INVESTIGATION INTO INSPECTION SYSTEM UTILISATION FOR ADVANCED MANUFACTURING SYSTEMS

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212 517 995

15 December 2017

MSc. Eng. (Mechanical) Dissertation

Submitted in fulfilment of the academic requirements for the degree of Masters of Science in Mechanical Engineering, College of Agriculture, Engineering and Sciences, University of KwaZulu-Natal.

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As the candidate's supervisor, I agree to the submission of this dissertation.

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As the candidate's co-supervisor(s), I agree to the submission of this dissertation.

Co-supervisor 1: ____________________ Date: ____________________

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The work in this dissertation has been presented in the following publications:

Publication 1:

Naidoo, T., Walker, A., Bright, G. and Davrajh, S. (2016) "Fuzzy Logic Control for Varied Inspection Applications in Advanced Manufacturing Cells", 2016 Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech), pages: 257-262.

Publication 2:

Naidoo, T., Walker, A., Bright, G. and Davrajh, S. (2017) "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", Proceedings of the 14th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2017), pages: 207-214.

Publication 3:

Naidoo, T., Walker, A., Bright, G. and Davrajh, S. (2017) "Fuzzy Logic Control for Varied Inspection" South African Journal of Industrial Engineering (SAJIE), [under review], October 2017.
This journal contains work done in Chapter 5 of the dissertation.

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Acknowledgements

I would like to thank my supervisor, Dr Anthony Walker, for his guidance, support, motivation and advice throughout this research period, as well as my co-supervisors, Prof Glen Bright and Dr Shaniel Davrajh, for their assistance and knowledge. I would like to express gratitude to my parents and family for their support and encouragement. Finally, my friends have always supported me throughout my academic career, and I am grateful to their backing.

The author wishes to acknowledge the "Blue Sky Research Grant" under the grant number 91339. The financial assistance of the National Research Foundation (NRF) towards this research is hereby acknowledged. Opinions expressed and conclusions arrived at, are those of the author and are not necessarily to be attributed to the NRF.

Abstract

Varied inspection is an aperiodic inspection utilisation methodology that was developed for advanced manufacturing systems. The inspection scheme was created as a solution to improve manufacturing performance where inspection hinders production, such as cases where inspection time is significantly larger than machining time. Frequent inspection impedes production cycles which result in undesirable blocking, starving, low machine utilisation, increased lead time and work-in-process. The aim of the inspection strategy was to aid manufacturing metrics by adjusting inspection utilisation through multiple control methods.

The novelty of the research lies in using an inspection strategy for improved manufacturing performance. Quality control was traditionally viewed as an unintegrated aspect of production. As such, quality control was only used as a tool for ensuring certain standards of products, rather than being used as a tool to aid production. The problem was solved by using the amount of inspection performed as a variable, and changing that variable based on the needs of the manufacturing process. "Inspection intensity" was defined as the amount of inspection performed on a part stream and was based on inputs such as part quality, required production rates, work-in-process requirements among other factors.

Varied inspection was executed using a two-level control architecture of fuzzy controllers. Lower level controllers performed varied inspection while an upper level supervisory controller measured overall system performance and made adjustments to lower level controllers to meet system requirements. The research was constrained to simulation results to test the effects of varied inspection on different manufacturing models. Simulation software was used to model advanced manufacturing systems to test the effects of varied inspection against traditional quality control schemes. Matlab's SimEvents® was used for discrete-event simulation and Fuzzy Logic Toolbox® was used for the controller design.

Through simulation, varied inspection was used to meet production needs such as reduced manufacturing lead time, reduced work-in-process, reduced starvation and blockage, and reduced appraisal costs. Machine utilisation was increased. The contribution of the research was that quality control could be used to aid manufacturing systems instead of slowing it down. Varied inspection can be used as a flexible form of inspection. The research can be used as a control methodology to improve the usage of inspection systems to enhance manufacturing performance.

Contents

Nomenclature

A, B	Linguistic values for a Mamdani-type fuzzy controller
$a_1, \dots, d_3$	Chromosome parameters for membership function optimisation
$\overline{BL}$	Mean backlog
$B_{(x),(y)}$	Buffer capacity for buffer (x),(y)
$b_{i,l}$	Downstream buffer level
$b_{j,i}$	Upstream buffer level
bs	Batch size input
C	Average inspection and consequence cost
C_{app}	Appraisal cost
C_b	Unit cost of backlog
C_I	Unit cost of inventory
Col	Scalar value of cost to run inspection machine per unit of time
d	Different types of defects
eps	End production surplus input for the supervisory controller
ew	Work-In-Process error for the supervisory controller
e_{EPS}	End Production Surplus Error
$EPS(t)$	End Production Surplus at time *t*
$\overline{EPS(t)}$	Mean End Production Surplus at time *t*
e_w	Work-In-Process Error
F	Fitness function
$floor$	Matlab® function that rounds down towards negative infinity
$FR^{(k)}$	Fuzzy relation
I_{final}	Final inspection intensity
I_i	Inspection intensity
IM	Inspection time to machining time ratio
$I_{(x)}$	Inspection time for inspection machine (x)
k_{DF}	Cost when a defective part fails inspection
k_{DU}	Cost when a defective part is sent on without inspection
k_I	Cost to inspect one part
k_{GF}	Cost when a good part fails inspection
k_{GP}	Cost when a good part passes inspection
k_{GU}	Cost when a good part is sent on without inspection
k	Rule number
k_1	Unit cost of the WIP error

k_2	Unit cost for the EPS error.
LB	Linguistic value for the buffer level (upstream or downstream)
LBS	Linguistic value for the batch size
$LEPS$	Linguistic value for the End Production Surplus
LEW	Linguistic value for the Work-In-Process Error
LI	Linguistic value for the inspection intensity
LM	Linguistic value for the Multiplier.
LMS	Linguistic value for the machine state
LPS	Linguistic value for the production surplus
LQ	Linguistic value for the defect rate
M	Multiplier
$M_{(x)}$	Machining time for machine (x)
ms_i	Machine state
p	Switching value
pc	Piece/Part
ps_i	Production surplus
q_i	Defect rate
$rand$	Uniformly distributed random number
t_i	Inspection time for appraisal costs.
$WIP(t)$	Work-In-Process at time *t*
$\overline{WIP(t)}$	Mean Work-In-Process
w_D	Probability for a nonconforming part to pass inspection
w_G	Probability for a good part to fail inspection
x_1, x_2	Controller inputs
X, Y	Inputs for a Mamdani-type fuzzy controller
y_1	Controller output
Z	Output for a Mamdani-type fuzzy controller
λ	Arrival rate
μ	Membership function
$\mu_{FR^{(k)}}$	Consequent membership function with fuzzy relation $FR^{(k)}$
$\mu^*_{premise}$	Certainty of the premise at time *t*
π	Probability for part to be inspected (sampling rate)
ρ	Probability of a nonconforming part
σ	Standard deviation
φ	Mean
*	State of the inputs

List of Acronyms

4IR	Fourth Industrial Revolution
CMM	Coordinate Measuring Machine
CNC	Computer Numerical Control
COG	Centre of Gravity
CoQ	Cost of Quality
DES	Discrete Event Simulation
DMS	Dedicated Manufacturing System
DOF	Degrees of Freedom
EA	Evolutionary Algorithm
EDF	Evolutionary Distributed Fuzzy
EPS	End Production Surplus
ESF	Evolutionary Supervisory Fuzzy
FIS	Fuzzy Inference System
FLC	Fuzzy Logic Controller
FL	Fuzzy Logic
GA	Genetic Algorithm
GDF	Genetic Distributed Fuzzy
GSF	Genetic Supervisory Fuzzy
ICINCO	International Conference on Informatics in Control, Automation and Robotics
IEEE	Institute of Electrical and Electronics Engineers
IID	Independent and Identically Distributed
IM	Inspection time to Machine time ratio
ISO	International Standards Organization
HDF	Heuristic Distributed Fuzzy
HSF	Heuristic Supervisory Fuzzy
MC	Mass Customization
MCE	Manufacturing Cycle Efficiency
MISO	Multiple-Input Single-Output
MLT	Manufacturing Lead Time
NRF	National Research Foundation
PAF	Prevention, Appraisal, Failure
PID	Proportional-Integral-Derivative
PKQC	Product Key Quality Characteristics
PRASA	Pattern Recognition Association of South Africa
PSO	Particle Swarm Optimisation

QC	Quality Control
QRA	Quantitative Risk Analysis
RIM	Reconfigurable Inspection Machine
RMS	Reconfigurable Manufacturing System
ROI	Regions Of Interest
SAJIE	South African Journal of Industrial Engineers
SISO	Single-Input-Single-Output
SPC	Statistical Process Control
TCM	Tool Condition Monitoring
WIP	Work-In-Process

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1 Introduction

1.1 Chapter Introduction

The aim of the chapter was to establish the nature and purpose of the research as well as outline the framework of the research. The background, existing research, motivation, scientific contribution and research objectives was outlined. A chapter guide for the dissertation was provided.

1.2 Background

Production is currently evolving through digital transformation and adaptation towards this trend is critical for economic success. Manufacturing entered a new era at the end of the 20th century where manufacturers aim to reduce costs to become competitive in global markets [1]–[3]. The Fourth Industrial Revolution (4IR) is rapidly evolving with growing influence throughout industry [4]. 4IR has the ability to improve global competitiveness and has provided solutions to problems that could not be solved with traditional technology [5].

Manufacturing is moving towards Mass Customisation (MC), which is the mass production of part variations through modular and flexible processes – due to the customer demand for unique products at costs similar to mass produced parts [6]–[11] and is viewed as the driver for financial growth in the 21st century [6]. Economic demands for MC as a prevailing form of production has increased in the manufacturing and automotive industry due to customers buying trends in favour of product diversification [9], [12]. As such, manufacturers will need to cope with erratic fluctuations in demands, diverse product mix and various disturbances associated with MC [11], [13].

Research gaps exist in the field of Quality Control (QC) for MC process - particularly in QC flexibility of inspection systems [12], [14], [15]. The movement towards MC brings new challenges in ensuring good quality for customers, due to differences between mass production and MC [14]. QC should become significant in MC due to its reactive environment and research shows that the main problem area in future QC techniques is how to adjust traditional QC methods for MC (single-unit production lots) [12]. Quality remains an vital requirement for customers, with customer satisfaction being the main norm for achievement [16]. Tuominen [17] stated that there was minimal research in on-line QC methods. Added flexibility may be used to adapt flexible inspection methods to on-line inspection, thus ensuring an acceptable degree of quality in products.

1.3 Existing Research

Traditional QC has shortcomings in modern production. QC is an important aspect of production as defects during production are inevitable [18]. Researchers state that quality control for MC has been limited and needs to be investigated [9], [12]. Traditional QC has had good success in Dedicated Manufacturing Systems (DMSs) as production of large quantities of the same parts allowed statistical tools to determine the behaviour of the occurrence of defects. Conversely, traditional QC methods cannot be used directly in MC. Existing inspection systems are not made to accommodate new products easily which leads to high initial set-up costs [9]. For example, Statistical Quality Control (SPC) is used in acceptance sampling and assumes a Gaussian distribution in the occurrence of defects [17]. However, due to the complex nature of the mass customization, SPC becomes ineffective as defect occurrences follow random distributions.

Reconfigurability allows for part variety production and inspection, however the technology has limited capabilities in providing accurate quality checks. The Reconfigurable Manufacturing System (RMS) paradigm allowed for high volume production with the ability for production changes. The modularity principles of RMSs was used in Reconfigurable Inspection Machines (RIMs), which possess the required flexibility to perform inspection for high variety production. Research performed by Davrajh, Bright and Stopforth [9] showed that modular inspection technology could cope with part variety. However, the reconfiguration process of modules with RMSs and RIMs create sites for misalignments resulting in quality issues such as dimensional errors [19]. Modular equipment has cost benefits, however it does present sites for variability due to the lack of stiffness, clearance and changes in clamping forces [20]. The misalignments compromise the results from RIM quality checks.

Emerging research shows attempts to reduce inspection for the benefit of production. Davrajh and Bright [21] stated that frequent inspection hinders production rates and developed a method to allow high inspection frequency without affecting production rates – this was performed by only inspecting user-defined Regions Of Interest (ROI). Research performed by He and Chang [22] focused quality measurements on Product Key Quality Characteristics (PKQCs) as these characteristics held majority of the desired quality requirements. Similar research performed by White et al. [23] utilised user-defined "weight factors" to determine the importance of features on a fin gripper. A selection algorithm was used to inspect only the important fin gripper features. The results obtained from the study showed a reduction in inspection costs (appraisal) and inspection time - which could reduce overall production time and costs associated with fin gripper production. Research performed by Naidoo et al. in [15], [24] showed that reduced inspection – through varied inspection – aided the reduction of Work-In-Process (WIP) and Manufacturing Lead Time (MLT) in a single-station manufacturing cell respectively. It was concluded that manufacturers strive for zero defects thus implement over-inspection (the inspection of every part, either conforming or nonconforming) where inspection only becomes significant when it detects nonconforming parts. However, useful production advantages exist by reducing inspection through varied inspection.

1.4 Motivation for Research

Researchers in QC have investigated the impacts of QC in multiple areas however, none have considered the possibility that inspection systems could be used to aid manufacturing performance rather than hindering production. Shifts towards MC has forced inspection systems to be integrated on-line, which slows down production. Highly flexible inspection is used for high variety QC checks, however the inspection methods are often time-consuming and only suited for low-volume quality control. Flexible inspection require flexible control to perform effectively in MC. Coordinate Measuring Machines (CMMs) allow for accurate and flexible inspection, however the process is time-consuming which affect production rates [19], [21], [25]. This research aims to reduce the negative effects of on-line inspection - such as low throughput, low machine utilisation, blocking and starving - as more manufacturing plans move towards MC and high variety production.

Over-inspection requires reduction. QC and inspection are essential in providing good parts, but do not add monetary value to the product [21], [26]. Therefore, over-inspection adds unnecessary costs to manufacturers. Over-inspection consequently adds time to production, which reduces responsiveness to demands.

1.5 Scientific Contribution

The research presented contributed to the following aspects:

- Varied inspection adds flexibility to QC. QC was viewed as an external component to the production process, thus it remained inflexible [27]. Flexibility had been identified as a key challenge in MC [6]. Varied inspection is a flexible inspection method which can be implemented into MC. Implementation of varied inspection was done through fuzzy controllers which are heuristic approaches, thus allowing for flexibility to exist within the control scheme.
- Quality has not been used previously as a function to dictate manufacturing processes. To achieve MC, control systems have to become more flexible and adaptable. With the proposed system in place, manufacturers can take a holistic approach to how quality control is performed and can choose to reduce inspection in the expectation of gaining advantages in other performance metrics.
- Varied inspection could be a solution for time-consuming inspection systems to reduce overall production rates [15]. The high flexibility of CMMs allows for a wide range of inspection however the operation is time-consuming. Varied inspection can be used alongside CMMs to allow for on-line inspection while the inspection process does not significantly slow down production.
- Varied inspection can be viewed as a solution to over-inspection. There was minimal focus and research on reducing over-inspection, which is significant as inspection of acceptable products adds no monetary value to the process [21], [26]. Varied inspection can be implemented to reduce over-inspection thus improving production. For example, varied inspection can be performed in-line with Six Sigma techniques as only an average four of a million parts are defective, thus reducing over-inspection [27]–[29].

1.6 Research Aims and Objectives

The aim of the research was to develop an inspection control plan that was able to vary the amount of inspection performed for the purpose of aiding manufacturing performance. The research objectives are as follows:

- Investigate the current state of QC, inspection techniques and controller design to determine the applicability of varied inspection in production.
- Research and develop the lower-level controllers, such as Heuristic Distributed Fuzzy (HDF) controllers, to perform varied inspection based on inputs related to the quality of parts produced and states of the surrounding buffers and machines.
- Research and develop the upper-level control, such as the Heuristic Supervisory Fuzzy (HSF) controller, to tune the lower-level controllers based on overall manufacturing outputs.
- Perform and test the optimisation of the upper-level and lower-level controllers to determine whether optimised fuzzy controllers are applicable to varied inspection.
- Test the controllers individually to determine how each input affects the amount of performed inspection.
- Apply the controller architecture to perform varied inspection in manufacturing subsystems, as prescribed by literature, and measure its performance in simplified manufacturing layout building blocks.
- Test varied inspection in case studies to measure its performance in different forms of production.
- Evaluate the impact and novelty of varied inspection with the generated results, make conclusions and provide suggestions for future research.

1.7 Chapter Guide

The dissertation guideline provides summaries for the proceeding chapters. The chapters are as follows:

- Chapter 1: Introduction: describes the nature, purpose, aims and objectives of the research.
- Chapter 2: Literature Review: outlines existing research pertaining to QC, varied inspection and fuzzy control.
- Chapter 3: Development of Fuzzy Logic Controllers for Varied Inspection: describes the complete development of Fuzzy Logic Controllers (FLCs) to perform varied inspection, as well as the Matlab® implementation and optimisation.
- Chapter 4: Individual Testing of the HDF and HSF Controllers: describes the testing of the HDF and HSF controllers in simplified simulation to assess their performance.
- Chapter 5: Varied Inspection for Subsystem Manufacturing Modules: varied inspection was implemented into subsystems namely transfer lines, assembly and disassembly.

- Chapter 6: Varied Inspection Testing for Production Case Studies: illustrates the effectiveness of varied inspection in different real-world advanced manufacturing systems.
- Chapter 7: Discussion: provides an in-depth analysis of the results obtained from varied inspection for various manufacturing environments.
- Chapter 8: Conclusion: concludes the research, highlights important aspects from results and provides areas for future research.

1.8 Chapter Summary

The introductory chapter outlined the background research that illustrated the need for QC attention and development. Existing research showed the shortcomings of traditional QC for MC and methods to reduce inspection frequency. The need and scientific contribution for the research was outlined as a solution to reduce over-inspection and to add flexibility to inspection system utilisation. The research aims and objectives explain the nature and development of the research. Fuzzy control was proposed as a flexible control solution for the implementation of varied inspection. The chapter concluded with a dissertation guide.

2 Literature Review

2.1 Chapter Introduction

The chapter establishes the required research for the implementation of varied inspection. The definition of QC was defined with comparisons between traditional and modern methods. The Costs of Quality (CoQ) was outlined. The state of inspection systems was researched. The chapter concludes with the characteristics of varied inspection and the application of Fuzzy Logic (FL) in varied inspection.

2.2 Quality Control and Definitions

The section of the literature outlined the important aspects of QC and definitions necessary to assess the applicability of varied inspection for MC. There are several definitions of quality and QC throughout years of research, and significant differences between traditional and modern QC.

2.2.1 Definition of Quality Control

QC was created to handle variations and defects which are unavoidable. The occurrence of defects can manifest from single machining processes or can result from inter-stage dependencies as variations can be conveyed from upstream process to downstream processes [30]. Quality has different meanings among researchers, and can be quantified either linguistically or with measurements [16]. The traditional view on quality was "*fitness of use*" whereas the modern view is that "*quality is inversely proportional to variance*" [31]. Davrajh and Bright [21] define quality as "*the extent to which a product can satisfy its given function*". Groover [27] explained QC as the methods to ensure parts/products have conformed to design specifications and Juran [32] stated that the purpose of QC was to maintain the control of producing parts that have "*freedom from deficiencies*".

2.2.2 Traditional Quality Control

Traditional QC methods had shortcomings in DMSs. Examples of traditional QC methods include check sheets, control charts and sampling [9]. Acceptance sampling is a common traditional QC tool, however there are problems and risks associated with this technique as parts may be detected as non-conforming after a large number of parts have been made [17], [19], [27]. Nikolaidis and Nenes [33] had shown that acceptance sampling such as ISO (International Standards Organization) 2859 has economic consequences and does not necessarily produce optimal economic choices. Davrajh and Bright [21] state that sampling has two major risks, where "producer risk" involves the manufacturer accepting nonconforming parts, and "consumer risk" where consumers buy products that were nonconforming but were adjudged as conforming based on the sampling technique. Sampling had become unpopular in the pursuit of 100% quality [27].

Traditional QC methods was designed for mass production of products with minimal variety and cannot be used for MC. QC techniques remained fixed because DMSs lack significant product variation [14]. Research had been done to determine whether traditional quality tools could be used in high variety manufacturing, with Hassan, Shariff Nabi Baksh and Shaharoun [34] stating that these methods cannot cope with customized quality and low production quantity. Tools like SPC charts were difficult to apply in low volume as control charts could not be made with such low production. Experiments in short-run manufacturing revealed that traditional quality tools have limited value or are not cheap to use [35].

2.2.3 Modern Quality Control Systems

RIMs provide the opportunity for frequent inspection but are limited to part families and require more extensive research. RIMs offer the flexibility required to inspect part variety through modular components that can be changed to accommodate different part configurations. RIMs are limited to part families, such as the RIM used by Barhak et al. [19] to inspect engine cylinder heads. Davrajh and Bright [21] stated that RIMs could be used to perform high inspection frequencies by only focusing on the important part features as prescribed by customers. RIM technology requires further development to increase rigidity and accuracy [15]. Davrajh, Bright and Stopforth [9] state that the implementation of reconfigurable inspection is new with a few countries using this technology.

CMMs offer flexible inspection, but are slow and expensive to use. CMMs are popular due to its high precision, reliability and flexibility [36]. CMMs are used for off-line sampling inspection - as Davrajh and Bright [21] state on-line CMM inspection significantly slows down inspection - where statistics are used to estimate the population quality [17]. The risks of off-line CMM inspection would increase wastage as defective parts are found after large batches are produced. CMM inspection is expensive, with Tuominen [17] stating that one hour of CMM use costs R 1165. Sampling inspection using CMM increases inspection cost linearly with higher sampling rates. Figure 2.1 [17] shows the relationship between sampling rate and inspection costs when using a CMM.

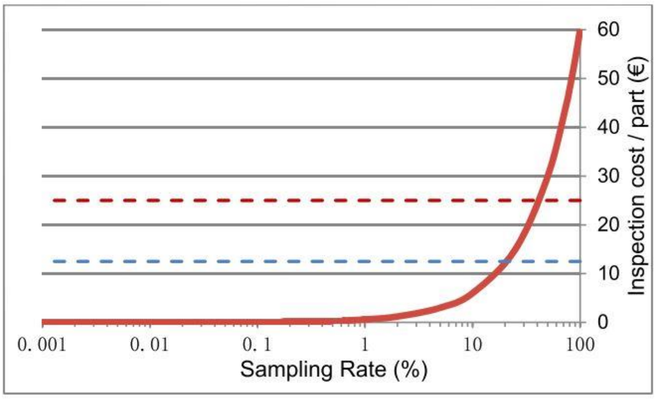

Figure 2.1: Inspection Cost for Sampling Rates using a CMM [17]

Current technologies employ on-line inspection – as opposed to off-line sampling techniques – that are used to inspect every product [17]. On-line inspection implement technologies such as laser and camera inspection [17] and sensor-based fixtures [20]. On-line inspection ensures that defects can be detected during production and adjustments can be made to avoid producing defective parts [37], [38]. Davrajh, Bright and Stopforth [9] state that QC should be integrated throughout processes to reduce waste and to halt the production of defective parts. Good monitoring of processes through inspection has advantages like early fault recognition, avoidance of scrape and improved tool life [38]. 100% On-line inspection is more feasible to use than CMM as it reduces consequence costs and has low operating costs [17]. The issue with 100% inspection is that it cannot be easily adapted to high variety production as different parts require different inspection needs.

Condition monitoring is currently being used to continuously monitor quality of parts and processes. Condition monitoring is an on-line QC method based on the premise that if the process is running within its working acceptable bounds, then the products produced by the process will be within acceptable quality bounds. The notion behind condition monitoring was that quality issues only arise when machines operate out of statistical control which could occur when tools wear and machines are infrequently used. Tool Condition Monitoring (TCM) is a common form of condition monitoring and was used to reduce chatter on part surfaces [36]. Tool tip conditions, such as tool breakage and chip tangling, were constantly monitored so ensure that turned parts are free from surface roughness [39]. Bryne et al. [40] explain that TCM can improve productivity as tools are constantly monitored, therefore information is known about the tool life and when to replace or repair the tools.

2.2.4 Cost of Quality

QC and inspection are essential in providing conforming products, however QC adds no monetary value to the product [21], [26]. The occurrence of defects leads to quality costs through inspection and testing, which can account for 20% to 40% of consumer sales [41], whereas quality costs can range from under 2% to over 25% in some low tolerance industries [42]. Understandably, the cheapest quality method would be to not inspect any product however, the need arises for process information to limit defective part production [17]. A study performed by Schiffauerova and Thomson [43] compared a traditional CoQ to a modern CoQ, shown in Figure 2.2. The traditional CoQ curve is known as the "Lindvall-Juran" curve [44]. From the figure, the modern CoQ model showed that the optimal choice for inspection was 100% inspection, therefore total CoQ becomes a minimal. Tuominen [17] reached the same conclusion as [43] and stated that the most cost effective inspection solution was on-line 100% inspection as consequence costs are significantly reduced.

There is no single method on how to calculate CoQ [43]. The most established method for reducing QC costs and maximizing quality of conformance is centred around the Cost of Quality (CoQ) model, with

Feigenbaum’s PAF (Prevention, Appraisal, Failure) cost model frequently adopted for determining CoQ [43], [45]. Feigenbaum’s PAF model is illustrated in Figure 2.3 [45] and is split as follows:

- Prevention: the costs associated with actions that avert future quality costs.
- Appraisal: the costs incurred through measurements of the process (inspection).
- Failure: divided into internal failure (where the product fails before delivery) and external failure (where the product fails at the site of the customer).

External failure costs dominate the large percentage of total CoQ, as the costs of a defective part reaching a customer is extremely high [17], [46]. The cost of defects increase the longer the defective part remains in the cycle. Figure 2.4 [47] shows the cost of a defect through a product’s life cycle. From Figure 2.4, defects should be detected as early as possible in the process to save failure costs.

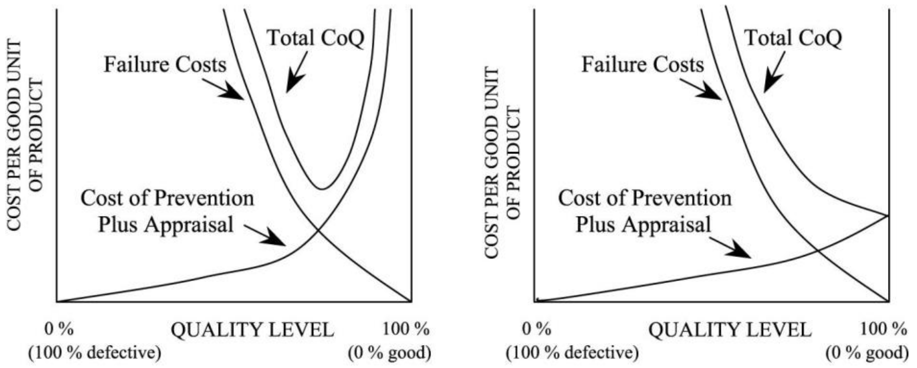

Figure 2.2: Classical View of CoQ (left) and Modern View of CoQ (right) [43]

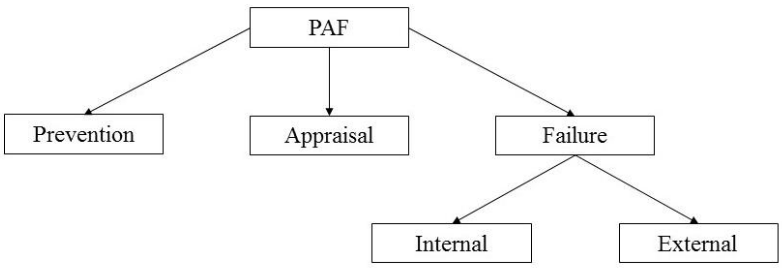

Figure 2.3: PAF CoQ Model [45]

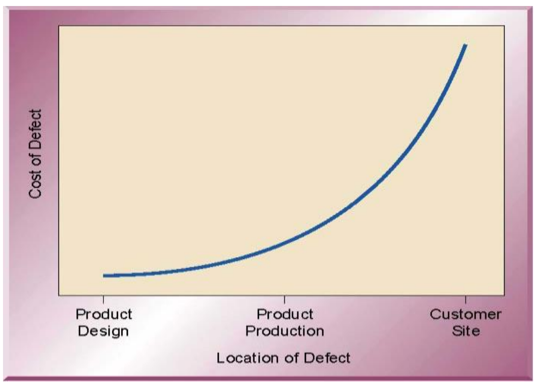

Figure 2.4: Cost of a Defect through a Product's Life Cycle [47]

Quality costs were difficult to quantify, which led to several methods on solving CoQ for inspection. Deming created a probability model to calculate the average inspection and consequence costs. The Deming cost model stated that the optimal solution was to inspect everything, or inspect nothing [17]. Wiel and Wardeman extended the Deming model for more practicality [17], [48]. The model is shown in equation 2.1. Table 2.1 [17] shows the factors of the cost model in terms of probability and cost. Varied inspection takes advantage of the fact that not inspecting a good part yields no cost.

$$C = \pi k_I + \sum_{d=1}^{n} \{\pi\left[(1-\rho_d)w_{G,d}k_{GF,d} + \rho_d\left(1-w_{D,d}\right)k_{DF,d} + \rho_d w_{D,d}k_{DP,d}\right] + (1-\pi)\rho_d k_{DU,d}\} \tag{2.1}$$

Where:

C = Average inspection and consequence cost

$d = 1, 2, 3, \dots, n$ for different types of defects

k_{DF} = Cost when a defective part fails inspection

k_{DU} = Cost when a defective part is sent on without inspection

k_{GF} = Cost when a good part fails inspection

k_I = Cost to inspect one part

ρ = Probability of a nonconforming part

w_D = Probability for a nonconforming part to pass inspection

w_G = Probability for a good part to fail inspection

π = Probability for part to be inspected (sampling rate)

Varied inspection deals directly with appraisal cost reduction. White et al. [23] developed an algorithm to determine the appraisal costs associated with inspecting features shown in equation 2.2.

$$C_{app} = Col * \sum_{i=1}^{m} t_i \tag{2.2}$$

Where:

C_{app} = Appraisal cost

Col = Scalar value of cost to run inspection machine per unit of inspection time t_i

Table 2.1: Factors of the Cost Model [17]

Inspection action		**Good part**		**Defective part**	
		Probability	**Cost**	**Probability**	**Cost**
Not inspected		$1-\rho_d$	0	ρ_d	$k_{DU,d}$
Inspected	**Acceptable result**	$(1-\rho_d)(1-w_{G,d})$	k_I	$\rho w_{D,d}$	$k_I + k_{DP,d}$
	Unacceptable result	$(1-\rho)w_{G,d}$	$k_I + k_{GF,d}$	$\rho(1-w_{D,d})$	$k_I + k_{DF,d}$

2.3 Varied Inspection

2.3.1 Definition

“Varied inspection” was coined by the author as an on-line inspection method where the amount of inspection could be altered based on the needs and properties of the manufacturing system [15], [24]. Varied inspection can be influenced by changes in part quality, supply/demand, blocking, starving, MLT and WIP requirements [24]. Through varied inspection, QC has the ability to influence important metrics to the aid of the manufacturer. For example, if part quality is acceptable, inspection can be reduced to allow conforming parts to pass through without inspection. If a machine is being starved, inspection can be reduced to allow more parts to feed into the machine. Conversely, if machines are producing defective parts, inspection can be increased. The effects of blocking can be reduced by reducing inspection. MLT and WIP can be decreased with reduced inspection thus improving robustness and responsiveness to demands.

2.3.2 Properties

Varied inspection shares properties with screening and acceptance sampling. Screening (inspecting every part) and acceptance sampling are the two most common inspection techniques [15]. Varied inspection was constrained to on-line inspection. Varied inspection was described as a control technique for inspection systems, particularly for CMMs. CMMs have good flexibility, but the inspection process is time-consuming as the probe touches the part’s surfaces. As stated previously, manufacturers are forced to use off-line sampling methods with CMMs. Varied inspection could be used to enable CMM inspection to be performed on-line during production, thus possibly reducing waste.

Varied inspection is mainly applicable where Manufacturing Cycle Efficiency (MCE) is low. MCE was defined as the percentage of the time spent adding value to the products (processing time) over the total cycle time [49], defined by equation 2.3.

$$MCE = \frac{Value\ added\ time}{Manufacturing\ cycle\ time} \tag{2.3}$$

The manufacturing cycle time is made of the processing time, inspection time, transport time and time spent in queues. The author modified MCE to determine the ratio of the inspection time to the machining (processing) time, coined as the “IM ratio” shown in equation 2.4.

$$IM = \frac{Inspection\ time\ [time\ unit]}{Machining\ time\ [time\ unit]} \tag{2.4}$$

IM determines how much of time is spent on inspection as compared to processing time. For IM ratios less than 1, machining dominates production times, which is advantageous. For IM ratios greater than

1, inspection dominates production, which is disadvantageous as parts spend more time in inspection (which does not add value) than in machining (which adds value). Varied inspection can be used to mitigate some of the lagging effects caused by high IM ratios.

2.3.3 Advantages and Disadvantages

The advantages and disadvantages of varied inspection was due to its shared properties with screening and sampling. 100% Inspection assures that 100% acceptable quality (assuming the inspection process is reliable), as only the conforming parts are allowed to pass through. The problems with 100% inspection is that expenses are incurred to inspect every part, either through costs of using inspection machines or through consequence costs of delayed production (as inspection time is attached to each part) [26]. With varied inspection, there are advantages and disadvantages, both acquired from sampling and from 100% inspection. Table 2.2 shows the advantages and disadvantages of varied inspection compared to sampling and 100% inspection [15], [24]. One main advantage was that over-inspection can be reduced. One major disadvantage was that varied inspection was not the most economical inspection plan [26].

Table 2.2: Advantages and Disadvantages of Varied Inspection [15], [24]

Advantages	**Disadvantages**
Reduction of over-inspection – over-inspection is reduced when parts are not inspected.	The probability of defective parts avoiding inspection is increased.
Reduction of appraisal costs – varied inspection reduces inspection thus reduces appraisal costs and time spent on inspection.	External failure costs may increase when defective parts are sent on without inspection.
Reduction of bottlenecking and starvation – inspection can be increased to reduce starving or increased to reduce bottlenecking.	Reduction of inspection reduces the amount of acquired information about part quality.
Increase production rates – reduction in inspection time reduces cycle time resulting in higher production rates.	Non-conforming components left uninspected can damage company reputation and customer perceptions.
WIP reduction – reduced inspection reduces the build-up of parts in production thus lowering WIP.	Changes in WIP are minimal (see Table 7.1) and must be assessed by the manufacturer to determine if this minimal reduction is viable.
MLT reduction – parts spend less time in production from less inspection.	The proposed inspection method focuses on quantity rather than quality.
Can be used for high IM ratio production.	Varied inspection must be tested in simulation before implementation in actual manufacturing.

2.3.4 The Effect of Varied Inspection on Overall Quality

The prevailing issue with varied inspection was that the chances of defective parts passing through can be increased with reduced inspection. As stated previously, the most significant failure was failure at the site of the customer, which is the most costly and affects the company's reputation. There is no method of knowing whether defective parts pass through without performing inspection of those parts, which defeats the purpose of varied inspection.

Varied inspection affects overall quality levels. The probability of defective parts passing through without inspection is increased when the inspection intensity is reduced. From Figure 2.4 [47], the most costly defect expense is when the product fails at the site of the customer (external failure cost). The following reasoning described by equations 2.5, 2.6 and 2.7 was used to determine the risk of varied inspection in monetary value. Rider et al. [50] explained that Quantitative Risk Analysis (QRA) could be used to determine the risk of any process by mathematically defining 'risk' as the product of 'hazard' and 'exposure'. Irrespective of the calculated risk, previous research in CoQ explicitly stated that the most cost effective form of inspection is the "inspect all or nothing" policy – which implied that varied inspection is more costly than 100% inspection and no inspection.

$$Risk = Probability\ of\ external\ failure \times Cost\ of\ external\ failure \tag{2.5}$$

$$\begin{gathered} Risk = Probability\ of\ a\ nonconforming\ part\ \times \\ cost\ when\ a\ defective\ part\ is\ sent\ on\ without\ inspection \end{gathered} \tag{2.6}$$

$$Risk = p \times k_{DU} \tag{2.7}$$

2.3.5 Applications

Varied inspection is applicable where on-line inspection times dominate processing time. Table 2.1 [17] shows that inspection of a conforming product yields no profit [21], [26]. Therefore, varied inspection can reduce appraisal costs and inspection time (from equation 2.2). Varied inspection was intended for Tier-1 manufacturing, and was advised against use in important products that directly affect the safety of its users. There exists the probability and monetary risk (equation 2.7) of defective parts skipping inspection which could lead to death or injury of its users. Prior publications by the author in [15], [24] showed that varied inspection could be used to reduce WIP and MLT in a single-station manufacturing cell respectively, as shown in Figure 2.5 and Figure 2.6. The controllers used for the results in Figure 2.5 and 2.6 were basic controllers with single purpose objectives.

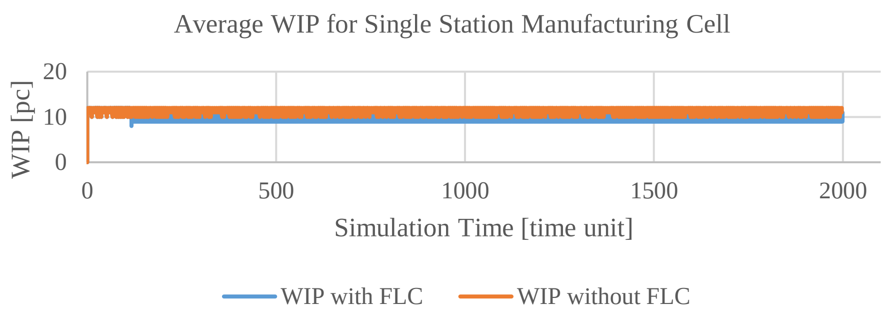

Figure 2.5: Average WIP Comparison for Varied Inspection vs. 100% Inspection [15]

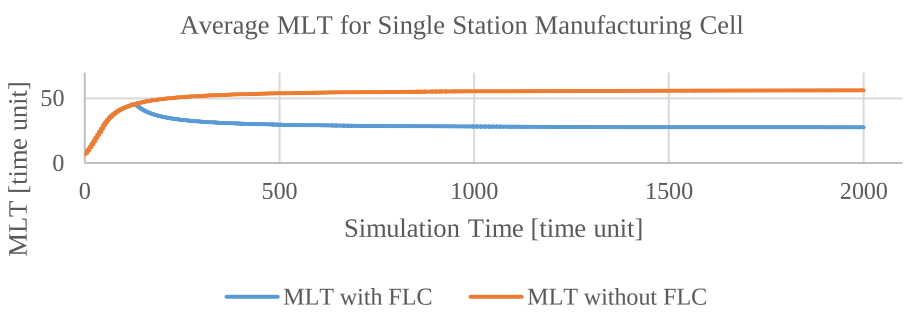

Figure 2.6: Average MLT for Varied Inspection vs. 100% Inspection [24]

2.4 Fuzzy Control

Fuzzy control was used to implement varied inspection because it can handle complex advanced manufacturing control tasks. Fuzzy control refers to the control of a system using FL. FL was created by Zadeh [51] with the concept of "fuzzy sets", which allow for non-crisp characterization of values [52]. Fuzzy sets are different to classical sets (Boolean logic) as fuzzy sets allows for non-deterministic simplifications of inputs through membership functions [53]. Fuzzy controllers are nonlinear, artificial decision makers and can provide control solutions for difficult control applications. The major difference between FLCs and conventional control is that fuzzy logic is based on heuristic rules while conventional control use differential equations [54].

2.4.1 Definitions

The basic terms regarding FL control are listed below.

- Fuzzy Logic (FL) – logic that is based on degrees of truth rather than crisp Boolean logic [55].
- Fuzzy set: A set of values that is described by a linguistic value. The values have different degrees of membership.
- Fuzzy logic control – the use of fuzzy logic to design FLCs.
- Fuzzy Inference System (FIS) – the mapping between inputs and outputs through fuzzy logic.

- Membership functions: a function that is used to quantify the certainty that a value (input or output) belongs to a set of values characterized by a linguistic value. The set of values characterized by a linguistic value is called a fuzzy set [54].
- Universe of discourse: The input/output space.
- Degree of membership: The certainty that an input/output is part of a linguistic value.
- Fuzzification – the process of making a crisp value into a fuzzy value [56].
- Defuzzification– converting a fuzzy number into a crisp number [56].
- Rule-base: contains all linguistic variables, values, membership functions and rules [54].
- Fuzzy rules: Fuzzy rules are in the form of linguistic rules (natural language). Fuzzy rules are formed by linguistic values. The general form of fuzzy rules are shown in equation 2.8. The "premise" is also known as the "antecedent" [54].

$$\text{IF } \textit{premise} \text{ THEN } \textit{consequent} \tag{2.8}$$

2.4.2 Applications in Manufacturing

Implementation of FL in manufacturing had increased in range and popularity due to its ability to handle complexity [57]. Uncertainty increases with complexity, in line with the multitude of processes and operations in production. Ioannidis, Tsoureveloudis and Valavanis [58] explained that many researchers believe that manufacturing scheduling problems cannot be solved analytically, which had favoured the use of heuristic approaches – such as fuzzy control. The same reasoning for using heuristic methods were proposed in [59]–[61]. Bai and Gershwin recommend heuristic approaches for job flow control in large production systems [59], [62], [63]. Wong and Lai [64] produced an eleven year evaluation of fuzzy sets theory in operations management and noticed a significant rise in fuzzy applications between 1998 and 2009. The study showed that scheduling had the highest percentage (16.49%) of applications among all operations research that implement FL. Azadegan et al. [65] performed a comprehensive study into the uses of FL for manufacturing problems. Nine sub-streams were identified, with over one hundred studies between 1990 and 2010. The nine sub-streams are listed below.

- Process control and optimisation.
- Manufacturing cells and machine controls.
- Scheduling and aggregate planning, see also [60], [64], [66].
- Manufacturing systems flexibility.
- Quality control and monitoring, see also [16], [67]–[71].
- Maintenance systems.
- Demand forecasting.
- Manufacturing strategy and location decisions.
- Supply chain and supplier selection.

2.4.3 Motivation for Use

FL was chosen for its ease of use in complicated problems through heuristics [15], [54]. Ross [56] stated that FL was successful where complex models were involved and when human reasoning was normally used. Fuzzy control allows other tools to be integrated for different purposes, such as Genetic Algorithm (GA) for optimisation or Analytical Hierarchy Process (AHP) for decision-making [15], [57]. FLCs have the advantage of being "*computationally simple*" which aids control and was used to implement varied inspection [72]. Conventional control (Proportional-Integral-Derivative (PID), robust control, stochastic control) is performed by developing mathematical models and then simplifying the models to deal with nonlinearities with methods such as linearization and state-space modelling. Controllers can then be built around the system model to meet control requirements (such as minimal overshoot and settling time). Due to the large scale of AMS, analytical models to measure and improve performance are difficult to obtain [61], [62]. Usually, conventional controllers undergo heuristic tuning to compensate for any inaccuracies in the model. However, fuzzy control applies heuristics from the start of development – independent of any intricate modelling and does not suffer any shortcomings faced by conventional control [54], [73]. The flaws of fuzzy control was that the method is not exact – as the premise for control is based on certainty. The accuracy of the FLCs is dependent on the amount of membership functions used, while increasing the number of membership functions increases computational requirements. Many factors in fuzzy control, such the membership functions shapes and the type of defuzzification, can influence the results which cannot ensure repeatability.

Fuzzy control outperformed traditional control in certain production objectives. Tsourveloudis, Dretoulakis and Ioannidis [61] showed that fuzzy control outperformed traditional flow control in reducing WIP as shown in Figure 2.7. The hedging point values are from Bai and Gershwin [63].

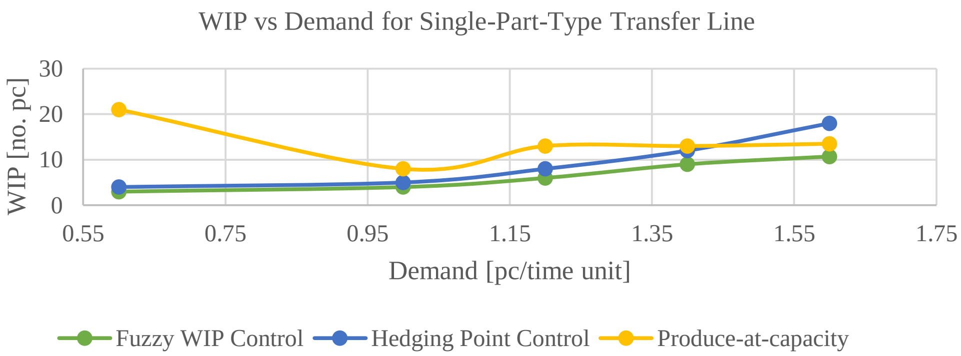

Figure 2.7: Control Methods for WIP Reduction through Increasing Demand [61]

2.4.4 Distributed Control of Fuzzy Logic Controllers

Combinations of fuzzy controllers were used in production scheduling and control. Controller design for varied inspection was based on the work performed in [58], [61], [72], [74], [75]. The most common form of fuzzy control for production control was the combination of distributed and supervisory controllers, with optimisation for either the distributed or supervisory controllers, or both. Tsourveloudis, Dretoulakis and Ioannidis [61] used distributed fuzzy controllers to control machine processing rates. The controllers were designed for three types of manufacturing subsystem: transfer lines, assembly and disassembly. Researchers state that the three subsystems can be used to model almost every manufacturing layout [58], [61], [72].The aim of those controllers was to adjust machine processing rates to reduce WIP and cycle times, while promoting machine utilisation by avoiding starving or blocking. Figure 2.8 shows the basic form of the distributed controller [61]. Three reasons to keep WIP low were outlined in [61], with more explanations for this requirement in [76], [77]:

- Parts provide no profit while they are unfinished and in production.
- High WIP leads to undesirable high cycle times.
- Parts are susceptible to quality issues the longer they remain in production.

Various tests were performed and the results showed that the distributed fuzzy control implementation reduced WIP, reduced cycle time, increased machine operating time and reduced machine idle time when compared to the produce-at-capacity scheme. Figure 2.9 shows the machine operation for both fuzzy WIP control and produce-at-capacity control [61]. Note that the machine utilisation increased and idle time decreased.

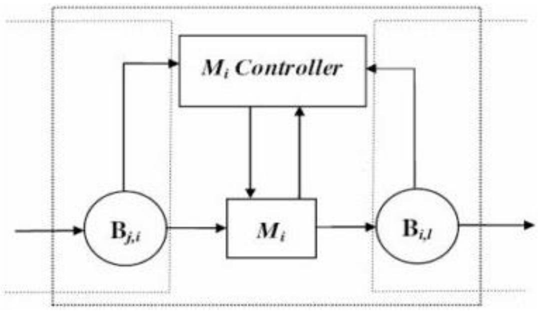

Figure 2.8: Distributed Fuzzy Controller [61]

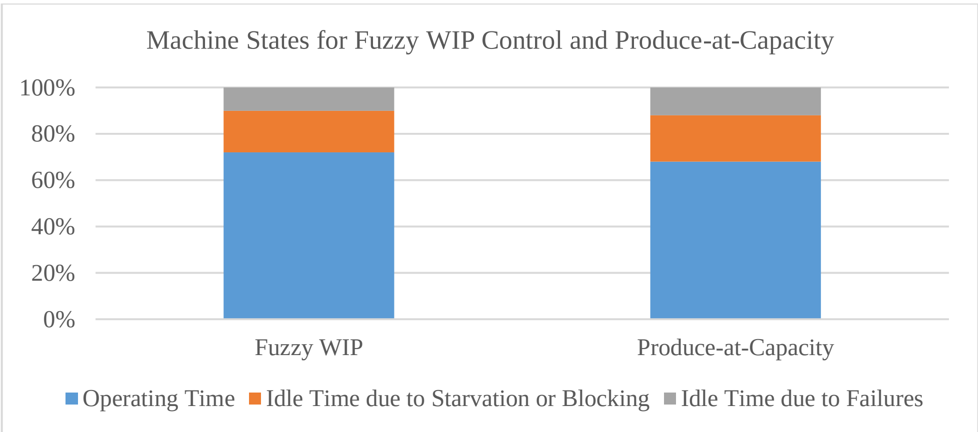

Figure 2.9: Machine States for Fuzzy WIP and Produce-at-Capacity Control Methods [61]

Supervisory control was implemented into the fuzzy WIP control by Ioannidis, Tsourveloudis and Valavanis [58]. Supervisor control was defined as the uppermost control level in a hierarchical controller [54]. The supervisory controller tuned the lower level distributed fuzzy controllers for the same purpose of keeping WIP and cycle times low, as shown in Figure 2.10 [72]. The entire fuzzy control architecture still remains modular, as the supervisory controller tunes the distributed fuzzy controllers without changing its structure or purpose. The supervisory controller measured the mean surplus of the end product, the error of the end-product surplus and the relative WIP error to calculate production upper and lower bounds correction factors. The correction factors changed the production surplus bounds. The results showed that the supervised case reduced WIP further than the distributed case for various levels of buffer capacities and demand, while backlog was decreased further in the supervised case as demand increased.

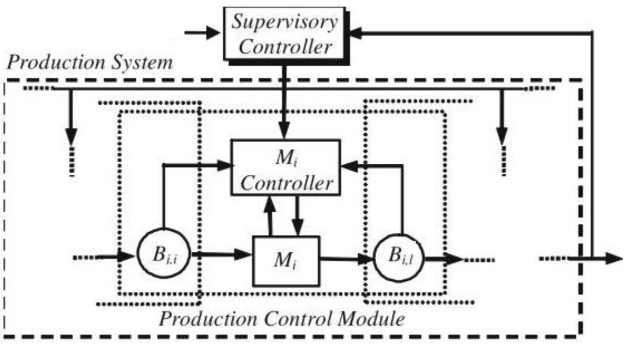

Figure 2.10: Supervisory Control of Distributed Controller [72]

Optimisation techniques were used to modify existing fuzzy control structures to improve performance further than non- optimised FLCs. Optimisation was used to reshape the existing membership functions. Tsourveloudis, Doitsidis and Ioannidis [72] used an Evolutionary Algorithm (EA) to convert HDF controllers to Evolutionary Distributed Fuzzy (EDF) controllers, and HSF to Evolutionary Supervisory Controllers (ESF). The evolution process made use of the GA operators, excluding the crossover operation. More in-depth information on optimisation is provided in Section 2.4.5. Figure 2.11 and Figure 2.12 shows the development of the EDFs and ESF respectively [72]. The evolutionary approach reduced mean WIP as shown in Figure 2.15 [72]. Homayouni and Ismail [74], [78] used a GA approach to only tune the HSF controller into a Genetic Supervisory Controller (GSF). The optimised supervisory controller had lower WIP compared to the HSF. Figure 2.13 shows the results of Homayouni and Ismail for WIP for different Buffer Capacities (BC) and various failure rates (P) [74].

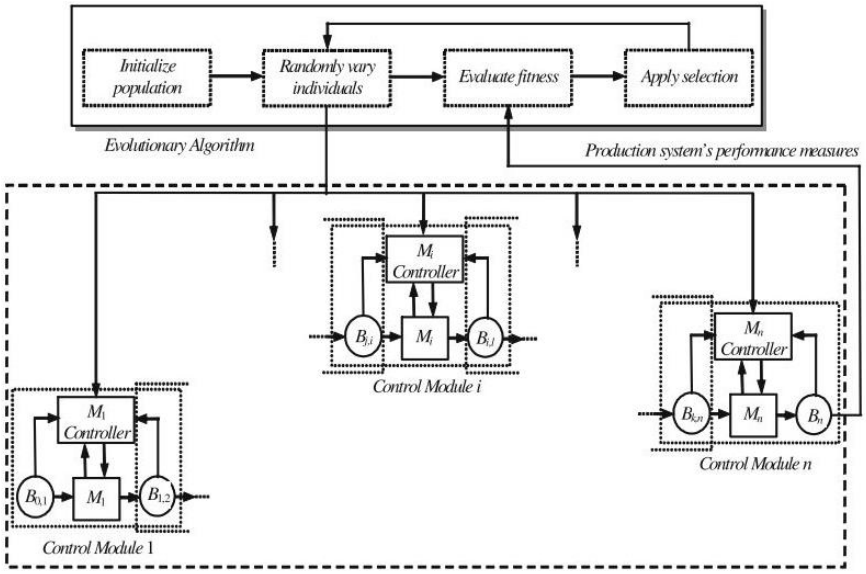

Figure 2.11: Evolutionary Algorithm for Distributed Controllers [72]

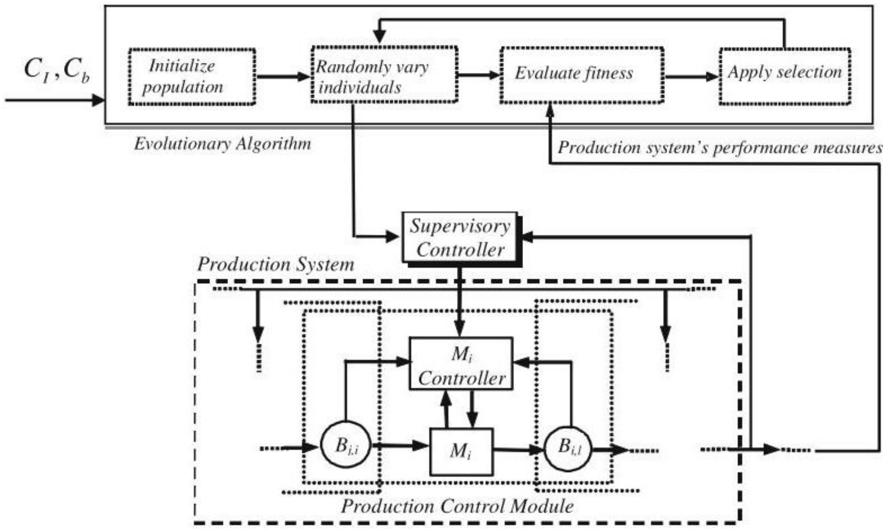

Figure 2.12: Evolutionary Algorithm for Supervisory Controller [72]

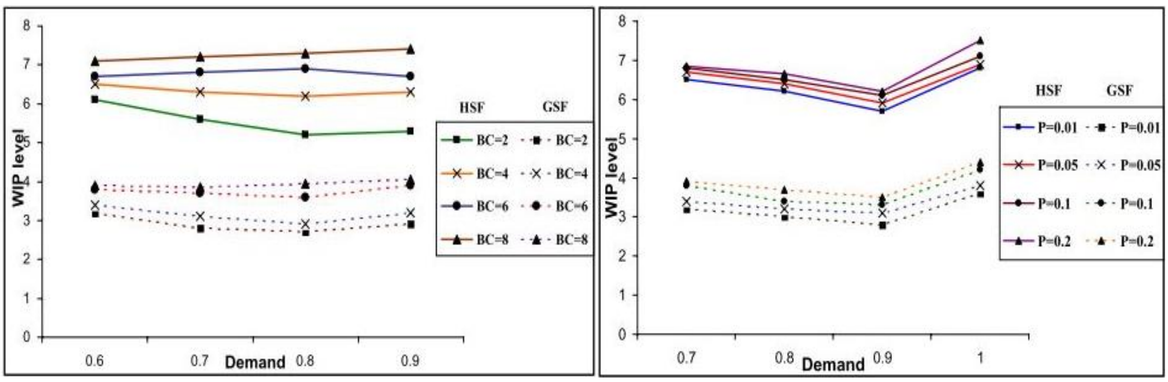

Figure 2.13: WIP Levels for Various Buffer Capacities (BC) and Failure Rates (P) [74]

Homayouni, Tang and Ismail [75] developed Genetic Distributed Fuzzy (GDF) controllers and combined them with the GSF. Mixed results were obtained from the study, with the two major conclusions:

- Use the HSF instead of the GSF when the backlog cost is more than the WIP holding cost.
- The GDFs accumulate less backlog when the backlog cost is more than the WIP costs.

2.4.5 Optimisation Techniques for Fuzzy Control

Optimisation techniques for fuzzy controllers have been used to improve fuzzy controller performance through membership function tuning. The most common form of optimisation for FLCs is the GA technique (or some form of GA) for membership function construction, however Cordon and Herrera quotes other techniques such as scaling factors and rule-base optimisation [73], [79]. GAs are powerful optimisation tools and simulate natural evolution through natural selection [38], [80]. Figure 2.14 shows the basic structure of a GA loop [80]. Each solution is evaluated against a "fitness function" which determines which solutions to keep for the next generation of solutions. Multiple generations produce stronger offspring to solve the optimisation problem.

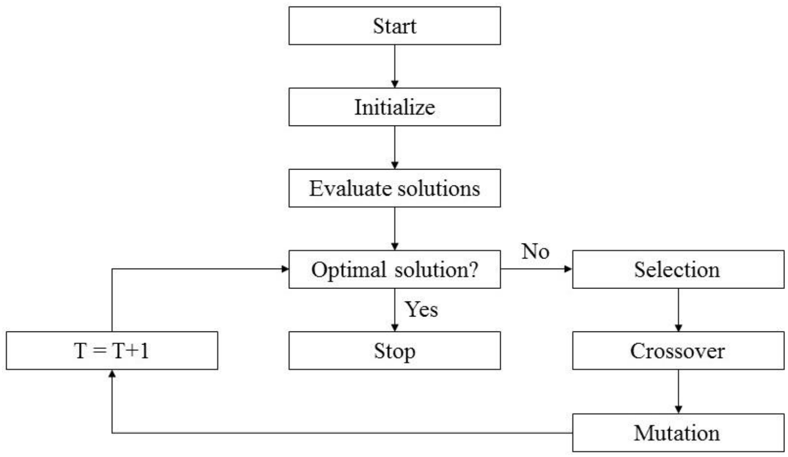

Figure 2.14: Basic Genetic Algorithm Loop [80]

The GA operators that mimic natural selection are shown below [80]:

- Selection: Determines which solutions are best and are kept and used for reproduction. Good solutions are chosen through a fitness function which ranks solutions against each other.
- Crossover: Creates new solutions from selected solutions in the mating pool by swopping information.
- Mutation: Sporadic change in the solution to main solution diversity.

There were multiple advantages of using GA in conjunction with FLCs. Foran [81] explained that GA could solve some of the shortcomings of FLCs when expert knowledge was not available. Bajpai and Kumar [82] agree on the same point made by Foran that GAs were an effective method of problem solving when there was minimal available knowledge. Much of the parameters of FLCs are chosen by trial-and-error, whereas GA can be used to find the most optimal parameters more efficiently than trial-and-error or other traditional methods [83]. GA provided a better solution that differentiation-based approaches to optimisation for FLCs [81]. Tsourveloudis, Doitsidis and Ioannidis [72] showed that an EA outperformed a standard fuzzy heuristic approach to WIP reduction. Figure 2.15 [72] shows the comparison of WIP reduction for the standard and the optimised evolutionary FLCs. The evolutionary optimisation is similar to GA optimisation, however evolutionary computing does not involve the "crossover" operator. Homayouni, Tang and Ismail [75] made use of the fitness function F shown in equation 2.9.

$$F = C_I * \overline{WIP} + C_b * \overline{BL} \tag{2.9}$$

Where:

C_I = unit cost of inventory

$\overline{WIP}$ = mean WIP

C_b = unit cost of backlog

$\overline{BL}$ = mean backlog

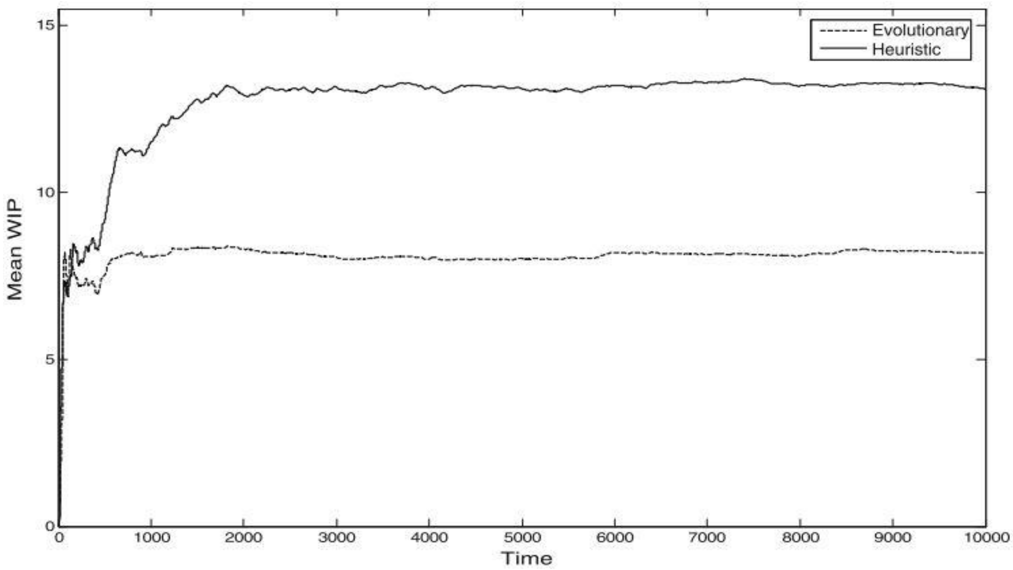

Figure 2.15: Comparison of Mean WIP for Evolutionary and Heuristic Fuzzy Controllers [72]

2.5 Chapter Summary

The literature review chapter outlined the concepts of quality control, varied inspection and fuzzy control. New methods of QC was required for MC, as traditional QC cannot be used. Varied inspection was discussed based on how it is performed, its characteristics and its advantages and disadvantages. Fuzzy control was reviewed as a viable control implementation for varied inspection. From the literature review, the following major points were outlined and were considered in the development of the controllers for varied inspection:

- On-line inspection is preferred to off-line inspection for various reasons, which is why varied inspection was designed as an on-line inspection scheme.
- Varied inspection is not the most economical inspection scheme however appraisal costs are reduced as described in equation 2.2.
- Fuzzy control is a viable control scheme for varied inspection. The development of the controllers described in Section 2.4.4 is used to construct the controllers used in this research. As such, varied inspection makes use of distributed and supervisory controllers to not just reduce inventory, but to also reduce blocking/starving, increase machine utilisation, reduce lead time and the effects of slow inspection on production.

3 Development of Fuzzy Logic Controllers for Varied Inspection

3.1 Chapter Introduction

The purpose of Chapter 3 was to outline the FLC design for both control levels: distributed and supervisory fuzzy control. The methodology of the controller design was outlined. Applications for both distributed and supervisory control were discussed. Optimisation techniques were implemented into the FLCs to improve performance. Lastly, pseudocode was provided for the controllers in Matlab®.

3.2 Controller Design

FLCs can be designed by choosing the inputs and outputs, choosing the pre-processing and post-processing of the inputs and outputs and forming the FLC shown in Figure 3.1 [54]. FLCs are constructed through trial-and-error rather than first principles [81]. Naidoo et al. [15] described a method to design an FLC, shown in Figure 3.1. Figure 3.2 [54] shows a fuzzy controller architecture in four main sections. The rule base is the sets of fuzzy rules and the inference mechanism decides which rules are relevant in each situation. Fuzzification converts crisp inputs into fuzzy sets to be used by fuzzy rules. Defuzzification converts the outcomes reached by the inference mechanism back to crisp values for use as inputs [54].

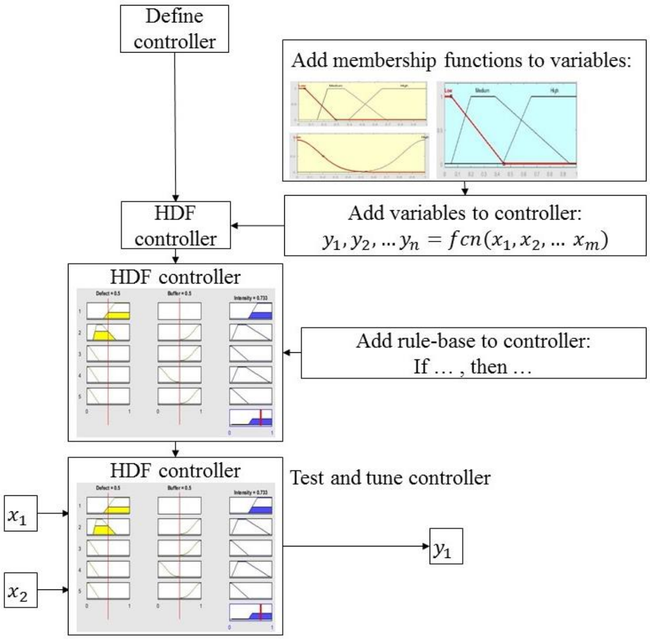

Figure 3.1: FLC Design Methodology [15]

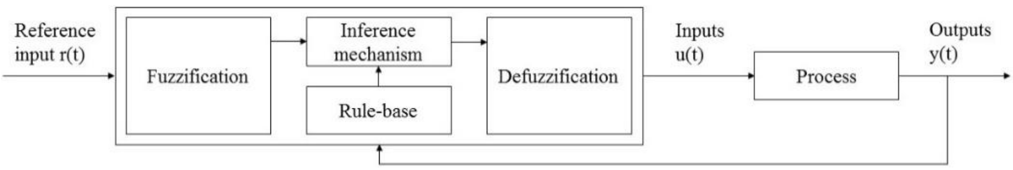

Figure 3.2: Fuzzy Controller Architecture [54]

3.3 Heuristic Supervisory and Distributed Control

Varied inspection was performed through a two-level control architecture. Figure 3.3 shows the two-level control architecture. HDF controllers were lower level controllers that perform varied inspection on the machine level. HDF controllers used buffer levels, machine states, defect rates and production surplus requirements to determine the amount of inspection to perform the inspection system for that machine. A HSF controller performed all adjustments for the HDF controllers from a supervisory control level. The main responsibilities of the HSF were to perform 100% inspection at the beginning of production and adjust the inspection of the HDF controllers to meet production demands through the use of a "multiplier" output. All controllers were developed using Matlab's Fuzzy Logic Toolbox® [84] and were implemented using Matlab® M-files as shown in Appendix C.

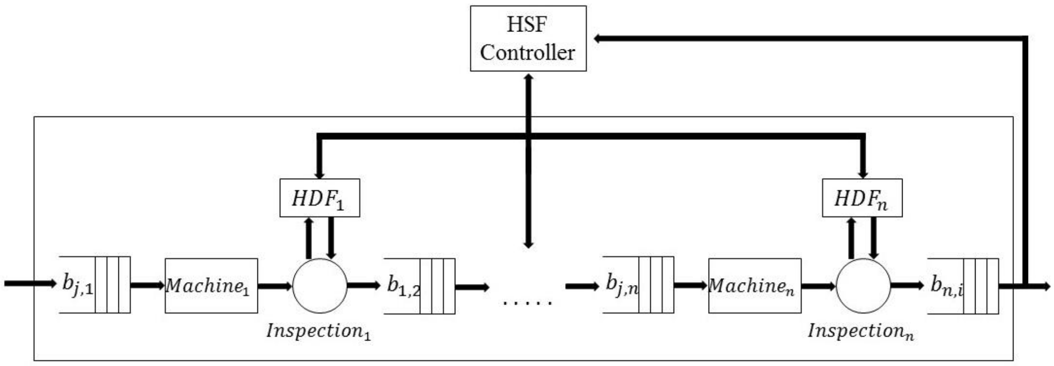

Figure 3.3: Supervisory and Distributed Fuzzy Control for Varied Inspection

3.4 Heuristic Distributed Fuzzy Controller Design

The design of the HDF controllers was explained in full detail.

3.4.1 Inputs and Output

The HDF controllers were based on Multiple-Input-Single-Output (MISO) control with the chosen inputs and output shown in Figure 3.4. The chosen inputs for the FLCs were based on the control metrics. The upstream and downstream buffer levels was measured for WIP, MLT and determination of starving or blocking. The machine state (whether the machine is running or in repair) indicated whether inspection should change based on a breakdown. Part quality was used as an input so that varied inspection was dictated by the quality of the parts produced. The production surplus was an indication of the amount of parts being produced. The output for the FLCs was "inspection intensity" which was the amount of inspection to perform on a part stream. For example, an inspection intensity of 60% for a batch of 100 parts would mean that 60 parts would be inspected and 40 parts would be left to continue without inspection.

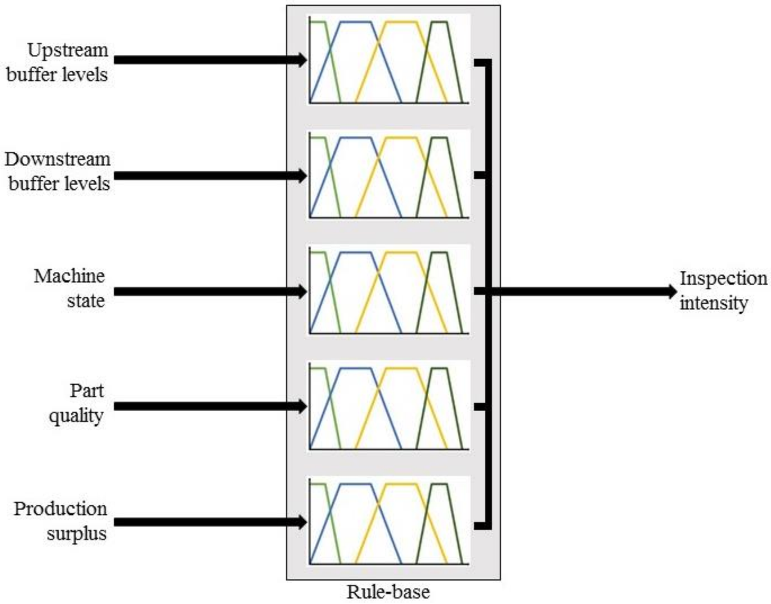

Figure 3.4: Input and Output of the HDF Controller

3.4.2 Rules

Linguistic Descriptions

FLCs make use of linguistic descriptions to describe the inputs and output. For example, the buffer levels can be described as “Empty” when there are no parts within it, “Almost Empty” when there are a few parts within it, “Middle” when the parts are at half the full capacity of the buffers, “Almost Full” when parts are filled up to around 75% of the buffer, and “Full” when the buffer is completely saturated. The linguistic descriptions form part of the “linguistic variables” where each input and output have the following linguistic terms:

- “B”, which is the linguistic term set for the buffer levels (upstream and downstream) = {Empty, AlmostEmpty, Middle, AlmostFull, Full}.
- “MS”, which is the linguistic term set for the machine state = {Repair, Transition, Running}.
- “Q”, which is linguistic term set for the defect rate = {ExtremeLow, ModerateLow, Average, ModerateHigh, ExtremeHigh}.
- “PS”, which is the linguistic term set for the production state = {Negative, Balanced, Positive}
- “I”, which is the linguistic term set for the inspection intensity = {ExtremeLow, VeryLow, Low, Medium, High, VeryHigh, ExtremeHigh}

Rule-Base

The rule base uses the linguistic descriptions prescribed previously to quantify the knowledge of how to implement varied inspection. The control objective was to reduce inspection. The general rules were as follows and the reasons for the rules were provided in bullet form.

1. If the part quality is unacceptable (high defect rate), then keep inspection as high as possible.

- This rule ensures that mass production of nonconforming parts does not occur.
- Production would not be feasible if majority of products were defective.

2. If the buffers are not full nor empty, and if the part quality is acceptable, then try to adjust the inspection to match the demand.

- When there is no threat of blocking or starving, aim to meet demand.
- Adjustments to inspection intensity can only be performed when the part quality is of an acceptable level.

3. If the buffers are about to become empty or full, and if the part quality is acceptable, then try to adjust inspection to prevent starving and/or blocking.

- Emptying of an upstream buffer will lead to starving and saturation of a downstream buffer will lead to blocking.
- Inspection should be adjusted to prevent blocking or starving.
- Inspection should be adjusted to reduce the effects of machine breakdown on production.

The general rules outlined can be transferred into a rule-base to fully control varied inspection. The controllers were "Mamdani" type with linguistic IF-THEN rules in the form of equation 3.1 [61].

$$\text{IF } X \text{ is } A \text{ AND } Y \text{ is } B \text{ THEN } Z \text{ is } C \tag{3.1}$$

Where:

X, Y are inputs.

A and B are linguistic values for X and Y respectively.

Z is the output.

C is the linguistic value for the Z output.

Figure 3.4 and equation 3.1 was used to construct the rule base for the FLC, shown in equation 3.2.

$$\begin{gathered}\text{IF } b_{j,i} \text{ is } LB^{(k)} \text{ AND } b_{i,l} \text{ is } LB^{(k)} \text{ AND } ms_i \text{ is } LBS^{(k)} \text{AND } q_i \text{ is } LQ^{(k)} \\ \text{AND } ps_i \text{ is } LPS^{(k)} \text{ THEN } I_i \text{ is } LI^{(k)}\end{gathered} \tag{3.2}$$

Where:

$b_{j,i}$ is the upstream buffer level
LB is the linguistic value for the buffer level (upstream or downstream)
$b_{i,l}$ is the downstream buffer level
ms_i is the machine state
LBS is the linguistic value for the machine state
q_i is the defect rate

LQ is the linguistic value for the defect rate
ps_i is the production surplus
LPS is the linguistic value for the production surplus
I_i is the inspection intensity
LI is the linguistic value for the inspection intensity
k is the rule number

Due to the amount of linguistic terms, the total amount of rules that can be conceived is shown in equations 3.3 and 3.4.

$$no.k = no.B\ terms \times no.MS\ terms \times no.PS\ terms \times \ldots \tag{3.3}$$

$$no.k = 5 \times 5 \times 3 \times 5 \times 3 \times 7 = 7875\ rules \tag{3.4}$$

7875 Rules was impractical to use, therefore 56 rules were used. The prescribed rules outline major control actions to be performed by the HDF controllers are prescribed by the rule-base. Table A.1 shows the prescribed rules in Appendix A.

3.4.3 Quantification of Knowledge

The quantification of knowledge of a FLC is done through membership functions and fuzzification.

Membership Functions

Linguistic values are quantified using membership functions "μ" which determine the certainty that an input or output belongs to a linguistic value. Trapezoidal and sigmoidal membership functions were chosen to represent the inputs and output of the FLC. Figures 3.5 to 3.7 shows the chosen membership function shapes based on the linguistic descriptions prescribed in Section 3.4.2.

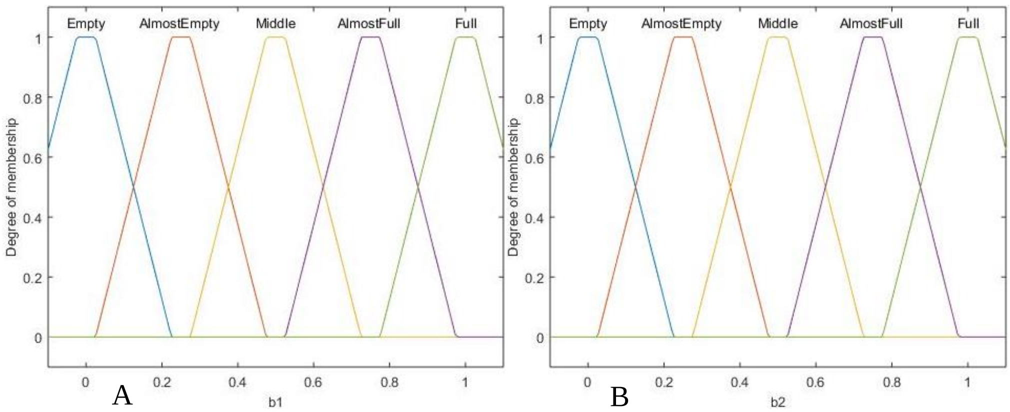

Figure 3.5: Membership Functions for A) Upstream Buffer Level Input and B) Downstream Buffer Levels Input

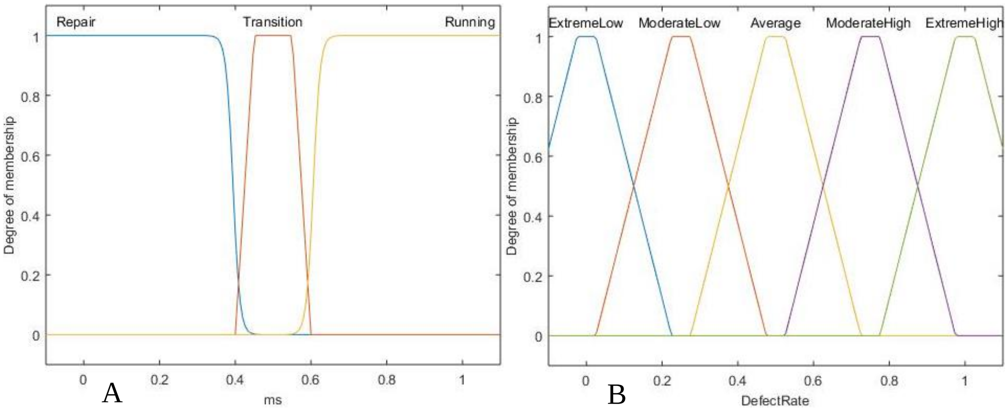

Figure 3.6: Membership Functions for A) Machine State Input and B) Defect Rate Input

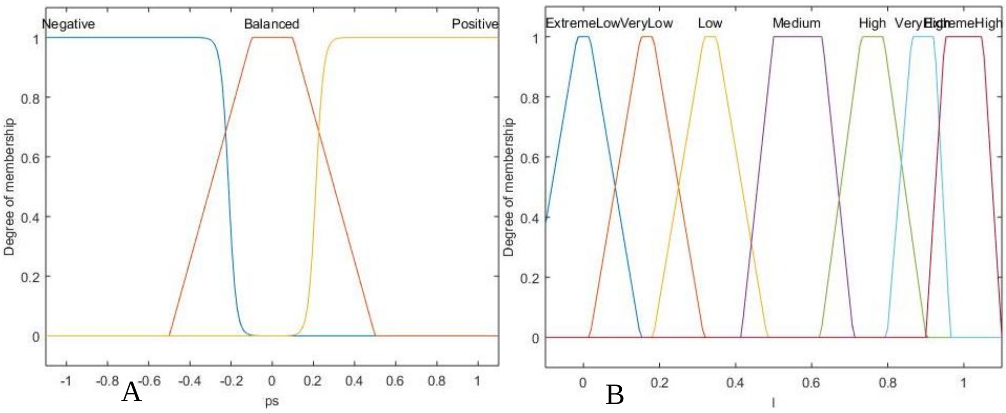

Figure 3.7: Membership Functions for A) Production Surplus Input and B) Inspection Intensity Output

Fuzzification

Fuzzification is the task of converting crisp inputs into numeric values for membership functions [84]. Figure 3.8 shows the fuzzification of a crisp value for the "defect rate" input. For a crisp input of 0.2, there is a 0.88 certainty that the defect rate is "Moderate Low" and a 0.16 certainty that the defect rate is "Extreme Low".

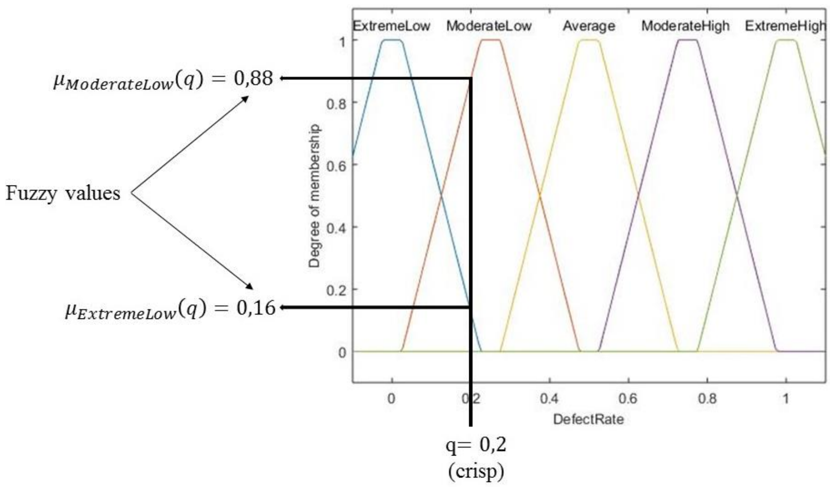

Figure 3.8: Fuzzification of a Crisp Value to a Fuzzy Value

3.4.4 Inference Mechanism

Inference is the process of mapping inputs to outputs through premise quantification and matching.

Premise Quantification

Premise quantification is the combination of multiple linguistic terms. The rules defined in Section 3.4.2 make use of the "AND" logical operator. Fuzzy control makes use of the "minimum" operator for the common standard Boolean "AND" operator, which is valid for both crisp and fuzzy sets. Premise quantification ensures that one certainty is obtained when multiple inputs are used in a rule. Let * denote the input states, where $b_{j,i}$* and $b_{i,l}$* represent the buffer levels with $\mu_B^*(b_{j,i})$ and $\mu_B^*(b_{i,l})$ membership functions respectively, bs_i* represents the batch size with $\mu_{BS}^*(bs_i)$, q_i* represents the defect rate with $\mu_Q^*(q_i)$ membership function and ps_i* represents the production surplus with $\mu_{PS}^*(ps_i)$ membership function. Let $\mu_{premise}^*$ in equation 3.5 define the certainty of the premise at time *t* for the inputs.

$$\mu_{premise}^*(b_{j,i}, b_{i,l}, ms_i, q_i, ps_i) = \min\{\mu_B^*\ (b_{j,i}), \mu_B^*\ (b_{i,l}), \mu_{MS}^*(ms_i), \mu_Q^*\ (q_i), \mu_{PS}^*\ (ps_i)\} \quad (3.5)$$

Matching

Matching is used to determine which rules and "on" and are applicable to the current inputs. A rule is activated when the certainty of the premise is greater than zero, shown in equation 3.6. The activated rules determine the output membership functions.

$$\mu_{premise}^*(b_{j,i}, b_{i,l}, ms_i, q_i, ps_i) > 0 \quad (3.6)$$

3.4.5 Conclusions from Inference

The recommendation from each rule that was activated through the matching process are used to determine what conclusions the FLC attains. Each rule provides a recommendation for the conclusion. For example, the fourth rule of the rule-base states that: "IF BatchSize is Cycle AND DefectRate is Moderate Low THEN InspectionIntensity is Medium." If the certainty of the premise of this rule is greater than zero, then this rule is activated and recommends that the output be "Medium". The recommended membership function is known as the "consequent membership function". Conclusions from each rule are calculated individually and then combined through defuzzification. Tsourveloudis, Dretoulakis and Ioannidis [61] used a "fuzzy relation" method to determine the consequent membership function for the *k*th activated rule. Define a fuzzy relation $FR^{(k)}$ with membership function $\mu_{FR^{(k)}}$ for the consequent membership function based on the *k*th activated rule shown in equation 3.7.

$$\mu_{FR^{(k)}}\big(b_{j,i}\,,b_{i,l}\,,ms_i\,,q_i\,,ps_i\,,I_i\big) = \min\{\mu_{LB^{(k)}}\big(b_{j,i}\big),\mu_{LB^{(k)}}\big(b_{i,l}\big),\mu_{LMS^{(k)}}(ms_i),$$
$$\mu_{LQ^{(k)}}(q_i),\mu_{LPS^{(k)}}(ps_i),\mu_{LI^{(k)}}(I_i)\} \tag{3.7}$$

Implication of the consequent membership function is done through the "minimum" operator of the premise membership function $\mu_{premise}$ and the fuzzy relation premise $\mu_{FR^{(k)}}$ shown in equation 3.8. The result of implication is known as the "implied fuzzy set".

$$Implied\ fuzzy\ set = \min[\mu^*_{premise}\big(b_{j,i}, b_{i,l}, ms_i, q_i, ps_i\big),$$
$$\mu_{FR^{(k)}}\big(b_{j,i}\,,b_{i,l}\,,ms_i\,,q_i\,,ps_i\,,I_i\big)] \tag{3.8}$$

The output membership function for the inspection intensity μ_I^* is calculated through the aggregation of the implied fuzzy sets. Aggregation is performed through the "maximum" operator of the implied fuzzy set, shown in equation 3.9 by combining equation 3.5 and equation 3.7.

$$\mu_I^*(I_i) = max_{b_{j,i},b_{i,l},ms_i,q_i,ps_i} \min[\mu^*_{premise}\big(b_{j,i}, b_{i,l}, ms_i, q_i, ps_i\big),$$
$$\mu_{FR^{(k)}}\big(b_{j,i}\,,b_{i,l}\,,ms_i\,,ps_i\,,q_i\,,bs_i\,,I_i\big)] \tag{3.9}$$

3.4.6 Defuzzification

Defuzzification is the process of converting a fuzzy value into a crisp value. Defuzzification was performed through the Centre of Gravity (COG) method, shown in equation 3.10, for output "I_i^*".

$$I_i^* = \frac{\sum I_i \mu_I^*(I_i)}{\sum \mu_I^*(I_i)} \tag{3.10}$$

3.5 Heuristic Supervisory Fuzzy Controller Design

The HSF controller design followed the same methodology as the HDF controllers. The HSF controller was based on MISO control. The tasks of the HSF controller was to:

1. Perform 100% inspection at the beginning of every cycle.
- Ensures the best realisation of the defect rate before varied inspection occurs.
2. Adjust the inspection intensity (which was calculated by the HDF controllers) to recompense for the desired WIP and end production surplus.
- Adjust the inspection intensity of the lower level HDF controllers to meet overall production demands.

The first 30% of the part production would be fully inspected. 30% was chosen as an estimation that the defect rate has minimal changes after 30% of the total parts had been produced. Based on the control objectives, the following inputs and output was chosen, shown in Figure 3.9.

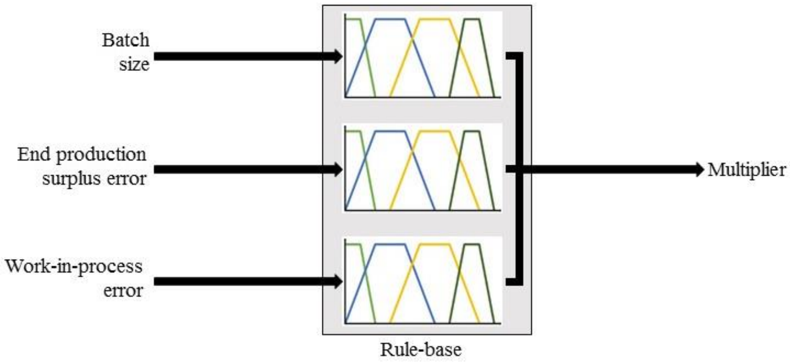

Figure 3.9: Input and Output of the HSF Controller

The batch size input was used to perform 100% inspection at the beginning of production. The end production surplus, e_{EPS}, is defined in equation 3.11 as the error between the actual end production rate and the desired mean end production rate. The WIP error, e_w, is defined in equation 3.12 as the error between the actual WIP level and the desired mean WIP level. The output "Multiplier" is a value that is used to adjust the values of inspection intensity calculated by the HDF controllers to either increase or decrease the amount of inspection performed on the machine level. The output, "M", is multiplied to each calculated I_i^* to adjust each inspection intensity proportionately to meet EPS and WIP goals.

$$e_{EPS} = \frac{EPS(t) - \overline{EPS(t)}}{\overline{EPS(t)}} \tag{3.11}$$

$$e_w = \frac{WIP(t) - \overline{WIP(t)}}{\overline{WIP(t)}} \tag{3.12}$$

Where:

e_{EPS} = EPS error

$EPS(t)$ = EPS at time t

$\overline{EPS(t)}$ = mean EPS

e_w = WIP error

$WIP(t)$ = WIP at time t

$\overline{WIP(t)}$ = mean WIP

The HSF was based on the Mamdani-type FLC described in equation 3.1. The linguistic descriptions for the HSF inputs and output are shown below:

"BS", which is the linguistic term set for the batch size = {Initial, Cycle}

"EPS", which is the linguistic term set for the EPS error = {Negative, Balanced, Positive}

“EW”, which is the linguistic term set for the WIP error = {Negative, Balanced, Positive}

“M”, which is the linguistic term set for the multiplier = {LessOne, One, MoreOne, Initial}

Equation 3.13 shows the rule-base for the HSF controller. From equation 3.13, seven rules were generated. The rule-base is shown in Table A.2 in Appendix A. Trapezoidal and sigmoidal membership functions were used to generate the rule-base. Figure 3.10 and Figure 3.11 show the membership functions for the HSF.

$$IF\ bs\ is\ LBS^{(k)}\ AND\ eps\ is\ LEPS^{(k)}\ AND\ ew\ is\ LEW^{(k)}\ THEN\ M\ is\ LM^{(k)} \qquad (3.13)$$

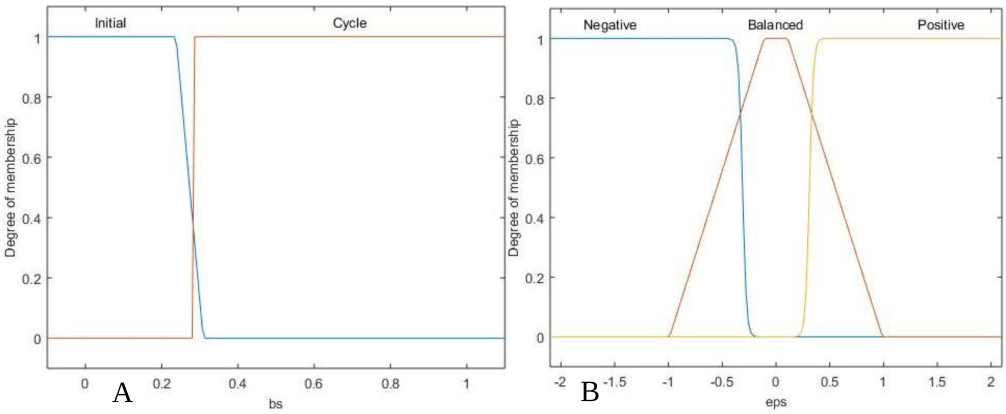

Figure 3.10: Membership Functions for A) Batch Size Input and B) End Production Surplus Input

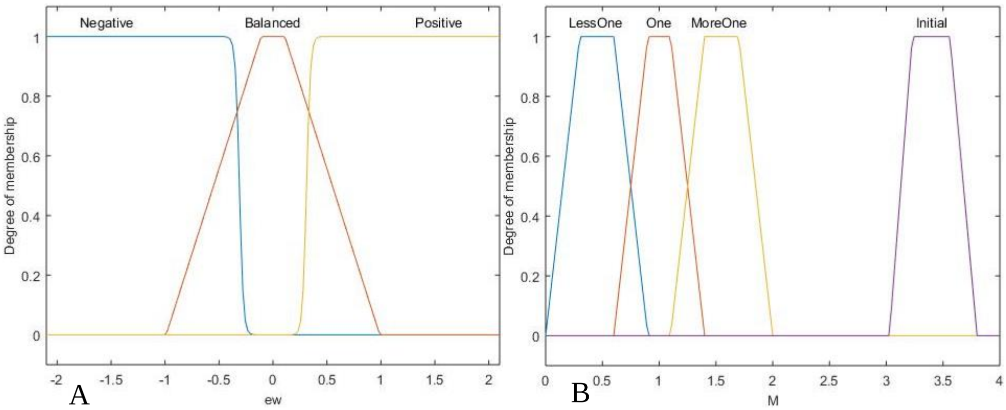

Figure 3.11: Membership Functions for A) WIP Error Input and B) Multiplier Output

From Figure 3.11 (B), note that “M” was set to the “Initial” membership function to fully saturate the inspection intensity to perform 100% inspection at the beginning of the cycle. A saturation module, developed in Matlab®, limits the product of M and the inspection intensity to “1”. After 30% of the parts were produced, M takes the values of “LessOne”, “One” or “MoreOne”. Equations 3.14 to 3.17 describe the design of the HSF with the same descriptions as that of the HDF controllers.

$$\mu^*_{premise}(bs, eps, ew) = \min\{\mu^*_{BS}\ (bs), \mu^*_{EPS}\ (eps), \mu^*_{EW}(ew)\} \qquad (3.14)$$

$$\mu_{FR^{(k)}}(bs, eps, ew, M) = min\{\mu_{LBS^{(k)}}(bs), \mu_{LEPS^{(k)}}(eps), \mu_{LEW^{(k)}}(ew), \mu_{LM^{(k)}}(M)\} \quad (3.15)$$

$$\mu_M^*(M) = max_{bs,eps,ew}\ min[\mu_{premise}^*(bs, eps, ew), \mu_{FR^{(k)}}(bs, eps, ew, M)] \quad (3.16)$$

$$M^* = \frac{\sum M\mu_M^*(M)}{\sum \mu_M^*(M)} \quad (3.17)$$

The final inspection, I_{final}, is the product of the inspection intensity calculated by the HDF controllers and the multiplier calculated by the HSF, shown in equation 3.18.

$$I_{final} = M^* \times I^* \quad (3.18)$$

3.6 Optimisation of Fuzzy Logic Controllers

Multiple forms of optimisation exist for FLCs – the most common form being the optimisation of membership functions, as performed in [72], [74], [75], [78]. For varied inspection, there were two choices for the optimisation of FLCs:

- Convert the HSF into a GSF or ESF only, as performed in [72], [74], [78].
- Convert the HSF into a GSF and convert the HDFs into GDFs, as performed in [75].

The decision was taken to only convert the HSF into a GSF for the following reasons:

- The HDF controllers performed satisfactorily in the individual testing in Section 4.2.
- Optimisation of the HDF controllers may move membership functions to extrema which would shift quality standards.
- Optimisation of the HSF would ultimately affect the HDF outputs more than an optimisation module.
- A GSF was favoured over an ESF as the crossover step would provide more solution variations.
- The GSF design would require less computing power when compared to a GSF and GDF combination.

The GSF controller would require three operations are prescribed in Section 2.4.5: selection, crossover and mutation. The membership functions of the output for the HSF were chosen to be optimised. The membership functions for the multiplier are shown in Figure 3.12. Notice that the focus was not to optimize the “Initial” membership function (Figure 3.10 (A)) as it provided a specific task of ensuring 100% inspection at the beginning of production and any form of optimisation would alter this function. The construction of the chromosomes are shown in Figure 3.13. Twelve genes were developed to describe three trapezoidal membership functions.

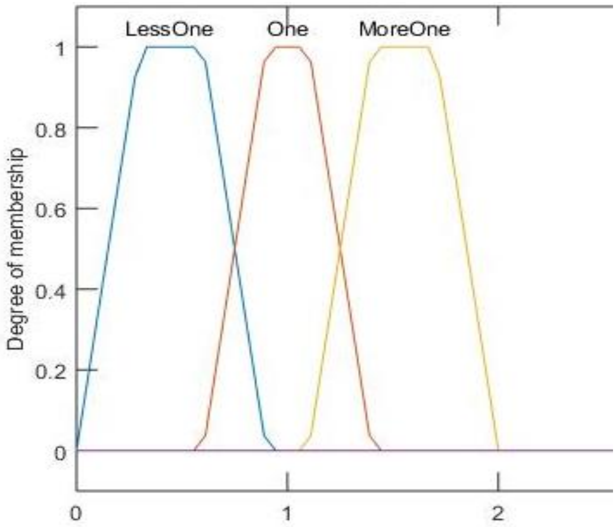

Figure 3.12: Membership Functions for the Multiplier for Optimisation

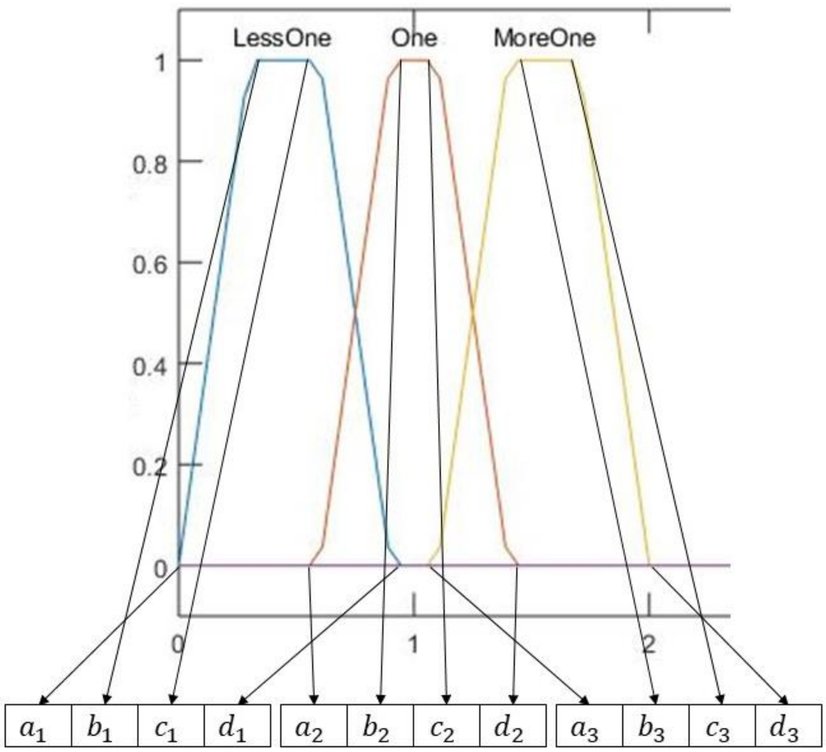

Figure 3.13: Chromosome Construction for Output Membership Function

Notice that the shapes of the membership functions in Figure 3.12 were not continuous – they have edges. This property would make the construction of the chromosomes difficult to perform by using piece-wise continuous functions. Therefore, the membership functions were approximated to Gaussian curves shown in Figure 3.14. Three Gaussian curves appear similar to the shapes of the membership functions. The parameters for the Gaussian curves are shown in Table 3.1.

Table 3.1: Gaussian Parameters for Membership Function Approximation

Membership Function	**Mean φ**	**Standard deviation σ**
LessOne	$\varphi_1 = 0.5$	$\sigma_1 = 0.9$
One	$\varphi_2 = 1$	$\sigma_2 = 0.9$
MoreOne	$\varphi_3 = 1.5$	$\sigma_3 = 0.9$

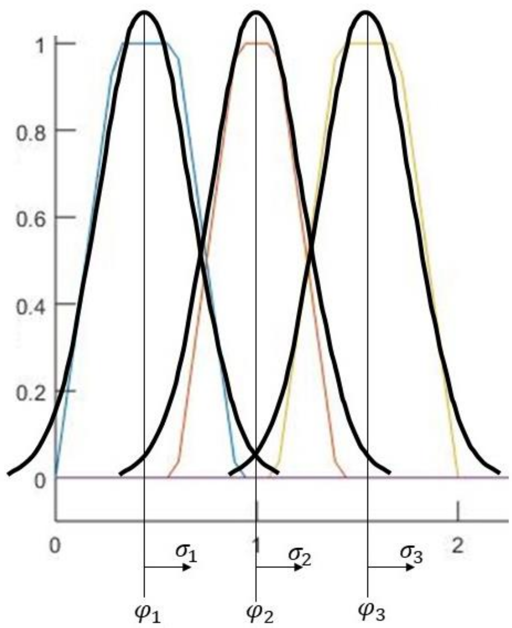

Figure 3.14: Gaussian Approximation of the Multiplier Membership Functions

Each Gaussian curve generates four random values using the "normrnd" function in Matlab®. Four random values for each membership function were generated, thus totalling twelve values that constitute a single chromosome. The values were sorted into ascending order where the lowest value would equal to a_1, the second lowest value would equal to a_2 and so on. Each chromosome was evaluated against the fitness function shown in equation 3.19.

$$F = k_1 * |e_w| + k_2 * |e_{EPS}| \tag{3.19}$$

Where:

k_1 = unit cost of the WIP error

k_2 = unit cost for the EPS error.

The aim of the optimisation based on the fitness function in equation 2.9 [75] was to minimize WIP and backlog, whereas the optimisation objective of varied inspection was to improve manufacturing performance. One common problem of production is the balance of reducing WIP while increasing throughput. The relationship between WIP and throughput is shown in Figure 3.15 [85]. To increase throughput, WIP must also increase. Conversely, reducing WIP reduces throughput. The optimisation objective was to minimize the fitness function, thus reducing WIP error and EPS error. Therefore, costs of inventory and EPS can be reduced. k_1 and k_2 are associated "cost" values which gives the optimisation a cost metric, where the aim is to reduce overall cost. The fitness function aims to find balances between WIP and throughput.

Twenty chromosomes were generated. From the results of the evaluation against equation 3.20, the ten fittest chromosomes are selected for crossover. Selection was done through the roulette wheel, where the fittest chromosomes occupy the most "area" on the roulette wheel. Arithmetic crossover is performed as shown in Figure 3.16.

Single-point mutation on the offspring occur and the chromosomes are sorted by ascending order again. The new offspring chromosomes are then re-evaluated against the fitness function. The process is run throughout the simulation. The solution space was bounded to [0; 5]. The constraints were based on the chromosome construction shown in equation 3.20.

$$a_1 < b_1 < c_1 < d_1 < a_2 < b_2 < c_2 < d_2 < a_3 < b_3 < c_3 < d_3 \tag{3.20}$$

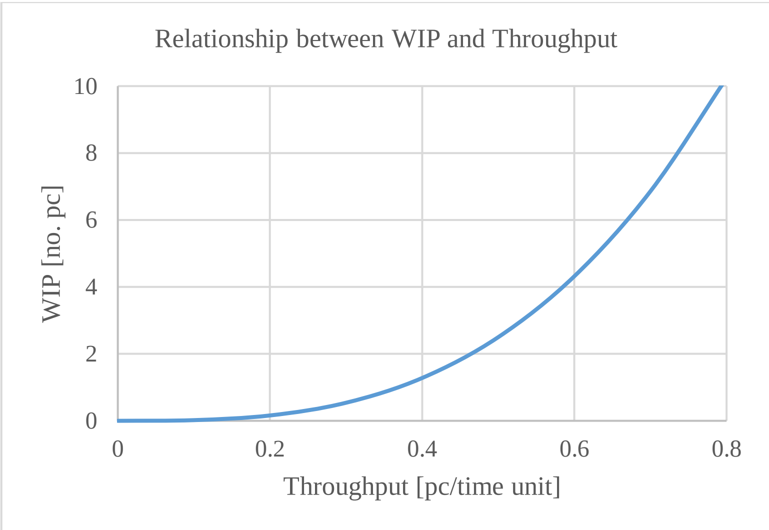

Figure 3.15: Relationship between WIP and Throughput [85]

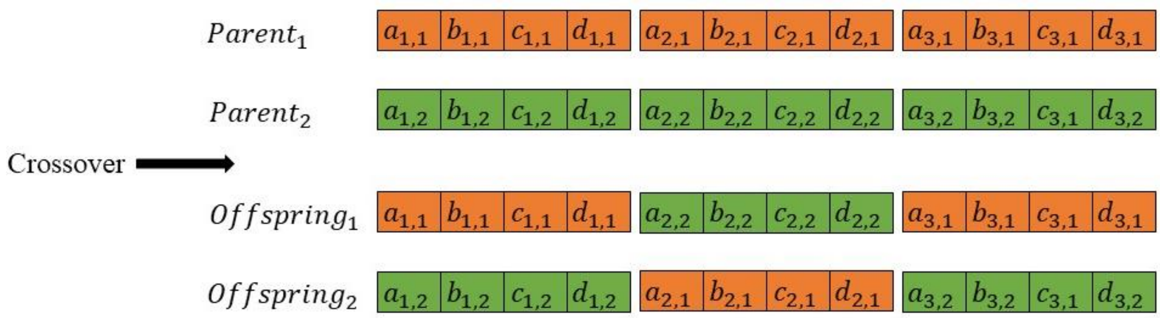

Figure 3.16: Arithmetic Crossover for Membership Function Chromosomes

3.7 Matlab Implementation

Matlab® was used for implementation of the FLCs. M-files were used to run the controllers and were communicated to SimEvents® for Discrete-Event Simulation (DES). The M-file approach allowed for easy manipulation of the FLCs as parameters could be changed in real time, such as the optimisation of the membership functions. The following pseudocode shows the basic steps to create an FLC with Matlab® M-file. The M-files for the HDF, HSF and GSF controllers are shown in Appendix C.

```
Function Output = Fuzzy Controller(Inputs)
Define controller space(newfis,'controller')
Add variables('Input or Output',' Input/Output Name',[Input/Output Range]);
Add  membership  functions('Input  or  Output',Variable  Number,'Linguistic
value','Membership function type',[Membership function parameters]);
Add rule list matrix = […
                        Input1 Input2 Input3 … Output AND/OR Weight
                          ⋮      ⋮      ⋮    …    ⋮      ⋮      ⋮
                          ⋮      ⋮      ⋮    …    ⋮      ⋮      ⋮];
Add rule list to controller(controller,rule list)
Evaluate FIS([Input1 Input 2 …])
```

3.8 Chapter Summary

The complete development of the fuzzy controllers were explained in the chapter. The two-level control architecture of the HSF and HDF controllers was discussed. The complete design of the HDF and HSF controllers were explained in detail in terms of inputs, outputs, rules, knowledge quantification, inference conclusions and defuzzification. GA optimisation was only performed on the membership functions of the HSF controller as the HDF optimisation would yield minimal performance increases as compared to HSF optimisation. Lastly, the Matlab® implementation of the FLCs was briefly outlined.

4 Individual Testing of the HDF and HSF Controllers

4.1 Chapter Introduction

The purpose of this chapter was to outline the individual testing of each controller to establish the effectiveness in performing its tasks. The premise of individual testing was that the controllers cannot be used for multiple objective control of manufacturing systems if they do not work in basic form i.e. the controllers cannot work in large scale systems if they do not work on the small scale systems. Both HDF and HSF controllers were tested for various performance measures. Single-Input-Single-Output (SISO) approximations were used for individual testing.

4.2 Heuristic Distributed Fuzzy Controller Testing

The purpose of the HDF controllers was to ensure that inspection intensity was dictated by part quality and to mitigate the effects of blocking, starving and machine breakdown. The effects of the HSF controller were taken out for the HDF testing. The first parameter to be tested was "averaging".

4.2.1 Averaging

"Averaging" was the term used to implement the inspection intensity output. As stated previously, inspection intensity was the amount of inspection performed on a part stream. For example, an inspection intensity of 80% would mean that 80 parts would be inspected out of 100 parts. The 80 parts would be chosen through Independent and Identically Distributed (IID) selection. An averaging module known as the "Switching Module" was developed in Matlab® and was based on equation 4.1 [24].

$$p = floor\left[\frac{-\log[rand(1,1) * (1 - Intensity)]}{\log\left[\frac{1}{(1 - Intensity)}\right]}\right] \tag{4.1}$$

Where:

p = 1 for "inspect" and p = 2 for "do not inspect".
"$floor$" is a function in Matlab® that rounds down towards negative infinity.
"$rand$" is a uniformly distributed random number
"$Intensity$" refers to the inspection intensity.

A typical result for the switching module and inspection intensity is shown in Figure 4.1. The result from the switching module should represent the inspection intensity as an average. Therefore, for an inspection intensity of 75%, the switching module integer p should be equal to 1 for 30% of that part stream and 75% for the rest.

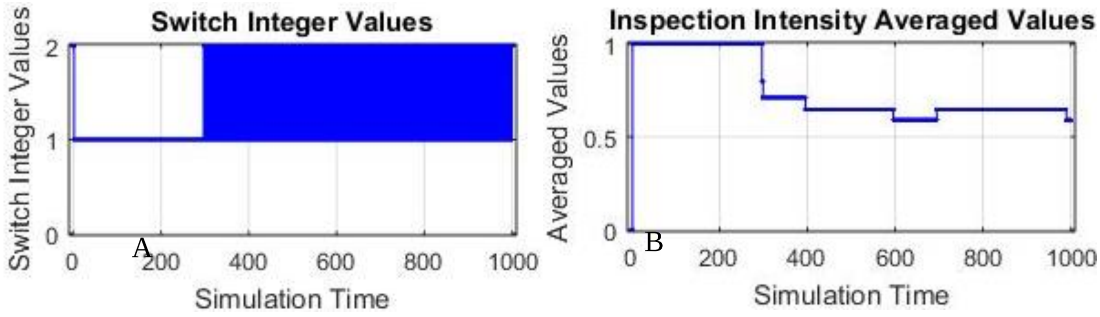

Figure 4.1: A) Switch Integer Values (p = 1, inspect; p = 2, do not inspect) and B) Averaged Values for Inspection Intensity (over 100 parts)

The switching of the switching module was done per part which makes the individual switching difficult to view in Figure 4.1. Table 4.1 shows the actual switching values as a percentage of Figure 4.1 along with the associated error with switching. The following parameters for DES of a single-station manufacturing cell was used to test the averaging module:

- Arrival rate: constant 1 part/time unit.
- Machining time, inspection time: 1 time unit
- Simulation time: 1000 time units

The arrival rate coincides with the simulation time. Therefore, for a simulation time between 0 time units to 100 time units, 100 parts were produced. An acceptable difference of 15% between the averaged inspection intensity and switch integer values was agreed upon. All values were in range therefore the averaging module was used as an appropriate method for averaging. The disadvantage of this method was that the error can fluctuate significantly which means that the repeatability of averaging is compromised.

Table 4.1: Averaging Module Testing

Simulation Time [time unit]	**Inspection Intensity Averaged Value**	**Switch Integer Value (percentage that p = 1, inspect)**	**Error as a difference**
0-100	1	0.98	2%
100-200	1	1	0
200-300	1	0.98	2%
300-400	0.711	0.66	5.1%
400-500	0.649	0.75	-10.1%
500-600	0.649	0.77	-12.1%
600-700	0.591	0.61	-1.9%
700-800	0.649	0.74	-9.1%
800-900	0.649	0.60	4.9%
900-1000	0.649	0.73	-8.1%

4.2.2 Blocking

Blocking is a common problem in production and arises when one process in a chain of processes limits the movement of parts through production due to large service rates. Blocking can significantly reduce production as slow machines limit dependent processes in its vicinity, as shown in Figure 4.2 - buffer $B_{1,2}$ becomes full which “blocks” machine M_1 from depositing parts into the buffer, which slows down production. The objective of the HDFs was to reduce the effects of blocking. Blocking induce buffers becoming completely full. Therefore, reducing buffer levels reduces blocking. A two-stage transfer line was used to simulate blocking, analogous to Figure 4.2. The DES parameters were:

- Arrival rate: exponential distribution with a mean of 1 time unit.
- Buffer capacities: $B_{j,1} = B_{1,2} = B_{2,k}$ =10 pc.
- Machining times: M_1 = 1 time unit; M_2 = 10 time units.
- Inspection time: $I_1 = I_2$ =5 time units.
- Simulation time: 1000 time units.

Figure 4.3 shows the buffer states for varied inspection. Figure 4.4 shows the averaged inspection intensity for both inspection systems. From Figure 4.3, note that the buffer level $B_{1,2}$ reached maximum capacity before the inspection intensity for the first inspection system increased to compensate for the high buffer level. The averaged inspection intensity for the second inspection system decreased to 40% to compensate for the large machining time of 10 time units ahead of the inspection system. Notice that the buffer level continued to increase to maximum capacity before reducing, which shows that varied inspection cannot fully mitigate blocking, but can aid in limiting its negative effects in production.

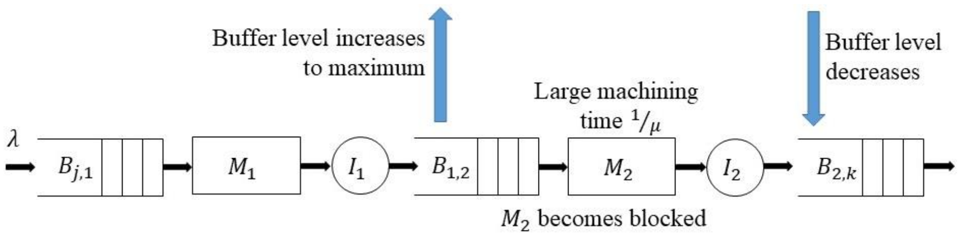

Figure 4.2: Blocking Example of a Two Stage Transfer Line

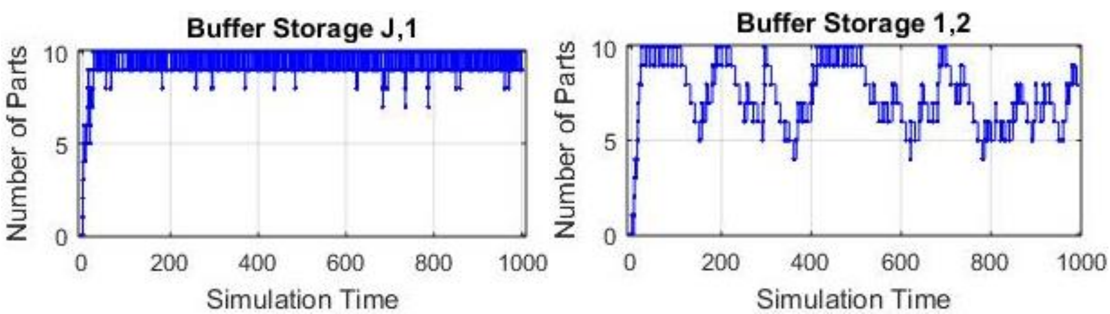

Figure 4.3: Buffer Levels for Varied Inspection for Blocking

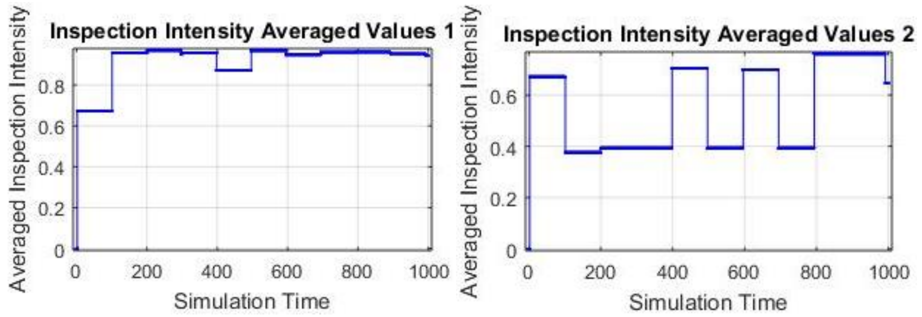

Figure 4.4: Averaged Inspection Intensity for Inspection System 1 and 2 for Blocking

4.2.3 Starving

Starving is the opposite of blocking and occurs when machines have to wait for parts to service, rather than having parts available to service. Starving results in low machine utilisation and is characterized by low buffer levels. Figure 4.5 shows an example of a machine being starved in a two stage transfer line. Starving induces emptying of buffers, such as in $B_{1,2}$. Therefore, avoiding buffer levels becoming empty can reduce starving. A two-stage transfer line (Figure 4.5) was used to simulate starving with parameters for DES as follows:

- Arrival rate: exponential distribution with a mean of 1 time unit.
- Buffer capacities: $B_{j,1} = B_{1,2} = B_{2,k}$ =10 pc.
- Machining times: M_1 = 10 time units; M_2 = 1 time unit.
- Inspection time: $I_1 = I_2$ =5 time units.
- Simulation time: 1000 time units.

Figure 4.6 shows the buffer states for varied inspection for starving. Figure 4.7 shows the averaged inspection intensity for both inspection systems for starving. From Figure 4.6, notice that the buffer was empty before the second average inspection increased to compensate for the low buffer level. The inspection for the first inspection system decreased to allow more parts to fill into buffer $B_{1,2}$. After the inspection actions, buffer $B_{1,2}$ then reached maximum capacity thus leading to a small reduction in inspection for the second inspection system, therefore the buffer level $B_{1,2}$ decreased again. As a result, varied inspection can mitigate starving but it may risk blocking (due to high buffer levels). However, varied inspection can mitigate blocking as shown in Section 2.2.2.

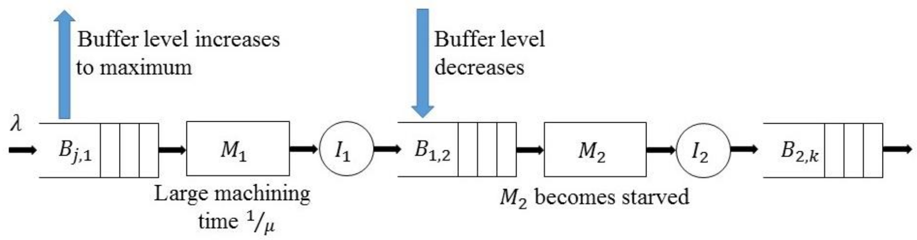

Figure 4.5: Starving Example of a Two Stage Transfer Line

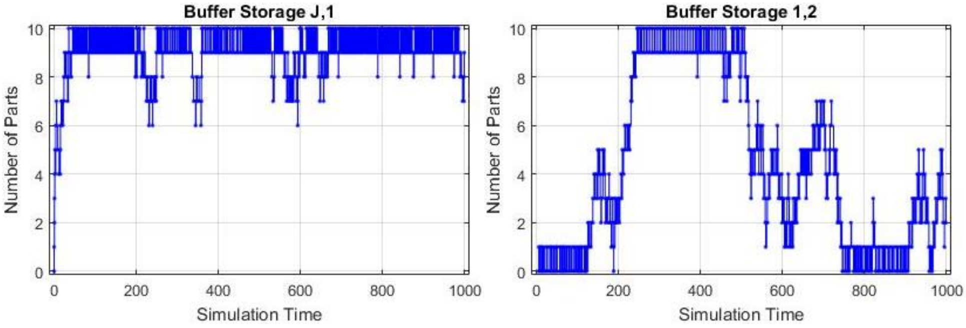

Figure 4.6: Buffer Levels for Varied Inspection for Starving

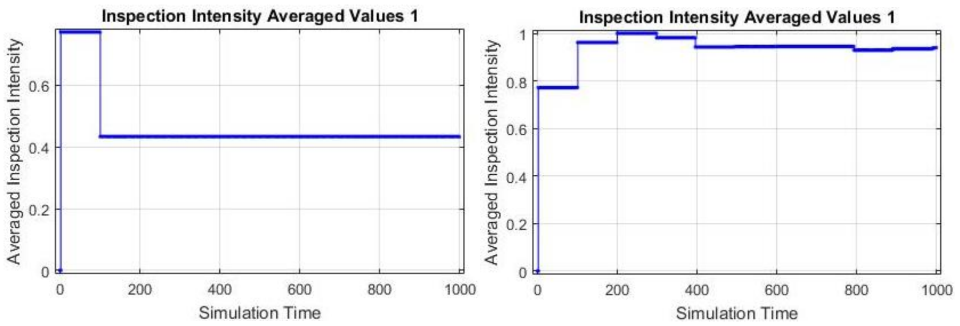

Figure 4.7: Averaged Inspection Intensity for Inspection System 1 and 2 for Starving

4.2.4 Machine Breakdown

Inspection intensity should increase after a machine is repaired because there exists the possibility that the part quality changes after machine repair. A repeating sequence was modeled as the machine state to test the effect of machine breakdown on inspection intensity, where a machine would run for a set period of time until it would breakdown and would require a set time to repair before returning to operation. Figure 4.8 shows the effect of machine breakdown on inspection intensity. The blue line represents the machine operation. When the machine operation drops below the breakdown line (grey line), the machine is in repair for a deterministic period of time and inspection intensity (orange line) increases to maximum such that a new defect rate is established. After repair, inspection intensity reduces as prescribed by the new defect rate after breakdown.

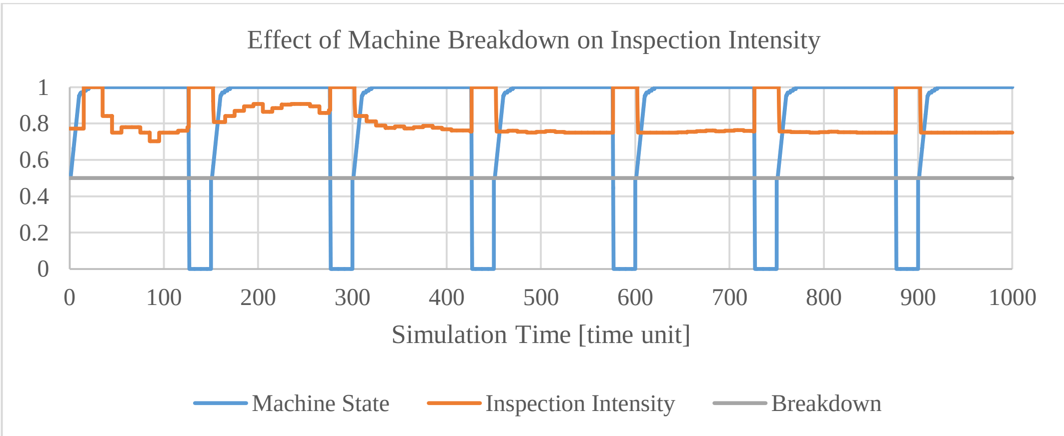

Figure 4.8: Effect of Machine Breakdown on Inspection Intensity

4.2.5 Varying Levels of Quality

This section of the HDF testing was to ensure that inspection intensity was dictated by the quality of the produced parts. The inspection intensity should not decrease lower than the defect rate, except in extreme cases of blocking or starving. A tolerance was used to change the levels of quality for the inspection system and a Poisson random number was used to model part quality. Tolerance values indicates which parts were in tolerance and out of tolerance. For example, a tolerance values of 10% for a measurement of 6 mm would mean that the inspection system would accept measurements within 5.4 mm and 6.6 mm, and reject measurements outside of this range. Averaged inspection intensity was tested against the defect rate for different tolerances. The following parameters were used for DES:

- Part quality: based on a Poisson distribution with a mean value of "6 mm"
- Simulation time: 1000 time units.

Figure 4.9 shows the relationship between averaged inspection intensity and defect rate. The important result to note was that inspection intensity was always higher than the defect rate for all tolerances. However, note that the inspection intensity was less than the defect rate for tolerances between 10% and 40% - concluding that varied inspection should not be used in low tolerance manufacturing.

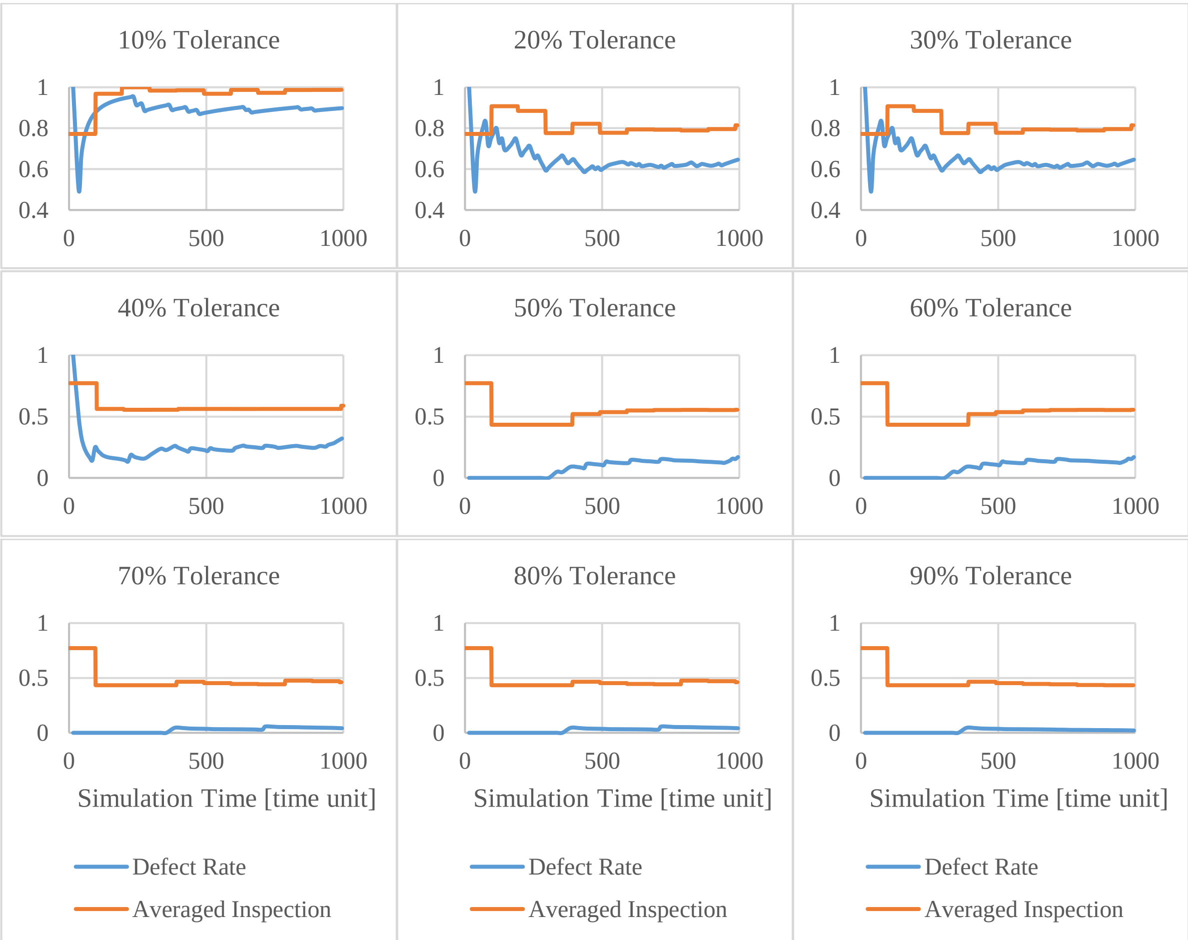

Figure 4.9: Comparison between Averaged Inspection Intensity and Defect Rate

4.2.6 Machine Production Surplus

The production surplus of each machine was tested to determine how inspection intensity should change with changes in production demands. If the required production surplus is higher than what the machine is producing, then inspection intensity must decrease to increase the machine production. If the production surplus is lower than the machine production surplus, inspection intensity should increase to reduce machine production to the required level. The following parameters were used to test production surplus in DES:

- Production surplus: sine wave with an amplitude of 1 and frequency of 0.01 radians/time unit.
- Part quality: tolerance of 90%.
- Simulation Time: 1000 time units.

Figure 4.10 shows the relationship between the inspection intensity and the machine production surplus. The inspection intensity decreases when the machine production surplus decreases and increases when the machine production surplus increases.

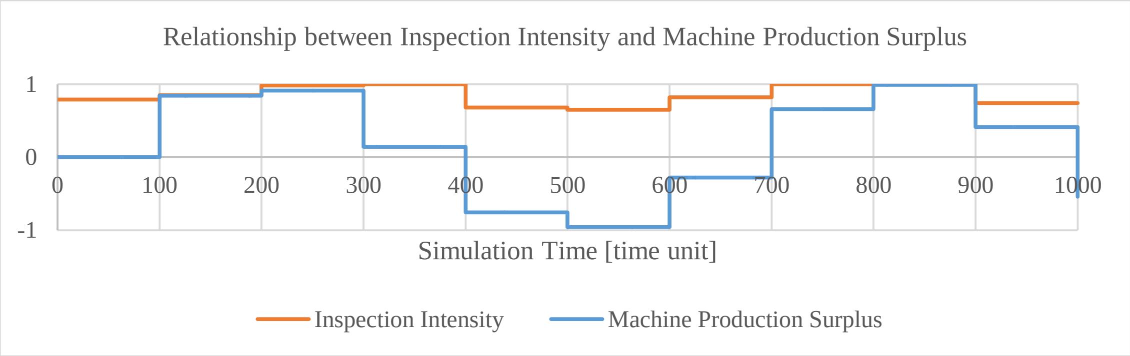

Figure 4.10: Relationship between Inspection Intensity and Machine Production Surplus

4.2.7 Machine Utilisation

A common goal of production is to have machines running all the time. High utilisation of machines is desirable as well as minimization of machine idle time. Varied inspection should improve machine utilisation by reducing the total time of production. Utilisation was used as a measure of the reduction of blocking or starving that occurs during production. A two-stage transfer line, similar to Figure 4.3, was used to measure the machine utilisation of two machines for varied inspection and 100% inspection. The following parameters were used:

- Arrival rate: exponential distribution with a mean of 1 time unit.
- Buffer capacities: $B_{j,1} = B_{1,2} = B_{2,k} = 10$.
- Machining times: $M_1 = M_2 = 1$ time unit.
- Inspection time: $I_1 = I_2 = 3$ time units.
- Simulation time: 1000 time units.

Figure 4.11 and Figure 4.12 show the machine utilisation for varied inspection and 100% inspection respectively. While the first machines show minimal differences in machine utilisation, the second machines show significant differences as varied inspection has utilisation over 80% (compared to 100% inspection with a utilisation of 15%). Machine utilisation increases due to the intervention of varied inspection reducing blocking or starving. While not conclusive, the following result shows that varied inspection can improve utilization in small-scale manufacturing such as Figure 4.3. Further research to investigate whether machine utilization increases in other scenarios was suggested in Chapter 8.4.

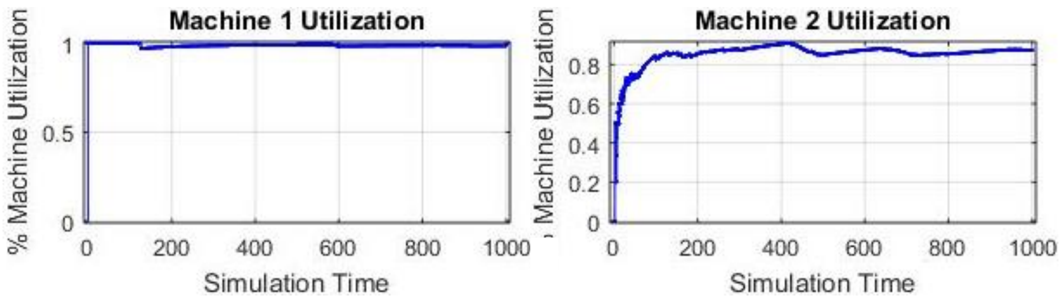

Figure 4.11: Machine Utilisation for Varied Inspection in Two Stage Transfer Line

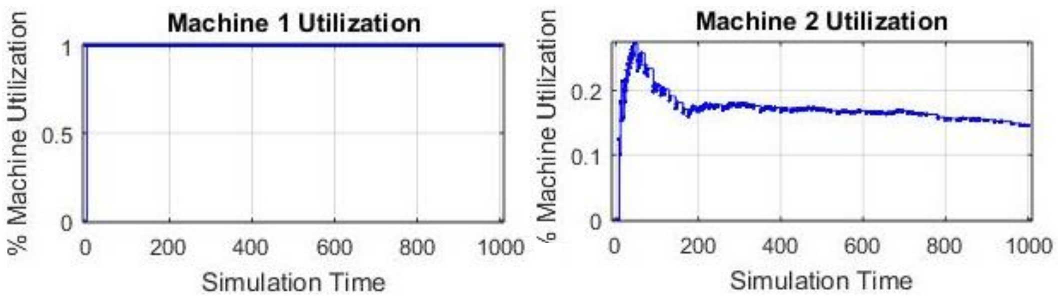

Figure 4.12: Machine Utilisation for 100% Inspection in Two Stage Transfer Line

4.3 Heuristic Supervisory Fuzzy Controller Testing

The HSF controller was designed to meet overall production aims. Each input and the optimisation module that was developed in Section 3.5 was tested. The results show that each input induced the appropriate control response and that GA optimisation improved the performance of the HSF.

4.3.1 Batch Size

The batch size input for the HSF was to ensure that 100% inspection was performed at the beginning of the production to ensure that the correct defect rate was calculated. If the first produced part is defective, it would mean that the defect rate is 1, which would cause the inspection systems to increase inspection intensity to maximum, which might be unnecessary if the defect rate does not converge to 1. The HSF was designed for the multiplier to be large for the first 30% of production. 30% was chosen as an estimate (however an optimal batch size can be calculated from the models produced in [70]) and can be adjusted by moving the membership function “Initial” for the batch size either forwards or backwards. The following parameters were used for DES:

- Arrival rate: exponential distribution with a mean of 1 time unit.
- Part quality: based on a random Poisson distribution.
- Simulation time: 1000 time units

Figure 4.13 shows the multiplier calculated from the HSF and the inspection intensity calculated from the HDF. Notice at the beginning of the simulation time, the multiplier is significantly large – this is to ensure that the product of the multiplier and inspection intensity is greater than 1. The result of the multiplication is shown in Figure 4.14 along with the saturated final inspection intensity. A saturation module was used to bound the result to 1 and below (a value of 1 means that 100% inspection was performed). Figure 4.15 shows the averaged final inspection next to the defect rate – note that the averaged final inspection intensity will always start at 1 irrespective of what the defect rate was.

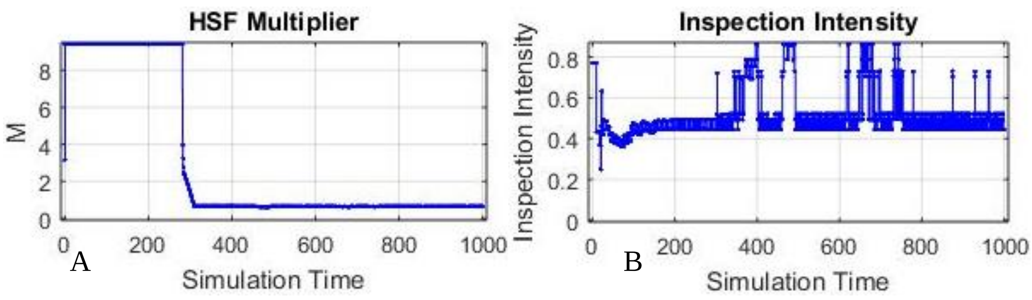

Figure 4.13: A) Multiplier from the HSF and B) Inspection Intensity from the HDF

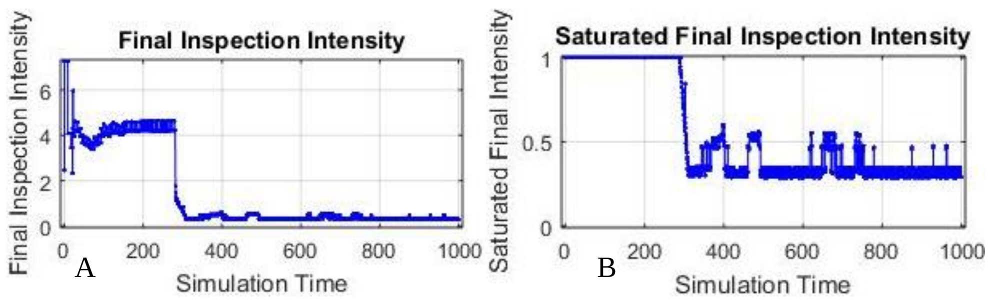

Figure 4.14: A) Final Inspection Intensity and B) Saturated Form

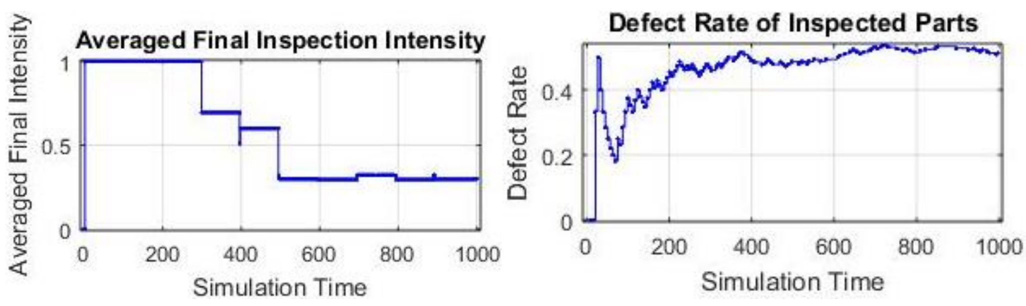

Figure 4.15: Averaged Final Inspection Intensity against Defect Rate

4.3.2 Optimisation

The optimisation of the HSF into a GSF was described in Section 3.6. As explained in Section 3.6, only the HSF would be optimised as the HDF performed satisfactorily in the individual testing (Section 4.2). A single-station manufacturing cell shown in Figure 4.16 was used to test the effectiveness of GA optimisation of overall HSF performance. Restated, the fitness function F is shown in equation 4.2. The aim of optimisation was to minimize the fitness function to reduce costs. The optimisation module that was used in SimEvents® is shown in Figure 4.17.

$$F = k_1 * |e_w| + k_2 * |e_{EPS}| \tag{4.2}$$

The test was to determine whether the optimised GSF works better than the HSF. The following assumptions were used for DES:

- Arrival rate: exponential distribution with a mean of 5 time units.
- Buffer capacities: $B_{j,1} = B_{1,k} = 10$ pc.
- Machining times: M_1 = 1 time unit.
- Inspection time: I_1 =3 time units.
- Simulation time: 1000 time units.
- Mean EPS = 0.15 pc/time unit
- Mean WIP = 10 pc
- $k_1 = k_2 =$ R 1 (South African Rand).
- The batch size input was commented out of the simulation.

Figure 4.18 shows the results of the DES. From the figure, it is noticeable that the GSF provides lower fitness function values than that of the HSF, which implies that for constant k_1 and k_2 values, the GSF reduces the EPS and WIP error significantly more than that of the HSF. The membership functions of the GSF continually change over each GA operation to minimize the fitness function. Therefore, the GSF outperforms the HSF as stated in the Section 2.4.4.

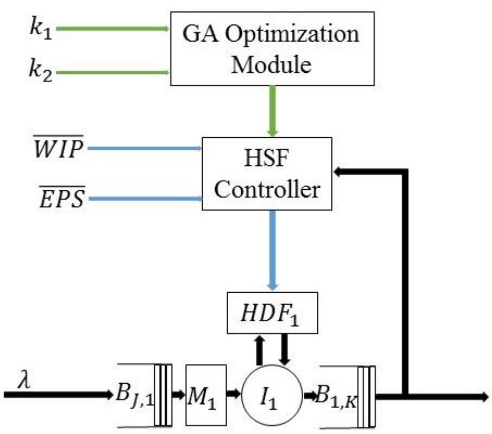

Figure 4.16: GA Optimisation for HSF in a Single-Station Manufacturing Cell

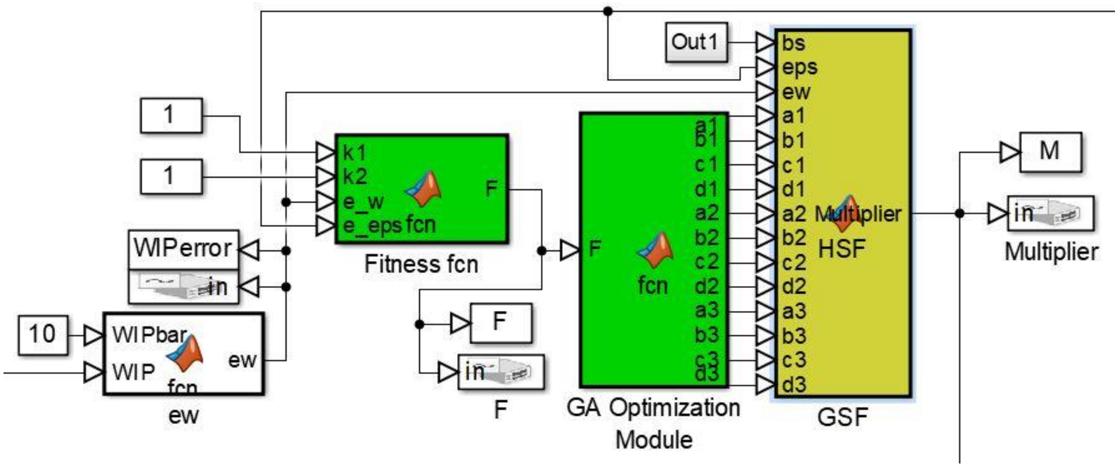

Figure 4.17: GA Optimisation Module in SimEvents®

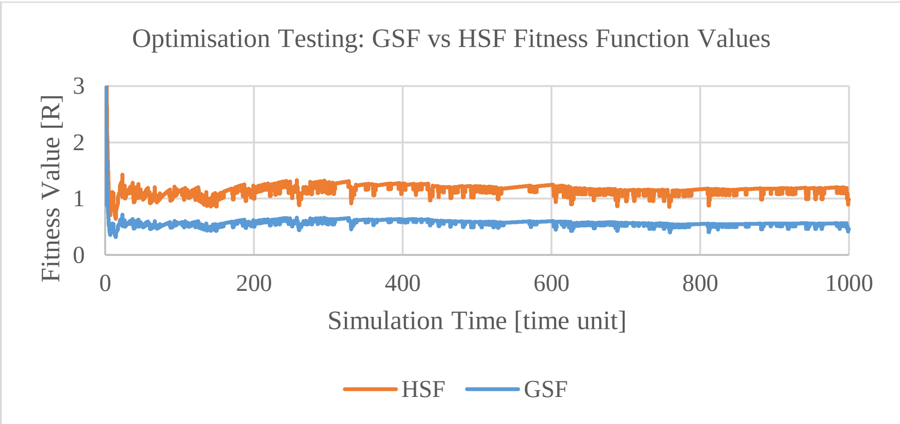

Figure 4.18: Fitness Function Values for GSF and HSF Controllers

4.3.3 Targeted Work-In-Process

A discretized sine wave was used as an input for the WIP error to measure the effect of the multiplier. The results of the simulation are shown in Figure 4.19. Notice that when the sine wave is at "0", the multiplier is at "1". When the WIP error increases, it means that the current WIP is larger than the mean WIP. Therefore, the multiplier increases to increase the final inspection intensity allowing more parts to be inspected. By increasing the final inspection intensity, the WIP should reduce to the mean WIP. The same principle applies to when the WIP error is lower than the mean WIP.

A two-stage manufacturing cell, similar to Figure 4.5, was simulated to determine how the multiplier would adjust to compensate for the WIP error. The HSF provides a feedback loop on how to adjust parameters to keep WIP error close to zero. The following parameters were used for DES:

- Arrival rate: exponential distribution with a mean of 2 time units.
- Buffer capacities: $B_{j,1} = B_{1,2} = B_{2,k} = 10$ pc.
- Machining times: $M_1 = M_2 = 3$ time units.

- Inspection time: $I_1 = I_2 = 6$ time units.
- End production surplus: commented out of the simulation
- Mean WIP = 12 pc
- Simulation time: 1000 time units.

Figure 4.20 shows the total WIP and WIP error. The targeted WIP was set for 12 pieces (prior tests were used to show that 12 pieces were attainable). The batch size input performed 100% inspection for the first 30% of production, which is why the total WIP increases to between 12 and 14 parts. When varied inspection was performed, the total WIP reduced to values near to the targeted value of 12. In a discrete system with parts moving through the system, the Total WIP would not visibly settle on a value of 12. However, the HSF does meet the target as shown by the WIP error shown in Figure 4.20 (B) where the error is close to zero and remains close to zero as a realisation of Lyapunov stability.

Analysis of the HSF multiplier showed that M increased to reduce total WIP to 12 parts, as shown in Figure 4.21. The figure is exploded to only show the values associated with varied inspection. The inspection intensity and final inspection intensity are shown in Figure 4.22. Notice that, due to the multiplier increasing to meet the targeted WIP, the inspection intensity also increased. The following experiment proved that the HSF could meet total WIP demands.

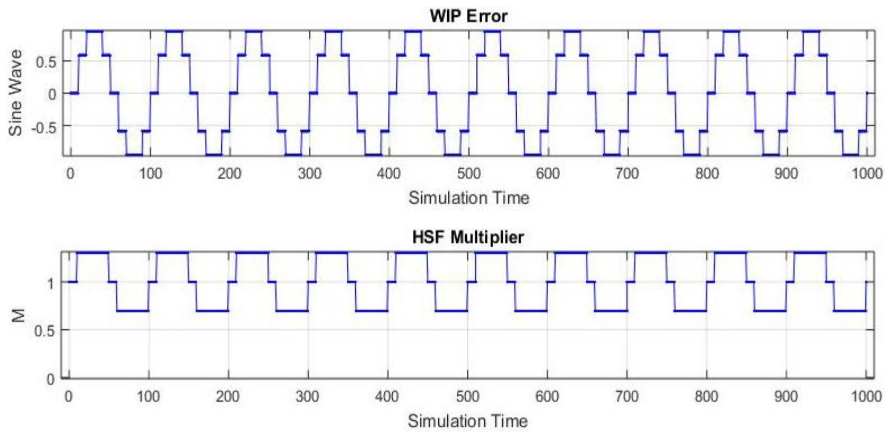

Figure 4.19: HSF Multiplier for Targeted WIP

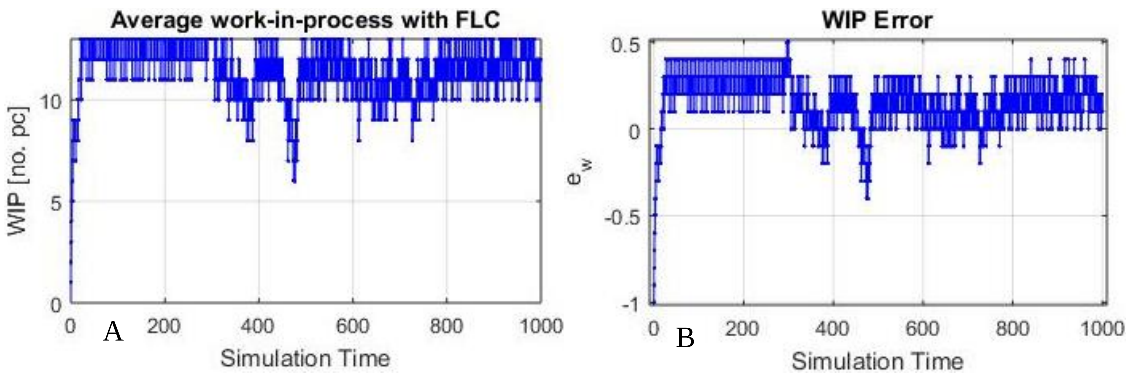

Figure 4.20: A) Total WIP and B) WIP Error for a Target of 12 Parts

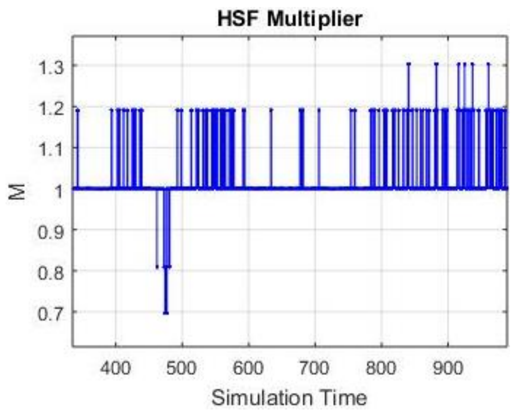

Figure 4.21: HSF Multiplier for Targeted Total WIP of 12 Parts

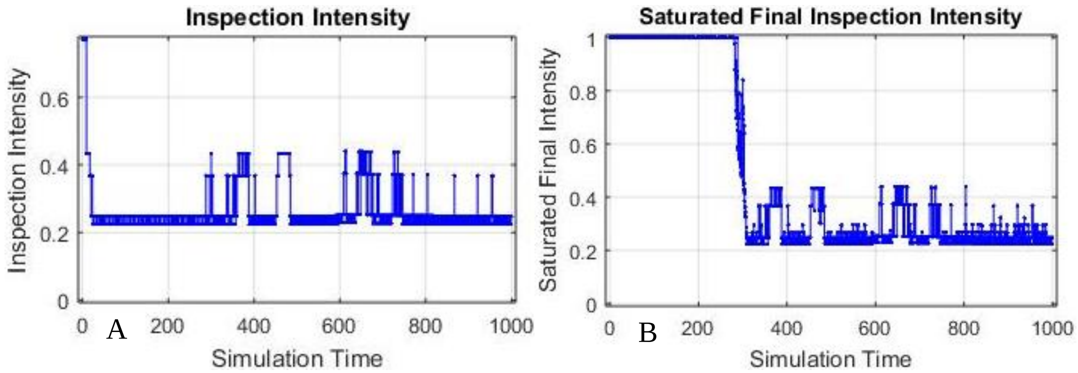

Figure 4.22: A) Inspection Intensity and B) Final Inspection Intensity for a Target Total WIP of 12 Parts

4.3.4 Targeted End Production Surplus

A similar discretized sine wave, shown in Figure 4.23 was used to test the effect of the EPS error on the HSF multiplier.

A two-stage manufacturing cell was developed to determine how the supervisor adjusts the multiplier to compensate for EPS, similar to Figure 4.5. The following parameters were used for DES:

- Arrival rate: exponential distribution with a mean of 2 time units.
- Buffer capacities: $B_{j,1} = B_{1,2} = B_{2,k} = 10$.
- Machining times: M_1 = M_2 = 3 time units.
- Inspection time: $I_1 = I_2$ =6 time units.
- Mean end production surplus: 0.2 pc/time unit
- Simulation time: 1000 time units.

Figure 4.24 shows the EPS and EPS error. The targeted EPS was set for 0.2 pc/time unit. The EPS remained low at 0.05 pc/time unit due to 100% inspection at the beginning of production. The EPS increased to the target of 0.2 pc/time units when varied inspection occurred. The EPS error shown in Figure 4.24 crossed “0” which means that the EPS reached its target value and overshot the target.

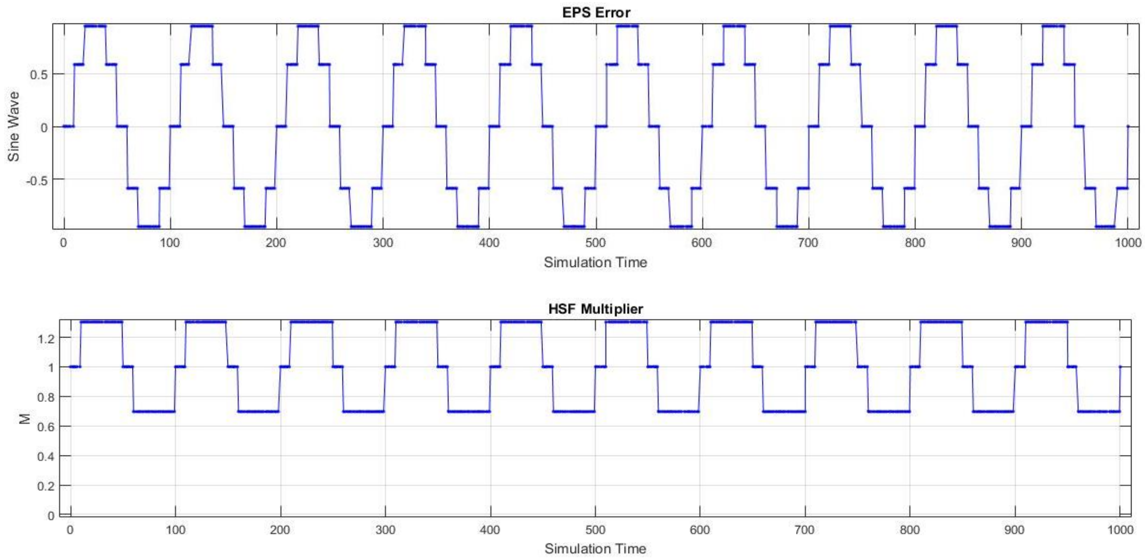

Figure 4.23: HSF Multiplier for Targeted EPS

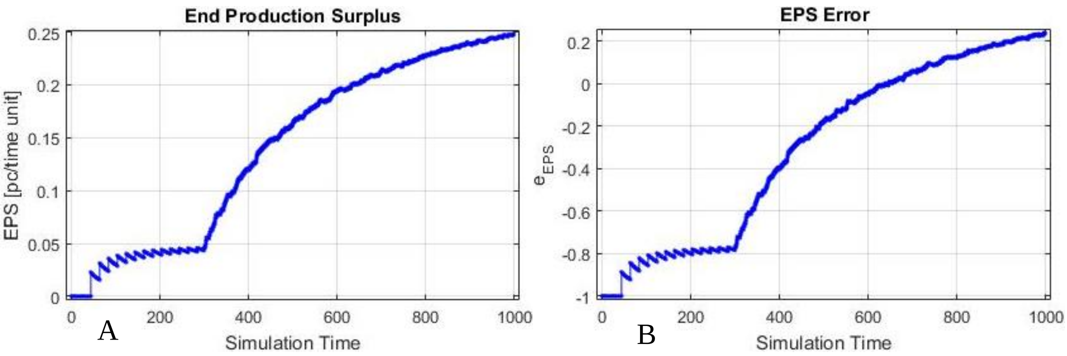

Figure 4.24: A) Total EPS and B) EPS Error for a Target of 0.2 pc/time unit

Analysis of the HSF multiplier showed that M decreased to 0.7 to increase EPS, as shown in the exploded view in Figure 4.25. The inspection intensity and final inspection intensity are shown in Figure 4.26. Notice that, due to the multiplier decreasing to meet the targeted EPS, the inspection intensity also increased. The following experiment showed that the HSF could adjust production to meet EPS demands.

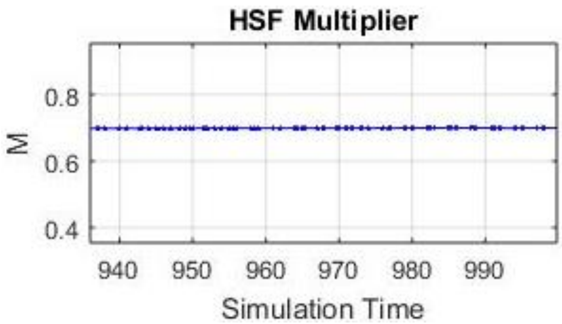

Figure 4.25: HSF Multiplier for Targeted EPS of 0.2 pc/time unit

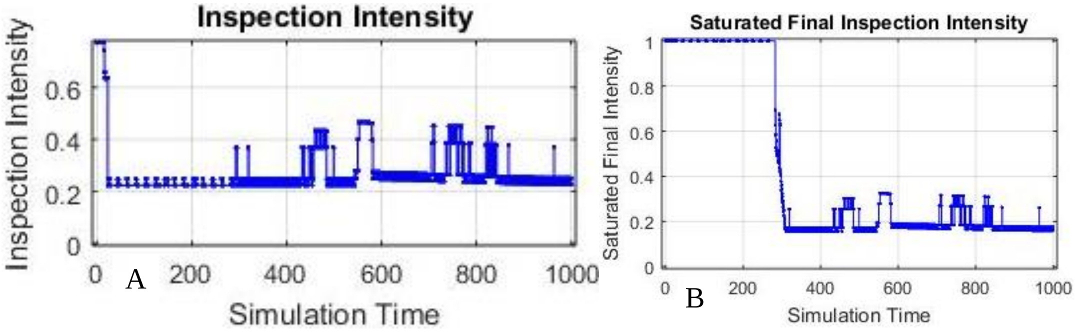

Figure 4.26: A) Inspection Intensity and B) Final Inspection Intensity for a Target EPS of 0.2 pc/time unit

4.4 Chapter Summary

The inputs of each controller was tested with acceptable results. The HDF controllers were tested against each input and the inspection intensity was measured. Favourable results were generated from the HDF controllers and each control action was executed as desired, however the disadvantages of averaging was outlined as the method can fluctuate significantly to yield errors. The HSF controller testing involved the testing of its inputs as well as optimisation. Each objective of the HSF was met. Testing had shown that optimisation of the HSF (into a GSF) provided significant improvement in the supervisory controller performance.

5 Varied Inspection for Subsystem Manufacturing Modules

5.1 Chapter Introduction

This chapter is the testing of varied inspection in the building blocks of complex manufacturing systems. Previous research states that multiple large production systems could be broken down into three subsystems: transfer line, assembly and disassembly [58], [61], [72]. The major advantage of splitting production systems into subsystems was that these subsystems can be connected together for a multitude of manufacturing layouts [61]. Each subsystem was tested individually as this testing would give an indication of how varied inspection would perform when the subsystems are interconnected.

5.2 Simulation Assumptions and Parameters for Subsystems

All assumptions and modelling parameters were based on the simulations produced in the third publication on page iii. The following assumptions were used for each subsystem:

- Part quality was based on a random Poisson number.
- Inspected nonconforming parts were removed from the system – there were no reworked parts.
- No machine failure.
- Machine production surplus was modelled with a random Gaussian number.

Assumptions from Tsourveloudis, Dretoulakis and Ioannidis [61] were used:

- All machines operated at known rates.
- Initial buffers were infinite sources of raw materials and consequently the initial machines were never starved.
- Buffers between adjacent machines had finite capacities.
- Set-up and transportation times were included in the machining processing times.

The following simulation parameters were used:

- Average arrival rate: 1 pc/time unit.
- Buffer capacities: 10 pc.
- Machining time: 1 time unit.
- Inspection time: 2 time units.
- Quality tolerance: 20% tolerance.
- Simulation time: 2000 time units.

5.3 Transfer Line

The transfer line is the most basic subsystem, shown in Figure 5.1. There is a single machine M_i and inspection system I_i surrounded by upstream buffer $B_{j,i}$ and downstream buffer $B_{i,l}$. Varied inspection was compared to 100% inspection and results for the EPS, WIP and MLT are shown in Figures 5.2, 5.3 and 5.4 respectively. The SimEvents® model is shown in Figure B.1 in Appendix B. The following results show an increase in EPS, no changes in WIP and a decrease in MLT.

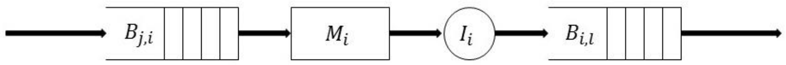

Figure 5.1: Transfer Line Module

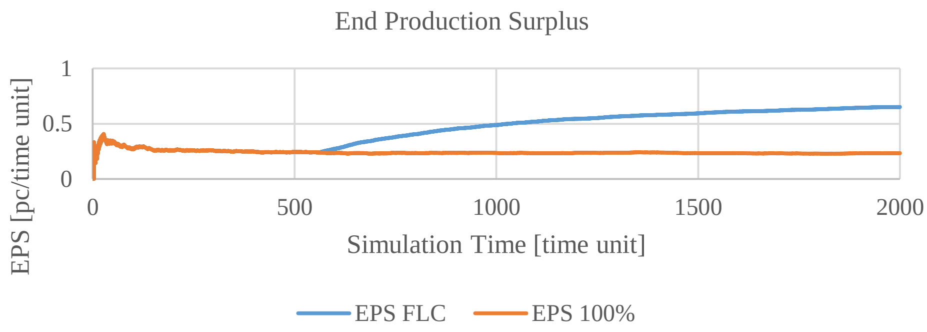

Figure 5.2: Transfer Line End Production Surplus Comparison

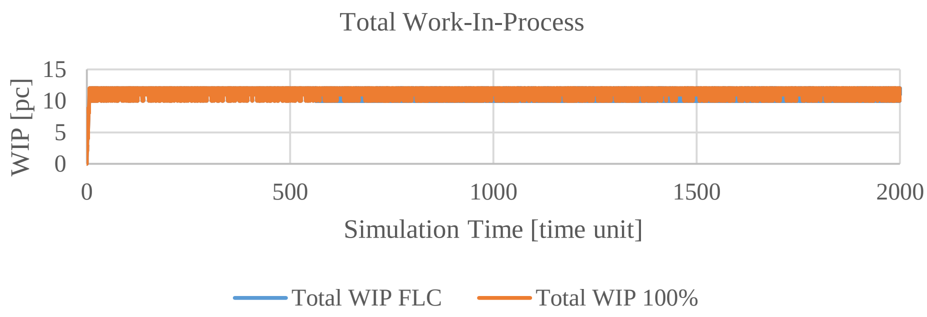

Figure 5.3: Transfer Line Total Work-In-Process Comparison

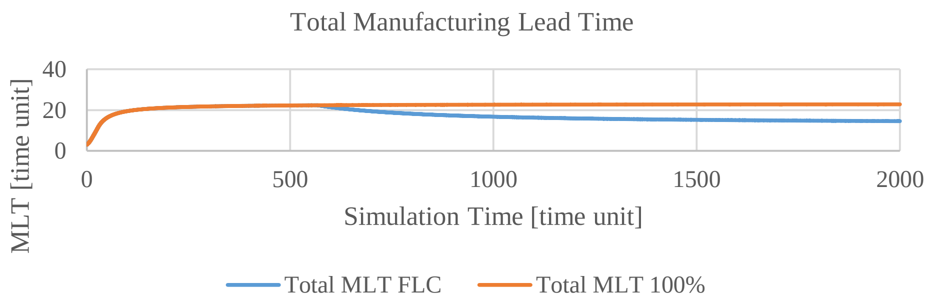

Figure 5.4: Transfer Line Manufacturing Lead Time Comparison

5.4 Assembly Module

The assembly module is the combining of unfinished parts to make a new part, which can involve bolted operations, welding and fitments. Figure 5.5 shows the assembly module. M_i combines unfinished parts from upstream buffers $B_{j,i}$ and $B_{k,i}$ which is then inspected by I_i. Varied inspection was compared to 100% inspection and results for the EPS, WIP and MLT are shown in Figures 5.6, 5.7 and 5.8. The SimEvents® model is shown in Figure B.2 in Appendix B. The following results show an increase in EPS, small increases in WIP and a decrease in MLT.

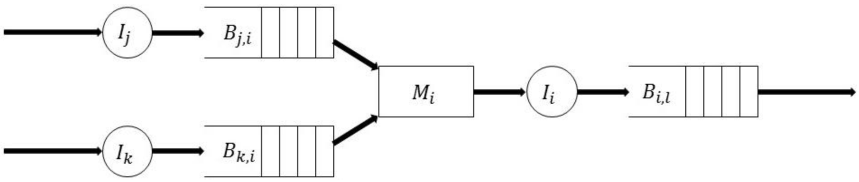

Figure 5.5: Assembly Module

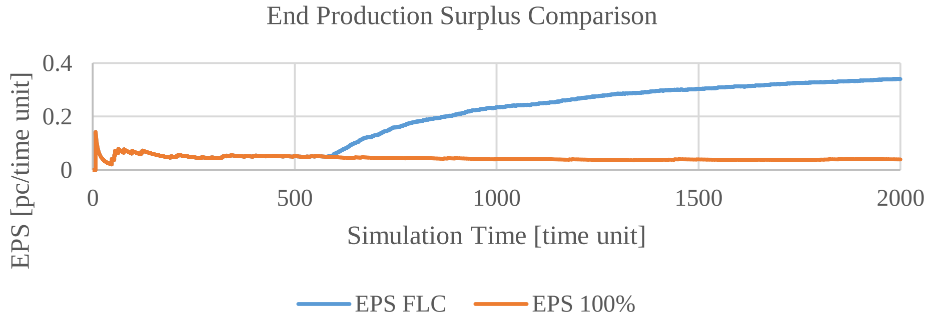

Figure 5.6: Assembly Module End Production Surplus Comparison

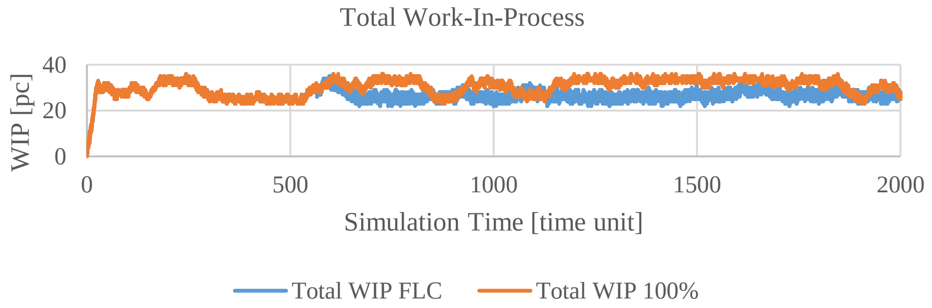

Figure 5.7: Assembly Module Work-In-Process Comparison

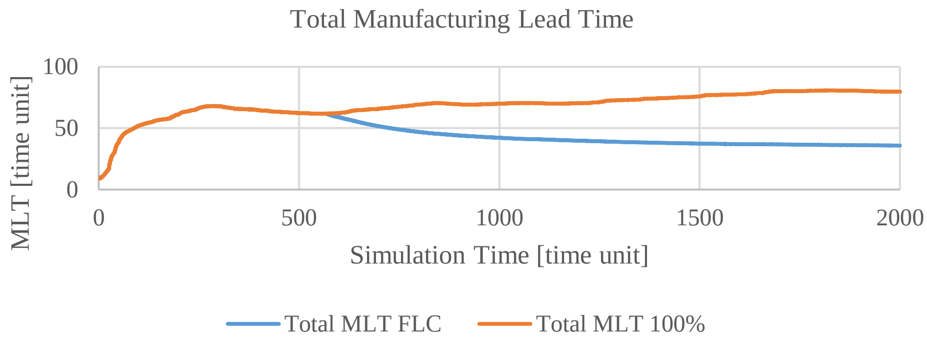

Figure 5.8: Assembly Module Manufacturing Lead Time Comparison

5.5 Disassembly Module

The disassembly module is the splitting of unfinished parts to make multiple new parts. Disassembly manufacturing process involve guillotine processes and unfastening operations. Figure 5.9 shows the disassembly module. M_i splits unfinished parts from upstream buffer $B_{j,i}$ which is then inspected by two inspection systems I_i and then being sent to downstream buffers $B_{i,l}$ and $B_{i,l}$. Varied inspection was compared to 100% inspection and results for the EPS, WIP and MLT are shown in Figures 5.10, 5.11 and 5.12 respectively. The SimEvents® model is shown in Figure B.3 in Appendix B. The following results show a decrease in EPS and MLT, and an increase in WIP.

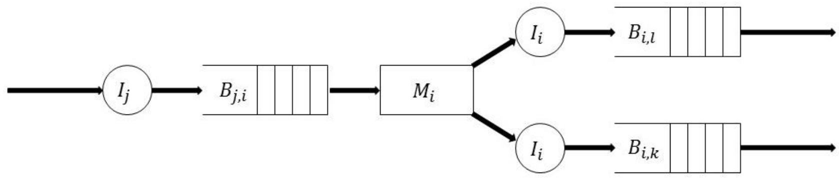

Figure 5.9: Disassembly Module

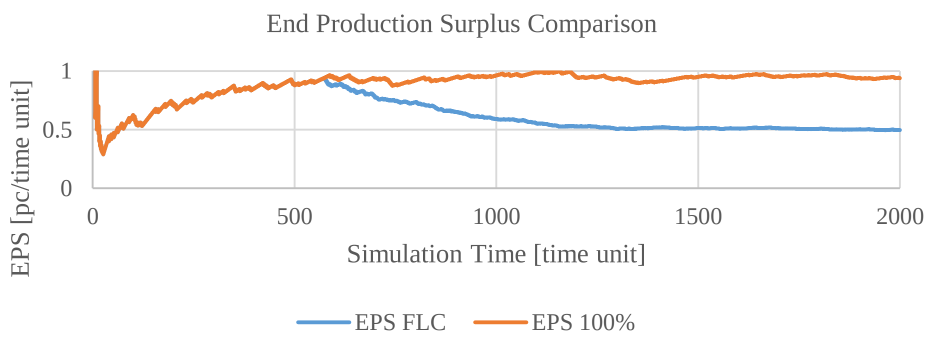

Figure 5.10: Disassembly Module End Production Surplus Comparison

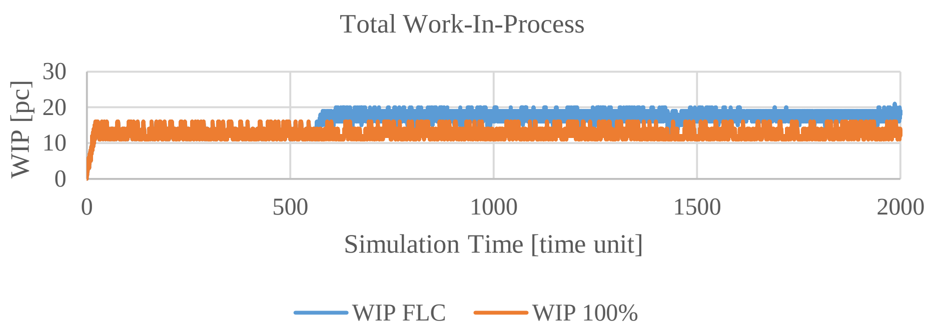

Figure 5.11: Disassembly Module Total Work-In-Process Comparison

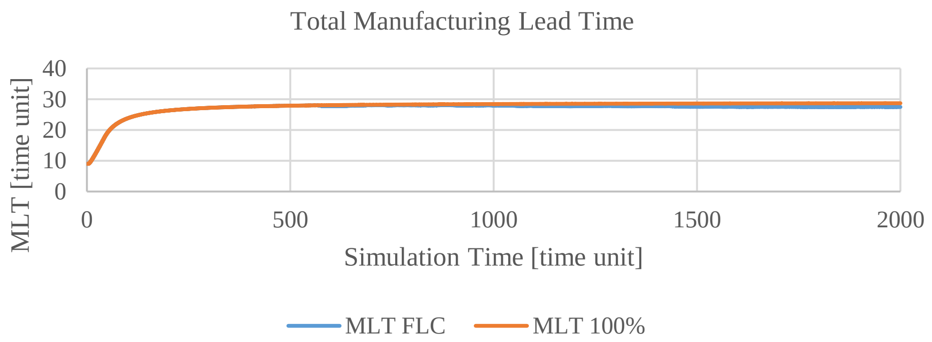

Figure 5.12: Disassembly Module Manufacturing Lead Time Comparison

5.6 Chapter Summary

There were differences between each subsystem, however the following results were common across all three simulations:

- The end production surplus always changed significantly.
- There were minimal changes in WIP.
- MLT decreased in all cases.

The following results show that varied inspection can influence the three subsystems, which provided insights into the performance of varied inspection when being used in manufacturing layouts that use combinations of the subsystems. Note that the results are majorly influenced by the assumptions used in Chapter 5.2. It is uncommon in production to have buffer capacities of the same size and machine failure was not considered.

6 Varied Inspection Testing for Production Case Studies

6.1 Chapter Introduction

The chapter outlined the implementation of varied inspection for different case studies. Four case studies were performed based on the areas that varied inspection could be implemented: DMS, multiple subsystem integration, MC manufacturing and multiple-part-type production. Each case study was explained in detail with references to the DES and assumptions used.

6.2 Dedicated Manufacturing System Case Study: Transfer Line

The first case study outlines the use of varied inspection in a multiple stage transfer line. The manufacturing process of a slider bearing was assumed and simulation assumptions were modelled for DES. Various IM ratios were tested and machine utilisation, MLT, WIP and EPS was measured.

6.2.1 Case Study: Slider Bearing

The slider bearing manufacturing is an example of a single-part type, multiple stage transfer line. The slider bearing is a common mechanical component used for smooth linear movement on shafts. The slider bearing was used in an automated flexible fixture system shown in Figure 6.1 [86].

Figure 6.1: Slider Bearing used for a Flexible Fixture System [86]

6.2.2 Manufacturing Process for Slider Bearing

The production of the slider bearing was assumed to follow the machining process shown in Figure 6.2. A solid block of aluminium is shaped using a Computer Numerical Control (CNC) mill and then chamfered. The four holes for the locating screws are drilled and threaded. Finally, the large hole for the plastic bearing is drilled through.

The manufacturing process that was modelled for DES is shown in Figure 6.3. Five inspection stations were used to determine the quality of the machining processes, however the chamfering process was not inspected as it is not a PKQC relating to the functioning of the product. As such, five HDF controllers were tuned by one GSF controller based on the manufacturing outputs.

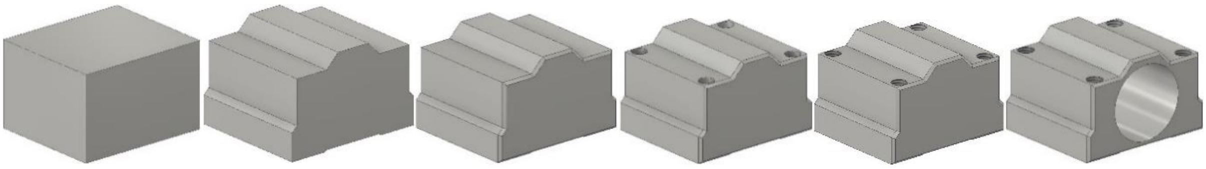

Figure 6.2: Machining Process of the Slider Bearing shown in [86]

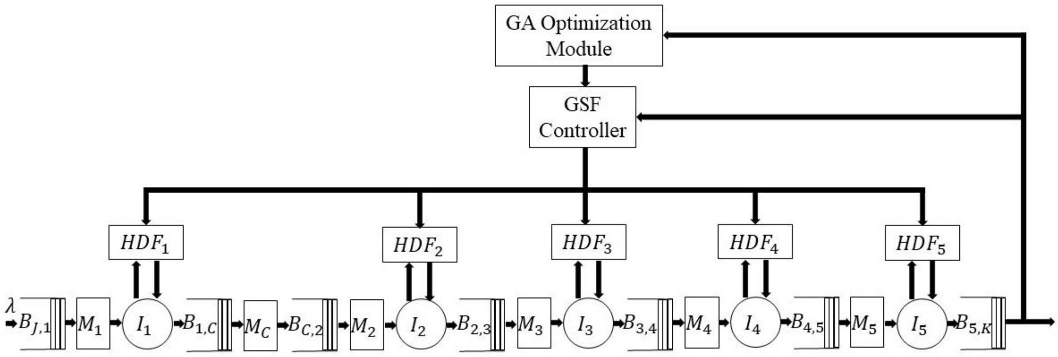

Figure 6.3: Manufacturing Process for the Slider Bearing in DES

6.2.3 Simulation Assumptions for Slider Bearing and Results

The simulations was used to test the effectiveness of varied inspection against different IM ratios. The slider bearing was tested against different IM ratios: 0.5, 1 and 2. The first IM ratio would simulate a situation when the inspection time is less than the machining time as is the case for most DMSs. When IM is greater than 1, inspection time dominates production. The SimEvents® model is shown in Figure B.4 (Appendix B). The following assumptions were used for DES:

- Arrival rate: exponential distribution with a mean of 2 time units.
- Buffer capacities: $B_{J,1} = B_{1,C} = B_{C,2} = B_{2,3} = B_{3,4} = B_{4,5} = B_{5,K} = 10$ units.
- Machine production surplus: Gaussian random numbers with a mean of 0 and variance of 0.5.
- Machining time: 1 time unit
- Inspection time: 0.5 time units, 1 time unit, 2 time units.
- Part quality: based on Poisson random numbers.
- Machine state: Random failure
- Mean WIP: 5 pc.
- Mean EPS: 0.2 pc/time unit
- Simulation time: 1000 time units

Three simulations (IM = 0.5, 1, 2) were performed for 100% inspection and three simulations were performed for varied inspection. The first simulations were for IM = 0.5. Machine utilisation, MLT, WIP and EPS was measured for 100% inspection. Machine utilisation, MLT, WIP and F was measured for varied inspection. The results of each simulation was compared.

The first simulation was based on IM = 0.5. Figure 6.4 shows the machine utilisation for each machine with 100% inspection and varied inspection. Figure 6.5 shows the total MLT, Figure 6.6 shows the total WIP, Figure 6.7 shows the EPS and Figure 6.8 shows the fitness value F.

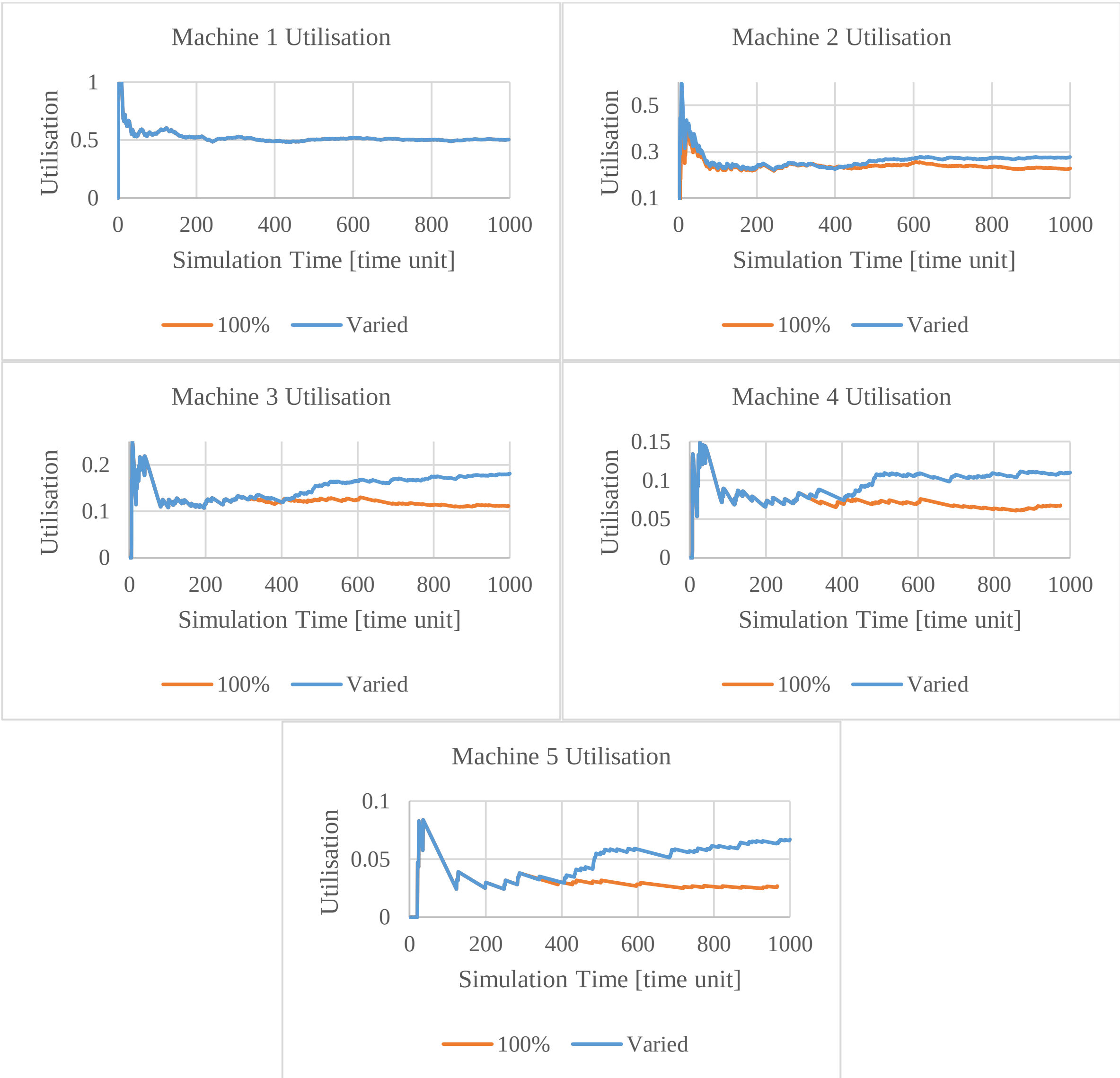

Figure 6.4: Slider Bearing Machine Utilisation (IM=0.5)

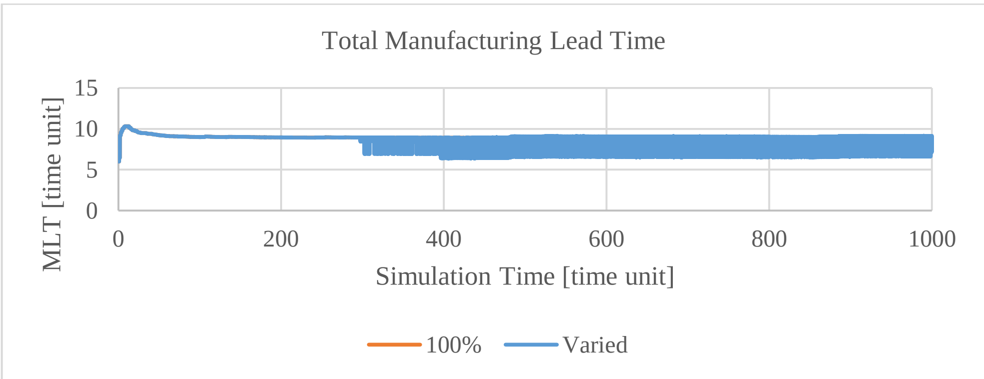

Figure 6.5: Slider Bearing Total MLT (IM=0.5)

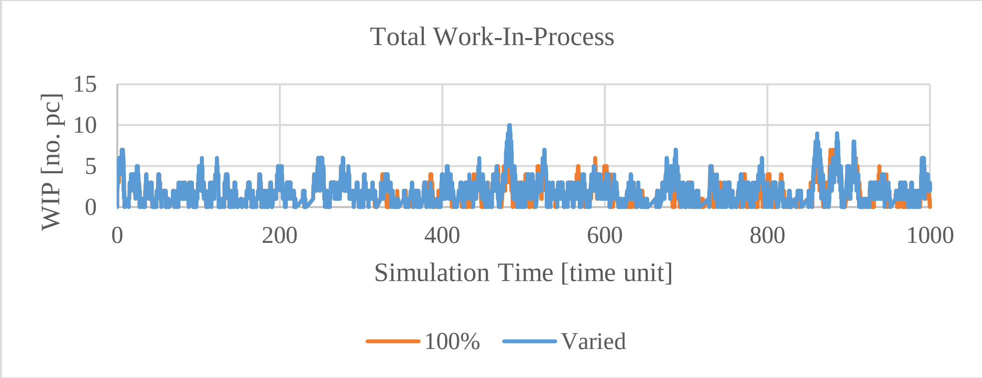

Figure 6.6: Slider Bearing Total WIP (IM=0.5)

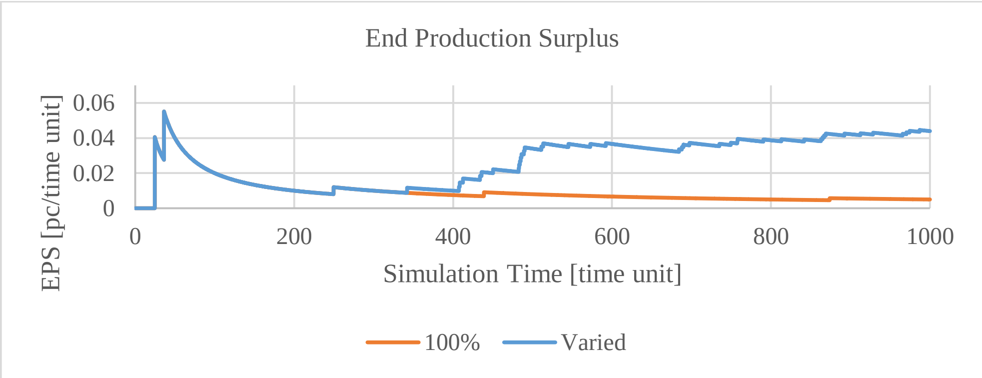

Figure 6.7: Slider Bearing EPS (IM=0.5)

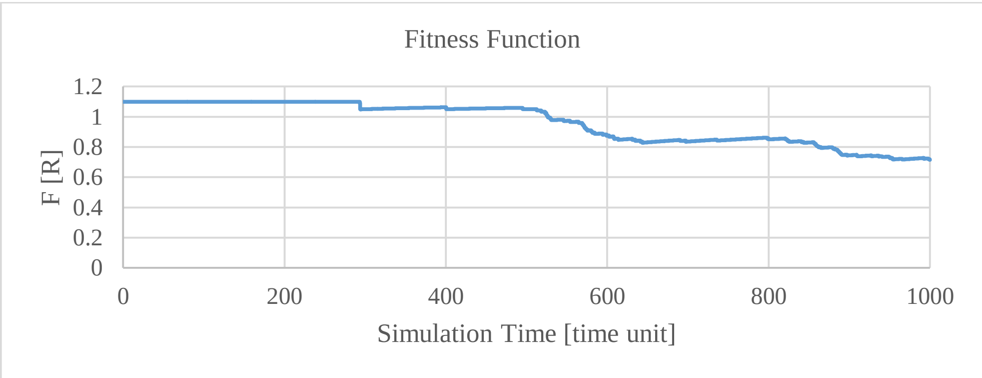

Figure 6.8: Slider Bearing Fitness Function (IM=0.5)

The following results were for IM = 1. Figure 6.9 shows the machine utilisation for each machine. Figure 6.10 shows the total MLT, Figure 6.11 shows the total WIP, Figure 6.12 shows the EPS and Figure 6.13 shows the fitness value F.

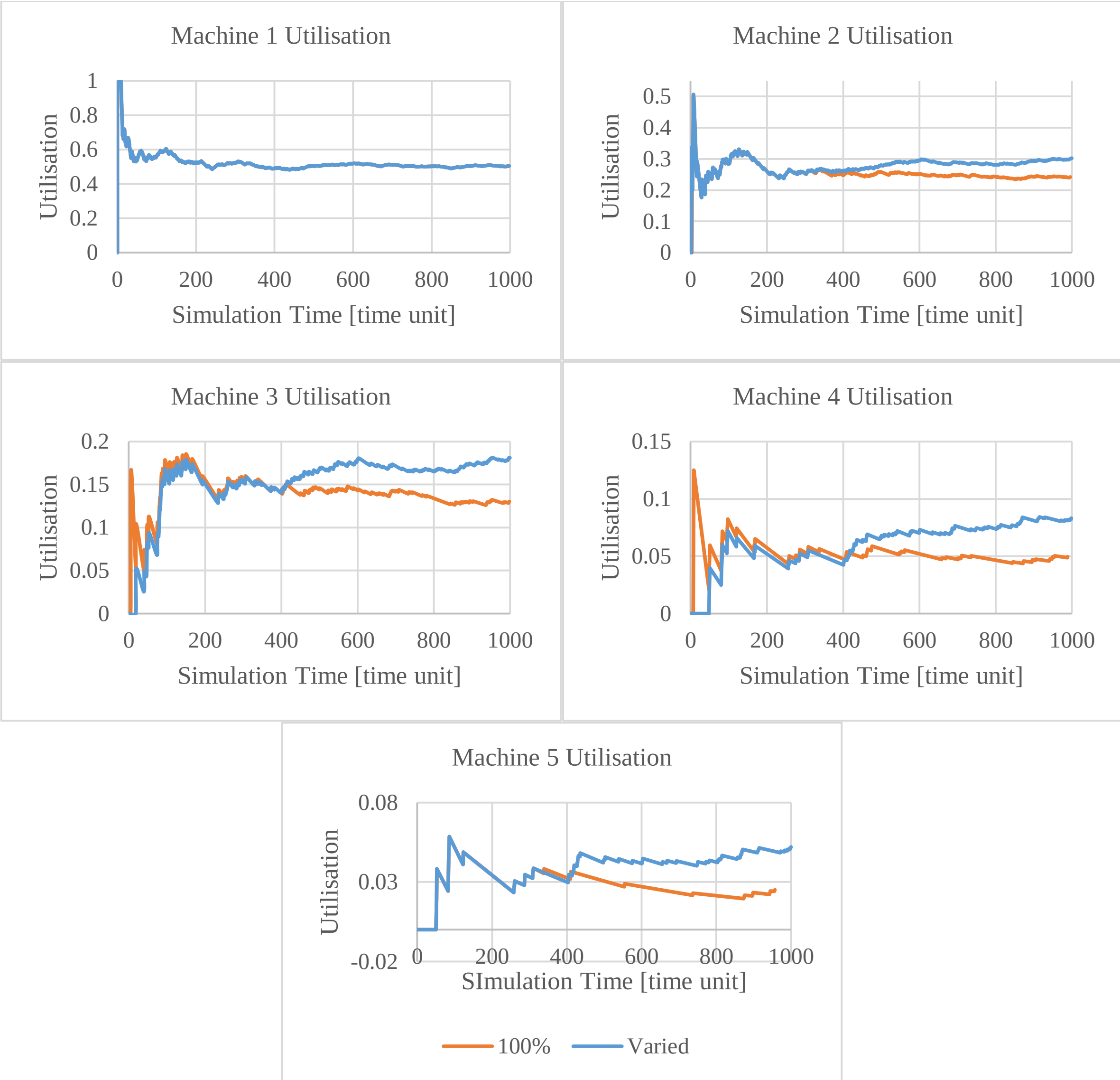

Figure 6.9: Slider Bearing Machine Utilisation (IM=1)

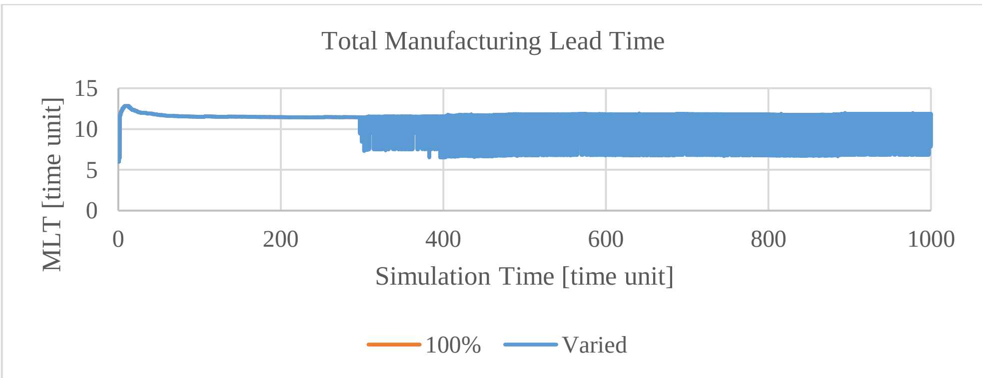

Figure 6.10: Slider Bearing Total MLT (IM=1)

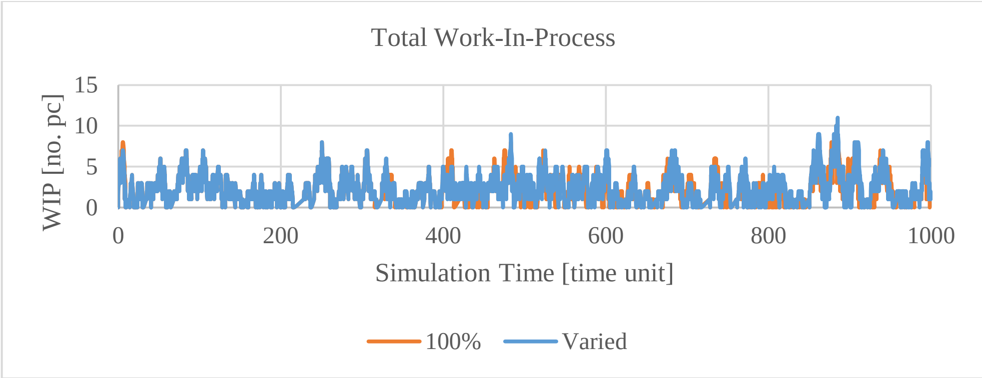

Figure 6.11: Slider Bearing Total WIP (IM=1)

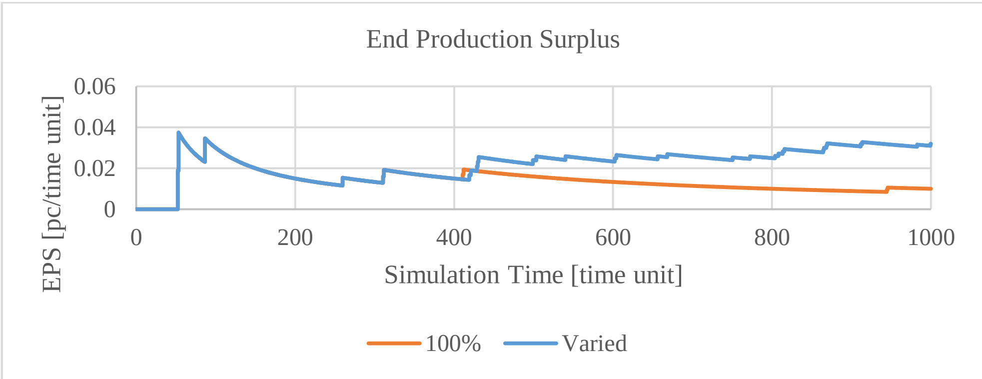

Figure 6.12: Slider Bearing End Production Surplus (IM=1)

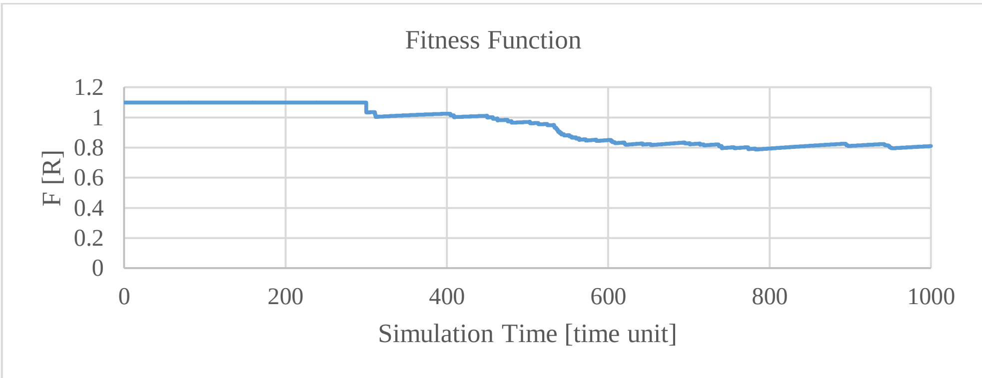

Figure 6.13: Slider Bearing Fitness Function (IM=1)

The following results were for IM = 2. Figure 6.14 shows the machine utilisation for each machine. Figure 6.15 shows the total MLT, Figure 6.16 shows the total WIP, Figure 6.17 shows the EPS and Figure 6.18 shows the fitness value F.

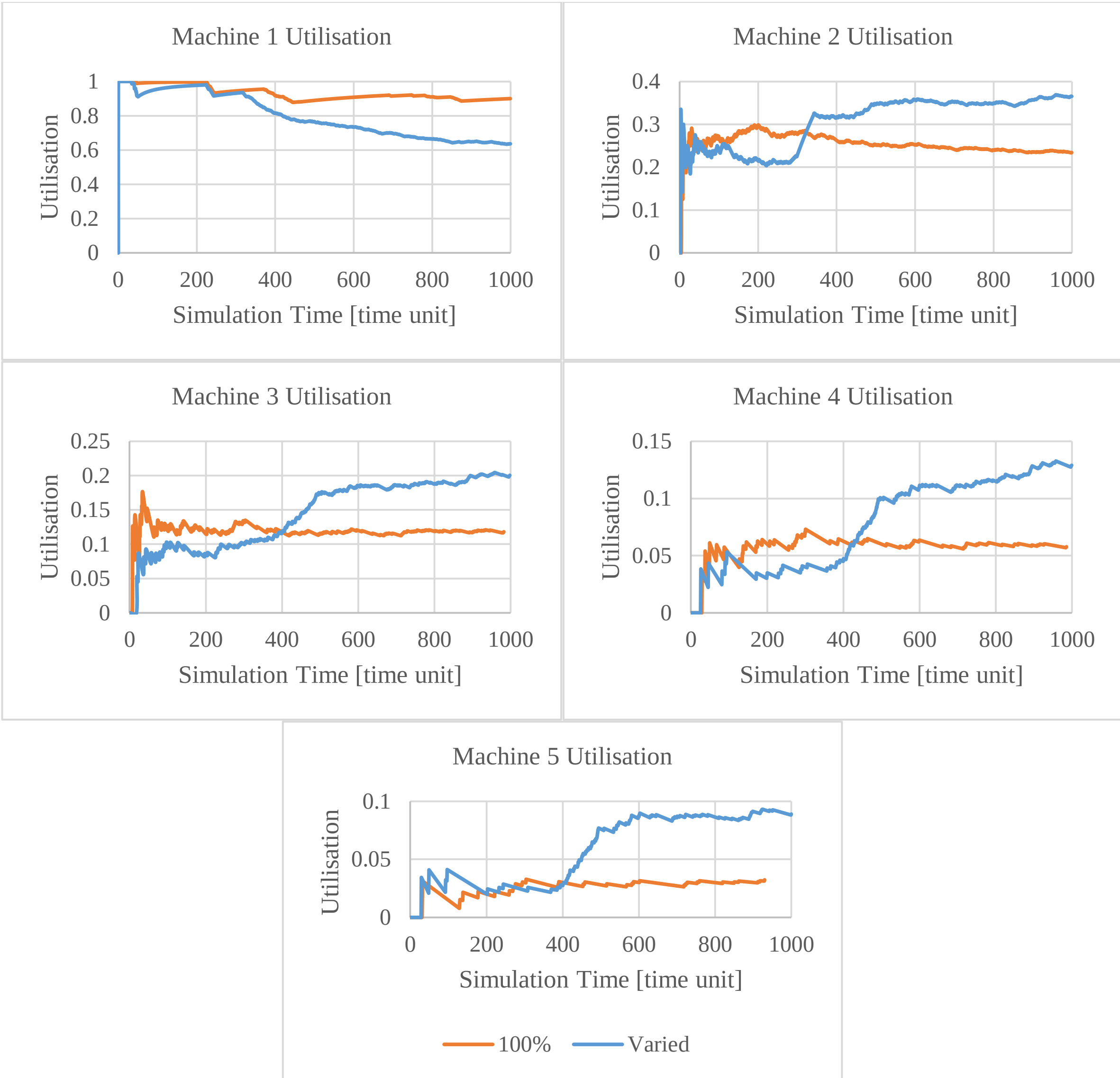

Figure 6.14: Slider Bearing Machine Utilisation (IM=2)

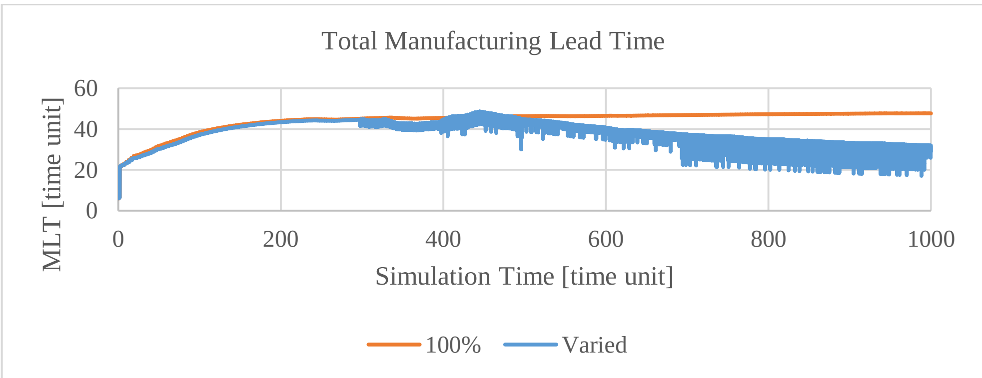

Figure 6.15: Slider Bearing Total MLT (IM=2)

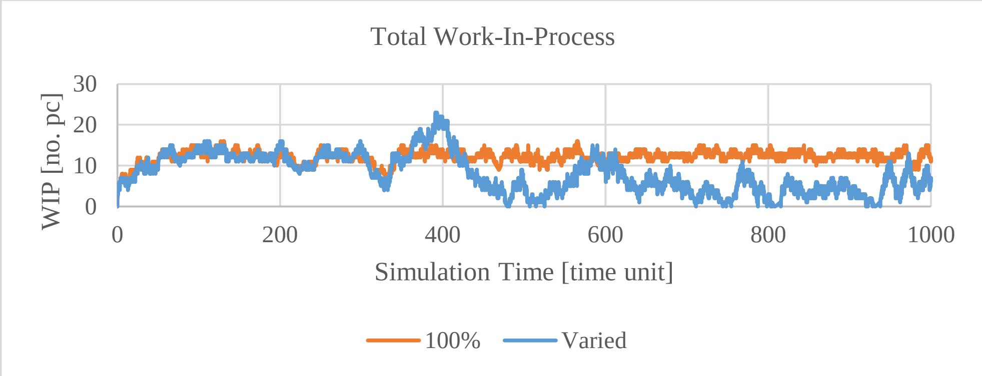

Figure 6.16: Slider Bearing Total WIP (IM=2)

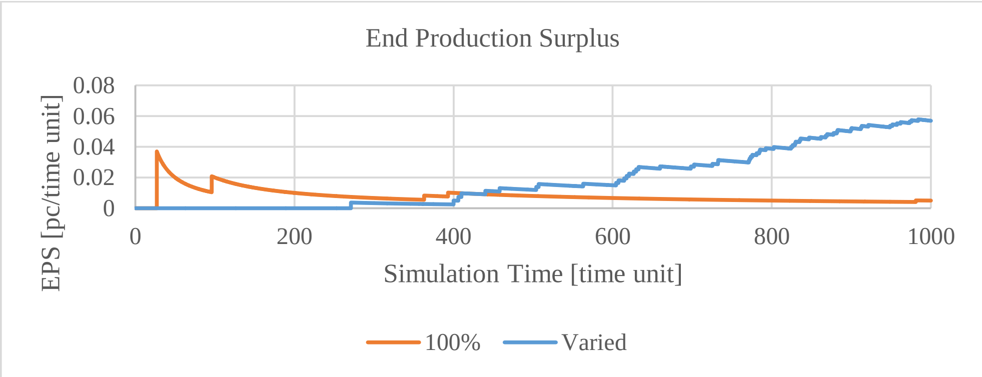

Figure 6.17: Slider Bearing EPS (IM=2)

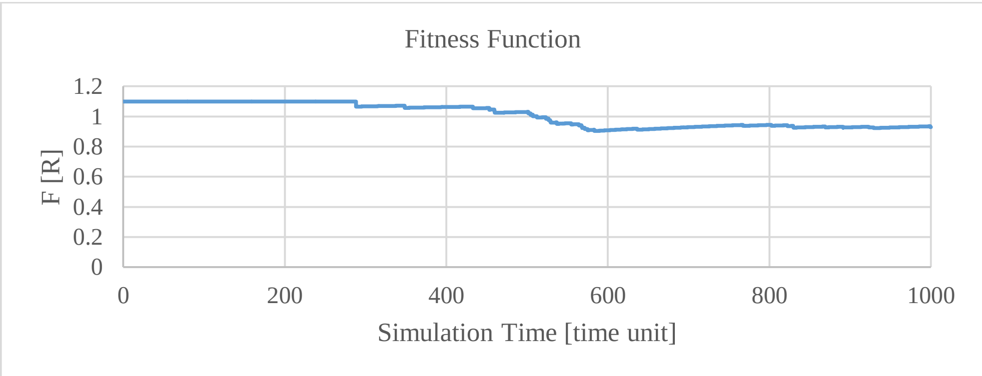

Figure 6.18: Slider Bearing Fitness Function (IM=2)

6.3 Multiple Subsystem Integration Manufacturing Case Study: Tsourveloudis

The case study was based on the test case proposed by Tsourveloudis, Dretoulakis and Ioannidis in [61] and will be known as "Tsourveloudis". The test case incorporates multiple subsystems (transfer line, assembly and disassembly) to produce a single-part-type. Simulations were performed for different IM ratios.

6.3.1 Case Study: Tsourveloudis

The manufacturing plant is hypothetical and used to test the integration of all three subsystems for single-part-type production. Tsourveloudis, Dretoulakis and Ioannidis [61] gives no indication of what manufacturing process the layout may represent, however it does serve as a useful layout for multiple subsystem integration.

6.3.2 Manufacturing Process for Tsourveloudis

The test case by Tsourveloudis, Drekoulatis and Ioannidis is shown in Figure 6.19 [61]. The manufacturing layout used for DES is shown in Figure 6.20. Note that due to the disassembly module, two inspection systems I_2 and I_4 were needed as disassembly doubles the number of parts through it. Therefore, the DES may seem as though an extra machine M_6 was used, however this is the same as M_5 as in Figure 6.19.

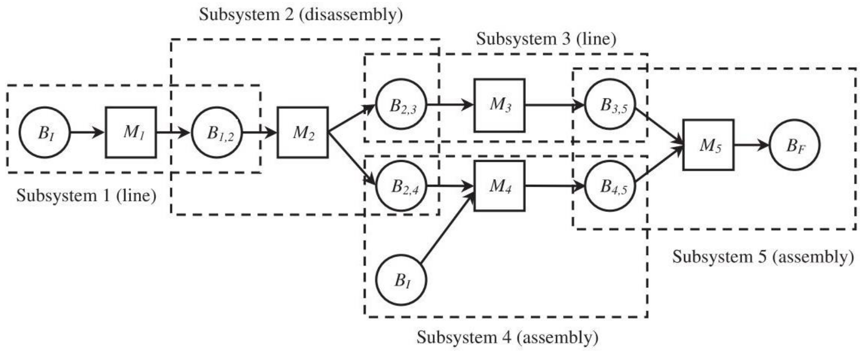

Figure 6.19: Manufacturing Process for Multiple Subsystem Integration [61]

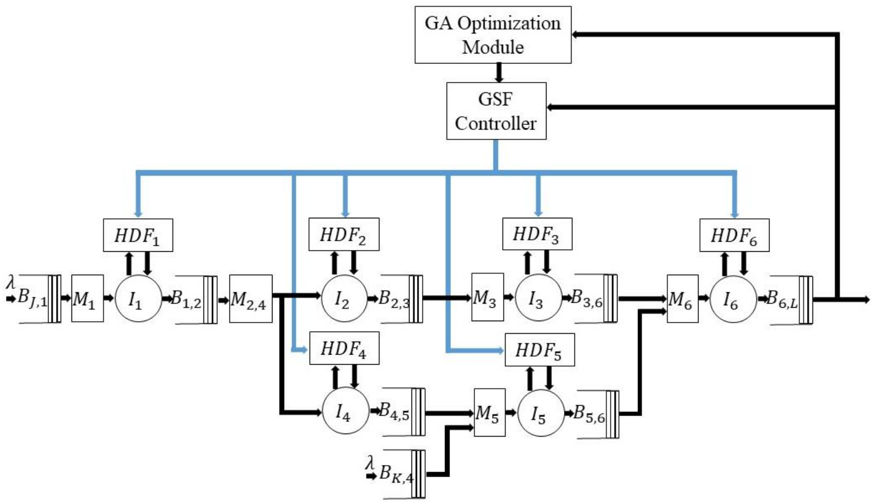

Figure 6.20: Manufacturing Process for the Multiple Subsystem Integration in DES

6.3.3 Simulation Assumptions for Tsourveloudis and Results

The SimEvents® model for Tsourveloudis is shown in Figure B.5 (Appendix B). The following assumptions were used for DES:

- Arrival rate: exponential distribution with a mean of 4 time units.
- Buffer capacities: $B_{J,1} = B_{1,2} = B_{2,3} = B_{3,6} = B_{4,5} = B_{K,4} = B_{5,6} = B_{6,L} = 10$ pc.
- Machine production surplus: random Gaussian numbers with a mean of 0 and variance of 0.5.
- Machining time: 1 time unit
- Inspection time: 0.5 time units, 1 time unit, 2 time units
- Part quality: based on Poisson random numbers.
- Machine state: Random failure
- Simulation time: more than 1500 time units

Three IM ratios (IM = 0.5, 1 and 2) were simulated. For IM = 0.5, Figure 6.21 shows the machine utilisation, Figure 6.22 shows the total MLT, Figure 6.23 shows the total WIP, Figure 6.24 shows the EPS and Figure 6.25 shows the fitness value F.

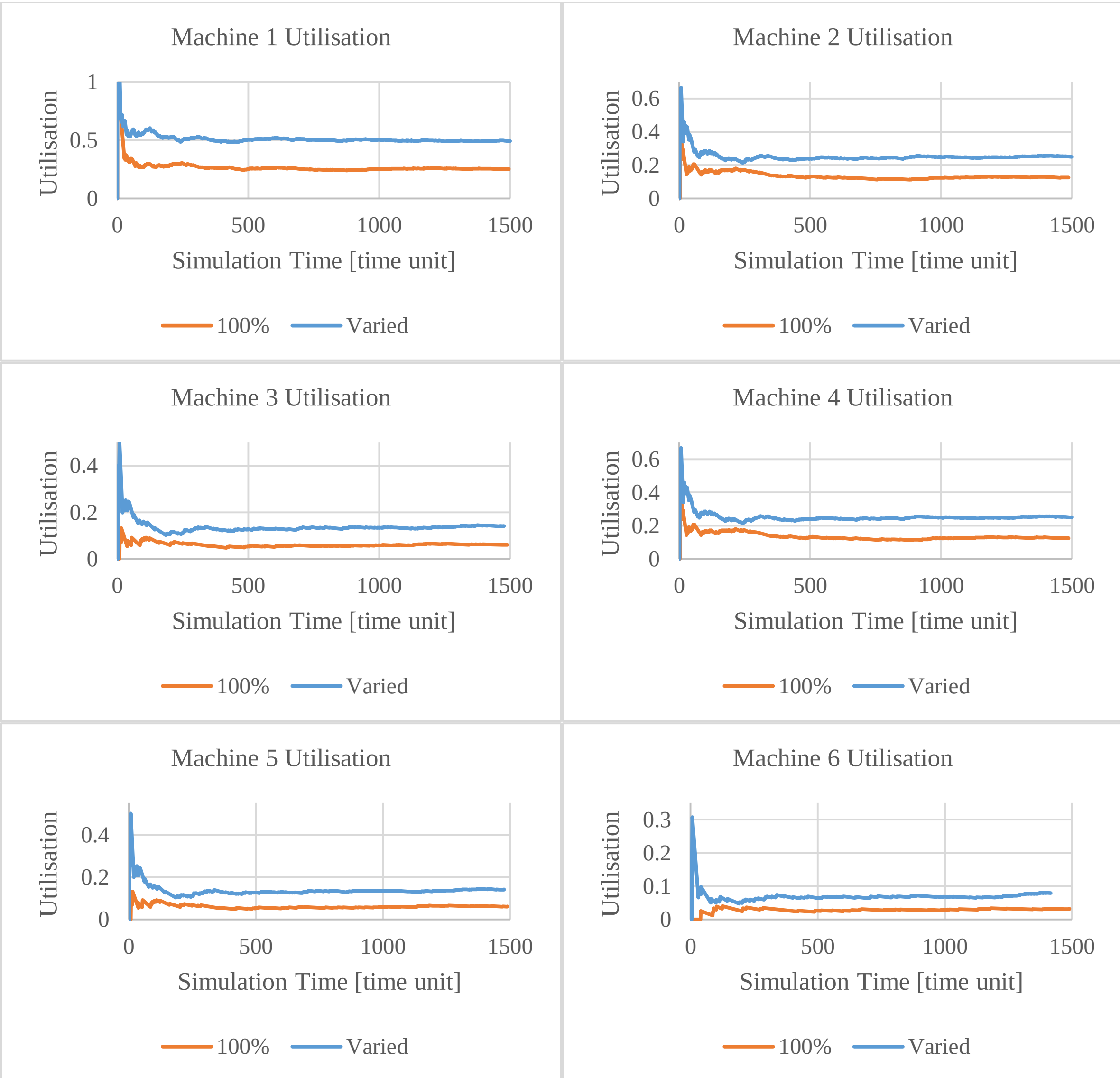

Figure 6.21: Tsourveloudis Machine Utilisation (IM=0.5)

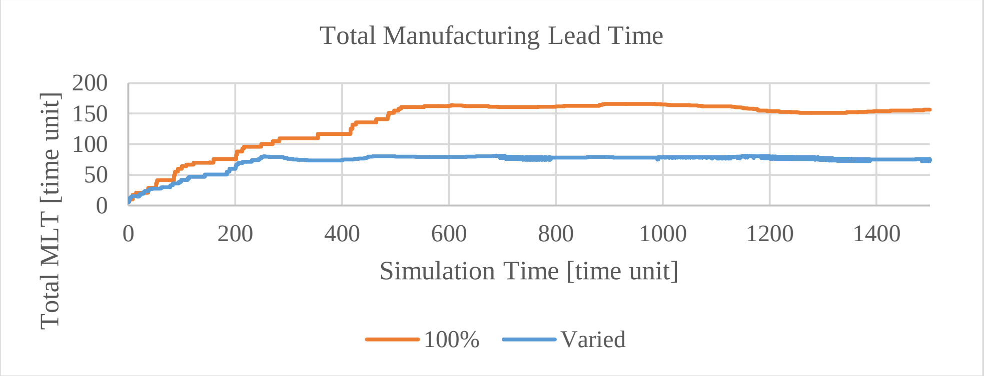

Figure 6.22: Tsourveloudis Total MLT (IM=0.5)

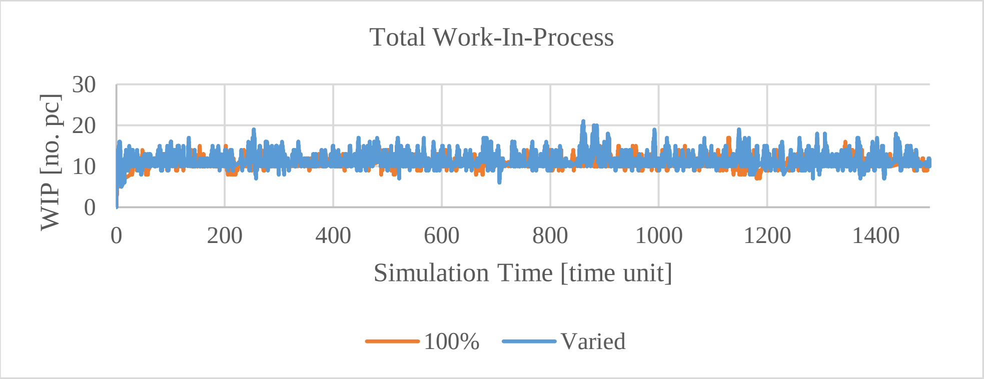

Figure 6.23: Tsourveloudis Total WIP (IM=0.5)

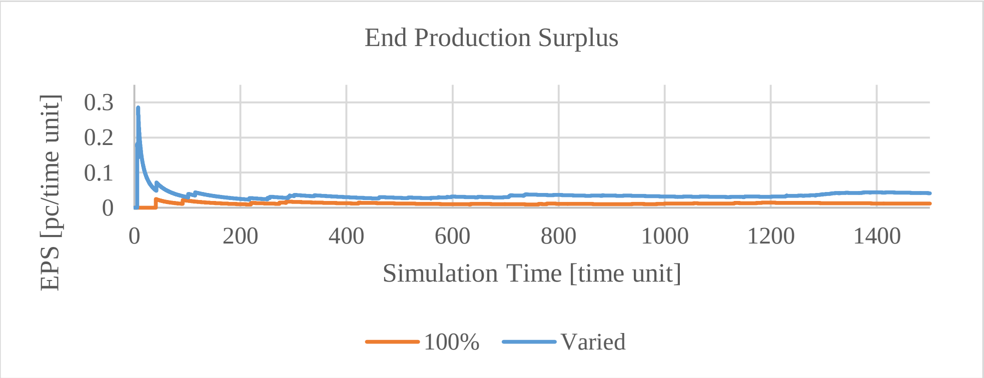

Figure 6.24: Tsourveloudis EPS (IM=0.5)

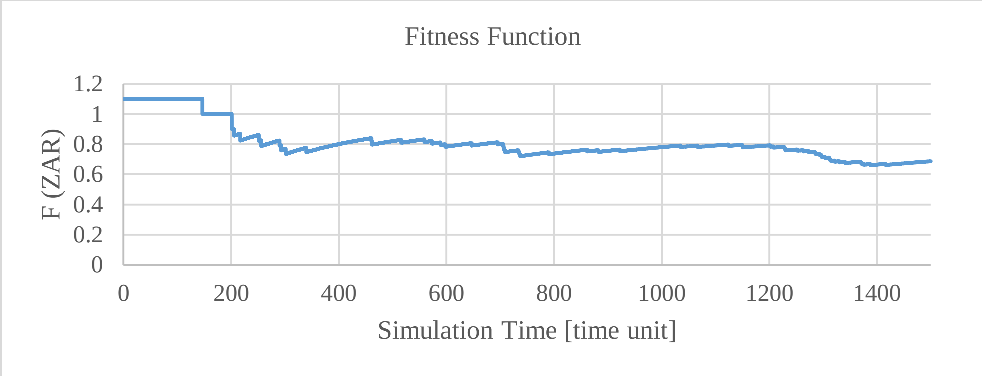

Figure 6.25: Tsourveloudis Fitness Value (IM=0.5)

The following results are for IM = 1. Figure 6.26 shows the machine utilisation for each machine. Figure 6.27 shows the total MLT, Figure 6.28 shows the total WIP, Figure 6.29 shows the EPS and Figure 6.30 shows the fitness value F.

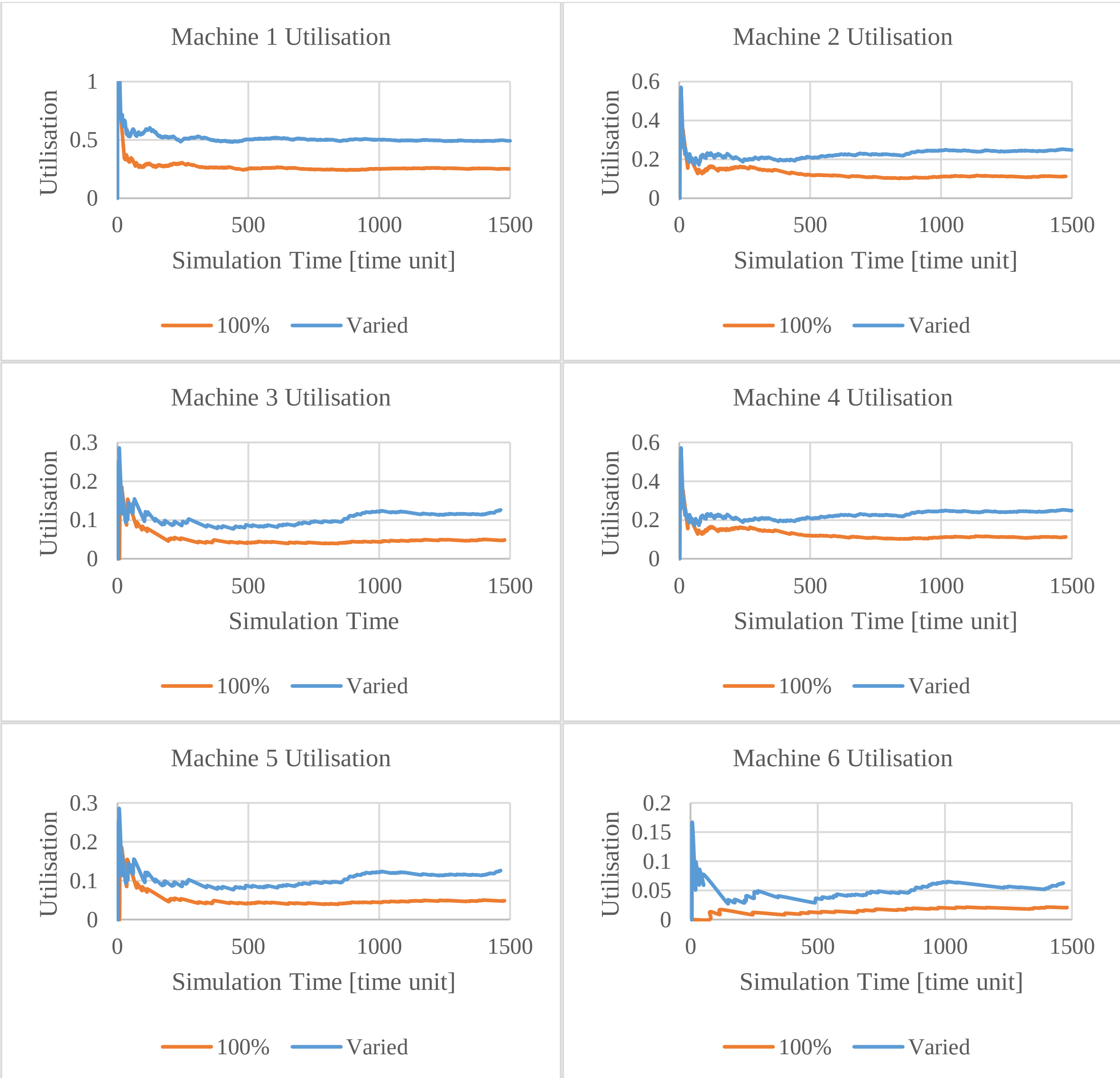

Figure 6.26: Tsourveloudis Machine Utilisation (IM=1)

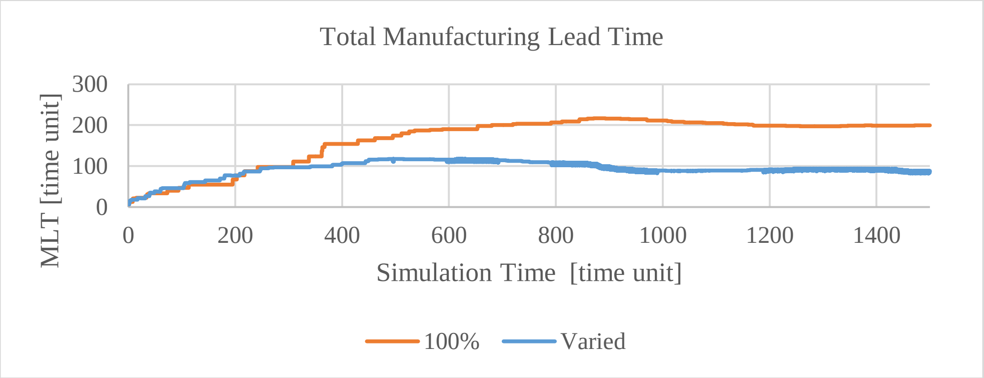

Figure 6.27: Tsourveloudis Total MLT (IM=1)

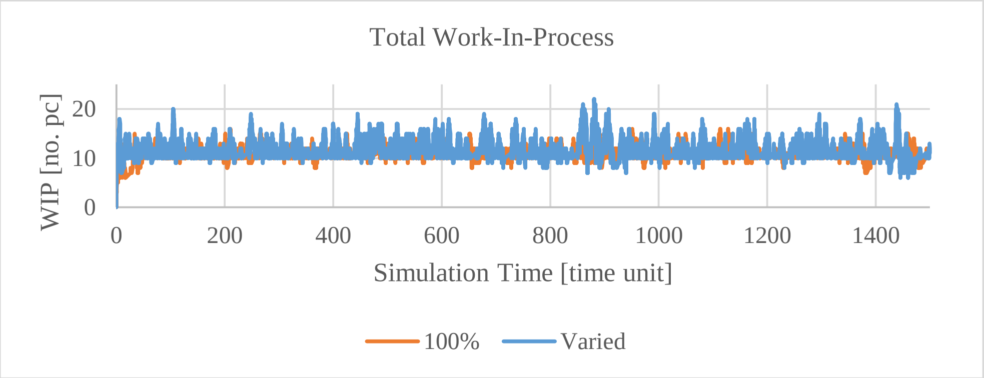

Figure 6.28: Tsourveloudis Total WIP (IM=1)

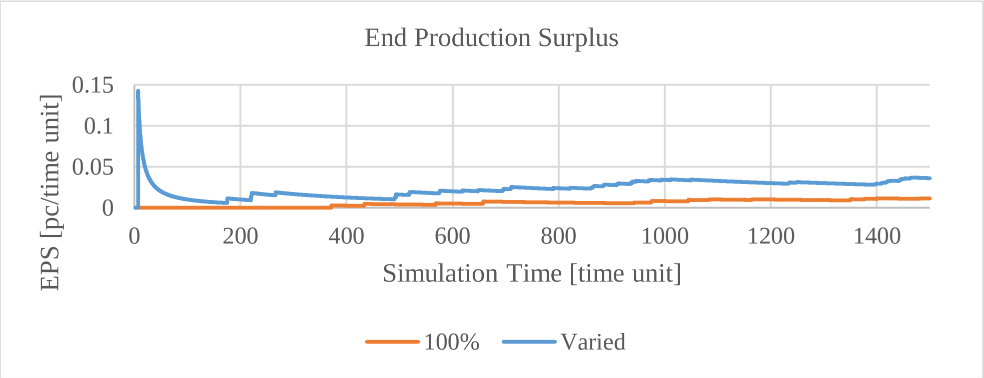

Figure 6.29: Tsourveloudis EPS (IM=1)

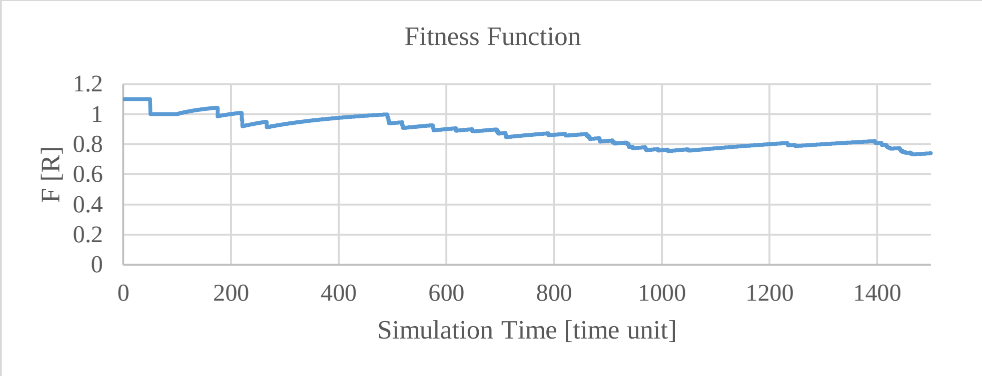

Figure 6.30: Tsourveloudis Fitness Value F (IM=1)

The following results were for IM = 2. Figure 6.31 shows the machine utilisation for each machine. Figure 6.32 shows the total MLT, Figure 6.33 shows the total WIP, Figure 6.34 shows the EPS and Figure 6.35 shows the fitness value F.

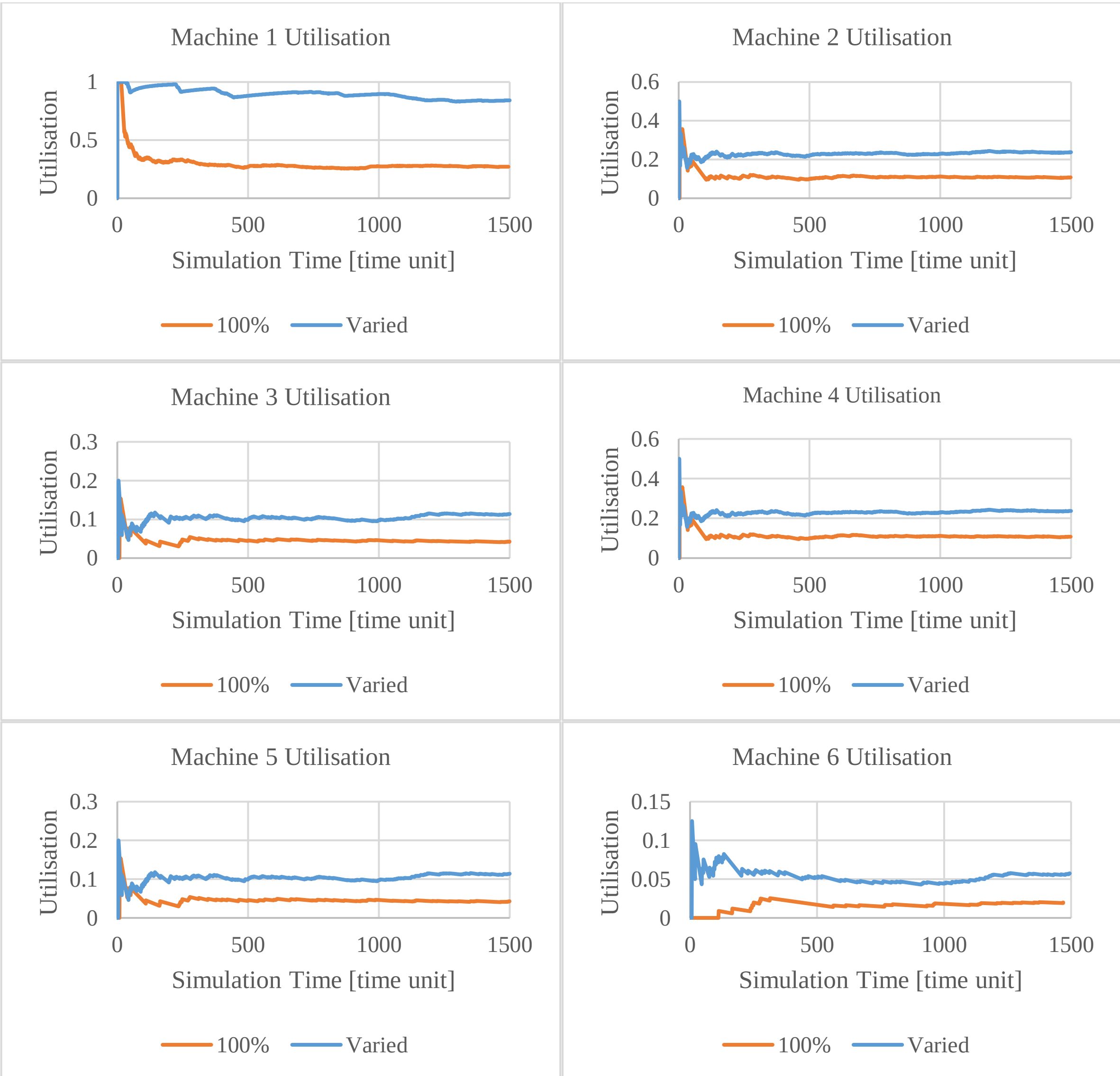

Figure 6.31: Tsourveloudis Machine Utilisation (IM=2)

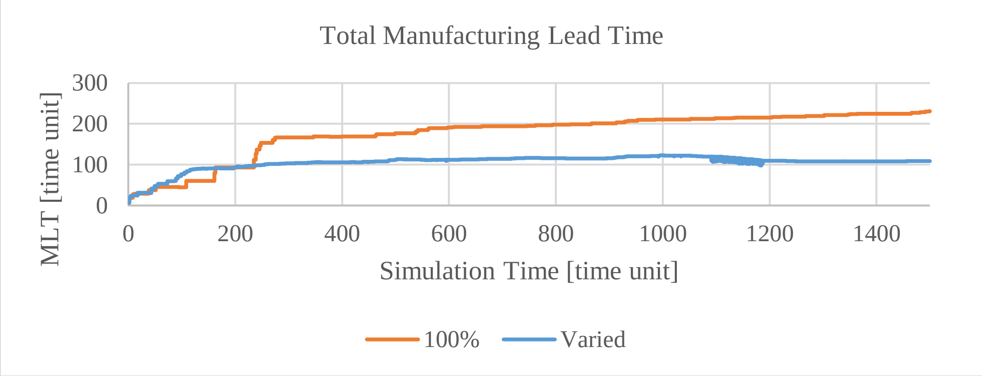

Figure 6.32: Tsourveloudis Total MLT (IM=2)

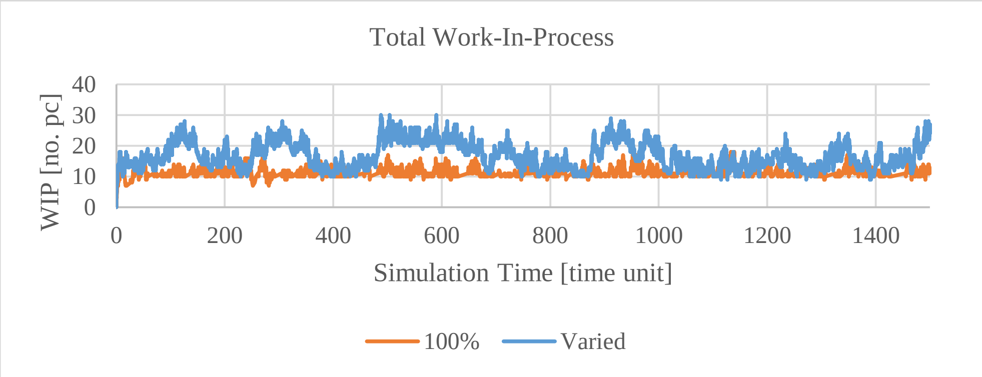

Figure 6.33: Tsourveloudis Total WIP (IM=2)

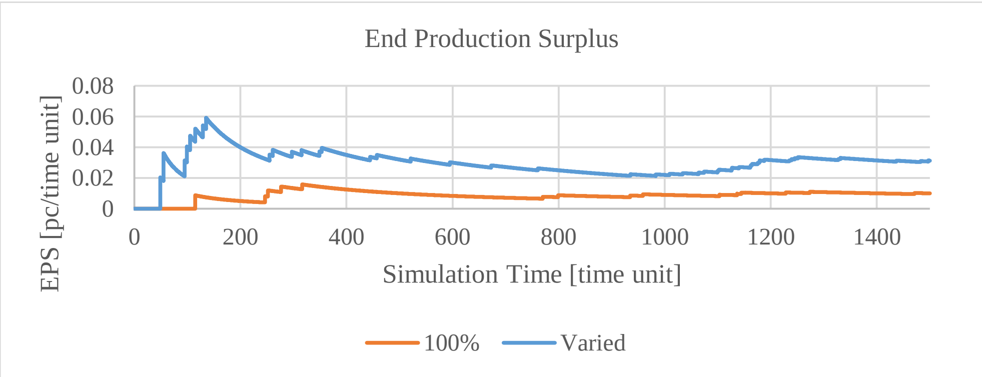

Figure 6.34: Tsourveloudis EPS (IM=2)

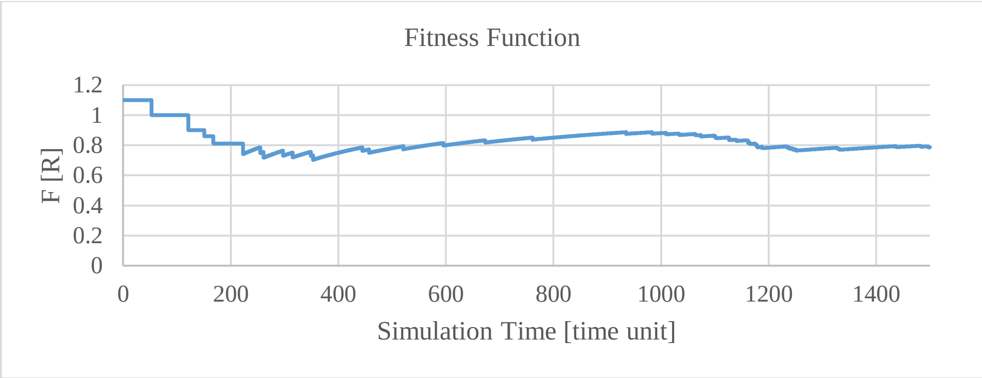

Figure 6.35: Tsourveloudis Fitness Value (IM=2)

6.4 Mass Customization Manufacturing Case Study: Fly Reel

This case study outlines the performance of varied inspection in a mass customization application. This case study is based on the simulation layout presented by Walker and Bright in [87]. Varied inspection was compared to 100% inspection for different IM ratios.

6.4.1 Case Study: Fly Reel

Walker and Bright [87] explain that fly reel construction is dependent on customer preference, experience and application, and that many companies in the United States of America such as Abel Reels [88] and Nautilus Reels [89] provide custom reels to their customers. The production of the fly reels is an example of MC manufacturing as customers decide the variance in product features that they desire.

6.4.2 Manufacturing Process for Fly Reel

There are three types of fly reels that can be manufactured, as shown in Figure 6.36: Drag A, Drag B and Drag C [87]. Drag A is an easy to maintain click and pawl system. Drag B is a water tight reel where the drag system is bounded in the frame. Drag C has a draw bar and friction disc which makes it resistant to vibrations [87].

The manufacturing process that was modelled for the fly reel DES is shown in Figure 6.37. M_1 represent the circular saw cutter for the frame and spool blanket. M_3 represent the circular saw cutters for the spindle and frame lid blanket. M_2 represent the mill-turn CNC for the frame and spool. M_4 represent the mill-turn CNC machine for the spindle and frame lid. M_5 is the laser cutter for the drag discs. M_6 is the spool sub-assembly, M_7 is the drag sub-assembly and M_8 is the final assembly.

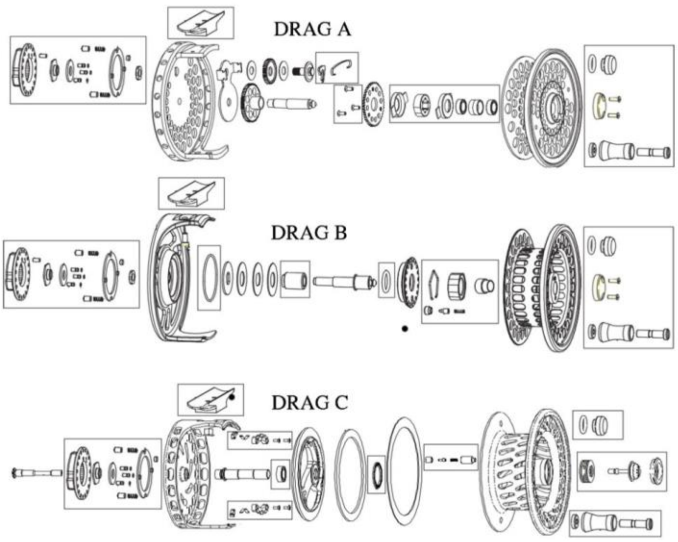

Figure 6.36: Fly Reel Production [87]

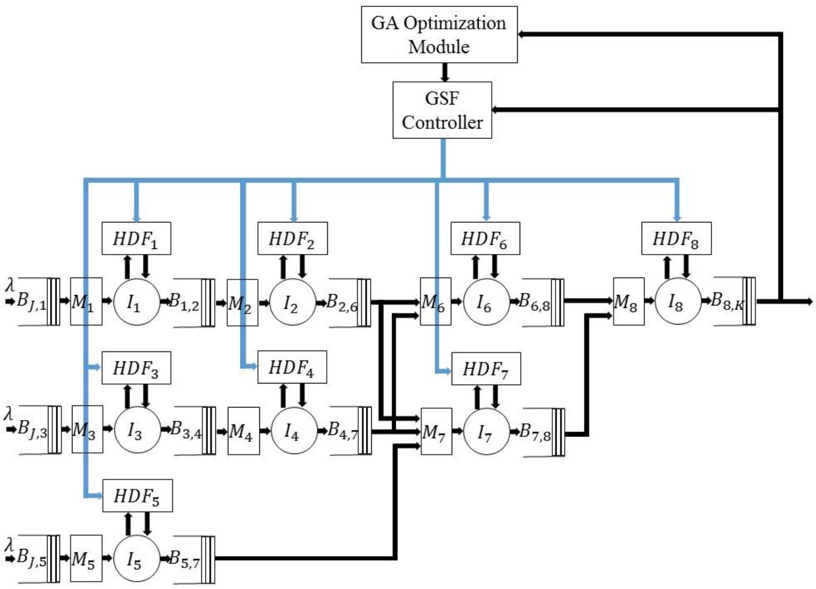

Figure 6.37: Manufacturing Process for the Fly Reel in DES

6.4.3 Simulation Assumptions for Fly Reel and Results

The SimEvents® model for the fly reel is shown in Figure B.6 (Appendix B). The following assumptions were used for DES:

- Arrival rate: exponential distribution with a mean of 2 time units.
- Buffer capacities: $B_{J,1} = B_{1,2} = B_{2,6} = B_{6,8} = B_{8,K} = B_{J,3} = B_{3,4} = B_{4,7} = B_{J,5}, B_{5,7}$= 10 pc.
- Machine production surplus: random Gaussian numbers with a mean of 0 and variance of 0.5.
- Machining time: 1 time unit
- Inspection time: 0.5 time units, 1 time unit, 2 time units
- Part quality: based on Poisson random numbers.

- Machine state: Random failure
- Simulation time: 2000 time units

The following results are for IM = 0.5. Figure 6.38 shows the machine utilisation for each machine. Figure 6.39 shows the Total MLT, Figure 6.40 shows the total WIP and Figure 6.41 shows the EPS. Figure 6.42 shows the fitness function F in Rands.

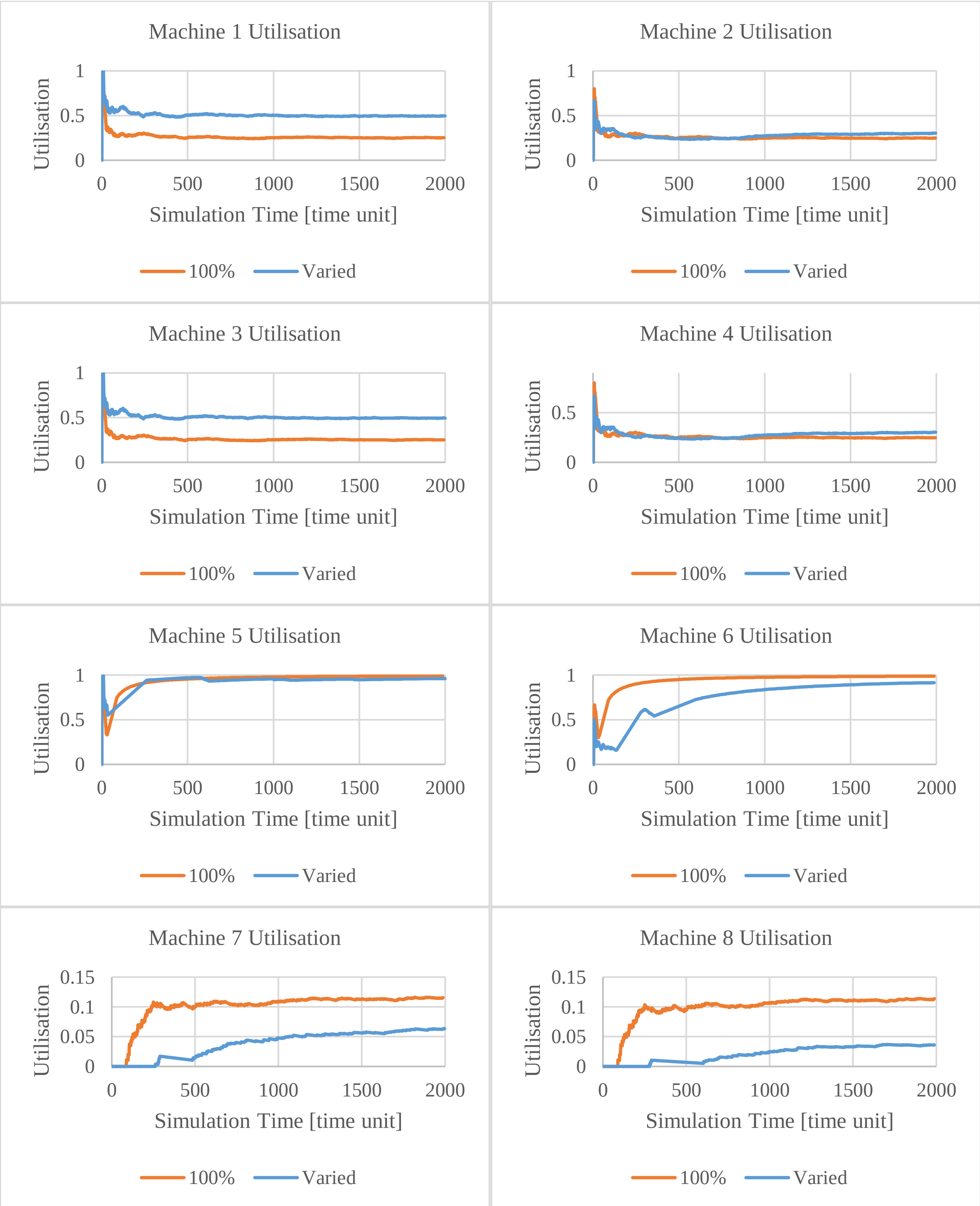

Figure 6.38: Fly Reel Machine Utilisation (IM=0.5)

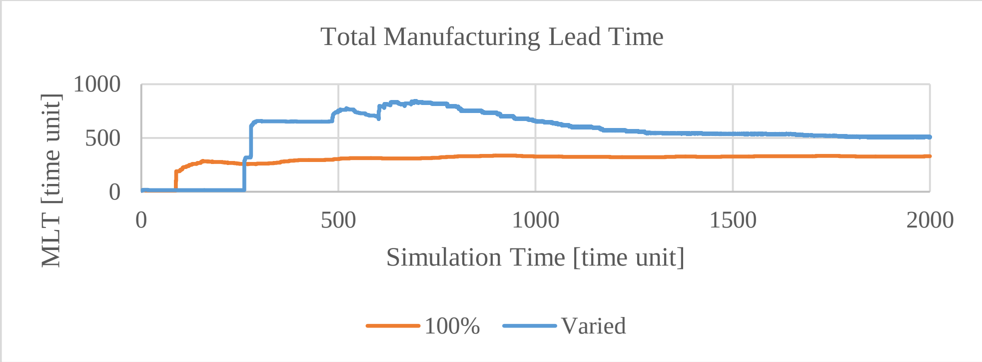

Figure 6.39: Fly Reel Total MLT (IM=0.5)

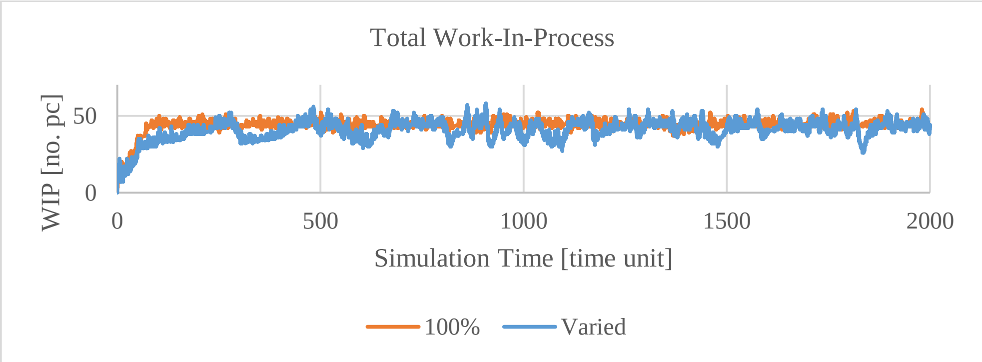

Figure 6.40: Fly Reel Total WIP (IM=0.5)

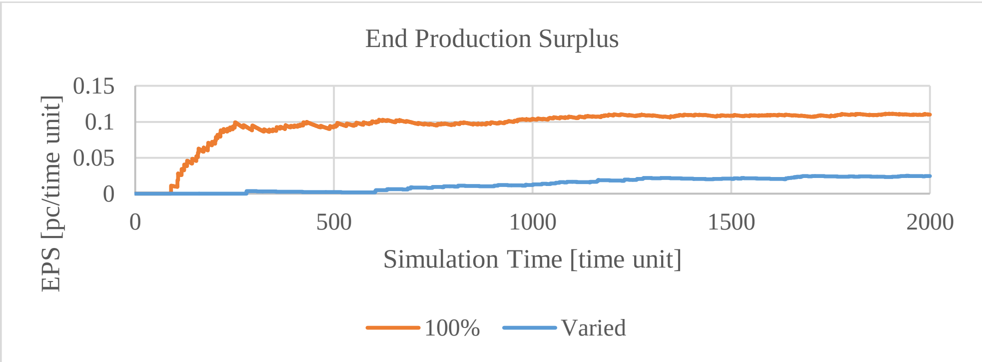

Figure 6.41: Fly Reel EPS (IM=0.5)

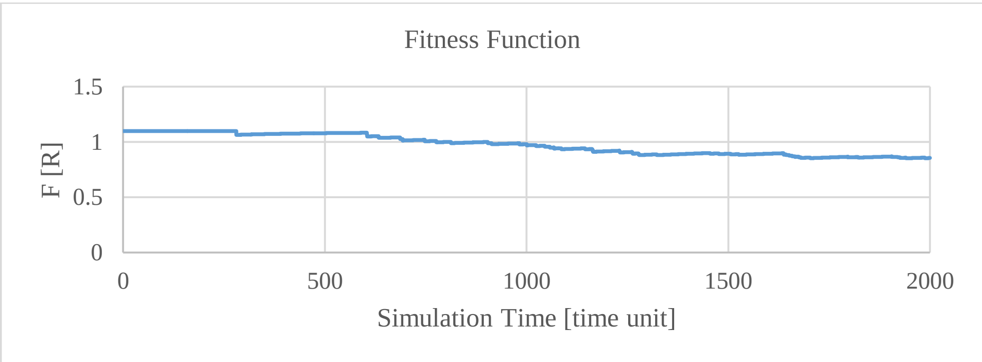

Figure 6.42: Fly Reel Fitness Value (IM=0.5)

The following results were for IM = 1. Figure 6.43 shows the machine utilisation for each machine. Figure 6.44 shows the Total MLT, Figure 6.45 shows the total WIP and Figure 6.46 shows the EPS. Figure 6.47 shows the fitness value for IM=1.

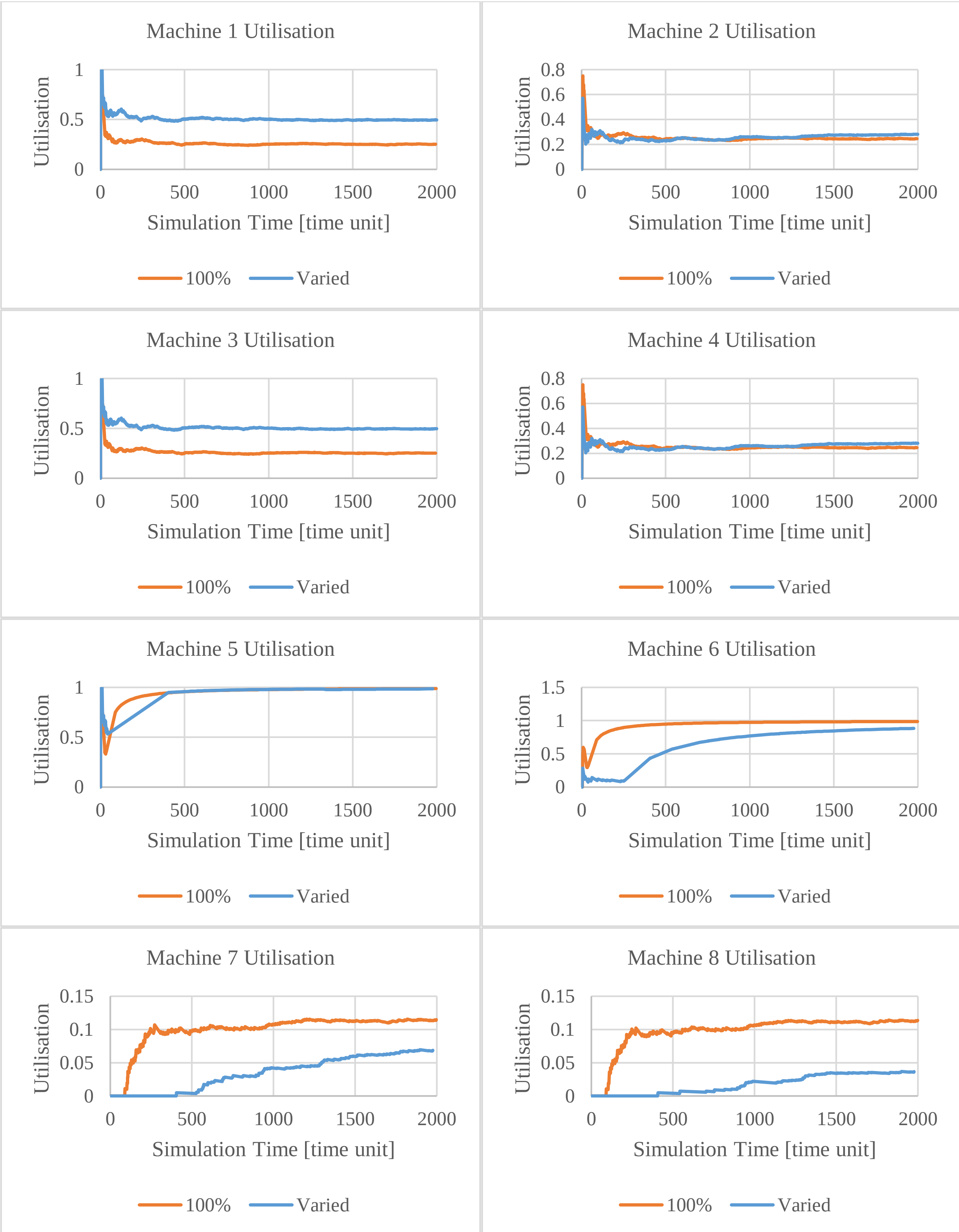

Figure 6.43: Fly Reel Machine Utilisation (IM=1)

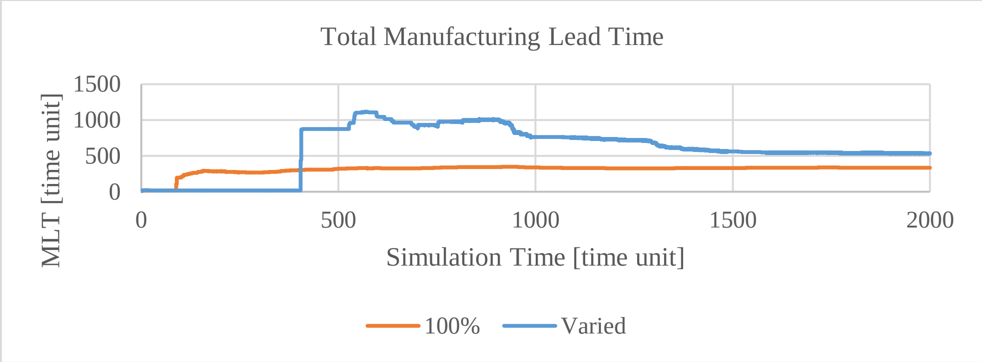

Figure 6.44: Fly Reel Total MLT (IM=1)

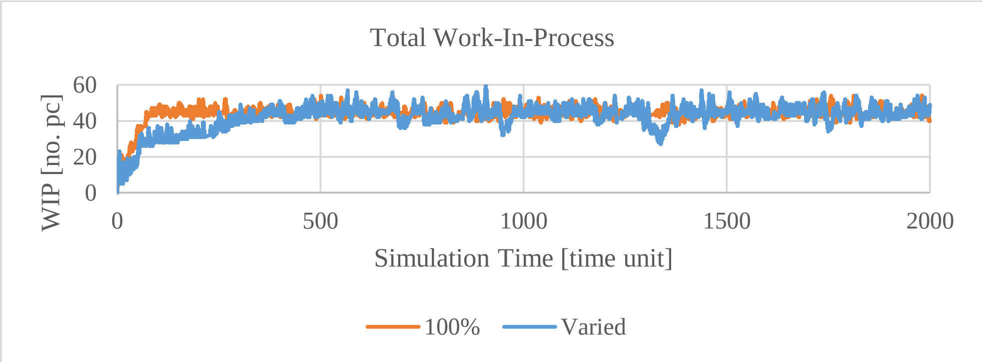

Figure 6.45: Fly Reel Total WIP (IM=1)

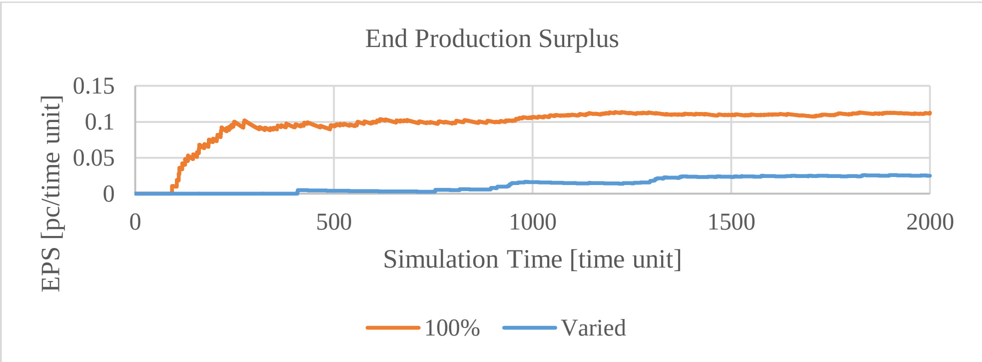

Figure 6.46: Fly Reel EPS (IM=1)

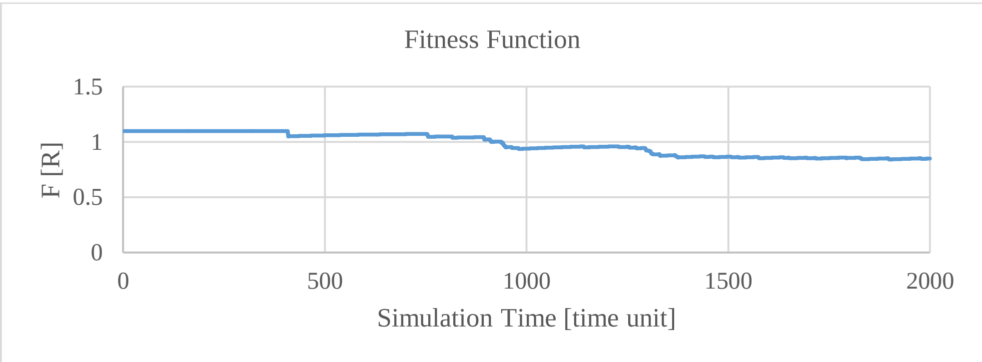

Figure 6.47: Fly Reel Fitness Value (IM=1)

The following results were for IM = 2. Figure 6.48 shows the machine utilisation for each machine. Figure 6.49 shows the total MLT, Figure 6.50 shows the total WIP and Figure 6.51 shows the EPS. Figure 6.52 shows the fitness value for IM = 2.

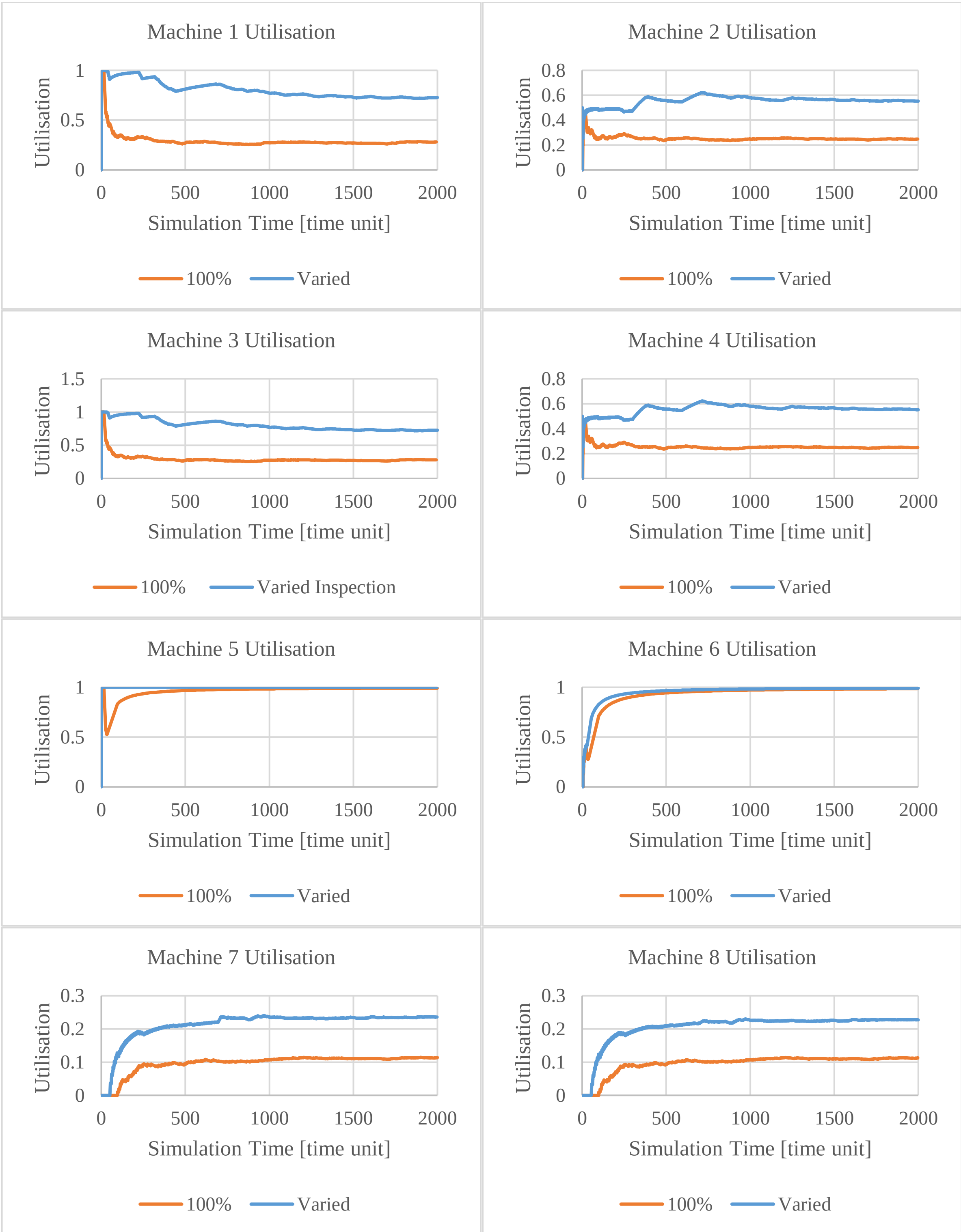

Figure 6.48: Fly Reel Machine Utilisation (IM=2)

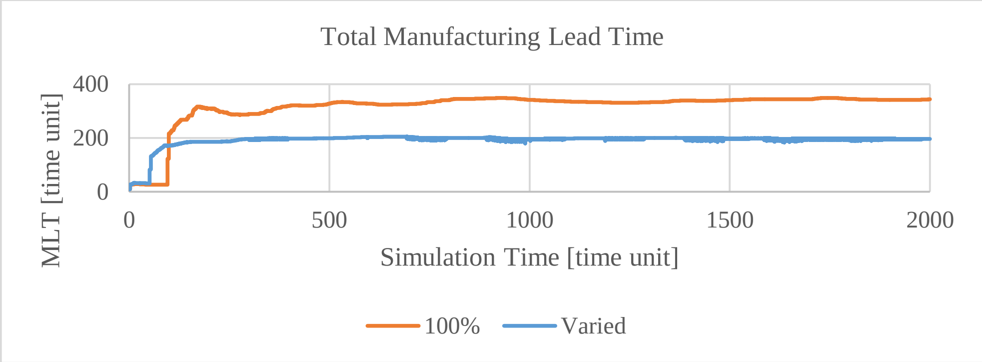

Figure 6.49: Fly Reel Total MLT (IM=2)

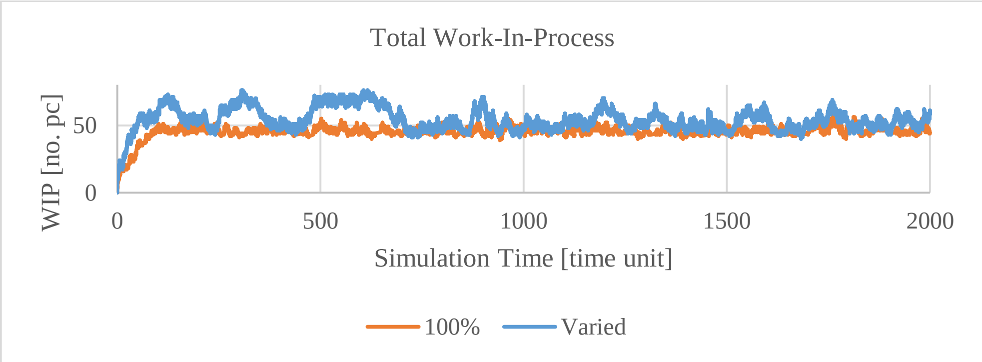

Figure 6.50: Fly Reel Total WIP (IM=2)

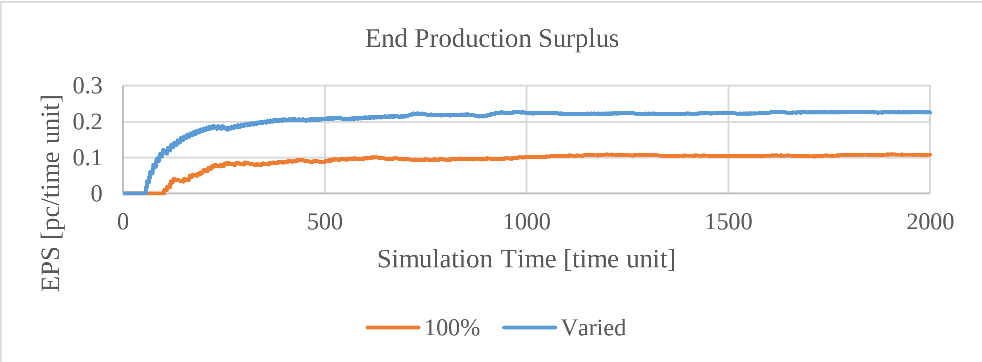

Figure 6.51: Fly Reel EPS (IM=2)

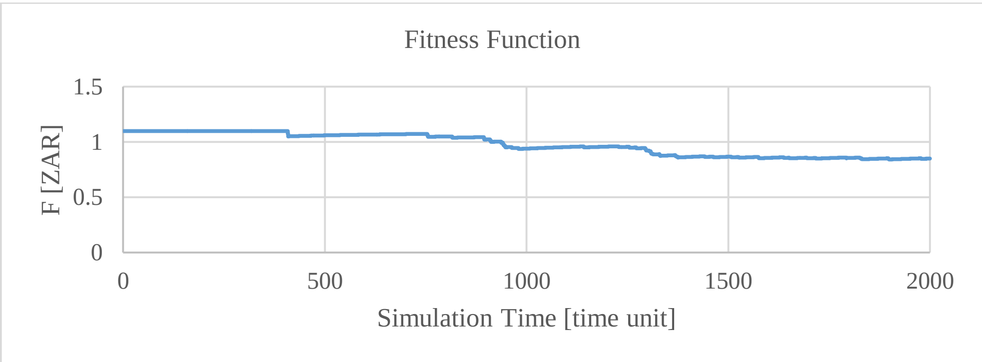

Figure 6.52: Fly Reel Fitness Value (IM=2)

6.5 Multiple-Part-Type Case Study: Three-Part-Type Production

This case study outlines the performance of varied inspection in a multiple-part-type production. This case study is based on the simulation test case presented by Tsourveloudis, Dretoulakis and Ioannidis in [61]. Varied inspection was again tested against 100% inspection.

6.5.1 Case Study: Three-Part-Type Production

Multiple-part-type production leads to high variety manufacturing, where different parts within a part family are produced by flexible machines. Machines are able to produce different parts by being highly flexible (for example CNC machines) or by incorporating some sort of reconfigurability in RMSs. Production is low-to-medium volume. The example represents a hypothetical 4IR layout as customers desire different products to be delivered timeously and cost-effectively. High variety manufacturing requires highly flexible inspection systems such as CMMs and RIMs.

6.5.2 Manufacturing Process for Three-Part-Type Production

Figure 6.53 shows the production of the three-part-type manufacturing. There are three machines, however each can produce three parts. Therefore, virtual machines were created for each machine, as described in [62]. The control structure remains the same. Ioannidis, Tsourveloudis and Valavanis [58] state that: "*a multiple-part-type system may be decomposed into as many single-part-type systems as the number of parts produced. The structure of the fuzzy controller remains the same.*" Figure 6.53 shows the DES model for the three-part-type production. Notice that each part type requires its own supervisory controller. Homayouni, Tang and Ismail [75] used two supervisory controllers (each with their own GA optimisation modules) in two-part-type production where each supervisor controlled each part type. Therefore, three separate GSFs each with their own GA optimisation modules were used for the three-part-type production. Notice that due to the control architecture used, separate multipliers for each part type cannot be used. As such, average multiplier values from the GSFs were calculated for each HDF controller, as shown in Figure 6.54.

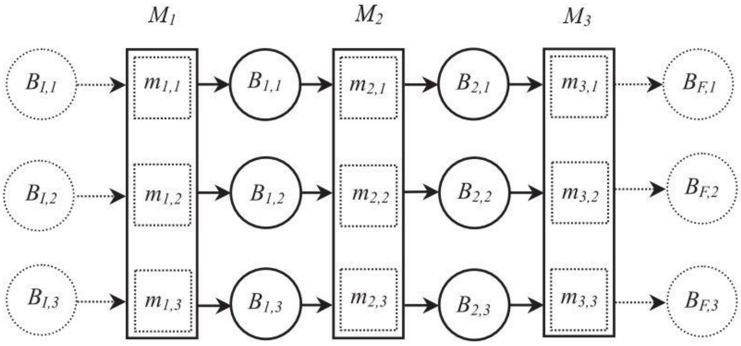

Figure 6.53: Three-Part-Type Production [61]

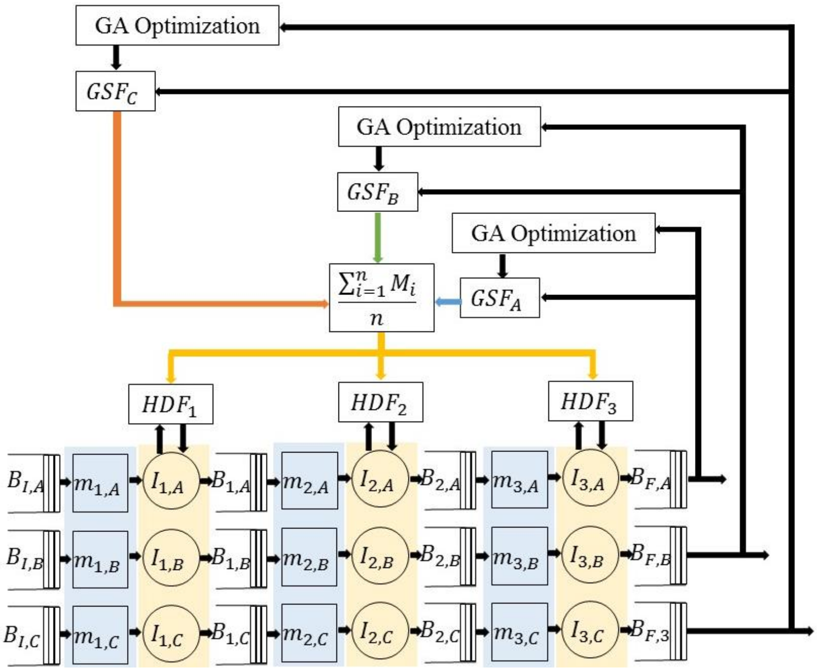

Figure 6.54: Manufacturing Process for the Three-Part-Type Production in DES

6.5.3 Simulation Assumptions for Three-Part-Type Production and Results

The SimEvents® model for three-part-type production is shown in Figure B.7 (Appendix B). The following assumptions were used for DES:

- Arrival rate: exponential distribution with a mean 5 time units
- Buffer capacities: $B_{I,(A,B,C)} = B_{1,(A,B,C)} = B_{2,(A,B,C)} = B_{F,(A,B,C)} = B_{I,2} = 10$ pc.
- Machine production surplus: random Gaussian numbers with a mean of 0 and variance of 0.5.
- Part quality: based on Poisson random numbers. Each part type had a different part quality characteristic.
- Machine state: Random failure
- Simulation time: 2000 time units

Three part types (A, B and C) were used. The part demand was set to "equiprobable" which means that each part type is randomly chosen for production. Each part type would require different procedures and thus different inspection procedures would be needed – which means that each part type requires different machining times and inspection times. It is uncommon that flexible inspection machines inspect quicker than flexible machines can process, therefore IM ratios less than 1 were not tested. Therefore, IM = 1 and IM = 2 were tested as reasonable assumptions. The parameters for the machining and inspection time are shown in Table 6.1 for IM=1.

Table 6.1: Three-Part-Type Production Parameters for IM=1

Part Type	M_1 [time unit]	I_1 [time unit]	M_2 [time unit]	I_2 [time unit]	M_3 [time unit]	I_3 [time unit]
A	1	1	1	1	1	1
B	2	2	2	2	2	2
C	3	3	3	3	3	3

The following results are for IM = 1. Figure 6.55 shows the machine utilisation. Figure 6.56 shows the total MLT, Figure 6.57 shows the total WIP and Figure 6.58 shows the EPS. Figures 6.59 to 6.61 shows the fitness function values for each part type (A, B and C).

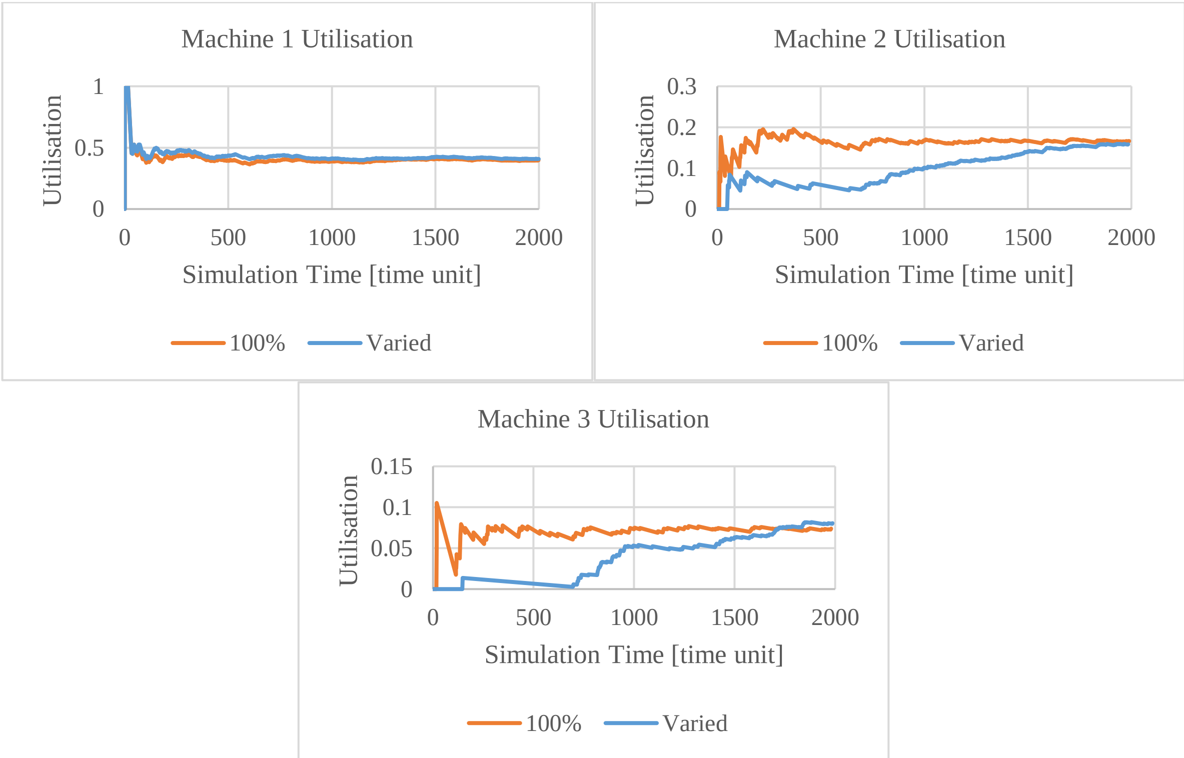

Figure 6.55: Three-Part-Type Machine Utilisation (IM=1)

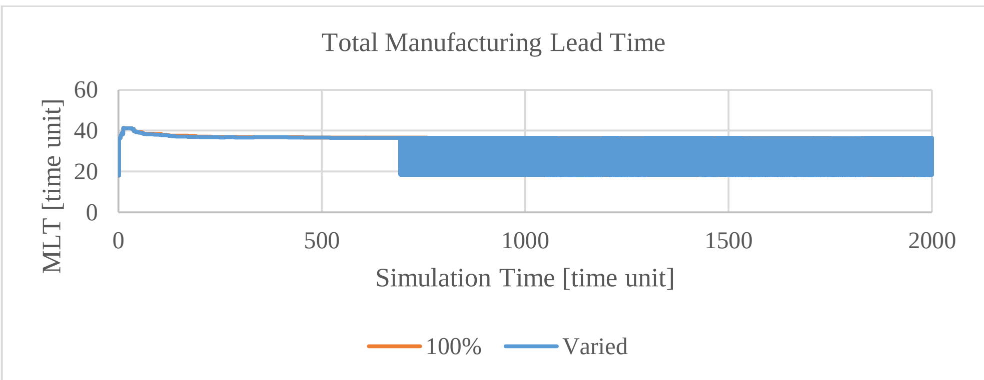

Figure 6.56: Three-Part-Type Total MLT (IM=1)

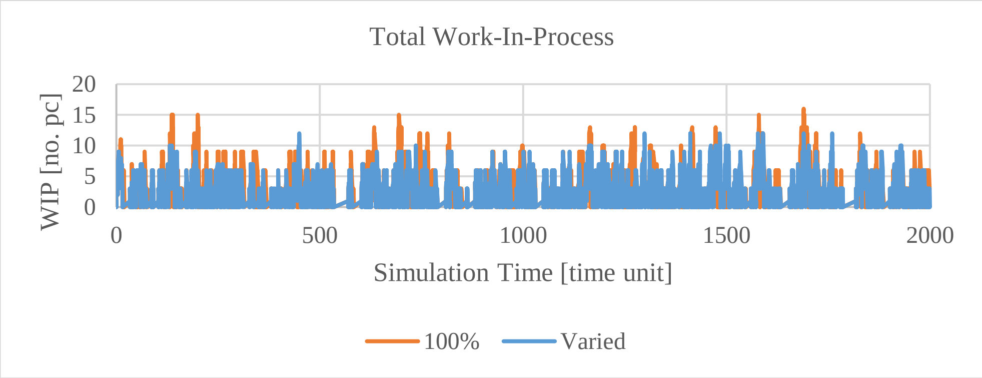

Figure 6.57: Three-Part-Type Total WIP (IM=1)

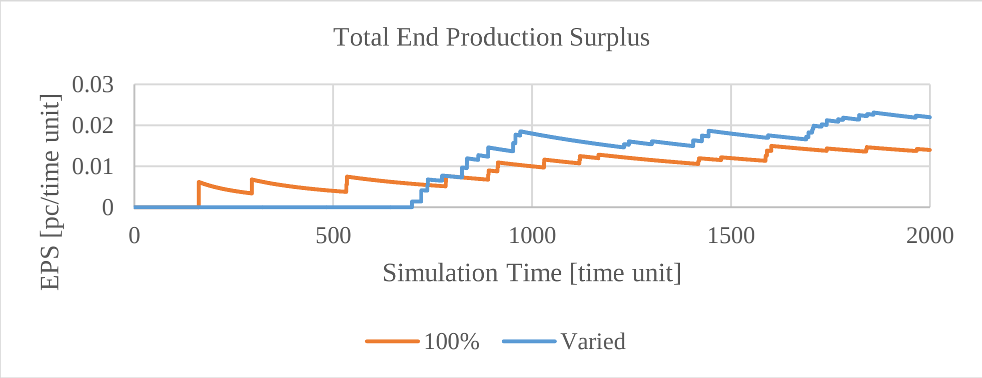

Figure 6.58: Three-Part-Type EPS (IM=1)

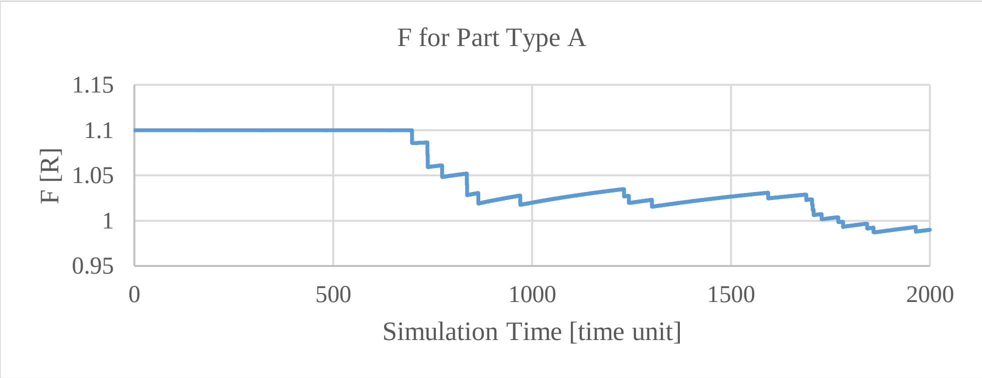

Figure 6.59: Three-Part-Type Fitness Value for Part Type A (IM=1)

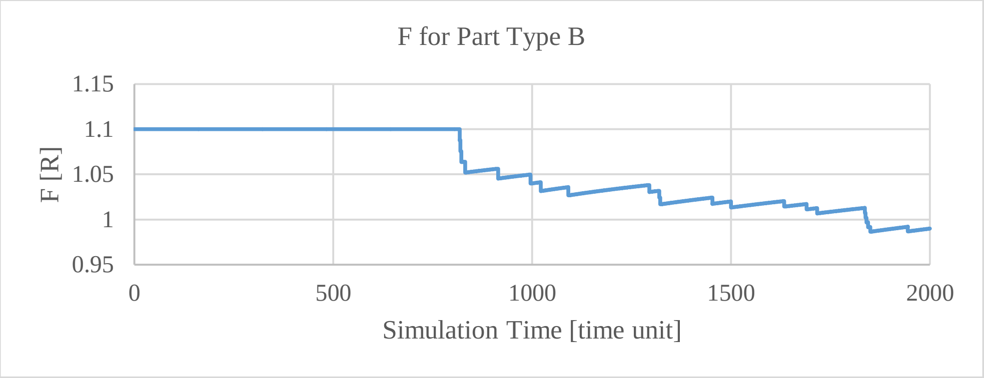

Figure 6.60: Three-Part-Type Fitness Value for Part Type B (IM=1)

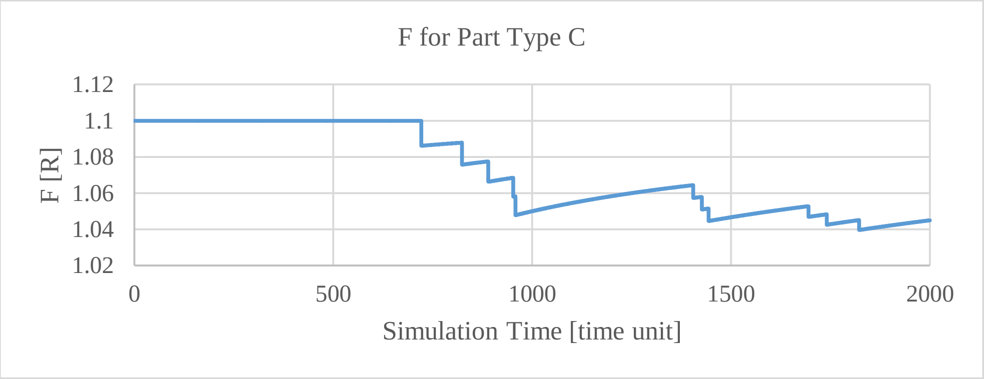

Figure 6.61: Three-Part-Type Fitness Value for Part Type C (IM=1)

Table 6.2 shows the parameters used for IM = 2. Figure 6.62 shows the machine utilisation for each machine. Figure 6.63 shows the total MLT, Figure 6.64 shows the total WIP and Figure 6.65 shows the EPS. Figure 6.66, Figure 6.67 and Figure 6.68 shows the fitness function values for each part type (A, B and C).

Table 6.2: Three-Part-Type Production Parameters for IM=2

Part Type	M_1 **[time unit]**	I_1 **[time unit]**	M_2 **[time unit]**	I_2 **[time unit]**	M_3 **[time unit]**	I_3 **[time unit]**
A	1	2	1	2	1	2
B	2	4	2	4	2	4
C	3	6	3	6	3	6

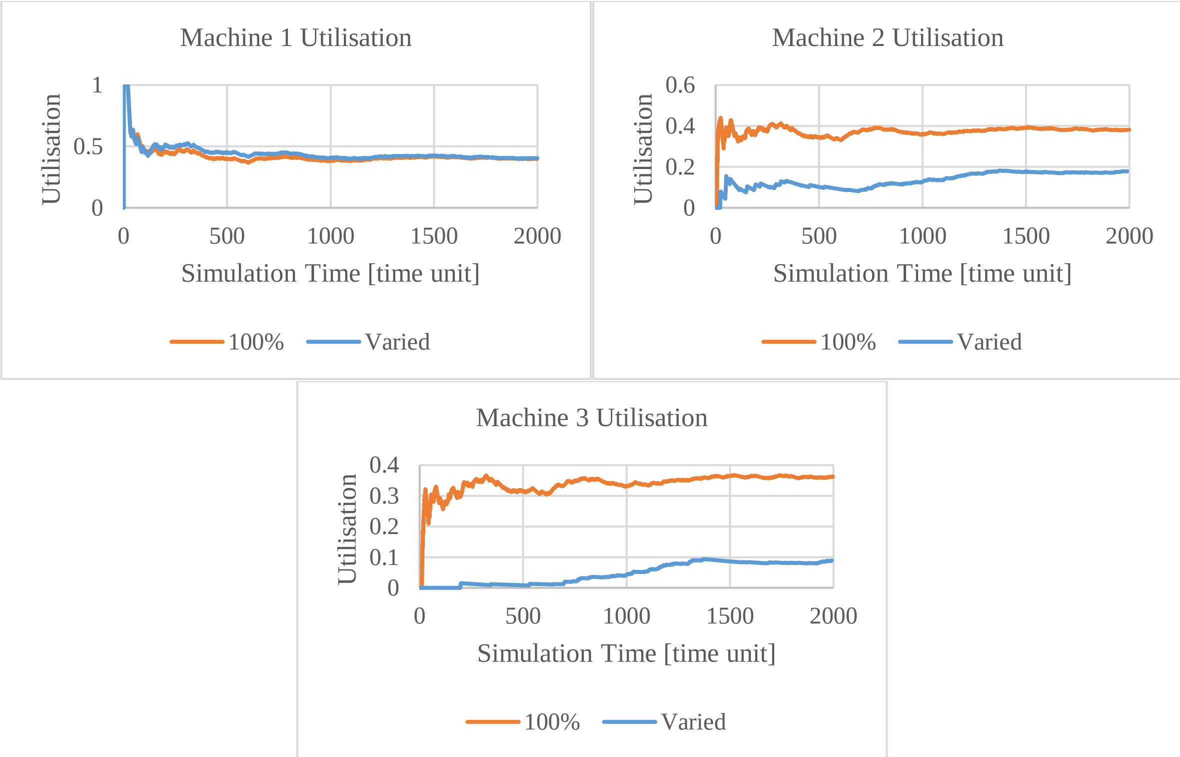

Figure 6.62: Three-Part-Type Machine Utilisation (IM=2)

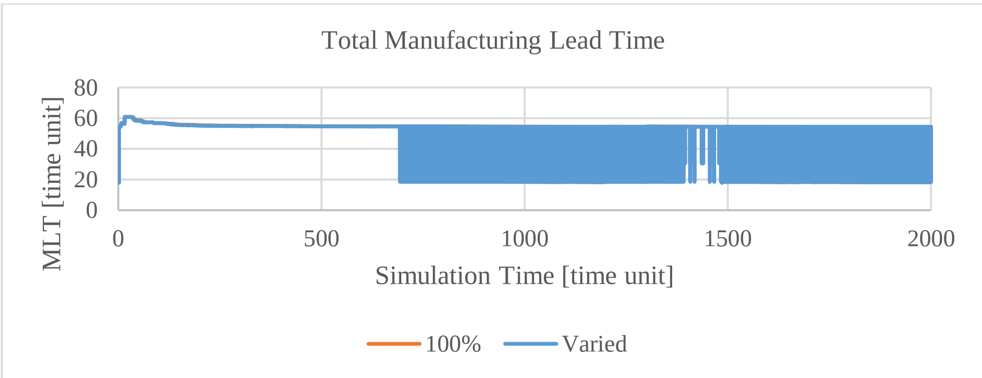

Figure 6.63: Three-Part-Type Total MLT (IM=2)

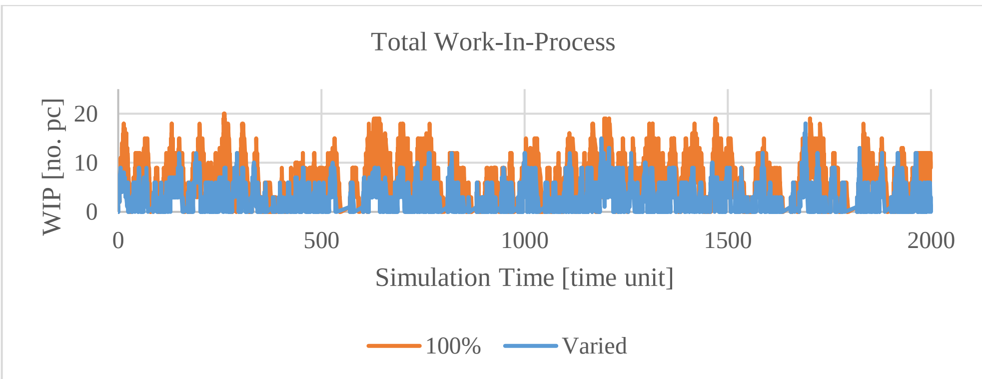

Figure 6.64: Three-Part-Type Total WIP (IM=2)

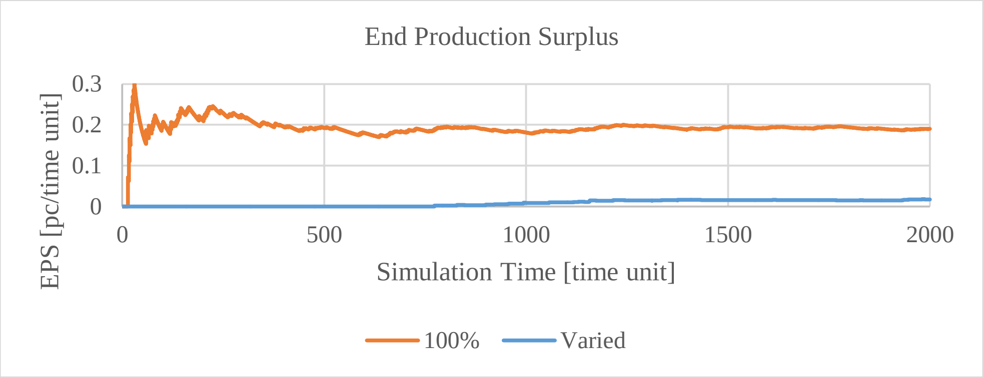

Figure 6.65: Three-Part-Type EPS (IM=2)

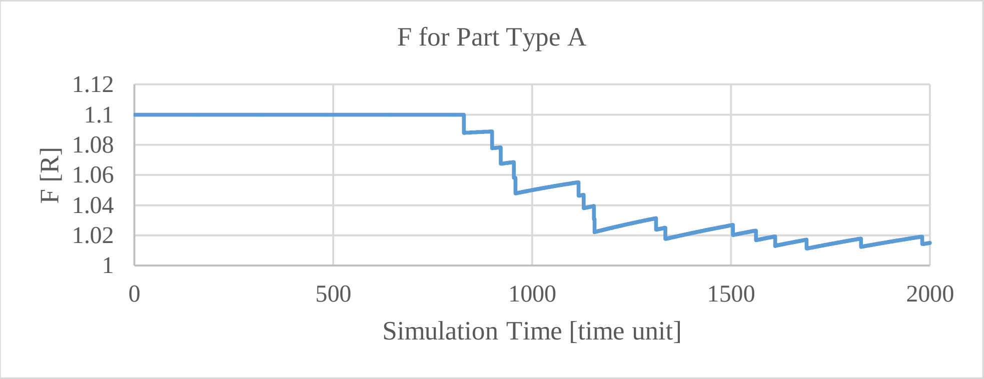

Figure 6.66: Three-Part-Type Fitness Value for Part Type A (IM=2)

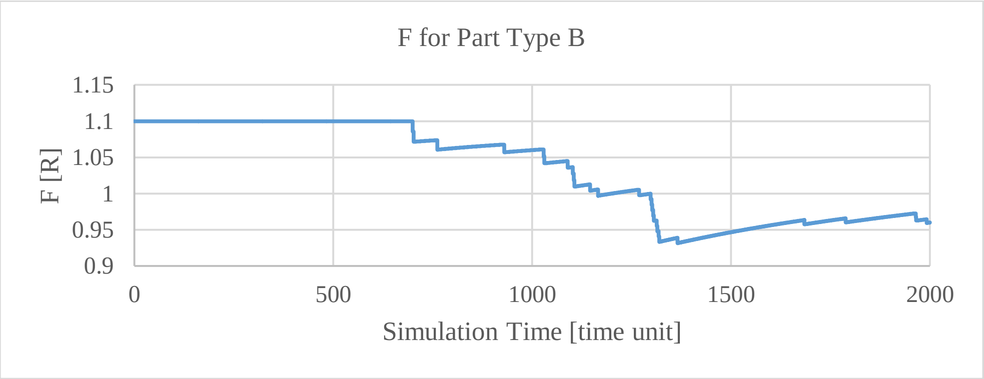

Figure 6.67: Three-Part-Type Fitness Value for Part Type B (IM=2)

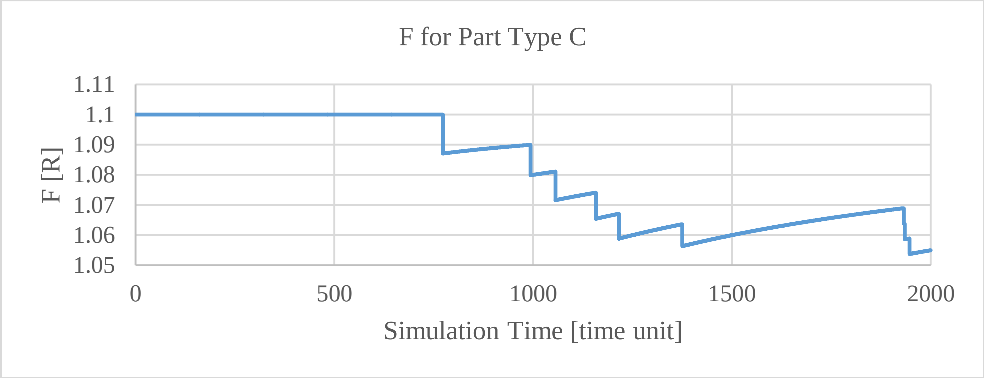

Figure 6.68: Three-Part-Type Fitness Value for Part Type C (IM=2)

6.6 Chapter Summary

Four case studies were evaluated – each case represented a different type of production. The manufacturing process for each case study was explained. Varied inspection was tested against 100% inspection for different IM ratios. The variation in results for each simulation was due to the different inspection usage strategies: varied inspection and 100% inspection. The performance metrics such as machine utilisation, MLT, WIP, EPS and fitness values were measured to determine how varied inspection affects production against 100% inspection. Different results were generated for each case study. The results were discussed in Chapter 7.

7 Discussion

7.1 Chapter Introduction

The chapter outline important research results found through simulation of varied inspection in multiple scenarios. The information from the literature review is discussed in-line with the results found through DES. The individual and combined testing of the controllers were outlined with emphasis on the performance measures to gauge the effects of varied inspection on production. Each test that was performed was explained and the significance of those results are highlighted in the chapter. The chapter fulfils objective 8 of the research objectives.

7.2 Application of Fuzzy Control for Varied Inspection

The literature review performed in Section 2.4 outlined the application of fuzzy control for multiple manufacturing problems. Majority of literature support the use of FL in manufacturing as favourable results were achieved in process control, scheduling and quality control. Major research in production control was based on using fuzzy control. The common approach was to use a series of distributed fuzzy controllers to perform the major control actions, while a supervisory controller would tune the lower-level controllers and make adjustments to aid production performance. The control methodologies described in the literature was used to model the control architecture for varied inspection.

Varied inspection made use of the same fuzzy controllers used in literature. Fuzzy control was for varied inspection because it allowed for multiple parameters to be used in conjunction to adjust inspection rates. Fuzzy control allowed for control modularity as the designed controller could straightforwardly be implemented into different production modules. The FLCs provide accurate control by designing them with many membership functions and conclusive rules about how to control the system. It was noted that more membership functions increases the accuracy of results, which is a shortcoming of FLC design. The aims of varied inspection were adequately met by the FLCs, thus satisfying objective 1 as specified in Section 1.6.

7.3 Development of Fuzzy Logic Controllers for Varied Inspection

Varied inspection was implemented by using fuzzy control architecture that was used by previous researchers in [58], [61], [72], [74], [75]. A two-level control approach was used. The lower-level HDF controllers performed varied inspection on the machine control level. The upper-level HSF and GSF controllers performed supervisory actions to improve manufacturing performance. Each controller was tested individually to test whether it could perform its given task. The purpose of the individual testing was to determine whether each controller input could perform its intended task in SISO control.

The HDF controllers had five objectives: perform averaging, ensure that inspection intensity was dictated by part quality, and reduce the negative effects of blocking, starving and machine breakdown.

Averaging was performed using the mechanism in equation 4.1. The purpose of averaging was to ensure that inspection intensity was implemented as a mean over a certain number of parts. Averaging negates the effects of the inspection intensity constantly changing. The largest error magnitude measured from the averaging testing was 12.1%, proving that equation 4.1 is a viable form of averaging. Blocking and starving were mitigated by the HDF controllers by reducing or increasing inspection intensity when the buffer levels are full or empty. Inspection intensity increases to maximum (100%) when machines have broken down and need to be repaired, ensuring that all parts produced from recently repaired machines are fully inspected. Inspection intensity was designed to be higher than the defect rate – the test was performed under different quality tolerances between 10% and 90%. Lastly, inspection intensity increases and decreases according to the machine production surplus. A measure of performance of the HDF controllers was machine utilisation – based on the premise that reducing blocking and starving increases machine utilisation. Simulation of a two-stage transfer line was used to measure machine utilisation and showed that varied inspection increased machine utilisation by 70% when compared to 100% inspection. The HDF controller performed satisfactorily in-line with its control aims. The development of HDF controllers fulfils Objective 2.

The purpose of the supervisory controller was to meet overall production aims. The supervisor had to perform 100% inspection at the beginning of the cycle and meet WIP and EPS targets by adjust the multiplier output. The batch size input was used to perform 100% inspection during the first 30% of production. Figure 7.1 A) shows that the HSF multiplier is large at the beginning of production, which increases the average inspection intensity to 100% in B).

In the simulations, the HSF controller does reduce the WIP error and EPS error but would not reach zero error. The results of the WIP error and EPS error does prove that the supervisory controller does improve manufacturing performance. The results showed that the supervisory control performance would benefit from an optimisation module which is discussed Section 7.4. The testing of the supervisory controller fulfils objective 3 and objective 5 of the research objectives.

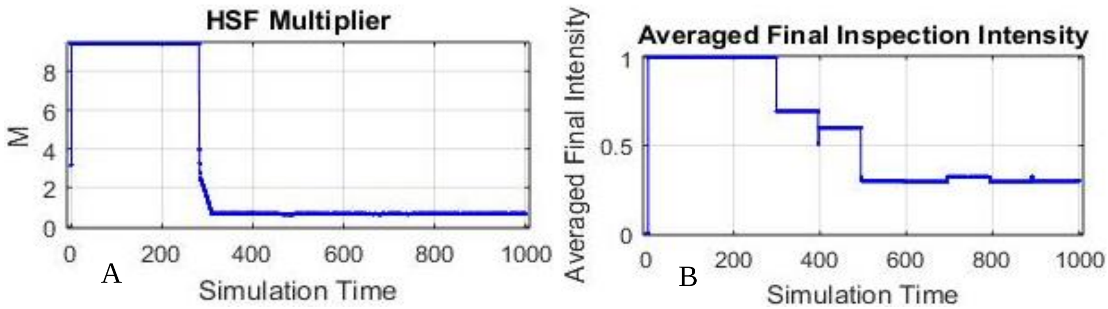

Figure 7.1: Large Multiplier Value at Beginning of Production

The HSF was designed to meet targeted WIP and EPS values by calculating WIP error and EPS error and then adjusting the multiplier to meet these targets. For the WIP target, the multiplier increases to reduce WIP and decreases to increase WIP until the WIP error becomes zero. The same methodology is used to meet EPS targets. However, one limitation of the controller design is that the number of control steps were limited. Traditional control methods perform real-time parameter adjustments, however varied inspection makes use of a limited amount of steps because of averaging (Section 4.2.1).

7.4 Optimisation of Supervisory Controller

Optimisation was a significant contributor to the FLC design as well as a formal technique for membership function generation of the HSF. The technique to approximate output trapezoidal membership functions as Gaussian curves was novel as no other research used this procedure. The reasons why only the HSF was optimised were described in Section 3.6 and are summarized below.

- No need for HDF controller membership function optimisation as favourable results were generated in Section 4.2.
- HDF optimisation could reduce quality standards.
- HDF optimisation would not drastically improve performance as its parameters are overall dependent on the supervisory controller.

GA was used over EA as the GA crossover step would provide more solution variations than EA. The GA optimisation module was tested in a single-station manufacturing cell against a standard heuristic non-optimised supervisory controller. Figure 7.2 shows that the GSF outperforms the HSF controller by minimizing the fitness function by 45%, therefore reducing the WIP error and EPS error further than the HSF controller. Based on the fitness function described in equation 3.19 and equation 4.2, the following fitness functions shown in Figure 7.3 were generated for the case studies. For each fitness function graph, the aim was to reduce WIP error and EPS error, thereby reduce the fitness value F. Each curves shows a reduction in the fitness value F which ensures that the GSF controller reduces errors to allow production to meet its WIP and EPS targets. The results satisfy objective 4 of the research objectives.

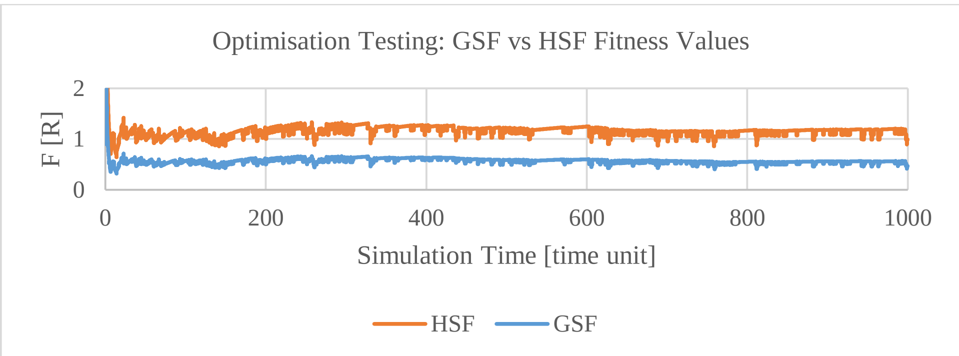

Figure 7.2: Optimisation Testing for GSF and HSF

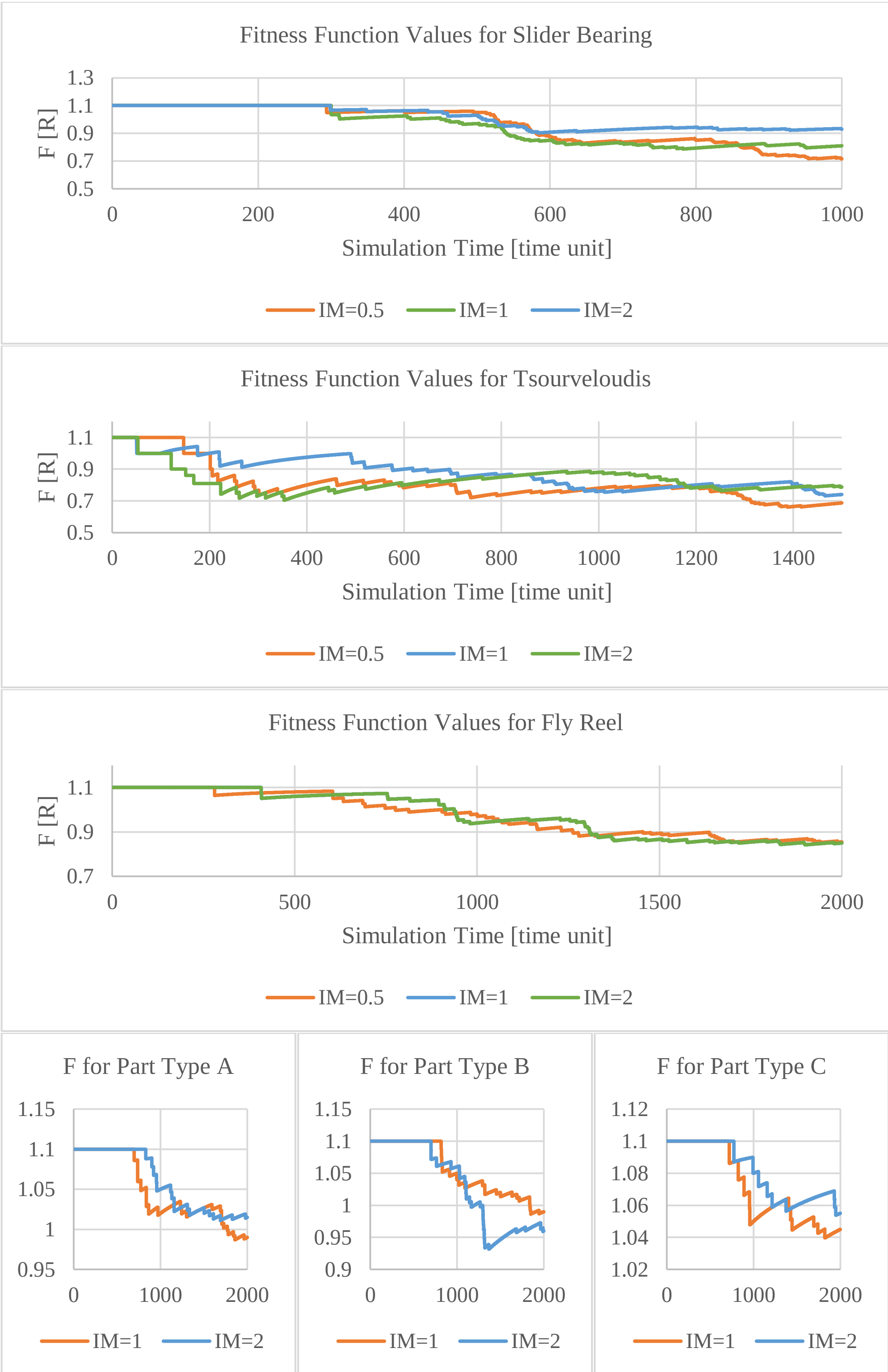

Figure 7.3: Fitness Function Trends for Case Studies

7.5 Implementation of Varied Inspection in Production

Varied inspection was applied to two major sectors: subsystems and case studies. The subsystems are the building blocks used to model manufacturing plants and the case studies were modelled to represent different production types, such as DMS, MC manufacturing and high variety production. The results of each sector was discussed with emphasis on important metrics for production. It was noted that over-inspection in each case was reduced, however it was difficult to quantify as performing inspection on the non-inspected parts would simply result in 100% inspection.

7.5.1 Subsystems

Each subsystem (transfer line, assembly and disassembly) that was used in literature was tested for performance metrics. Table 7.1 shows the results of the simulations after each production cycle, with reference to the measured performance metrics MLT, WIP and EPS. The same simulation assumptions were used for each subsystem module and varied inspection was tested against 100% inspection. Favourable results were achieved when MLT and WIP was reduced while EPS was increased.

Table 7.1: Results from Subsystem Module Testing

Subsystem	MLT Percentage Increase	WIP Percentage Increase	EPS Percentage Increase
Transfer Line	-35.78%	No difference	195.45%
Assembly Module	-52.5%	No difference	250%
Disassembly Module	-2%	13.33%	44.44%

The results show the common outcomes:

- The EPS was always altered between 100% inspection and varied inspection.
- Changes in WIP were minimal.
- MLT decreased in all subsystems.

The favourable results of MLT reduction appeared across all subsystems. The conclusion based on this common result was that varied inspection will always reduce MLT when compared to 100% inspection plans. The conclusion is based on the premise that the “building blocks” nature of the subsystems provide insights on what the results would be when these systems are integrated together. Minimal changes were noticed in WIP. One reason for the lack of WIP reduction may be due to no-optimised states of the HSF membership functions. The result was unfavourable however, it does show that optimisation supervisory controller is advantageous. The EPS significantly changed in all subsystems. Favourable results were recorded in the transfer line and assembly module however, the disassembly module recorded a 44.44% decrease. The reason for the decrease was that the total number of parts through a disassembly module increases based on disassembly factors.

The subsystem testing provided insights on the results of the performance measures when these modules were used for modelling of DMS, multiple system integration, MC manufacturing and multiple-part-type production. This testing satisfied objective 6 of the research.

7.5.2 Case Studies

Four case studies were researched. Each case study represented a different type of production: DMS (slider bearing), multiple subsystem integration (Tsourveloudis), MC (fly reel) and multiple-part-type production (three-part-type). The machine utilisation, MLT, WIP, EPS and fitness values were measured for each case. The assumptions were used to simplify production. Note that the generated results were significantly dependent on the assumptions made. For example, various machines had low utilisation – this was based on the arrival rates and buffer capacities used. The aim was to measure the effect that varied inspection would have on these performance metrics when compared to 100% inspection. The differences in the results between varied inspection and 100% inspection was used as a performance measure. Different IM ratios were used for testing.

The results for the DMS (slider bearing case study) are shown in Table 7.2 for the machine utilisation and Table 7.3 for the overall performance against 100% inspection. Three different IM ratios were tested where each case represents situations where inspection time and processing time dominates, and when both times are equal. Each case for machine utilisation (with the exception of Machine 1 for IM=2) showed an increase in utilisation when compared to 100% inspection. By total, IM = 2 had provided the largest percentage increase in machine utilisation. The recommendation from the result is that varied inspection should be considered when inspection time dominates processing time and inspection has to be performed on-line. The performance measures (MLT, WIP, and EPS) from the DMS case study show the same trend as the machine utilisation in Table 7.2. Results are most favourable when IM = 2 as MLT decreased by 33.33%, WIP decreased by 54.55% and EPS increased by 1060%. The conclusion from the DMS case study was that varied inspection is well suited when part variety is minimal and when inspection time is greater than processing time.

Table 7.2: DMS Machine Utilisation for Varied Inspection against 100% Inspection

IM ratio	**Machine Utilisation Percentage Increase (%)**				
	Machine 1	**Machine 2**	**Machine 3**	**Machine 4**	**Machine 5**
0.5	0	18.42	62.51	62.41	149.21
1	0	24.82	38.97	67.69	107.32
2	-29.29	55.97	69.72	123.23	176.01

Table 7.3: DMS Performance Metrics for Varied Inspection against 100% Inspection

IM Ratio	**Performance Metrics Percentage Increase (%)**		
	MLT	**WIP**	**EPS**
0.5	0	10.13	780.00
1	0	3.60	220.00
2	-33.33%	-54.55	1060.00

Table 7.4 and Table 7.5 show the results of the multiple subsystem integration case study for machine utilisation and performance respectively. The machine utilisation increased in each case. Based on Table 7.5, the MLT decreased in all cases – as was the result of the subsystem testing in Chapter 5. Changes in WIP were minimal except for when IM = 2 and the EPS increased in all cases. The recommendation for varied inspection based on the case study is to consider varied inspection when the inspection time is less than processing time. The EPS will increase and will coincide with a small increase in WIP, as stipulated by the relationship between WIP and throughput in Figure 3.15. It was noted that the results were highly dependent on the configuration of the subsystems – different configurations would produce different results however the performance measures would follow the same trends.

Table 7.6 and Table 7.7 show the results for the MC simulation for machine utilisation and performance respectively. The machine utilisation decreases for certain machines when IM = 0.5 and IM = 2. The only situation when all machine utilisation increased was when IM = 2 and it can be concluded that varied inspection outperforms 100% inspection when the inspection time is greater than processing time. Mixed results were generated for the performance metrics for MC. For IM = 0.5 and IM = 1, MLT increased while WIP and EPS decreased. For IM = 2, MLT decreased while WIP and EPS increased. The most favourable result was when IM = 2 as MLT decreased and EPS increased.

Table 7.4: Multiple Subsystem Integration Machine Utilisation for Varied Inspection against 100% Inspection

IM ratio	**Machine Utilisation Percentage Increase (%)**					
	Machine 1	**Machine 2**	**Machine 3**	**Machine 4**	**Machine 5**	**Machine 6**
0.5	94.31	98.99	131.60	98.99	131.60	153.09
1	94.91	120.00	159.52	120.00	159.52	199.74
2	211.37	120.00	167.10	120.00	167.10	191.47

Table 7.5: Multiple Subsystem Integration Performance Metrics for Varied Inspection against 100% Inspection

IM Ratio	**Performance Metrics Percentage Increase (%)**		
	MLT	**WIP**	**EPS**
0.5	-53.30	10.43	264.71
1	-55.79	12.60	217.66
2	-52.79	44.74	213.33

Table 7.6: MC Machine Utilisation for Varied Inspection against 100% Inspection

IM ratio	**Machine Utilisation Percentage Increase (%)**							
	Machine 1	**Machine 2**	**Machine 3**	**Machine 4**	**Machine 5**	**Machine 6**	**Machine 7**	**Machine 8**
0.5	96.58	22.35	96.58	22.35	-2.80	-7.36	-45.05	-68.13
1	96.58	14.20	96.58	14.20	-0.41	-10.51	-39.98	-67.93
2	158.49	122.41	158.49	122.41	0.8	0.57	108.03	101.93

Table 7.7: MC Performance Metrics for Varied Inspection against 100% Inspection

IM Ratio	Performance Metrics Percentage Increase (%)		
	MLT	WIP	EPS
0.5	54.99	-6.34	-77.73
1	60.15	-3.21	-77.77
2	-42.73	18.90	107.77

Table 7.8 and Table 7.9 show the results for the three-part-type production. Note that IM = 0.5 was not tested as it was unrealistic for a flexible inspection machine to have a lower inspection time than the machine processing time. Therefore, two IM ratios were tested. Different trends were experienced for machine utilisation – some utilisation increased and some decreased. The WIP in Table 7.9 decreased in both IM values, no MLT changes were measured and EPS increased for IM = 1 and decreased for IM = 2. Overall, the recommendation for inspection was to not use varied inspection for multiple-part-type production. Each part type has different party quality characteristics, which the HDF controllers cannot detect. Each part passing through the system was treated as the same part with consequently different defect rates, hence the performance metrics were mixed and inconclusive.

The following recommendations were made as to when to apply varied inspection:

- Consider varied inspection when inspection has to be performed on-line, as opposed to the "inspect all-or-nothing" policy.
- Use varied inspection for small manufacturing subsystems such as transfer lines, assemblies and disassemblies as there is a guaranteed reduction in MLT with small changes in WIP.
- Use varied inspection when inspection time dominates processing time, as majority of the results showed greater performance increases when IM =2 compared to other IM ratios.
- Use varied inspection in DMS because there is minimal part variety therefore the defect rate parameters are well defined.
- Do not use varied inspection for high variety production as the defect rates for each part (which would be different) would be read as the same part-type with large discrepancies by the HDF controllers. Due to the volatile nature associated with MC, trends in new products cannot be observed until quality characteristics can be extracted from the part stream. Large fluctuations in the defect rates lead to unnecessary high inspection rates which would increase MLT and WIP, while decreasing EPS.
- Varied inspection cannot be used for effective feedback control as control actions are dictated by averaging of the HDF controllers, which means that a finite amount of inspection intensity states exist. The GSF aids production by reducing WIP error and EPS error to certain extents, however the controller cannot satisfy both conditions under the characteristic curve of Figure 3.15.

The following recommendations prescribed above satisfy Objective 6 and Objective 7 of the research.

Table 7.8: Multiple-Part-Type Machine Utilisation for Varied Inspection against 100% Inspection

IM Ratio	Machine Utilisation Percentage Increase (%)		
	Machine 1	Machine 2	Machine 3
1	0	3.60	220.00
2	-33.33%	-54.55	1060.00

Table 7.9: Multiple-Part-Type Performance Metrics for Varied Inspection against 100% Inspection

IM Ratio	Performance Metrics Percentage Increase (%)		
	MLT	WIP	EPS
1	0	-19.64	57.14
2	0	-49.34	-90.79

7.6 Chapter Summary

The literature revealed the applicability of using FL for process control. The controllers were individually tested and performed adequately. The HDF controllers performed all control tasks while the HDF controllers performed their task of reducing WIP error and EPS error to a certain limit. The HSF controller was aided by the GA optimisation module which helped to reduce WIP error and EPS error further. The results of the subsystems and case studies at steady state were tabulated which revealed overall characteristics of varied inspection against 100% inspection for various IM ratios. Recommendations were made on when to use varied inspection and when the inspection technique is not applicable.

8 Conclusion

8.1 Chapter Introduction

The conclusion summarises the overall research findings of varied inspection as well as the significance of the simulated results. Suggestions are provided for areas of future development within inspection system utilisation for advanced manufacturing systems.

8.2 Overall Research Findings

The overall research findings provided insights into the properties and performance of varied inspection. Through the research, the following objectives were fulfilled:

- The current state of the literature in QC, inspection and fuzzy control was investigated and the information was used to develop the concept of varied inspection.
- HDF controllers were developed to perform varied inspection on a machine level.
- An HSF controller was developed to tune the HDF controllers for the purpose of meeting overall production needs.
- Each controller was independently tested and yielded acceptable results for fuzzy control.
- Optimisation was performed on the HSF controller, transforming it to a GSF controller with improved supervisory controller performance.
- The fuzzy controller architecture was applied to common manufacturing subsystems with favourable results such as improved end production surplus and lower WIP and MLT as compared to a traditional inspection method.
- Varied inspection was applied to four case studies to determine the performance in DMSs, multiple system integration, MC and multiple-part type production. The results show that varied inspection improved production and increased machine utilisation when in situations when inspection time dominated production time.
- The impact of the results was evaluated.

The significant research findings show that QC can aid manufacturing metrics even though inspection does not add value to the process, however it is mainly applicable in production with high IM ratios and is not suited for high variety production. The literature review described QC as an unattached component of production – it slowed production down, too much of inspection was performed and added no value. Over-inspection in each test was reduced. Through varied inspection, QC can now aid production to keep lead time and in-process inventory low, while improving EPS.

8.3 Significance of Results

The important result of varied inspection is that CMMs can be used in-line with production – inspection does not have to be performed off-line when using a varied inspection scheme. On-line inspection was preferred to off-line inspection as prescribed by the literature. CMM inspection takes significant time to perform accurate inspection, which is why CMM inspection is mainly performed off the production line as it would slow down production (high IM ratios). Through varied inspection, CMM inspection can be incorporated on-line was required. One should consider varied inspection when inspection has to be performed on-line, as opposed to the "inspect all-or-nothing" policy.

Varied inspection aided production when inspection time dominated production time. Production is not favourable when MCE as low as there is more time spent on processes that do not add monetary value – such as inspection procedures. Results from the case studies showed that varied inspection improved machine utilisation more significantly as the IM ratios increased. Increased machine utilisation showed a reduction in blocking and starving. Therefore, varied inspection would be suitable where slow on-line inspection procedures are unavoidable.

Optimisation is recommended for membership function formation of the FLC. The development of the membership functions for the FLCs is mainly done through trial-and-error in deciding which membership function type to use (trapezoidal, Gaussian, sigmoidal), how to size the membership functions and how many membership functions to have. Optimisation solves the problem of the sizing of the membership functions and provides feedback control action by constantly aiming to minimize the fitness function.

8.4 Areas for Further Development

The application of varied inspection can be implemented into manufacturing systems with integration in inspection system control. This research was limited to simulation-based results with certain assumptions on how the production was carried out. Further research into varied inspection should attempt to implement the inspection scheme into actual manufacturing plants, with the following points to consider:

- It is impractical to constantly monitor buffer levels.
- Inspection times may change over operation, which will affect IM ratios.
- Part quality may change outside of machining, such as when parts are stored in buffers or transported to cells.
- Inspection machines are not 100% accurate and may lead to Type I (rejection of conforming parts) and/or Type II (acceptance of non-conforming parts) errors.
- A critical assessment of overall quality changes should be performed, as varied inspection compromises quality for production.
- The simulated results cannot fully emulate the variability of advanced manufacturing systems.
- Perform more research into the machine utilization of large-scale manufacturing environments as the current research was constrained to small-scale manufacturing (Chapter 4.2.7)

- Consider the development of CMM technology as more advancements in technology can lead to faster quality implementation using these machines.
- Compare varied inspection to other forms of modern QC techniques (other than 100% inspection) to evaluate if this form of inspection usage is useful to the production scheme.

The optimisation model and techniques can be further researched to determine which techniques provide the best control. GA is the most common form of optimisation, however there exists other techniques found in literature, such as Particle Swarm Optimisation (PSO) to automatically generate membership functions [90]. The assumption made was that the most common form of FLC optimisation would provide the best solutions for the task of varied inspection, however further research is required to test the assumption. Optimisation can be extended to acquiring the optimised "Batch Size" input (as prescribed in Section 3.5), optimised control steps (as opposed to a constant value) by implementing a larger search space and more membership functions.

8.5 Chapter Summary

The overall research findings was described in-line with the research aims and objectives. The results show that varied inspection can be used for on-line inspection as opposed to off-line sampling. Varied inspection strives when inspection time is larger than machining time. Optimisation is recommended for the membership function development step of FLC design. Suggestions for future research was provided and recommendations on how to implement varied inspection into real production lines and how to improve controller performance through further optimisation was outlined.

References

[1] Y. Koren, "General RMS Characteristics . Comparison with Dedicated and Flexible Systems," in *Reconfigurable Manufacturing Systems and Transformable Factories*, no. 1, 2006, pp. 27–45.

[2] C. Herrmann, C. Schmidt, D. Kurle, S. Blume, and S. Thiede, "Sustainability in Manufacturing and Factories of the Future," *Int. J. Precis. Eng. Manuf. - Green Technol.*, vol. 1, no. 4, pp. 283–292, 2014.

[3] E. Alfnes and J. O. Strandhagen, "Enterprise Design for Mass Customization: The Control Model Methodology," *Int. J. Logist. Res. Appl.*, vol. 3, no. 2, pp. 111–125, 2000.

[4] K. Schwab, "The Fourth Industrial Revolution: what it means, how to respond," *World Economic Forum*, 2016. [Online]. Available: https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/. [Accessed: 16-Jun-2016].

[5] R. Davies, "Industry 4.0: Digitalisation for productivity and growth," *European Parliamentary Research Service*. p. 10, 2015.

[6] H. Kazan and M. Baydar, "Benefit of Mass Customization as a Manufacturing Strategy with a Case Study," *Journal of Global Strategic Management*, no. 2. pp. 116–125, 2007.

[7] S. M. Davis, "From 'future perfect': Mass customizing," *Plan. Rev.*, vol. 17, no. 2, pp. 16–21, Feb. 1989.

[8] G. Da Silveira, D. Borenstein, and H. S. Fogliatto, "Mass customization : Literature review and research directions," *Int. J. Prod. Econ.*, vol. 72, no. 49, pp. 1–13, 2001.

[9] S. Davrajh, G. Bright, and R. Stopforth, "Modular Research Equipment for On-line Inspection in Advanced Manufacturing Systems," *South African J. Ind. Eng.*, vol. 23, no. May, pp. 136–150, 2012.

[10] Z. M. Bi and W. J. Zhang, "Flexible fixture design and automation: Review, issues and future directions," *Int. J. Prod. Res.*, vol. 39, no. 13, pp. 2867–2894, 2001.

[11] Y. Koren *et al.*, "Reconfigurable Manufacturing Systems," *CIRP Ann. - Manuf. Technol.*, vol. 48, no. 2, pp. 527–540, 1999.

[12] F. S. Fogliatto, G. J. C. Da Silveira, and D. Borenstein, "The mass customization decade: An updated review of the literature," *Int. J. Prod. Econ.*, vol. 138, no. 1, pp. 14–25, 2012.

[13] J. Zhong, "Manufacturing System Variation Reduction Through Feed-forward Control Considering Model Uncertainties," University of Michigan, 2009.

[14] P. G. Brabazon and B. MacCarthy, “Consideration of the relevance of standard quality techniques in mass customisation,” *Int. J. Mass Cust.*, vol. 2, no. 1/2, pp. 76–94, 2007.

[15] T. Naidoo, A. Walker, G. Bright, and S. Davrajh, “Fuzzy Logic Control for Varied Inspection Applications in Advanced Manufacturing Cells,” in *2016 Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech)*, 2016, pp. 257–262.

[16] D. Gien, “Towards a unified representation of quality in manufacturing systems,” *Int. J. Comput. Integr. Manuf.*, vol. 12, no. 2, pp. 141–155, 1999.

[17] V. Tuominen, “Cost Modeling of Inspection Strategies in Automotive Quality Control,” *Eng. Manag. Res.*, vol. 1, no. 2, pp. 33–45, 2012.

[18] B. C. Giri and S. Sharma, “Optimizing a closed-loop supply chain with manufacturing defects and quality dependent return rate,” *J. Manuf. Syst.*, vol. 35, pp. 92–111, 2015.

[19] J. Barhak, D. Djurdjanovic, P. Spicer, and R. Katz, “Integration of reconfigurable inspection with stream of variations methodology,” *Int. J. Mach. Tools Manuf.*, vol. 45, no. 4–5, pp. 407–419, 2005.

[20] J. V. Abellan-Nebot, J. Liu, and F. Romero Subiron, “Quality prediction and compensation in multi-station machining processes using sensor-based fixtures,” *Robot. Comput. Integr. Manuf.*, vol. 28, no. 2, pp. 208–219, 2012.

[21] S. Davrajh and G. Bright, “An automated apparatus for dynamic inspection of mass-produced custom parts,” *Assem. Autom.*, vol. 30, no. 1, pp. 47–55, 2010.

[22] Y. He and W. Chang, “Systematical Design Quality Control model based on Key Quality Characteristics,” in *2009 16th International Conference on Industrial Engineering and Engineering Management*, 2009, pp. 1208–1212.

[23] D. White, G. Bright, A. Walker, and S. Davrajh, “Development of an Optimization Algorithm for Inspection of Customizable Jigs and Fixtures,” in *2017 IEEE International Conference on Mechatronics and Machine Vision in Practice (M2VIP2017)*, 2017, pp. 456–461.

[24] T. Naidoo, A. Walker, G. Bright, and S. Davrajh, “Fuzzy Logic Control for Varied Inspection for Manufacturing Lead Time Reduction,” in *14th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2017)*, 2017, pp. 207–214.

[25] The Free Library, “Moving from process inspection to process control: CMMs take the lead,” 2003. [Online]. Available: http://www.thefreelibrary.com/Moving+from+process+inspection+to+process+control%3A+C

MMs+take+the+lead.-a0111648379. [Accessed: 21-Jul-2016].

[26] M. P. Groover, “Inspection Principles and Practices,” in *Automation, Production Systems, and Computer-Integrated Manufacturing*, 3rd ed., Edinburgh: Pearson Education Limited, 2014, pp. 643–672.

[27] M. P. Groover, “Quality Programs for Manufacturing,” in *Automation, Production Systems, and Computer-Integrated Manufacturing*, 3rd ed., Edinburgh: Pearson Education Limited, 2014, pp. 599–642.

[28] V. Arumugam, J. Antony, and K. Linderman, “The influence of challenging goals and structured method on Six Sigma project performance: A mediated moderation analysis,” *Eur. J. Oper. Res.*, vol. 254, no. 1, pp. 202–213, 2014.

[29] D. C. Montgomery and W. H. Woodall, “An overview of six sigma,” *Int. Stat. Rev.*, vol. 76, no. 3, pp. 329–346, 2008.

[30] J. Liu, “Variation reduction for multistage manufacturing processes: A comparison survey of statistical-process-control vs stream-of-variation methodologies,” *Qual. Reliab. Eng. Int.*, vol. 26, no. 7, pp. 645–661, 2010.

[31] D. C. Montgomery, “Introduction to Statistical Quality Control,” *Arizona State University*, 2005. [Online]. Available: http://dl4a.org/uploads/pdf/ch01.pdf. [Accessed: 25-Apr-2016].

[32] J. M. Juran and A. B. Godfrey, *Juran’s Quality Control Handbook*, 5th ed. New York: McGraw-Hill, Inc, 1998.

[33] Y. Nikolaidis and G. Nenes, “Economic Evaluation of ISO 2859 Acceptance Sampling Plans Used with Rectifying Inspection of Rejected Lots,” *Qual. Eng.*, vol. 21, no. 1, pp. 10–23, Dec. 2008.

[34] A. Hassan, M. Shariff Nabi Baksh, and A. M. Shaharoun, “Issues in quality engineering research,” *Int. J. Qual. Reliab. Manag.*, vol. 17, no. 8, pp. 858–875, Nov. 2000.

[35] T. Burgees, “Quality management for manufacturers of short run semi-customized products,” *The TQM Magazine*, pp. 248–251, 1999.

[36] T.-L. B. Tseng and Y. J. Kwon, “Characterization of machining quality attributes based on spindle probe, coordinate measuring machine, and surface roughness data,” *J. Comput. Des. Eng.*, vol. 1, no. 2, pp. 128–139, 2014.

[37] R. Anjoran, “Inspection during production: a necessity?,” *QualityInspection.org*, 2010. [Online]. Available: https://qualityinspection.org/inspection-during-production/. [Accessed: 08-Aug-2016].

[38] A. Grauel, L. A. Ludwig, and G. Klene, “Comparison of different intelligent methods for process and quality monitoring,” *Int. J. Approx. Reason.*, vol. 16, no. 1, pp. 89–117, 1997.

[39] I. Inasaki, “Application of acoustic emission sensor for monitoring machining processes,” *Ultrasonics*, pp. 273–281, 1998.

[40] G. Bryne, D. Dornfeld, I. Inasaki, W. Ketteler, and R. Teti, “Tool Condition Monitoring (TCM) - The Status of Research and Industrial Application,” *CIRP Ann. - Manuf. Technol.*, vol. 44, no. 2, pp. 541–567, 1995.

[41] C. Kaner, “Quality Cost Analysis: Benefits and Risks,” no. 1990. 1996.

[42] P. A. Osanaiye, “An Economic Choice of Sampling Inspection Plans under Varying Process Quality.,” *J. R. Stat. Soc. Ser. C (Applied Stat.*, vol. 38, no. 2, p. 301, 1989.

[43] A. Schiffauerova and V. Thomson, “A review of research on cost of quality models and best practices,” *Int. J. Qual. Reliab. Manag.*, vol. 23, no. 6, pp. 647–669, 2006.

[44] H. Zaklouta, “Cost of quality tradeoffs in manufacturing process and inspection strategy selection,” Massachusetts Institure of Technology, 2011.

[45] S. Suthummanon and N. Sirivongpaisal, “Investigating the relationship between quality and cost of quality in a wholesale company,” *J. Oper. Manag.*, vol. 21, no. 4, pp. 1–13, 2003.

[46] B. P. M. Duarte, N. M. C. Oliveira, and L. O. Santos, “Dynamics of quality improvement programs - Optimal investment policies,” *Comput. Ind. Eng.*, vol. 91, pp. 215–228, 2016.

[47] D. R. Reid and N. R. Sanders, *Operations Management: An Integrated Approach*, 5th ed. Wiley, 2013.

[48] S. A. Vander Wiel and S. B. Vardeman, “A discussion of all-or-none inspection policies,” *Technometrics*, vol. 36, no. 1, pp. 102–109, 1994.

[49] AccountingVerse, “Manufacturing Cycle Efficiency (MCE),” *Managerial Accounting*, 2017. [Online]. Available: http://www.accountingverse.com/managerial-accounting/responsibility-accounting/manufacturing-cycle-efficiency.html. [Accessed: 10-Oct-2017].

[50] G. Rider, S. Milkovich, D. Stool, T. Wiseman, C. Doran, and X. Chen, “Quantitative risk analysis,” *Int. J. Inj. Contr. Saf. Promot.*, vol. 7, no. 2, pp. 115–133, 2000.

[51] L. A. Zadeh, “Fuzzy sets,” *Inf. Control*, vol. 8, no. 3, pp. 338–353, 1965.

[52] M. Hellmann, “Fuzzy Logic Introduction,” *Universite de Rennes 1, UFR*, vol. 18, no. 1. pp. 319–328, 2001.

[53] F. Dernoncourt, “Introduction to Fuzzy Logic Control,” no. 1. MIT, Massachusetts, pp. 1–20, 2013.

[54] K. M. Passino and S. Yurkovich, *Fuzzy Control*, 1st ed. Menlo Park: Addision Wesley Longman, Inc, 1998.

[55] L. A. Zadeh, “Fuzzy logic systems: origin, concepts, and trends,” *Computer Science Division, Department of EECS, UC Berkeley*, 2004. [Online]. Available: wi-consortium.org/wicweb/pdf/Zadeh.pdf. [Accessed: 05-May-2016].

[56] T. J. Ross, *Fuzzy Logic with Engineering Applications*, 1st ed. Michigan: McGraw-Hill, 1995.

[57] M. R. Abdi and A. W. Labib, “Feasibility study of the tactical design justification for reconfigurable manufacturing systems using the fuzzy analytical hierarchical process,” *Int. J. Prod. Res.*, vol. 42, no. 15, pp. 3055–3076, 2004.

[58] S. Ioannidis, N. Tsourveloudis, and K. Valavanis, “Fuzzy Supervisory Control of Manufacturing Systems,” *IEEE Trans. Robot. Autom.*, vol. 20, no. 3, pp. 379–389, 2004.

[59] S. X. Bai and S. B. Gershwin, “Scheduling manufacturing systems with work-in-process inventory control: Formulation of single part type systems,” in *29th IEEE Conference on Decision and Control*, 1990, pp. 557–564.

[60] L. Custodio, J. Senteiro, and C. Bispo, “Production planning and scheduling using a fuzzy decision system,” *IEEE Trans. Robot. Autom.*, vol. 10, no. 2, pp. 160–168, 1994.

[61] N. Tsourveloudis, E. Dretoulakis, and S. Ioannidis, “Fuzzy work-in-process inventory control of unreliable manufacturing systems,” *Inf. Sci. (Ny).*, vol. 127, no. 1–2, pp. 69–83, 2000.

[62] S. X. Bai and S. B. Gershwin, “Scheduling manufacturing systems with work-in-process inventory control: multiple-part-type systems,” *Int. J. Prod. Res.*, vol. 32, no. 2, pp. 365–386, 1994.

[63] S. X. Bai and S. B. Gershwin, “Scheduling manufacturing systems with work-in-process inventory control: single-part-type systems,” *IEE Trans.*, vol. 27, pp. 599–617, 1995.

[64] B. K. Wong and V. S. Lai, “A survey of the application of fuzzy set theory in production and operations management: 1998-2009,” *Int. J. Prod. Econ.*, vol. 129, no. 1, pp. 157–168, 2011.

[65] A. Azadegan, L. Porobic, S. Ghazinoory, P. Samouei, and A. Saman Kheirkhah, “Fuzzy logic in manufacturing: A review of literature and a specialized application,” *Int. J. Prod. Econ.*, vol. 132, no. 2, pp. 258–270, 2011.

[66] F. T. S. Chan, H. K. Chan, and A. Kazerooni, “Real time fuzzy scheduling rules in FMS,” *J.*

Intell. Manuf., vol. 14, no. 3–4, pp. 341–350, 2003.

[67] L. Yaqiong, L. K. Man, and W. Zhang, “Fuzzy theory applied in quality management of distributed manufacturing system: A literature review and classification,” *Eng. Appl. Artif. Intell.*, vol. 24, no. 2, pp. 266–277, 2011.

[68] Y. Peng, “Intelligent condition monitoring using fuzzy inductive learning,” *J. Intell. Manuf.*, vol. 15, no. 3, pp. 373–380, 2004.

[69] H. Rowlands and L. R. Wang, “An Approach of Fuzzy Logic Evaluation and Control in SPC,” *Qual. Reliab. Eng. Int.*, vol. 16, no. April 1999, pp. 91–98, 2000.

[70] M. Al-Salamah, “Economic production quantity in batch manufacturing with imperfect quality, imperfect inspection, and destructive and non-destructive acceptance sampling in a two-tier market,” *Comput. Ind. Eng.*, vol. 93, pp. 275–285, 2016.

[71] B. Al-Najjar and I. Alsyouf, “Selecting the most efficient maintenance approach using fuzzy multiple criteria decision making,” *Int. J. Prod. Econ.*, vol. 84, pp. 85–100, 2003.

[72] N. Tsourveloudis, L. Doitsidis, and S. Ioannidis, “Work-in-process scheduling by evolutionary tuned fuzzy controllers,” *Int. J. Adv. Manuf. Technol.*, vol. 34, no. 7–8, pp. 748–761, 2007.

[73] O. Cordón, B. Gomide, F. Herrera, F. Hoffmann, and L. Magdalena, “Ten years of genetic fuzzy systems: current framework and new trends,” *Fuzzy Sets Syst.*, vol. 141, no. 1, pp. 5–31, 2004.

[74] S. M. Homayouni and N. Ismail, “Modeling and Simulation of Genetic Supervisory Fuzzy Controllers for Multi-Part-Type Production Line,” *Int. J. Eng. Technol.*, vol. 4, no. 1, pp. 114–122, 2007.

[75] S. M. Homayouni, S. H. Tang, and N. Ismail, “Development of genetic fuzzy logic controllers for complex production systems,” *Comput. Ind. Eng.*, vol. 57, no. 4, pp. 1247–1257, 2009.

[76] R. Conway, W. Maxwell, J. O. McClain, and L. Joseph Thomas, “The role of work-in-process inventory control: single-part-type systems,” *Oper. Res.*, vol. 36, no. 2, pp. 229–241, 1988.

[77] E. Dretoulakis, S. Ioannidis, and N. Tsourveloudis, “Distributed intelligent control of unreliable manufacturing systems,” in *Proceedings of the Third IMACS/IEEE International Multiconference on Circuits, Systems, Communication and Computers*, 1999.

[78] S. M. Homayouni, “Optimization of fuzzy logic controllers with genetic algorithm for two-part-type and re-entrant production systems,” Universiti Putra Malaysia, Malaysia, 2007.

[79] O. Cordón and F. Herrera, “A General Study on Genetic Fuzzy Systems,” *Sample Contributed Book*. pp. 33–57, 1993.

[80] R. K. Bhattacharjya, "Introduction to Genetic Algorithms." Department of Civil Engineering, Guwahati, pp. 1–90, 2008.

[81] J. Foran, "Optimisation of a Fuzzy Logic Controller Using Genetic Algorithms," Dublin City University, 2002.

[82] P. Bajpai and M. Kumar, "Genetic Algorithm–an Approach to Solve Global Optimization Problems," *Indian J. Comput. Sci. Eng.*, vol. 1, no. 3, pp. 199–206, 2010.

[83] B. Zupancic, M. Klopcic, and R. Karba, "Tuning of Fuzzy Logic Controller with Genetic Algorithm." pp. 1–6, 1993.

[84] MathWorks, "Fuzzy Logic Toolbox User's Guide," 2015. [Online]. Available: https://www.mathworks.com/help/pdf_doc/fuzzy/fuzzy.pdf. [Accessed: 01-Feb-2017].

[85] E. Lefeber and J. E. Rooda, "Modeling and Analysis of Manufacturing Systems," *Eindhoven Tech. Univ. Eindhoven*, vol. 1, pp. 1–22, 2006.

[86] A. Illidge, "An Automated Flexible Fixture System for Mass Customization," University of KwaZulu-Natal, 2016.

[87] A. Walker and G. Bright, "Stabilisation and control of configurable product manufacturing through Biased Decision Feedback decoupling," *J. Manuf. Syst.*, vol. 32, pp. 271–280, 2013.

[88] Abel Automatics Inc., "Fly Reels," 2012. [Online]. Available: https://abelreels.com/. [Accessed: 10-Oct-2017].

[89] Nautilus Reels, "Custom Colors," 2012. [Online]. Available: https://www.nautilusreels.com/custom-shop/custom-colors/. [Accessed: 10-Oct-2017].

[90] K. E. Permana and S. Z. M. Hashim, "Fuzzy membership function generation using particle swarm optimization," *Int. J. Open Probl. Compt. Math*, vol. 3, no. 1, 2010.

Appendices

Appendix A: Fuzzy Logic Controller Rule-Bases

Table A.1: Rule-Base for the HDF Controllers

Rule	Upstream Buffer Level	Downstream Buffer Level	Machine State	Defect Rate	Production Surplus	Inspection Intensity	Weight
1	0	0	Running	Extreme High	0	Extreme High	1
2	0	0	Running	Moderate High	0	Very High	1
3	0	0	Running	Average	0	High	1
4	0	0	Running	Moderate Low	0	Medium	1
5	0	0	Running	Extreme Low	0	Low	1
6	0	0	Repair	0	0	Extreme High	1
7	0	0	Transition	0	0	Extreme High	1
8	Almost Empty	Almost Empty	Running	Average	Negative	Low	1
9	Almost Empty	Almost Empty	Running	Average	Balanced	Medium	1
10	Almost Empty	Almost Empty	Running	Average	Positive	High	1
11	Almost Empty	Almost Empty	Running	Moderate Low	Negative	Very Low	1
12	Almost Empty	Almost Empty	Running	Moderate Low	Balanced	Low	1
13	Almost Empty	Almost Empty	Running	Moderate Low	Positive	Medium	1
14	Almost Empty	Almost Empty	Running	Moderate High	Negative	Medium	1
15	Almost Empty	Almost Empty	Running	Moderate High	Balanced	High	1
16	Almost Empty	Almost Empty	Running	Moderate High	Positive	Very High	1
17	Middle	Middle	Running	Average	Negative	Low	1
18	Middle	Middle	Running	Average	Balanced	Medium	1
19	Middle	Middle	Running	Average	Positive	High	1
20	Middle	Middle	Running	Moderate Low	Negative	Very Low	1

Rule	Upstream Buffer Level	Downstream Buffer Level	Machine State	Defect Rate	Production Surplus	Inspection Intensity	Weight
21	Middle	Middle	Running	Moderate Low	Balanced	Low	1
22	Middle	Middle	Running	Moderate Low	Positive	Medium	1
23	Middle	Middle	Running	Moderate High	Negative	Medium	1
24	Middle	Middle	Running	Moderate High	Balanced	High	1
25	Middle	Middle	Running	Moderate High	Positive	Very High	1
26	Almost Full	Almost Full	Running	Average	Negative	Low	1
27	Almost Full	Almost Full	Running	Average	Balanced	Medium	1
28	Almost Full	Almost Full	Running	Average	Positive	High	1
29	Almost Full	Almost Full	Running	Moderate Low	Negative	Very Low	1
30	Almost Full	Almost Full	Running	Moderate Low	Balanced	Low	1
31	Almost Full	Almost Full	Running	Moderate Low	Positive	Medium	1
32	Almost Full	Almost Full	Running	Moderate High	Negative	Medium	1
33	Almost Full	Almost Full	Running	Moderate High	Balanced	High	1
34	Almost Full	Almost Full	Running	Moderate High	Positive	Very High	1
35	Almost Empty	Almost Full	Running	Average	Negative	Low	1
36	Almost Empty	Almost Full	Running	Average	Balanced	Medium	1
37	Almost Empty	Almost Full	Running	Average	Positive	High	1
38	Almost Empty	Almost Full	Running	Moderate Low	Negative	Very Low	1
39	Almost Empty	Almost Full	Running	Moderate Low	Balanced	Low	1
40	Almost Empty	Almost Full	Running	Moderate Low	Positive	Medium	1
41	Almost Empty	Almost Full	Running	Moderate High	Negative	Medium	1

Rule	Upstream Buffer Level	Downstream Buffer Level	Machine State	Defect Rate	Production Surplus	Inspection Intensity	Weight
42	Almost Empty	Almost Full	Running	Moderate High	Balanced	High	1
43	Almost Empty	Almost Full	Running	Moderate High	Positive	Very High	1
44	Almost Full	Almost Empty	Running	Average	Negative	Low	1
45	Almost Full	Almost Empty	Running	Average	Balanced	Medium	1
46	Almost Full	Almost Empty	Running	Average	Positive	High	1
47	Almost Full	Almost Empty	Running	Moderate Low	Negative	Very Low	1
48	Almost Full	Almost Empty	Running	Moderate Low	Balanced	Low	1
49	Almost Full	Almost Empty	Running	Moderate Low	Positive	Medium	1
50	Almost Full	Almost Empty	Running	Moderate High	Negative	Medium	1
51	Almost Full	Almost Empty	Running	Moderate High	Balanced	High	1
52	Almost Full	Almost Empty	Running	Moderate High	Positive	Very High	1
53	Empty	Empty	Running	0	0	Extreme High	1
54	Full	Full	Running	0	0	Extreme High	1
55	Full	Empty	Running	0	0	Extreme Low	1
56	Empty	Full	Running	0	0	Extreme High	1

Table A.2: Rule-Base for the HSF Controllers

Rule	Batch Size	End Production Surplus Error	Work-In-Process Error	Multiplier	Weight
1	Initial	0	0	Initial	1
2	Cycle	Negative	0	Less One	1
3	Cycle	Balanced	0	One	1
4	Cycle	Positive	0	More One	1
5	Cycle	0	Negative	Less One	1
6	Cycle	0	Balanced	One	1
7	Cycle	0	Positive	More One	1

Appendix B: SimEvents® Models

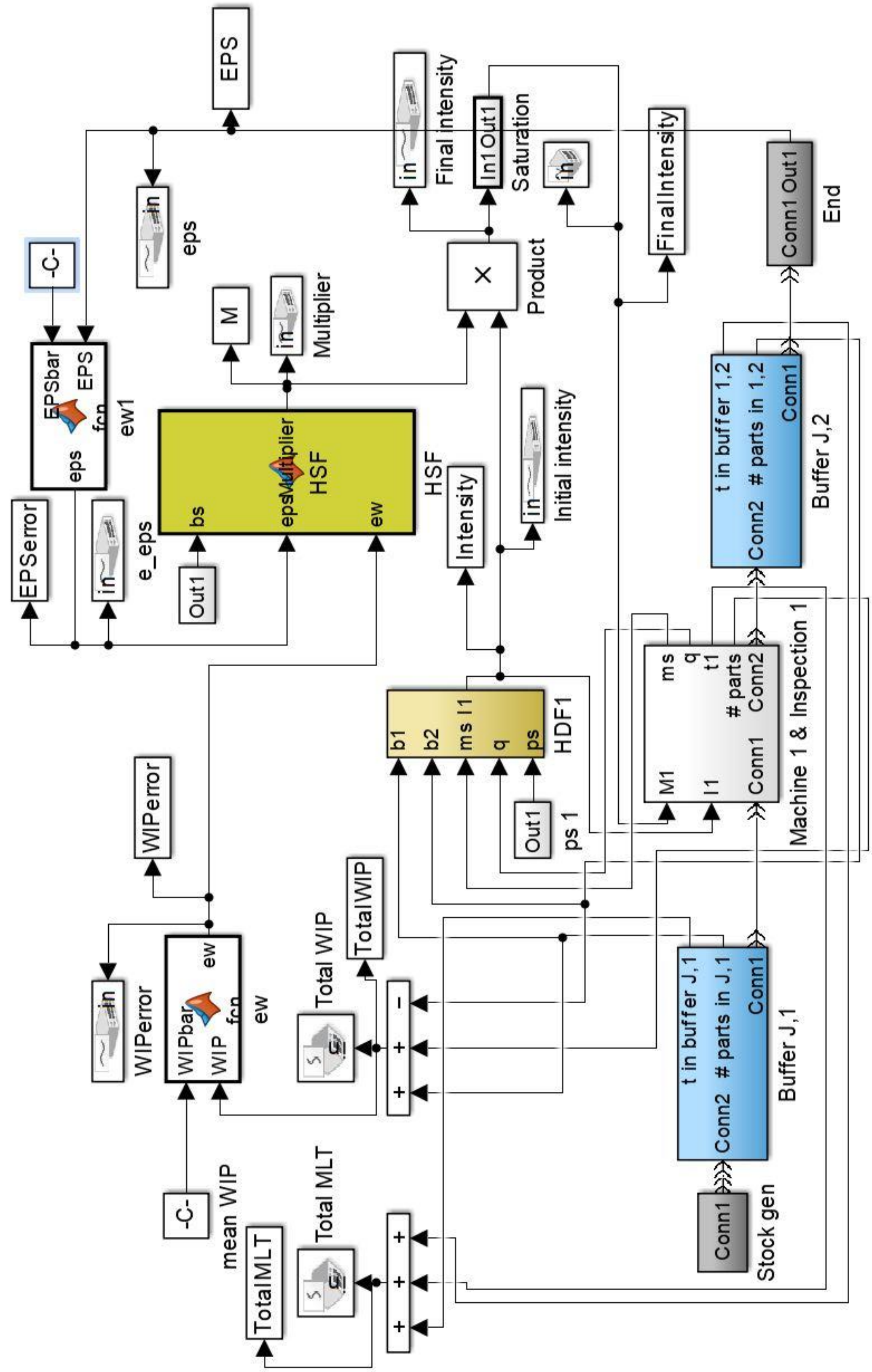

Figure B.1: SimEvents® Model for Transfer Line DES

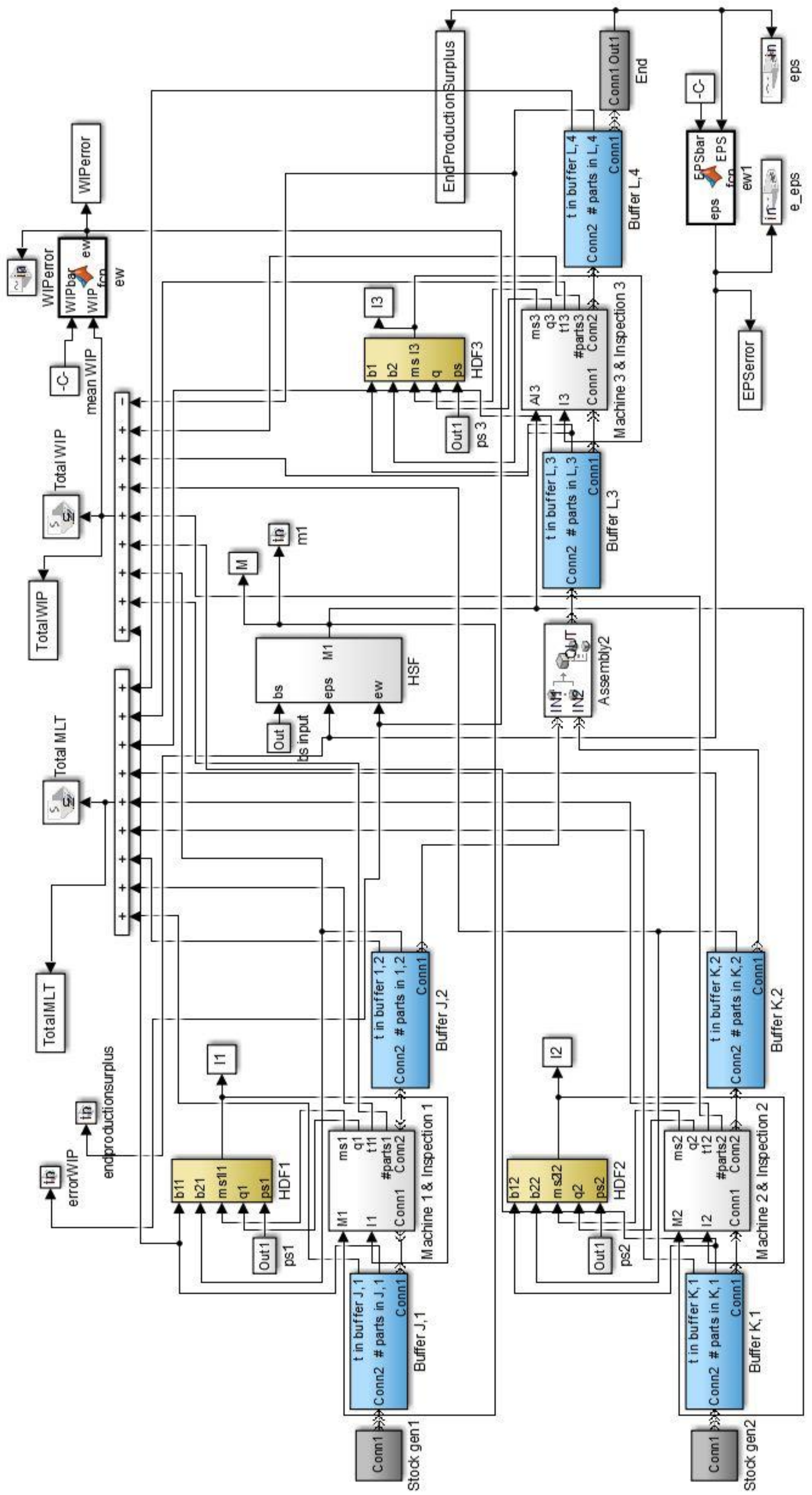

Figure B.2: SimEvents® Model for Assembly Module DES

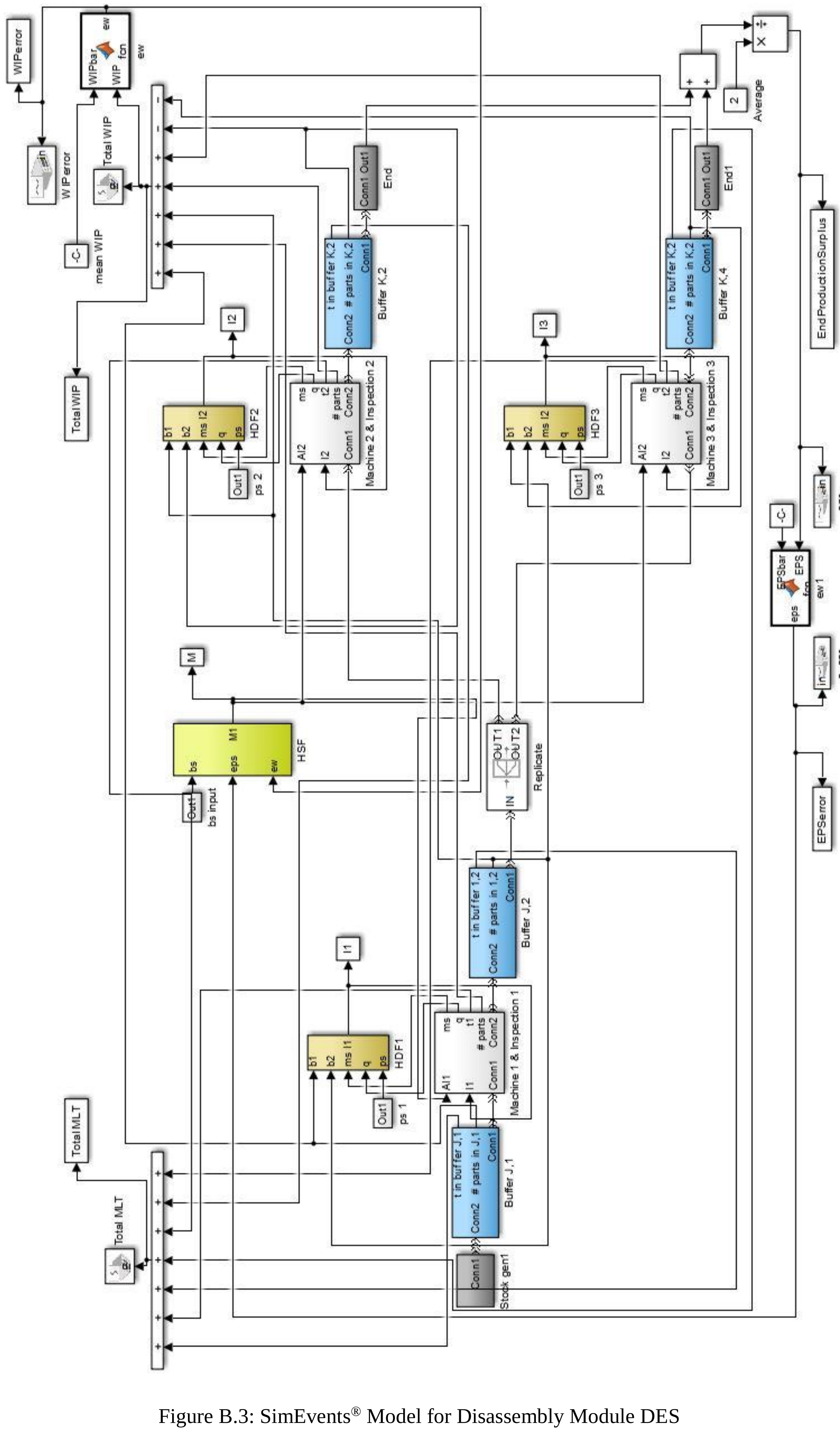

Figure B.3: SimEvents® Model for Disassembly Module DES

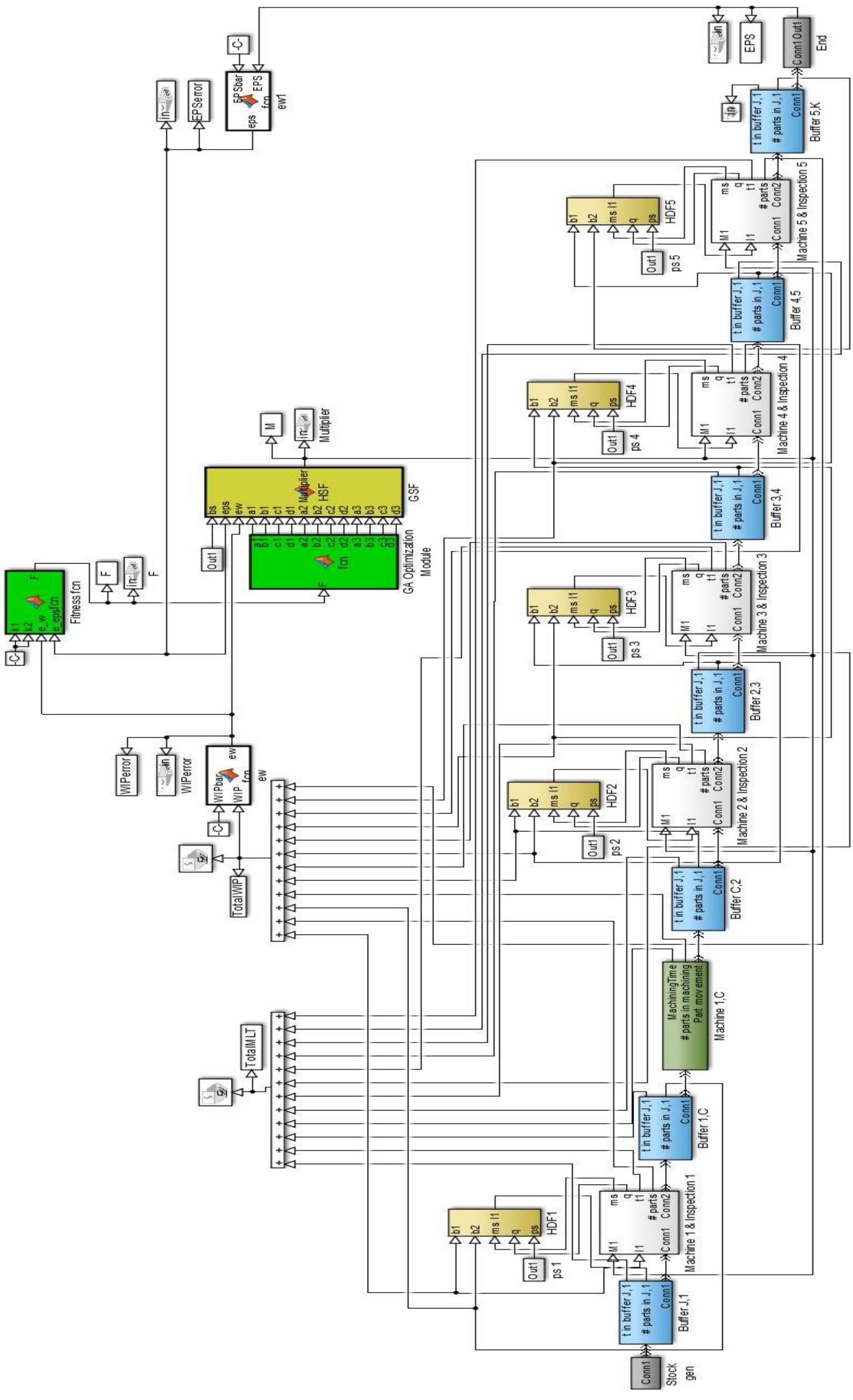

Figure B.4: SimEvents® Model for Slider Bearing DES

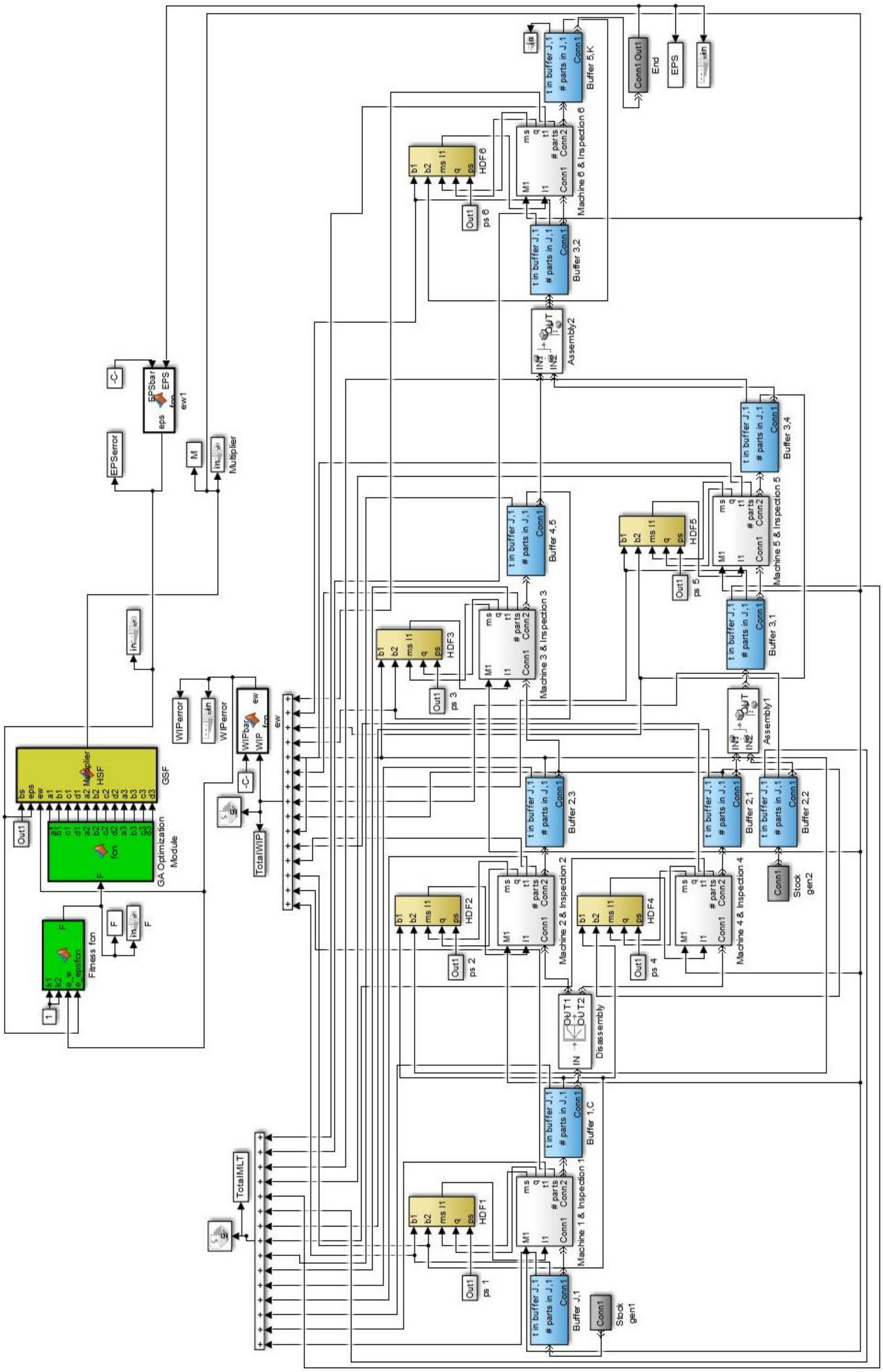

Figure B.5: SimEvents® Model for Tsourveloudis DES

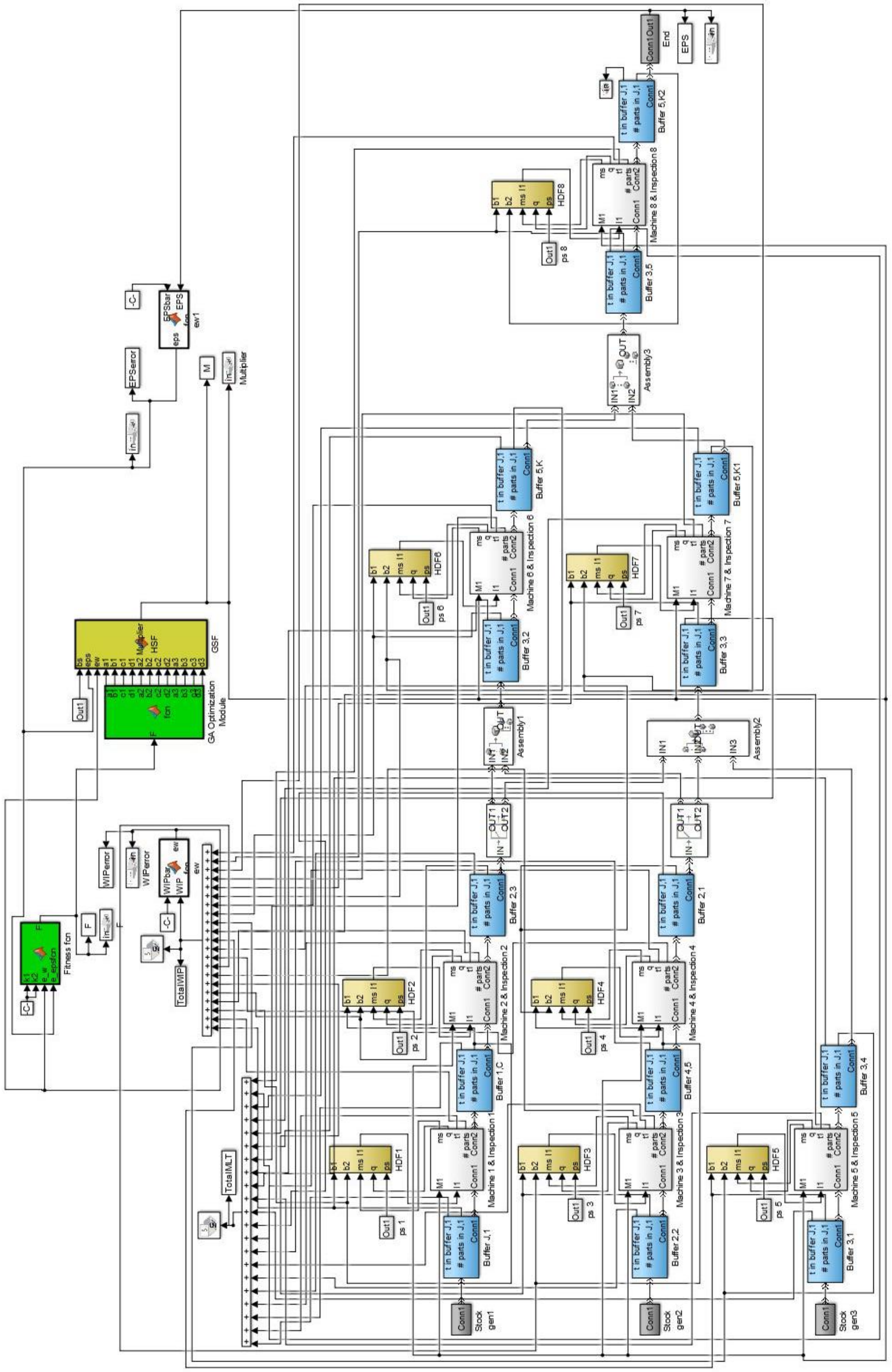

Figure B.6: SimEvents® Model for Fly Reel DES

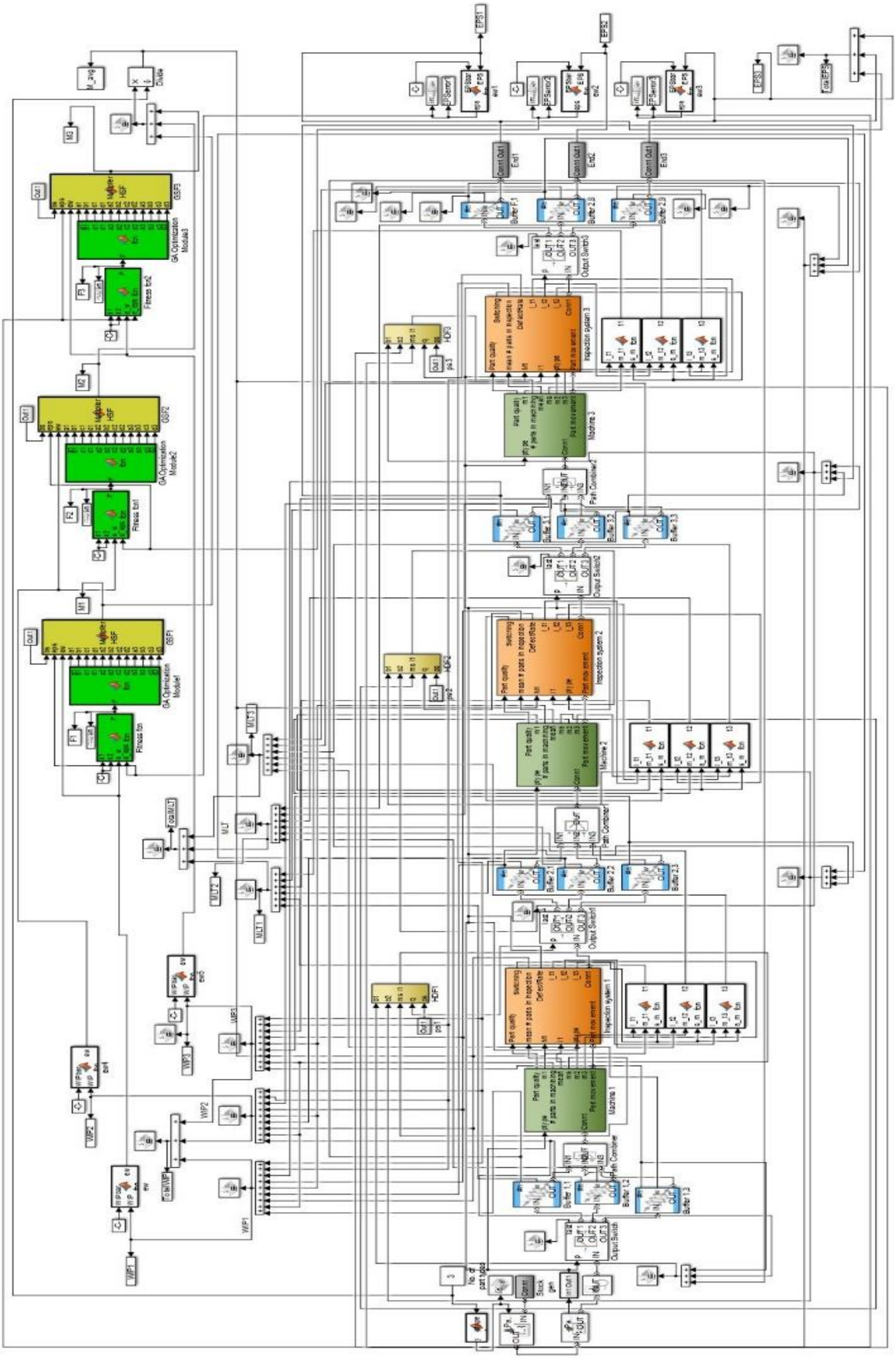

Figure B.7: SimEvents® Model for Three-Part-Type DES

Appendix C: Matlab® Code

Appendix C.1: Heuristic Distributed Fuzzy (HDF) Controller Matlab® Code

```
%Heuristic Distributed Fuzzy (HDF) controller
%%
% Inputs:
% Upstream buffer level = b1
% Downstream buffer level = b2
% Machine state = ms
% Part quality = q
% Production surplus = ps
% Output:
% Inspection intensity = I
%%
function I = HDF(b1,b2,ms,q,ps)
coder.extrinsic('newfis', 'addvar', 'addmf', 'plotmf', 'addrule', 'showfis',
'showrule', 'evalfis');
a =newfis('controller');
% Add upstream buffer level input: b1
a=addvar(a,'input','b1',[-0.1 1.1]);
a=addmf(a,'input',1,'Empty','trapmf',[-0.225 -0.025 0.025 0.225]);
a=addmf(a,'input',1,'AlmostEmpty','trapmf',[0.025 0.225 0.275 0.475]);
a=addmf(a,'input',1,'Middle','trapmf',[0.275 0.475 0.525 0.725]);
a=addmf(a,'input',1,'AlmostFull','trapmf',[0.525 0.725 0.775 0.975]);
a=addmf(a,'input',1,'Full','trapmf',[0.775 0.975 1.025 1.225]);
% Add downstream buffer level input: b2
a=addvar(a,'input','b2',[-0.1 1.1]);
a=addmf(a,'input',2,'Empty','trapmf',[-0.225 -0.025 0.025 0.225]);
a=addmf(a,'input',2,'AlmostEmpty','trapmf',[0.025 0.225 0.275 0.475]);
a=addmf(a,'input',2,'Middle','trapmf',[0.275 0.475 0.525 0.725]);
a=addmf(a,'input',2,'AlmostFull','trapmf',[0.525 0.725 0.775 0.975]);
a=addmf(a,'input',2,'Full','trapmf',[0.775 0.975 1.025 1.225]);
% Add machine state input: ms
a=addvar(a,'input','ms',[-0.1 1.1]);
a=addmf(a,'input',3,'Repair','trapmf', [-0.45 -0.05 0.4 0.45]);
a=addmf(a,'input',3,'Transition','trapmf', [0.4 0.45 0.55 0.6]);
a=addmf(a,'input',3,'Running','trapmf', [0.55 0.6 1.05 1.45]);
% Add defect rate input: q
a=addvar(a,'input','DefectRate',[-0.1 1.1]);
a=addmf(a,'input',4,'ExtremeLow','trapmf',[-0.225 -0.025 0.025 0.225]);
a=addmf(a,'input',4,'ModerateLow','trapmf',[0.025 0.225 0.275 0.475]);
a=addmf(a,'input',4,'Average','trapmf',[0.275 0.475 0.525 0.725]);
a=addmf(a,'input',4,'ModerateHigh','trapmf',[0.525 0.725 0.775 0.975]);
a=addmf(a,'input',4,'ExtremeHigh','trapmf',[0.775 0.975 1.025 1.225]);
% Add production surplus input: ps
a=addvar(a,'input','ps',[-1.1 1.1]);
a=addmf(a,'input',5,'Negative','sigmf',[-55 -0.212]);
a=addmf(a,'input',5,'Balanced','trapmf',[-0.5 -0.1 0.1 0.5]);
a=addmf(a,'input',5,'Positive','sigmf',[55 0.212]);
% Add inspection intensity output: I
a=addvar(a,'output','I',[-0.1 1.2]);
a=addmf(a,'output',1,'ExtremeLow','trapmf',[-0.15 -0.01667 0.01667 0.15]);
a=addmf(a,'output',1,'VeryLow','trapmf',[0.11667 0.25 0.2833 0.4167]);
a=addmf(a,'output',1,'Low','trapmf',[0.2833 0.4167 0.45 0.5833]);
a=addmf(a,'output',1,'Medium','trapmf',[0.5145 0.6 0.728 0.81]);
a=addmf(a,'output',1,'High','trapmf',[0.723 0.83 0.889 1.001]);
a=addmf(a,'output',1,'VeryHigh','trapmf',[0.898 0.963 1.023 1.065]);
a=addmf(a,'output',1,'ExtremeHigh','trapmf',[1 1.055 1.15 1.2]);
RuleList=[...
    0 0 3 5 0 7 1 1
    0 0 3 4 0 6 1 1
    0 0 3 3 0 5 1 1
    0 0 3 2 0 4 1 1
    0 0 3 1 0 3 1 1
    0 0 1 0 0 7 1 1
    0 0 2 0 0 7 1 1
```

```
    2  2  3  3  1  3  2  1
    2  2  3  3  2  4  1  1
    2  2  3  3  3  5  1  1
    2  2  3  2  1  2  1  1
    2  2  3  2  2  3  1  1
    2  2  3  2  3  4  1  1
    2  2  3  4  1  4  1  1
    2  2  3  4  2  5  1  1
    2  2  3  4  3  6  1  1
    3  3  3  3  1  3  1  1
    3  3  3  3  2  4  1  1
    3  3  3  3  3  5  1  1
    3  3  3  2  1  2  1  1
    3  3  3  2  2  3  1  1
    3  3  3  2  3  4  1  1
    3  3  3  4  1  4  1  1
    3  3  3  4  2  5  1  1
    3  3  3  4  3  6  1  1
    4  4  3  3  1  3  1  1
    4  4  3  3  2  4  1  1
    4  4  3  3  3  5  1  1
    4  4  3  2  1  2  1  1
    4  4  3  2  2  3  1  1
    4  4  3  2  3  4  1  1
    4  4  3  4  1  4  1  1
    4  4  3  4  2  5  1  1
    4  4  3  4  3  6  1  1
    2  4  3  3  1  3  1  1
    2  4  3  3  2  4  1  1
    2  4  3  3  3  5  1  1
    2  4  3  2  1  2  1  1
    2  4  3  2  2  3  1  1
    2  4  3  2  3  4  1  1
    2  4  3  4  1  4  1  1
    2  4  3  4  2  5  1  1
    2  4  3  4  3  6  1  1
    4  2  3  3  1  3  1  1
    4  2  3  3  2  4  1  1
    4  2  3  3  3  5  1  1
    4  2  3  2  1  2  1  1
    4  2  3  2  2  3  1  1
    4  2  3  2  3  4  1  1
    4  2  3  4  1  4  1  1
    4  2  3  4  2  5  1  1
    4  2  3  4  3  6  1  1
    1  1  3  0  0  7  1  1
    5  5  3  0  0  7  1  1
    5  1  3  0  0  1  1  1
    1  5  3  0  0  7  1  1
    ];
a=addrule(a,RuleList);
% Show controller
% showfis(a);
% showrule(a);


I = coder.nullcopy(zeros(size(q)));
I = evalfis([b1 b2 ms q ps],a);
end
```

Appendix C.2: Heuristic Supervisory Fuzzy (HSF) Controller Matlab® Code

```
%Heuristic Supervisory Fuzzy (HSF) controller
%%
% Inputs:
% Batch size = bs
% End production surplus = eps
% WIP error = ew
```

```
% Output:
% Inspection intensity multiplier = M
%%
function Multiplier = HSF(bs,eps,ew)
coder.extrinsic('newfis', 'addvar', 'addmf', 'plotmf', 'addrule', 'showfis',
'showrule', 'evalfis');
b =newfis('controller');
% Add batch size input: bs
b=addvar(b,'input','bs',[-0.1 1.1]);
b=addmf(b,'input',1,'Initial','trapmf',[-0.9 -0.1 0.2376 0.309]);
b=addmf(b,'input',1,'Cycle','trapmf',[0.281 0.284 1.1 1.9]);
% Add end production surplus input error: e_eps
b=addvar(b,'input','e_eps',[-2.1 2.1]);
b=addmf(b,'input',2,'Negative','sigmf', [-55 -0.3112]);
b=addmf(b,'input',2,'Balanced','trapmf',  [-0.99 -0.11 0.11 0.99]);
b=addmf(b,'input',2,'Positive','sigmf',  [55 0.3112]);
% Add WIP error: ew
b=addvar(b,'input','ew',[-2.1 2.1]);
b=addmf(b,'input',3,'Negative','sigmf', [-55 -0.3112]);
b=addmf(b,'input',3,'Balanced','trapmf',  [-0.99 -0.11 0.11 0.99]);
b=addmf(b,'input',3,'Positive','sigmf',  [55 0.3112]);
% Add Inspection Multiplier output: M
b=addvar(b,'output','M',[0 4]);
b=addmf(b,'output',1,'LessOne','trapmf', [0 0.3 0.6 0.9]);
b=addmf(b,'output',1,'One','trapmf', [0.6 0.9 1.1 1.4]);
b=addmf(b,'output',1,'MoreOne','trapmf', [1.1 1.4 1.7 2]);
b=addmf(b,'output',1,'Initial','trapmf', [3.027 3.23 3.56 3.8]);
RuleList=[...
    1 0 0 4 1 1
    2 1 0 1 1 1
    2 2 0 2 1 1
    2 3 0 3 1 1
    2 0 1 1 1 1
    2 0 2 2 1 1
    2 0 3 3 1 1
    ];
b=addrule(b,RuleList);
% Show controller
% showfis(a);
% showrule(a);
Multiplier = coder.nullcopy(zeros(size(bs)));
Multiplier = evalfis([bs eps ew],b);
end
```

Appendix C.3: Genetic Supervisory Fuzzy (GSF) Controller Matlab® Code

```
%Genetic Supervisory Fuzzy (GSF) controller
%%
% Inputs:
% Batch size = bs
% End production surplus = eps
% WIP error = ew
% Output:
% Inspection intensity multiplier = M
%%
function Multiplier = GSF(bs,eps,ew,a1,b1,c1,d1,a2,b2,c2,d2,a3,b3,c3,d3)
coder.extrinsic('newfis', 'addvar', 'addmf', 'plotmf', 'addrule', 'showfis',
'showrule', 'evalfis');
b =newfis('controller');
% Add batch size input: bs
b=addvar(b,'input','bs',[-0.1 1.1]);
b=addmf(b,'input',1,'Initial','trapmf',[-0.9 -0.1 0.2376 0.309]);
b=addmf(b,'input',1,'Cycle','trapmf',[0.281 0.284 1.1 1.9]);
% Add end production surplus input: eps
b=addvar(b,'input','eps',[-2.1 2.1]);
b=addmf(b,'input',2,'Negative','sigmf', [-55 -0.3112]);
b=addmf(b,'input',2,'Balanced','trapmf',  [-0.99 -0.11 0.11 0.99]);
b=addmf(b,'input',2,'Positive','sigmf',  [55 0.3112]);
```

```
% Add WIP error: ew
b=addvar(b,'input','ew',[-2.1 2.1]);
b=addmf(b,'input',3,'Negative','sigmf', [-55 -0.3112]);
b=addmf(b,'input',3,'Balanced','trapmf',  [-0.99 -0.11 0.11 0.99]);
b=addmf(b,'input',3,'Positive','sigmf',  [55 0.3112]);
% Add Inspection Multiplier output: M
b=addvar(b,'output','M',[0 10]);
b=addmf(b,'output',1,'LessOne','trapmf', [a1 b1 c1 d1]);
b=addmf(b,'output',1,'One','trapmf', [a2 b2 c2 d2]);
b=addmf(b,'output',1,'MoreOne','trapmf', [a3 b3 c3 d3]);
b=addmf(b,'output',1,'Initial','trapmf', [3.027 3.23 3.56 3.8]);
% figure (1)
% clf
% plotmf(b,'ouput',1)
RuleList=[...
    1 0 0 4 1 1
    2 1 0 1 1 1
    2 2 0 2 1 1
    2 3 0 3 1 1
    2 0 1 1 1 1
    2 0 2 2 1 1
    2 0 3 3 1 1
    ];
b=addrule(b,RuleList);
% Show controller
% showfis(a);
% showrule(a);
Multiplier = coder.nullcopy(zeros(size(bs)));
Multiplier = evalfis([bs eps ew],b);
end
```

Appendix C.4: Genetic Algorithm (GA) Module Matlab® Code

Fitness Function

```
function F = fcn(k1,k2,e_w,e_eps)
%#codegen
F = k1*abs(e_w)+k2*abs(e_eps);
F=1/F;
```

Genetic Algorithm Optimisation Module

```
function TNGA
clear all
var=12; % Number of genes
n=20;   % Population
m0=100
nmutationG=20;
nmutationR=20;
nelit=2;
valuemin=[-1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1];     % Upper bound
valuemax=[5 5 5 5 5 5 5 5 5 5 5 5];      % Lower bound
nmutation=nmutationG+nmutationR;
sigma=0.9;
max1=zeros(nelit,var);
parent=zeros(n,var);
cu=[valuemin(1) valuemax(1) valuemin(2) valuemax(2) valuemin(3) valuemax(3)...
    valuemin(4) valuemax(4) valuemin(5) valuemax(5) valuemin(6) valuemax(6)...
    valuemin(7) valuemax(7) valuemin(8) valuemax(8) valuemin(9) valuemax(9)...
    valuemin(10) valuemax(10) valuemin(11) valuemax(11) valuemin(12)
valuemax(12)...
    ];
C = sort((horzcat((normrnd(0.5,sigma,[n 4])),(normrnd(1,sigma,[n
4])),normrnd(1.5,sigma,[n 4]))),2);  % Chromosomes
for l=1:var
    p=C(:,1);
end
initial=p;
m=m0;
maxvalue=ones(m,1)*-1e10;
```

```
maxvalue(m)=-1e5;
g=0;
meanvalue(m)=0;
    for i=1:n
        y(i)=fun00(p(i,:));
    end
    s=sort(y);
    maxvalue1(1:nelit)=s(n:-1:n-nelit+1);
    if nelit==0
        maxvalue1(1)=s(n);
        for i=1:n
            if y(i)==maxvalue1(1)
                max1(1,:)=p(i,:);
            end
        end
    end
    for k=1:nelit
        for i=1:n
            if y(i)==maxvalue1(k)
                max1(k,:)=p(i,:);
            end
        end
    end
    y=y-min(y)*1.02;
    sumd=y./sum(y);
    meanvalue=y./(sum(y)/n);
    for l=1:n
        sel=rand;
        sumds=0;
        j=1;
        while sumds<sel
            sumds=sumds+sumd(j);
            j=j+1;
        end
        parent(l,:)=p(j-1,:);
    end
    p=zeros(n,var);
        for j=1:ceil((n-nmutation-nelit)/2)
            t=rand*1.5-0.25;
            p(2*j-1,l)=t*parent(2*j-1,l)+(1-t)*parent(2*j,l);
            p(2*j,l)=t*parent(2*j,l)+(1-t)*parent(2*j-1,l);
        end
        for i=n-nmutation+1:n-nmutationR
            phi=1-2*rand;
            z=erfinv(phi)*(2^0.5);
            p(i,l)=z*sigma(l)+parent(i,l);
        end
        for i=n-nmutationR+1:n
            p(i,1:var)=valuemin(1:var)+rand(1,var).*(valuemax(1:var)-...
                valuemin(1:var));
        end
        for i=1:n
            for l=1:var
                if p(i,l)<valuemin(l)
                    p(i,l)=valuemin(l);
                elseif p(i,l)>valuemax(l)
                    p(i,l)=valuemax(l);
                end
            end
        end
    end
    p;
    m=m+1;
    max1;
    maxvalue(m)=maxvalue1(1);
    maxvalue00(m-m0)=maxvalue1(1);
    mean00(m-m0)=sum(s)/n;
    meanvalue(m)=mean00(m-m0);
```