Fuzzy Logic Control for Varied Inspection for Manufacturing Lead Time Reduction

A Fuzzy Control Implementation of a Dynamic Inspection Technique to Reduce Manufacturing Lead Time

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Abstract: Varied inspection is an online dynamic inspection method where the amount of parts inspected can be changed based on the quality of the part stream and characteristics of the production system. The research outlines the development of a supervisory and distributed Fuzzy Logic Controller (FLC) to perform varied inspection. The supervisory fuzzy controller was used to tune the weights of the rules used in the distributed fuzzy controller that initiates the varied inspection in quality control systems. Simulation of a single-station manufacturing cell showed that varied inspection had significantly reduced Manufacturing Lead Time (MLT) through reduced inspection, which could help manufacturers handle fluctuating demands. The contribution of the study was to illustrate the benefit of varied inspection through MLT reduction and to add flexibility to control architectures for quality control systems to aid manufacturers meet demands.

1 INTRODUCTION

Recent trends towards Mass Customization (MC) had led to the research and development of flexible technologies to mass produce different products within a product family (Fogliatto et al., 2012). Global market trends have fuelled companies to adapt to customers' demands (Tsourveloudis, 2000). Research had been focused on flexible fixtures, flexible machining, supply chain coordination, MC economics and scheduling however, there has been minimal emphasis on Quality Control (QC) for high variety manufacturing environments (Fogliatto et al., 2012). QC was traditionally defined by Juran (1998) as methods to produce products that were "*free from deficiencies*". Traditional QC techniques include control charts, check sheets and sampling (Davrajh et al., 2012). QC needed to be developed to handle product variations while still ensuring that customers receive products of acceptable functionality. Traditional QC hinged upon statistical inference as part variation was minimal, therefore only samples were inspected to deduce the quality of the entire product population (Davrajh and Bright, 2010). Increased part variation poses challenges to QC as new strategies require flexible inspection methods (Brabazon and MacCarthy, 2007).

Varied inspection was investigated as a flexible form of inspection for MC. Varied inspection was defined by the authors as a QC strategy where the frequency of inspection could be increased or decreased based on the needs of the manufacturer. Naidoo et al. (2016) illustrated that varied inspection could be used in reducing Work-In-Process (WIP). WIP reduction remains a goal in lean, agile and Just-In-Time (JIT) manufacturing (Tsourveloudis, 2000), (Tsourveloudis et al., 2007). A Fuzzy Logic Controller (FLC) was used to perform the varied inspection because it could handle imprecise inputs while performing adequate control. The aim of the research was to test the performance of varied inspection on reducing Manufacturing Lead Time (MLT) with a supervisory and distributed fuzzy controller. MLT reduction warrants that parts spend less time in processing thus ensuring robust response to demands, which is a requirement for the successful operation of MC. The motivation for this research was to illustrate the advantages of varied inspection by aiding a common performance metric such as MLT reduction. The novelty lies in using QC to regulate production for better responsiveness and

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robustness to demands. Existing approaches to MLT reduction rely on flow control techniques that required mathematical models to predict MLT. Varied inspection can be viewed as a flow control technique however, it does not require mathematical modelling because of the fuzzy implementation– which is useful in complex manufacturing situations where the models are difficult to acquire.

2 LITERATURE REVIEW

2.1 Varied Inspection for Quality Control in Mass Customization

Varied inspection is an aperiodic inspection method compared to traditional methods. The inspection system may choose to inspect or not inspect parts as they pass through production based on factors such as part quality, supply/demand, WIP, MLT, bottlenecking, starving or other needs of the manufacturer (Naidoo et al., 2016). The research was focused on part quality and MLT reduction, whereas previous research done by Naidoo et al., (2016) focused on WIP reduction. MLT reduction was desired as parts provide no profit while they remain unfinished and in production. Through reducing the amount of time on inspection, parts spend less time in production thus reducing lead time. Shorter lead time ensures better robustness to manufacturers in supplying demands. Table 1 shows common characteristics of varied inspection in terms of advantages and disadvantages (Naidoo et al., 2016).

Table 1: Characteristics of Varied Inspection.

Advantages	Disadvantages
Appraisal costs are reduced through reduced inspection.	Could allow defective parts to move throughout the system.
Can be used to prevent bottlenecking by increasing/decreasing the number of inspected products.	May result in external failure costs when products fail at the site of the customer.
Over-inspection is reduced.	High average consequence costs.
Reduced average MLT as reduced inspection reduces overall production time.	
Reduced WIP as some parts are sent through the production without inspection.	

The significant advantage of varied inspection (as compared to 100% inspection and acceptance sampling) was that the inspection frequency was not fixed – it could be adjusted to suit the production requirements. Varied inspection could be implemented as a solution to slow inspection that affects production rates (Davrajh and Bright, 2010). However, Groover (2014) stated that this type of inspection yielded high average consequence costs.

2.2 Fuzzy Logic Control for Production Systems and Varied Inspection

FLCs had been used in production systems to improve control since the 1990s (Homayouni et al., 2009). However, Azadegan et al., (2011) stated that there was minimal FL applications in the field of QC. Complex manufacturing environments are difficult to analytically model and probability theory cannot be used to solve all manufacturing issues, which was why fuzzy set theory was supported for control over production (Tsourveloudis, 2000), (Gien, 1999). A FLC was used in this research as it could handle imprecise inputs and does not require a model of the system to control it (Naidoo et al., 2016). Classical control methods require accurate mathematical models for effective control- fuzzy control is a heuristic control approach thus the complex task of obtaining mathematical models are not required. A great advantage of FLCs is that it represents an extension of human logic and can be based on human evaluations, therefore it can replicate how a human expert would control a system (Tsourveloudis, 2000). FLCs have learning capabilities and can be improved with other computational tools such as neural networks and Evolutionary Algorithms (EA) (Homayouni et al., 2009). Research done by Naidoo et al. (2016) showed that a FLC could be used to perform varied inspection for the purpose of WIP reduction. This research was to investigate the effects of varied inspection on MLT, where fuzzy controllers are “Mamdani-type” with rules in the form of (1).

$$\text{IF } X \text{ is } A \text{ AND } Y \text{ is } B \text{ THEN } Z \text{ is } C \; (\mathit{RuleWeight}) \tag{1}$$

X and Y are the inputs with A and B linguistic values respectively, and Z is the output with C linguistic values. Linguistic values are the fuzzy sets that consist of membership functions (Ioannidis et al., 2004). The “*RuleWeight*” determines the strength of the rule with ‘1’ having the strongest weight. The fuzzy controllers designed used minimum for “AND” and the centroid method for defuzzification. The controllers were designed with the Fuzzy Logic Toolbox® in Simulink®.

2.3 Supervisory and Distributed Fuzzy Control in Production Systems

Ioannidis, Tsourveloudis and Valavanis (2004) stated that production systems could be viewed as a "*network of machines/work-stations and buffers*". The authors introduced another module to the network which was the "inspection system". Inspection systems are strategically placed in the production system based on quality checks after processing, assembly and/or disassembly. Figure 1 shows the control architecture for the research that implemented a two-level control system. This research was restricted to a single-station manufacturing cell, where a single machine performs machining on raw material to produce a finished product. From Figure 1, $B_{I,1}$ represents a buffer, M_1 represents machining cell and I_1 represents the inspection system.

The supervisory fuzzy control was previously used by Ioannidis, Tsourveloudis and Valavanis (2004) for a production network where it tuned parameters in multiple distributed fuzzy controllers (that control the processing rates of individual machines) for the purpose of WIP reduction. This research was similar to the work performed by (Ioannidis et al., 2004), however the amount of inspection was varied instead of the machining processing rate, and the inputs to the supervisory fuzzy controller was supplied from the distributed controller and not from the overall production rate.

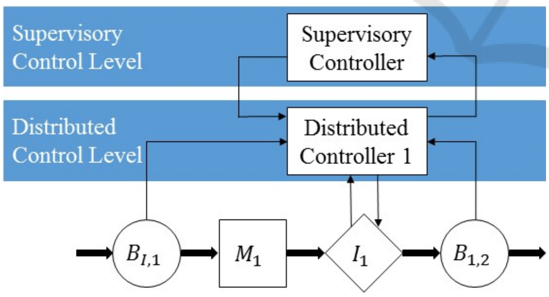

Figure 1: Supervisory Control Architecture for Varied Inspection.

3 SUPERVISORY AND DISTRIBUTED FUZZY CONTROLLER DESIGN

The supervisory controller was used to tune the distributed controller. The supervisory controller used the Defect Rates (DRs) of the part stream to calculate the weights of the rules (within the distributed controller) that are affected by the buffer level input. The supervisory fuzzy controller used the DR as an input to determine the rule weights of the distributed fuzzy controller only when the buffer levels were high, as high buffer levels slow down production thus leading to high MLT. The purpose of the supervisory fuzzy controller was to ensure that MLT reduction would not become a higher priority such that part quality would be significantly compromised. An FLC approach to supervisory control was used as it could effectively tune lower-level controllers. The supervisory FLC could also be easily extended for more objectives other than MLT reduction.

3.1 Supervisory Fuzzy Controller

The supervisory controller used the DR inputs from the distributed controller to determine the rule weights that concern the buffer levels reaching maximum capacity of the distributed controller. The supervisory control contained the rules of the form:

$$\text{IF } SDR1 \text{ is } DR^{(k)} \text{ THEN } BufferWeight1 \text{ is } BW^{(k)} \quad (2)$$

Where k was the rule number (1,2,3) , DR was the fuzzy set of the "Sampled Defect Rate" (*SDR1*) input with linguistic values DR = {High, Average, Low} using three Gaussian membership functions and BW was the fuzzy set of the *BufferWeight1* output with linguistic values BW = {Low, Medium, High}. All rules have the same weight of 1 with a generated curve relating the BufferWeight1 output to the SDR1 input shown in Figure 2.

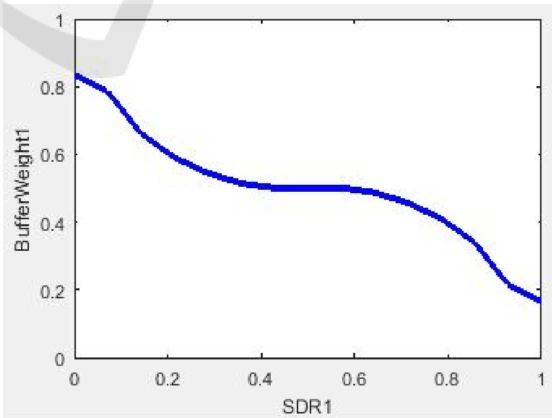

Figure 2: Relationship between BufferWeight1 and Sampled Defect Rate (SDR).

3.2 Distributed Fuzzy Controller

Three inputs were described for the distributed fuzzy controller i.e. DR, buffer level and batch size. The DR was used as an input to ensure that the inspection intensity was dictated by the quality of the parts. Trapezoidal membership functions were used for the DR input with the linguistic values DR = {ExtremeHigh, ModerateHigh, Average, ModerateLow, ExtremeLow}. Buffer level was used as in input to prevent buffers from reaching maximum capacity or becoming too low that starving occurs, described by two Gaussian membership functions for “Low” and “High”. The batch size input was used to ensure that 100% inspection (screening) always occurred at the beginning of the production as a means of establishing the most accurate DR. The amount of 100% inspection performed at the start was determined by the Gaussian membership function shown in Figure 3, where screening was performed for the ‘Initial’ membership function and varied inspection for the ‘Cycle’ membership function. The “Initial” membership function ensures that the first 30% (pre-determined value) parts of the part stream would be fully inspected. Ten rules were outlined for the distributed controller, shown in Table 2. The control actions were to perform 100% inspection at the start of production, and to reduce the inspection intensity where buffer levels were high – thus reducing MLT. The prescribed rules ensured that inspection intensity was always high at the start of production, and that intensity should only be reduced significantly when the DR input was also lowered to reduce the occurrences of defective parts not being inspected. The four rules associated with high buffer levels (rules 4, 6, 8 and 10) have rule weights that were set by the supervisory fuzzy controller. Only the major rules were outlined as each input covered its respective solution space.

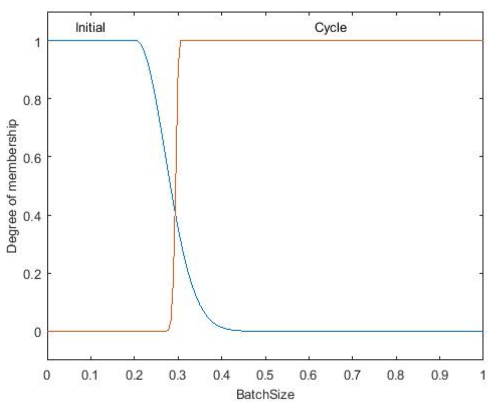

Figure 3: Batch Size Membership Function.

Table 2: Distributed Fuzzy Controller Rule Set.

Defect Rate	Buffer Level	Batch Size	Inspection Intensity	Weight
0	0	Initial	Extreme High	1
Extreme High	0	Cycle	Extreme High	1
Extreme High	Low	Cycle	Extreme High	1
Moderate High	High	Cycle	Moderate High	Buffer Weight1
Moderate High	Low	Cycle	Moderate High	1
Average	High	Cycle	High	Buffer Weight1
Average	Low	Cycle	Medium	1
Moderate Low	High	Cycle	Low	Buffer Weight1
Moderate Low	Low	Cycle	Medium	1
Extreme Low	High	Cycle	Low	Buffer Weight1

The output was the inspection intensity, which was how much of the part stream to inspect. For example, for an inspection intensity of 0.70 and 100 parts, 70 parts would be inspected and would be Independent and Identically Distributed (IID) throughout the 100 parts. IID implementation of the inspection intensity was perform through (3):

$$p = floor\left[\frac{-\log[rand(1,1)*(1-Intensity)]}{\log[\frac{1}{(1-Intensity)}]}\right] \tag{3}$$

Where p = 1 for “inspect” and p = 2 for “do not inspect”. The “floor” function in Matlab® rounds down towards negative infinity to the nearest integer, “rand” was used for uniformly distributed random number generation and “Intensity” was the inspection intensity calculated from the distributed FLC. Equation (3) was tested to determine how effective the IID inspection could be performed. Multiple runs showed that (3) was acceptable as a good realisation of the inspection intensity when averaged out. An averaging approach was used for the best realisation of the inspection intensity with a sample size of 100 parts. Results between the actual intensity and the averaged intensity were discussed in Section 5. From the rules in Table 2 and membership functions, surfaces can be used to view the relationships between the inputs and outputs. Figure 4 shows the relationships between the DR and buffer levels on inspection intensity. Figure 5 shows the relationship between the DR and batch size on the inspection intensity output. Yellow areas (lightly shaded) indicate when inspection intensity was high and blue areas (dark shaded) indicate low inspection intensity.

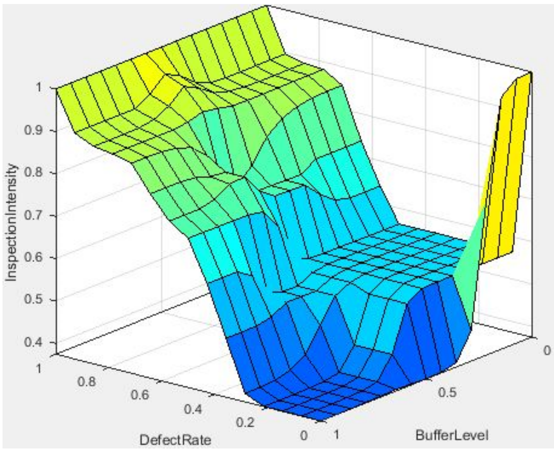

Figure 4: Surface View of Distributed Fuzzy Controller for Defect Rate and Buffer Level Inputs.

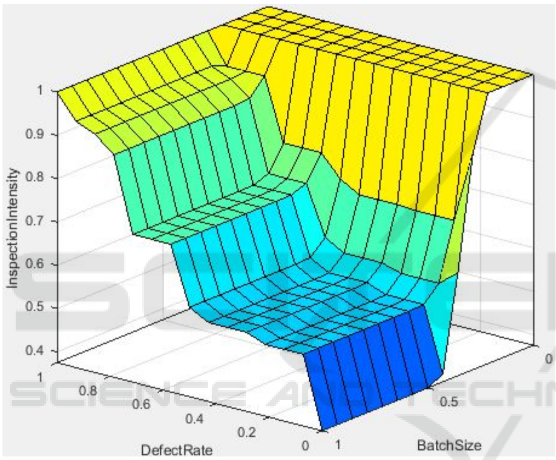

Figure 5: Surface View of Distributed Fuzzy Controller for Defect Rate and Batch Size Inputs.

4 SIMULATION OF FUZZY LOGIC CONTROLLERS IN MANUFACTURING CELL

The supervisory and distributed fuzzy controllers were implemented into a single-station manufacturing cell, shown in Figure 1, to determine the effects of varied inspection on MLT. From Figure 1, raw material arrived in buffer $B_{I,1}$ with an arrival rate of 1 piece per time-unit (note the time-unit may represent seconds, minutes, hours, days etc. as long as consistency was kept). Buffers have a maximum capacity of 10 storage spaces. Machine M_1 was modelled to produce at capacity with a machining time of 2 time-units per part. Inspection I_1, if performed, was 5 time-units. The "Poisson" random distribution was used to simulate the quality of the incoming parts, with a threshold range of 10% to determine the parts that were conforming and non-conforming. Nonconforming parts were removed from the part stream. The distributed fuzzy controller (that was tuned by the supervisory fuzzy controller) used the prescribed inputs to calculate the inspection intensity that was averaged out for IID realisation. SimEvents® in Simulink® was used for discrete-event simulation and the Fuzzy Logic Toolbox® was used to design and tune the FLCs.

5 RESULTS AND DISCUSSION

Important parameters from the simulation were recorded to determine the effects of the two-level fuzzy controllers on MLT. Figure 6 and Figure 7 show the DR input and buffer level input respectively. The buffer level input was scaled to a maximum of 1. Figure 8 shows the buffer weight that was determined by the supervisory fuzzy controller (based on the DR input shown in Figure 6) for use in the distributed fuzzy controller. It was noted the buffer weight had an average of 0.53, indicating that MLT reduction - by lowering the buffer levels - was less important than the actual part stream quality. Figure 9 shows the real-time inspection intensity. The intensity started at 1 (100%) due to the batch size input membership function shown in Figure 3. By performing 100% inspection at the beginning of the cycle, the best form of the DR can be obtained. After 1400 time-units, the intensity significantly reduced to ensure parts spend less time in production by reducing the amount of inspected parts. Figure 10 shows the averaged inspection intensity, where 100 parts were used as a sample size. A size of 100 was chosen intuitively as a large sample size would incur large discrepancies between the real-time and the averaged inspection intensity, while a small sample size would not accurately realise the inspection intensity as a mean. Real-time inspection intensity could not be used as it would be unrealisable with unacceptable errors. The error between the averaged and real-time inspection is shown in Figure 11. The error was calculated using (4):

$$e\_I = \text{(Intensity-Mean Intensity)/(Mean Intensity)} \tag{4}$$

Where "Intensity" is the real-time inspection intensity, the "Mean Intensity" was averaged over 100 parts and "e_I" was the intensity error. A positive error indicated that less inspection was performed than what was desired, while a negative error indicated that more inspection was perform than the desired amount. The maximum error of 46% occurred at 1375 time-units.

The amount of switching between “inspection” and “no inspection” is shown in Figure 12. Although not clear, the distributed fuzzy controller performs the switching independently based on the average inspection intensity shown in Figure 10. Where the switch integer value (“p” value from (3)) was 1, inspection was performed and no inspection was performed when the integer value was 2.

Two simulations were performed to determine the effects of the fuzzy controllers on MLT. Figure 13 shows the MLT when the controllers implemented varied inspection. Figure 14 shows the average MLT where 100% inspection was performed. By comparison, varied inspection reduced MLT by 37 time-units over 1500 cycles, which represented a 35% reduction in MLT.

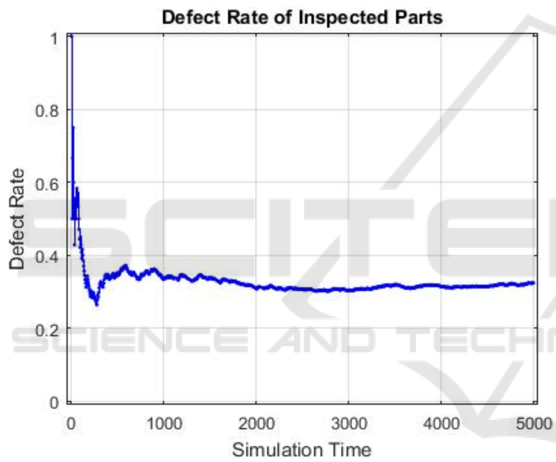

Figure 6: Defect Rate Input of Inspected Parts.

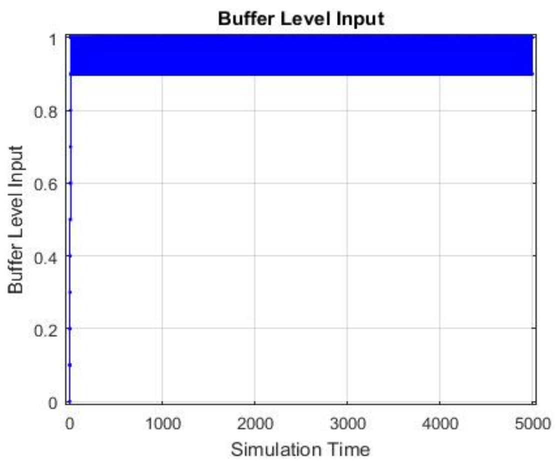

Figure 7: Buffer Level Input.

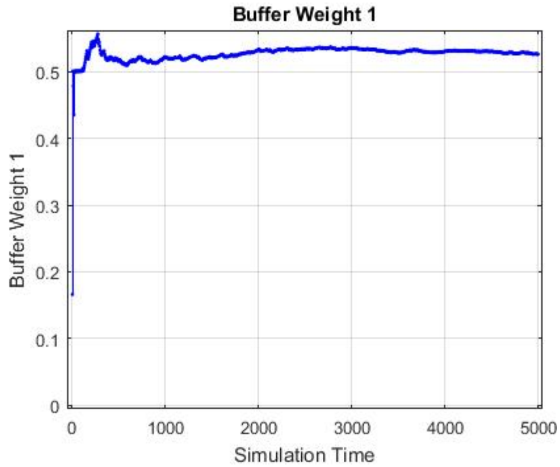

Figure 8: Buffer Weight from Supervisory Controller.

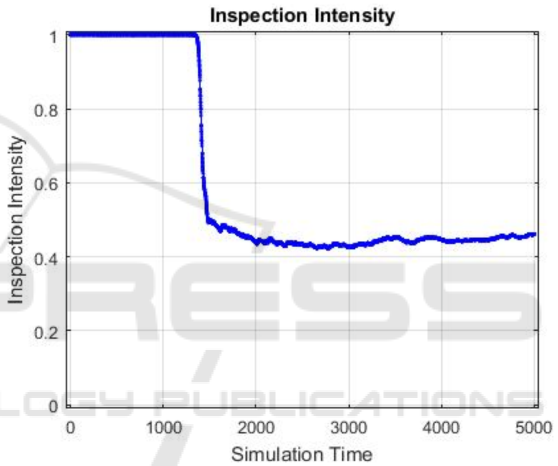

Figure 9: Inspection Intensity (Percentage of Inspection Performed on Incoming Parts).

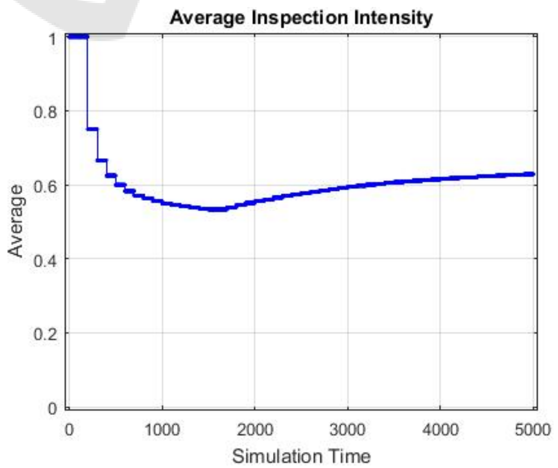

Figure 10: Average Inspection Intensity Based on 100 Part Batches.

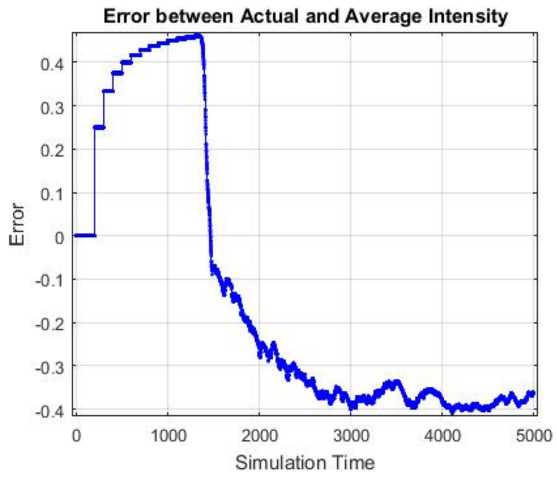

Figure 11: Error between Actual and Average Inspection Intensity.

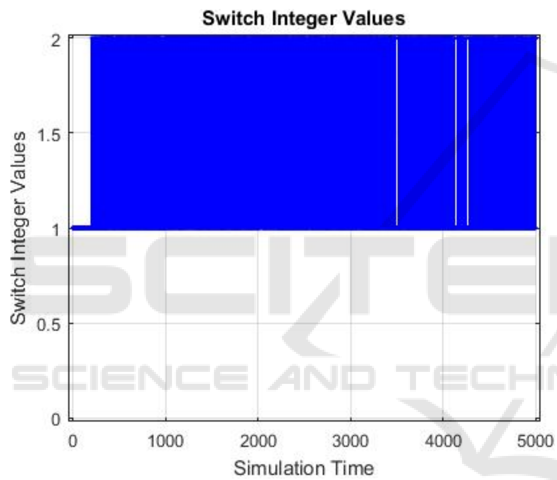

Figure 12: Switch Values (1 – Inspect; 2 – Do Not Inspect).

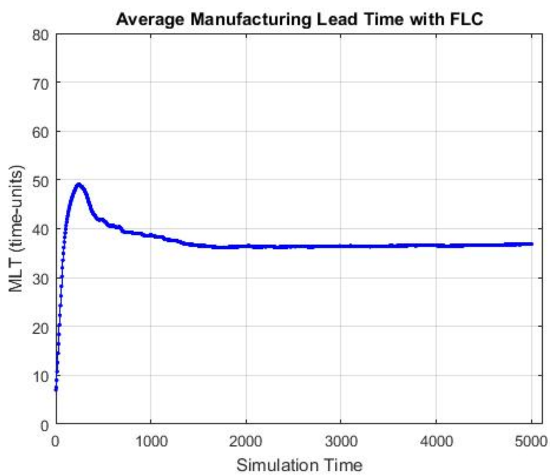

Figure 13: Average MLT with the Distributed and Supervisory Fuzzy Controller.

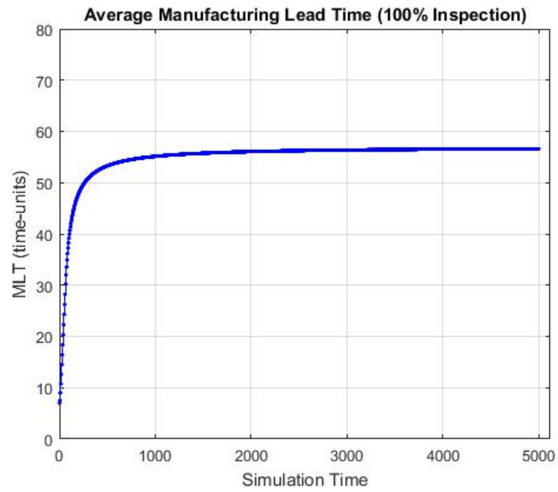

Figure 14: Average MLT with 100% Inspection.

6 CONCLUSION AND FURTHER RESEARCH

The results showed that varied inspection could be used to reduce MLT and that a fuzzy solution could facilitate the dynamic inspection method. The results showed a 35% reduction in MLT. However, Tsourveloudis (2000) outlined two major problems with FL control for complex systems:

- It is impractical to constantly monitor buffer levels.
- FLCs require a large amount of rules which adds complexity to control.

Other limitations of this type of inspection was that overall quality cannot be quantified, as parts were allowed to pass through without inspection. Lastly, there existed an error between the real-time inspection intensity and the IID implementation, shown in Figure 11, as the inspection was done in sample batch sizes of 100 which resulted in a maximum error of 46%. Real-time varied inspection may result in larger errors as the inspection intensity averages would not be executed accurately. Future research will seek to reduce the errors and to investigate the cost effectiveness of implementing varied inspection. The FLC approach to varied inspection will be extended for complex manufacturing layouts. Lastly, a fuzzy solution will be employed into the supervisory fuzzy controller to address product-mix-prioritization.

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