow time, machine utilization, work-in-process, AGV utilization, for each of the 21 simulated design configurations over a set of 8 noise combinations, and averaged across three replications.

The expected value of each function estimate is obtained by simulating the system for 60,000 minutes with 3 independent replications. For each replication, a warm-up time of 15,000 minutes is set in order to remove the initial transient effects. The remaining 45,000 minutes represent more or less a month continuous operation. For each design configuration simulated, the mean $\bar{y}$ and the variance σ^2 of these 3 independent replications have been estimated.

Table 4: TR Simulation Results (parts/day).

	Noise 1	Noise 2	Noise 3	Noise 4	Noise 5	Noise 6	Noise 7	Noise 8
Des 1	53.87	94.00	33.63	91.87	99.70	76.13	77.23	61.17
Des 2	25.47	25.93	23.23	25.70	26.00	25.63	25.63	23.93
Des 3	90.13	95.37	68.13	93.43	99.80	83.03	100.70	92.40
Des 4	24.40	24.13	22.07	23.87	25.47	22.60	25.07	23.30
…								
Des 18	41.07	93.97	32.80	91.87	99.63	76.03	46.83	44.20
Des 19	25.87	26.03	25.17	26.23	26.23	25.90	25.77	24.23
Des 20	89.53	96.37	70.97	93.27	99.33	83.00	101.83	94.63
Des 21	91.23	95.77	73.17	92.30	99.93	84.10	101.23	91.80

Because the intent is to minimize the Var TR and MFT the variances with respect to noise factors (variance $_{(wrtnf)}$) are computed for each run. Table 6 partially depicts the values of $\bar{y}_i$ and *log* $\sigma^2_{(wrtnf)i}$ at various design configuration for each of the two primary performance. The *logarithm of* σ^2_{wrtnf} is taken to improve statistical properties of the analysis. The objective of the proposed scheme is to quickly seek

Table 5: MFT Simulation Results (min/part).

	Noise 1	Noise 2	Noise 3	Noise 4	Noise 5	Noise 6	Noise 7	Noise 8
Des 1	18.99	1.83	32.8	0.26	0.45	4.26	11.98	16.12
Des 2	43.47	33.06	45.07	32.81	34.7	32.63	43.72	43.74
Des 3	8.71	0.81	7.61	1.22	0.38	2.07	8.03	7.99
Des 4	42.34	17.73	40.42	21.07	29.88	14.21	42.45	40.62
…..	…..	.....	…..	…..	….	…..	…..	…..
Des 18	26.14	1.18	33.77	1.7	0.45	4.28	21.99	23.69
Des 19	43.95	34.92	43.13	34	34.73	34.75	43.93	44.46
Des 20	8.6	0.93	7.63	1.77	0.33	2.09	7.98	8.03
Des 21	8.6	1.08	7.68	1.36	0.44	2.08	8.05	7.96

for a near optimum by making TR and MFT variances as small as possible and while shifting their means as close as possible to maximum and minimum, respectively. The focus is to minimize the variances. For each design configuration, σ^2_{wrtnf} is first calculated before deriving the *log* $\sigma^2_{(wrtnf)i}$ that will be used to enhance analysis sensitivity.

Table 6: Average and Log $\sigma^2_{(wrtnf)i}$ for TR (parts/day)and MFT (min/part).

Design Config.	*MFT* $\bar{y}_i$	MFT log $\sigma^2_{(wrtnf)i}$	Design Config.	TR $\bar{y}_i$	TR log $\sigma^2_{(wrtnf)i}$
Des 1	10.84	2.12	Des 1	73.45	2.71
Des 2	38.65	1.52	Des 2	25.19	0.02
Des 3	4.60	1.15	Des 3	90.38	2.05
…..	…..	…..	…..	.....	......
Des 9	18.09	1.32	Des 18	.....	......
Des 10	3.92	0.97	Des 19	65.8	2.86
……		……	Des 20	25.68	-0.34
Des 20	4.67	1.13	Des 20	91.12	2
Des 21	4.65	1.13	Des 21	91.191	1.91

4.5 Effects on Variances and Means - (a)

After calculating the *log* $\sigma^2_{(wrtnf)i}$ for each design configuration defined in the robust DOE formulation, the effects of each control factor on the mean and the variance (or *log* σ^2_{wrtnf}) are calculated by using the normal probability data plotting technique.

The computed effects at high and low level will be used in identifying the controllable factor levels (settings) that have the largest effect on *log* σ^2_{wrtnf}. The results of the effects of various input factors on TR and MFT variances are given in Tables 7 and 8. It can be seen (in bold) for instance, that for TR, the control factor X_1 (fleet size) has the highest effect on the variance while the parameter X_3 (queue discipline) has the most significant effect on the mean flow time variability. Figures 1 and 2 provide a Minitab visual display of control factor's magnitude effect on the performance variabilities.

The same procedure is applied to TR and MFT means $\bar{y}$ in order to determine the effects of the control parameters on these two performance measures as depicted in Tables 10 and 11.

Once identified, these factors will be set at the settings (levels) that minimize *log* σ^2_{wrtnf}. The author had proposed a four-step optimization procedure (Tshibangu 2013) that represented a departure from the traditional approaches in the sense that interactions between factors were for the first time considered and integrated in the optimization approach. Interaction effects on both TR and MFT *log* $\sigma^2_{(wrtnf)}$ MFT are depicted in Figures 3 and 4 for illustration purpose.

Table 7: Effects of the Control Factors on Log σ2(wrtnf) TR.

Control Factors	Effect TR log σ^2_{wrtnf} at Level (+1)	Effect TR log σ^2_{wrtnf} at Level (-1)	Delta
X_1	2.57	0.05	2.53
X_2	1.463	1.08	0.38
X_3	1.26	1.36	-0.10
X_4	1.29	1.33	-0.04
X_5	1.20	1.46	-0.26

Table 8: Effects of Control Factors on Log σ2(wrtnf) MFT.

Control Factors	Effect MFT log σ^2_{wrtnf} Level (+1)	Effect on log σ^2_{wrtnf} at Level(-1)	Delta
X_1	1.62	1.66	-0.04
X_2	1.61	1.56	0.05
X_3	1.49	1.78	-0.29
X_4	1.63	1.64	-0.01
X_5	1.60	1.67	-0.07

Table 9: Effects of Control Factors on TR.

Control Factors	Effect TR Avg. at Level (+1)	Effect TR Avg. at Level (-1)	Delta
X_1	76.31	34.97	41.34
X_2	58.18	55.00	3.17
X_3	58.35	52.94	5.40
X_4	55.60	55.69	-0.10
X_5	53.00	55.08	-2.09

Table 10: Effects of Control Factors on MFT.

Control Factors	Effect MFT Avg. at Level (+1)	Effect MFT Avg. at Level(-1)	Delta
X_1	8.25	25.97	-17.73
X_2	12.63	20.90	-8.267
X_3	13.86	20.35	-6.49
	16.97	17.24	-0.27
X5	17.61	16.60	1.01

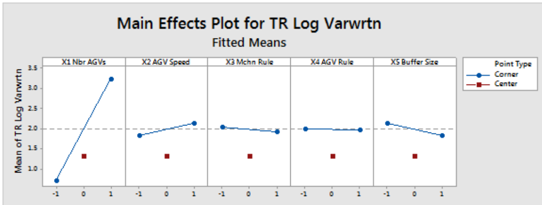

Figure 1: Effects of Control Factors on Log σ2(wrtnf) TR.

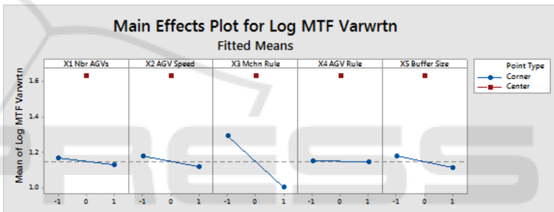

Figure 2: Effects of Control Factors on Log σ2(wrtnf) MFT.

4.6 Optimization Procedure - (I, C)

Let us assume that X_v^T, X_m^T, and X_0^T, are not empty sets representing the vectors of controllable factors that have a significant effect on the variance, the mean, and neither, respectively. Implementing the four-step optimization procedure (Tshibangu, 2013) for TR the following results are obtained at the end of Step 3, just before the follow-up confirmatory runs (Step 4): X_v^T: [X_1(-1), X_2(-1)], pending tradeoff (X_1 and X_2 need adjustment and follow-up)

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

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

Small follow-up experiments are needed to determine the tradeoff and economical settings, while adjusting the mean to optimum when possible. Factors needed in the follow-up and mean adjustment runs are X_1(-1), X_2(-1). X_2 is used as tuning factor to adjust the mean. Its effect on the mean is tested at level (-1) first, and levels (+1) and (0) next. A quick look at the collected data (Table 4) reveals that levels (0) and (+1)

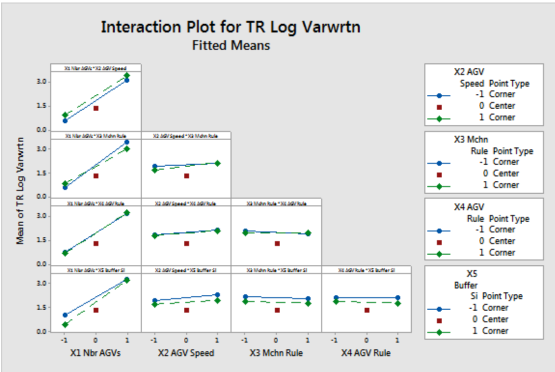

Figure 3: Interaction Effects of Control Factors on Log $\sigma^2_{(wrtnf)}$ TR.

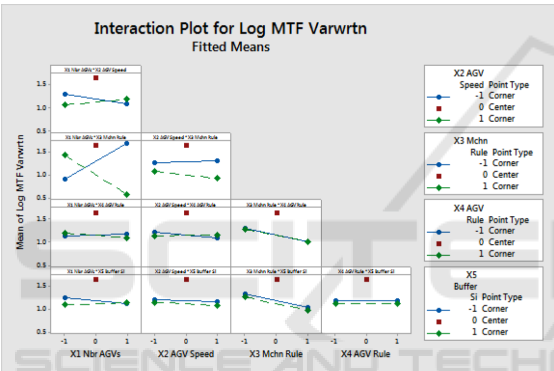

Figure 4: Interaction Effects of Control Factors on Log $\sigma^2_{(wrtnf)}$ MFT.

are the best X_2 (AGV speed) settings for mean improvement. However, this has to be confirmed by the results of the follow-up runs. Because X_1 has a large effect on both mean and variance in opposite directions, then a trade-off is found at the center point. Based on this analysis, the most robust optimal setting is implemented as displayed in Table 11.

Table 11: Most Robust TR Design Configuration.

Factor	Variable Name	Value-code	Natural Value
X_1	AGV Fleet Size	0 (-1?)	6 (3)
X_2	AGV Speed	0 (-1?)	150 (100) ft/min
X_3	Machine Rule	+1	SPT
X_4	AGV Rule	-1	FCFS
X_5	Buffer Capacity	-1	8 units

Note that this design configuration is not among the 21 designs originally simulated. This illustrates the powerfulness of the applied approach.

Follow-up and confirmatory experiments have been carried out under these system conditions. The results of the follow-up indicate that setting X_2 at level (0) is the best implementation in terms of TR maximization. In addition, the follow-up runs also confirm the first intuition about X_1 trade-off level. The center point has been proven to be the best compromise. Because X_1 is also considered as the most expensive component or input parameter to implement, the overall economical setting was confirmed by varying the AGV fleet size (3 to 8 AGVs) around the value found to be the optimal with regard to the throughput rate. The final design to be implemented as optimal is therefore, X_1 (0), X_2 (0), X_3 (+1), X_4 (-1), X_5 (-1).

Machine utilization, WIP, and AGV utilization are additional information that can be used in deciding which system configuration to implement. At this stage, the implemented design, highlighted **in bold** in Table 12 seems to represent the best option leading to the highest TR (100 parts/day), an excellent machine utilization (89.73%), an acceptable WIP (81 parts/day) and a relatively high AGV utilization (97.87%).

The equivalent optimal performance under failure-free robust design configuration is indicated between parentheses in the optimum column (6 AGVs).

Table 12: TR Optimization Follow-Up/Confirmation Runs under various AGV Fleet Size (X_1) and AGV Speed (X_2).

X_2 X_1 → (*) System saturated

	5 AGVs	6 AGVs	7 AGVs	8 AGVs	9 AGVs
TR_{100}	*	*	87.67	99.73	99.87
TR_{150}	87.57	100	99.87	100	99.93
TR_{200}	99.80	99.90	99.83	99.90	99.93
(TR^*_{ZF}) (parts/day)		(100)			
MU_{100}	*	*	79.47	89.55	89.77
MU_{150}	79.70	89.73	89.76	89.78	89.77
MU_{200}	89.71	89.79	89.77	89.76	89.76
(MU^*_{ZF}) (%)		(89.72**)**			
WIP_{100}	*	*	380	100	81
WIP_{150}	377	81	79	78	80
WIP_{200}	78	77	78	79	80
(WIP^*_{ZF}) (parts/day)		(81)			

Table 13: Most Robust MFT Design Configuration.

Factor	Variable Name	Coded Value	Natural Value
X_1	AGV Fleet Size	+1	9
X_2	AGV Speed	+1	200 ft./min
X_3	Machine Rule	+1	SPT
X_4	AGV Rule	-1	FCFS
X_5	Buffer Capacity	-1	8 units

Note that if X_2 (AGV speed) has been set at high level (+1), i.e., 200 ft./min, there would have been a slight depreciation in the TR, almost 5% decrease in WIP, and an excellent AGV utilization. The AGV utilization, excluded from the table for space reason, ranged from 89.20% to 100% with an optimal of 97.87% at 6 AGV-fleet. The decision on which configuration to implement depends on the FMS management and alignment with company's goal or "menu du jour". Because the purpose is to maximize TR, then X_2 is set up to coded level (0) or 150 ft./min.

Following the same procedure for MFT leads to the implemented best MFT optimal robust design configuration displayed in Table 13. Note that this design corresponds to the simulated design # 13.

In the follow-up experiments, X_1 (AGV fleet size) has been identified as the tuning (mean adjustment) factor because it has a large effect on the mean and less effect on the variability of the MFT. X_1 being the most expensive component of the system has been varied at different settings to identify its economical setting.

In order to gain some insight into the impact of AGV rules, and also determine whether or not the X_4X_5 interaction effect observed has any effect on the MFT the follow-up runs and confirmation included testing X_4 at low level (FCFS rule), and high level (STD rule). The MFT minimum of 0.3666 min/part is achieved with the following coded values for the variables X_1 (0), X_2 (+1), X_3 (+1), X_4 (-1), X_5 (-1) (Table not displayed). Using the natural values, the optimum of MFT is achieved with a fleet of 6 AGVs, at 200ft/min, SPT queue discipline, FCFS AGV dispatching rule, and a buffer capacity of 8 units.

5 CONCLUSIONS

This research uses a quick empirical technique to optimize the FMS performances modeled using discrete-event simulation and robust DOE. Data analysis confirms prior knowledge about the number of vehicles. TR variability with respect to noise is influenced by the following factors, ranked according to their importance: AGV Fleet size X_1, AGV speed X_2, AGV dispatching rule X_4, buffer capacity X_5, and machine scheduling rule X_3. The following interaction effects contribute to TR variability: AGV Fleet size X_1 and all other factors, to the exception of AGV speed, i.e., X_1X_3, X_1X_4, X_1X_5. Interactions such as X_3X_4 and X_4X_5 also account for the TR variability. Overall, the interactions with an impact on TR are as follows, in ascending order of magnitude: X_1X_2, X_1X_3, and X_2X_3 with X_2X_3 is almost equal to X_3X_4.

AGV fleet size X_1 seems to have the most significant effect on the MFT. AGV speed X_2, machine rule X_3 come next, and the buffer capacity X_5 at a relatively lower degree. Interaction X_1X_2 has a large effect in influencing the MFT, while the effects of X_1X_3, X_3X_5, X_4X_5 also need to be considered.

Based on the performance of SPT/FCFS and SPT/STD on TR and MFT it can be stated that a combination of machine scheduling and AGV dispatching rules that include job/part information (local rule) in the implemented queue discipline might yield better system performance. Note also that X_5, identified as non-significant on the mean and the variance, could have been set at high level, i.e., a buffer capacity of 40. The resulting design configuration in this case would have been the same as the simulated design #17. Results indicate that this would result into a MFT of 0.7876, almost the double the MFT with X_5 at low level (Capacity = 8). Not only is this design not economical, but it does not yield the optimal performance measure. This finding suggests that, the principle of setting the non-significant control factors at any level when they do affect neither the mean nor the variance may lead to non-optimum design configurations. Thus, effects of interactions should be considered even when main effects are not significant, as is in the case of the proposed optimization procedure. Future research intends to compare the effectiveness of the proposed procedure against other popular, well known and established techniques.

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