A Framework for Creating Production and Inventory Control Strategies

By

OLADIPUPO A. OLAITAN
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Supervisors:

Dr. John Geraghty
Dr. Paul Young

Dublin City University
School of Mechanical & Manufacturing Engineering

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DECLARATION

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy (PhD) is entirely my own work, that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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TABLE OF CONTENTS

Page

DECLARATION .... **I**

ACKNOWLEDGEMENTS .... **II**

TABLE OF CONTENTS .... **III**

LIST OF FIGURES .... **VIII**

LIST OF TABLES .... **X**

LIST OF ABBREVIATIONS AND NOTATIONS .... **XII**

ABSTRACT .... **XV**

CHAPTER - 1: Introduction **1**

1.1 BACKGROUND **1**

1.2 MOTIVATION AND OBJECTIVES **2**

1.3 STRUCTURE OF THESIS **3**

CHAPTER - 2: Literature Review **5**

2.1 INTRODUCTION **5**

2.2 PRODUCTION CONTROL STRATEGIES **6**

2.2.1 Materials Requirements Planning – A Push Strategy 6
2.2.2 Traditional Kanban Control Strategy – A Pull Strategy 7
2.2.3 Constant Work in Progress (CONWIP) 9
2.2.4 Base Stock Control Strategy (BSCS) 10
2.2.5 Extended Kanban Control Strategy (EKCS) 11
2.2.6 Generalized Kanban Control Strategy (GKCS) 12

2.3 OTHER CLASSES OF PRODUCTION CONTROL STRATEGIES **14**

2.3.1 Bottleneck and Workload Oriented Concepts 14
2.3.2 Product Grouping Concepts 15
2.3.3 Flexible or Adaptive Control Strategies 16

2.4 HYBRID CONTROL STRATEGIES **16**

2.4.1 Hybrid Push-Pull 17
2.4.2 Other Hybrid Strategies 18

2.5 EXTENSION OF PULL PRODUCTION CONTROL STRATEGIES TO MULTIPRODUCT MANUFACTURING ENVIRONMENTS. 18

2.5.1 Kanban Allocation Policies 19
2.5.2 Dedicated Kanban Allocation Policy (DKAP) 20
2.5.3 Shared Kanban Allocation Policy (SKAP) 20
2.5.4 Logic of Operation of Kanban Allocation Policies Under EKCS and GKCS 22

2.6 HYBRID KANBAN ALLOCATION POLICY 25

2.7 SIMULATION MODELLING AND OPTIMISATION 28

2.7.1 Simulation Warmup Period 29
2.7.2 Simulation Run Length and Number of Replications 30
2.7.3 Performance Measures 31

2.8 MANUFACTURING SYSTEM OPTIMIZATION 33

2.8.1 Optimisation of Multiproduct Systems 35
2.8.2 Robustness of Pull Production Control Strategies 37
2.8.3 Design of Experiments for Sensitivity Analysis 38

2.9 REVIEW OF TECHNIQUES AND TOOLS FOR DESIGN OF EXPERIMENTS AND RESULTS ANALYSIS 39

2.9.1 Latin Hypercube Sampling for Design of Experiments 39
2.9.2 Stochastic Dominance Test of Robustness 40
2.9.3 ExtendSim – Simulation Modelling 42
2.9.4 JMP – LHS Design of Experiments and Results Analysis 42
2.9.5 ModelRisk – Stochastic Dominance Tests 42

2.10 KEY INSIGHTS FOR THIS RESEARCH FROM REVIEWED LITERATURE 43

CHAPTER - 3: Research Outline and Preliminary Comparison of Control Strategies 44

3.1 INTRODUCTION 44

3.2 RESEARCH OUTLINE 45

3.3 PRELIMINARY COMPARISON OF STRATEGIES 45

3.4 SETUP OF TWO PRODUCT SYSTEM AND EXPERIMENTS 46

3.4.1 Full Factorial Experiments at Two Levels of Products' Demand Variability ... 48
3.4.2 System Assumptions ... 49
3.4.3 Simulation Warmup Period ... 50
3.4.4 Simulation Run Length and Number of Replications ... 51
3.4.5 Common Random Number Seeds ... 52

3.5 SYSTEM OPTIMISATION ... 53

3.6 DESIGN OF EXPERIMENTS FOR SENSITIVITY ANALYSIS ... 56

3.7 RESULTS FROM SCENARIO 1: HIGH PRODUCT 1 VARIABILITY – LOW PRODUCT 2 VARIABILITY ... 57

3.7.1 Robustness of Products' Service Levels ... 57
3.7.2 Inventory Control Effectiveness of Strategies ... 60
3.7.3 Insights into Robustness of Strategies ... 61
3.7.4 Insights into Performance of Kanban Allocation Policies ... 62

3.8 CONCLUSIONS ... 65

CHAPTER - 4: Evaluation of Kanban Allocation Policies ... 66

4.1 INTRODUCTION ... 66

4.2 SECOND SET OF EXPERIMENTS FOR POLICY COMPARISONS ... 67

4.3 SYSTEM OPTIMISATION ... 67

4.4 RESULTS FROM COMPARISON OF POLICIES FOR EKCS AND GKCS ... 69

4.4.1 Criteria 1: Ability of Products to achieve Service Levels corresponding to their Demand Variability Levels ... 70
4.4.2 Criteria 2: Service Levels and WIP Control Robustness ... 79

4.5 IMPACT OF SENSITIVITY ANALYSIS FACTORS ... 80

4.5.1 Demand Variability of Products ... 81
4.5.2 Mean Time Between Demands ... 84
4.5.3 Level of Availability of Machines ... 89

4.6 INSIGHTS FOR THE DEVELOPMENT OF A NEW POLICY ... 93

4.6.1 Selection of Suitable Strategy for New Policy ... 94
4.6.2 Combination of Policies ... 98

4.7 SUMMARY AND CONCLUSIONS FROM THIS CHAPTER ... 99

CHAPTER - 5: Comparison of Proposed Policy against Existing Policies 100

5.1 INTRODUCTION 100

5.2 SETUP OF EIGHT PRODUCT SYSTEM AND EXPERIMENTS .. 101

5.2.1 Setup of Experimental Scenarios (Product Mix Scenarios) 102
5.2.2 SimPy – Simulation Modelling 105
5.2.3 Simulation Warmup Period, Run Length & Number of Replications 106

5.3 LOGIC OF OPERATION OF PROPOSED POLICY 108

5.4 SYSTEM OPTIMISATION 109

5.5 DESIGN OF EXPERIMENTS FOR SENSITIVITY ANALYSIS 116

5.6 RESULTS FROM COMPARISON OF PROPOSED POLICY AGAINST EXISTING POLICIES 117

5.6.1 50% System Capacity Load Level 119
5.6.2 72.5% System Capacity Load Level 121
5.6.3 95% System Capacity Load Level 124

5.7 Impacts of Demand Arrival Rates on Inventory 133

5.8 Conclusions from this Chapter 136

CHAPTER - 6: Conclusions & Recommendations 139

6.1 INTRODUCTION 139

6.2 KEY FINDINGS AND CONTRIBUTIONS 140

6.3 IMPACT OF THIS WORK 141

6.4 FURTHER WORK 142

REFERENCES 144

LIST OF PUBLICATIONS 159

EU-FP7 DREAM PROJECT RESEARCH 160

DEMONSTRATIONS AND TUTORING 161

APPENDIX - A : TWO PRODUCT SYSTEM'S LHS RUNS TABLES A-1

APPENDIX - B : LHS RUNS WITH STATISTICALLY SIGNIFICANT DIFFERENCE IN PRODUCTS' SERVICE LEVELS UNDER DKAP **B-1**

APPENDIX - C : ROBUSTNESS OF PRODUCT SERVICE LEVELS UNDER DKAP and SKAP **C-1**

APPENDIX - D : IMPACT OF VARIATION IN PRODUCTS' DEMAND VARIABILITY **D-1**

APPENDIX - E : IMPACT OF VARIATION IN PRODUCTS' MEAN TIME BETWEEN DEMANDS **E-1**

APPENDIX - F : IMPACT OF THE LEVEL OF AVAILABILITY OF STAGES... .... **F-1**

APPENDIX - G : EIGHT PRODUCT SYSTEM'S OPTIMISED SETTINGS AND LHS RUNS TABLES **G-1**

APPENDIX - H : GROUP SERVICE LEVEL ROBUSTNESS **H-1**

APPENDIX - I : IMPACTS OF MEAN DEMAND ARRIVAL RATES **I-1**

LIST OF FIGURES

Page

Figure 2-1: The Kanban Control Strategy from [10] 8
Figure 2-2: The CONWIP strategy 9
Figure 2-3: The Base Stock Control Strategy 10
Figure 2-4: The Extended Kanban Control Strategy from [10] 11
Figure 2-5: The Generalized Kanban Control Strategy from [10] 12
Figure 2-6: DKAP in a Multiproduct environment 20
Figure 2-7: SKAP in a Multiproduct environment.. 21
Figure 2-8: Operation of the DKAP under the EKCS from [10] 23
Figure 2-9: Operation of the SKAP under the EKCS from [10] 23
Figure 2-10: Operation of the DKAP under the GKCS from [10] 24
Figure 2-11: Operation of the SKAP under the GKCS from [10]............................... 25
Figure 2-12: First Order Dominance [172] 40
Figure 2-13: Second Order Dominance [172]... 41
Figure 3-1: Simplified Two Product Manufacturing System.................................... 46
Figure 3-2: MTTF and MTTR of the manufacturing stages 46
Figure 3-3: CONWIP and BSCS Warmup period Welch graph............................... 51
Figure 3-4: Confidence Intervals for different replication numbers 52
Figure 3-5: Cumulative Density Function Plot for SL1 58
Figure 3-6: Cumulative Density Function Plot for SL2 58
Figure 3-7: Cumulative Density Function Plot for WIP 60
Figure 3-8: EKCS DKAP SLs for Products 1 and 2 63
Figure 3-9: EKCS SKAP SLs for Products 1 and 2 63
Figure 3-10: GKCS DKAP SLs for Products 1 and 2 64
Figure 3-11: GKCS SKAP SLs for Products 1 and 2 64
Figure 4-1: SLs under EKCS DKAP and SKAP (Scenario 2) 72
Figure 4-2: Significant Differences in SL1 and SL2 EKCS (Scenario 3).................. 73
Figure 4-3: SLs under EKCS DKAP and SKAP (Scenario 3) 74
Figure 4-4: Significant Differences in SL1 and SL2 EKCS DKAP (Scenario 4)...... 75
Figure 4-5: SLs under GKCS DKAP and SKAP (Scenario 2).................................. 77

Figure 4-6: Significant Differences in SL1 and SL2 GKCS DKAP (Scenario 3) 77
Figure 4-7: Significant Differences in SL1 and SL2 GKCS DKAP (Scenario 4) 78
Figure 4-8: Correlation between SL1 and SL2 79
Figure 4-9: Mean Demand Impact on SLs and WIP EKCS (Scenario 4) 88
Figure 4-10: Stage Avail. Impact on SLs and WIP GKCS SKAP (Scenario 1) 91
Figure 4-11: SKAP Demand, Part and Kanban synchronisation from [10] 96
Figure 4-12: Suitability of strategies and corresponding policies 99
Figure 5-2: Warmup Period estimation for Eight Product System 107
Figure 5-1: HKAP Logic of Operation 109
Figure 5-3: ACO Path Representation 110
Figure 5-4: ACO Paths for Stage 1 after Pheromone Update 111
Figure 5-5: ACO process with Total Kanban cap 114
Figure 5-6: Group 1 Average SL Robustness – 50% Load Level Scenario 4 119
Figure 5-7: Group SL Robustness – 72.5% Load Level Scenario 2 122
Figure 5-8: WIP across LHS Runs at 72.5% Load Level (Scenario 2) 123
Figure 5-9: Group SL Robustness – 95% Load Level Scenario 4 125
Figure 5-10: Products 5-8 Demand Arrival rate impact on SLs 130
Figure 5-11: Products' Demand Arrival rates impact on WIP 135
Figure 5-12: Suitability of strategies and corresponding policies 137

LIST OF TABLES

Page

Table 2-1: LHS factor division and sampling 40
Table 3-1: Setting Products' Mean Times between Demands 47
Table 3-2: Demand CV Levels for the Products 48
Table 3-3: Experimental Scenarios 48
Table 3-4: Strategies and Policies for the First Set of Experiments 49
Table 3-5: Scenario 1: BSCS Solution Space and Optimal Settings 55
Table 3-6: Scenario 1: KCS Solution Space and Optimal Settings 55
Table 3-7: Scenario 1: EKCS DKAP Sample Space and Optimised Settings 55
Table 3-8: Scenario 1: EKCS SKAP Sample Space and Optimised Settings 55
Table 3-9: Scenario 1: GKCS DKAP Sample Space and Optimised Settings 56
Table 3-10: Scenario 1: GKCS SKAP Sample Space and Optimised Settings 56
Table 3-11: Part One Experiments: LHS Ranges for Sensitivity Analysis 57
Table 3-12: Product 1 SL Robustness Test results 59
Table 3-13: Product 2 SL Robustness Test results 59
Table 3-14: Average System WIP Robustness Test results 61
Table 4-1: Scenarios 3 to 4 (Second Set of Experiments) 67
Table 4-2: Optimised S and AK for EKCS DKAP and SKAP 68
Table 4-3: Optimised S and AK for GKCS DKAP and SKAP 69
Table 4-4: Policies' ability to differentiate product performances under EKCS 71
Table 4-5: Policies' ability to differentiate product performances under GKCS 76
Table 4-6: Stochastic Dominance Comparison of EKCS DKAP & SKAP 80
Table 4-7: Stochastic Dominance Comparison of GKCS DKAP & SKAP 80
Table 4-8: Impact of Products' Demand CVs under EKCS DKAP 81
Table 4-9: Impact of Products' Demand CVs under EKCS SKAP 81
Table 4-10: Impact of Products' Demand CVs under GKCS DKAP 83
Table 4-11: Impact of Products' Demand CVs under GKCS SKAP 83
Table 4-12: Impact of Products' Demand Arrival Rates under EKCS DKAP 85
Table 4-13: Impact of Products' Demand Arrival Rates under EKCS SKAP 85
Table 4-14: Impact of Products' Demand Arrival Rates under GKCS DKAP 87
Table 4-15: Impact of Products' Demand Arrival Rates under GKCS SKAP 87

Table 4-16: Impact of Stage Availability Level under EKCS DKAP 90
Table 4-17: Impact of Stage Availability Level under EKCS SKAP 90
Table 4-18: Impact of Stage Availability Level under GKCS DKAP 91
Table 4-19: Impact of Stage Availability Level under GKCS SKAP......................... 91
Table 4-20: Stoch. Dominance Comparison of GKCS & EKCS (DKAPs)................ 94
Table 4-21: Stoch. Dominance Comparison of GKCS & EKCS (SKAPs) 94
Table 5-1: Eight Product System: Scenario 1 104
Table 5-2: Eight Product System: Scenario 2 105
Table 5-3: Eight Product System: Scenario 3 105
Table 5-4: Eight Product System: Scenario 4 105
Table 5-5: Eight Product System: Scenario 5 105
Table 5-6: Setting of Kanban and basestock under the three policies 108
Table 5-7: Sample Ant AK and S Settings... 110
Table 5-8: LHS Ranges for Sensitivity Analysis on Eight Product System 116
Table 5-9: Significant declines in Group Average SLs – 50% 119
Table 5-10: WIP Control Effectiveness – 50% Load Level 120
Table 5-11: Significant declines in Group Average SLs – 72.5% 121
Table 5-12: WIP Control Effectiveness – 72.5% Load Level 123
Table 5-13: Significant declines in Group Average SLs – 95% 124
Table 5-14: WIP Control Effectiveness – 95% Load Level 126
Table 5-15: Instances of Products' Demand Variation Impact................................ 127
Table 5-16: Demand Arrival rate impact on Product SLs (Scenario 1).................... 128
Table 5-17: Demand Arrival rate impact on Product SLs (Scenario 2).................... 129
Table 5-18: Demand Arrival rate impact on Product SLs (Scenario 3).................... 131
Table 5-19: Demand Arrival rate impact on Product SLs (Scenario 4).................... 132
Table 5-20: Demand Arrival rate impact on Product SLs (Scenario 5).................... 133

LIST OF ABBREVIATIONS AND NOTATIONS

ABBREVIATION	**EXPLANATION**
ACO	Ant Colony Optimisation
ADI	Advance Demand Information
BK-CONWIP	Basestock Kanban CONWIP
BSCS	Base Stock Control Strategy
C.I	Confidence Interval
CDF	Cumulative Density Function
CONFLOW	Constant Flow
CONLOAD	Constant Load
CONWIP	Constant Work In Progress
CONWORK	Constant Work
D	Demand Buffer
DBR	Drum Buffer Rope
DKAP	Dedicated Kanban Allocation Policy
EKCS	Extended Kanban Control Strategy
ERP	Enterprise Resource Planning
FIFO	First In First Out
GA	Genetic Algorithm
GKCS	Generalised Kanban Control Strategy
HKAP	Hybrid Kanban Allocation Policy
I	Input Part Buffer
ICT	Information and Communications Technology
IEKCS	Independent Extended Kanban Control Strategy
K	Total Kanban setting
KAP	Kanban Allocation Policy
KCS	Kanban Control Strategy
LHS	Latin Hypercube Sampling
M	Mean demand arrival rate
MP	Manufacturing Stage

MRP	Materials Requirements Planning
MRP II	Manufacturing Resource Planning
MS	Microsoft
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
Opt.	Optimised Setting
PA	Part + Kanban Buffer
PCS	Production Control Strategy
PFB	Pull From Buffer
POLCA	Paired-cell Overlapping Loops of Cards with Authorisation
PPCS	Pull Production Control Strategy
S	Basestock setting
SA	Starvation Avoidance
SEKCS	Simultaneous Extended Kanban Control Strategy
SKAP	Shared Kanban Allocation Policy
SL	Service Level
$SL1$	Service Level of Product 1
$SL2$	Service Level of Product 2
$SLG1$	Average Service Level of Group 1
$SLG2$	Average Service Level of Group 2
SLi	Service Level of Product i
T	Throughput rate
WIP	Work In Progress
WIPLOAD	Constant Work in Progress Load
λ	Product Demand Arrival rate
μ	Mean of Normal distribution
σ	Standard Deviation of Normal Distribution
τ	Product Processing time
CV	Coefficient of Variation
C	Probability of selection of a Kanban or basestock setting
A^j	Stage, j, Kanban Buffer
A^j_{Gi}	Stage, j, Group, i, Shared Kanban Buffer
AK	Extra Unattached Kanban setting

AK_{ij}	Number of unattached Kanbans for part type, i, at stage, j
DA_i^j	Stage, j, buffer for demands for part type, i, merged with Kanbans
D_i	Demand information for product, i
D_i^j	Stage, j, demand buffer for part type, i
$F_Y(x)$	Cumulative Density Function of x
K_d	Ratio of Demand Arrival rates between Group 1 and 2
K_i^j	Dedicated Kanban for product, i, at Stage, j
K^j	Shared Kanban for Stage, j
K_p	Ratio of Processing times between Group 1 and 2
PA_i^j	Stage, j, buffer for finished part type, i, with attached Kanban
P_i	Part type, i
P_i^j	Finished parts buffer for product, i, at Stage, j
S_{ij}	Basestock setting for product, i, at Stage, j
S_{ij}	Basestock level for for part type, i, at stage, j
$TK_{cap(i)}$	Total Kanban cap
n_{EltPop}	Size of elite population
n_{EltRep}	Number of ants in the elite population that have selected an AK or S
$n_{InitRep}$	Number of initial representations of an AK or S in the options list
n_{opt}	Total number of representations of all AK or S in the options list
n_{rep}	Number of representations of an AK or S in the options list

ABSTRACT

OLADIPUPO OLAITAN

A Framework for Creating Production and Inventory Control Strategies

In multiproduct manufacturing systems, it is difficult to assure that an optimised setting of a pull production control strategy will be able to maintain its service level and inventory control performances. This is because the competition for resources among products is liable to make them affect the service levels of one another.

By comparing different pull strategies, this research has observed that tightly coupled strategies are able to maintain lower amount of inventory than decoupled strategies, but they do so at the detriment of service level robustness. As a result, tightly coupled strategies are better suited to manufacturing environments with low variability, while decoupled strategies are more robust in high variability environments. Here, robustness is a measure of how well a strategy is able to minimise the drop below its original optimised service level when the initial system conditions change.

Furthermore, the Kanban allocation policy applied under a strategy plays a major role in its ability to manage the performances of multiple products. Experimental results show that the Shared Kanban Allocation Policy (SKAP) keeps a lower amount of inventory than the Dedicated Kanban Allocation Policy (DKAP), but it is more susceptible to the variability in the demand or processing times of one product impacting the service level of another. Therefore, a Hybrid Kanban allocation policy (HKAP) that combines both the DKAP and the SKAP has been implemented. This approach considers products' demand and processing time attributes before categorising them into the same Kanban sharing group. The results of the implementation of the HKAP show that it can keep as low inventory as the SKAP and avoid products impacting the service levels of one another. Additionally, it offers a better approach to managing large multiproduct systems, as the performances of product groups can be differentially managed through the combination of Kanban sharing and dedication policies.

Lastly, the observations on the performances of strategies and policies under different system conditions can be used as a framework through which line designers select strategies and policies to suit their manufacturing system.

CHAPTER - 1: Introduction

1.1 BACKGROUND

The aim of this research is to develop a new production and inventory control approach. To this end, it will look into the necessities that have led to the development of production and inventory control approaches in the past. It will also review the methodologies that were followed in the development of those approaches.

The Toyota manufacturing concept (also called Lean Manufacturing) was the first widely acknowledged success story of a manufacturing approach [1, 2]. The company's success in cutting down on waste and remaining responsive to customer demands generated a lot of interest in the industry. The development of the lean manufacturing concept led to the introduction of pull based manufacturing control where a product is only produced to meet a specific demand. The pull based control uses authorisation cards called Kanbans to limit the amount of inventory in the system to just what is needed to be immediately responsive to customer demands. It is called *pull* production control because it uses the Kanbans to also serve the purpose of pulling the parts through the system in response to arriving customer demands.

About the same period when the Lean Manufacturing concept and the Kanban control approach appeared, an approach called Material Requirements Planning (MRP) was developed to *push* items through the system in anticipation of demand forecasts [3]. It allowed companies to use computers to centrally coordinate the amount of inventory items kept within the system. The success of its central coordination of inventory must have encouraged the subsequent incorporation of other enterprise related functions into it. The widening of its scope beyond materials requirement planning thus made it to become known as Manufacturing Resource Planning (MRP II) [4] and later as the present day Enterprise Resource Planning (ERP), due to the incorporation of even more functions. Also, having realised that the original MRP had high throughput benefits which can be combined with the inventory control benefits of the Kanban control approach, from the mid-1980s, some researchers developed a hybrid push-pull concept that would combine the throughput benefits of the push (MRP) with the inventory control benefit of the pull (Kanban control approach) [5]. The hybrid strategy's push component was expected to loosen the pure pull strategy's inventory control which had become a deterrent for some high variability companies that wanted to adopt the pull strategy. It also improved the applicability of the pull approach to multiproduct manufacturing environments [6, 7].

Not too long afterwards was the development of the CONWIP – a pure pull strategy, which was also developed to suit manufacturing environments that are prone to different sources of variability [8]. Similar to the hybrid push-pull, its localised push control was expected to make it applicable to such environments. Over time, there have been numerous strategies developed from either combining existing ones or developing entirely new ones that still retain the original pull philosophy. These will be discussed in further details in Chapter 2.

1.2 MOTIVATION AND OBJECTIVES

As the application of pull control strategy extended into multiproduct environments more thought was given to the operational details of how the Kanban control was going to be operated among different products. A study suggested two possible approaches of either sharing Kanbans between the different products or dedicating separate sets of Kanbans to each one [9]. Prior to this study, the default assumption in literature was that each product would have its own set of Kanbans, and this is probably due to it being the straightforward extension from a single product environment. However, a later study which reinforced the two approaches contributed to the recently increased research interests in them [10]. The two were termed the Shared Kanban Allocation policy (SKAP) and the Dedicated Kanban Allocation policy (DKAP) [10]. Research works that have been done since then have found that the two policies have pros and cons that depend on the condition of the manufacturing system in which they are deployed [11-13], just like it has been observed with the push and the pull strategies [8, 14]. Interestingly, there has been no attempt in literature to combine both policies in the way it has been done with the push and the pull strategies.

Therefore, it is the aim of this research to fill this research gap by developing a framework for combining the two policies into a Hybrid Kanban Allocation policy (HKAP). This will be achieved by first conducting investigations into the behaviour of both policies before applying the outcomes in the implementation of the HKAP in a case study manufacturing system. The performance of the HKAP will then be compared against the pure application of either policy. The intended benefits of this HKAP policy are: (1) to achieve the benefits of both policies in the same system, (2) to use it in a way that the performance of multiple products can be differentially managed in a system by categorising them into different Kanban sharing groups.

This research is somewhat related to the simultaneous EKCS (SEKCS) and independent EKCS (IEKCS) approaches proposed in [15], or, to some extent, the independent and simultaneous traditional Kanban control policies of [16, 17]. However, the simultaneous and independent approaches are aimed specifically at managing the release of components in assembly lines, while this research is applicable to any system that involves the processing of multiple part types in at least one of its stages.

1.3 STRUCTURE OF THESIS

This thesis is organised into seven chapters. The present chapter gives a background of key breakthrough stages in the development of production and inventory control strategies. It briefly describes how research into this area has evolved over time from the pull, push to hybrid production control strategies.

Chapter 2 starts by briefly looking into the basis for the categorisation of production control strategies in general before going into further elaboration on the development of the specific production control strategies briefly described in Chapter 1. It reviews the techniques that have been applied in simulation modelling and optimisation of production control strategies. It discusses the techniques that have been applied in the comparison of strategies and how recent developments are shaping those techniques. It reviews the studies that have been the sources of those developments in relation to the bearing they might have on the conduct of this research.

Chapter 3 provides a brief overview of the sets of experiments involved in the thesis, followed by a detailed description of the setup of the first set of experiments on the two product system. It also covers the discussion of the results obtained from these experiments.

In chapter 4, the results obtained from the second set of experiments on the simplified two product system are presented. This chapter is then concluded with a general overview of the observations about the performance of the different strategies and their corresponding Kanban allocation policies. This overview also specifically highlights the key observations that would influence the conduct of the last set of experiments.

In Chapter 5, the outcomes of the comparisons of the performance of the HKAP against those of the pure DKAP and SKAP are presented. It shows the results of comparing the three policies' service level robustness performances, their inventory control effectiveness and their ability to differentiate the performances of product groups.

Chapter 6 concludes the thesis by presenting an overview of the general outcomes of this research, its achievements and contributions to this area of research. It highlights the research gap that has been filled by this work and discusses possible future work.

CHAPTER - 2: Literature Review

2.1 INTRODUCTION

This chapter describes the two main categories of production control strategies. In particular, it focusses on the pull category, which is studied in this work, by looking at how it has evolved over time. It discusses the approaches that have been followed to develop new strategies from the original pull strategy in order to achieve improved performances and widen its applicability to new manufacturing environments.

Also, as part of looking into these approaches, it will review the techniques generally applied in pull controlled manufacturing systems' simulation modelling and optimisation, and their experimentation and analysis, as well as those applied in comparing the performances of different strategies. The comparison has become a key aspect of production control strategies' research because as new strategies are being proposed, their performances have to be compared against existing ones. Furthermore, it will look at how the desire to extend the pull strategy into more complicated multiproduct environments is shaping those techniques.

The review starts in the following section by briefly looking into the basis for categorising production control strategies before going into more details on the pull strategy.

2.2 PRODUCTION CONTROL STRATEGIES

Production control strategies are often categorised as pull or push systems, meaning that they either wait for actual occurrence of demands to pull parts through the manufacturing system or, on the other hand, push parts through in anticipation of demands. Other definitions that are used to classify strategies as pull or push are as follows [18]:

a.) A pull strategy initiates production in response to actual demands for finished products, while a push's production is independent of demands,

b.) A pull strategy places explicit limit on the amount of system work in progress (WIP), while a push strategy does not have such explicit limit on the amount of system WIP.

However, a strategy that falls under pull category based on the first definition can as well be placed under the same category in the second definition, because, by only initiating production in response to actual demand, it would exhibit some level of control over its WIP, even if not very tight [19]. It means that every item released into the system in response to actual demands would only contribute to WIP for the duration of its cycle time, unless the system is unstable. Meanwhile, a strategy that falls under the pull category based on the second definition does not automatically fall under the same category based on the first definition, irrespective of its level of WIP control. The second definition is expected to be a natural outcome of strategies that fall under pull in the first two definitions. Therefore, a benefit of pull strategies is the ability to control inventory (WIP), while push systems can achieve higher throughput and consequently faster response to customer demands [8, 20].

2.2.1 Materials Requirements Planning – A Push Strategy

One of the earliest approaches to production and inventory control is Materials Requirements Planning (MRP) [3]. MRP controlled systems are run to achieve high throughput in anticipation of meeting demand forecasts. It estimates components and raw materials requirements through time-phased explosion of the Master Production Schedule (MPS) combined with the Bill of Materials (BOM) and the inventory status file [21].

MRP gained wide acceptability as a computerized planning system for job shop and batch manufacturing systems [20]. However, the possibility of using the lean manufacturing control concept to achieve a more effective inventory control than the MRP made it less attractive to some practitioners and researchers in that regard [21, 22]. Nevertheless, it remained applicable for its high throughput benefits and computerised central coordination of functions. In fact, there have been subsequent significant improvements that transformed the original MRP into Manufacturing Resource Planning (MRP II) [4] and later Enterprise Resource Planning (ERP), and these have along the line incorporated more enterprise-wide functionalities that go beyond production or materials requirements planning.

2.2.2 Traditional Kanban Control Strategy – A Pull Strategy

A production and inventory control strategy that aims to control the WIP of a system while still maintaining a satisfactory response to customer demands is the traditional Kanban Control Strategy (KCS). KCS was first applied in Toyota's assembly lines as an integral part of an overall management strategy called Lean or Just in Time (JIT) manufacturing [1, 2]. Other constituents of the JIT system are total quality control, set up time reduction, and worker involvement [8, 19]. These are identified as sources of variability to a system that will need to be reviewed before the strategy can be fully applied to a system.

KCS uses signal cards, known as Kanbans, to authorise the processing of parts at each stage of a manufacturing system in order to control the level of inventory in the system. The KCS, as a materials handling technique, allows perfect synchronization between what the downstream station requires and what the upstream station produces [23, 24], and it does not necessarily have to be a physical card but can be represented by electronic boards or by the WIP container itself.

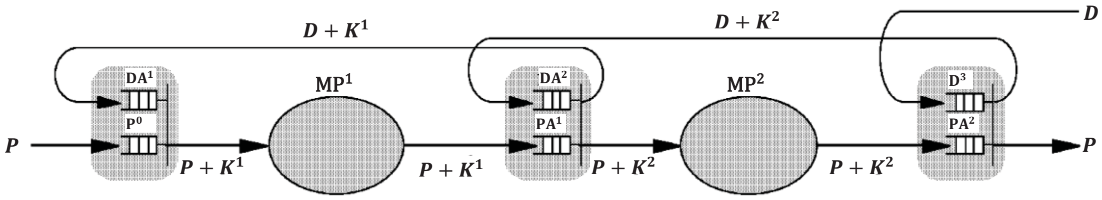


Figure 2-1: The Kanban Control Strategy from [10]

As shown in Figure 2-1, when a customer demand, D, arrives to the finished products demand buffer, D^3, a product is released from the finished products buffer, PA^2, and used to satisfy the demand. The Kanban, K^2, attached to the released product is then detached, merged with the demand information, and sent to the next upstream stage. When the merged demand and Kanban pair, $D+K^2$, arrive at the next upstream stage, it seeks for a part from the buffer, PA^1, to release to the input buffer of Stage, MP^2. If there is no part available immediately, $D+K^2$ is queued in DA^2 until a part becomes available. When a part is released downstream from buffer, PA^1, its Kanban is detached again, merged with the demand information and sent to the next upstream stage's demand-Kanban buffer, DA^1 . At this stage, the pair will seek for a raw part from the buffer, P^0. In studies that assume infinite availability of raw materials, as done in this research, the $D+K^1$ arriving to DA^1 will always find a part in P^0 to release into the first stage, and as such DA^1 will always be empty. The inventory level at the first stage will therefore always be equal to the set Kanban number for that stage.

Toyota's success in meeting customer demands with a low level of inventory attracted so much attention that the strategy became highly studied, resulting in the development of variations of the original KCS through works such as those of Generalised Kanban Control Strategy (GKCS) [25, 26], CONWIP [8], Hybrid CONWIP/Kanban [27], Extended Kanban Control Strategy (EKCS) [28], Extended CONWIP/Kanban [29]. The Base Stock Control Strategy is another production control strategy which is often researched alongside these KCS variants, as it allows a direct comparison under the same pull concept as them [19, 30, 31].

The KCS is traditionally known to be suited to high process reliability, low setup times, and low variability systems [6, 32-36]. However, these variants, which still retain the original pull concept of the traditional KCS, are believed to offer greater applicability in more complex environments such as those described in previous studies [8, 37].

2.2.3 Constant Work in Progress (CONWIP)

The CONWIP strategy was developed to possess the benefits of a pull strategy and be applicable in a wide variety of manufacturing environments in which the KCS was not entirely suitable [8]. Its development can be attributed to the desire of manufacturing environments that are more prone to system variability to adopt pull strategies. It is able to combine the low inventory levels of pull strategies with the high throughput of push strategies [38], and it only responds to the actual occurrence of demands [27]. It controls the system WIP with a single set of Kanbans which are attached to parts upon their release into the system and retained throughput their processing at the stages [20].

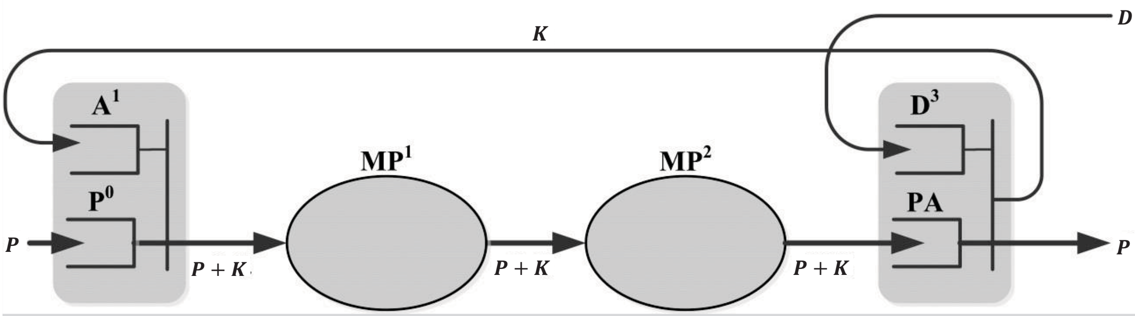


Figure 2-2: The CONWIP strategy

As shown in Figure 2-2, a Kanban is finally detached from a part upon its release from buffer, PA, to satisfy a demand, D, that arrived to the finished products demand buffer, D^3. The Kanban is then immediately sent upstream to the first stage's Kanban buffer, A^1, for use in authorising the release of a new raw part into the system. In this case, an assumption of an infinite availability of raw materials will ensure that A^1 is always empty, and that the level of inventory (WIP) in the system is maintained at a constant level which is tied to the set number of Kanbans; hence the name CONWIP (Constant Work In Progress). The CONWIP's use of a single set of cards to regulate the system WIP is similar to how the KCS uses a single set of Kanbans to regulate the stage WIP [11, 39]. Similarly, its stage level control has been likened to a push control because it does not regulate the stage WIP [37].

2.2.4 Base Stock Control Strategy (BSCS)

The BSCS does not use Kanbans to authorize production but it has been referred to as a special case of the EKCS with infinite number of Kanbans at each of the stages [39]. Also, it remains a pull strategy because it only responds to actual customer demands. Although the BSCS offers the advantage of immediate response to demands with its demand transmission approach, it is often criticized for its loose coordination between stages which results in excessive WIP accumulation [28].

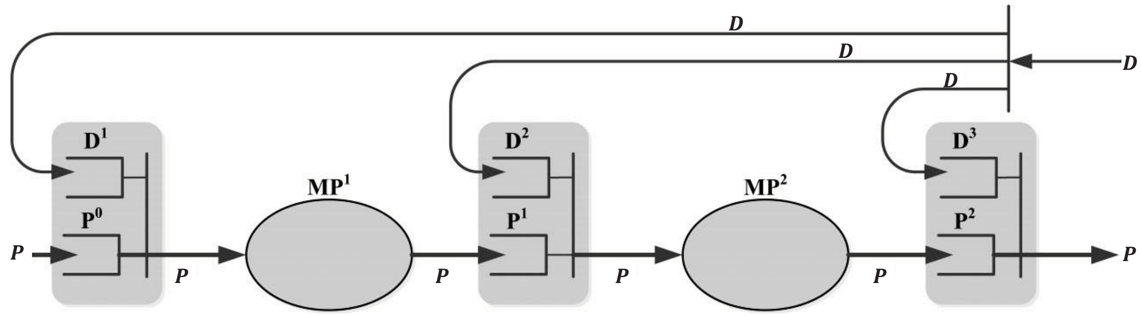


Figure 2-3: The Base Stock Control Strategy

In the BSCS, target levels of inventory called basestock are set at every stage. As shown in Figure 2-3, a customer demand, D, arriving to the finished products demand buffer, D^3, is instantly replicated and transmitted to the demand buffers, D^2 and D^1 of the other stages [30, 31]. This thus ensures immediate response and replenishment of the basestock levels to their initial states [28]. The demand information transmitted to D^3 will release a finished product from the buffer, P^2, to the customer, while that transmitted to D^2 will be used to release a part from the output buffer, P^1, of Stage MP^1 downstream into the input buffer of Stage MP^2. The demand information that arrives to D^1 will release a new raw part from the buffer, P^0, into the input buffer of the first stage, MP^1. It should be noted that if any of the demand information does not immediately find a part in the buffer, it would be queued until one becomes available. Also, in studies which assume infinite availability of raw materials, as done in this research, the demand arriving to D^1 will always find a part in P^0 to release into the first stage, and as such D^1 will always be empty.

2.2.5 Extended Kanban Control Strategy (EKCS)

The EKCS is a combination of the BSCS and the KCS, and it is described as combining the advantage of immediate response to demands offered by the BSCS with the tight WIP control of the KCS [28]. Its introduction of Kanbans into the BSCS to coordinate production between the manufacturing stages is seen as a means of overcoming the BSCS's excessive WIP shortcoming.

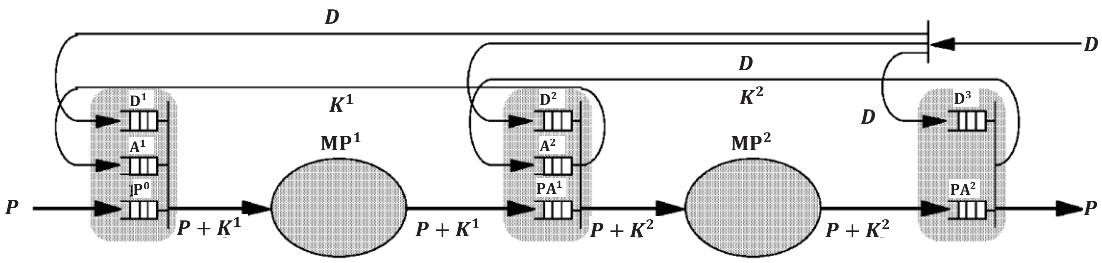


Figure 2-4: The Extended Kanban Control Strategy from [10]

As shown in Figure 2-4, it retains the same demand information transmission approach as the BSCS; however, the demands have to be synchronised with Kanbans before they can they can authorise the release of a finished part downstream, except at the finished products buffer, PA^2. It is only if there is no finished part available in the finished parts buffer, PA^2, that the demand, D, will have to be queued in D^3, until a part becomes available. When a part is being released from PA^2, the Kanban, K^2, of Stage, MP^2, that was attached to it upon its release into that stage is detached and sent back upstream into the Kanban buffer, A^2. A new part will be released into the input buffer of MP^2, as soon as there is a demand in D^2, a Kanban in A^2 and a waiting part in PA^1. Similar requirement applies for a part to be released into the input buffer of MP^1. As a result, the assumption of an infinite availability of raw materials at the first stage will not necessarily make demand buffer, D^1, empty always. This is because the release of a raw part into the input buffer of Stage MP^1 in response to a demand can be delayed by the unavailability of a Kanban in A^1 to synchronise it with. The stage's Kanbans could be presently attached to finished parts waiting in PA^1 or parts waiting to be processed or being processed in MP^1.

It should be noted that under the EKCS, the Kanbans of a stage remain attached to the finished parts in its output buffer, until they are to be released downstream into the input buffer of the succeeding stage. In addition to the Kanbans attached to those finished parts, there are usually some free Kanbans in the stage's Kanban buffer. As a result, the total number of Kanbans set for a stage in the EKCS cannot be less than the basestock level.

Since in the KCS, the number of Kanbans at a stage corresponds to the number initially attached to the finished parts in its output buffer, it can be inferred that an EKCS with $K = S$ (i.e. with no extra unattached Kanbans) at all stages is equivalent to a KCS with the same Kanban setting [28], because such EKCS will authorise production in the same way as a KCS – which is after finished parts are moved downstream. Likewise, the EKCS is equivalent to the BSCS, if it has infinite numbers of Kanbans available per stage [39].

2.2.6 Generalized Kanban Control Strategy (GKCS)

The GKCS [25, 26] is a two parameter, localised information flow strategy which, like the EKCS, requires setting the basestock level and the Kanbans per stage [10]. However, its own approach to demand information transmission is not global and the timing of its Kanban detachment differs. When a demand information arrives, it duplicates and transmits it to the last and penultimate stages only. From the penultimate stage the demand information is transmitted locally upstream one stage at a time.

Also, it detaches Kanbans from parts as soon as they complete processing, before storing them in the stage's output buffer. Therefore, parts in the output buffers are without their Kanbans attached to them, unlike in the KCS and the EKCS where Kanbans remain attached to parts until they are transported to the input buffer of the next stage [10].

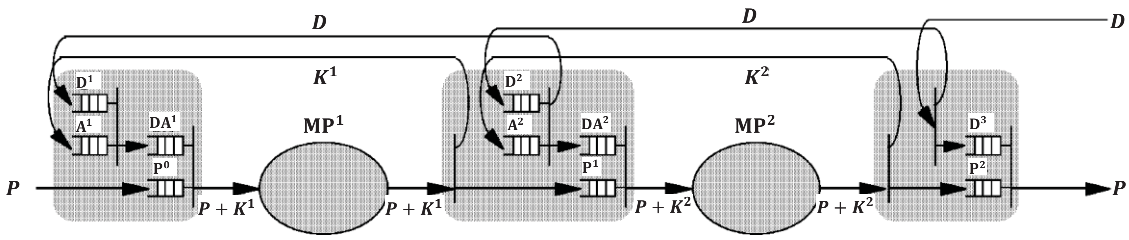


Figure 2-5: The Generalized Kanban Control Strategy from [10]

As shown in Figure 2-5, when a demand, D, arrives, it only duplicates and transmits it to the finished products buffer demand buffer, D^3, and the demand buffer, D^2, of the penultimate stage. If a product is available in P^2, it is immediately released to satisfy the demand, or else the demand will have to be queued in D^3 until a product becomes available. For the demand that was transmitted to D^2, it will first seek a Kanban, K^2, from buffer, A^2, to merge with in order to be able to authorise the release of a part downstream from the buffer, P^1. If there is no part available in P^1, the merged demand and Kanban pair, $D + K^2$, is queued in the buffer, DA^2, until one becomes available. Meanwhile, the merger of D and K^2 would be sufficient to continue the transmission of the demand information upstream to the demand buffer, D^1. This demand transmission would have otherwise needed to wait until the demand was able to merge with a Kanban.

Similarly to the EKCS, the assumption of infinite raw material availability does not imply that D^1 will always be empty, as the release of a part downstream can again be delayed by the unavailability of a Kanban in buffer, A^1. The Kanbans could be presently attached to parts waiting to be processed or being processed in MP^1. Also, similarly to the condition of equivalence of the EKCS to the KCS, it has been shown that the GKCS is equivalent to the KCS, and the EKCS too, when its $K = S$ (i.e. the number of Kanbans and basestock are equal) for all the stages [10, 39].

On the other hand, the level of coupling between the transmission of demand information and Kanban varies in the KCS, EKCS and the GKCS. The KCS has a tight coupling in the transmission of the two items, the GKCS is partially decoupled, while the EKCS is totally decoupled [10]. In the EKCS, the Kanban only plays the role of production authorisation; while in the GKCS, it is further needed for the transmission of demand information upstream, which is done globally in the EKCS. The EKCS's total decoupling has been described in past studies as making it more simple and flexible than the GKCS [28, 40]. However, the GKCS too exhibits its own flexibility with respect to the ability to set the Kanban level independently of the basestock level [10].

2.3 OTHER CLASSES OF PRODUCTION CONTROL STRATEGIES

There have been other classes of production control strategies which cannot be directly classified into any of the groups above. Unlike the push or pull strategies that have set rules for transmitting demands and authorising the processing of parts, these strategies have been developed to work flexibly in synchronisation with the state of the system. Some of them are briefly described in the following sub-sections under wide classification that are based on their production control concepts.

2.3.1 Bottleneck and Workload Oriented Concepts

The main aim of the bottleneck oriented concept is to achieve the best utilisation of the bottleneck station without accumulating excess amount of inventory before it or starving the station after it of work to do. It regulates the release of materials into the system in synchronisation with the capacity of the bottleneck station. It was first proposed through the Theory of Constraints [41-43] before it found production scheduling application in the form of the Drum-Buffer-Rope [43, 44]. A technique called Starvation Avoidance similarly seeks to avoid starvation of the bottleneck station through a regulated release of new jobs into the system to ensure that the bottleneck station is kept running without an accumulation of inventory before it [45].

The workload oriented concepts on the other hand seek to regulate the amount of workload in a manufacturing system by always taking into account the current level of workload on the system – particularly at the bottleneck station, before releasing new jobs into it. They are similar to the CONWIP's regulation of the number of items in the system, but they go further to consider the amount of load each item's processing requirement translates to on the system's capacity. There have been many variations of the workload oriented concepts in research in terms of how they measure the load resulting from the WIP items at the bottleneck station and in the system [46, 47]. Examples of such variations are the CONLOAD [48], the Workload Regulation or CONWORK [49, 50], the WIPLOAD [51], the Pull-From-Bottleneck (PFB) [46] and the CONFLOW [47]. The applications of the workload oriented concepts have been mostly in semiconductor fabrication environments.

There have been comparisons between the two concepts and the push or the pull control strategies [45, 47, 48, 52]. One of such comparisons is that which reports that the PFB concept is able to protect and keep the bottleneck station running even if a station downstream of it was broken down; unlike the KCS and CONWIP which would at some point under such situation cease to have Kanbans to release items into the upstream stage [43, 46, 47].

2.3.2 Product Grouping Concepts

An approach that has gained popularity in managing manufacturing resources between multiple products is Cellular manufacturing whereby similar products are grouped into families and assigned to cells of machines for the processing of one or more families of products [53-56]. In addition to machining requirements and part design features, which are mostly used to group products, other external factors such as demand attributes have also been used recently [57]. However, there are situations whereby products only have minor differences in design features which would only require slightly different processing requirements through the same production route. In such situations, a cellular design may not be a viable option because it would possibly require a duplication of all the machines. Therefore, a line manager who is consigned to a situation of having to share manufacturing resources will have to determine the best way to setup the system to ensure a balanced delegation of production capacity between the products. The allocation of Kanbans and the setting of basestock levels for products have been shown to influence the performance of individual products [13, 14, 58], most especially because they have impact on how much access a product will have to the manufacturing resources. As a result, focussing on the management of such aspects might be the only option for such managers. Moreover, within the shared or dedicated cells of the cellular manufacturing, there is still need to manage the access to the manufacturing resources within and between the product families.

The Paired-cell Overlapping Loops of Cards with Authorisation (POLCA) [59, 60] is another category of multiproduct control strategy which uses signal cards to control the flow of parts between cells in a shared configuration. However, it does not implement Kanban control to coordinate the flow between the workstations that are within a cell. POLCA is mostly used for signalling when capacity becomes available downstream while Kanban is an inventory signal to control the replenishment of inventory for a specific product [60].

2.3.3 Flexible or Adaptive Control Strategies

Another category of production control strategies that can be found in literature are the Flexible or Adaptive KCS which operate like the traditional KCS, except that they propose a dynamic review of the initial Kanban settings in response to the state of the system [61-64]. They adjust the number of available Kanbans in accordance to a rise or fall in the demand arrival rate, inventory level or demand backlog level. Another study however suggests that adjusting the number of Kanbans may not be sufficient in some system variability situations, and that observing inventory level as a means of knowing when to adjust the number of Kanbans might not give prompt indication of when the system is undergoing instabilities [65]. The study thus proposes a robust Kanban design that would instead involve making adjustments to operational, tactical and strategic system settings to offset instabilities [65]. Such adjustments would be made to the average service time of machines, the number of machines and the materials supplier. However, this might be difficult and costly to achieve for production line designers whose desire is to be able to sustain a particular system design for a long time without the need for constant re-evaluation. Moreover, as a result of cost, time and some technical considerations, organisations cannot always afford to make such continuous changes for their manufacturing system to be adaptable to running a particular pull strategy. Therefore, instead of trying to continuously fine tune a single strategy, some studies have proposed the combination of desirable traits from different strategies into a single hybrid strategy.

2.4 HYBRID CONTROL STRATEGIES

Combining different production control strategies is an area that has been very active since the 1980s [66-68]. Particularly, it seems to have originated from the desire to incorporate the throughput benefits of push and the tight inventory control of pull into a single strategy [5-7], and since then there have been numerous works done to create hybrid strategies, including from multiple pull strategies.

2.4.1 Hybrid Push-Pull

Push and Pull strategies have individual advantages and disadvantages [6], and it has been shown that easier implementation and better results are achieved when the two strategies are integrated. Two integration approaches have been reported for hybrid push-pull strategies, namely vertically and horizontally integrated hybrid strategies [69, 70]. The vertically integrated hybrid strategies are those that consist of an upper level push-type production control and a lower level pull-type production control [71-74], while the horizontally integrated hybrid strategies consist of a series of push stations that are succeeded downstream by a series of pull stations, with semi-finished products stored at a junction point between them [70, 75-77].

It has been observed that the application of a hybrid strategy will often give better results compared to a pure application of either strategy [27, 70, 71, 76]. They are reported to be more easily implemented than either push or pull strategies, and that they have an edge over pure pull strategies in dealing with high demand variability [38, 71, 78, 79]. In fact, some studies conclude that the application of pure pull strategies should be restricted to situations where variability in demand, as measured by its standard deviation, is not very large [6, 7, 80].

The location of the integration point between strategies has been shown to be a major deciding factor in the performance of a hybrid strategy [66-68], and this integration point is often located in reference to the bottleneck resource, the product structure and the customer order point [75, 77, 78]. The customer order point has been defined as the point in the manufacturing process where a product is ultimately assigned to a specific customer order [78].

Other possible locations are batch production stages, value adding stages and assembly stages [79]. Another study recommends that the junction point be located immediately after the bottleneck station and that a single junction point should be used for all products in the system in order to save optimization resources [70].

2.4.2 Other Hybrid Strategies

Another generation of hybrid strategies that can be found in literature are those that combine different variants of pull strategies; for example the Hybrid CONWIP/Kanban [27], the Extended CONWIP/Kanban [29] and the Basestock Kanban-CONWIP [81]. The EKCS [28] can also be placed under this category, as earlier explained in Section 2.2.5. These strategies are also direct results of the desire to select and combine suitable traits from different variants of pull strategies [40]. These traits that influence the performance of strategies can be attributed to inherent features such as the demand information or Kanban transmission philosophy, which can be classified as local or global [27, 38, 40]. A study has devised a very dynamic approach that can be followed to combine these traits from different strategies to form completely new demand information and Kanban transmission philosophies [38]. The study suggests that the formation of hybrid strategies does not have to always be a combination of the three fundamental pull strategies, which another study had previously identified as the KCS, CONWIP and BSCS [82].

2.5 EXTENSION OF PULL PRODUCTION CONTROL STRATEGIES TO MULTIPRODUCT MANUFACTURING ENVIRONMENTS

Several studies have been conducted on pull control strategies in single product manufacturing environments [20, 39, 40, 83], while multiproduct manufacturing environments, on the other hand, are usually more complicated to study. Aspects such as the assumption made on the significance of machine changeover time between the processing of different product types have an impact on how multiproduct studies are conducted [84]. A significant changeover time would necessitate the determination of the best approach to minimize the setup cost, and this in itself constitutes a research question that has been advanced in studies [84].

For instance, a study describes a setup time minimization strategy, called continuous review policy, such that there are two thresholds r and R that are respectively used to monitor when to begin and discontinue the production of a particular product type [33]. Threshold, r, is the level below which, when the WIP of a product type falls, its production is signalled to be started at a workstation, while the other threshold, R, is that which when reached implies that the production of a product type is to be stopped. These thresholds, according to the study, are determined by the scale of the setup time or other costs associated with setting up the machine to changeover to the production of a different product type. Another similar approach is that which assumes that products are batch processed in such a way that the processing of a product type will continue until its Kanbans are exhausted before a switch to another product type takes place [85].

On the other hand, studies that assume negligible setup times have pointed to recent advances in manufacturing equipment, which make rapid and low-cost changeovers between product types possible [86]. An example of such systems is the reconfigurable system described in Marek et al. (2001) [20], where parts are not batch processed but processed on a FIFO basis as they arrive, because there is only a negligible changeover time in switching between product types. Interestingly, in a consideration of both assumptions, a study observed that irrespective of whether changeover time is considered significant or not, the fixed capacity allocations to the different products in a system affected its performance in the same way [33].

2.5.1 Kanban Allocation Policies

Furthermore, applying some pull strategies in multiproduct environments poses the question of how the Kanbans are allocated between the different product types. The most natural extension of the single product Kanban control strategy to the multiproduct environment is to treat each product as if it constituted its own line, dedicating a specific number of Kanbans to each product. This number would be optimised for the expected demand profile to share the production capacity of the system between the products, effectively allowing each product equal opportunity to meet its demand. Such policies are considered Dedicated Kanban Allocation Policies (DKAP). The alternative is to set the Kanban level for the system and allow products to claim a Kanban based on whatever queue discipline (usually FIFO) is applied between stations. This ensures that the processing stations operate at their maximum level, but leads to the potential that one product may be delayed as the capacity is all claimed by another product. Such policies are termed Shared Kanban Allocation Policies (SKAP).

These two policies were first outlined in a study [9], however the first detailed analysis was presented in a more recent paper [10]. The two policies are discussed in the following sub-sections, followed by a description of the logic of their operation under the EKCS and the GKCS.

2.5.2 Dedicated Kanban Allocation Policy (DKAP)

In the DKAP, Kanbans are strictly allocated to a part type and can only be used by that part type. This implies that even if at a point in time a part type is short of Kanbans while another part type has a surplus of them, those surplus Kanbans are not usable for the part type that is short of Kanbans. Therefore, part types only share production capacity while other entities within the system such as the demands, part type and Kanbans are strictly attributed to a particular part type.

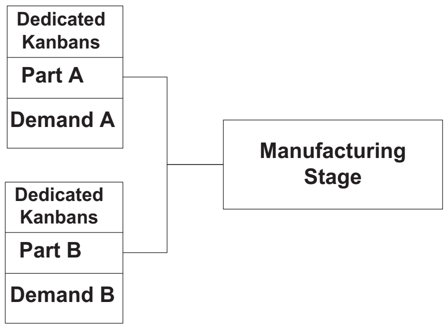


Figure 2-6: DKAP in a Multiproduct environment

As shown in Figure 2-6, the Kanbans are separated into different buffers as they arrive from downstream of the manufacturing system.

2.5.3 Shared Kanban Allocation Policy (SKAP)

In the SKAP, the products do not only have to share the production capacity but also the available Kanbans. The Kanbans are released based on a FIFO discipline to the part type for which demand first arrived, provided a part is available to release downstream.

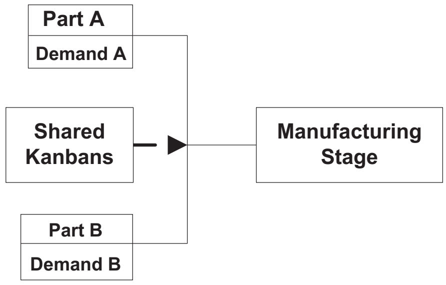


Figure 2-7: SKAP in a Multiproduct environment

In Figure 2-7, it is shown how the Kanbans that are detached from parts downstream are kept in a common buffer, from where they can be used to authorise the downstream processing of any of the parts. It should be noted that apart from the FIFO discipline, other possible disciplines can also be applied in the release of Kanbans to the parts. Such disciplines could prioritise the release of Kanbans to parts based on their current numbers of unfulfilled demands at a particular stage, or even globally using the current levels of customer demand backlogs at the last stage. Such approaches have been applied in the scheduling of operations for multiple parts in order to minimise setup times, as earlier described in Section 2.5 [33, 85, 87].

It has been reported that some pull strategies are not able to operate a SKAP owing to the tight level of coupling that exists in these strategies in the movement of demands, Kanbans and parts [10]. Demands, which are always synonymous with the part from which they originally emanated, will consequently extend their affiliation to the Kanbans. This limitation applies to CONWIP and the KCS because there is a tightly coupled Kanban and demand information transmission, and to the BSCS because there is no Kanban transmission at all [88]. It should however be mentioned that a recent study made modifications to CONWIP to enable it operate a SKAP in a strategy referred to as Basestock Kanban-CONWIP (BK-CONWIP) [81]. The study decoupled the return of Kanbans to the first stage from the upstream transmission of demand information, in such a way that the Kanban does not always end up being used to authorise the processing of the same product type as that from which it was detached. Another factor that has made the application of SKAP to CONWIP achievable, specifically in assembly lines, is the possibility to follow either the simultaneous or independent Kanban release approaches [11] which were earlier noted in Section 1.2. The SEKCS approach uses a joint Kanban to authorise the release of components for assembly, while the IEKCS uses separate Kanbans to independently authorise the release of individual components for assembly. The effect of this variation in approach is that the joint Kanban requires all the components to be available before simultaneously releasing them into the assembly stage and sending their respective Kanbans upstream to authorise the processing of replenishment parts. On the other hand, the use of separate Kanbans means that the components can be released into the assembly stage independently and have their respective Kanbans sent upstream immediately to authorise the processing of replenishment parts.

2.5.4 Logic of Operation of Kanban Allocation Policies under EKCS and GKCS

The logic of a policy differs slightly depending on the pull strategy under which it is being operated. For instance, it has been observed that the EKCS DKAP and the GKCS DKAP are equivalent to the KCS DKAP when the number of Kanbans, K, is equal to the basestock level, S; whereas this does not apply to either the EKCS SKAP or the GKCS SKAP [10]. Therefore, the following sub-sections will provide further descriptions of how the policies operate under the EKCS and the GKCS, which are the two strategies that can operate either policy. The other strategies that are only able two operate the DKAP will not be further described, since their logic is a direct extension of the single product system, with each product having its own Kanbans independently of the other products.

EKCS DKAP and SKAP

A DKAP policy operates in a multiproduct system as a direct extension of the single product system. As shown in Figure 2-8, each part type has its own demand information and set of stage Kanbans which are synchronised and transmitted independently of the other products in the system, as earlier described in Section 2.2.5.

The only points of contact are at the manufacturing stages where parts that have been authorised for processing are queued in the input buffer and processed in a FIFO discipline based on their order of arrival to the input buffer. It should be noted that the FIFO discipline pays no attention to when the demand actually arrived for a part, instead it recognises when it was able to synchronise with a Kanban and a part for processing.

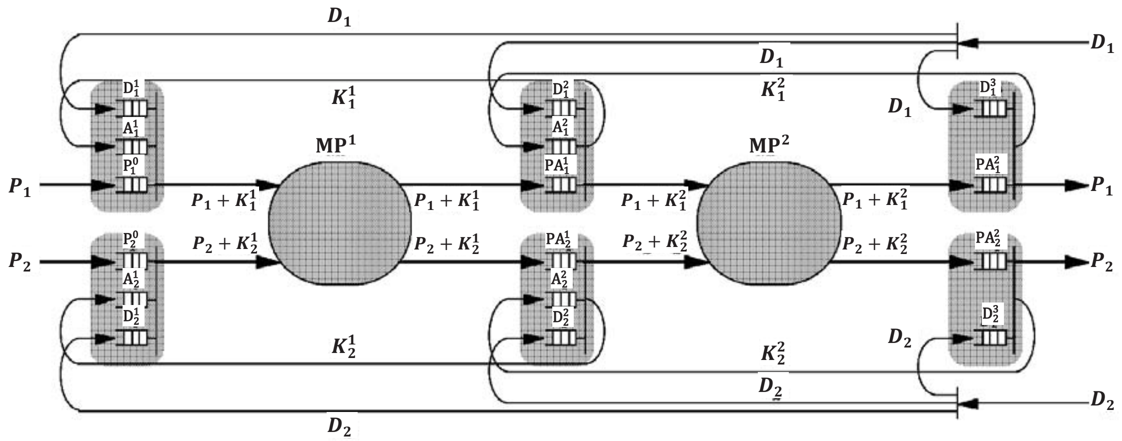


Figure 2-8: Operation of the DKAP under the EKCS from [10]

So, for instance in Figure 2-8, the order of processing of Parts, P_1 and P_2, at Stage MP^2, will be based strictly on the order in which they arrived at its input buffer, without any consideration for when their respective demand information, D_1 and D_2, arrived to their demand buffers, D_1^2 and D_2^2. Other disciplines as described in Section 2.5 might handle this differently.

The SKAP would use the same FIFO discipline as the DKAP to order parts for processing at the manufacturing stage. However, additionally in the SKAP, the parts have to be prioritised for accessing the shared pool of Kanban. As shown in Figure 2-9, there is a shared buffer to which the Kanbans detached from the parts are returned for use by any of them. A Kanban will be released to the parts based on the time of arrival of their demand to a stage, provided there is a part available to be released downstream.

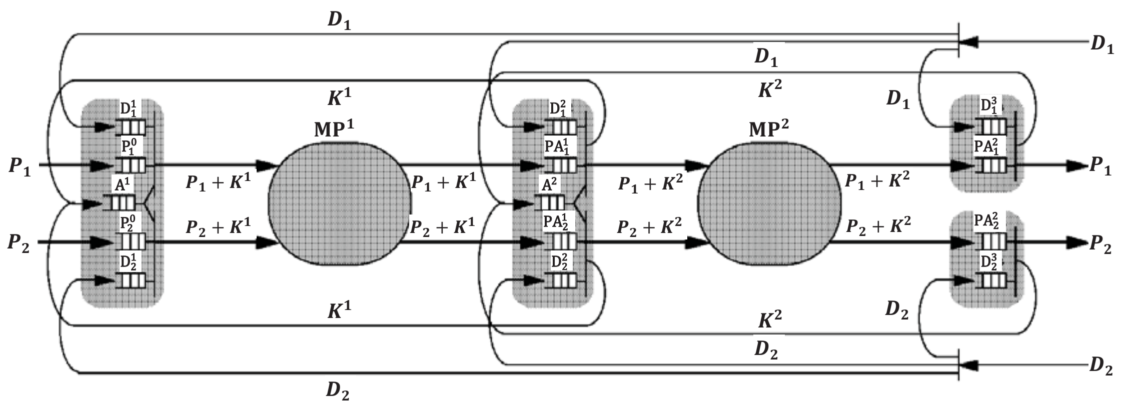


Figure 2-9: Operation of the SKAP under the EKCS from [10]

For instance, at Stage MP^2 in Figure 2-9, when a demand, D_1, for part type 1 arrives to buffer, D_1^2, a Kanban is assigned from the buffer, A^2, to that part type to merge with it, provided there is a part in the buffer, PA_1^1, that can be immediately released downstream. If there is no part, D_1 is queued in D_1^2 until one becomes available. But, if while D_1 is waiting a demand arrives to buffer, D_2^2, for the other part type 2 and there is a part in its own buffer, PA_2^1, then a Kanban is immediately assigned from the buffer, A^2, to part type 2 so that a part, P_2, can be released downstream. The release of a Kanban to part type 2 will not be affected by the fact that part type 1 had a waiting demand in its own demand buffer. Therefore, the Kanban buffer does not recognise the individual time of arrival of a part or a demand to their separate buffers, it only recognises the time they become merged.

GKCS DKAP and SKAP

Similarly to the EKCS DKAP, the GKCS DKAP is a direct extension of the single product system. As shown in Figure 2-8, each part type has its own demand information and set of stage Kanbans which are synchronised and transmitted independently of the other products in the system, as earlier described in Section 2.2.6.

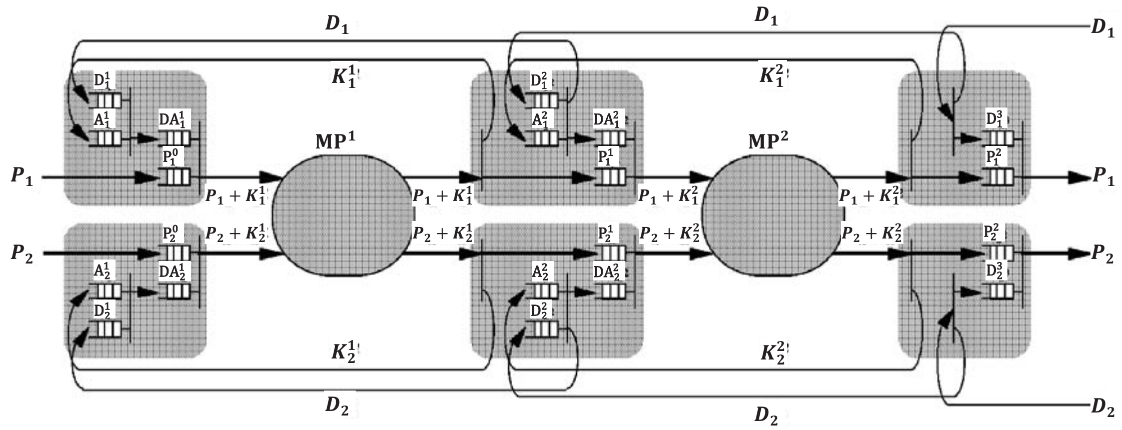


Figure 2-10: Operation of the DKAP under the GKCS from [10]

The parts only come into contact at the input buffer of the manufacturing stages where their processing is again done based on a FIFO discipline. The FIFO discipline is also entirely based on the order in which the parts arrived at a stage's input buffer, without any consideration for when their respective demand information.

Although, the GKCS SKAP follows the same FIFO discipline in the processing of parts from the input buffer of the manufacturing stages, its rule for assigning the shared pool of Kanbans differs. As shown in Figure 2-11, the Kanbans that are detached from parts downstream are returned to a common buffer from which they can be used to authorise the release of any of the parts downstream. The Kanbans are assigned to parts based on the order of arrival of their demands.

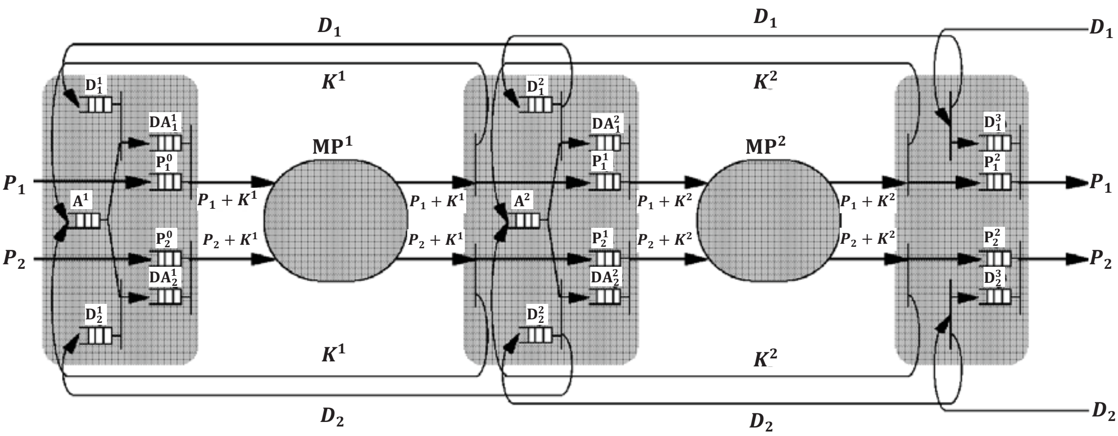


Figure 2-11: Operation of the SKAP under the GKCS from [10]

As shown in Figure 2-11, at Stage MP^2, when a demand, D_1, for part type 1 arrives to buffer, D_1^2, a Kanban is assigned from the buffer, A^2, to merge with it before the merged pair is added to the queue, DA_1^2. The pair, $D_1 + K^2$, then seek for a corresponding part from the buffer, P_1^1, to release downstream. If there is no part available in P_1^1, $D_1 + K^2$ remains queued in DA_1^2 until a part becomes available. Demands that arrive to this stage subsequently for both part types will have Kanbans released to them from A^2 in the order in which they arrive.

2.6 HYBRID KANBAN ALLOCATION POLICY

Works that have studied the two Kanban allocation policies have shown that differences exist in their levels of performance, e.g. the SKAP was observed to outperform the DKAP in a CONWIP controlled assembly line [11], while another study reports the same finding in several serial and assembly line configurations [12].

This variation in the performances of the two available Kanban allocation policies pose similar questions to that of identifying suitable strategies for manufacturing systems and, perhaps, looking into the possibility of combining them, as done with the hybrid push-pull strategies [5, 6, 77]. It poses questions such as: *For which type of* *environments are the two policies suitable? What are the advantages of one over the other?, and Can the two policies be combined in a single strategy to get the benefits of both, similarly to the hybrid strategies?*

The aim of this research is to try to answer the above questions through a series of experiments that would investigate the suitability of strategies and their corresponding Kanban allocation policies for different manufacturing system scenarios, and, ultimately, the possibility of combining the SKAP and the DKAP in a hybrid setting.

In furtherance of existing studies which have mostly investigated how system and product attributes directly affect the performance of a system, this research will look into how products' attributes affect one another. It is worth mentioning though that there have been studies that consider the attributes of the products manufactured within a system, albeit for other purposes not related to Kanban allocation. An example of such study used ABC Pareto in classifying products in such a way that products corresponding to low cost of inventory are pushed through a system while products of high inventory value are pulled [78]. Another study used processing time and demand attributes to group products for Cellular manufacturing. Furthermore, Cochran and Kaylani's [70] observation about the junction point policy of the hybrid push-pull is similar to the intention of this research with respect to Kanban sharing or dedication. They found that a single common junction point is the best option for the transition from push to pull for all the products in a system, except if the products have extremely different ratios of tardiness to inventory cost. This is related to the proposed consideration of products' attributes in deciding on Kanban sharing among them.

A closely related research is that of a study that used perturbation analysis to dynamically vary the number of Kanbans allocated to the different part-types in a multiproduct system, as a means of counteracting undesirable effects of changes in product mix on system throughput [89]. This appears to be the first work to have recognised the impact products attributes can have on one another under the DKAP, before the SKAP was proposed in another study [9]. Another more closely related work is that which proposes the dynamic adjustment of the number of Kanbans initially allocated to the two products of a system, in response to their respective current levels of demand backlog and inventory [87]. It also suggests using these in deciding on the next product type to schedule for processing on a machine. Other related studies have observed the effect the number of product types can have on the performance of a system. For instance, it has been reported that having a high number of product types results in a lower customer service level, and this was attributed to the production time lost when changing over from the processing of one product to another [90, 91]. On the contrary, another study observed that manufacturing systems with fewer products suffer a more significant decline in service level when there is an increase in demand arrival rate [33]. This was attributed to the fact that a system with more products is likely to have a higher ratio of production capacity to an individual product's demand, such that an increase in demand arrival rate for a single product consumes a lesser proportion of the overall production capacity.

Meanwhile, it is also worth reviewing the observations of those existing researches that have mostly looked into the effects of product related and system level factors on its performance, as they might help in this research to differentiate outcomes that are due to product interaction from those resulting from system level factors. Most of these researches have investigated the effects of factors such as demand and its variability, processing times and its variability, machine availability and the number of machine stages etc.

In studying the effects of demand variability, production time, backlog cost and inventory holding cost, on the Kanban size and the service level of a single stage multiproduct system, a study concluded that a manufacturing system is able to adjust itself accordingly to offset the changes that occur to most of these parameters [23]. However, a contrary observation was made in another study which suggests that even a well-designed pull system is hardly able to avoid the starvations and overproduction that result from the large and unpredictable fluctuations in demand [32]. In fact, the only case where a beneficial inventory reduction effect was reported for high demand variability was in the work of [92], and this must have been at the expense of the system service level which was not reported in the study. From another perspective, a study reports that a high variability situation made it difficult to differentiate the performance of different strategies, as they observed in the hybrid push-pull, pure push and pure pull strategies they studied [80]. It would be of interest to see if there would be similar confounding effect in differentiating the performances of products, under the high demand variability situations that might arise in this research.

For processing time variability, its increase has been reported to cause shortages and consequently significant decrease in service level [33, 35, 90, 93-95]. It is however reported to have no significant impact on system WIP [96], and this is understandable as the Kanbans continue to regulate the amount of WIP in the system irrespective of the processing time variability. On the other hand, increased demand variability causes WIP increase because it directly influences the use of the Kanbans to release more items into the system. WIP also linearly increases with the number of stages in a system [97].

Many more studies have shown that a link exists between the level of system variability and the level of Kanban and safety stock needed by such system [13, 70]. The excess Kanban required in high variability systems has been attributed to performing a cushioning effect to reduce the impact of the variability [21, 63, 98, 99]. Similarly, another study acknowledges that there is a relationship between the performance of a system and the variability of its stages; however, they also highlight that there is difficulty in establishing a clear link between the two [33]. They nevertheless reiterate that it is more beneficial for line designers to reduce variability at stages closer to the customer than at more upstream stages [33]. Another study observes that, even if a balanced line is achieved by a uniform allocation of capacities along a line, the variability of processing time at different stations will continue to differ due to factors such as the nature of the tasks to be completed and the reliability of the machines at the different stations [97]. The study cites an instance of an *unpaced* line with manual workers that perform tasks ranging from straightforward assembly to testing and adjustment activities.

2.7 SIMULATION MODELLING AND OPTIMISATION

The availability of several variants of pull strategies and corresponding policies usually poses a challenge to prospective users on which one would be the most suitable for their manufacturing environment. Simulation modelling approaches, such as in [8, 40, 83, 100-102], and some analytical techniques have been applied in conducting studies to determine the suitability of available strategies under different conditions. Markov Time

Chain Analysis [62], Multiclass queuing network approximation technique [84, 103, 104] and State Space representation approach [24, 29], are some of the most commonly used analytical methods of study.

Discrete event simulation has been recommended as a preferred method for studying the complex dynamics of stochastic manufacturing systems because of its ability to handle the unpredictability of such systems [61, 105]. It has been widely applied in existing literature and a lot of the present understandings of manufacturing systems has stemmed from it, mostly because it allows for an offline representation and experimentation of a system without tampering with it physically.

However, there are steps that must be taken to ensure a successful conduct of a simulation study, as described in the following sub-sections in regard to the steady state (or non-terminating) type of simulation that will be conducted in this research. The other type of simulation is the terminating simulation, and there are many available texts which provide detailed explanation of the two types [106, 107].

2.7.1 Simulation Warmup Period

In steady state simulation studies, it is of importance to eliminate the possible bias of the initialisation state of the system, in order not to defeat the essence of conducting such studies, which is to be able to make judgements about a system at any point in time irrespective of its initial state. Three popular approaches have been followed to reduce/eliminate the bias of this initial state – called the warmup period – on the statistics collected from the system [108]. First is to delete the initial set of data that is believed to be affected by this warmup period. The second approach runs the simulation for a very long time that would be sufficient for the effect of the warmup period to have been overshadowed. The third approach attempts to set the simulation in a steady state right from the beginning. The most effective is a combination of the first and the third approach, and, in a Kanban controlled manufacturing system, this might mean filling the buffers with the basestock items right at the beginning, so that the first set of demands that arrive to the system do not arrive to an empty buffer. This would give a close estimate of the steady state performance of the system, and would therefore reduce the length of data that has to be removed for the warmup period. However, rare system events, such as machine breakdowns, would nevertheless necessitate that a longer duration of data is deleted, because of the need for them to have occurred multiple times during the system's warmup period [106, 107].

Welch's graphical procedure is the most commonly applied technique for identifying the warmup period, and this is mostly due to its relative simplicity [109, 110]. However, Welch's procedure, like some of the other methods of determining the warmup period, is reported to be sometimes conservative in its estimation of the deletion point [106, 108]. Nevertheless, the method is generally considered acceptable, and studies that have compared different methods often recommend its use [111-113].

2.7.2 Simulation Run Length and Number of Replications

Furthermore, in conjunction with the warmup period data removal, two possible approaches are applied to conducting the subsequent steady state statistics collection. The first, which is called the deletion and replication method, is to replicate the warmup-deleted run multiple times and use the statistics from all the runs to construct averages and confidence intervals for the statistics of interest [106]. The second approach – the batching method – involves conducting a very long single run which is then partitioned into batches across which the desired statistics' averages and confidence intervals can be estimated. The first approach is more suitable for studies comparing alternative systems, especially when combined with random number synchronisation.

In both approaches, the confidence interval is often used as a measure of the adequacy of the simulation run length and the number of replications, as a higher number of replications often yields narrower confidence interval, meaning higher precision in the statistic being estimated [114]. However, there needs to be a trade-off between the computational resource requirements for a high number of replications and the level of precision that stands to be achieved. A sequential approach is commonly applied in determining this trade-off point by starting with a pilot number of replications, measuring the confidence interval obtained to see if it is within acceptable limit and gradually increasing the number of replications until it falls within the acceptable limit.

The acceptable limit of confidence interval depends on the nature of the research and the intended application of the result.

2.7.3 Performance Measures

The common measures for comparing the performance of pull strategies are service level (SL), WIP, cycle time, stability of throughput rate, average wait time of backlogged demands, and the average duration and frequency of demand backlog [8, 12, 21, 33]. Historically, according to a study [115], SL and WIP have been the most desirable performance measures in the study of pull strategies [11, 40, 83], and this can be attributed to them having direct relationships with the outcomes of the other performance measures.

Service Level (SL)

Service level or Fill rate is the proportion of customer demands that were immediately satisfied on arrival to the system. It is a measure of system responsiveness which is the main aim of operating a pull control strategy, albeit with the added and equally important goal of reducing the level of WIP [115]. Its application as a performance measure has varied in literature; for instance, a study compared the number of Kanbans that would be needed by different pull strategies to meet a target service level at different levels of machine reliability, demand variability and safety stock levels [21].

An approach which is slightly different from direct service level measurement is to define a penalty cost for not immediately fulfilling demands and incorporate it into an objective function [62, 116]. Also, demands that cannot be fulfilled immediately have been treated in different ways in existing literature. Some allow such demand items to be backlogged in a demand item buffer until finished products become available [14, 14, 23, 63, 63, 115, 115, 117, 117, 118], while others simply regard them as sales that are lost to competitors [33, 80, 115, 119]. The true effect of lost sales resulting from the latter approach cannot be fully quantified because, in addition to the loss of a potential sales opportunity, it might also mean an outright loss of the custom of the unimpressed customer [120], and ideally the consequence of such loss should be quantified and dynamically deducted from the demand arrival rate during the long term simulation of the manufacturing system. However, this would result in severe intractability in the experimentation and analysis of systems. Therefore, the former approach of backlogging demand items is more directly captured within the scope of production and inventory control research. It penalises the backlog of demand items by, in some cases, assigning penalty costs corresponding to the duration of the delay [23, 63, 70]. This cost is then included as part of the objective function in a cost minimization optimization process.

As an alternative in cases when an unlimited demand is assumed, the throughput is used instead of the SL [8, 82, 96, 121]. Another category of studies consider the situation whereby there is advance demand information (ADI) that can be used to initiate production at a lead time ahead of the actual required time of fulfilment of the demand [120, 122-126]. The aim of such studies is to compare the value of the advance information on the ability of different strategies to keep inventory level low. For instance, a study reports that if the ADI lead time is long enough and stable, a system can operate with zero basestock [127].

Work In Progress (WIP)

WIP has been described as a key factor, among others, for the success of a manufacturing system, based on a study's findings in a case implementation of lean controlled manufacturing system [37]. It is a hold up of resource and it has quantifiable cost implications which can be in the form of storage space, depreciation cost, pilferage cost, cost of monitoring, and the profits that could be derived if the economic resources tied down in inventory were used in other business ventures. As a result, it is common for studies to be carried out to compare different pull strategies based on the level of WIP they needed to achieve a target SL [12, 40]. They measure the WIP by assigning cost to every unit of inventory in the system, and this cost is multiplied by the average time for which the inventory was kept in the system. The total cost obtained is then used as part of a minimization type objective function, in a similar fashion as the demand backlog cost [23]. Other WIP measurement variations involve either assigning different costs to semi-finished inventory and finished goods inventory in the objective function [116], or simply assigning equal values (costs) to inventories across all the stages [8, 40]. In some cases, the total number of Kanbans or buffer space needed by a system is counted instead of measuring the WIP [21].

The items that should constitute system WIP also differs in literature. While some studies regard raw parts as WIP as soon as they have been authorised for processing at the first stage [81, 101], others do not count them until their processing has actually commenced at that first stage [14, 29, 102, 115]. This impacts the WIP measured from study to study, especially in the CONWIP. In studies that use the former approach, the average WIP measured will be constantly equal to the CONWIP's set total number of system Kanbans, while it would be slightly lower or equal in the latter approach.

SL versus WIP trade-off remains the most common performance measure applied in studies [11, 40, 83, 101, 102], and it involves seeking to achieve the best (or a target) SL with the least amount of WIP possible.

2.8 MANUFACTURING SYSTEM OPTIMIZATION

The essential parameters in the design of a Kanban controlled manufacturing system are the number of Kanbans needed to link the processes together, the number of machines, and the appropriate unit of lot size [128, 129]. The settings for these parameters must be determined in a way that achieves the desired performance measure(s) at the lowest possible cost [99]. However, the combinatorial property of estimating these parameters makes it difficult and, as such, warrants the development of efficient methodology or heuristics to obtain good solutions [128]. For instance, a study observes that the number of feasible solutions increases non-polynomially with the size of the system and it is going to be impractical to search through all alternative solutions to arrive at the optimal one [70, 130].

As a result, a range of techniques have been adopted for the optimisation of manufacturing systems, mostly from other fields of application. Existing studies have applied approaches such as Perturbation Analysis [89, 131, 132] and mathematical programming [133, 134] in the optimisation of pull control systems. The mathematical programming approach usually involves a mathematical formulation and optimisation of the system.

An approach that is widely adopted is the simulation-based optimisation [135], which, according to Bowden and Hall (1998) [136], is *''... the practice of linking an optimisation method with a simulation model to determine appropriate settings of* *certain input parameters so as to maximise the performance of the simulated system*". The system's performance is usually expressed in the form of an objective function that would assign penalty costs or benefits to a statistical measure that can be outputted directly from the simulation model. For example, some studies built objective functions in the form of an equation consisting of the inventory holding and the demand backlog costs for minimisation [24, 62, 65, 87, 137]. Another commonly applied approach is to set the objective function to achieve a target level of a performance measure, e.g. SL [40, 83].

The optimisation method generates settings based on certain algorithms and sends them for simulation to evaluate their suitability to meeting the specified objective function. The optimisation algorithm then learns from the simulated outcomes of its generated settings and tries to use the knowledge to generate better settings subsequently. Some of the optimisation algorithms that have been applied in previous studies are Genetic Algorithms [62, 70, 105, 138, 139], Simulated Annealing [69, 128], Tabu Search [140] and Ant Colony Optimisation [141].

Because of the effectiveness of this simulation-based optimisation approach, some simulation software now have inbuilt optimisation blocks that are based on some of these algorithms; for example, ExtendSim^{TM}, which is applied in this study, uses a Genetic Algorithm to which an objective function and the parameters for optimisation can be specified. The Genetic Algorithm [142] has been described as a mechanism that imitates the genetic evolution of species [143]. It operates by reproduction, crossover and mutation of populations; the population being the solution space to the specified problem [62]. The reproduction operator selects an initial population of solutions, evaluates them for fitness and ranks them. Individuals with good fitness are combined as parents to produce offspring with the hope that the offspring will retain some of the desirable traits of the parents. The offspring then go through some mutation and evaluation in order to see if they can evolve into even better individuals. In the context of optimising pull strategies, an individual can be seen as a particular setting of Kanbans and/or basestocks for all the manufacturing stages, and its mutation would involve interchanging these settings.

The Ant Colony Optimisation (ACO) [144], which is also applied in this study, has not been much applied as natural evolution algorithms in the optimisation of pull strategies. However, its learning nature, which it shares with algorithms such as Artificial Neural Networks [145] and Reinforcement Learning [146] [147], makes it much applicable in simulation-based optimisation [141]. The ACO was developed to emulate the techniques used by ants to identify the shortest path between their nest and the food source, through communication between travelling ants [144]. The ants lay a chemical called pheromone as they travel along the paths and it is through this that oncoming ants are able to identify the shortest paths based on the frequency of ants laying pheromone on a path and the level of pheromone it retains. Shorter paths are likely to have many ants following them and their pheromone level is likely to last long between the time of passage of one ant and the next. By mimicking this natural information exchange that takes place between ants, the ACO algorithm is expected to guide the optimisation process towards finding the optimal settings for the parameters of interest.

However, the main challenge, as with natural evolution algorithms too, is that of determining the suitable solution representation approach that would allow a seamless exchange of parameters between the optimisation algorithm and simulation. Furthermore, the solution representation has to be implemented in such a way that would efficiently mimic the philosophy of the underlying natural process. It should be able to explore wide range of solutions within the limited time available and avoid converging at a local minimum. As a result, there have been numerous modifications to the original ACO algorithm in order to improve and adapt it to wide variety of system optimisation [147-152]. Some examples are the population based ACO [152]– which is applied in this research, the elitist approach [153] and the min-max Ant system [151]. Some of these have also looked into different possible solution representation approaches, which in particular should be based on the nature of the problem being dealt with, as done for this research.

2.8.1 Optimisation of Multiproduct Systems

Because multiproduct systems are even more complicated to optimise, some techniques have been devised to solve the intractability that results from the volume of parameters involved in them. One of such approaches, which is called a decomposition-based approximation, involves breaking the multistage-multiproduct system into smaller multistage-single product systems and/or single stage-multiproduct systems. These smaller systems are then analysed separately and their outcomes are used to approximate the larger more complicated systems. Examples of this approach can be found in studies such as [33, 85, 104, 154-159]. Also, as stated in Section 2.6, Perturbation analysis has been applied in a previous study to determine the number of Kanbans to allocate to the different part types in a multiproduct system [89]. This was aimed at counteracting any effect unavoidable changes in product mix might have on the system throughput.

Another approach which has been used in simplifying the optimisation of multiproduct systems is to make inferences and assumptions about the more complex strategies based on the results of more easily optimised single parameter strategies. For instance, the optimisation of two parameter per stage strategies is sometimes simplified by performing the search for optimal values around the values obtained from single parameter strategies. A study reports that the same basestock levels are required for the BSCS and the GKCS in a single stage system [116], and this can for example serve as a good basis for starting the optimisation of a GKCS model. Another study suggests that the search for the optimal Kanban and basestock could start with a zero basestock and seek to determine the number of Kanbans that would maximise the throughput using single stages in isolation. This would then be followed by gradually increasing the basestock level and reducing the Kanban number sequentially [28]. It is also useful to conduct a preliminary solution space evaluation in order to pre-determine reasonable ranges for the parameters [14, 99, 130].

Finally, it is worth taking note of the observation of a previous study which reports that the estimation of performance measures is usually more prone to errors when the system is overloaded with customer demands [16, 33]. Although, it is not clear if this extends beyond the analytical technique employed by them, it is still worth keeping in mind for the optimisation of high system capacity load scenarios.

2.8.2 Robustness of Pull Production Control Strategies

As noted in the previous section, there is a significant level of complexity in the management of multiple products which are affected by both internal and external factors. This complexity is further exacerbated by the variability of such factors which effectively changes the scenario under which any optimisation must be applied over time. According to a previous study, the uncertainty and constant variation in system parameters render optimal solutions inapplicable to real life manufacturing environments [160]. They therefore propose the notion of robustness for scheduling policies, which they describe as the one that can deliver good and stable performance resilient to variations in system parameters (such as buffers sizes, processing rates, and setup times). An approach that has been applied to achieve this is to seek to design robustness into a pull strategy during optimisation. For example, a study applied Taguchi's design method to the design of experiments in the optimisation of a KCS, such that the ranges of expected fluctuations of the system factors would have been anticipated in its initial Kanban settings [115]. Such strategy would then be able to cope adequately with any of these fluctuations, if they eventually occur after the optimization. The same approach has been followed in another study [161].

Although, it cannot be disputed that robust Kanban design, as advanced by these studies, is of importance in the eventual robustness of a strategy, more emphasis could be placed on trying to identify the pull strategy variants that are naturally more robust than others. The available variants, due to their inherent characteristics, offer different levels of robustness to system variability and, as a result, trying to identify the best for a particular system condition, out of many alternatives, would be a more straightforward method to achieving a robust performance. With this approach, a general understanding can be established on how different strategies would perform under conditions of uncertainty and the most suitable (robust) one can be identified [13, 162].

Sensitivity analysis, which has been described as "*the systematic investigation of the reaction of the simulation response to extreme values of the model's input or to drastic changes in the model's structure*" [163], has been mostly applied in conducting robustness tests, and it has provided a different perspective to comparing strategies. For instance, the outcomes of a study [162] conducted on an existing work [83] show disparity between the conclusion derived from conducting the experiments on an optimised base scenario and when the robustness of the different strategies to variability are considered through sensitivity analysis. Other studies have made similar observations [13, 164], and their outcomes show that lesser effort should be placed on trying to obtain absolutely optimal parameter settings, while most of the effort should instead be concentrated on evaluating the robustness of the near optimal outcomes obtained from minimal optimization efforts.

Another approach that has been followed to test the robustness of strategies is that which compares the amount of time taken for them to recover from sudden disruptions to the system [65, 165]. Disruptions in the form of machine breakdown or sudden rise in demand are introduced during the simulation run, and the impact on and the recovery time of different strategies are then compared. Furthermore, a study emphasises the need to consider variance related performance measures which could give an indication of a strategy's long term likelihood of maintaining its optimised level of performance [115].

Finally, it is worth mentioning that the flexible or adaptive KCS earlier described in Section 2.3.3 are also geared towards achieving strategy robustness.

2.8.3 Design of Experiments for Sensitivity Analysis

The number of factors involved in the sensitivity analysis of manufacturing systems simulation models renders fractional or full factorial design of experiments unsuitable. A method that has been successfully applied is the Latin Hypercube Sampling (LHS) [166, 167], and this is mostly due to its flexible sample size, which is irrespective of the number of experimental factors involved [167-169]. In a study that recommends taking a minimum LHS sample size of 100, they were able to achieve sufficient coverage for a 17 factor experiment [164].

It is also common in the design of experiments to classify the factors based on the nature of their influence on the manufacturing system. A study identified two classes of factors, namely noise and parameters [115]. The noise factors are those that are either outright not within the control of management or very costly to control, while the parameters are, on the contrary, within the control of management and can be easily manipulated. The study developed metamodels to depict the effect of noise on a pull strategy's performance, and then applied this knowledge in identifying the best parameter setting to overcome the noise and achieve a robust performance [115]. Additionally, this classification of factors can also be used to screen out factors and reduce the number of factors to those that are relevant to an experiment.

Also importantly, an outcome of sensitivity analysis which this research would benefit from is that it can be used to understand the relationship between variables. It can measure the level of impact product related factors and system level factors have on a strategy's performance. A further application of sensitivity analysis is that it can be used to test the validity of a model through the nature of relationship observed between its factors and responses [163].

2.9 REVIEW OF TECHNIQUES AND TOOLS FOR DESIGN OF EXPERIMENTS AND RESULTS ANALYSIS

The experimental design and analysis techniques and tools to be applied in this research are discussed in the following sub-sections. The techniques have been chosen based on their suitability for the required analysis and their ease of implementation. An overview is given of the software tools used for the design of experiments and results analysis. MS Excel spreadsheets have been used to facilitate the exchange of data between them.

2.9.1 Latin Hypercube Sampling for Design of Experiments

Latin Hypercube Sampling (LHS) [166] is the preferred method for this research because of the possibility of achieving better coverage over the ranges of variation of the factors. It is often difficult to use classical design of experiment techniques, such as Factorial designs (full or fractional) and Central Composite Designs, for the design of simulation experiments because of the often large number of design factors involved. If, for instance, a full factorial experiment was to be used for the 10 and the 8 factor experiments conducted in this research, it would necessitate conducting 1024 and 256 experimental runs respectively, and yet these would only evaluate the factors at their lowest and highest levels. However, LHS offers a more flexible approach to the number of runs for any number of simulation factors, by allowing to specify a desired number of runs, n, into which each factor is equally divided. As shown in Table 2-1, a sample is then randomly taken from each division for all the factors to form different factor level combinations in the n experimental runs.

Table 2-1: LHS factor division and sampling

	Factor B, n= 5 divisions				
Factor A, n= 5 divisions	x				
					x
		x			
				x	
			x		

2.9.2 Stochastic Dominance Test of Robustness

Stochastic dominance tests [170, 171] on the service level performances of the system will give indications of how well a strategy/policy is able to maintain close to the original target service levels. The tests are conducted on the LHS outputs. Stochastic dominance test results can be of first-order, second-order or inconclusive, depending on the level of difference between the outputs. As shown in Figure 2-12, a first-order dominance is often recognisable by visual observation because the CDF curves of the two options being compared do not intersect.

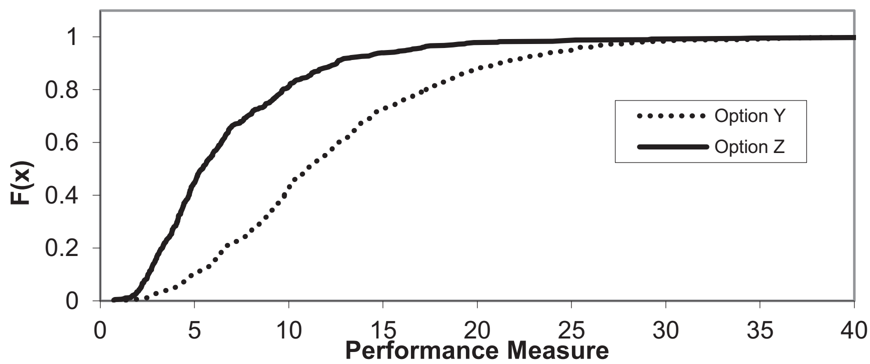


Figure 2-12: First Order Dominance [172]

Mathematically expressed, it implies that for two options Y and Z with cumulative density functions $F_Y(x)$ and $F_Z(x)$ where the objective is to maximise the value of x;

Option Y is said to first-order stochastically dominate Z, if:

$$F_Y(x) \leq F_z(x), for\ all\ x \qquad (1)$$

However, as shown in Figure 2-13, a second-order dominance is not visually identifiable, and it requires the use of the area under the CDF curve to identify the dominant option. Thus, Option Y second-order stochastically dominates Z, if:

$$\int_{min}^{k} F_Y(x)dx \leq \int_{min}^{k} F_z(x)dx\,, for\ all\ k \qquad (2)$$

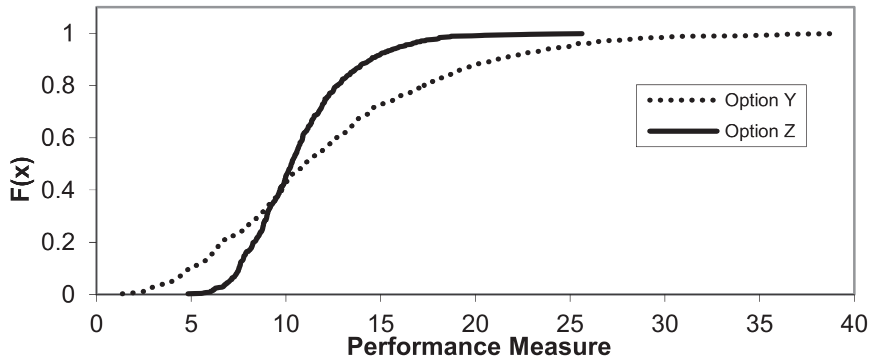


Figure 2-13: Second Order Dominance [172]

Vose software has a MS Excel™ plugin, named ModelRisk, which is able to compute this area and identify the level of dominance between sets of raw data.

Meanwhile, in real life situations, there are usually other justifications for taking decisions about the suitability of systems based on the outcome of sensitivity analysis tests and, especially when the first or second order of dominance cannot be established. Therefore, 95% confidence intervals for the performance measures are also used in this study as a means of observing the superiority of one option over the other. The confidence intervals will give a measure of relative achievement for the different options, irrespective of how close or distant they are to the original target, while the stochastic dominance test serves as a way of measuring how well they remain close to the original target under the influence of environmental stability.

2.9.3 ExtendSim – Simulation Modelling

ExtendSim is a commercial software product of Imagine That! Incorporated, U.S.A for simulation modelling of different types of systems. The software's dedicated manufacturing blocks and libraries can be used to model manufacturing system entities, which include parts, buffers, demands, workstations and operators (if considered), and the events they undergo. These blocks can be manipulated to model the typical events that occur in Kanban controlled manufacturing systems, such as the breakdown and repair of machines, the introduction of parts into the system, the arrival of customer demands, the flow of Kanbans, the transmission of demand information between stages, the synchronisation of parts with demand and Kanban information and the authorization of part release downstream. Its animation feature is also useful for verifying that these events are correctly executed in the model, most especially the flow of parts and the adherence to the Kanban dedication. There are also blocks for setting up the parameters of the different strategies and for collecting their output statistics. Although, most discrete event simulation packages possess the above features, the eventual choice of ExtendSim for this research is further due to the applicability of the skills already gained from its previous use.

2.9.4 JMP – LHS Design of Experiments and Results Analysis

For experimental design, JMP™ software by SAS Institute, offers a range of experimental design methods depending on the number of factors and the nature of analysis to be done. Its LHS space filling design is especially useful for achieving sufficient coverage with lesser number of experiments than required in factorial designs, especially when the number of experimental factors is high. JMP is also generally applied in six sigma, quality control, metamodeling, and in results analysis. Its LHS functionality was used for the LHS designs for the three sets of experiments.

2.9.5 ModelRisk – Stochastic Dominance Tests

Stochastic dominance (Robustness) test is a form of sensitivity analysis which is widely applied in financial and investment analysis. Stochastic dominance comparisons can be conducted in Vose software's ModelRisk™ tool. It is an MS Excel add-in which works in a way that the data sets to be compared can be ordered by column or rows for robustness comparison. The results of the comparisons are tabulated in a pairwise mode for ease of interpretation. ModelRisk is also used for Monte Carlo simulation, multivariate analysis, time series and optimization.

2.10 KEY INSIGHTS FOR THIS RESEARCH FROM REVIEWED LITERATURE

The DKAP appears to be the default policy that is commonly assumed by most studies [14, 23, 84, 87, 89, 117, 119], even after the SKAP was first proposed [9]. However, since a later work [10] on both policies, there seems to have been some comparative works undertaken on them [11-13, 81, 101], and some of these have shown that both have their pros and cons, as well as varying levels of compatibility with different system conditions.

Interestingly, no research up to date has looked into the possibility of combining both policies in a single manufacturing system, as has been done with control strategies [5-7, 27-29, 77, 81, 101]. This is what this research aims to achieve in a way that would combine the benefits of both policies into a single hybrid policy. It will investigate how this can be achieved by first investigating the behaviours of different strategies and their corresponding Kanban allocation policies under different manufacturing scenarios. It will then use the outcomes to further investigate the possible application of processing time and demand attributes in grouping products for Kanban sharing. This principle will be similar to what is done in cellular manufacturing whereby products are grouped based on the similarity of their processing requirements [53-56].

CHAPTER - 3: Research Outline and Preliminary Comparison of Control Strategies

3.1 INTRODUCTION

This research will be conducted in three sets of experiments. The first set of experiments involves a preliminary comparison of different production control strategies, followed by a second set of experiments to evaluate Kanban allocation policies. The third set of experiments will involve the development and implementation of a new policy. This chapter will provide a brief overview of the three sets of experiments before going into specific description of the setup of the first set of experiments and the discussion of its results. The setup of the other two sets of experiments and the discussion of their results will be done in subsequent chapters.

3.2 RESEARCH OUTLINE

The three sets of experiments are conducted on two manufacturing systems of varying levels of complexity. The first two sets of experiments are conducted on a simplified two product system, while the third set uses an eight product system. The first set which compares different pull strategies serves as a preliminary evaluation of strategies that can operate both the DKAP and SKAP against those that can only operate the DKAP. The simulation and optimisation methodologies applied in the first set of experiments are described in the present chapter, along with discussions of its results.

In the second set of experiments, the two product system is used again, but with particular focus on evaluating the performance of the two Kanban allocation policies for the strategies that can operate both. Most of the system modelling and optimisation methodologies for the first set of experiments are again applied in conducting the second set of experiments. Other experimentation and analysis techniques that are specific to the second set of experiments will be discussed in the Chapter 4 before the presentation and discussion of its results.

In the third set of experiments, some of the experimentation and analysis technique of the first two sets of experiments are again applied. However, different simulation modelling tool and optimisation approaches are adopted, because of the higher level of complexity of the system. These will be described in Chapter 5 before the results of the experiments are discussed.

3.3 PRELIMINARY COMPARISON OF STRATEGIES

In the following sections, a two product system is setup and used to compare the different strategies and their applied policies. The comparisons are based on sensitivity analysis and stochastic dominance testing which investigate the ability of an optimised production control strategy to maintain its level of performance under different sources of variability, without it being re-optimised for the changes that occur. In this case, the sources of variability are system unreliability, product demand variability and having to cope with multiple products of disparate demand profiles. The latter scenario is a particular case in the semiconductor manufacturing sector which often must manufacture, newly introduced, mature, soon to be phased out, and legacy products, which would have different demand profiles, at the same time.

3.4 SETUP OF TWO PRODUCT SYSTEM AND EXPERIMENTS

The simplified two product manufacturing system, shown in Figure 3-1, was used in order to isolate the factors of interest for investigation, and to be able to focus on setting the products' demand CV values to reflect different levels of disparity in product demand profiles.

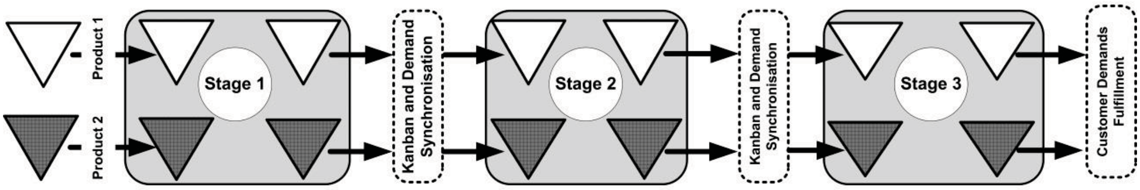


Figure 3-1: Simplified Two Product Manufacturing System

First, in order to achieve a realistic representation for the manufacturing system, the processing time, mean time to failure ($MTTF$), mean time to repair ($MTTR$) and the products' mean times between demands are set to result in an overall system capacity load that does not exceed 100%. Also, reflective of a corrective maintenance policy [97, 173] in which the time of occurrence and the nature of the next breakdown are unpredictable, the three manufacturing stages have exponentially distributed $MTTF$ and $MTTR$ with means of 90 *hours* and 10 *hours* respectively, which result in 90% availability of each of them. Examples of simulation studies in which the exponential distribution has been similarly used are [38, 83, 174]. The $MTTF$ and the $MTTR$ are as illustrated in Figure 3-2.

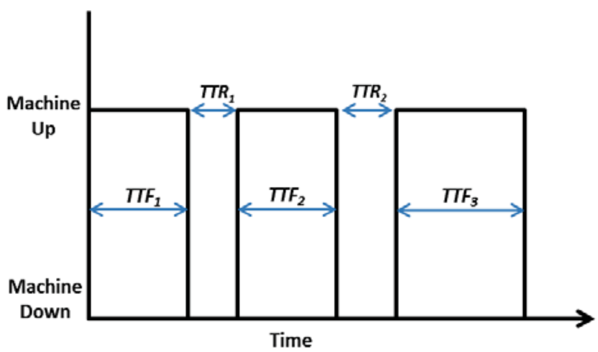


Figure 3-2: MTTF and MTTR of the manufacturing stages

A simulation model of the system developed in ExtendSim™ is used in setting its load level by first determining the throughput capacity in a push mode, without Kanban restrictions and under the assumption of unlimited demands. Raw parts are released in equal proportion into the system for the two products and processed at the manufacturing stages on a FIFO basis. Product 1 requires 1.5 hours processing time at each of the manufacturing stages, while Product 2 requires twice as much time at the three stages.

The mean inter-release time of each product type from the system is measured and then used to set the respective product's mean time between demands to 110% of the value obtained as shown in Table 3-1. This corresponds to a load level of 90.9% on the system's production capacity.

Table 3-1: Setting Products' Mean Times between Demands

Product	Mean Inter-release time under Push (hours)	Mean Time between Demands (hours) at 90.9% of Production Capacity
1	5.1	5.61
2	5.2	5.72

The products' mean times between demands are specified with a normal distribution because of its suitability for modelling distributions that represent a combination of events [106], and in this case the demand events are from different customer sources. Moreover, this distribution has been chosen because of the ease in setting the variability level with a combination of standard deviation, σ, and mean, μ, values [46, 63]. The coefficient of variation (CV) of a normal distribution is defined as shown in equation (3).

$$CV = \frac{\sigma}{\mu} \tag{3}$$

It has been observed that the CV range mostly applied in Kanban controlled systems research is between 0 and 1.0 [38]. Specifically for demand, two separate studies ([22] cited in [21]) and [32] suggest 0.1 and 0.2 respectively as the maximum CV level under which the traditional KCS would thrive properly. Later studies have used up to 0.5 because those maximum CV limits are not usually realisable in western manufacturing systems [21]. Moreover, the subsequent pull control variants are more resilient [38, 115]. Therefore, the demand standard deviation values for this system are set to 0.1 and 0.5 of the mean values in order to represent low and high CV levels respectively. These levels are then applied in a full factorial experiment with the demand variabilities of the two products, as shown in Table 3-2.

Table 3-2: Demand CV Levels for the Products

Product	Fixed Mean	Demand CV Levels	
		Low (0.1)	High (≈0.47)
1	$\mu = 5.61$	$\sigma = 0.561$	$\sigma = 2.805$
2	$\mu = 5.72$	$\sigma = 0.572$	$\sigma = 2.860$

It should be noted that the normal distribution is truncated by setting any negative variate it generates for the time between two consecutive demands to zero and assuming such demands arrived simultaneously [115]. It was observed from the inspection of the truncated data that the high CV levels are effectively 0.47, while the low CV levels remain 0.1.

3.4.1 Full Factorial Experiments at Two Levels of Products' Demand Variability

With the low and high levels of demand CVs for the two products, a full factorial design of experiments is developed to create four scenarios that correspond to varying levels of disparity in the demand profiles of the products, as shown in Table 3-3.

Table 3-3: Experimental Scenarios

Scenario	Product 1 Demand CV	Product 2 Demand CV
1	High	Low
2	Low	Low
3	Low	High
4	High	High

The first scenario, which is the most extreme among the four scenarios, is first applied in comparing the SKAP and DKAP of the GKCS and the EKCS alongside the other production control strategies, as shown in Table 3-4. The aim of this is to investigate if there are underlying advantages in such scenarios for strategies that can operate different Kanban allocation policies.

Table 3-4: Strategies and Policies for the First Set of Experiments

Scenario	Product 1 Demand CV	Product 2 Demand CV	Strategies Compared	Policies Applied
1	High	Low	CONWIP	DKAP
			BSCS	DKAP
			KCS	DKAP
			GKCS	DKAP
				SKAP
			EKCS	DKAP
				SKAP

The comparisons between the strategies involve first optimising them for a base system setting, followed by conducting sensitivity analyses to determine their robustness.

3.4.2 System Assumptions

In order to simplify the simulation models by eliminating aspects that are not likely to have significant impact on the accuracy of its results, and to give adequate consideration to the limitations and capabilities of the simulation modelling tool, the following assumptions are made about the two systems:

- Parts are assumed to be always available to the system so the first stage is never starved of raw parts [14, 87, 87, 118].
- The WIP measurement approach that considers parts as WIP as soon as they have been authorised for processing at the first stage is followed. The alternative approach is described in Section 2.7.3.
- A minimal blocking policy [83, 174] is applied by having an input and output buffer for each manufacturing stage's machine. This means that a machine does not have to stop processing parts if the succeeding machine is busy processing another part. It can continue processing parts and store them in its output buffer until its basestock limit has been reached. Also, parts that are authorised for processing at a machine while it is busy processing another part can be kept in its input buffer and released to it as it becomes available.
- Negligible setup time is assumed, so that the different part types waiting for processing at a stage are processed in FIFO order [20].
- A demand information and a Kanban both represent single items and the parts are also processed a single unit at a time [6].

- The transmission of demand and Kanban information and the movement of parts are instantaneous and take negligible time.
- Demands that cannot be immediately satisfied are backlogged as described in Section 2.7.3.

3.4.3 Simulation Warmup Period

Welch's procedure is applied for determining the warmup period of the system, and based on a pessimistic approach, the two strategies (BSCS and CONWIP) that are most susceptible to the initialisation bias are chosen for the analysis. BSCS does not use Kanbans and as such has looser WIP control compared to the others. As the initialisation of inventory only occurs at the final stage of a CONWIP controlled system, it will require a relatively longer time to overcome any initialisation bias effect. Using these two in estimating the warmup period for the other strategies can only overestimate the warmup periods. While this may result in a waste of useful data, it does not give as much cause for concern as when the warmup period is underestimated and the data used is not truly representative of the system.

Since system optimisation cannot be done before the warmup period analysis, arbitrary Kanban and basestock settings that would yield close to the eventual target service level of 95% are set for the two strategies in conducting their warmup period analysis. Seven replications of 40,000 hours run length each are conducted with the basestock levels of the BSCS set to 2, 4 and 20 for the two products at Stages 1, 2 and 3 respectively. For the CONWIP strategy, 27 cards are allocated to each product type. The average WIP at the last stage is recorded for every 100 hour time frame and averaged across the seven replication runs. With smoothing window sizes of 20 and 10 for the CONWIP and the BSCS respectively, it was observed as shown in Figure 3-3 that the CONWIP model assumes consistency from around 12,000 hours while for the BSCS, the consistency begins from about 11,000 hours.

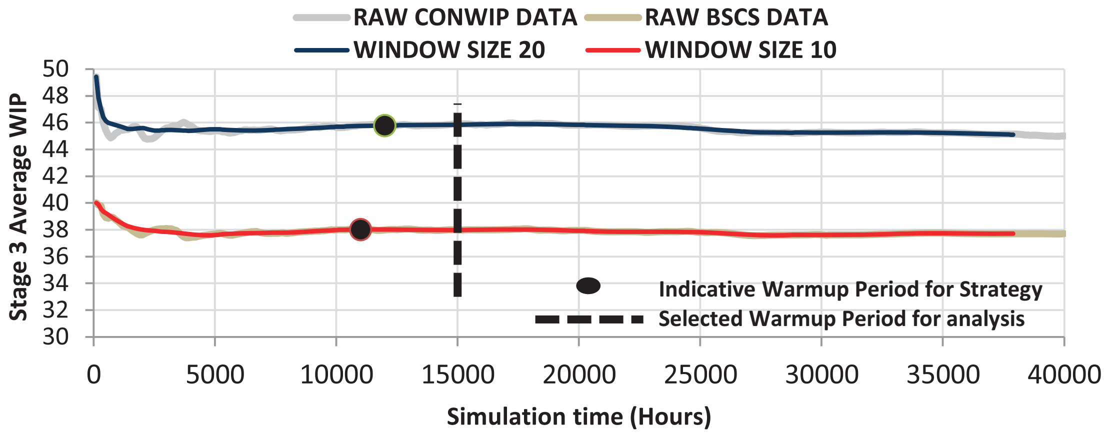


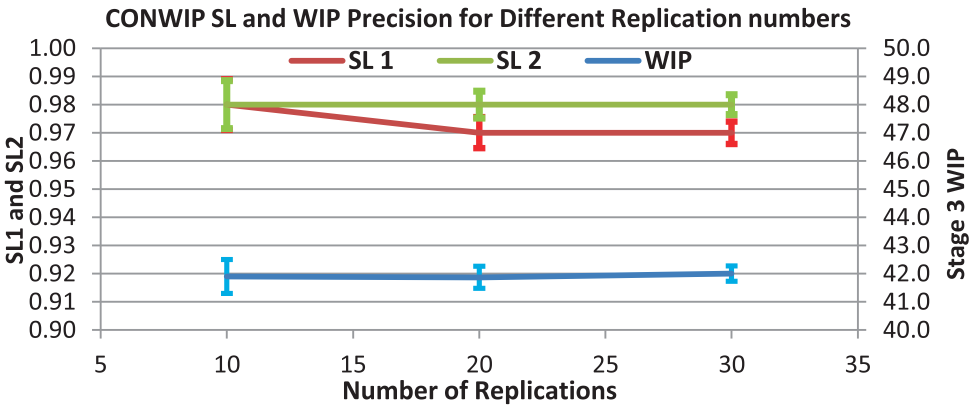
Figure 3-3: CONWIP and BSCS Warmup period Welch graph

Based on recommendations in literature to allow for a considerable number of occurrences of infrequent events such as machine breakdowns, a 15,000 hours warmup period in which up to 100 breakdown and restart cycles would have occurred was eventually chosen [106, 107].

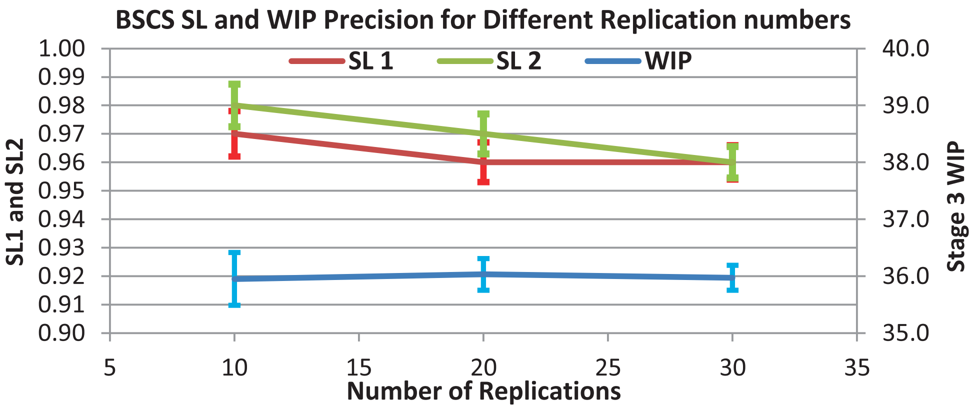
3.4.4 Simulation Run Length and Number of Replications

In addition to removing the initialisation bias, the subsequent simulation run length has to be sufficient for the system to run adequately in its steady state, and to achieve this, the deletion and replication method, which involves running multiple replications of warmup-deleted simulation runs, is applied.

A trial of different run lengths and numbers of replications was used to determine the right combination of both that would yield a desirable level of precision in the mean values of the performance measures, i.e. the run length and number of replications that would yield a confidence interval half-width that does not exceed 3% of the mean value, at a 95% confidence level. For the CONWIP, it can be observed in Figure 3-4 (a) that this was achieved for SL1 and SL2 with 20 replications, at which the half-widths were about 0.005 to mean values of 0.97 and 0.98 respectively. For the BSCS, 30 replications yielded half-widths of about 0.006 to mean values of 0.96 for SL1 and SL2, as shown in Figure 3-4 (b). Since 30 replications also reduced the width of the confidence intervals for the WIP in both models to less than 1 unit, this number of replications of 50,000 hours run length each was eventually chosen.



(a) CONWIP



(b) BSCS

Figure 3-4: Confidence Intervals for different replication numbers

This implies ending up with a simulation data of 35,000 hours per replication, after the 15,000 hours warmup period has been deleted. In total 1,050,000 hours of simulation data would be collected over the 30 replications.

3.4.5 Common Random Number Seeds

In simulation experiments comparing alternative systems, it is desirable that fluctuations in experimental conditions do not contribute to the differences observed between the systems. Using common random number seeds achieves a positive correlation between corresponding replications in the experimental runs of the systems being compared [97, 106, 107]. This ensures that the systems have similar initial conditions and that the same variates are generated for the theoretical distributions used in modelling system events. However, it is difficult to assure that the random numbers are fully synchronised for every event across all the strategies. The machine breakdown and repair and demand arrival events for which the generated random variates are used might differ because of the multiple products involved in the system. Moreover, the initialised basestock level and the quantity and mix of the product types completed in each strategy might differ. Nevertheless, the retention and application of the random number seeds used for the base settings in the subsequent LHS runs helps ensure that a strategy is evaluated only for the impact of the variations made to the system factors in the LHS runs.

In the following sections, the methodologies for conducting the system modelling and optimisation for the different sets of experiments are discussed.

3.5 SYSTEM OPTIMISATION

Meta-heuristics techniques are mostly applied in the optimisation of multiproduct systems because of the number of parameters involved in them. A Genetic Algorithm library offered by the simulation modelling software is applied to determine the stage by stage optimal settings of the basestock (S) and/or the Kanbans (K) for the strategies. The solution search space for each stage's setting is predetermined by conducting preliminary evaluations to identify the reasonable ranges within which to carry out their optimisation evaluations, as described in Section 2.8.1. An objective function is then specified to the genetic algorithm library which generates alternative settings, simulate and evaluate them until a 95% target SL for both products is achieved with the lowest average system inventory level.

The minimisation-type objective function was formulated as follows:

$$MinCost = \begin{cases} WIP \text{ if } SL1 \ and \ SL2 \geq 0.95 \\ X \text{ otherwise} \end{cases} \tag{4}$$

where X is a penalty cost for not meeting the target SL

In the objective function in equation (4), it is verified if a parameter setting achieved up to the target SL of 95% for both products. If it does, its objective function is calculated based on the WIP. Otherwise, a penalty cost, X, is assigned to the objective function. The value of X is chosen to be significantly greater than the maximum possible WIP so that such parameter setting becomes an unattractive candidate for further evaluation. The same optimisation approach is followed for all the strategies.

In general, the optimisations are done in an order of increasing complexity of the strategies, starting with the CONWIP – the easiest of them all, followed by the BSCS and the KCS – the single parameter per stage strategies. Then, as a means of facilitating the optimisation process of the two parameter per stage strategies, their link to some of the single parameter per stages strategies are exploited, by initialising their solution search spaces based on the optimised settings obtained for the single parameter per stage strategies. In this vein, despite the DKAP policies of the EKCS and the GKCS having more optimisation parameters, they are optimised before the SKAP because they have been reported in Sections 2.2.5 and 2.2.6 to exhibit more direct relation to the single parameter per stage strategies than the SKAP.

Similarly, since the EKCS was developed as a combination of the BSCS and the KCS, the initial search for its S settings is conducted close to the values obtained for the BSCS. From this search, it was observed that the EKCS would require at least the same S level as that of the optimised BSCS in order to achieve the target SL, irrespective of its number of Kanbans. It should be noted that because the philosophy of the EKCS is to keep Kanbans attached to the basestock parts while they wait in a stage's output buffers, the simulation model has been implemented such that the initialised finished parts of the set basestock level, S, have a corresponding number of Kanbans, K. Therefore, the Kanban number being optimised for the EKCS's DKAP and SKAP are the extra unattached Kanbans, AK, where

$$AK = K - S \tag{5}$$

Based on the above approach, an initial evaluation reduced the solution space of the CONWIP strategy to a range of 20 – 27 from which the final optimised settings of 24 and 23 units were then obtained for the number of cards needed for Products 1 and 2 respectively. Similarly, for the BSCS and the KCS, the optimal settings shown in Table 3-5 and Table 3-6 respectively were achieved from the evaluation of the solution search spaces shown in the tables. A notable observation from the optimisation results is that the largest number of Kanbans and basestocks are set at the last stages. These are consistent with the observations of previous studies that more Kanbans and basestock are needed at the last stage to absorb demand variations and minimise demand backlog [6, 29]. Moreover, since there was no differentiation in the value of the items at the early stages of processing and those at the final stages, it was more effective to set all the basestock at the last stage.

Table 3-5: Scenario 1: BSCS Solution Space and Optimal Settings

Manufacturing Stage	Product 1 S		Product 2 S	
	Range	Opt.	Range	Opt.
1	0 – 2	0	0 – 2	0
2	0 – 3	0	0 – 3	0
3	22 – 26	24	22 – 25	24

Table 3-6: Scenario 1: KCS Solution Space and Optimal Settings

Manufacturing Stage	Product 1 K		Product 2 K	
	Range	Opt.	Range	Opt.
1	1 – 3	2	1 – 3	2
2	7 – 10	8	7 – 10	8
3	14 – 20	18	14 – 18	15

The optimised settings for the DKAP and SKAP of the EKCS and the GKCS are presented in Table 3-7 to Table 3-10, along with their respective solution search spaces.

Table 3-7: Scenario 1: EKCS DKAP Sample Space and Optimised Settings

Manufacturing Stage	Product 1				Product 2			
	AK		S		AK		S	
	Range	Opt.	Range	Opt.	Range	Opt.	Range	Opt.
1	4 – 8	**6**	0 – 2	**0**	4 – 8	**6**	0 – 2	**0**
2	6 – 10	**9**	0 – 3	**0**	6 – 10	**8**	0 – 3	**0**
3	13 – 17	**13**	22 – 24	**24**	13 – 16	**12**	22 – 24	**24**

Table 3-8: Scenario 1: EKCS SKAP Sample Space and Optimised Settings

Manufacturing Stage	Product 1		Shared Settings		Product 2	
	S		AK		S	
	Range	Opt.	Range	Opt.	Range	Opt.
1	0 – 2	0	6 – 10	7	0 – 2	0
2	0 – 3	0	15 – 17	16	0 – 2	0
3	23 – 25	25	23 – 25	23	23 – 24	24

Table 3-9: Scenario 1: GKCS DKAP Sample Space and Optimised Settings

Manufacturing Stage	Product 1				Product 2			
	K		*S*		*K*		*S*	
	Range	Opt.	Range	Opt.	Range	Opt.	Range	Opt.
1	1 – 3	1	0 – 1	0	1 – 3	1	0 – 1	0
2	7 – 10	10	0 – 2	0	8 – 9	9	0 – 2	0
3	18 – 22	22	24 – 25	25	18 – 20	20	23 – 25	25

Table 3-10: Scenario 1: GKCS SKAP Sample Space and Optimised Settings

Manufacturing Stage	Product 1		Shared Settings		Product 2	
	S		*K*		*S*	
	Range	Opt.	Range	Opt.	Range	Opt.
1	0 – 2	0	1 – 6	1	0 – 2	0
2	0 – 3	0	16 – 19	17	0 – 2	0
3	24 – 25	25	40 – 46	42	23 – 25	25

3.6 DESIGN OF EXPERIMENTS FOR SENSITIVITY ANALYSIS

In the sensitivity analysis, factors that are usually susceptible to changes from the environment, i.e. those factors that are not within the control of production line designers/managers, are selected and varied within the range of ±5% to simulate different experimental scenarios. The following environmental variables are chosen to reflect the possibility of an increase or decrease in the demand arrival rate and its variability, as well as the in-process variability which could create bottlenecks within the system.

- Mean and Standard deviation of the demand distributions of the two products; a total of 4 factors
- MTTF and MTTR for the three stages of the system give a total of 6 factors.

In total there are 10 factors, and the LHS technique is applied in setting up the sensitivity analysis experiments. As recommended in a previous study that was cited in Section 2.8.3, 100 experimental runs are derived from combinations of factor levels that are sampled from within ±5% of their base values shown in Table 3-11. Complete tables of the 100 LHS runs for each of the scenarios are shown in APPENDIX - A. The LHS experiments are designed in JMP® software which was briefly described in Section 2.9.4.

Table 3-11: Part One Experiments: LHS Ranges for Sensitivity Analysis

	PRODUCT 1			PRODUCT 2			
	-5%	Base	+5%		-5%	Base	+5%
DEMAND	Low *CV*			Low *CV*			
MEAN (Hours)	5.540	5.610	5.681	**MEAN**	5.648	5.720	5.792
S.D. (Hours)	0.281	0.561	0.842	**S.D.**	0.286	0.572	0.858
DEMAND	High *CV*			High *CV*			
MEAN (Hours)	5.258	5.610	5.962	**MEAN**	5.361	5.720	6.079
S.D. (Hours)	2.525	2.805	3.086	**S.D.**	2.574	2.860	3.146
WORKSTATIONS 1 – 3							
MTTF (Hours)	78.50	90.0	103.00				
MTTR (Hours)	8.72	10.0	11.50				

Similarly to the base settings experiments, each LHS run is replicated 30 times. Stochastic dominance tests are then conducted on the results obtained from the LHS experiments. The LHS results are also applied in determining the level of impact the system and product related factors have on the service levels and the system WIP under the different strategies and their policies. It should be noted that the systems are not re-optimised for the LHS run settings, since the aim is to investigate their robustness to variations that were unforeseen during their optimisation.

3.7 RESULTS FROM SCENARIO 1: HIGH PRODUCT 1 VARIABILITY – LOW PRODUCT 2 VARIABILITY

This section presents the results of the strategy and policy comparison experiments that were conducted on the first scenario of the two product system. The results consist of the outcomes of the sensitivity analysis and the robustness tests performed to compare how well the strategies and policies are able to maintain close to their original optimised service levels, while also keeping control of the average system WIP under conditions of internal and external system instabilities.

3.7.1 Robustness of Products' Service Levels

The service levels achieved for the two products, as well as the average total WIP, are used as the performance measures in comparing the strategies. For illustration purposes, cumulative density function (CDF) plots are constructed with incremental class intervals of 0.001 (0.1%) for the service levels achieved for Product 1 and 2, as shown in Figure 3-5 and Figure 3-6 respectively. The stochastic dominance test results reported in this chapter were conducted on the raw data without grouping them into classes, as explained in Section 2.9.2. This makes it possible to identify second-order dominance which is usually more difficult to read from the CDF plot. It also allows the robustness comparisons to be made across the entire range of the data in such a way that would take full account of cases where strategies achieve adequate service level at the expense of high average WIP, as well as cases of not attaining adequate service level because of strict maintenance of a low average WIP.

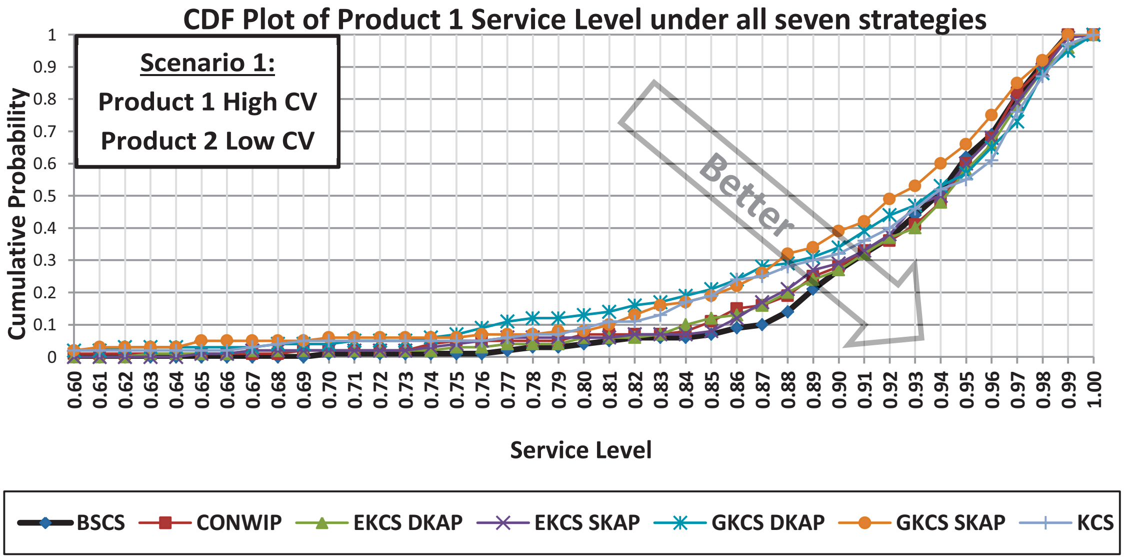


Figure 3-5: Cumulative Density Function Plot for SL1

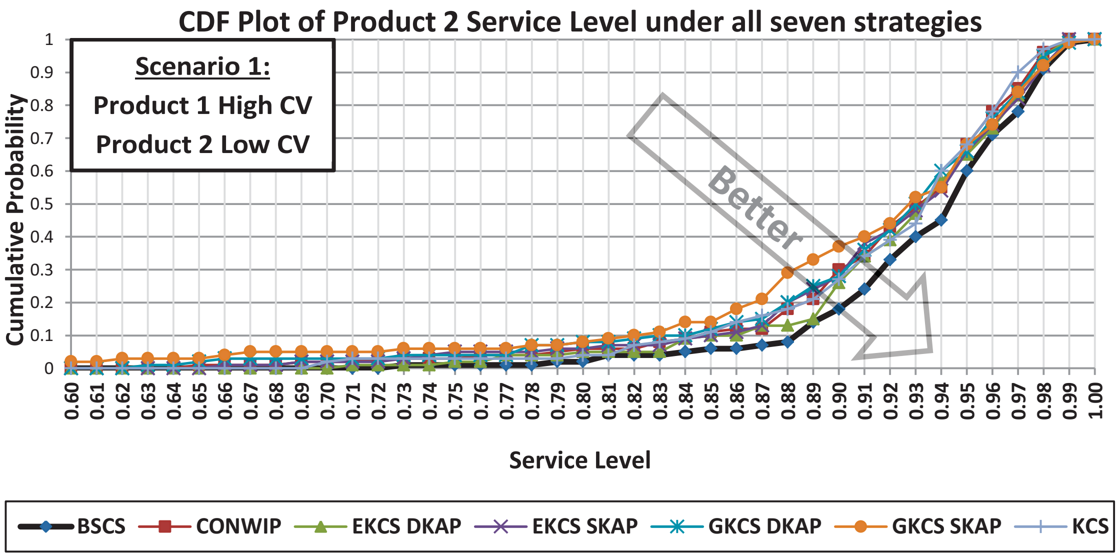


Figure 3-6: Cumulative Density Function Plot for SL2

Comparisons of the seven strategies in terms of Product 1's service level robustness are presented in Table 3-12. It shows that BSCS stochastically dominates all other strategies followed by the EKCS DKAP and the EKCS SKAP. KCS dominates the two GKCS policies, among which there was an inconclusive stochastic dominance result. Inconclusive dominance test outcomes were also recorded between CONWIP and the EKCS SKAP, and between the DKAP and SKAP of EKCS. All the Stochastic Dominance results reported are second-order, except in the comparisons between the GKCS SKAP and the two policies of the EKCS, where first-order dominance results were recorded.

Table 3-12: Product 1 SL Robustness Test results

Strategies	BSCS	CONWIP	EKCS DKAP	EKCS SKAP	GKCS DKAP	GKCS SKAP	KCS
BSCS		BSCS (2nd Order)	BSCS (2nd Order)	BSCS (2nd Order)	BSCS (2nd Order)	BSCS (2nd Order)	BSCS (2nd Order)
CONWIP			EKCS DKAP (2nd Order)	Inconclusive	CONWIP (2nd Order)	CONWIP (2nd Order)	CONWIP (2nd Order)
EKCS DKAP				Inconclusive	EKCS DKAP (2nd Order)	EKCS DKAP (1st Order)	EKCS DKAP (2nd Order)
EKCS SKAP					EKCS SKAP (2nd Order)	EKCS SKAP (1st Order)	EKCS SKAP (2nd Order)
GKCS DKAP						Inconclusive	KCS (2nd Order)
GKCS SKAP							KCS (2nd Order)
KCS							

Table 3-13: Product 2 SL Robustness Test results

Strategies	BSCS	CONWIP	EKCS DKAP	EKCS SKAP	GKCS DKAP	GKCS SKAP	KCS
BSCS		BSCS (2nd Order)	BSCS (1st Order)	BSCS (1st Order)	BSCS (1st Order)	BSCS (2nd Order)	BSCS (1st Order)
CONWIP			EKCS DKAP (2nd Order)	Inconclusive	CONWIP (2nd Order)	CONWIP (2nd Order)	KCS (2nd Order)
EKCS DKAP				EKCS DKAP (2nd Order)	EKCS DKAP (2nd Order)	EKCS DKAP (2nd Order)	EKCS DKAP (2nd Order)
EKCS SKAP					EKCS SKAP (2nd Order)	EKCS SKAP (2nd Order)	Inconclusive
GKCS DKAP						GKCS DKAP (2nd Order)	KCS (2nd Order)
GKCS SKAP							KCS (2nd Order)
KCS							

In the case of Product 2 service level, as shown in Table 3-13, BSCS again stochastically dominates all other strategies, with four of the cases being first-order dominance. Two second-order dominance results are recorded in its comparisons with

CONWIP and the GKCS SKAP. The EKCS DKAP dominates all the other strategies, while its SKAP counterpart, which should have come after it in superiority, has inconclusive stochastic dominance comparisons against the KCS and CONWIP, but dominates both GKCS policies – just like the KCS does. The KCS similarly stochastically dominates CONWIP, and the GKCS DKAP has second-order stochastic dominance over its SKAP counterpart in this case.

3.7.2 Inventory Control Effectiveness of Strategies

As shown in Figure 3-7, the dominance of the BSCS in terms of service level was at the expense of keeping high inventory in the system, as it is evident that it dominates the other strategies with a higher average system WIP.

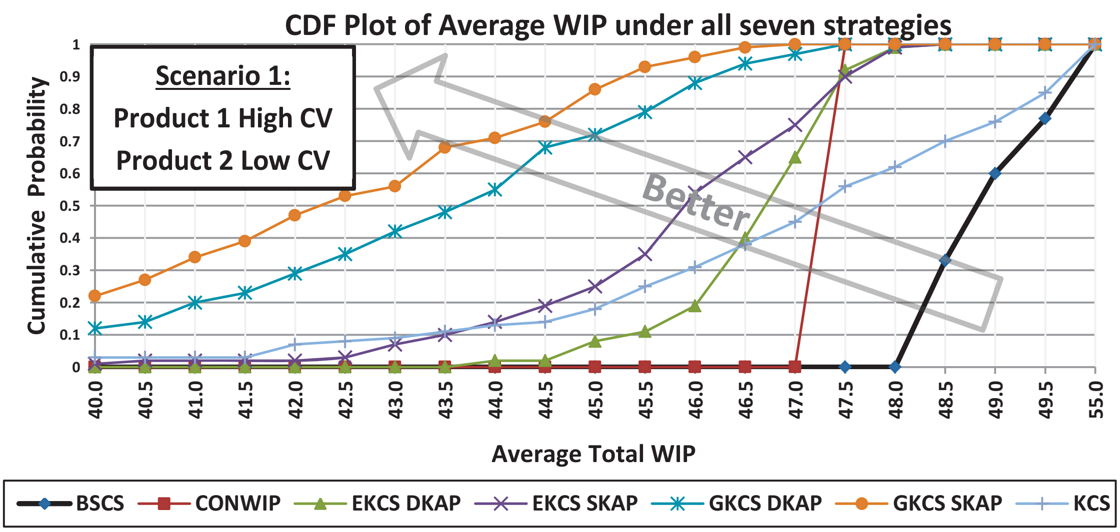


Figure 3-7: Cumulative Density Function Plot for WIP

It could be observed that the CONWIP consistently maintained an average WIP level corresponding to the total optimal card number set for the two product. This is because infinite raw materials were assumed to be available at the first stage, thereby ensuring that a new raw part is immediately released into the system to replace a finished item that is used to satisfy customer demand. Also, the BSCS's average WIP level never dropped below 48 which was the total optimal basestock level set for the two products. This is again due to the assumption of infinite availability of raw materials and because the BSCS always orders immediate replenishment of the basestock in response to demands. The BSCS can therefore only exceed the set basestock level, during periods when the rate of processing of items through them system lags behind the rate of arrival of demands.

3.7.3 Insights into Robustness of Strategies

As shown in Table 3-14, out of all the 21 stochastic dominance comparisons performed in pairs between the 7 strategies for Average WIP, 14 are first-order, 5 are second-order while the rest are inconclusive. Overall, at one extreme is the BSCS offering the most robust service level for the two products at the expense of high WIP, while at the other extreme is the GKCS SKAP keeping WIP effectively low but with poor service levels. Other strategies in between these two extremes offer a trade-off between the two performance measures, most especially the EKCS DKAP.

Table 3-14: Average System WIP Robustness Test results

Strategies	BSCS	CONWIP	EKCS DKAP	EKCS SKAP	GKCS DKAP	GKCS SKAP	KCS
BSCS		BSCS (1st Order)	BSCS (1st Order)	BSCS (1st Order)	BSCS (1st Order)	BSCS (1st Order)	BSCS (1st Order)
CONWIP			CONWIP (2nd Order)	CONWIP (2nd Order)	CONWIP (2nd Order)	CONWIP (1st Order)	CONWIP (2nd Order)
EKCS DKAP				EKCS DKAP (2nd Order)	EKCS DKAP (1st Order)	EKCS DKAP (1st Order)	Inconclusive
EKCS SKAP					EKCS SKAP (1st Order)	EKCS SKAP (1st Order)	Inconclusive
GKCS DKAP						GKCS DKAP (1st Order)	KCS (1st Order)
GKCS SKAP							KCS (1st Order)
KCS							

These observations put into question the commonly applied approach of comparing PPCSs based on the results obtained from optimising them for a particular base condition. With such approach, the GKCS, particularly its SKAP, would have been the recommended strategy because of its lowest WIP level. Even though, the GKCS SKAP still continues to offer the least average WIP during the robustness test, the other strategies now possess better service levels. KCS, CONWIP and the two EKCS policies lie in between achieving the high service level at one extreme and keeping inventory tightly low at the other end. Out of these four strategies, the EKCS DKAP is recommended for manufacturing setups seeking a trade-off, because it clearly outshines the KCS and the CONWIP in terms of service levels and average total WIP. It is also a better option ahead of its SKAP counterpart whose dominance over CONWIP and KCS is not as clear.

The outcome of these experiments has also succeeded in highlighting how the two Kanban allocation policies will perform when multiple products of disparate levels of demand fluctuations are involved. This is a very common scenario in modern multiproduct manufacturing environments whereby several products at different stages of life cycle have to share the same production facility. Furthermore, the importance of the level of interaction involved in the Kanban and basestock settings of individual product types was observed in the optimisation of the systems. The Kanban and basestock settings for individual products depend on factors such as their individual processing times and demand arrival rates [58].

3.7.4 Insights into Performance of Kanban Allocation Policies

In order to investigate the behaviour of the two Kanban allocation policies, their service level and WIP robustness were compared for the EKCS and the GKCS, the two strategies being the only two that can operate either policy. It was observed that the SKAPs of both strategies maintain lower levels of average system WIP than their DKAP counterparts. On the other hand, their DKAPs stochastically dominate their SKAP counterparts in the service level robustness of the lower demand variability level Product 2. However, there was no clear differentiation between their performances in the case of Product 1 which had the higher level of demand variability. These service level robustness results show that the product with the lower level of demand variability achieves a more robust service level when it did not share Kanbans with the high demand variability product, while the high demand variability product was indifferent to Kanban sharing or dedication.

This is further explained by how individual products are able to maintain a service level that corresponds to their level of demand variability under the DKAP, as shown in the plots in Figure 3-8 – Figure 3-11. However, the two products tend to have similar service levels under the SKAP. This implies that Product 2, with the low variability demand, had its service level impaired by the demand variability of Product 1.

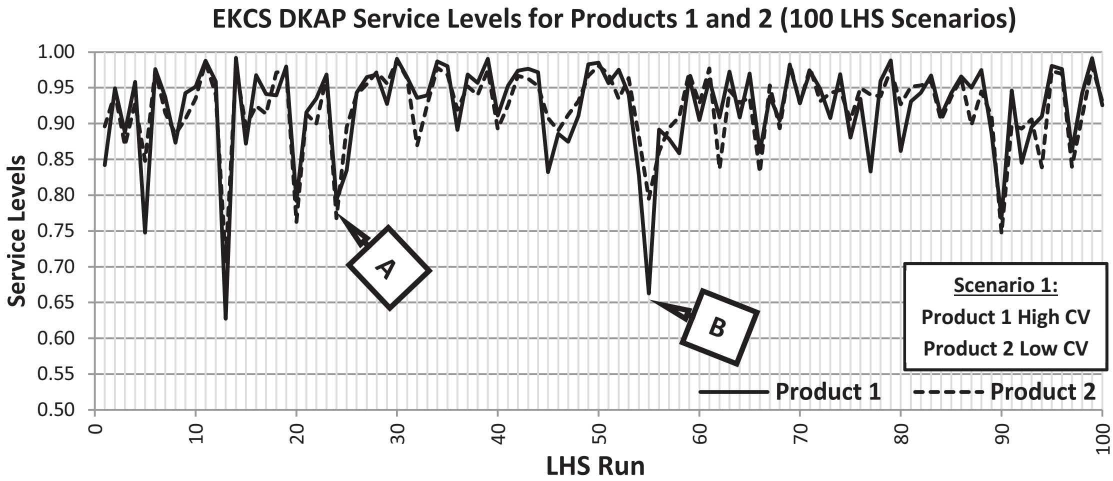


Figure 3-8: EKCS DKAP SLs for Products 1 and 2

For instance, the sharp declines in service levels observed in the EKCS DKAP plot in Figure 3-8 are due to the LHS runs in which the machines had lower availability (labelled as A) and when the mean time between demand arrivals is lower than the base setting for Product 1 (labelled as B). As shown in Figure 3-8, in the former situation, the decline in service levels applies to both products, while in the latter situation the DKAP isolated the decline in service level to only the product with an increased frequency of demand arrival.

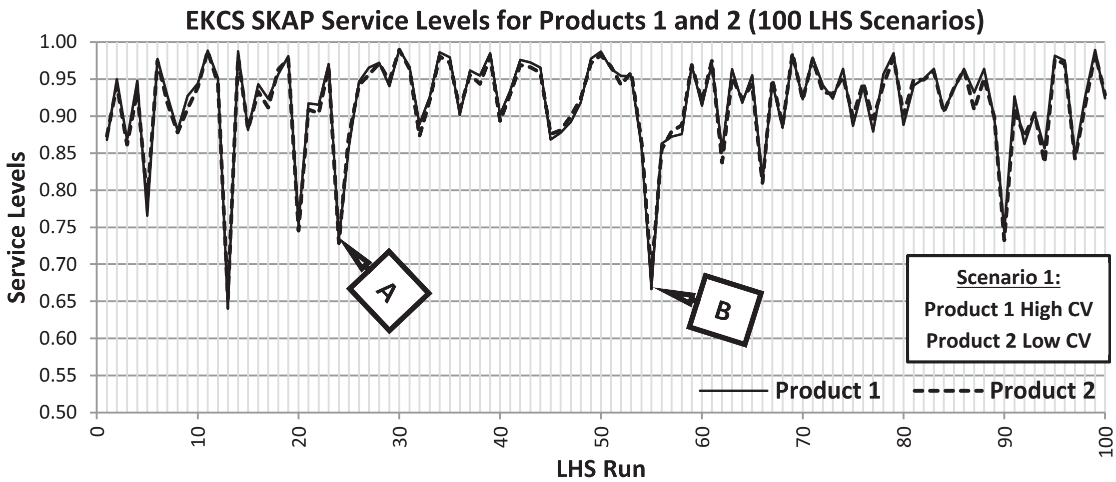


Figure 3-9: EKCS SKAP SLs for Products 1 and 2

However, as shown in Figure 3-9, this was not the case in the SKAP under which both products suffered the same fate, irrespective of whether the increased frequency of demand was only to one of the products. The behaviours of the system for the two policies were similar under the GKCS, perhaps with more pronounced service level declines in both situations, as evident in Figure 3-10 and Figure 3-11.

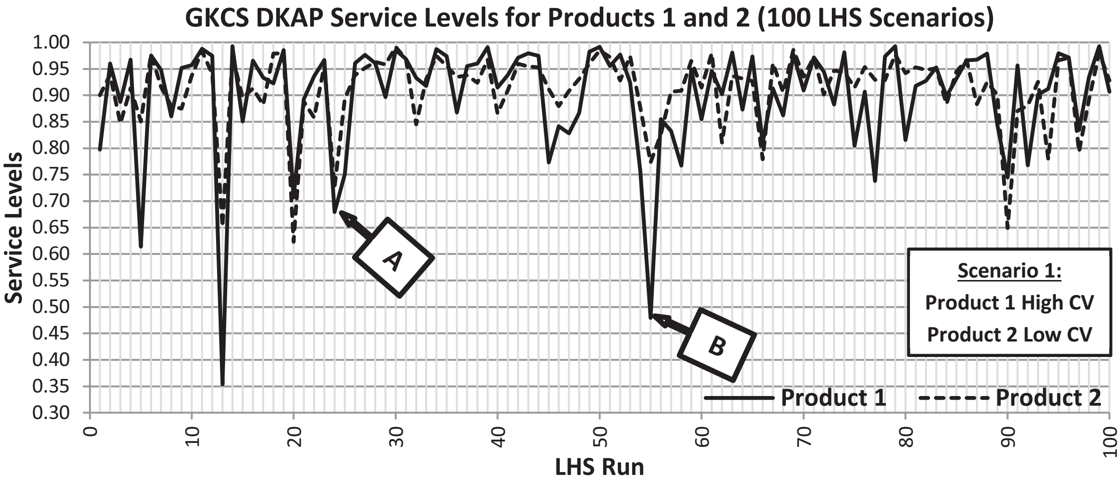


Figure 3-10: GKCS DKAP SLs for Products 1 and 2

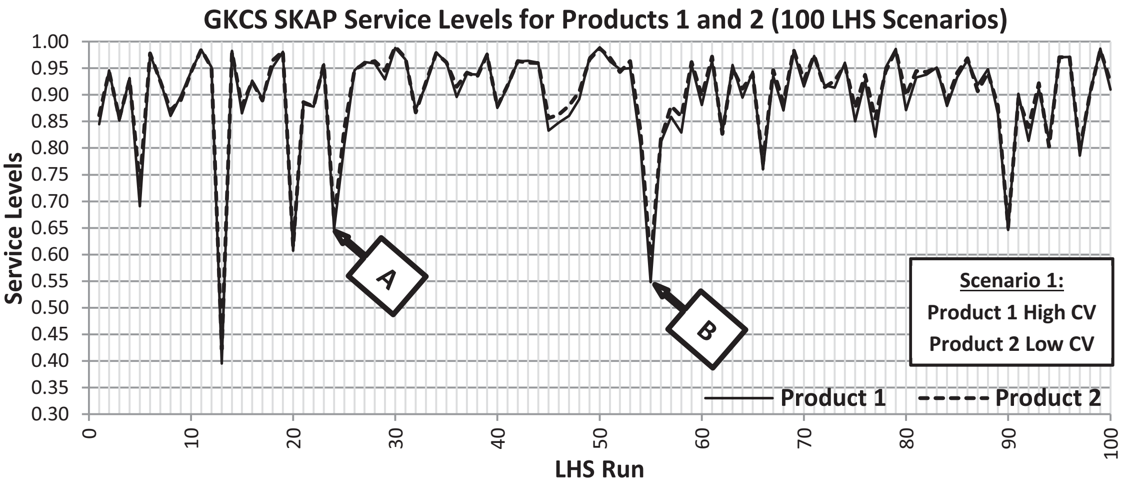


Figure 3-11: GKCS SKAP SLs for Products 1 and 2

As such, the lower WIP levels of the SKAPs might not always justify the undue degradation it might cause to the service level of some of the products involved, especially to a product with a low level of demand variability. As a result, further investigations will be conducted to determine the conditions that are suitable for Kanban sharing between products.

3.8 CONCLUSIONS

The results from these first sets of experiments have shown that the level of decoupling between the Kanban and demand information plays a major role in the service level robustness of strategies. The BSCS, which is the most decoupled (in fact uncoupled since it does not use Kanbans), is the most robust but has poor WIP control. On the other hand, tightly coupled strategies have better WIP control but are less robust, as evident in the KCS and the GKCS. It might be argued that the KCS is more tightly coupled than the GKCS but does not achieve a tighter WIP control. However, this is due to the fact that the KCS sets all its Kanbans as basestock, which leads to the proliferation of inventory, more so in a multiproduct system, as a study similarly observed [14]. The GKCS and the EKCS are able to minimise what that study referred to as resident WIP in the KCS. The EKCS, which is totally decoupled, can be said to provide the best trade-off for both performance measures. The CONWIP too provides a relatively good trade-off. Those less robust strategies with tight WIP control are mostly suitable for low variability manufacturing conditions.

In conclusion, observations from the first set of experiments have shown that different Kanban allocation policies deliver varying levels of inventory (WIP) control and service level (SL) robustness performances. Therefore, in a second set of experiments comprising of the last three scenarios in Table 3-3, their performances are further investigated under different demand profile disparity levels between the two products involved.

CHAPTER - 4: Evaluation of Kanban Allocation Policies

4.1 INTRODUCTION

The observations from the first of the four scenarios under which the two product system is to be experimented have shown that different Kanban allocation policies deliver varying levels of inventory (WIP) control and service level (SL) robustness performances. Therefore, in the last three scenarios, the two policies will be further compared for the EKCS and the GKCS which are the only two strategies that can operate the two policies. The aim is to investigate the observations from Section 3.7.4 more critically by further experimenting with the two product system at different levels of disparity in the two products' demand profiles. The observations from these scenarios will then be used in selecting from the two strategies and eventually in formulating a Kanban allocation policy for a more complex manufacturing system.

4.2 SECOND SET OF EXPERIMENTS FOR POLICY COMPARISONS

A second set of experiments consisting of the last three scenarios of the full factorial experiments in Table 3-3 will focus on comparing the performances of the SKAP and DKAP for the GKCS and the EKCS, as shown in Table 4-1.

Table 4-1: Scenarios 3 to 4 (Second Set of Experiments)

Scenario	Product 1 Demand CV	Product 2 Demand CV	Strategies Compared	Policies Applied
2	Low	Low	GKCS	DKAP
				SKAP
			EKCS	DKAP
				SKAP
3	Low	High	GKCS	DKAP
				SKAP
			EKCS	DKAP
				SKAP
4	High	High	GKCS	DKAP
				SKAP
			EKCS	DKAP
				SKAP

The warmup period, simulation run length and the number of replications determined in Section 3.4 were again applied. Also, the same approach used in optimising the systems, followed by conducting sensitivity analysis on the optimised settings is again applied, as done in the first scenario.

4.3 SYSTEM OPTIMISATION

The same optimisation approach described in Section 3.5 was applied in determining the optimal basestock and Kanban settings under the three scenarios, for which the results presented in Table 4-2 and Table 4-3 were obtained for the EKCS and the GKCS respectively. It is interesting to note that unlike in the first Scenario, all the system basestock parts were not set at the last stage, except for the GKCS DKAP in Scenario 3. This was because although it is most effective to set all the basestock parts at the last stage – as explained previously in Section 3.5, it becomes more difficult for that stage to sustain the replenishment of the basestock parts if the two products have similar levels of demand variability or demand arrival rates. Therefore, it would be necessary in such situations to buttress the capacity of that stage by allowing some finished parts in the output buffers of the penultimate stages. Thus, this justifies the non-zero basestock levels set in Scenarios 2 and 4. In Scenario 3 in which the products' levels of demand variability differed, the lower demand arrival rate product having the higher demand variability, and the other product's reverse condition, would have the same effect of the last stage struggling to replenish the basestock parts for the two products. When an attempt was made to set all the basestocks to the last stage for each of these scenarios, higher total basestock levels were required for the products, and these resulted in higher WIP than the settings obtained below.

Table 4-2: Optimised S and AK for EKCS DKAP and SKAP

	Scenario 2: Low Product 1 CV – Low Product 2 CV						
	DKAP				SKAP		
Manufacturing Stage	Product 1		Product 2		Product 1	Shared	Product 2
	S	AK	S	AK	S	AK	S
1	0	1	0	1	0	1	0
2	6	0	5	1	5	1	5
3	13	1	12	2	13	0	13
	Scenario 3: Low Product 1 CV – High Product 2 CV						
	DKAP				SKAP		
Manufacturing Stage	Product 1		Product 2		Product 1	Shared	Product 2
	S	AK	S	AK	S	AK	S
1	0	1	0	1	0	1	0
2	5	1	5	1	5	2	5
3	13	6	14	3	14	0	14
	Scenario 4: High Product 1 CV – High Product 2 CV						
	DKAP				SKAP		
Manufacturing Stage	Product 1		Product 2		Product 1	Shared	Product 2
	S	AK	S	AK	S	AK	S
1	0	1	0	1	0	1	0
2	3	6	3	6	4	3	4
3	15	14	15	13	15	2	15

Table 4-3: Optimised S and AK for GKCS DKAP and SKAP

	Scenario 2: Low Product 1 CV – Low Product 2 CV						
	DKAP				SKAP		
Manufacturing Stage	Product 1		Product 2		Product 1	Shared	Product 2
	S	K	S	K	S	K	S
1	0	1	0	1	0	1	0
2	3	6	2	6	4	9	4
3	18	12	18	11	18	19	18
	Scenario 3: Low Product 1 CV – High Product 2 CV						
	DKAP				SKAP		
Manufacturing Stage	Product 1		Product 2		Product 1	Shared	Product 2
	S	K	S	K	S	K	S
1	0	1	0	1	0	1	0
2	0	7	0	7	4	9	4
3	20	15	21	15	18	19	18
	Scenario 4: High Product 1 CV – High Product 2 CV						
	DKAP				SKAP		
Manufacturing Stage	Product 1		Product 2		Product 1	Shared	Product 2
	S	K	S	K	S	K	S
1	0	1	0	1	0	1	0
2	5	6	4	6	4	9	4
3	17	12	17	12	18	19	18

Sensitivity analysis was then similarly conducted on the optimised settings by varying the same set of factors varied in Section 3.6 for the first scenario and simulating the system across 100 LHS runs of 30 replications each.

4.4 RESULTS FROM COMPARISON OF POLICIES FOR EKCS AND GKCS

The results from the LHS experiments were used in further comparing the two policies based on the preliminary observations from Section 3.7.4. The aim is to further compare them across the fours scenarios of having different levels of disparity in the levels of demand variability of the two products in order to establish the following:

- If the DKAP always ensures better than the SKAP that products maintain service levels corresponding to their levels of demand variability, as observed in Section 3.7.4
- If the DKAP always achieves a more robust service level than the SKAP, and if the SKAP always achieves a more robust WIP control than the DKAP, as observed in Section 3.7.4

The first criterion is investigated by conducting a paired comparison across the 100 LHS runs to identify the number of runs under the two policies in which the two products had statistically significant difference in their service levels. This would show at 95% confidence level the extent to which the two policies were able to differentiate the performances of the two products at the different levels of disparity in their demand profiles in the three scenarios. Additionally, the extent of impact the products' mean demand arrival rates and demand variability have on one another's service levels under the two policies will be investigated. This will be used to investigate if the impact the products' demand attributes have on one another's service level is more severe under the SKAP than the DKAP.

For the second criterion, stochastic dominance tests will be conducted to compare the service level robustness of both products under the DKAP and the SKAP. This would help identify the policy that was most suitable across the four scenarios in terms of products' service level robustness. The WIP control effectiveness of the two policies will also be compared through stochastic dominance testing of their average system WIP across the 100 LHS runs.

Establishing the above would help identify the strengths and weakness of the two policies. Finally, the sensitivity analysis results will be used to analyse the impact of the levels of availability of the machines on the products' service levels under the two strategies. These will be used to compare the robustness of the EKCS and the GKCS to machine breakdowns. The impact of the products' demand CVs, arrival rates and the machines' levels of availability on the system WIP will also be reported.

4.4.1 Criteria 1: Ability of Products to achieve Service Levels corresponding to their Demand Variability Levels

The numbers of LHS runs in which both policies maintained statistically significantly different service levels for the two products at 95% confidence level are reported in this section. The charts displaying these analyses are presented in APPENDIX - A, while those for the stochastic dominance tests conducted to determine the policy under which each of the products achieved better service level robustness are presented in APPENDIX - A. It should be noted that in this section, a chart format different from those of Figure 3-5 – Figure 3-7 is used to illustrate the comparison of the policies' robustness, because, as only pairwise comparisons are being made here, this chart format would be better at showing how the two policies' service levels compare on a run by run basis. Complete unordered tables of the 100 LHS runs for each of the scenarios are shown in APPENDIX - A

EKCS

As shown in Table 4-4, it was observed that at a 95% confidence level, under the SKAP there was no single LHS run with statistically significant difference in the service levels of the two products in all the scenarios. This shows that the SKAP did not differentiate the service level performance of the products, irrespective of the level of disparity in their demand variabilities. The DKAP, on the other hand, had LHS runs with statistically significant difference in the service levels of the two products, except in Scenario 2 in which the levels of demand variability of the two products were similar and low.

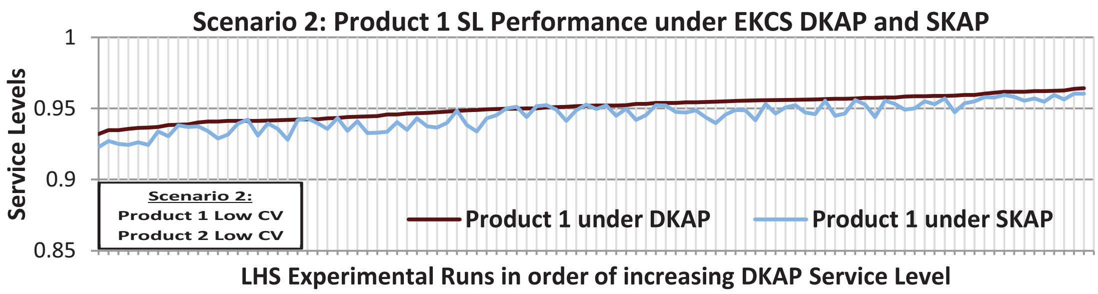
Table 4-4: Policies' ability to differentiate product performances under EKCS

Scenario	Product CV Levels under scenario		Number of LHS runs with statistically significant difference in product service levels		Policy under which Product's SL is most robust	
	Product 1	Product 2	DKAP	SKAP	Product 1	Product 2
1	High	Low	25	0	Both	DKAP
2	Low	Low	0	0	DKAP	Both
3	Low	High	52	0	DKAP	SKAP
4	High	High	58	0	DKAP	DKAP

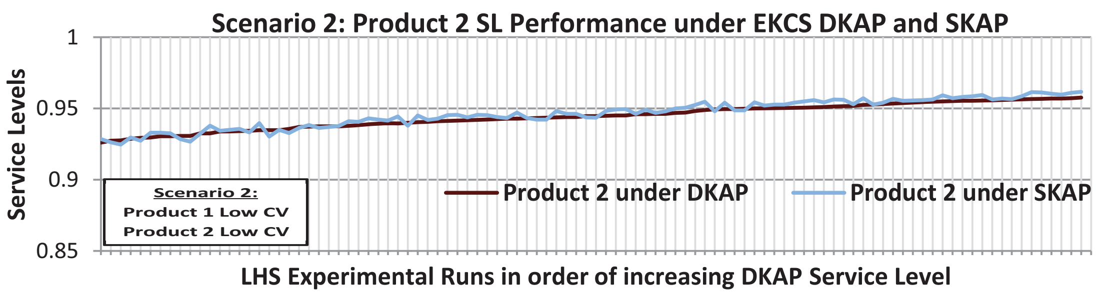
Under the DKAP, the number of LHS runs with statistically significant difference in the service levels of the two products varied across the four scenarios, as shown in Table 4-4.

In Scenario 1, under the DKAP, there were 25 LHS runs in which the service levels of the two products differed statistically significantly. Table 4-4 also shows that Product 2 achieved a more robust service level under the DKAP than under the SKAP, while it made no difference if Product 1 shared Kanbans or had its own dedicated Kanbans. This implies a scenario whereby a high demand variability product (Product 1) affected the lower demand variability product without deriving any improvement to its own performance under a Kanban sharing policy. As such, it would be of no advantage to share Kanbans in such scenario, and this could be due to the difference in the demand arrival rates, and possibly processing times, of the two products. Perhaps, the product with a high demand variability might have benefitted from Kanban sharing if its own demand arrival rate was lower than that of the other product, as evident in Scenario 3 which is a reverse of this scenario.

In Scenario 2, there was no single LHS run with statistically significant difference in the service levels of the two products under the DKAP, as shown in Table 4-4. The lack of difference in the service levels of the two products can be attributed to their similarly low levels of demand variability. On the other hand, Product 1 enjoyed a more robust service level under the DKAP than under the SKAP – as shown in Figure 4-1 (a), while Product 2's service level robustness was similar under the two policies – as shown in Figure 4-1 (b). Hence, it can be said that in the absence of a high level of demand variability in any of the products involved under the SKAP, the service level robustness of the product with the lower demand arrival rate (Product 2) is as good as if it was under a DKAP.



(a) Product 1 SL Performance under DKAP and SKAP



(b) Product 2 SL Performance under DKAP and SKAP

Figure 4-1: SLs under EKCS DKAP and SKAP (Scenario 2)

In Scenario 3, the DKAP had 52 LHS runs with statistically significant difference in the service levels of the two products, as shown in Table 4-4. Also, Figure 4-2 shows that in the LHS runs in which Product 1 had the statistically significantly higher service level, the margins were wider than in those in which Product 2 had the higher service level. This can be attributed to Product 1's less variable demand, and its slightly lower demand arrival rate must have made this more prominent because Product 2 did not have the same wider margins of service level superiority in Scenario 1 when it had a lower demand variability.

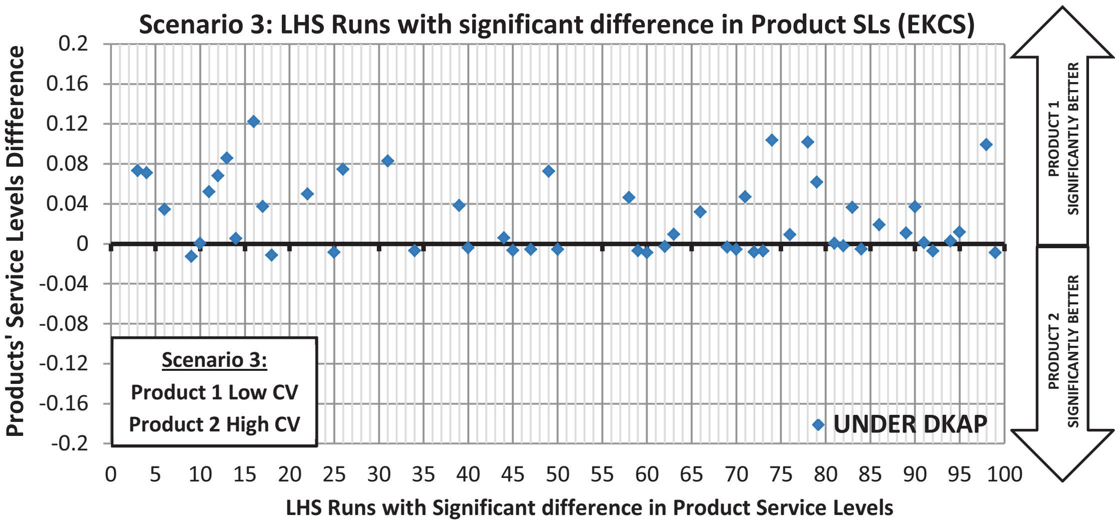
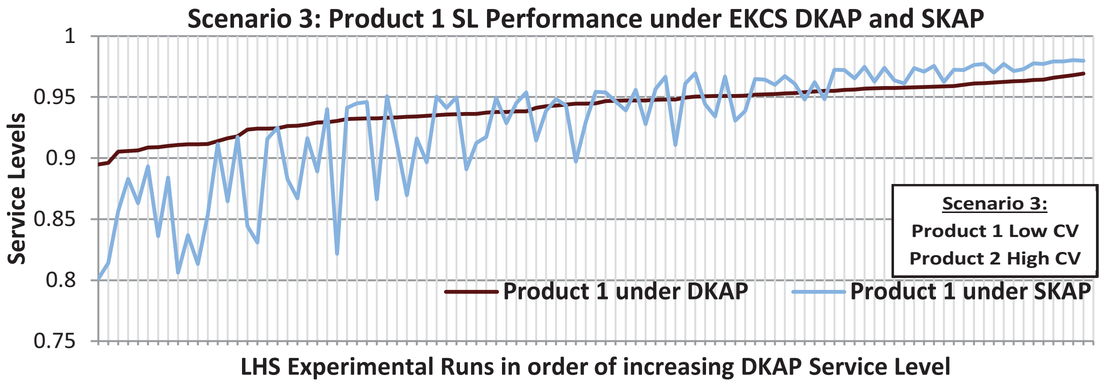
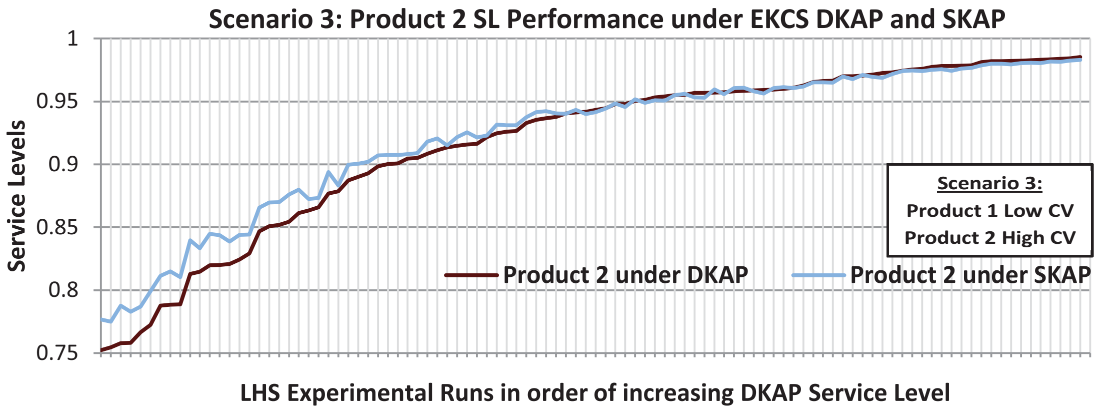


Figure 4-2: Significant Differences in SL1 and SL2 EKCS (Scenario 3)

Furthermore, Product 1's service level was more robust under the DKAP than under the SKAP – as shown in Figure 4-3 (a), while Product 2's service level was interestingly more robust under the SKAP than under the DKAP – as shown in Figure 4-3 (b). The improvement observed for Product 2 under the SKAP is an example of how a product with a high level of demand variability can be made to achieve better results by sharing Kanbans with a less variable product. Such decision would however need to carefully consider its impact on the service level robustness of the less variable product.



(a) Product 1 SL Performance under DKAP and SKAP



(b) Product 2 SL Performance under DKAP and SKAP

Figure 4-3: SLs under EKCS DKAP and SKAP (Scenario 3)

In Scenario 4, although both products had a similar level of demand variability as they had in Scenario 2, the higher levels of variability in this scenario seems to have aggravated the effect of the little difference in the products' demand arrival rates. Hence, this results in statistically significant differences in their service levels in 58 LHS runs under the DKAP, as shown in Table 4-4.

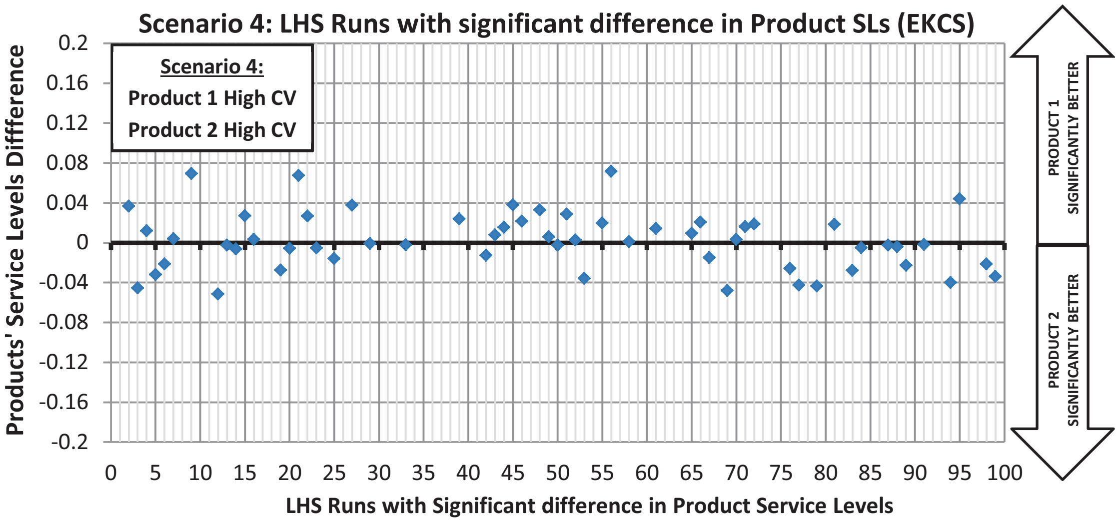


Figure 4-4: Significant Differences in SL1 and SL2 EKCS DKAP (Scenario 4)

Also, as shown in Figure 4-4, the margins by which each product's service level was higher than the others were balanced, unlike in Scenario 3 in which the lower demand variability product's margins were wider, as earlier shown in Figure 4-2. Finally, as reported in Table 4-4, both products enjoyed more robust service levels under the DKAP than under the SKAP.

GKCS

The numbers of LHS runs in which the two policies achieved statistically significant difference in the service levels of the two products at a confidence level of 95% are presented in Table 4-5. It shows that similarly to under the EKCS SKAP, the GKCS SKAP too did not differentiate the service level performances of the two products across all the four scenarios. The DKAP, on the other hand, differentiated the products' service level performances to different extents across the four scenarios. It also shows that the two products always enjoyed more robust service levels under the DKAP than the SKAP, except in Scenario 1 in which Product 1 maintained a similar service level robustness under both policies. On the contrary, under the EKCS the SKAP was able to achieve a service level as robust as the DKAP in two instances. It achieved a service level as robust as the DKAP for Product 2 in Scenario 2, and an even more robust service level than it in Scenario 3.

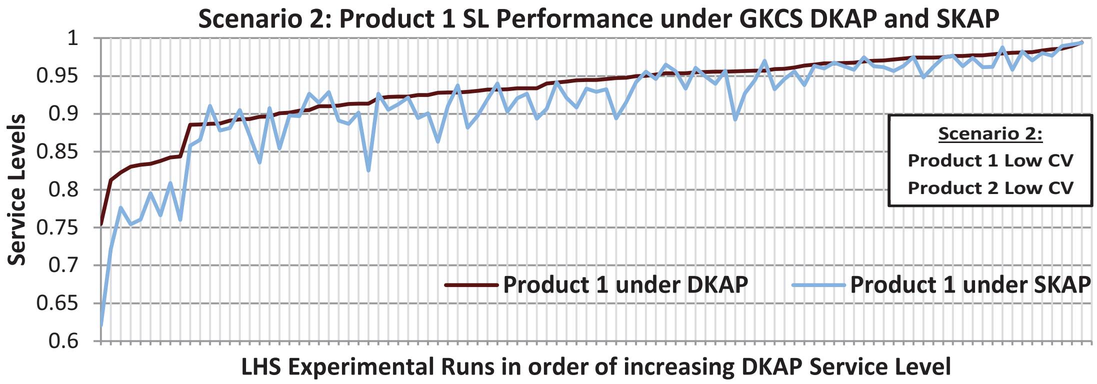
Table 4-5: Policies' ability to differentiate product performances under GKCS

Scenario	Product CV Levels under scenario		Number of LHS runs with significant difference in product service levels		Policy under which Product's SL is most robust	
	Product 1	Product 2	DKAP	SKAP	Product 1	Product 2
1	High	Low	50	0	Both	DKAP
2	Low	Low	5	0	DKAP	DKAP
3	Low	High	60	0	DKAP	DKAP
4	High	High	61	0	DKAP	DKAP

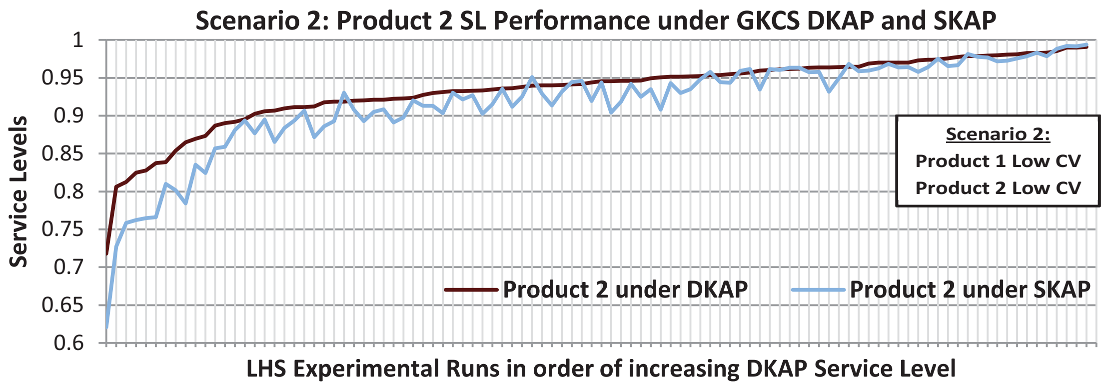
In Scenario 1, under the DKAP there were 50 LHS runs with statistically significant difference in the products' service levels, as show in Table 4-5. Comparing how the products performed under the DKAP and SKAP shows that Product 1 achieved similar service level robustness under both policies, while Product 2's service level was more robust under the DKAP – as shown in Table 4-5. Similarly to what was observed under the EKCS, even though Kanban sharing did not affect the robustness of Product 1's service level, it did not improve that of Product 2 either.

In Scenario 2, there were only 5 runs in which the two products had statistically significant difference in their service levels under the DKAP. This can be attributed to the low levels of demand variability of the two products. Also, both products had more robust service levels under the DKAP than the SKAP, as shown in Figure 4-5 (a) and (b).

In Scenario 3, under the DKAP there were 60 LHS runs in which the service levels of the two products differed statistically significantly at 95% confidence level. It was also observed that Product 1's margins of superiority were wider than those of Product 2, as shown in Figure 4-6. This is similar to the observation under the EKCS, and it can again be attributed to Product 1's lower level of demand variability and its slightly lower demand arrival rate.



(a) Product 1 SL Performance under DKAP and SKAP



(b) Product 2 SL Performance under DKAP and SKAP

Figure 4-5: SLs under GKCS DKAP and SKAP (Scenario 2)

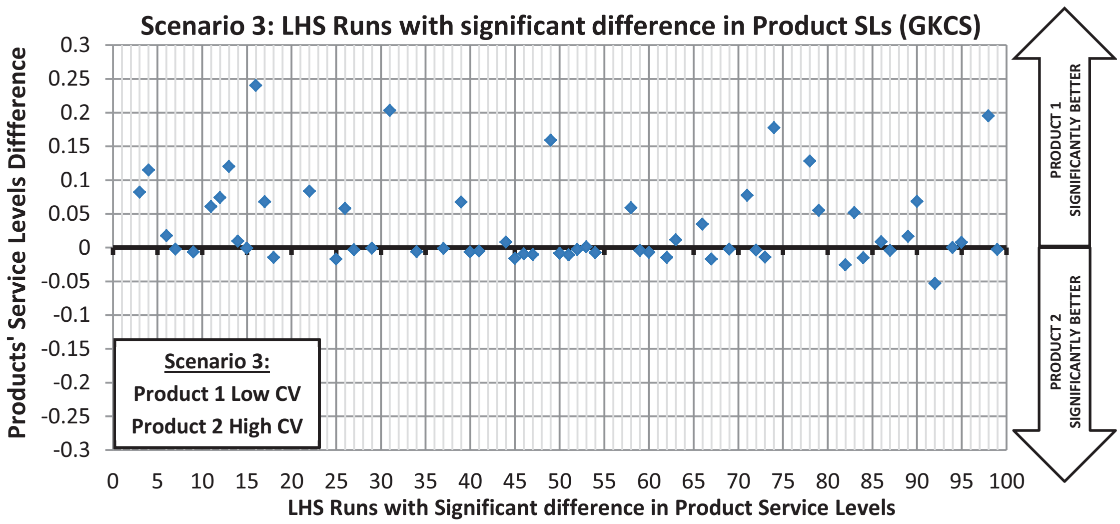


Figure 4-6: Significant Differences in SL1 and SL2 GKCS DKAP (Scenario 3)

In Scenario 4, there were there were 61 LHS runs under the DKAP in which there was statistically significant difference in the service levels of the two products at 95%

confidence level. As shown in Figure 4-7, each product had the higher service level in about half of the 61 LHS runs, and the margins of superiority of both products were similar, unlike in Scenario 3. This was because the products had similar high levels of demand variability.

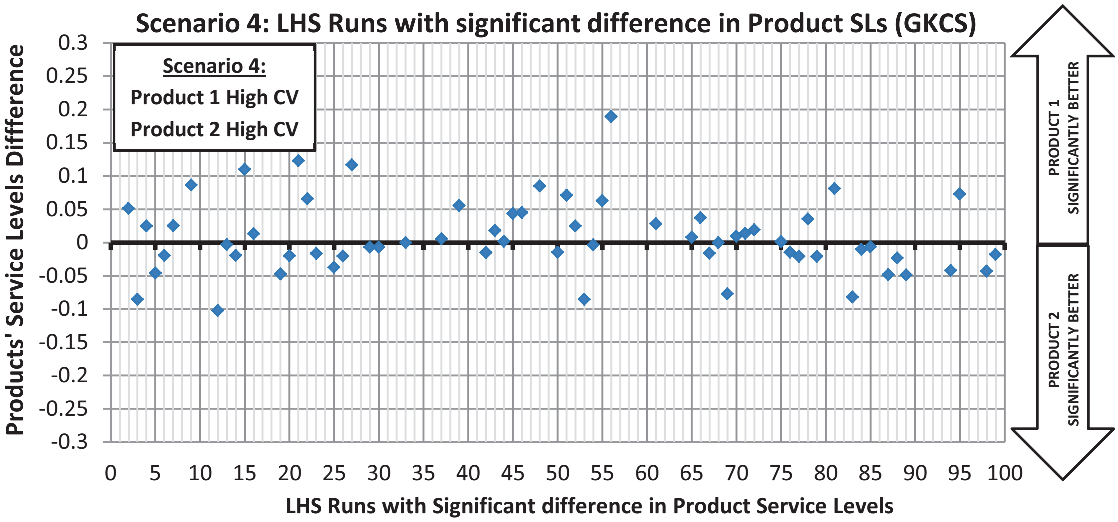


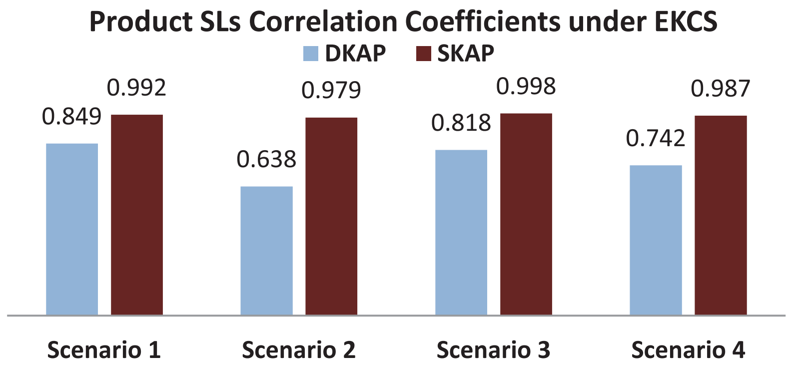
Figure 4-7: Significant Differences in SL1 and SL2 GKCS DKAP (Scenario 4)

Similarly to the EKCS, both products had better service level robustness under the DKAP than under the SKAP, as reported in Table 4-5.

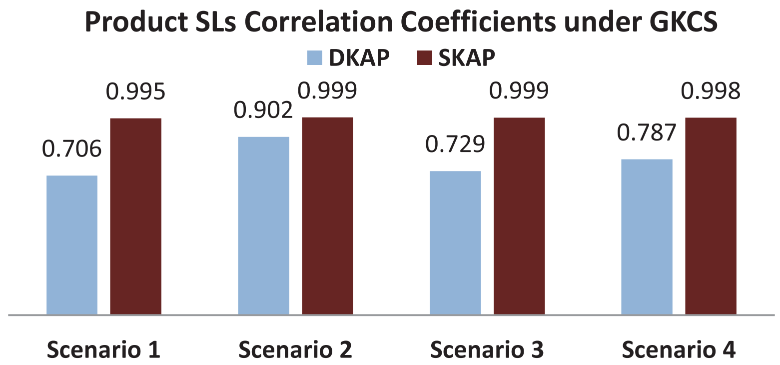
In conclusion, from these analyses it was observed that operating a SKAP under both strategies always results in less robust service level for the higher demand arrival rate product. Additionally, the policy in operation makes no difference to its service level robustness if its higher demand arrival rate is combined with a higher level of demand variability than the other product. Under the GKCS, the service level of the lower demand arrival rate product too is always less robust when operating the SKAP than when operating the DKAP. However, operating a SKAP under the EKCS is able to achieve a service level that is as robust as the DKAP for the lower demand arrival rate product, if the level of demand variability of the other product is not high – as observed in Scenarios 2 and 3 in Table 4-4. Therefore, under the GKCS both products are better managed under a DKAP, while operating a SKAP under the EKCS can be applied in some situations.

<u>Product Service Levels Correlation under DKAP and SKAP</u>

Furthermore, by estimating the correlation coefficients between the products' service levels across the 100 LHS runs, the difference between the DKAP and the SKAP can be better understood. Figure 4-8 shows that for both the EKCS and the GKCS the correlation (i.e. the similarity) between the service levels of the two products is higher under the SKAP than the DKAP. It is also evident from the same figure that the SKAP correlations are relatively stronger under the GKCS than under the EKCS. Under the SKAPs, the correlation coefficients are close to one, which indicates that the LHS-varied factors mostly affected both products similarly.



(a) EKCS



(b) GKCS

Figure 4-8: Correlation between SL1 and SL2

4.4.2 Criteria 2: Service Levels and WIP Control Robustness

A comprehensive overview of the results obtained from the robustness tests indicate that the DKAP offers better service level robustness than the SKAP, as presented in Table 4-6 and Table 4-7. In the 16 robustness comparisons conducted across the four scenarios for each of the two products' service levels under both strategies, the DKAP was stochastically dominant in 12 of them, out of which two were first-order dominance. Three of the tests were inconclusive, while the SKAP dominated in one of them.

Table 4-6: Stochastic Dominance Comparison of EKCS DKAP & SKAP

EKCS	SL 1		SL 2		WIP	
Scenario	DKAP	SKAP	DKAP	SKAP	DKAP	SKAP
1	Inconclusive	Inconclusive	2nd Order		2nd Order	
2	1st Order		Inconclusive	Inconclusive	1st Order	
3	2nd Order			2nd Order	2nd Order	
4	2nd Order		2nd Order		2nd Order	

Table 4-7: Stochastic Dominance Comparison of GKCS DKAP & SKAP

GKCS	SL 1		SL 2		WIP	
Scenario	DKAP	SKAP	DKAP	SKAP	DKAP	SKAP
1	Inconclusive	Inconclusive	2nd Order		1st Order	
2	2nd Order		2nd Order		1st Order	
3	2nd Order		1st Order		2nd Order	
4	2nd Order		2nd Order		2nd Order	

However, the WIP control robustness comparison results for the two policies show that the SKAP is more effective at controlling WIP than the DKAP under the two strategies. It should be noted that the WIP results are interpreted in the reverse from the service level results, because of it being a minimisation type performance measure.

4.5 IMPACT OF SENSITIVITY ANALYSIS FACTORS

Having established in Section 4.4.1 that the SKAP is unable to differentiate the service level performances of the two products based on their demand profiles, more analysis is done to determine how the products' mean time between demands and demand variability factors affect the service level of one another, as well as the average system WIP under the two policies. Additionally, the impacts of the variations in the levels of availability of the three manufacturing stages on the system performance are also investigated. These will be achieved by determining at a 95% confidence level if there was statistically significant difference in a performance measure between the set of LHS runs in which a factor's settings were 5% below the base level and the set of runs in which they were 5% above the base level. The uniformly distributed sampling nature of the LHS means that half of the 100 runs will have settings below the base level, while the other half will be above it. Analysing these two sets of runs will help identify the factors whose variations have statistically significant impact on each of the performance measures.

4.5.1 Demand Variability of Products

In this sub-section, the impacts of the ±5% variations in the demand CVs of the products on the service levels of one another and the average system WIP are presented. As a reminder, the demand CV is the ratio of a product's demand standard deviation to its mean.

EKCS

Across the four scenarios, the DKAP was able to prevent the variation in the demand CV of a product from having statistically significant impact on the service level of the other product – as shown in Table 4-8, while the SKAP could not prevent this from happening to the service level of Product 1 in Scenarios 3, and to the service levels of both products in Scenario 4 – as shown in Table 4-9.

Table 4-8: Impact of Products' Demand CVs under EKCS DKAP

Scenario	Product CV Levels under scenario		Product 1 Demand CV variation had statistically significant impact on			Product 2 Demand CV variation had statistically significant impact on		
	Product 1	Product 2	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	High	Low	No	No	No	No	No	No
2	Low	Low	No	No	No	No	No	No
3	Low	High	No	No	No	No	Yes	Yes
4	High	High	Yes	No	Yes	No	Yes	Yes

Table 4-9: Impact of Products' Demand CVs under EKCS SKAP

Scenario	Product CV Levels under scenario		Product 1 Demand CV variation had statistically significant impact on			Product 2 Demand CV variation had statistically significant impact on		
	Product 1	Product 2	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	High	Low	No	No	No	No	No	No
2	Low	Low	No	No	No	No	No	No
3	Low	High	No	No	No	Yes	Yes	Yes
4	High	High	Yes	Yes	Yes	Yes	Yes	Yes

However, the variations in the Products' demand CVs had statistically significant impacts on the system WIP in exactly the same scenarios under both policies, as shown in Table 4-8 and Table 4-9. It thus appears that the policy in operation does not have any bearing on how the variations in the products' demand CVs impact the system WIP.

In Scenarios 1 and 2, the variation in the demand CVs of both products did not have statistically significant impacts on the two products' service levels and the system WIP, under the DKAP and the SKAP.

In Scenario 3, under the DKAP, the variation in Product 1's demand CV did not have statistically significant impact on the two products' service levels and the system WIP, while the variation in Product 2's demand CV had statistically significant impact only on its own service level and the system WIP. However, under the SKAP, the variation in Product 2's demand CV had statistically significant impact on both its own service level and that of Product 1, as well as on the system WIP. This shows that the operation of an SKAP caused the variation in the demand CV of Product 2 to impact the service level of the other product, unlike under the DKAP. However, similarly to the DKAP, Product 1's demand CV did not have significant impact on any of the performance measures under the SKAP.

In Scenario 4, under the DKAP, each product's demand CV variation only had statistically significant impact on its own service level, as well as on the system WIP. However, under the SKAP, the variation in the demand CVs of the two products had statistically significant impacts on one another's service level and the system WIP.

GKCS

Similarly to the EKCS, the DKAP was again able to completely avoid the variation in the demand CV of a product having statistically significant impact on the service level of the other product across the four scenarios, as shown in Table 4-10. However, under the SKAP, the variation in the demand CV of Product 2 had statistically significant impact on the service level of Product 1 in Scenario 3, as shown in Table 4-11.

The observations from Scenarios 1, 2 and 3 were exactly the same for corresponding policies under the EKCS and the GKCS. Also, it again appears that the policy in operation does not have any bearing on how the variations in the products' demand CVs impact the system WIP. As shown in Table 4-10 and Table 4-11, the variations in the Products' demand CVs had statistically significant impacts on the system WIP in exactly the same scenarios under both policies, similarly to under the EKCS.

Table 4-10: Impact of Products' Demand CVs under GKCS DKAP

Scenario	Product CV Levels under scenario		Product 1 Demand CV variation had statistically significant impact on			Product 2 Demand CV variation had statistically significant impact on		
	Product 1	Product 2	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	High	Low	No	No	No	No	No	No
2	Low	Low	No	No	No	No	No	No
3	Low	High	No	No	No	No	Yes	Yes
4	High	High	Yes	No	Yes	No	Yes	Yes

Table 4-11: Impact of Products' Demand CVs under GKCS SKAP

Scenario	Product CV Levels under scenario		Product 1 Demand CV variation had statistically significant impact on			Product 2 Demand CV variation had statistically significant impact on		
	Product 1	Product 2	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	High	Low	No	No	No	No	No	No
2	Low	Low	No	No	No	No	No	No
3	Low	High	No	No	No	Yes	Yes	Yes
4	High	High	Yes	No	Yes	No	No	Yes

In Scenarios 1 and 2, the variation in the CV of both products did not have statistically significant impacts on the service levels of the two products and the system WIP, under the DKAP and the SKAP.

In Scenario 3, under the DKAP, Product 2's demand CV variation had statistically significant impacts on its own service level and the system WIP, but it did not have statistically significant impact on Product 1's service level. On the contrary, under the SKAP, Product 2's demand CV had significant impact on its own service level and that of Product 1, as well as on the system WIP. This is similar to what was observed under the EKCS, and it again shows that the operation of the SKAP between the two products has resulted in the variation of the CV of Product 2 having statistically significant impact on the service level of the low demand CV Product 1. The variation in the demand CV of Product 1 did not have significant impact on any of the performance measures.

In Scenario 4, similarly to the EKCS, under the DKAP, each product's demand CV variation had statistically significant impact only on its own service level and the system WIP. Under the SKAP, the variation in Product 1's demand CV had statistically significant impact only on its own service level, while that of Product 2 did not have statistically significant impact on any product's service level. They however both have statistically significant impacts on the system WIP.

Under the EKCS and the GKCS, it was generally evident that a variation in a product's demand CV is more prone to affect the other product's service level performance under the SKAP than under the DKAP. This corroborates the observations in Section 4.4.1, and it can be attributed to their use of separate dedicated Kanbans under the DKAP which minimises the interaction between the products.

4.5.2 Mean Time Between Demands

In this sub-section, the impacts of the ±5% variations in the mean times between demands of the products on the service levels of one another and the average system WIP are presented for the EKCS and the GKCS.

EKCS

Unlike the observations from the impact of the products' demand CV variations, the DKAP was not able to completely isolate the variation in the mean time between demands of one product from having statistically significant impact on the service level of the other product. It however performed slightly better than the SKAP. As shown in Table 4-12, under the DKAP, the variation in Product 1's mean time between demands had statistically significant impact on Product 2's service level in Scenario 4, while that of Product 2 had statistically significant impacts on Product 1's service level in Scenarios 2, 3 and 4. As shown in Table 4-13, under the SKAP, the variation in Product 1's mean time between demands had statistically significant impacts on Product 2's service level in Scenarios 2 and 4 – one more than under the DKAP, while that of Product 2 on Product 1's service level was in the same scenarios as under the DKAP.

However, as shown in Table 4-12 and Table 4-13, the variations in the products' mean times between demands did not have statistically significant impacts on the system WIP in the same scenarios under both policies, as was the case with the demand CVs. Therefore, the impact the variation in a product's mean time between demands has on the system WIP is likely influenced by the policy in operation.

Table 4-12: Impact of Products' Demand Arrival Rates under EKCS DKAP

Scenario	Product CV Levels under scenario		Product 1 Mean Demand Arrival rate Impact on			Product 2 Mean Demand Arrival rate Impact on		
	Product 1	Product 2	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	High	Low	No	No	No	No	No	No
2	Low	Low	Yes	No	Yes	Yes	Yes	Yes
3	Low	High	Yes	No	No	Yes	Yes	Yes
4	High	High	Yes	Yes	Yes	Yes	Yes	Yes

Table 4-13: Impact of Products' Demand Arrival Rates under EKCS SKAP

Scenario	Product CV Levels under scenario		Product 1 Mean Demand Arrival rate Impact on			Product 2 Mean Demand Arrival rate Impact on		
	Product 1	Product 2	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	High	Low	No	No	No	No	No	No
2	Low	Low	Yes	Yes	Yes	Yes	Yes	Yes
3	Low	High	No	No	No	Yes	Yes	Yes
4	High	High	Yes	Yes	Yes	Yes	Yes	Yes

In Scenario 1, the variations in the two products' mean times between demands did not have statistically significant impact on the products' service levels and on the system WIP under the DKAP and the SKAP. This is similar to the observation from the demand CV impact analysis.

In Scenario 2, under the DKAP, the variation in the mean time between demands of Product 2 had statistically significant impacts on both products' service levels, while that of Product 1 only had statistically significant impact on its own service level. Also, the system WIP was significantly affected by both products' mean times between demands. Under the SKAP, the variations in the two products' mean times between demands had statistically significant impacts on the system WIP, as well as on their own service levels and that of the other product.

In Scenario 3, under the DKAP, the variation in Product 2's mean time between demands had statistically significant impacts on the service levels of the two products and the system WIP, while the variation in Product 1's mean time between demands had statistically significant impact its own service level only. Under the SKAP, the variation in Product 2's mean time between demands again had statistically significant impacts on the service levels of the two products and the system WIP, but that of Product 1 did not have statistically significant impact on any of the performance measures.

In Scenario 4, under both the DKAP and the SKAP, the variations in both products' mean times between demands had statistically significant impacts on the service levels and the system WIP.

GKCS

Under the GKCS, in terms of the number of instances in which the variation in the mean time between demands of a product had statistically significant impact on the other product's service level, the DKAP had one while the SKAP had two. As shown in Table 4-14, the only instance under the DKAP was in Scenario 3 in which the variation in the mean time between demands of Product 2 had statistically significant impact on the service level of Product 1. The two instances under the SKAP were in Scenario 3 and 4 in which the variation in the mean time between demands of Product 2 had statistically significant impact on the service level of Product 1, as shown in Table 4-15. Also, similarly to the EKCS, the impact the variation in a product's mean time between demands has on the system WIP appears to be linked to the policy in operation. As shown in Table 4-14 and Table 4-15, the scenarios in which the variations in the products' mean times between demands had statistically significant impact on the system WIP, differed between the two policies.

Table 4-14: Impact of Products' Demand Arrival Rates under GKCS DKAP

Scenario	Product CV Levels under scenario		Product 1 Mean Demand Arrival rate Impact on			Product 2 Mean Demand Arrival rate Impact on		
	Product 1	Product 2	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	High	Low	No	No	No	No	No	No
2	Low	Low	No	No	No	No	No	No
3	Low	High	Yes	No	No	Yes	Yes	Yes
4	High	High	Yes	No	Yes	No	Yes	Yes

Table 4-15: Impact of Products' Demand Arrival Rates under GKCS SKAP

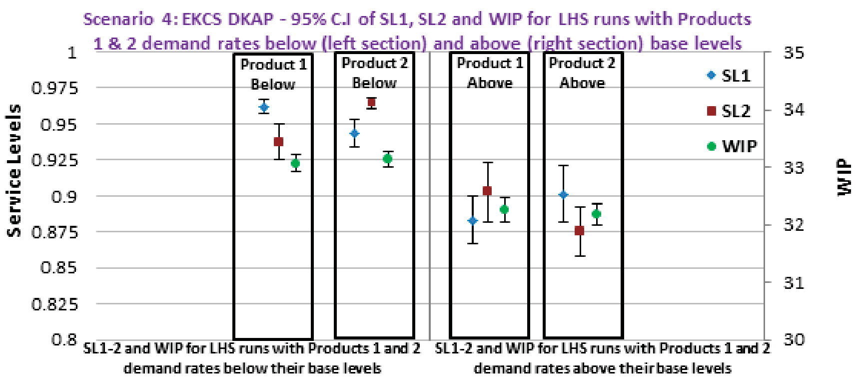
Scenario	Product CV Levels under scenario		Product 1 Mean Demand Arrival rate Impact on			Product 2 Mean Demand Arrival rate Impact on		
	Product 1	Product 2	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	High	Low	No	No	No	No	No	No
2	Low	Low	No	No	No	No	No	No
3	Low	High	No	No	No	Yes	Yes	Yes
4	High	High	Yes	No	Yes	Yes	Yes	Yes

In Scenarios 1 and 2, the variations in the mean times between demands of the two products did not have statistically significant impact on the products' service levels and the system WIP under the DKAP and the SKAP, as also observed under the EKCS.

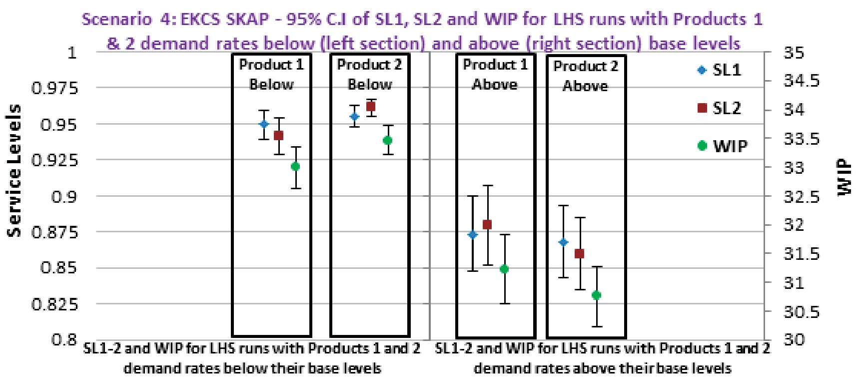
In Scenario 3, the observation from operating the DKAP was similar to that under the EKCS. The variation in the mean time between demands of Product 2 had statistically significant impacts on the service levels of the two products and the system WIP, while that of Product 1 only had statistically significant impact on its own service level. Under the SKAP, the variation in the demand arrival rate of Product 2 again had statistically significant impacts on the service levels of the two products and on the system WIP. Product 1, on the other hand, did not have statistically significant impact on any of the performance measures.

In Scenario 4, under the DKAP, the variation in each product's mean time between demands had statistically significant impact only on its own service level and the system WIP. In addition to that, under the SKAP, the variation in the mean time between demands of Product 2 further had statistically significant impact on the service level of Product 1.

Similarly to what was observed for the demand CV, a variation in a product's mean time between demands was more likely to impact the other product's service level under the SKAP than under the DKAP. This was also evident in the relative service levels achieved for the products in the different sets of LHS runs in which their respective mean times between demands were below or above the base levels. For instance, in Scenario 4 under the EKCS, each product had the statistically significantly higher service level across the set of runs in which its mean times between demands were above the base levels (i.e. when the demand arrival rates were below the base levels), as shown Figure 4-9 (a). However, under the SKAP, there was no statistically significant difference in the service levels of the two products in any of the sets of runs – even in the ones in which one of them had a lower demand arrival rate, as shown in Figure 4-9 (b). This shows that unlike under the DKAP in which a lower demand arrival rate than the base level for a product made it achieve a statistically significantly higher service level than the other product, the SKAP instead used the spare Kanbans resulting from such lower demand arrival rate to improve the service levels of both products.



(a) DKAP



(b) SKAP

Figure 4-9: Mean Demand Impact on SLs and WIP EKCS (Scenario 4)

It was also observed that the policy in operation had a bearing on the impact the variation in a product's mean time between demands has on the system WIP. Another general observation was that the variation in the mean time between demands of Product 2, which has the longer processing time and the longer mean time between demands, was more likely than that of Product 1 to have statistically significant impact on the system WIP. It is difficult to categorically state if this is due to its longer processing time – which would mean that it stays longer in the system and contribute more to the WIP; or its longer mean time between demands – which would mean that it might have to wait for longer in the system before being released by customer demands. Nevertheless, the next phase of this research in Chapter 5 would provide the opportunity to make this clarification.

4.5.3 Level of Availability of Machines

In this sub-section, the effects of the variation in the level of availability of each of the manufacturing stages on the products' service levels and the system WIP are presented for each of the experimental scenarios. The level of availability/reliability of a machine is derived by dividing its mean time to failure by the sum of its mean time to repair and its mean time to failure (i.e. $MTTF/(MTTR + MTTF)$). The base level of availability of each machine was set to 90% in Section 3.4; therefore, the aim here is to determine at a 95% confidence level if the ±5% variation in the level of availability of each of the manufacturing stages had statistically significant impact on the products' service levels and the system WIP.

EKCS

Under the DKAP and the SKAP, it was only in Scenario 1 that the variation in the levels of availability of the three stages had any statistically significant impact on the performance measures, as shown in Table 4-16 and Table 4-17.

Table 4-16: Impact of Stage Availability Level under EKCS DKAP

Scenario	Stage 1 Level of Availability on			Stage 2 Level of Availability on			Stage 3 Level of Availability on		
	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No
2	No	No	No	No	No	No	No	No	No
3	No	No	No	No	No	No	No	No	No
4	No	No	No	No	No	No	No	No	No

Table 4-17: Impact of Stage Availability Level under EKCS SKAP

Scenario	Stage 1 Level of Availability on			Stage 2 Level of Availability on			Stage 3 Level of Availability on		
	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
2	No	No	No	No	No	No	No	No	No
3	No	No	No	No	No	No	No	No	No
4	No	No	No	No	No	No	No	No	No

In Scenario 1, under the DKAP, the variations in the levels of availability of the first two stages had statistically significant impacts on the two products' service levels, while that of the last stage only had statistically significant impact on Product 1's service level. Additionally, it was only Stage 1's variation in the level of availability that had statistically significant impact on the system WIP. Under the SKAP, it was only Stage 3's variation in the level of availability that did not have statistically significant impact on any of the three performance measures. Those of Stages 1 and 2 had statistically significant impacts on the products' service levels and the system WIP

GKCS

Unlike under the EKCS, the variations in the levels of availability of the manufacturing stages – specifically the first two stages – had statistically significant impact on at least one of the performance measures in all the four scenarios, as shown for the DKAP and the SKAP respectively in Table 4-18 and Table 4-19. The variation in the level of availability of Stage 3 did not have any statistically significant impact on the products' service levels and the system WIP across the four scenarios. This could be attributed to the GKCS's demand information transmission philosophy which is done stage by stage and thus relies on the availability of the stages. The last stage is not as critical because the demand information transmission process by-passes it.

Table 4-18: Impact of Stage Availability Level under GKCS DKAP

Scenario	Stage 1 Level of Availability on			Stage 2 Level of Availability on			Stage 3 Level of Availability on		
	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
2	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
3	Yes	No	Yes	Yes	Yes	Yes	No	No	No
4	Yes	Yes	Yes	No	No	No	No	No	No

Table 4-19: Impact of Stage Availability Level under GKCS SKAP

Scenario	Stage 1 Level of Availability on			Stage 2 Level of Availability on			Stage 3 Level of Availability on		
	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP	Product 1 SL	Product 2 SL	WIP
1	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
2	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
3	No	No	Yes	Yes	Yes	Yes	No	No	No
4	Yes	Yes	Yes	No	No	No	No	No	No

In Scenarios 1 and 2, under both policies, the variations in the levels of availability of Stages 1 and 2 had statistically significant impacts on the two products' service levels and the system WIP. Also, the statistically significantly higher service level resulting from an increased level of availability of Stage 1 results in a correspondingly higher WIP level, as shown for Scenario 1 in Figure 4-10. The same was observed in the other scenarios in cases whereby the variation in the level of availability of any stage caused statistically significant difference in the service levels.

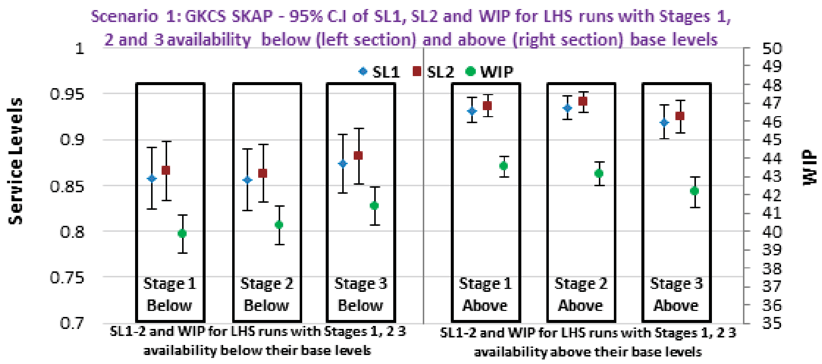


Figure 4-10: Stage Avail. Impact on SLs and WIP GKCS SKAP (Scenario 1)

In Scenario 3, under the DKAP, the variations in the levels of availability of Stages 1 and 2 had statistically significant impacts on the service level of Product 1 and the system WIP. Additionally, that of Stage 2 had statistically significant impact on the service level of Product 2. Under the SKAP, the variations in the levels of availability of Stages 1 and 2 again had statistically significant impacts on the system WIP, while it was only Stage 2 that had statistically significant impact on the service levels of the two products.

In Scenario 4, under the DKAP and the SKAP, only the variation in the level of availability of Stage 1 had statistically significant impact on the products' service levels and the system WIP. This might be due to the high levels of demand variability of the two products and the fact that those are the two stages to which a demand information is transmitted directly as it arrives to the system. A lower or higher level of availability of those stages might not have made significant difference in their ability to overcome the high levels of product demand variability.

In general, across the four scenarios, the variations in the levels of availability of the stages had more statistically significant impact on the performance measures under the GKCS than under the EKCS. In particular, the first two stages had statistically significant impacts more consistently than the last stage, and this could be explained as follows. Firstly, the impact of stage availability on the GKCS shows that because it relies on a stage by stage demand information transmission, if the manufacturing stages are not reliable to complete the processing of parts on time, the demand information will be frequently delayed waiting for Kanbans to be detached from parts that complete processing. Secondly, under the GKCS, the first two stages are more crucial because the last stage is by-passed in the transmission of demand information upstream. As described in Section 2.2.6, when a customer demand arrives to the last stage, it is transmitted directly to the penultimate stage without having to first couple with a free Kanban, as done at the other stages. Therefore, even if the last stage is less available, the upstream transmission of the demand information is not delayed. The same logic can be applied to understanding why the EKCS's global demand information transmission ensured that the levels of availability of the stages had lesser impacts on the system's performance. The EKCS seems to have been affected under Scenario 1 because Product

1 with the higher demand arrival rate also had the higher CV level, and this could have had a confounding effect on the products' service levels. This was also evident in the robustness analysis of Section 4.4.1.

Furthermore, it can be concluded from these observations that the statistically significant impacts of the variations in the levels of availability of the stages on the GKCS's system WIP was also as a result of the delay in the demand information transmission, especially due to low levels of availability of Stages 1 and 2. The GKCS's release of new parts into the system only occurs after the demand information has passed through all the stages to reach the upstream raw parts buffer. On the contrary, the EKCS's demand information reaches the upstream raw parts buffer as soon as it arrives to the last stage and it can release new parts into the system as soon as a first stage Kanban is available.

In conclusion, it seems a study that proposes a flexible routing of information transmission to create entirely new controls as needed is very promising for the customisation of pull strategies to suit specific manufacturing systems [38]. Such approach can be used to by-pass the localised flow of demand information through an unreliable manufacturing stage.

4.6 INSIGHTS FOR THE DEVELOPMENT OF A NEW POLICY

The purpose of this section is to derive insights from the results presented in this chapter that would allow the implementation and experimental analysis of a new Kanban allocation policy. It is aimed that it would be possible to achieve a tight WIP control similar to the SKAP with a service level robustness similar to the DKAP in a single policy. First, in sub-section 4.6.1, a control strategy that would be used for the new policy implementation is selected. Then, in sub-section 4.6.2, the possible approaches to designing the new Kanban allocation policy will be discussed based on the observations in this chapter about the performances of the DKAP and the SKAP.

4.6.1 Selection of Suitable Strategy for New Policy

As shown in Table 4-20 and Table 4-21, the EKCS service level robustness stochastically dominated the GKCS on a like for like DKAP or SKAP comparison, in all the scenarios. However, the GKCS's perceived superiority in terms of tighter WIP control was only evident in two scenarios.

Table 4-20: Stoch. Dominance Comparison of GKCS & EKCS (DKAPs)

DKAP	SL 1		SL 2		WIP	
Scenario	EKCS	GKCS	EKCS	GKCS	EKCS	GKCS
1	2nd Order		2nd Order		1st Order	
2	2nd Order		2nd Order		Inconclusive	Inconclusive
3	2nd Order		2nd Order		Inconclusive	Inconclusive
4	2nd Order		2nd Order		Inconclusive	Inconclusive

Table 4-21: Stoch. Dominance Comparison of GKCS & EKCS (SKAPs)

SKAP	SL 1		SL 2		WIP	
Scenario	EKCS	GKCS	EKCS	GKCS	EKCS	GKCS
1	1st Order		2nd Order		1st Order	
2	2nd Order		2nd Order		Inconclusive	Inconclusive
3	2nd Order		2nd Order		Inconclusive	Inconclusive
4	2nd Order		2nd Order		Inconclusive	Inconclusive

It was also observed in Section 4.5.3 that the GKCS's requirement that demand information is synchronised with a free Kanban at each stage before being transmitted upstream makes the demand information prone to delay if the machines are unreliable and not processing parts in time to release their Kanbans. This is less of a threat to the EKCS because the demand information is transmitted globally to all the stages.

Furthermore, under the EKCS and the GKCS, the SKAPs were observed to be tighter controllers of WIP but with less robust service levels than the DKAPs. However, this does not seem to be linked to a strategy's demand transmission logic, since the two policies were operated under the same strategy. An explanation for this is that because the SKAP often keeps a lower number of total shared Kanbans than the total Kanbans dedicated across the products under the DKAP, it would not be able to summon extra Kanbans to raise production in demand surge situations [6, 21, 28]. This observation might also be related to the earlier cited studies in Section 1.2 that propose the simultaneous and independent Kanban control approaches [15-17]. The independent approach, which is logically close to the DKAP, is reported to be more responsive to customer demands [15, 16], especially at high system capacity load [16]. It is also reported to be more susceptible to keeping higher amount of inventory [15].

Also, it was observed that the application of the SKAP between multiple products often leads to the products achieving similar service level performances, irrespective of if one of them has a less variable demand that should make it achieve a relatively more robust service level. Under the DKAP, on the other hand, each product would achieve a service level performance that corresponds to its level of demand variability. Operating a SKAP among a group of products seems to cause the demand variability of one product to affect the service levels of the other products with which it shares Kanban, and this was observed to be again more pronounced under the GKCS than under the EKCS. The competition for shared Kanbans is particularly unbalanced in the GKCS because of the Kanban and demand synchronisation process that takes place in its logic. Usually, a shared Kanban becomes assigned to a particular part type as soon as it is synchronised with a demand or a part, since those two are already synonymous with a particular part type.

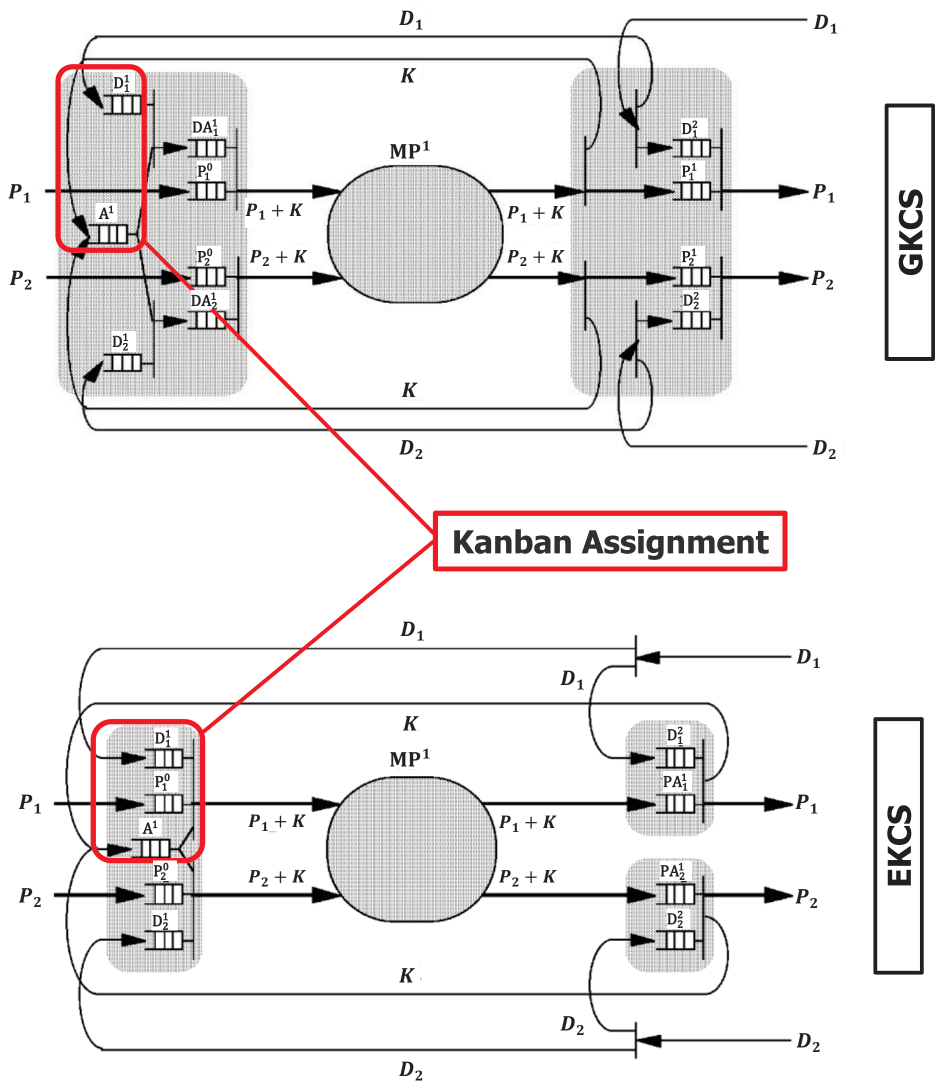


Figure 4-11: SKAP Demand, Part and Kanban synchronisation from [10]

In the two product system illustrated in Figure 4-11, under the GKCS, the Kanban assignment at Stage MP^1, takes place as soon as a Kanban, K, from the shared buffer, A^1, becomes merged with a demand, D_1, for part type 1. The merged pair, $D_1 + K$, then seek for a corresponding part from the buffer, P_1^0, to release downstream. If there is no part available in P_1^0, $D_1 + K$ remains queued in DA_1^1 until a part becomes available. During this time, K cannot be detached and reassigned to another part type. Therefore, if K was the only available free Kanban at MP^1, a subsequent demand, D_2, for part type 2 will have to wait until $D_1 + K$ obtains a part type 1 and completes its processing, even if there was a part type 2 in P_2^0 that can be authorised for processing immediately. This would result in avoidable machine idle times that could otherwise be spent processing other part types. It seems the assignment of Kanbans to a particular part type under the GKCS takes place prematurely and this would have significant effect in cases whereby the products' demand attributes differ significantly.

On the other hand, the EKCS does not assign a Kanban to a part type without a corresponding part type being available for processing. As shown in Figure 4-11, a demand, D_1, for a part type 1 must have been synchronised with a part that is available for processing from P_1^0 before a Kanban, K, is assigned from the shared buffer, A^1, to it. As such, there cannot be any subsequent delay in the use of the Kanban to release a part for processing. It is worth mentioning that an alternative interpretation of the EKCS, which does not seem probable, is if the demands are merged with Kanbans as they arrive without regard for the availability of a part for processing. Such minor difference in interpretation would lead to significant variation in performance, similar to the difference a Minimal blocking or Blocking policy could make in a pull strategy, as observed in a study [83].

It might also be argued that in the EKCS, a Kanban can also become stuck to a part type in the finished parts buffer, but it should be remembered that the EKCS already sets a separate basestock level with attached Kanbans for each part type. To some extent, the set basestock levels limit the number of parts that can be in the finished parts buffer. Having extra parts beyond the basestock level would only occur during demand surges and such parts usually end up being moved downstream as soon as they arrive into the finished parts buffer. Therefore, it won't happen for too long that extra number of Kanbans beyond a part type's basestock level will remain in its finished parts buffer.

Also, the initial sets of Kanbans that are attached to each product's basestock parts under the EKCS ensure that the different part types will have a balanced level of access to the shared pool of Kanbans. A Kanban that was initialised on a product's basestock part is very likely to be reused by the same product, except if there is a lopsided demand arrival rate or processing time between the products. The GKCS does not have such balanced level of access because the basestock parts are not initialised with any Kanbans. However, a possible remedy to achieve the same outcome in the GKCS would be to set aside certain proportions of the shared pool of unattached Kanbans and strictly dedicated them to specific products. It would provide for an interesting research to investigate how these proportions can be determined and the factors that should influence that decision.

As a result of the above observations, the EKCS will be used for the implementation of the newly proposed Kanban allocation policy in Chapter 5.

4.6.2 Combination of Policies

Based on the two criteria used in comparing the two policies in Section 4.4, it was observed that operating the SKAP results in products achieving similar service level performances, even if one of them has a less variable demand which should make it achieve a better service level performance than the other product. The DKAP, on the other hand, is able to avoid this by maintaining a service level that corresponds to each product's level of demand variability. Also, the SKAP is able to achieve a tighter WIP control than the DKAP, but its service level robustness is worse than that of the DKAP. A possible approach to achieving the WIP control and service level benefits of both policies is to combine them, by only sharing Kanbans among products with similar demand and processing time attributes.

An alternative approach to combining both policies based on the observations in Section 4.4 will be to integrate them in a large manufacturing system in a similar fashion to the hybrid push-pull strategies. This would involve partitioning the system into different sections and applying the most suitable policy to each section, in order to benefit from the advantages of both policies. A less variable section could then have a SKAP deployed, while a more variable one will be run under the DKAP, since the SKAP has been observed to be less robust to product and system variability than the DKAP. This would be similar to the segmented control approach proposed in a previous study [38]. This system segmentation could also help reduce the proliferation of WIP which has been reported to affect large systems [97]. However, a major bottleneck with adopting this type of integration is that the complexity in its implementation might defeat the purpose of the exercise and still not achieve the purpose. For instance, it would be difficult to decide on the policy to operate in a system segment that has a low variability level which should favour the application of a SKAP in it, but a high disparity in the demand profiles of the products involved which does not favour operating the SKAP.

As a result, the next phase of this research will focus on the first integration approach that would consider the demand and processing time attributes of products in deciding whether to share or dedicate Kanbans among them.

4.7 SUMMARY AND CONCLUSIONS FROM THIS CHAPTER

In this chapter, the DKAP and the SKAP have been analysed under four different scenarios that depict various levels of disparity in the demand variability of two products. The merits and demerits of each policy were established in relation to the performance measures of service level and WIP. The SKAP was observed to offer WIP savings as a way of compensating for its less robust service levels when compared with the DKAP.

In general, it was found that the EKCS is a better strategy than the GKCS, especially in environments with a high level of variability. But the performance of the EKCS varies depending on the Kanban allocation policy applied under it and the manufacturing system's configuration.

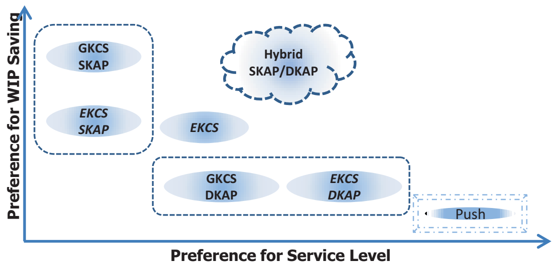


Figure 4-12: Suitability of strategies and corresponding policies

As shown in Figure 4-12, the aim of the next phase of this research is to combine the DKAP and the SKAP, in order to achieve the benefits of both under a single policy. This combination of the two policies will be compared against the pure application of the DKAP and the SKAP.

CHAPTER - 5: Comparison of Proposed Policy against Existing Policies

5.1 INTRODUCTION

The main purpose of proposing to combine the DKAP and the SKAP under a Hybrid Kanban Allocation Policy (HKAP) is the possibility of it serving as a trade-off between the WIP control benefit of the SKAP and the service level robustness of the DKAP, based on the observations from the experiments conducted on the simplified system in Chapters 3 and 4. Those experiments showed that the SKAP is mostly able to maintain lower WIP than the DKAP; however, it is not as resilient in isolating the system from internal and external sources of product and system variability. Therefore, in order to investigate the HKAP's ability to satisfy this purpose, its performance will be compared against the pure application of the DKAP and the SKAP in running a larger manufacturing system.

5.2 SETUP OF EIGHT PRODUCT SYSTEM AND EXPERIMENTS

The case study manufacturing system, which has been adopted from a previous study [14], consists of eight product types and three manufacturing stages, and it has been similarly applied in two other studies [175, 176]. In the original study, the system was configured variedly with products having different demand and processing time combinations. Therefore, the system offers further possibility than the previous manufacturing system to investigate the impact of other factors on the performance of Kanban allocation policies. Moreover, its higher number of products will also ensure that the HKAP can be experimented with.

The system's eight products were divided into two groups of four products each, with products in each group having the same processing time and demand profiles. The aim was to create different product mix scenarios by setting different demand arrival rates and processing times for the two product groups. Furthermore, the different product mix scenarios are experimented at different system capacity load levels, in order to also investigate its effect.

The load levels were set with respect to an average system throughput rate, T, of 1. Therefore, for load levels of 50%, 72.5% and 95%, the respective mean system overall demand arrival rates, M, are 0.5, 0.725 and 0.95 items per unit time. The demand arrival rates, λ_1 and λ_2, of products in Groups 1 and 2 respectively contribute to this overall mean demand arrival rate as expressed in equation (6).

$$\text{Overall mean demand arrival rate}, M = 4\lambda_1 + 4\lambda_2 \tag{6}$$

The mean time between the demands for each product is assumed to be exponentially distributed with mean values corresponding to $\frac{1}{\lambda_1}$ and $\frac{1}{\lambda_2}$ for products in Group 1 and Group 2 respectively.

The processing time, τ_{ij}, of a product, i, at a stage, j, is assumed to be beta distributed and bounded within the parameters a and b of a shifted beta distribution. The density function, $f(x, \alpha, \beta)$, of the shifted beta distribution from which the random variates are sampled is given in equation (7).

$$f(x, \propto, \beta) = \frac{1}{B(\alpha,\beta)} \frac{(x-a)^{\alpha-1}(b-x)^{\beta-1}}{(b-a)^{\alpha+\beta+1}}, \quad a \leq x \leq b, \alpha > 0, \beta > 0 \tag{7}$$

The same shape parameters $\alpha = 0.75$ and $\beta = 1.5$ are used for all the scenarios experimented, while the lower and upper bounds, a and b, are set differently such that they would result in coefficients of variation (CV) of 0.39 when substituted into equation (10). The mean, variance and CV of a shifted beta distribution are estimated using the formulas in equations (8), (9) and (10) respectively.

$$Mean\ E(Y) = \frac{\propto b + \beta a}{\propto + \beta} \tag{8}$$

$$Variance\ (Y) = \frac{(b-a)^2 \propto \beta}{(\propto + \beta)^2 (\propto + \beta + 1)} \tag{9}$$

$$CV(Y) = \sqrt{\frac{(b-a)^2 \propto \beta}{(\propto b + \beta a)(\propto + \beta + 1)}} \tag{10}$$

Lastly, the system is a balanced one with each product requiring a similar amount of processing time at all the three manufacturing stages, as expressed in equation (11).

$$\tau_{i1} \equiv \tau_{i2} \equiv \tau_{i3} \equiv \tau_i \tag{11}$$

5.2.1 Setup of Experimental Scenarios (Product Mix Scenarios)

Five product mix scenarios were formulated based on the two product groups having processing time and demand arrival rate ratios of $1{:}1$, $1{:}5$ and $5{:}1$. Conducting experiments on each scenario at the three load levels results in 15 system configurations under which the three Kanban allocation policies are compared.

With the Group 1 to Group 2 processing time ratio represented as k_p and the demand arrival rate ratio as k_d, the possible product mix scenarios are as follows:

1) Scenario 1: Homogeneous Processing time and Demand ($k_p = 1:1\ and\ k_d = 1:1$), i.e. Group 1 products and Group 2 products have similar processing times and demand arrival rates.
2) Scenario 2: Homogeneous Processing time and Heterogeneous Demand ($k_p = 1:1\ and\ k_d = 1:5$), i.e. products in both groups have similar processing times, but the Group 2 ones have 5 times higher demand arrival rates.
3) Scenario 3: Heterogeneous Processing time and Homogeneous Demand ($k_p = 5:1\ and\ k_d = 1:1$), i.e. Group 1 products have five times higher processing times, but the two groups' products have similar demand arrival rates.
4) Scenario 4: Heterogeneous (Higher) Processing time and Heterogeneous (Higher) Demand ($k_p = 5:1\ and\ k_d = 5:1$), i.e. the processing times and the demand arrival rates of products in Group 1 are both five times higher than those in Group 2. It implies raising the demand arrival rate of the previous scenario's higher processing time group.
5) Scenario 5: Heterogeneous (Higher) Processing time and Heterogeneous (Lower) Demand ($k_p = 5:1\ and\ k_d = 1:5$), i.e. Products in Group 1 have five times higher processing times, but five times lower demand arrival rates. This scenario gives the opportunity to understand the effects of swapping the higher demand arrival rate group of the previous scenario; increasing the processing time of the lower demand arrival rate group of Scenario 2; and increasing the demand arrival rate of the shorter processing time group of Scenario 3.

The above product mix scenarios represent all the unique combinations that can be achieved with the desired $k_p\ and\ k_d$ ratios. Since what really differentiates the groups from one another are the ratios, it can be said that a symmetry exists between the product groups and a reversal of any of the above ratios will only yield a product mix that is equivalent to an already listed one [14]. For instance, reversing the demand ratios in Scenario 2's $k_p = 1:1\ and\ k_d = 1:5$ to $k_p = 1:1\ and\ k_d = 5:1$ remains the same, as the processing time does not differentiate Group 1 from Group 2.

The demand arrival rates and processing times for each of the product mix scenarios are estimated using equations (6) to (11) in a way that ensures that the effective system load levels correspond to the desired 50%, 72.5% and 95%. Using equation (6), the demand arrival rates for the two groups are set to proportions corresponding to the desired demand ratios, $k_d = \frac{\lambda_1}{\lambda_2}$, for the different product mix scenarios. The mean processing times are then set to correspond to the desired load levels. These are calculated using a combination of the desired processing time ratios, $k_p = \frac{\tau_1}{\tau_2}$, and the relationship between the overall throughout rate of the system and the throughput rate per product group, as expressed in equation (12).

$$M \text{ x } T = 4\tau_1\lambda_1 + 4\tau_2\lambda_2 \tag{12}$$

Recall from equation (11) that τ_1 *and* τ_2 represent the mean processing times at the three stages for products in the two Groups 1 and 2 respectively. M x T is the effective throughput rate of the system, while $4\tau_1\lambda_1$ *and* $4\tau_2\lambda_2$ are the throughput rates for Groups 1 and 2 respectively.

The demand arrival rates obtained from equation (6) for the different load levels and demand ratios, k_d, are substituted into equation (12) to obtain the processing time values for the desired processing time ratios, k_p. The processing times and the mean times between demands $\left(\frac{1}{\lambda}\right)$ obtained for the five product mix scenarios and their respective load levels are shown in Table 5-1 to Table 5-5.

Table 5-1: Eight Product System: Scenario 1

Load Level (%)	**Processing times (hours)** $\boldsymbol{K_p = 1:1}$		**Mean Times between Demands (hours)** $\boldsymbol{K_d = 1:1}$	
	Group 1	**Group 2**	**Group 1**	**Group 2**
95	1	1	8.42	8.42
72.5	1	1	11.03	11.03
50	1	1	16.00	16.00

Table 5-2: Eight Product System: Scenario 2

Load Level (%)	Processing times (hours) $K_p = 1:1$		Mean Times between Demands (hours) $K_d = 1:5$	
	Group 1	Group 2	Group 1	Group 2
95	1	1	25.26	5.05
72.5	1	1	33.10	6.62
50	1	1	48.00	9.60

Table 5-3: Eight Product System: Scenario 3

Load Level (%)	Processing times (hours) $K_p = 5:1$		Mean Times between Demands (hours) $K_d = 1:1$	
	Group 1	Group 2	Group 1	Group 2
95	1.667	0.333	8.421	8.421
72.5	1.667	0.333	11.034	11.034
50	1.667	0.333	16.000	16.000

Table 5-4: Eight Product System: Scenario 4

Load Level (%)	Processing times (hours) $K_p = 5:1$		Mean Times between Demands (hours) $K_d = 5:1$	
	Group 1	Group 2	Group 1	Group 2
95	1.154	0.231	5.053	25.263
72.5	1.154	0.231	6.621	33.103
50	1.154	0.231	9.600	48.000

Table 5-5: Eight Product System: Scenario 5

Load Level (%)	Processing times (hours) $K_p = 5:1$		Mean Times between Demands (hours) $K_d = 1:5$	
	Group 1	Group 2	Group 1	Group 2
95	1.154	0.231	25.263	5.053
72.5	1.154	0.231	33.103	6.621
50	1.154	0.231	48.000	9.600

For each of these system configurations, the performances of the HKAP, the SKAP and the DKAP are compared by optimising them to achieve a target service level of 99%, followed by conducting sensitivity analyses to investigate their robustness to sources of variability, as well as their ability to isolate the demand variability of one product group from affecting the other group's performance.

5.2.2 SimPy – Simulation Modelling

The number of optimisation parameters in this case is higher than in the simplified system; therefore, in order to achieve more control over the optimisation process and improve the chances of achieving near optimal results, the simulation model is built in SimPy. SimPy is a Python programming language based simulation library which offers the desired flexibility for both the simulation and optimisation processes. It consists of code classes for modelling system entities and their interactions, alongside means of collecting system statistics. The four main code classes are the Process, Resource, Level and Store. A Process class is the core of SimPy's modelling capability, as it is used to invoke the process thread of an item and encapsulate all the events that will take place during its life cycle, and these will include its interactions with other system entities. The process thread of a part will for example include its request for the use of raw materials, machines and operators and the required quantity or duration of use. Indivisible resources, such as machines and personnel, are modelled using SimPy's resource class, while divisible ones are modelled by either a Level or Store class. SimPy creates a log of the interactions that take place between the different entities in such a way that they can be used to output relevant system statistics for analysis.

Furthermore, additional codes have been written in Python to enable the use of SimPy in modelling more complex events that are peculiar to Kanban controlled systems. These events include the synchronisation of parts, demands and Kanbans, especially in order to correspond to the different philosophies of the Kanban allocation policies under consideration. Additional codes have also been written to facilitate the experimentation and results analysis processes by being able to directly read and output simulation data to MS Excel spreadsheets.

5.2.3 Simulation Warmup Period, Run Length & Number of Replications

The original study used a warmup period equivalent to the time needed to complete 6,000 customer orders and recorded statistics from 60,000 orders completed afterwards, over six replications. In order to verify that these would be sufficient for this work or if they could, in fact, be reduced, Welch's procedure is applied to Scenario 5 of the 95% load level. This scenario is suspected to be the most susceptible to initialisation bias because of its load level, combined with its highly disparate product mix. This is similar to the pessimistic approach earlier applied in determining the warmup period of the simplified system in Section 3.4.3.

Moreover, in this case, the loss of computational effort, in terms of deleted useful data, is not as significant as the extra computational effort that would be required to determine the warmup period for each of the 45 scenarios experimented. Also, instead of using time intervals for specifying the statistics collection window in the test for the presence of initial transient conditions, item count is used because it would ensure a fair representation of each product type in the statistics collected. Hence, the average flow time statistics of successive 96 items, which would consist of about 4 and 20 of each group's products, are collected and used in the analysis. Also, the average flow time statistic is used because of its relation to the service level and the average system inventory level, which are the two performance measures of interest.

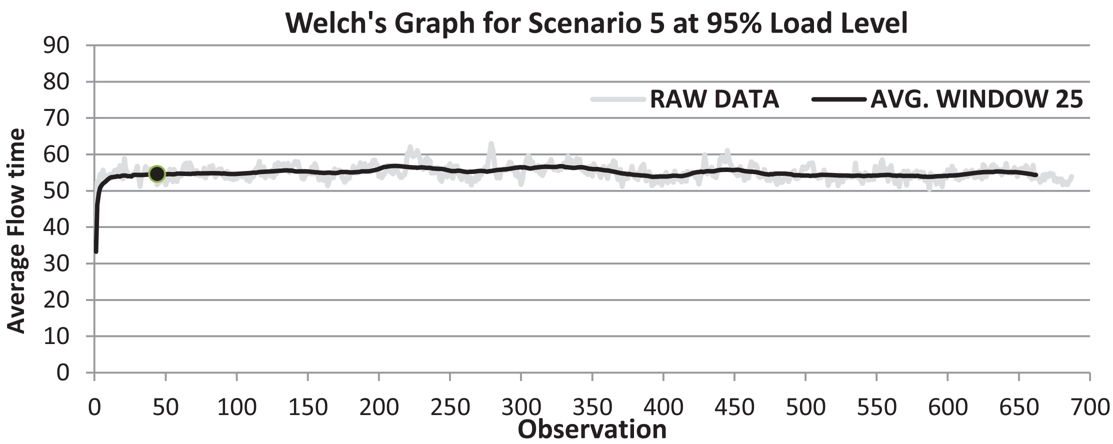


Figure 5-1: Warmup Period estimation for Eight Product System

As shown in Figure 5-1, the warmup period was estimated to be the time taken for approximately the first 4,224 (44x96) items to exit the system, and this was rounded up to 5,000. It was also determined from a sequential trial that collecting the statistics from 50,000 subsequent items over 5 replications would be sufficient to achieve confidence interval half-widths of less than 3% of the mean values of the performance measures, at 95% confidence levels.

Furthermore, the same set of assumptions made in Section 3.4.2 about the two product system was again adopted for this system. Common random number seeds were also applied across the simulation models of the systems being compared. These random number seeds were further used for the LHS runs of the sensitivity analyses, as previously described in Section 3.4.5.

5.3 LOGIC OF OPERATION OF PROPOSED POLICY

The aim of the hybrid Kanban allocation policy will be to operate the SKAP only among products with similar processing times and demand arrival rates. Based on the use of processing times and demand arrival rates to setup the product mix scenarios of the case study system, it means that Products 1 to 4 will be in the same Kanban sharing group, while Products 5 to 8 will be in another Kanban sharing group. The HKAP will then set a shared pool of Kanbans per stage for each of the groups, as shown in Table 5-6. Under the DKAP, each product will have its own set of dedicated Kanbans per stage, while the SKAP will have a shared pool of Kanbans for all the products per stage, as shown in Table 5-6. It should be noted from the table that the basestock remains dedicated per stage under the three policies.

Table 5-6: Setting of Kanban and basestock under the three policies

Setup	DKAP	HKAP	SKAP
Kanban Setting	Dedicated Kanbans for each product	Two shared pools of Kanbans dedicated separately to products in Group 1 and Group 2	Shared pool of Kanbans for all the eight products
Basestock Setting	Dedicated basestock for each product	Dedicated basestock for each product	Dedicated basestock for each product
Optimisation Parameter per stage	AK per product per stage S per product per stage	AK per group per stage S per product per stage	AK per stage S per product per stage

The HKAP will operate a SKAP among the products within the same group and a DKAP between the different groups. This implies that Kanbans detached from products from the same group are detached and returned to a common buffer from which they can be used to authorise the processing of any of the products belonging to the group. The shared pool of Kanbans for a group is strictly dedicated to it and, as such, cannot be used for products belonging to another group. The logic of operation of the HKAP is illustrated in Figure 5-2 with a system consisting of four products that have been categorised in two groups, $G1$ and $G2$. As shown in the figure, Products 1 and 2 (P_{1G1} and P_{2G1}) belong to $G1$, while Products 3 and 4 (P_{3G2} and P_{4G2}) belong to $G2$. At Stage MP1, $G1$ and $G2$ have dedicated pools of Kanbans, A_{G1}^{1} and A_{G2}^{1} that are shared among the products in the respective groups. P_{1G1} and P_{2G1} will obtain Kanban, K_{G1}, from A_{G1}^{1} and the Kanban will be returned to the same buffer upon its detachment downstream. Similarly, P_{3G2} and P_{4G2} will obtain Kanban, K_{G2}, from A_{G2}^{1}, and it will be returned to the same buffer upon its detachment downstream. The assignment of Kanbans to products in the same group will follow the EKCS SKAP logic as explained in Section 2.5.4. Also, products from both groups will be processed from the input buffer of the manufacturing stage based on a FIFO discipline.

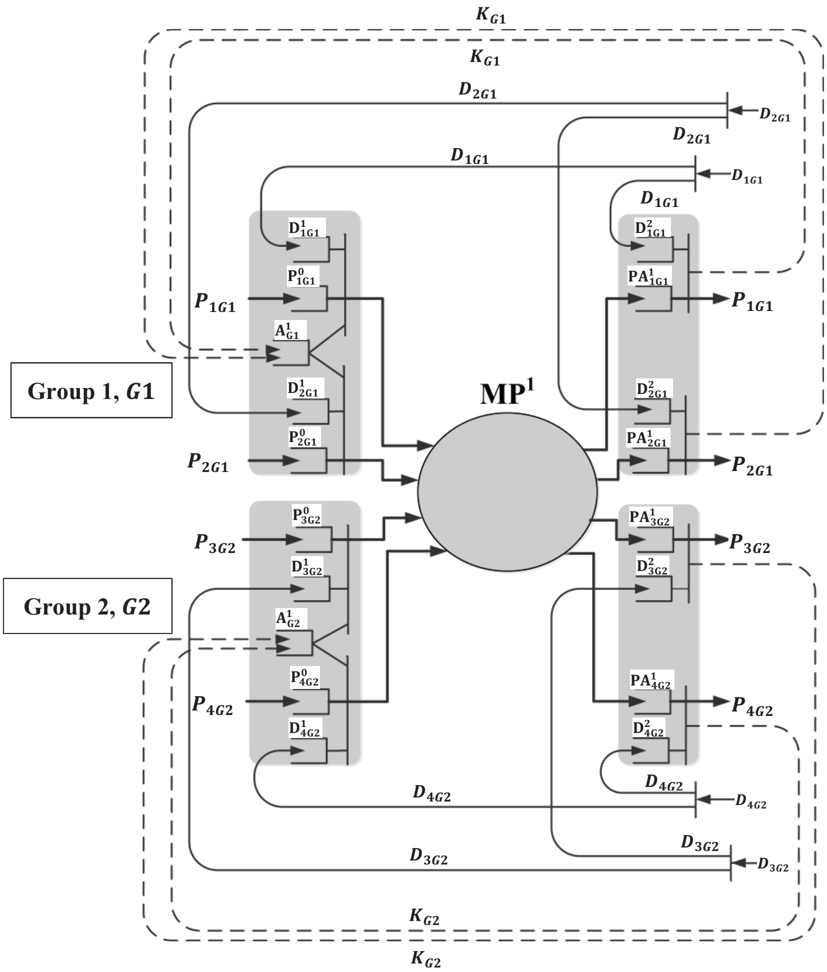


Figure 5-2: HKAP Logic of Operation

5.4 SYSTEM OPTIMISATION

The unattached Kanbans and basestock settings for the DKAP, SKAP and the HKAP will be optimised for the five scenarios at the three different load levels setup in Section 5.2.1. An optimisation algorithm that is based on the Ant Colony Optimisation (ACO) is written separately in Python and used in conjunction with the SimPy simulation model for determining the optimal Kanban and basestock settings. In the implemented ACO algorithm, the extra Kanban and the basestock settings, AK and S respectively, depict the path followed by the ants, and these are used to update the pheromone level. An ant traces a path and selects unique AK and S values for each manufacturing stage, as shown in Figure 5-3.

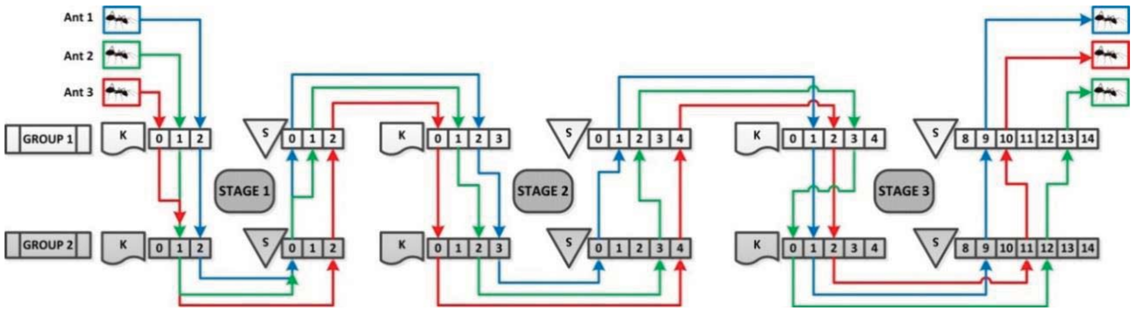


Figure 5-3: ACO Path Representation

A successive number of ant generations are created, with each consisting of a population of ants having different AK and S settings. For example, the three ants generated in Figure 5-3 have selected the AK and S settings shown in Table 5-7 for the two product groups.

Table 5-7: Sample Ant AK and S Settings

Ant	Manufacturing Stage	Product Group 1		Product Group 2	
		AK	S	AK	S
1	1	2	0	2	0
	2	2	1	3	0
	3	1	9	1	9
2	1	1	1	1	0
	2	1	2	2	3
	3	3	13	0	12
3	1	0	2	1	2
	2	0	4	0	4
	3	2	10	2	11

The ants are then simulated to determine the service levels and the average system WIP they achieve, and these are applied in ranking and selecting them for use in updating the pheromone. The pheromone update involves adding an extra representation for each of the AK and S values that were selected by the top ranked ants. For instance, if Ant 2 in Table 5-7 was to be used in a pheromone update, one extra representation each will be added for its AK and S values in the original options lists at the different manufacturing stages, as shown in Figure 5-4 for Stage 1.

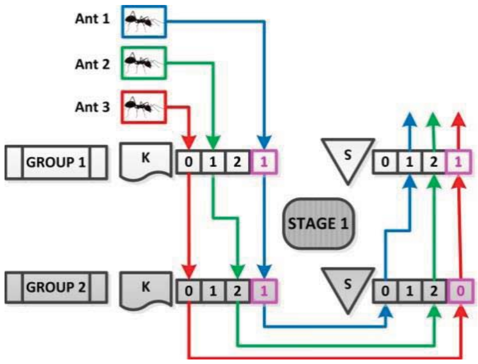


Figure 5-4: ACO Paths for Stage 1 after Pheromone Update

Previously in Figure 5-3, the original options list at Stage 1 for AK was [0,1,2], such that each one of them had an equal probability of $\frac{1}{3}$ of being set as the AK for Stage 1. However, having found that Ant 2 achieved a good solution with an AK setting of 1 at Stage 1, an extra representation is added for 1 in the options list to become [0,1,2,1], as shown in Figure 5-4. Thus, this increases the probability of future ants selecting 1 for that stage to $\frac{2}{4}$, while the other options in the options list will each have a probability of $\frac{1}{4}$. The same approach is followed in directing the optimisation process towards finding good solutions for the other stages.

At any point in time during the optimisation process, the probability of selection of a AK or S value is its number of representations, n_{rep}, in the options list divided by the total number of options, n_{opt}, available in the list, as expressed in equation (13).

$$Probability\ of\ selection, C = \frac{n_{rep}}{n_{opt}} \tag{13}$$

This is equivalent to the pheromone deposition step of the original ACO, and that step is usually preceded by a pheromone evaporation, which involves the reduction of the current probabilities of selection of all AK and S values by a predetermined amount [141, 150, 177]. The essence of the pheromone evaporation is to reduce the level of influence of previous high ranking solutions as new ones are discovered. This is achieved in this work in a different way, through a population based approach [152].

This approach involves keeping a fixed population of the best performing ants so far (i.e. elite ants), and comparing the new ants generated in every generation against them. An ant (a AK and S setting) that outperforms a member of the elite population displaces that member and its AK and S values are deposited in the pheromone. Similarly, pheromone evaporation is done on the displaced ant by removing the extra AK and S representations that had been added to the selection lists due to it being in the elite population. Basically, at the end of every generation, the pheromone update is only done for the new entrants to the elite population and those that are displaced from it. An advantage of this approach is that, unlike the original ACO pheromone evaporation approach in which a AK or S value could end up being completely erased from the options list, this ensures that every AK and S have future probabilities of being selected. However, the probabilities correspond to the performances of the previous ants in which a AK or S value was selected. Based on the expression in equation (13) for the probability of selecting a AK or S value, after depositing pheromones from the current elite population, the n_{rep} and n_{opt} in equation (13) will become as shown in equations (14) and (15), and the probability of selection changes as expressed in equation (16).

$$n_{rep} = n_{InitRep} + n_{EltRep} \tag{14}$$

$$n_{opt} = n_{opt} + n_{EltPop} \tag{15}$$

$n_{InitRep}$ is the starting number of representations of each AK or S value in the options list – usually one,

n_{EltRep} is the number of ants in the elite population that have selected a particular AK or S value, while

n_{EltPop} is the size of the elite population.

$$Probability\ of\ selection, C = \frac{n_{InitRep} + n_{EltRep}}{n_{opt} + n_{EltPop}} \tag{16}$$

As such, the highest probability of selection will occur if a particular AK or S value was selected by all the ants in the elite population, while the lowest is if none of them selected it and it only has its initial $n_{InitRep}$ in the selection list.

Additional controls have also been applied to facilitate the optimisation process. The most prominent of these is that the total number of Kanbans, TK, that the best among the current elite ants used for each product is set as a cap for the total number of Kanbans that subsequent ants can select for the corresponding product. As shown in equation (17), the ants in a generation will only be allowed to use at most three Kanbans more than the number used for a product i in the current best ant. The extra three Kanbans allowed beyond the $TK_{cap(i)}$ are to allow a reshuffling and redistribution of the total Kanbans among the system's stages, thereby encouraging an exploration of different solution configurations from the current best ant.

$$\text{for } i \in (1 \; to \; 8); \qquad \sum_{j=1}^{3} \left(AK_{ij} + S_{ij} \right) \leq TK_{cap(i)} + 3 \qquad (17)$$

where AK_{ij} and S_{ij} respectively represent the extra Kanbans and the basestock settings for product, i, at stage, j; and $TK_{cap(i)}$ is the total system Kanban for product, i, in the current best ant.

Within this cap, the ants in upcoming generations will be constrained to identify alternative allocations of the Kanbans and basestocks, and their distribution among the stages, without exceeding the cap. Since the distribution of Kanbans has been reported to have impact on the service level achieved by a manufacturing system [6, 14, 21, 82], this approach should result in the identification of better allocations and distributions, and even lower TK values, and possibly S, that would achieve the target service level with lower amount of WIP. It should be noted that there will also be inefficient distributions that would lead to higher WIP levels, as evident in Figure 5-5.

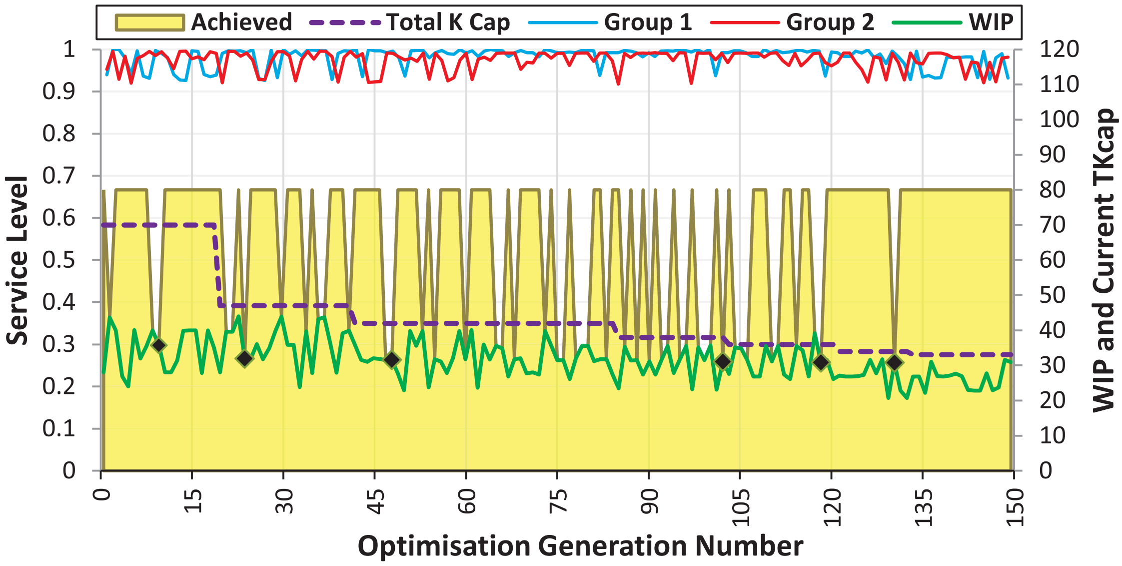


Figure 5-5: ACO process with Total Kanban cap

It can be observed from Figure 5-5 that although the TK_{cap} limits the amount of WIP in the system, there were ant settings whose WIP exceeded those of the current best ants, which are identified with the black dots. The TK_{cap} nevertheless reduces as the optimisation progresses and this ensured that settings that result in lesser WIP were generated. It can also be observed from Figure 5-5 that ant settings that did not achieve the target service levels were penalised by setting their resulting WIP to a very high value of 80, which was higher than any ant setting would result in. This thus reduces the chances of such ant settings being selected in subsequent ant generations.

Additionally, the following facilitations were made to the optimisation process:

- Due to the high number of optimisation parameters, the AK and S values are set at group level and applied to all the products in the group. This simplification is justified by the similarity in the settings obtained for similar products in the EKCS optimisation under the simpler system. Moreover, Kanban and basestock settings are known to be linked to demand or processing time attributes which form the basis for classifying the products into groups [63, 98, 178]. With this simplification, it is possible to reduce the number of parameters for the DKAP, the SKAP and the HKAP respectively from 48 to 12, 27 to 9 and 30 to 12, and this significantly reduces the number of evaluations required to achieve near optimal solutions.

- Secondly, a control added in the algorithm's code avoids the unnecessary re-simulation of previously evaluated AK and S settings by always verifying that an ant has not been previously evaluated before sending it for simulation.
- Thirdly, in order to avoid wastage of time and computational resource, AK and S settings that result in very poor service level are discontinued after their first replication run. The convergence and mean service level achieved by those that make it beyond the first replication are continually tested until the required 5 replications have been completed. Therefore, a setting's simulation can still be stopped before completing the five replications if the chance of it eventually achieving the target service level is poor.

The optimisation results obtained for the different load levels and product mix scenarios under the three Kanban allocation policies are shown in APPENDIX - G. As observed from the optimisation of the two product system in Section 3.5, the largest number of Kanbans and basestocks are again set at the last stages. As observed in Section 4.3, non-zero basestock levels were similarly set for the penultimate stages in some of the systems.

Another notable observation from the optimisation results was that, contrary to the results from the previous experiments, the SKAP required significantly higher amount of WIP than the DKAP and the HKAP to achieve the 99% target group average service levels, in Scenario 2 at the 72.5% load level. It was observed that the SKAP's optimised setting required one more basestock item at the penultimate stage for the lower demand arrival rate group than the other two policies, which resulted in its higher WIP level. Trying to reduce the WIP by reducing this basestock level and adding more unattached Kanbans, in line with the observations of previous studies on the relationship between the basestock and Kanban settings [15, 118], only increased the average service level of the higher demand arrival rate group.

Although, it did not lead to a desirable outcome in terms of the WIP, the difference made by the additional basestock for the lower demand arrival rate group seems to corroborate the earlier cited benefit of the EKCS in Section 4.6.1, which observed that the basestock of the EKCS can be used to achieve a balanced level of access to resources between multiple products.

5.5 DESIGN OF EXPERIMENTS FOR SENSITIVITY ANALYSIS

Sensitivity analysis is again applied in this part of the research; however, this time, with the intention of comparing the robustness of the newly developed HKAP against the other two policies. Because the robustness test will focus on the impact of product related variability on system performance, the eight products' mean times between demands are varied within ±5% of the original values for which the system was optimised. The mean times between demands of the eight products are varied per scenario between the ranges shown in Table 5-8, and these are covered in 100 LHS runs. The factor combinations in the LHS runs are presented in APPENDIX - A for each of the product mix scenarios. It should be noted that similarly to the sensitivity analyses in the first and second sets of experiments, the systems are not re-optimised for the LHS run settings.

Table 5-8: LHS Ranges for Sensitivity Analysis on Eight Product System

Product Mix Scenario $(K_p - K_d)$	Load Level (%)	Group 1 Mean Time between Demands (Hours)			Group 2 Mean Time between Demands (Hours)		
		Lower Level	Base Level	Upper Level	Lower Level	Base Level	Upper Level
Scenario 1 1:1–1:1	50	15.20	16.00	16.80	15.20	16.00	16.80
	72.5	10.48	11.04	11.59	10.48	11.04	11.59
	95	8.00	8.42	8.84	8.00	8.42	8.84
Scenario 2 1:1–1:5	50	45.60	48.00	50.40	9.12	9.60	10.08
	72.5	31.45	33.11	34.76	6.29	6.62	6.95
	95	24.00	25.27	26.53	4.80	5.06	5.31
Scenario 3 5:1–1:1	50	15.20	16.00	16.80	15.20	16.00	16.80
	72.5	10.48	11.04	11.59	10.48	11.04	11.59
	95	8.00	8.42	8.84	8.00	8.42	8.84
Scenario 4 5:1–5:1	50	9.12	9.60	10.08	45.60	48.00	50.40
	72.5	6.29	6.62	6.95	31.45	33.11	34.76
	95	4.80	5.06	5.31	24.00	25.27	26.53
Scenario 5 5:1–1:5	50	45.60	48.00	50.40	9.12	9.60	10.08
	72.5	31.45	33.11	34.76	6.29	6.62	6.95
	95	24.00	25.27	26.53	4.80	5.06	5.31

It should be noted that the same set of LHS runs was applied in scenarios in which the product demand ratios were the same, in order to be able to observe the effect of the processing time variations separately. Therefore, the same sets of LHS runs were applied for Scenarios 1 and 3; Scenarios 2 and 5; while Scenario 4 had a different set of LHS runs.

Stochastic dominance tests on the LHS outputs are subsequently used to compare how closely the three policies come to fulfilling the original target service levels under the demand variability conditions. Also, the LHS-varied factors whose ±5% variation had significant impact on the products' service levels and the system WIP are identified. This would help determine the extent to which the products' demand variabilities affect the service levels of products within and outside their own Kanban sharing group. The effectiveness of the HKAP's processing time and/demand based product grouping in isolating the effect of individual product's instabilities to within its Kanban sharing group will be evaluated through this means.

5.6 RESULTS FROM COMPARISON OF PROPOSED POLICY AGAINST EXISTING POLICIES

The HKAP aims to achieve the tight WIP control of the SKAP, while avoiding its downside of products affecting the service level performances of one another. It aims to achieve this by applying demand and processing time related attributes in separating products into different Kanban sharing groups, in order to reduce the impact dissimilar products can have on one another. The manufacturing system on which the HKAP is being implemented consists of eight products which have been formed into five different product mix scenarios, with each scenario representing different levels of disparities in the products' demand and processing time attributes. The HKAP applies these attributes in separating the products into two Kanban sharing groups, and the results obtained are then compared against the application of the DKAP – which does not do any Kanban sharing between products, and the SKAP – which shares Kanbans across all the products.

The three policies are compared based on the following criteria:

- the robustness of their service level performances,

- the effectiveness of their WIP control, and
- their effectiveness in isolating one product group's demand variability from affecting the other group.

For the first criterion, the group average service level robustness will be compared. But, unlike in Chapter 4, the averages will not be used directly for the comparisons, because such point estimates might not give adequate indication if there are products within the group whose individual service levels have fallen drastically below the optimised level. Instead, a 95% confidence interval of each group's average service level is constructed for each LHS run and compared against the group's original optimised average service level's 95% confidence interval. A policy's ability to maintain a service level that does not fall statistically significantly below this optimised interval at 95% confidence level is then used as a measure of robustness. Essentially, this would be a measure of the confidence a line manager could have that the average service level of a product group will not fall below an optimised level of performance. The robustness results which are referenced in the following sub-sections are presented in APPENDIX - G.

The second criterion will be based on the average system WIP of the three policies across the 100 LHS runs, and this will compare the effectiveness of the three policies' WIP control. As a reminder, the WIP stochastic dominance comparisons are interpreted in the reverse because the WIP is a minimisation type performance measure.

The third criterion will seek to identify the extent to which the demand variation of each product affects products within and outside its own group. Similarly to the approach of Section 4.5, it will be used to determine the products whose service levels differed statistically significantly at 95% confidence level between the sets of runs in which each of the products had demand arrival rates that were 5% below and 5% above their respective base levels. Based on these analyses, it can be determined if the HKAP's grouping of products was able to isolate the effect of a product's demand variability to only among the products with which it shares Kanbans.

5.6.1 50% System Capacity Load Level

CRITERIA 1: ROBUSTNESS OF SERVICE LEVELS

It was observed from the robustness tests done at this load level that there were very few instances in which the average service levels achieved for the two groups significantly dropped below the base optimised target service levels. This can be attributed to the availability of spare production capacity which would ensure that the products did not have to deprive one another of Kanbans or production resource in order to off-set any increase in their demand arrival rates.

Table 5-9: Significant declines in Group Average SLs – 50%

Scenario	Number of LHS runs with statistically significant declines in Group Average Service Level at 95% confidence Level under					
	DKAP		HKAP		SKAP	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
1	0	0	0	0	0	0
2	0	0	0	4	1	0
3	0	0	3	1	3	4
4	0	0	11	0	0	1
5	0	0	0	6	0	0

As shown in Table 5-9, the DKAP had no single instance of decline in group average service level across the five scenarios, while the HKAP had 25 instances and there were 9 under the SKAP.

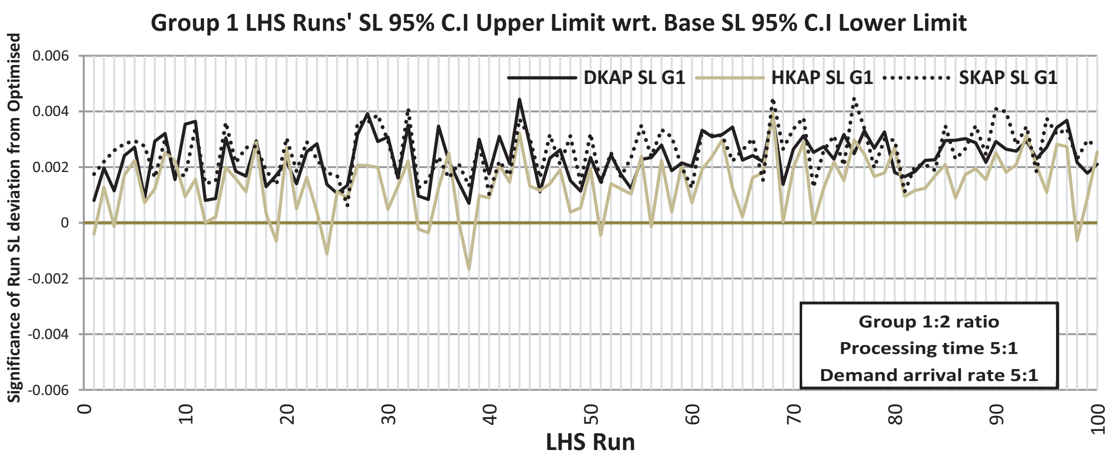


Figure 5-6: Group 1 Average SL Robustness – 50% Load Level Scenario 4

As shown in Table 5-9, the highest number of instances of group service level decline in a scenario occurred to Group 1 in Scenario 4 under the HKAP which is shown in Figure 5-6. This could have been because the products in the group had high demand arrival rates and processing times which made the competition for Kanbans high. The HKAP would not have afforded the products the opportunity to summon spare Kanbans from the other group, as the system-wide Kanban sharing under the SKAP did. Generally, under the HKAP, the group with the higher demand arrival rates and/or processing times was generally more prone to statistically significant average service level declines below the optimised level, as evident in Scenarios 2, 3 and 5 in Table 5-9.

Considering that there were very few instances of significant service level declines and that the magnitudes of the declines were less than 0.002 from the optimised target average service level, therefore, any of the three policies – particularly the DKAP or the SKAP – could have been used without the threats of severe deviations from the target service levels.

CRITERIA 2: INVENTORY CONTROL EFFECTIVENESS

The results obtained from the comparison of the WIP control effectiveness of the three policies, as shown in Table 5-10, clearly breaks the tie between the SKAP and the DKAP for service level robustness. The SKAP achieves a more effective WIP control than both the DKAP and the HKAP across the five scenarios, as shown in Table 5-10.

Table 5-10: WIP Control Effectiveness – 50% Load Level

Scenario	WIP control effectiveness (Stochastic Dominance test)		
	HKAP versus		DKAP versus SKAP
	DKAP	SKAP	
1	DKAP (1st Order)	HKAP (1st Order)	DKAP (1st Order)
2	DKAP (1st Order)	HKAP (1st Order)	DKAP (1st Order)
3	DKAP (1st Order)	HKAP (1st Order)	DKAP (1st Order)
4	DKAP (1st Order)	HKAP (1st Order)	DKAP (1st Order)
5	DKAP (1st Order)	HKAP (1st Order)	DKAP (1st Order)

Therefore, based on the first two criteria, the SKAP can be concluded to be the most suitable of the three policies at this load level. The last criterion will not be considered because the service level declines were not frequent or severe enough to be able to differentiate the products whose demand arrival rate variations were responsible for the declines.

5.6.2 72.5% System Capacity Load Level

<u>CRITERIA 1: ROBUSTNESS OF SERVICE LEVELS</u>

At this medium level of system capacity load, the impacts of the variations in the demand arrival rates on the groups' average service levels become a little more obvious than in the low system capacity load condition.

Table 5-11: Significant declines in Group Average SLs – 72.5%

Scenario	Number of LHS runs with statistically significant declines in Group Average Service Level at 95% confidence Level under					
	DKAP		HKAP		SKAP	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
1	0	2	1	0	1	0
2	0	0	0	7	0	9
3	2	4	0	0	1	1
4	1	0	2	0	0	0
5	0	15	4	0	1	4

As shown in Table 5-11, the DKAP had 24 instances of statistically significant group average service level declines, while the HKAP had 14 instances and the SKAP had 17. Similar to the 50% load level, it was observed that under the HKAP the higher demand arrival rate or processing time group was more prone to statistically significant average service level declines, as evident in Scenarios 2, 4 and 5 in Table 5-11. However, this was not the case in Scenario 3 for the Group with the higher processing time. It also appears that the Kanban and basestock allocation/distribution within a group in the original optimised setting also plays a role in the robustness of a group to overcome its susceptibility to service level declines. This was the case in Scenario 3 under the DKAP in which the higher processing time group had lower number of instances of statistically significant service level declines. Also, under the SKAP in Scenario 2, the extra basestock level set for Group 1 under the SKAP (as explained in Section 5.4) seems to have made it avoid any statistically significant decline in its average service level, as shown in Table 5-11. On the other hand, the use of the extra basestock directly for Group1, instead of extra unattached Shared Kanbans for both groups, in order to achieve a balance between the two groups' optimised average service levels, seems to have had an effect on the interaction between the two groups. As shown in Figure 5-7, it seems to have been impossible for the higher demand arrival rate group to draw spare Kanbans to offset its demand surges as it did in the same scenario at the 50% load level. This observation might imply a means by which group service level performances can be differentiated under the SKAP through their respective basestock settings. However, the consequent excess WIP makes the SKAP a less attractive alternative to the HKAP in achieving such goal.

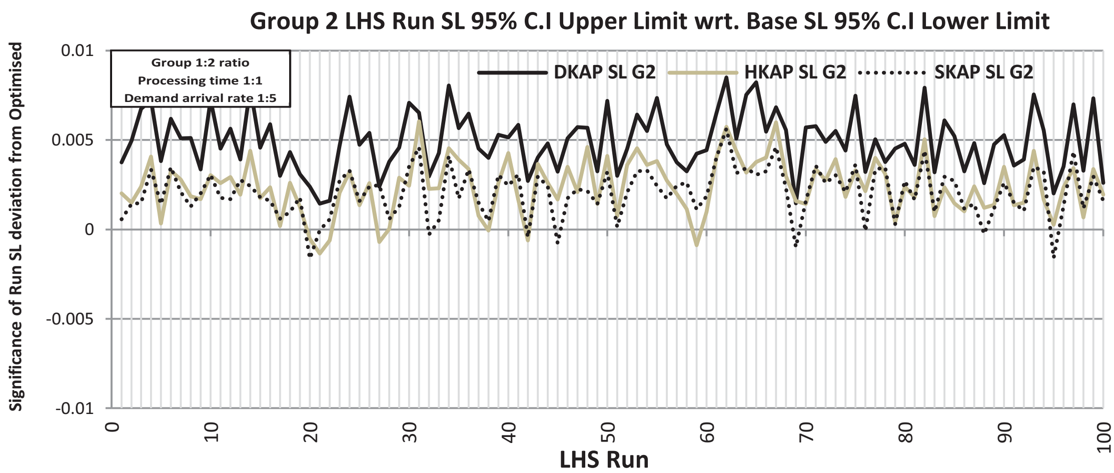


Figure 5-7: Group SL Robustness – 72.5% Load Level Scenario 2

Across the five scenarios, the reported instances of statistically significant group average service level declines were again less than 0.002 from the optimised target service level of 0.99. The HKAP followed by the SKAP achieved the least numbers of statistically significant average service level declines.

CRITERIA 2: INVENTORY CONTROL EFFECTIVENESS

If the WIP control robustness was considered in addition to the service level robustness, the SKAP still remains the best policy to adopt at this load level. As presented in Table 5-12, the SKAP achieved a more effective WIP control than the DKAP in all the scenarios, except in Scenario 2. It was similarly better than the HKAP, except in Scenarios 1 and 2 in which it had a less and an equally effective WIP control respectively.

Table 5-12: WIP Control Effectiveness – 72.5% Load Level

Scenario	WIP control effectiveness (Stochastic Dominance test)		
	HKAP versus		DKAP versus SKAP
	DKAP	SKAP	
1	DKAP (1st Order)	Inconclusive	DKAP (1st Order)
2	DKAP (1st Order)	SKAP (1st Order)	SKAP (1st Order)
3	DKAP (1st Order)	HKAP (1st Order)	DKAP (1st Order)
4	DKAP (1st Order)	HKAP (1st Order)	DKAP (1st Order)
5	DKAP (1st Order)	HKAP (1st Order)	DKAP (1st Order)

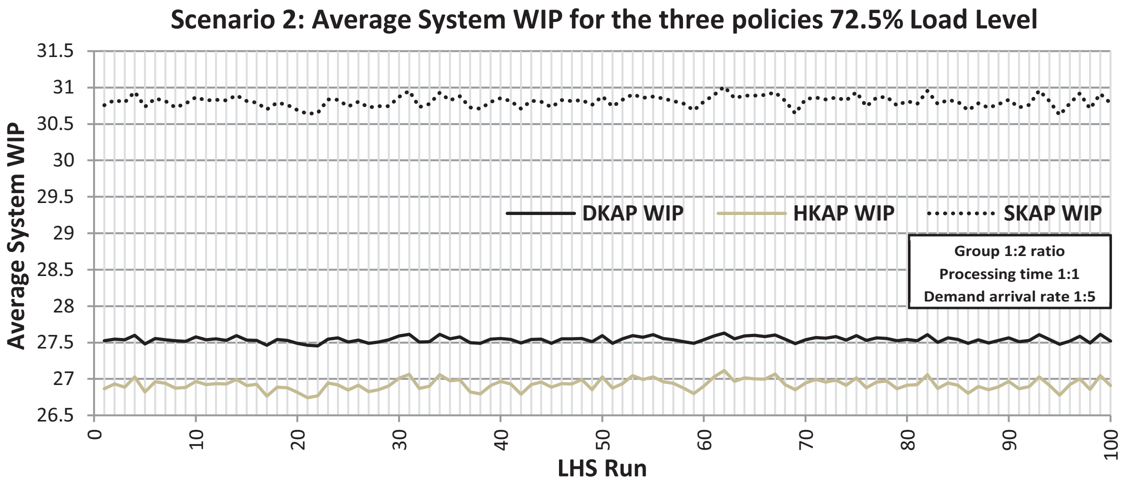


Figure 5-8: WIP across LHS Runs at 72.5% Load Level (Scenario 2)

The higher WIP level of the SKAP in Scenario 2 was a result of the extra basestock level set for the Group 1 products in order to achieve the target service level for the base setting, as explained in Section 5.4. It achieved the aim and continued to ensure that the group's average service level did not fall statistically significantly below the optimised service level, but it resulted in a higher WIP level.

Finally, the last criterion will again not be considered at this load level because even though the service level declines were more frequent than at the 50% load level, they were still not severe enough to be able to differentiate the products whose demand arrival rate variations were responsible for the declines. The first two criteria prove the SKAP's suitability for this load level.

5.6.3 95% System Capacity Load Level

<u>CRITERIA 1: ROBUSTNESS OF SERVICE LEVELS</u>

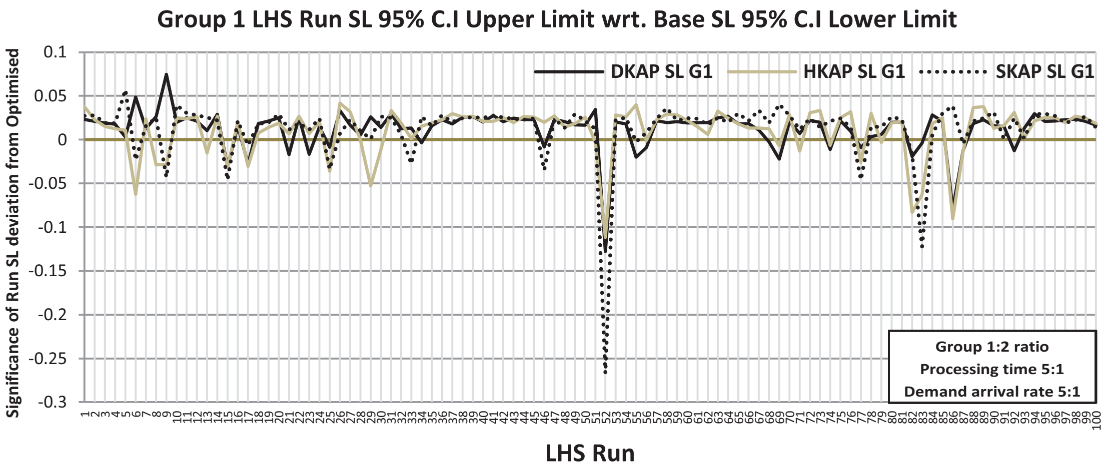
An important observation from the results obtained from experimenting at this system capacity load level is that the interaction between multiple products' Kanban and basestock settings, as reported in previous studies [58], actually increases with the system capacity load. A possible explanation for the connection between the degree of interaction of the products' settings and the system's capacity load level is that the products' access to the limited spare system capacity will be more dependent on their available Kanbans and basestocks. Therefore, the competition for Kanbans and the impact products sharing Kanbans can have on one another become stronger.

Table 5-13: Significant declines in Group Average SLs – 95%

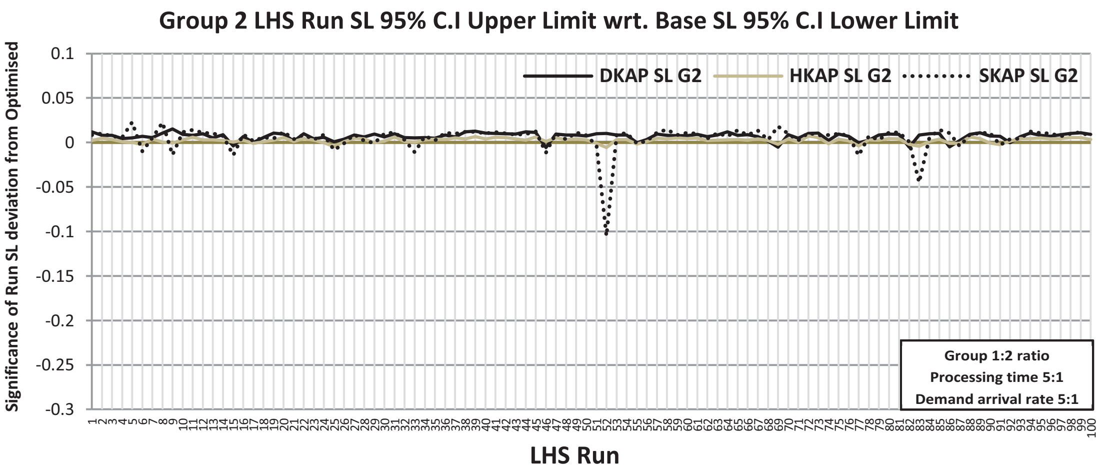
Scenario	Number of LHS runs with statistically significant declines in Group Average Service Level at 95% confidence Level under					
	DKAP		HKAP		SKAP	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
1	8	17	4	18	26	22
2	24	27	7	18	12	22
3	10	18	7	3	25	24
4	19	8	22	18	13	15
5	5	8	3	2	7	10

As shown in Table 5-13, the average service levels of the two product groups suffered significant declines under the three policies. The HKAP had the least number of instances of statistically significant service level declines – 102 across the 5 scenarios, followed by the DKAP which had 144 instances. The SKAP was the worst with 176 instances.

At this load level, a significant number of the observed statistically significant service level declines were severe, resulting in more than 0.01 drop below the optimised target service level of 0.99. It was observed that while the DKAP and the HKAP were able to isolate the severe service level declines were to the higher demand arrival rate and/or processing time group, it usually affected both groups under the SKAP. For instance, in Scenario 4, the DKAP and the HKAP suffered the severe statistically significant average service level declines only to Group 1 which had the higher demand arrival rate and processing time, as shown in Figure 5-9 (a) and (b). The SKAP, on the other hand, suffered the severe statistically significant service level drops to both groups. This would have been because of the Kanbans being drawn towards Group 1 to offset its demand surges under the SKAP. It should be highlighted that despite the benefits of the other two policies in this regards, the DKAP and the HKAP have the respective challenges of leaving the service level of an individual product or a Kanban sharing group isolated to deteriorate severely.



(a) Group 1 Average SL with respect to Base Optimised SL



(b) Group 2 Average SL with respect to Base Optimised SL

Figure 5-9: Group SL Robustness – 95% Load Level Scenario 4

Criteria 2: Inventory Control Effectiveness

From the robustness tests, it has been observed that the HKAP is more effective than the other two policies in reducing the number of instances of statistically significant declines in the product groups' average service levels. In this section, its WIP control effectiveness is compared against the other two policies.

Table 5-14: WIP Control Effectiveness – 95% Load Level

Scenario	WIP control effectiveness (Stochastic Dominance test)		
	HKAP versus		DKAP versus SKAP
	DKAP	SKAP	
1	Inconclusive	HKAP (1st Order)	DKAP (1st Order)
2	DKAP (1st Order)	Inconclusive	DKAP (1st Order)
3	DKAP (1st Order)	SKAP (1st Order)	DKAP (2nd Order)
4	DKAP (1st Order)	SKAP (1st Order)	DKAP (1st Order)
5	DKAP (1st Order)	HKAP (2nd Order)	DKAP (2nd Order)

As shown in Table 5-14, the HKAP was able to achieve a more effective WIP control than the DKAP is all the scenarios, except in Scenario 1 in which there was no clear differentiation. The SKAP too was consistently worse than the DKAP in all the 5 scenarios. The HKAP's WIP control was as good as or better than that of the SKAP in 3 out of the 5 scenarios. Considering that the SKAP is the benchmark for this criterion, it can be concluded that the HKAP offers a WIP control that is as effective as that of the SKAP. Hence, the next consideration will be to determine if the HKAP can offer the benefit of the DKAP in reducing the impacts products demand variability have on the service level performance of one another, or at least reduce the impact products' demand variability have on the service level of one another.

CRITERIA 3: Effectiveness in Isolating Product Group's Demand Variability

It is evident from the service level robustness test results that the products suffered the most significant service level declines at the 95% load level. Therefore, in this section, the products whose demand arrival rate variations caused the observed statistically significant service level declines are identified for the 95% load level. The aim is to verify if the HKAP is able to isolate the impact of the variation in a product's demand arrival rate to among the products with which it shares Kanbans. This would help determine if the HKAP can offer the DKAP's benefit of differentiating products' service level performances, in addition to the WIP control effectiveness it has been shown to offer.

In the following sub-sections, the products whose service levels are affected by the variation in the demand arrival rate of each of the products are identified in the five scenarios. First, a summary of the number of instances per scenario in which the variation in the demand arrival rates of products affected the service levels of products in another group is presented in Table 5-15.

Table 5-15: Instances of Products' Demand Variation Impact

Scenario	Number of products whose service levels were affected by the demand variation of a product in another group		
	DKAP	HKAP	SKAP
1	7	7	14
2	6	4	13
3	12	7	12
4	8	8	12
5	4	8	13

As shown in Table 5-15, the SKAP was the worst in all the five scenarios, while the HKAP was as good as the DKAP in 4 out of the 5 scenarios, in terms of the number of instances of a product's service level being affected statistically significantly by the variation in the demand arrival rate of a product external to its group. The HKAP was better than the DKAP in Scenarios 2 and 3, and as good as it in Scenarios 1 and 4.

As evident in Table 5-15, the results varied across the five scenarios; therefore, in the following sub-sections, the performances of the three policies are going to be discussed for each of the scenarios. It should be mentioned that the earlier identified shortcomings of the HKAP and the DKAP to cause a particular product group or individual product's performance to deteriorate in isolation were observed.

Scenario 1: Homogeneous Processing time and Demand

Under the DKAP, as shown in Table 5-16, each product had statistically significant impact on its own service level and, in some cases, those of other products. For instance, Products 2, 3 and 7 had significant impact on the service levels of products in the other group.

Table 5-16: Demand Arrival rate impact on Product SLs (Scenario 1)

	Scenario 1: Homogeneous Processing time and Homogeneous Demand						
	Mean Demand Arrival Rate Impact of:	Products with significantly different SL between ±5% of factor settings under:					
		DKAP		HKAP		SKAP	
		Same Group	Other Group	Same Group	Other Group	Same Group	Other Group
Group 1	Product 1	SL 1		SLs 1, 2, 3 and 4	SLs 5, 6, and 7	SLs 1	SLs 5 and 7
	Product 2	SL 2	SL 8	SL 2		SL 2	
	Product 3	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8
	Product 4	SL 4		SL 4			
Group 2	Product 5	SL 5		SLs 5, 7 and 8		SLs 5, 7 and 8	SLs 1, 2, 3 and 4
	Product 6	SL 6		SL6		SL 6	
	Product 7	SL 7	SLs 1 and 4	SL7		SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4
	Product 8	SL 8				SL 8	

Similarly under the HKAP, each product in Group 1 had significant one its own service level and, in some cases, other products' service level. The HKAP does well at isolating Group 2 products' impacts to within the group, unlike under the DKAP and SKAP in which they significantly affected products from Group 1.

In Group 1, across the three policies, the impacts of products demand variations was not completely isolated to within their own Kanban sharing groups. This could have been because the products were only arbitrarily grouped, as no demand or processing attributes was applied in their grouping. Also, it was observed that under the HKAP the Group 1 products' service levels were significantly higher than those of Group 2. As there was no difference in processing time and demand attributes in this scenario, it can be concluded that the difference in performance was a result of their Kanban and basestock settings. Therefore, if a balanced performance was desired across the two groups, an even Kanban and basestock allocation would be needed. Alternatively, the Kanban and basestock settings can be used to deliberately prioritise the service level performance of one group of products above the other, and the HKAP would be the most suitable for achieving this.

Scenario 2: Homogeneous Processing time and Heterogeneous Demand

In this scenario, it was observed that the low demand arrival rate Group 1 products did not have as much significant impact on the service levels of the products within and outside their group when compared with Group 2 products.

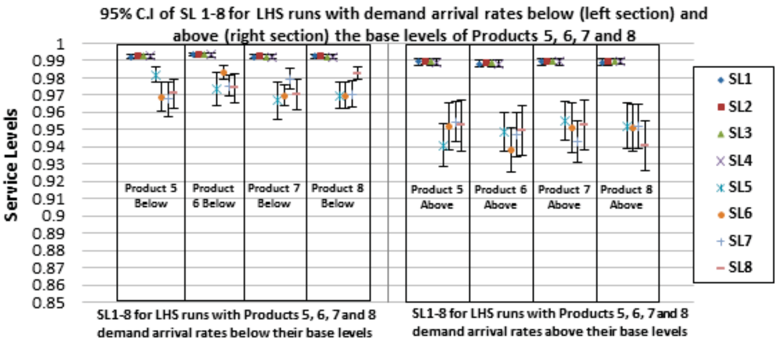
Table 5-17: Demand Arrival rate impact on Product SLs (Scenario 2)

	Scenario 2: Homogeneous Processing time and Heterogeneous Demand						
	Mean Demand Arrival Rate Impact of:	Products with significantly different SL between ±5% of factor settings under:					
		DKAP		HKAP		SKAP	
		Same Group	Other Group	Same Group	Other Group	Same Group	Other Group
Group 1	Product 1						
	Product 2	SL 2		SL 2			
	Product 3			SL3			
	Product 4						
Group 2	Product 5	SL 5	SLs 3 and 4	SLs 5, 7 and 8		SLs 5	SLs 3 and 4
	Product 6	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4
	Product 7	SL 7		SLs 5, 6 and 7		SL 7	SLs 1, 2 and 3
	Product 8	SL 8		SL 8		SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4

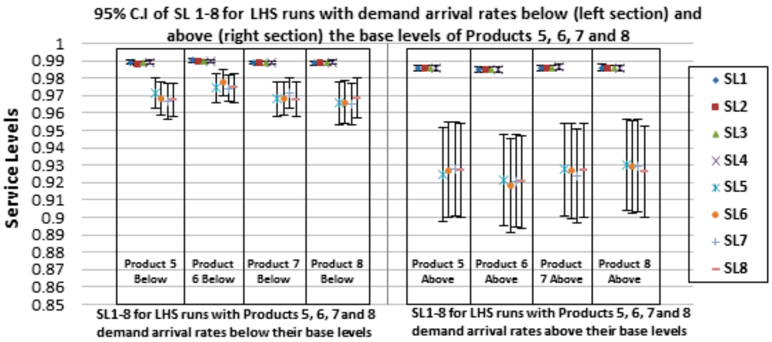
Under the DKAP, only Product 2 had significant impact which was on its own service level. Products 2 and 3 similarly had significant impact on their respective service levels under the HKAP, while there was no Group 1 product with significant impact under the SKAP.

As shown in Table 5-17, products in Group 2 had statistically significant impact that in some cases extended beyond their group under all the three policies. Under the SKAP, all the four Group 2 products had statistically significant effects on the service levels of products in the other group, while the HKAP only had one product (Product 6) significantly affecting the service levels of products in the other group. The DKAP, despite not sharing Kanbans at all, still had two products from Group 2 affecting the performances of other products; therefore, it seems this group's products affecting the other group's products was not totally avoidable.

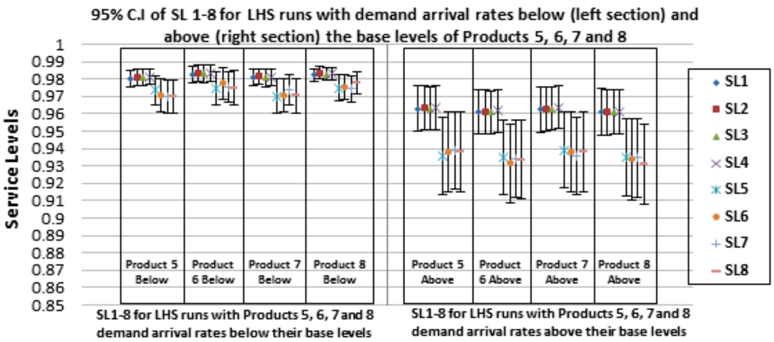
Additionally, as shown in Figure 5-10 (a) and Figure 5-10 (b) respectively, the lower demand arrival rate group's products maintained statistically significantly higher service levels across all the sets of runs under the DKAP and the HKAP. This was however not the case under the SKAP in which the service levels of products from the two groups did not differ statistically significantly, as shown in Figure 5-10 (c). This is also an indication that the higher demand arrival rate Group 2 products were able to impact the service level of the products in Group 1 when they shared a common pool of Kanbans.



(a) DKAP Scenario 2



(b) HKAP Scenario 2



(c) SKAP Scenario 2

Figure 5-10: Products 5-8 Demand Arrival rate impact on SLs

Scenario 3: Heterogeneous Processing time and Homogeneous Demand

In this scenario, the higher processing time products of Group 1 had the most significant impacts on their own group and the other group. Under the DKAP and the SKAP, three of the four products in this group had statistically significant impact on the service levels of products external to their group. It was only Product 4 that impacted its own service level only under the two policies. Under the HKAP, it did not have statistically significant impact on any product's service level, including its own.

Table 5-18: Demand Arrival rate impact on Product SLs (Scenario 3)

	Scenario 3: Heterogeneous Processing time and Homogeneous Demand						
	Mean Demand Arrival Rate Impact of:	Products with significantly different SL between ±5% of factor settings under:					
		DKAP		HKAP		SKAP	
		Same Group	Other Group	Same Group	Other Group	Same Group	Other Group
Group 1	Product 1	SL 1	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5 and 6	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8
	Product 2	SLs 1 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SL 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8
	Product 3	SLs 1, 2 and 3	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8
	Product 4	SL 4				SL 4	
Group 2	Product 5	SL 5		SL5			
	Product 6			SL6			
	Product 7			SL7			
	Product 8						

It is also evident from Table 5-18, that the HKAP was able to prevent Products 1-3 from significantly affecting all the products in the other group, as was the case under the DKAP and the SKAP. The Group 2 products' demand arrival rates did not have statistically significant effects on any of the products' service levels under the SKAP. It was the same under the DKAP, except for Product 5 which had significant impact on its own service level. Under the HKAP, three of the Products had significant effect on their respective service levels. It was only Product 8 that did not have significant impact on any product's service level.

Another notable observation relating to the performances of the two product groups was that under the HKAP, the lower processing time Group 2 products had statistically significantly higher service level than the Group 2 products, across all the sets of runs. This was unlike the DKAP and SKAP in which the groups' products' service levels were not significantly different.

It is worth noting that the LHS runs used in this scenario is the same as that used in Scenario 1, and it could be observed that the Group 1 products significantly affected higher number of products from the other group, especially under the SKAP. It can be concluded that in this scenario, the higher processing time of Group 1 products has played a role in increasing their impacts. This could have also contributed to why products in Group 2 did not have many statistically significant impacts when compared with Scenario 1. Their impacts seem to have been overshadowed by those of the higher processing time group's products.

Hence, it is evident that processing time similarity should be a key consideration in the formation of Kanban sharing groups.

Scenario 4: Higher Processing time and Higher Demand for Group 1

In this scenario, Group 1 products' higher processing times combined with higher demand arrival rates meant that they had the most impact on the service levels of products within their group and in the other group.

Table 5-19: Demand Arrival rate impact on Product SLs (Scenario 4)

	Scenario 4: Higher Processing time and Higher Demand for Group 1						
	Mean Demand Arrival Rate Impact of:	Products with significantly different SL between ±5% of factor settings under:					
		DKAP		HKAP		SKAP	
		Same Group	Other Group	Same Group	Other Group	Same Group	Other Group
Group 1	Product 1	SL 1		SL 1			
	Product 2	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8
	Product 3	SL 3		SL 3		SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8
	Product 4	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8
Group 2	Product 5						
	Product 6						
	Product 7						
	Product 8						

As shown in Table 5-19, under the SKAP, all the Group 1 products, except Product 1, had significant effects on the service levels of all the products within and outside their group. The HKAP and the DKAP were able to isolate the impacts of two of these Group 1 products to their own service levels only. The products in Group 2 did not have statistically significant impact on any product's service levels, including their own. This again must have been due to the Group 1 products' effects overshadowing any effect the Group 2 products had.

Another observation from the analysis was that under the DKAP and the HKAP, Group 2 products benefitted from having lower demand arrival rate, and possibly shorter processing time, by having statistically significantly higher service levels. On the contrary, the service levels of the two groups' products were not significantly different under the SKAP.

Scenario 5: Higher Processing time and Lower Demand for Group 1

In Scenarios 2, 3, and 4, it was straightforward to identify that it was the higher processing time, higher demand arrival rate or a combination of both that was causing a particular product group to have the most impact on the products' service levels. However, since opposing groups have the higher demand arrival and processing times in this scenario, it would provide an opportunity to identify which one of the factors would have the overbearing effect in causing a product group to have the most impact on the products' service levels.

Table 5-20: Demand Arrival rate impact on Product SLs (Scenario 5)

	Scenario 5: Higher Processing time and Lesser Demand for Group 1						
	Mean Demand Arrival Rate Impact of:	Products with significantly different SL between ±5% of factor settings under:					
		DKAP		HKAP		SKAP	
		Same Group	Other Group	Same Group	Other Group	Same Group	Other Group
Group 1	Product 1	SL 1				SLs 1 and 4	SL 6
	Product 2	SLs 1 and 2		SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8
	Product 3	SL 3		SLs 1 to 4		SLs 3 and 4	SLs 5, 6, 7 and 8
	Product 4	SL 4		SLs 1 to 4		SL 2 and 4	
Group 2	Product 5	SL 5		SL 5			
	Product 6	SLs 5, 7 and 8	SLs 1, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4	SLs 5, 6, 7 and 8	SLs 1, 2, 3 and 4
	Product 7	SL 7	SL 1			SL 7	
	Product 8	SL 8				SL 8	

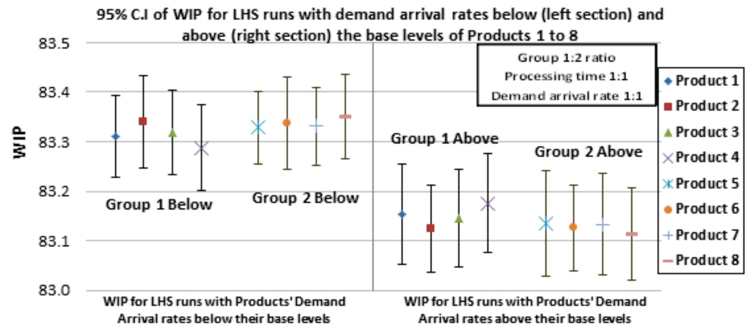
Under the SKAP in Scenario 2, which also used the same LHS runs as this scenario, the lower demand arrival rate Group 1 products did not have statistically significant impact on any product's service level. However, in this scenario in which the Group 1 products now have higher processing times than the other group, they have significant impact on the service levels of product within and outside their group, as shown in Table 5-20. Under the SKAP, three of the four products in Group 1 had significant impact on the service levels of products in the other group. The HKAP ensured only one product had significant impact on products in the other group. Also, the DKAP successfully isolated the impacts of the four Group 1 products to within their group, with three out of them only affecting their respective service levels.

The SKAP was as effective as the HKAP in keeping the effects of Group 2 products to their own service levels and to within their groups. Under the SKAP, it was only one product that had statistically significant impact on products in the other group, while the DKAP had two products.

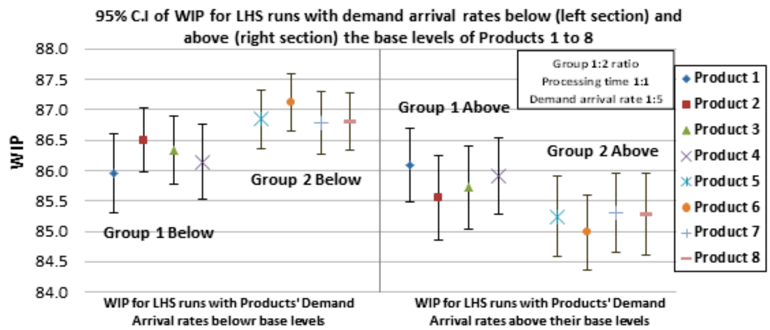
5.7 IMPACTS OF DEMAND ARRIVAL RATES ON INVENTORY

From a similar analysis to the previous section, it was observed that the system WIP was most significantly affected by the demand arrival rates of products from the groups with higher processing time and/or demand arrival rate. This is in addition to the same group of products being the most susceptible to service level declines, and having the most impact on the products' service levels, as observed in Section 5.6.3.

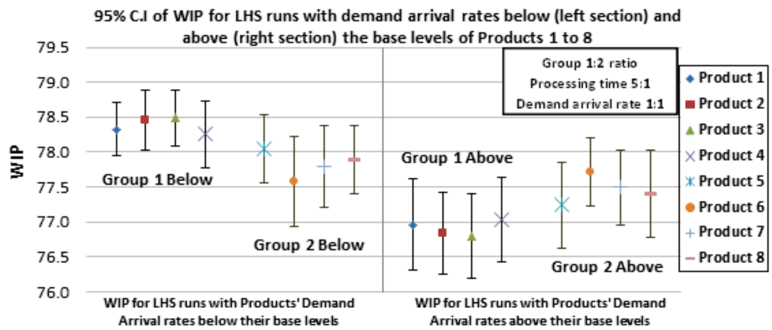
In Scenario 1, which was a homogeneous mix, both groups had products whose demand arrival rates had statistically significant impact on the system WIP, as shown in Figure 5-11 (a). However, it was observed that only Group 2 and Group 1 products had significant impacts on system WIP in Scenarios 2 and 3 respectively, as shown in Figure 5-11 (b) and Figure 5-11 (c). These were respectively the higher demand arrival rate group and the higher processing time group under the two scenarios. A similar plot for Scenario 4 showed that Group 1, which had a combination of higher processing time and demand arrival rate, had the most impact on system WIP. In Scenario 5, both groups had products whose demand arrival rates had statistically significant impact on the system WIP, as shown in Figure 5-11 (d). The higher processing time of Group 1 and the higher demand arrival rate of Group 2 must have contributed to this. In particular, more products from Group 1 had statistically significant impact on the system WIP.



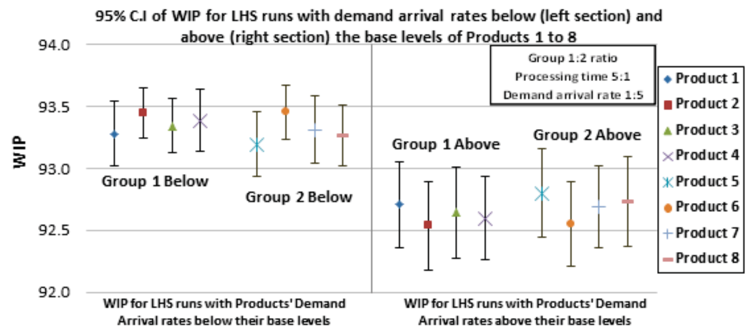
(a) Scenario 1: Homogeneous Processing time and Demand



(b) Scenario 2: Homogeneous Processing time and Heterogeneous Demand



(c) Scenario 3: Heterogeneous Processing time and Homogeneous Demand



(d) Scenario 5: Higher Processing time and Lower Demand for Group 1

Figure 5-11: Products' Demand Arrival rates impact on WIP

5.8 CONCLUSIONS FROM THIS CHAPTER

This chapter has further confirmed the observations about the pros and cons of the DKAP and the SKAP, and it has used the HKAP to show how the two policies can co-exist by applying the SKAP only between products with similar demand or processing time attributes. The effectiveness of applying a HKAP has been verified and it has been observed to be most critical in situations where there is disparity in the processing times and/or demands of the products.

When processing time and/or demand arrival rate were used in the HKAP to group products, it was able to differentiate the performances of the product groups. This is an indication that it can be used to minimise the impact high variability products have on the less variable ones. The comparisons of the HKAP against the DKAP and the SKAP showed that it can achieve a similar service level robustness to the DKAP and a WIP control that is as effective as the SKAP. As shown in Section 5.6.3, it reduces the number of products whose service levels are affected by the demand variation of products outside their own group.

The results also show that it is not possible to isolate entirely the variability of products from affecting one another, as the products still affected the performances of one another even under the DKAP which is supposed to be the best possible approach to completely separating products. The fact that products still share machines means that they will never be completely isolated from one another. A more drastic approach would be the Cellular manufacturing described in Section 2.3.2. Nevertheless, the HKAP's product grouping still plays a significant role in isolating the products' impacts to within their groups, as has been shown in the scenarios analysed in this chapter. Also, because the HKAP isolates the effects of products' variabilities to within their group, including an incompatible product in a group might result in undesirable consequences.

Also, it was observed that the level of interaction between products' service level performances increases as the level of system capacity load increases. An explanation for this is that since the Kanban acts as a ticket for products to access manufacturing resources, products sharing Kanbans end up competing for this access and one of the products might – due to its demand or processing time attributes – enjoy more of this access than the others. As such it becomes more crucial to consider the attributes of products before sharing Kanbans between them, especially at high system capacity load levels.

The above observations are the most comprehensive up to date on Kanban allocation policies and their impact on the performance of a multiproduct system. These observations can serve as a framework through which production line designers can select production control strategies and policies to suit their manufacturing system. This framework was earlier presented in Section 4.7 based on the results of the first two sets of experiments. Now, the observations from the third set of experiments have been incorporated into it as shown in Figure 5-12. This can also be used to partition large manufacturing systems into sections, with each section then having the most suitable strategy or policy deployed to it, similar to a previously proposed segmented control approach [38].

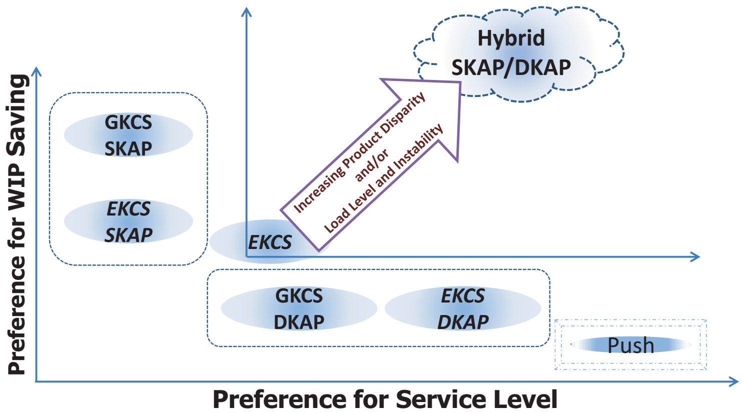


Figure 5-12: Suitability of strategies and corresponding policies

Furthermore, the results in this chapter have provided better clarifications on the effects of certain factors that could not be experimented in the previous sets of experiments. This has resulted in findings such as that which shows that the interaction between the service level performance of a product and the Kanban and basestock settings of other products in the system increases with the system's capacity load level. This could not be observed in Chapter 4 as only one system capacity load level was experimented. Also importantly, the analysis done on the impacts of products on the system WIP confirms that the longer processing time of Product 2 in Chapter 4 was mainly responsible for its higher contribution to the system WIP, and not its longer mean time between demands, as initially suspected in Section 4.5.2. In fact, as observed in Section 5.7 for Scenarios 2 and 4, it is a shorter mean time between demands (or higher demand arrival rate) that is likely to make a product contribute more to increased WIP rather than a longer mean time between demands.

CHAPTER - 6: Conclusions & Recommendations

6.1 INTRODUCTION

One of the aims of this research was to investigate the performances of different production control strategies and their corresponding Kanban allocation policies under different manufacturing scenarios. It determined the suitable conditions for the application of the different strategies and policies. From this, it identified the EKCS as the strategy that offers the best trade-off for WIP and service level robustness performances. It then carried out a test implementation of the EKCS under the application of a hybrid combination of the DKAP and the SKAP. It used this implementation to show that the hybrid Kanban allocation policy (HKAP) can achieve the WIP control effectiveness of the SKAP and minimise its disadvantage of products impacting the service level performance of one another.

6.2 KEY FINDINGS AND CONTRIBUTIONS

This research has investigated the service level robustness of different production control strategies in situations whereby changes occur to the original conditions for which they were optimised. It has also compared the effectiveness of their WIP control in such situations. It has found that the higher the level of coupling in the transmission of the demand information and the Kanban of a strategy, the less robust its service level performance is likely to be, whereas the same factor improves the WIP control effectiveness of a strategy. Therefore, at one extreme is BSCS, which can be said to be totally uncoupled because it does not use Kanbans, achieving the best service level robustness but the worst WIP control, while at the other extreme, is the GKCS – its SKAP to be more specific – with the tightest WIP control but the worst service level robustness. Then, in between these two extremes, with good trade-off between service level robustness and tight WIP control, are the EKCS and CONWIP strategies.

This research also found that the logic of Kanban and demand transmission in a strategy determines its susceptibility to instabilities emanating from machine breakdowns. Specifically, it found that because the GKCS operated a localised demand information transmission upstream – unlike the EKCS's global transmission, it was more susceptible to machine breakdowns affecting its service level performance due to the delays they might cause in the transmission of the demand information upstream. Additionally, it found that this Kanban and demand transmission logic effect also extends to the level of impact products can have on one another if a SKAP was operated between them. Under the GKCS, products in a Kanban sharing group were more likely to suffer from the effect of one another's demand variability than under the EKCS. This was found to be due to the GKCS attributing Kanbans too early to a particular product type.

Also, when each product had its own set of dedicated Kanbans under the EKCS and the GKCS, the products were able to maintain service levels that correspond to their respective levels of demand variability. Similarly, it found that the products generally achieved more robust service levels under the DKAP than the SKAP, but the SKAP is able to maintain a lower amount of WIP.

It then used those findings on the possible downside of sharing Kanbans between products to propose a hybrid policy that would always consider products' attributes in determining whether they are compatible for Kanban sharing. Until now, existing studies have mostly assumed that a system can only operate either a shared or dedicated policy across all the products. Therefore, this study has compared the performances of those approaches against its proposed hybrid policy, and it has found that there is indeed a need for production line designers, as well as research studies, to consider the processing time and demand attributes of products before grouping them together for Kanban sharing, especially in situations whereby the system's capacity is highly loaded with demands. The results obtained show that in such high demand load situations, there is a high probability that products that share Kanbans will affect the service level performances of one another. As a result, it would be better to operate a dedicated Kanban policy or the newly proposed hybrid policy, which will respectively either let each product have its own set of Kanbans or only share Kanbans between products that have similar profile,. The former option is less effective in inventory control; therefore, the latter approach is recommended.

It should be mentioned that the hybrid push-pull strategy still remains very relevant to managing operations in manufacturing systems (most especially single product environments), and the proposed hybrid policy is mostly seen as an option in large multiproduct environments, where operations' managers would be interested in balancing the performances achieved for different product categories.

6.3 IMPACT OF THIS WORK

Having developed the HKAP, a major first step has been taken to implement it in a case study system and compare its performance against existing policies. The results obtained have shown that the HKAP is indeed useful in managing multiproduct manufacturing systems that want to adopt a pull production control strategy that can operate both the DKAP and the SKAP. The benefits of the HKAP are the following:

- It ensures that the effective WIP control and the service level robustness benefits of the shared and the dedicated Kanban allocation policies respectively can be achieved under a single strategy

- It makes it possible for line designers and operations managers to categorise products into groups and differentially manage their performances

In a broader sense, the results can be extended to non-manufacturing systems; for example, the purchasing patterns of products can be used in assigning display shelves to them, so that there will always be a balanced representation of products on the shelf. It is also relevant to the segregation of commercial parking spaces for categories of customers based on their observed patterns of arrival and duration of stay.

Additionally, this research has advanced existing knowledge on the robustness of strategies by further investigating the factors that affect them and their corresponding Kanban allocation policies. It has also described the impact a strategy's Kanban and demand information transmission and synchronisation logics have on its performance.

6.4 FURTHER WORK

There are steps that can be taken to further experiment with this hybrid policy in other scenarios to test its wider applicability. Such scenarios could incorporate the following manufacturing situations:

- Different number of products in the Kanban sharing groups would be useful for understanding if the size of a product group will determine the impact its internal variabilities will have on the products in the other groups,

- It would be useful to experiment with a higher number of manufacturing stages. This could be used to investigate the possibility of doing the product grouping at stage level based on the similarity of the products' processing time requirements at that particular stage. As this research has shown that the processing times of products is vital to grouping them, the use of processing times and stage level grouping might be more effective and easier to implement.

- An unbalanced line in which products would have different processing time requirements at the manufacturing stages would also make the investigation described above possible,

- This research has proved that the SKAP is best suited to low variability manufacturing conditions, especially if it is going to be operated alongside a DKAP in different segments of the same manufacturing system. But, it would be worth investigating if the transformation from one policy to another can be connected to system or process related features. These could be the bottleneck station, order customisation point or an assembly point, as suggested for the hybrid push-pull strategy in the studies cited in Section 2.4.1.

- Also, it would be worth investigating if negative or positive correlation between the demands of products with seasonal demand patterns should encourage or discourage grouping them together.

- Finally, it would be worth investigating the applicability of the DKAP, SKAP and the HKAP in some of the pull production control variants cited in Section 2.4.2.

The above steps could provide new insights and improvements on the benefits of the hybrid policy to academic and industry practitioners, just as similar studies that proposed new production control approaches in the past have benefitted from such. For example, the hybrid push-pull strategy, which first appeared in literature in 1986 [5], has remained active in research for a long time, with the most recent works reported in 2008 [70], 2009 [71] and 2014 [179].

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1) Olaitan, O.A., Rotondo, A., Young, P., and Geraghty, J. 2014, On Designing Robust Kanban Production Control Strategies in Multiproduct Manufacturing Environments. *Handbook of Research on Design and Management of Lean Production Systems*, pp. 68-88, IGI Global.

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EU-FP7 DREAM PROJECT RESEARCH

This research work was sponsored by an EU-FP7 project (DREAM) which involved the development of a decision support tool for four industrial pilot cases. I was responsible for developing the simulation and optimisation methodologies for two of the pilot cases. This involved research into job shop and project shop scheduling literatures, from which a Resource-Constrained Project Scheduling Problem solution for capacity allocation and an Ant Colony Optimisation algorithm for scheduling were developed in Python. These solution techniques were applied in solving the two industrial pilot case problems and their outcomes led to two conference presentations and proceedings as follows:

1) Olaitan O.A, Young, P., and Geraghty, J. 2015, Variable Intensity RCPSP Approach to a Case Study Flow Shop, *Summer Simulation Multi-Conference, July 26-29, Chicago, USA.*

2) Olaitan et al. 2014, Implementing ManPy, a semantic-free open-source Discrete Event simulation package, in a Job Shop, *8th International Conference on Digital Enterprise Technology, 25-28 March 2014, Stuttgart Germany*.

This also involved collaboration with researchers from two other universities (University of Limerick and University of Stuttgart), a research institute (Fraunhofer IAO, Stuttgart); and with industry-based experts from a software development company (Nexedi SA France) and four manufacturing companies. The manufacturing companies were:

- Leotech GmbH, Germany
- Balkan Textile and Cotton Gin Machinery Ltd., Turkey
- Boston Scientific Cork Ltd., Ireland
- Infineon Technologies AG, Germany

DEMONSTRATIONS AND TUTORING

1) Measurement and Signal Processing laboratory demonstrations for Third year undergraduate students (2012 – 2015)

2) Manufacturing Automation for Final year undergraduate students (2012 – 2015)

3) Mechanical Systems Simulation for Final year undergraduate students (2012 – 2015)

4) Provision of one Masters and two Final year project topics and guidance in their completion

APPENDIX - A : TWO PRODUCT SYSTEM'S LHS RUNS TABLES

In this appendix the tables of the LHS Runs of experiments used for the three sets of experiments are presented. Those for the two product system are presented in Section A.1 followed by those for the eight product system in Section APPENDIX - G.

TABLE OF CONTENTS

Page

A.1 LHS RUNS A-2

LIST OF TABLES

Page

Table A-1: Scenario 1: High Product 1 CV – Low Product 2 CV A-2
Table A-2: Scenario 2: Low Product 1 CV – Low Product 2 CV A-4
Table A-3: Scenario 3: Low Product 1 CV – High Product 2 CV A-6
Table A-4: Scenario 4: High Product 1 CV – High Product 2 CV A-8

A.1 LHS RUNS

Table A-1: Scenario 1: High Product 1 CV – Low Product 2 CV

Run	PRODUCT 1		PRODUCT 2		STAGE 1		STAGE 2		STAGE 3	
No.	Mean	S.D.	Mean	S.D	MTTF	MTTR	MTTF	MTTR	MTTF	MTTR
1	5.414	2.695	5.700	0.355	84.192	11.388	98.793	9.282	86.667	9.647
2	5.791	2.735	5.741	0.846	79.737	9.956	90.626	8.832	80.232	10.461
3	5.571	3.001	5.684	0.742	97.803	10.349	93.843	11.388	84.934	10.601
4	5.813	2.888	5.673	0.384	82.707	9.984	79.985	9.450	81.717	9.871
5	5.294	2.803	5.754	0.760	81.717	10.573	92.854	11.079	80.727	9.899
6	5.592	2.995	5.692	0.737	87.657	8.973	97.308	9.478	79.737	8.888
7	5.749	2.587	5.719	0.731	87.409	9.338	101.515	11.416	87.409	11.079
8	5.578	3.075	5.743	0.430	85.429	10.714	98.545	10.264	79.242	11.051
9	5.919	2.661	5.747	0.298	82.955	11.472	83.202	9.591	88.894	11.023
10	5.713	2.831	5.689	0.506	91.369	10.742	100.278	10.910	78.995	8.720
11	5.649	2.973	5.753	0.667	102.010	8.720	94.586	9.759	95.823	9.703
12	5.841	2.978	5.767	0.627	102.505	9.731	85.182	10.545	85.182	10.882
13	5.258	2.763	5.674	0.725	87.904	11.247	88.894	10.629	88.399	11.388
14	5.948	3.024	5.722	0.552	98.545	10.377	85.924	9.675	86.419	8.945
15	5.471	3.058	5.696	0.581	91.864	11.500	85.429	9.254	79.490	9.478
16	5.727	3.012	5.651	0.529	96.071	9.927	90.131	11.135	99.783	9.450
17	5.642	2.718	5.652	0.852	94.338	11.135	93.596	10.321	101.268	10.405
18	5.336	2.910	5.744	0.494	97.556	10.321	101.020	9.984	91.616	8.748
19	5.827	2.922	5.783	0.621	88.399	8.748	82.212	8.720	86.914	10.573
20	5.557	2.842	5.713	0.315	90.874	10.910	78.747	11.107	81.470	10.910
21	5.585	3.018	5.655	0.679	78.995	10.545	92.111	8.917	96.071	10.658
22	5.770	2.638	5.740	0.413	95.081	10.517	80.232	10.882	99.535	11.472
23	5.742	2.797	5.761	0.604	78.747	9.422	102.505	10.658	82.460	9.506
24	5.450	2.712	5.658	0.448	80.232	10.461	79.490	10.573	98.051	10.040
25	5.286	3.035	5.731	0.818	85.182	9.366	82.460	10.040	94.091	10.995
26	5.685	2.927	5.711	0.748	92.854	9.001	96.813	9.422	83.449	11.500
27	5.884	2.650	5.735	0.419	83.697	9.534	95.823	9.225	84.687	11.135
28	5.635	2.820	5.766	0.303	88.894	10.629	98.051	9.562	103.000	10.012
29	5.379	2.990	5.772	0.696	81.965	8.888	100.525	10.854	96.318	10.096
30	5.614	2.706	5.785	0.373	99.040	9.394	86.419	9.029	91.864	9.029
31	5.663	2.950	5.788	0.806	96.566	10.012	99.783	10.601	81.222	9.619
32	5.734	2.723	5.665	0.800	79.985	9.703	81.222	10.995	87.904	9.113
33	5.599	2.593	5.725	0.326	80.975	10.180	97.556	10.966	93.348	9.085
34	5.862	2.582	5.715	0.563	100.525	9.871	95.328	9.169	100.030	10.770
35	5.798	3.080	5.708	0.656	98.298	10.264	89.389	9.113	100.773	11.163
36	5.393	2.956	5.770	0.286	96.813	10.040	84.934	10.742	80.480	9.057
37	5.756	3.007	5.738	0.789	81.222	10.208	81.717	9.506	93.843	9.282
38	5.934	2.859	5.786	0.662	89.884	11.079	93.348	10.068	89.636	11.416
39	5.898	2.604	5.756	0.633	86.172	9.197	82.707	10.180	95.081	8.860
40	5.606	2.939	5.649	0.442	102.753	10.995	83.449	9.871	90.626	10.854
41	5.678	3.046	5.734	0.534	83.944	9.141	84.439	11.303	90.874	9.254
42	5.763	2.531	5.751	0.586	88.152	10.826	91.369	9.197	80.975	8.973
43	5.834	2.780	5.705	0.841	84.439	9.113	95.081	9.927	101.515	11.247
44	5.720	2.837	5.718	0.396	103.000	8.917	80.480	10.124	97.308	10.349

45	5.322	2.791	5.670	0.829	87.162	11.275	96.071	9.534	88.152	9.001
46	5.386	3.052	5.664	0.292	89.636	9.619	86.667	10.461	90.131	9.956
47	5.365	2.752	5.697	0.338	93.101	10.236	86.914	8.804	82.955	10.714
48	5.422	2.610	5.721	0.835	92.606	10.601	78.995	9.141	93.596	9.815
49	5.941	2.684	5.782	0.378	100.278	10.966	93.101	10.798	94.338	9.310
50	5.855	2.814	5.729	0.332	101.515	10.405	101.763	8.973	85.429	9.787
51	5.478	2.559	5.776	0.575	96.318	9.506	102.010	9.366	87.162	10.517
52	5.870	2.808	5.716	0.766	99.535	10.770	79.242	10.433	99.288	9.338
53	5.350	2.899	5.760	0.702	97.308	9.647	89.141	8.748	82.212	9.731
54	5.443	2.689	5.779	0.638	86.419	11.163	94.091	9.085	79.985	11.303
55	5.279	2.882	5.732	0.350	84.934	11.444	91.864	11.332	91.121	10.152
56	5.656	2.865	5.763	0.517	83.202	11.360	81.470	10.714	83.944	9.225
57	5.315	2.916	5.661	0.777	94.586	9.478	82.955	10.405	92.111	9.169
58	5.272	2.701	5.699	0.569	80.480	9.029	87.409	10.208	86.172	9.675
59	5.550	2.616	5.750	0.407	80.727	9.282	84.192	9.001	98.298	10.208
60	5.407	3.086	5.706	0.523	90.626	10.433	99.535	10.349	100.278	11.219
61	5.308	2.967	5.680	0.592	91.121	8.804	96.566	8.888	96.813	9.843
62	5.706	2.525	5.690	0.500	92.359	11.332	85.677	11.360	88.646	9.562
63	5.905	2.848	5.702	0.367	100.030	10.068	98.298	11.163	98.793	11.332
64	5.464	2.905	5.775	0.540	101.020	11.107	79.737	9.787	94.586	10.264
65	5.820	2.621	5.676	0.714	101.268	9.310	88.399	11.219	95.576	10.629
66	5.542	3.029	5.727	0.610	88.646	10.882	80.975	11.191	101.763	10.377
67	5.343	2.627	5.677	0.321	97.061	9.450	92.359	9.956	85.677	8.776
68	5.436	2.655	5.709	0.402	95.576	9.562	83.944	11.500	101.020	8.917
69	5.507	2.678	5.769	0.673	85.677	8.860	99.040	9.394	97.803	8.804
70	5.535	2.871	5.745	0.823	93.596	10.686	95.576	11.247	99.040	9.197
71	5.699	2.961	5.764	0.719	84.687	10.293	101.268	8.776	95.328	10.068
72	5.806	3.063	5.703	0.361	79.490	9.759	89.636	10.377	94.833	11.107
73	5.429	2.876	5.748	0.771	100.773	11.416	100.773	9.703	92.359	10.489
74	5.848	2.553	5.724	0.511	102.258	10.152	80.727	9.731	83.697	10.236
75	5.301	2.672	5.757	0.754	98.793	9.169	84.687	11.023	102.258	10.545
76	5.358	2.769	5.671	0.309	99.288	9.787	90.874	9.647	102.505	10.124
77	5.265	2.933	5.792	0.488	78.500	10.489	89.884	9.338	92.606	9.984
78	5.877	2.984	5.681	0.644	92.111	11.191	97.061	9.057	84.192	10.826
79	5.955	2.757	5.686	0.783	93.348	10.124	100.030	9.899	89.141	9.366
80	5.329	2.576	5.791	0.390	94.091	10.854	99.288	10.938	82.707	9.534
81	5.372	2.944	5.759	0.425	93.843	8.776	88.152	9.310	92.854	11.275
82	5.621	2.536	5.789	0.690	85.924	11.051	94.338	10.096	98.545	9.759
83	5.628	3.069	5.679	0.465	82.460	9.843	103.000	10.152	93.101	9.141
84	5.500	2.633	5.668	0.344	86.914	8.945	92.606	10.770	97.061	11.444
85	5.528	2.570	5.737	0.812	99.783	9.591	88.646	10.686	83.202	9.394
86	5.514	2.644	5.654	0.708	90.131	9.225	102.753	10.293	97.556	9.422
87	5.962	2.893	5.667	0.546	90.379	9.254	87.162	11.444	78.500	10.321
88	5.926	2.565	5.695	0.650	81.470	10.658	87.904	9.619	102.753	10.293
89	5.493	2.542	5.712	0.477	89.141	11.219	96.318	10.012	102.010	11.360
90	5.564	2.548	5.648	0.459	83.449	11.303	86.172	9.843	78.747	10.798
91	5.912	2.740	5.683	0.858	89.389	10.938	81.965	9.815	85.924	10.938
92	5.400	2.667	5.780	0.482	86.667	10.096	91.121	10.826	89.884	11.191
93	5.457	2.729	5.660	0.471	98.051	9.815	102.258	10.236	84.439	10.742
94	5.784	2.854	5.663	0.598	79.242	11.023	94.833	11.275	91.369	10.180

95	5.692	2.746	5.657	0.615	95.823	9.085	87.657	8.860	87.657	9.927
96	5.670	2.825	5.687	0.558	91.616	10.798	90.379	8.945	100.525	8.832
97	5.521	2.774	5.693	0.685	94.833	9.057	78.500	10.489	81.965	10.966
98	5.777	2.786	5.773	0.794	82.212	9.675	83.697	11.051	90.379	10.686
99	5.891	2.599	5.728	0.436	95.328	8.832	97.803	10.517	89.389	9.591
100	5.486	3.041	5.777	0.454	101.763	9.899	91.616	11.472	96.566	10.433

Table A-2: Scenario 2: Low Product 1 CV – Low Product 2 CV

Run	PRODUCT 1		PRODUCT 2		STAGE 1		STAGE 2		STAGE 3	
No.	Mean	S.D.	Mean	S.D	MTTF	MTTR	MTTF	MTTR	MTTF	MTTR
1	5.552	0.298	5.666	0.546	87.409	8.748	87.162	9.450	87.657	10.742
2	5.681	0.660	5.677	0.575	92.854	10.742	97.061	9.001	95.328	11.444
3	5.545	0.802	5.728	0.500	80.480	9.815	87.904	10.349	101.020	10.293
4	5.601	0.326	5.670	0.656	81.470	11.023	92.359	10.040	93.348	9.366
5	5.562	0.388	5.792	0.534	97.556	11.191	82.955	9.675	91.121	10.826
6	5.571	0.774	5.785	0.442	96.071	10.517	85.924	9.169	102.010	9.815
7	5.638	0.626	5.695	0.321	80.727	9.759	91.864	11.107	79.985	9.141
8	5.584	0.638	5.687	0.742	101.020	8.804	95.823	10.714	93.101	11.500
9	5.663	0.519	5.655	0.673	88.152	9.282	94.091	10.321	98.793	9.619
10	5.631	0.666	5.737	0.766	78.747	8.973	86.172	10.882	86.914	9.787
11	5.666	0.819	5.758	0.350	91.369	9.113	91.369	9.394	91.864	9.169
12	5.541	0.536	5.725	0.523	82.707	10.882	98.793	10.180	79.737	8.917
13	5.619	0.700	5.773	0.482	92.111	10.798	79.985	9.591	81.470	9.899
14	5.594	0.428	5.770	0.378	100.278	10.208	96.318	10.770	89.636	9.450
15	5.653	0.757	5.680	0.615	100.030	11.416	89.141	11.500	97.308	10.629
16	5.676	0.451	5.729	0.610	84.934	10.938	95.081	10.658	100.773	11.023
17	5.635	0.751	5.711	0.454	78.500	10.096	101.020	9.534	96.318	9.984
18	5.589	0.541	5.682	0.841	80.232	9.787	80.232	9.338	100.525	10.124
19	5.564	0.303	5.767	0.465	83.697	10.264	86.419	10.264	99.535	9.085
20	5.614	0.564	5.777	0.303	85.677	10.545	79.490	10.854	90.626	11.360
21	5.668	0.655	5.657	0.448	97.308	9.956	83.697	10.293	83.697	9.675
22	5.591	0.791	5.650	0.326	93.843	10.040	93.596	8.888	94.091	10.433
23	5.615	0.717	5.783	0.760	87.904	10.966	85.429	10.489	95.823	9.591
24	5.629	0.581	5.716	0.338	85.429	10.910	86.914	9.310	91.616	8.776
25	5.574	0.598	5.772	0.702	102.753	10.629	94.586	11.247	102.505	10.910
26	5.587	0.354	5.757	0.783	91.616	9.619	96.813	10.826	83.944	9.197
27	5.611	0.842	5.658	0.731	89.141	10.658	89.636	11.163	88.399	9.254
28	5.577	0.309	5.674	0.552	90.379	9.647	100.030	11.416	97.556	9.703
29	5.624	0.281	5.788	0.529	86.914	11.360	90.379	10.208	84.192	8.973
30	5.596	0.694	5.751	0.604	81.965	9.478	102.258	10.686	78.747	10.236
31	5.561	0.473	5.664	0.540	92.606	10.826	99.040	11.303	81.965	10.770
32	5.598	0.320	5.705	0.725	100.525	11.444	94.833	9.731	81.717	9.310
33	5.608	0.394	5.764	0.402	88.894	9.029	80.975	8.973	83.449	9.422
34	5.661	0.615	5.776	0.396	98.793	9.534	101.515	9.815	96.566	11.135
35	5.675	0.462	5.779	0.650	90.874	9.141	82.707	10.573	101.268	10.264
36	5.652	0.366	5.769	0.471	81.717	8.917	97.803	10.405	92.854	9.282
37	5.662	0.677	5.731	0.407	80.975	11.472	79.242	9.984	100.030	10.489
38	5.622	0.558	5.708	0.459	96.318	9.254	84.687	9.113	103.000	11.388

39	5.616	0.785	5.668	0.685	79.242	10.236	85.677	9.029	84.934	9.057
40	5.679	0.706	5.774	0.598	91.864	11.163	90.131	10.433	86.419	11.332
41	5.645	0.502	5.744	0.777	86.419	11.303	103.000	10.995	86.667	9.871
42	5.579	0.405	5.782	0.581	79.490	9.057	90.626	9.619	101.763	11.079
43	5.643	0.349	5.693	0.286	84.192	9.591	99.535	10.012	100.278	10.882
44	5.648	0.479	5.703	0.627	103.000	8.888	92.854	9.197	90.131	8.748
45	5.669	0.808	5.671	0.355	97.061	9.310	97.556	10.545	93.843	10.601
46	5.609	0.711	5.667	0.477	102.505	10.770	102.010	10.096	84.439	10.040
47	5.565	0.609	5.654	0.662	82.212	10.601	100.525	8.776	81.222	10.658
48	5.595	0.547	5.651	0.806	94.586	10.854	99.783	10.517	98.298	10.573
49	5.646	0.683	5.709	0.367	83.202	9.338	86.667	11.275	99.040	10.208
50	5.599	0.689	5.763	0.344	88.646	11.275	102.753	10.966	94.338	9.534
51	5.606	0.592	5.661	0.719	91.121	9.001	95.328	10.798	79.490	9.843
52	5.625	0.513	5.692	0.667	89.884	11.332	78.500	11.191	80.727	9.927
53	5.554	0.496	5.724	0.315	85.182	10.489	81.717	9.057	92.359	10.517
54	5.567	0.445	5.697	0.812	99.288	10.349	85.182	9.282	92.606	11.416
55	5.655	0.383	5.689	0.390	82.955	10.124	83.202	9.871	88.152	10.686
56	5.628	0.422	5.648	0.430	96.813	11.247	88.399	9.956	98.545	10.377
57	5.604	0.830	5.748	0.621	93.101	11.135	99.288	8.945	85.924	9.759
58	5.671	0.400	5.743	0.714	83.449	9.984	90.874	8.720	92.111	11.219
59	5.602	0.490	5.721	0.708	95.576	9.085	96.071	8.748	80.232	10.545
60	5.621	0.343	5.732	0.679	81.222	10.293	91.121	11.079	80.975	11.472
61	5.618	0.740	5.676	0.569	101.268	9.450	78.747	10.601	102.753	9.562
62	5.649	0.570	5.750	0.633	95.823	9.843	84.934	11.332	86.172	8.804
63	5.578	0.813	5.690	0.690	99.535	9.927	81.222	9.254	84.687	10.096
64	5.641	0.530	5.780	0.488	92.359	10.377	100.773	8.804	101.515	8.945
65	5.659	0.360	5.712	0.592	96.566	11.079	83.449	8.860	80.480	11.051
66	5.658	0.411	5.699	0.835	93.596	9.197	79.737	10.068	85.677	11.275
67	5.581	0.553	5.786	0.644	98.051	8.776	83.944	9.899	89.141	11.107
68	5.592	0.337	5.734	0.737	102.258	10.686	82.460	10.377	98.051	9.506
69	5.540	0.779	5.754	0.506	102.010	10.180	84.439	11.023	89.884	9.113
70	5.678	0.468	5.735	0.361	90.626	10.461	98.545	10.629	78.500	10.461
71	5.665	0.286	5.702	0.517	99.040	8.832	88.894	11.051	88.894	10.180
72	5.656	0.604	5.696	0.846	94.833	11.107	87.657	9.366	90.874	9.731
73	5.557	0.575	5.660	0.425	88.399	9.899	80.480	10.910	87.162	10.938
74	5.588	0.825	5.713	0.858	86.172	9.422	93.348	9.787	97.061	8.860
75	5.605	0.332	5.679	0.419	89.389	9.675	98.298	9.478	82.955	9.001
76	5.542	0.621	5.683	0.638	90.131	10.714	96.566	8.832	96.813	9.225
77	5.547	0.728	5.753	0.373	93.348	9.169	100.278	9.703	95.081	10.405
78	5.585	0.643	5.663	0.292	82.460	11.388	94.338	10.152	85.182	10.321
79	5.544	0.524	5.761	0.771	100.773	9.366	92.606	9.225	96.071	9.338
80	5.549	0.485	5.652	0.332	98.298	10.995	89.389	10.742	88.646	8.888
81	5.639	0.507	5.684	0.754	83.944	10.433	80.727	11.444	99.783	8.832
82	5.626	0.723	5.747	0.511	95.328	9.394	89.884	11.472	82.212	10.854
83	5.555	0.434	5.740	0.794	84.687	10.321	81.470	9.422	79.242	10.152
84	5.568	0.745	5.715	0.384	98.545	11.219	88.646	10.236	91.369	11.163
85	5.575	0.762	5.722	0.823	94.091	10.012	78.995	11.360	90.379	10.798
86	5.672	0.649	5.745	0.413	101.763	11.500	93.101	9.506	95.576	10.068
87	5.572	0.292	5.738	0.818	87.657	9.871	87.409	11.219	97.803	10.966
88	5.582	0.417	5.760	0.558	85.924	11.051	101.763	9.141	94.586	10.714

89	5.569	0.456	5.789	0.436	79.737	8.945	84.192	11.135	87.409	9.956
90	5.636	0.836	5.766	0.800	95.081	9.562	92.111	9.647	99.288	11.247
91	5.558	0.439	5.686	0.696	94.338	9.225	82.212	10.461	89.389	8.720
92	5.642	0.734	5.741	0.748	99.783	9.703	102.505	10.938	93.596	9.478
93	5.612	0.768	5.700	0.494	87.162	10.573	101.268	11.388	94.833	11.191
94	5.551	0.315	5.718	0.298	97.803	9.506	91.616	9.843	102.258	10.012
95	5.673	0.377	5.673	0.789	86.667	9.731	81.965	9.927	83.202	9.029
96	5.632	0.587	5.756	0.829	78.995	10.152	98.051	8.917	82.460	9.394
97	5.651	0.371	5.790	0.586	101.515	10.068	88.152	10.124	78.995	10.349
98	5.559	0.796	5.727	0.852	89.636	10.405	97.308	9.759	85.429	11.303
99	5.548	0.632	5.706	0.563	79.985	8.860	95.576	9.085	87.904	9.647
100	5.634	0.672	5.719	0.309	84.439	8.720	93.843	9.562	82.707	10.995

Table A-3: Scenario 3: Low Product 1 CV – High Product 2 CV

Run	PRODUCT 1		PRODUCT 2		STAGE 1		STAGE 2		STAGE 3	
No.	Mean	S.D.	Mean	S.D	MTTF	MTTR	MTTF	MTTR	MTTF	MTTR
1	5.666	0.757	5.687	3.071	92.111	10.686	89.884	11.219	85.429	11.275
2	5.612	0.785	5.695	3.065	89.884	9.815	99.783	9.506	89.636	8.973
3	5.559	0.547	5.397	3.025	88.152	8.917	94.833	9.899	80.975	9.843
4	5.652	0.473	5.433	3.048	84.439	9.478	87.409	11.500	102.753	10.517
5	5.651	0.286	5.658	2.805	81.717	11.135	96.566	9.815	102.010	10.068
6	5.636	0.309	5.506	2.874	93.843	8.832	86.419	9.085	93.596	11.500
7	5.638	0.825	5.949	2.788	78.747	10.742	93.843	9.057	89.141	9.478
8	5.615	0.366	5.774	2.591	90.131	11.500	86.914	9.141	79.490	9.731
9	5.551	0.723	5.978	2.909	89.389	9.310	90.379	8.748	94.833	11.023
10	5.611	0.445	5.571	2.776	80.975	9.927	84.687	10.854	100.030	8.860
11	5.679	0.354	5.484	2.915	100.773	10.489	85.677	10.938	99.535	10.012
12	5.585	0.326	5.419	2.666	90.379	10.096	88.399	9.225	95.328	9.787
13	5.632	0.604	5.404	2.880	79.985	8.973	78.995	9.562	96.318	10.293
14	5.624	0.343	5.564	2.586	89.141	10.405	102.258	10.293	80.232	10.180
15	5.598	0.581	5.912	2.973	101.763	9.141	96.318	10.124	79.985	11.079
16	5.673	0.796	5.361	2.707	83.202	10.770	89.389	10.208	93.101	9.450
17	5.614	0.530	5.491	2.753	80.232	10.601	86.667	8.860	91.369	11.444
18	5.562	0.332	6.058	2.892	102.010	9.057	82.707	11.079	92.606	10.236
19	5.549	0.779	5.716	3.106	78.995	11.472	92.606	10.068	86.419	9.647
20	5.578	0.564	5.709	2.684	80.727	9.506	98.545	8.832	84.192	9.759
21	5.554	0.609	5.796	2.609	98.051	11.023	101.763	9.169	92.359	9.534
22	5.582	0.536	5.448	2.718	102.753	10.349	81.717	11.163	89.389	9.254
23	5.555	0.672	5.753	2.938	81.222	10.040	102.753	10.377	101.020	9.899
24	5.646	0.700	5.862	3.111	100.278	9.956	101.268	10.152	100.278	10.433
25	5.595	0.791	6.065	2.846	93.596	10.966	92.854	10.489	94.091	10.714
26	5.653	0.422	5.426	2.724	87.409	8.776	100.525	10.236	84.687	8.832
27	5.661	0.383	5.920	3.129	91.369	9.001	83.449	10.545	89.884	10.658
28	5.622	0.683	5.666	2.996	95.081	8.720	82.212	9.394	82.460	9.141
29	5.540	0.677	5.803	2.614	98.545	9.029	89.636	9.927	90.379	9.703
30	5.584	0.292	5.593	3.123	93.348	10.461	92.111	10.770	94.338	11.332
31	5.565	0.649	5.390	2.822	82.212	10.068	100.030	11.275	86.667	10.910
32	5.592	0.298	5.818	2.978	94.338	11.275	80.727	10.349	99.288	9.562

33	5.604	0.836	5.782	3.030	102.258	9.113	84.192	11.444	86.914	10.489
34	5.548	0.320	5.956	2.955	99.040	10.124	99.535	9.647	93.348	10.349
35	5.676	0.751	5.680	2.967	96.318	8.804	84.439	9.478	97.803	10.770
36	5.544	0.774	5.542	3.013	99.288	10.629	98.051	11.135	95.576	10.573
37	5.577	0.394	5.825	3.059	83.449	9.338	85.429	10.882	83.449	8.888
38	5.665	0.666	5.833	3.117	85.924	11.107	88.152	9.534	99.040	10.966
39	5.561	0.496	5.462	3.054	101.515	9.422	78.500	9.984	88.152	10.686
40	5.662	0.575	6.072	2.834	99.783	10.798	87.904	10.601	102.258	9.310
41	5.571	0.717	5.760	2.638	86.914	11.051	98.793	11.416	94.586	8.917
42	5.575	0.570	5.738	3.134	94.833	11.416	91.369	11.303	78.500	9.984
43	5.669	0.507	5.905	3.042	84.192	11.303	89.141	9.450	95.081	8.748
44	5.606	0.479	5.557	3.036	101.020	9.282	97.308	10.658	93.843	9.197
45	5.648	0.456	6.079	2.701	92.359	10.714	79.737	10.012	91.616	11.191
46	5.594	0.371	5.898	3.100	81.470	10.910	98.298	8.917	87.904	10.264
47	5.645	0.400	6.036	2.742	92.606	10.995	100.278	10.826	87.162	9.085
48	5.564	0.643	5.651	2.603	86.419	10.545	80.232	10.629	98.793	10.461
49	5.589	0.519	5.411	2.903	85.182	11.163	81.222	10.461	84.439	9.506
50	5.629	0.592	6.014	2.643	103.000	10.180	86.172	10.966	79.242	10.096
51	5.609	0.711	5.891	2.597	85.677	9.534	81.470	9.254	83.944	10.629
52	5.552	0.303	5.724	2.851	84.687	9.169	78.747	9.591	85.182	10.405
53	5.547	0.524	5.528	2.770	100.525	11.247	97.061	10.096	80.727	10.798
54	5.631	0.638	5.927	2.782	80.480	10.152	97.556	10.264	78.747	10.882
55	5.545	0.468	5.637	2.817	91.121	8.860	90.131	10.714	97.308	11.303
56	5.642	0.768	5.876	2.626	95.823	11.360	101.515	9.675	81.222	10.601
57	5.658	0.439	5.673	2.736	84.934	10.938	83.697	11.472	97.556	11.051
58	5.655	0.694	5.477	2.690	100.030	10.882	87.657	9.843	96.813	11.107
59	5.601	0.281	6.029	2.672	91.864	8.945	93.348	10.798	82.707	9.675
60	5.602	0.315	6.050	2.863	81.965	9.366	94.091	9.956	96.566	11.219
61	5.628	0.337	5.854	2.828	96.071	9.619	93.101	9.113	91.864	8.720
62	5.572	0.411	5.934	3.082	87.657	9.787	101.020	11.388	84.934	10.545
63	5.668	0.451	5.586	2.921	93.101	11.191	79.490	9.619	81.717	11.163
64	5.567	0.417	5.767	2.661	90.626	11.219	94.338	9.787	97.061	11.360
65	5.634	0.813	5.869	3.094	82.460	8.888	96.071	10.405	90.874	10.854
66	5.568	0.830	5.470	2.857	92.854	9.899	91.864	9.310	82.955	11.135
67	5.541	0.349	5.847	2.759	83.944	10.854	95.328	10.180	87.409	8.945
68	5.542	0.558	5.615	3.088	82.707	9.871	88.894	9.029	95.823	9.394
69	5.656	0.689	6.007	2.649	91.616	8.748	95.823	10.517	90.626	10.742
70	5.625	0.513	6.043	2.926	79.242	9.394	83.944	8.776	91.121	9.422
71	5.599	0.740	5.455	2.580	85.429	9.703	87.162	10.686	80.480	9.815
72	5.569	0.734	5.985	2.950	94.091	10.826	85.924	9.338	96.071	8.776
73	5.588	0.706	5.992	2.932	86.667	9.085	84.934	11.191	98.051	9.619
74	5.608	0.819	5.368	2.961	88.646	9.591	80.975	11.332	88.646	9.001
75	5.596	0.655	5.731	2.984	99.535	11.332	95.576	8.720	92.854	10.938
76	5.675	0.502	5.622	3.140	90.874	10.293	88.646	11.360	87.657	8.804
77	5.557	0.802	5.745	2.799	79.490	9.731	80.480	9.871	86.172	9.029
78	5.639	0.360	5.382	2.869	97.803	10.236	90.874	9.731	78.995	9.366
79	5.635	0.808	5.440	2.713	97.061	10.264	91.121	8.945	82.212	9.169
80	5.659	0.842	5.811	2.730	89.636	10.517	79.985	9.422	101.268	9.282
81	5.672	0.615	5.644	2.840	87.162	11.444	102.010	10.742	92.111	10.377
82	5.626	0.598	5.963	2.678	82.955	10.573	83.202	11.023	85.677	9.113

83	5.678	0.541	5.513	3.077	79.737	9.647	94.586	9.366	83.202	10.208
84	5.581	0.428	6.000	3.002	97.556	10.377	82.460	9.759	79.737	9.871
85	5.663	0.377	5.941	2.886	95.328	10.321	96.813	10.910	88.894	11.388
86	5.643	0.388	5.535	3.146	94.586	10.208	92.359	8.804	100.525	10.040
87	5.591	0.485	5.883	2.794	97.308	9.450	79.242	9.282	102.505	10.124
88	5.621	0.762	5.702	2.695	78.500	9.984	93.596	10.433	98.298	11.247
89	5.681	0.434	5.578	2.574	95.576	9.225	85.182	10.321	88.399	9.956
90	5.616	0.462	5.499	2.811	87.904	9.197	82.955	10.995	81.470	11.472
91	5.649	0.626	5.607	2.620	98.793	10.012	100.773	10.040	99.783	9.057
92	5.587	0.553	5.970	3.007	83.697	10.658	81.965	11.107	85.924	10.995
93	5.618	0.745	5.629	2.765	96.566	9.759	102.505	11.051	81.965	9.927
94	5.558	0.660	5.520	2.898	101.268	9.675	90.626	9.001	100.773	9.225
95	5.619	0.728	5.549	2.944	88.894	9.562	103.000	8.973	98.545	11.416
96	5.574	0.405	5.600	2.747	96.813	10.433	99.288	11.247	103.000	10.152
97	5.641	0.490	5.789	2.632	98.298	9.843	97.803	8.888	90.131	10.826
98	5.605	0.587	5.375	2.990	86.172	11.388	91.616	10.573	101.763	10.321
99	5.579	0.621	6.021	2.655	88.399	9.254	99.040	9.197	101.515	9.338
100	5.671	0.632	5.840	3.019	102.505	11.079	95.081	9.703	83.697	9.591

Table A-4: Scenario 4: High Product 1 CV – High Product 2 CV

Run	PRODUCT 1		PRODUCT 2		STAGE 1		STAGE 2		STAGE 3	
No.	Mean	S.D.	Mean	S.D	MTTF	MTTR	MTTF	MTTR	MTTF	MTTR
1	5.322	2.542	5.448	2.834	87.409	8.748	87.162	9.450	87.657	10.742
2	5.963	2.904	5.506	2.863	92.854	10.742	97.061	9.001	95.328	11.444
3	5.286	3.046	5.760	2.788	80.480	9.815	87.904	10.349	101.020	10.293
4	5.564	2.570	5.470	2.944	81.470	11.023	92.359	10.040	93.348	9.366
5	5.371	2.632	6.079	2.822	97.556	11.191	82.955	9.675	91.121	10.826
6	5.414	3.018	6.043	2.730	96.071	10.517	85.924	9.169	102.010	9.815
7	5.749	2.870	5.593	2.609	80.727	9.759	91.864	11.107	79.985	9.141
8	5.478	2.882	5.557	3.030	101.020	8.804	95.823	10.714	93.101	11.500
9	5.877	2.763	5.397	2.961	88.152	9.282	94.091	10.321	98.793	9.619
10	5.713	2.910	5.803	3.054	78.747	8.973	86.172	10.882	86.914	9.787
11	5.891	3.063	5.912	2.638	91.369	9.113	91.369	9.394	91.864	9.169
12	5.265	2.780	5.745	2.811	82.707	10.882	98.793	10.180	79.737	8.917
13	5.656	2.944	5.985	2.770	92.111	10.798	79.985	9.591	81.470	9.899
14	5.528	2.672	5.970	2.666	100.278	10.208	96.318	10.770	89.636	9.450
15	5.827	3.001	5.520	2.903	100.030	11.416	89.141	11.500	97.308	10.629
16	5.941	2.695	5.767	2.898	84.934	10.938	95.081	10.658	100.773	11.023
17	5.735	2.995	5.673	2.742	78.500	10.096	101.020	9.534	96.318	9.984
18	5.507	2.785	5.528	3.129	80.232	9.787	80.232	9.338	100.525	10.124
19	5.379	2.547	5.956	2.753	83.697	10.264	86.419	10.264	99.535	9.085
20	5.628	2.808	6.007	2.591	85.677	10.545	79.490	10.854	90.626	11.360
21	5.898	2.899	5.404	2.736	97.308	9.956	83.697	10.293	83.697	9.675
22	5.514	3.035	5.368	2.614	93.843	10.040	93.596	8.888	94.091	10.433
23	5.635	2.961	6.036	3.048	87.904	10.966	85.429	10.489	95.823	9.591
24	5.706	2.825	5.702	2.626	85.429	10.910	86.914	9.310	91.616	8.776
25	5.428	2.842	5.978	2.990	102.753	10.629	94.586	11.247	102.505	10.910
26	5.493	2.598	5.905	3.071	91.616	9.619	96.813	10.826	83.944	9.197

27	5.614	3.086	5.411	3.019	89.141	10.658	89.636	11.163	88.399	9.254
28	5.443	2.553	5.491	2.840	90.379	9.647	100.030	11.416	97.556	9.703
29	5.678	2.525	6.058	2.817	86.914	11.360	90.379	10.208	84.192	8.973
30	5.542	2.938	5.876	2.892	81.965	9.478	102.258	10.686	78.747	10.236
31	5.364	2.717	5.440	2.828	92.606	10.826	99.040	11.303	81.965	10.770
32	5.549	2.564	5.644	3.013	100.525	11.444	94.833	9.731	81.717	9.310
33	5.599	2.638	5.941	2.690	88.894	9.029	80.975	8.973	83.449	9.422
34	5.863	2.859	6.000	2.684	98.793	9.534	101.515	9.815	96.566	11.135
35	5.934	2.706	6.014	2.938	90.874	9.141	82.707	10.573	101.268	10.264
36	5.820	2.610	5.963	2.759	81.717	8.917	97.803	10.405	92.854	9.282
37	5.870	2.921	5.774	2.695	80.975	11.472	79.242	9.984	100.030	10.489
38	5.671	2.802	5.658	2.747	96.318	9.254	84.687	9.113	103.000	11.388
39	5.642	3.029	5.462	2.973	79.242	10.236	85.677	9.029	84.934	9.057
40	5.955	2.950	5.992	2.886	91.864	11.163	90.131	10.433	86.419	11.332
41	5.784	2.746	5.840	3.065	86.419	11.303	103.000	10.995	86.667	9.871
42	5.457	2.649	6.029	2.869	79.490	9.057	90.626	9.619	101.763	11.079
43	5.777	2.593	5.586	2.574	84.192	9.591	99.535	10.012	100.278	10.882
44	5.799	2.723	5.637	2.915	103.000	8.888	92.854	9.197	90.131	8.748
45	5.906	3.052	5.477	2.643	97.061	9.310	97.556	10.545	93.843	10.601
46	5.606	2.955	5.455	2.765	102.505	10.770	102.010	10.096	84.439	10.040
47	5.386	2.853	5.390	2.950	82.212	10.601	100.525	8.776	81.222	10.658
48	5.535	2.791	5.375	3.094	94.586	10.854	99.783	10.517	98.298	10.573
49	5.792	2.927	5.666	2.655	83.202	9.338	86.667	11.275	99.040	10.208
50	5.557	2.933	5.934	2.632	88.646	11.275	102.753	10.966	94.338	9.534
51	5.592	2.836	5.426	3.007	91.121	9.001	95.328	10.798	79.490	9.843
52	5.685	2.757	5.578	2.955	89.884	11.332	78.500	11.191	80.727	9.927
53	5.329	2.740	5.738	2.603	85.182	10.489	81.717	9.057	92.359	10.517
54	5.393	2.689	5.607	3.100	99.288	10.349	85.182	9.282	92.606	11.416
55	5.834	2.627	5.564	2.678	82.955	10.124	83.202	9.871	88.152	10.686
56	5.699	2.666	5.361	2.718	96.813	11.247	88.399	9.956	98.545	10.377
57	5.578	3.074	5.862	2.909	93.101	11.135	99.288	8.945	85.924	9.759
58	5.913	2.644	5.833	3.002	83.449	9.984	90.874	8.720	92.111	11.219
59	5.571	2.734	5.724	2.996	95.576	9.085	96.071	8.748	80.232	10.545
60	5.663	2.587	5.782	2.967	81.222	10.293	91.121	11.079	80.975	11.472
61	5.649	2.984	5.499	2.857	101.268	9.450	78.747	10.601	102.753	9.562
62	5.806	2.814	5.869	2.921	95.823	9.843	84.934	11.332	86.172	8.804
63	5.450	3.057	5.571	2.978	99.535	9.927	81.222	9.254	84.687	10.096
64	5.763	2.774	6.021	2.776	92.359	10.377	100.773	8.804	101.515	8.945
65	5.856	2.604	5.680	2.880	96.566	11.079	83.449	8.860	80.480	11.051
66	5.849	2.655	5.615	3.123	93.596	9.197	79.737	10.068	85.677	11.275
67	5.464	2.797	6.050	2.932	98.051	8.776	83.944	9.899	89.141	11.107
68	5.521	2.581	5.789	3.025	102.258	10.686	82.460	10.377	98.051	9.506
69	5.258	3.023	5.891	2.794	102.010	10.180	84.439	11.023	89.884	9.113
70	5.948	2.712	5.796	2.649	90.626	10.461	98.545	10.629	78.500	10.461
71	5.884	2.530	5.629	2.805	99.040	8.832	88.894	11.051	88.894	10.180
72	5.841	2.848	5.600	3.134	94.833	11.107	87.657	9.366	90.874	9.731
73	5.343	2.819	5.419	2.713	88.399	9.899	80.480	10.910	87.162	10.938
74	5.500	3.069	5.687	3.146	86.172	9.422	93.348	9.787	97.061	8.860
75	5.585	2.576	5.513	2.707	89.389	9.675	98.298	9.478	82.955	9.001
76	5.272	2.865	5.535	2.926	90.131	10.714	96.566	8.832	96.813	9.225

77	5.293	2.972	5.883	2.661	93.348	9.169	100.278	9.703	95.081	10.405
78	5.485	2.887	5.433	2.580	82.460	11.388	94.338	10.152	85.182	10.321
79	5.279	2.768	5.927	3.059	100.773	9.366	92.606	9.225	96.071	9.338
80	5.307	2.729	5.382	2.620	98.298	10.995	89.389	10.742	88.646	8.888
81	5.756	2.751	5.542	3.042	83.944	10.433	80.727	11.444	99.783	8.832
82	5.692	2.967	5.854	2.799	95.328	9.394	89.884	11.472	82.212	10.854
83	5.336	2.678	5.818	3.082	84.687	10.321	81.470	9.422	79.242	10.152
84	5.400	2.989	5.695	2.672	98.545	11.219	88.646	10.236	91.369	11.163
85	5.436	3.006	5.731	3.111	94.091	10.012	78.995	11.360	90.379	10.798
86	5.920	2.893	5.847	2.701	101.763	11.500	93.101	9.506	95.576	10.068
87	5.421	2.536	5.811	3.106	87.657	9.871	87.409	11.219	97.803	10.966
88	5.471	2.661	5.920	2.846	85.924	11.051	101.763	9.141	94.586	10.714
89	5.407	2.700	6.065	2.724	79.737	8.945	84.192	11.135	87.409	9.956
90	5.742	3.080	5.949	3.088	95.081	9.562	92.111	9.647	99.288	11.247
91	5.350	2.683	5.549	2.984	94.338	9.225	82.212	10.461	89.389	8.720
92	5.770	2.978	5.825	3.036	99.783	9.703	102.505	10.938	93.596	9.478
93	5.621	3.012	5.622	2.782	87.162	10.573	101.268	11.388	94.833	11.191
94	5.314	2.559	5.709	2.586	97.803	9.506	91.616	9.843	102.258	10.012
95	5.927	2.621	5.484	3.077	86.667	9.731	81.965	9.927	83.202	9.029
96	5.720	2.831	5.898	3.117	78.995	10.152	98.051	8.917	82.460	9.394
97	5.813	2.615	6.072	2.874	101.515	10.068	88.152	10.124	78.995	10.349
98	5.357	3.040	5.753	3.140	89.636	10.405	97.308	9.759	85.429	11.303
99	5.300	2.876	5.651	2.851	79.985	8.860	95.576	9.085	87.904	9.647
100	5.728	2.916	5.716	2.597	84.439	8.720	93.843	9.562	82.707	10.995

APPENDIX - B : LHS RUNS WITH STATISTICALLY SIGNIFICANT DIFFERENCE IN PRODUCTS' SERVICE LEVELS UNDER DKAP

TABLE OF CONTENTS

Page

B.1 SCENARIO 1: High Product 1 CV – Low Product 2 CV B-2

B.1.1 EKCS B-2
B.1.2 GKCS.. B-2

B.2 SCENARIO 2: Low Product 1 CV – Low Product 2 CV B-2

B.2.1 EKCS B-2
B.2.2 GKCS.. B-3

B.3 SCENARIO 3: Low Product 1 CV – High Product 2 CV B-3

B.3.1 EKCS B-3
B.3.2 GKCS.. B-4

B.4 SCENARIO 4: High Product 1 CV – High Product 2 CV B-4

B.4.1 EKCS B-4
B.4.2 GKCS.. B-5

LIST OF FIGURES

Page

Figure B-1: Significant Differences in SL1 and SL2 EKCS (Scenario 1)....................B-2
Figure B-2: Significant Differences in SL1 and SL2 GKCS (Scenario 1) B-2
Figure B-3: Significant Differences in SL1 and SL2 GKCS (Scenario 2) B-3
Figure B-4: Significant Differences in SL1 and SL2 EKCS (Scenario 3)....................B-3
Figure B-5: Significant Differences in SL1 and SL2 GKCS (Scenario 3) B-4
Figure B-6: Significant Differences in SL1 and SL2 EKCS (Scenario 4)....................B-4
Figure B-7: Significant Differences in SL1 and SL2 GKCS (Scenario 4) B-5

B.1 SCENARIO 1: HIGH PRODUCT 1 CV – LOW PRODUCT 2 CV

B.1.1 EKCS

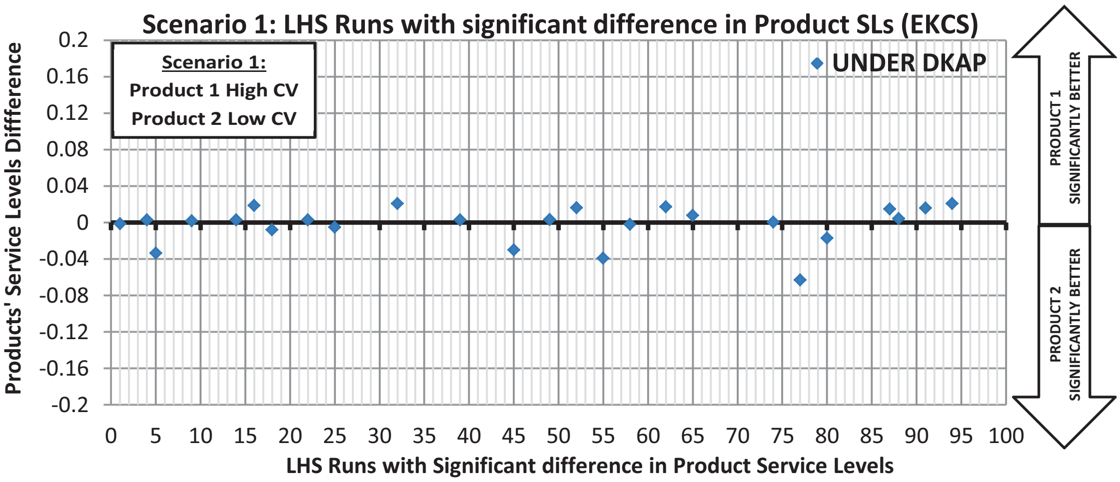


Figure B-1: Significant Differences in SL1 and SL2 EKCS (Scenario 1)

B.1.2 GKCS

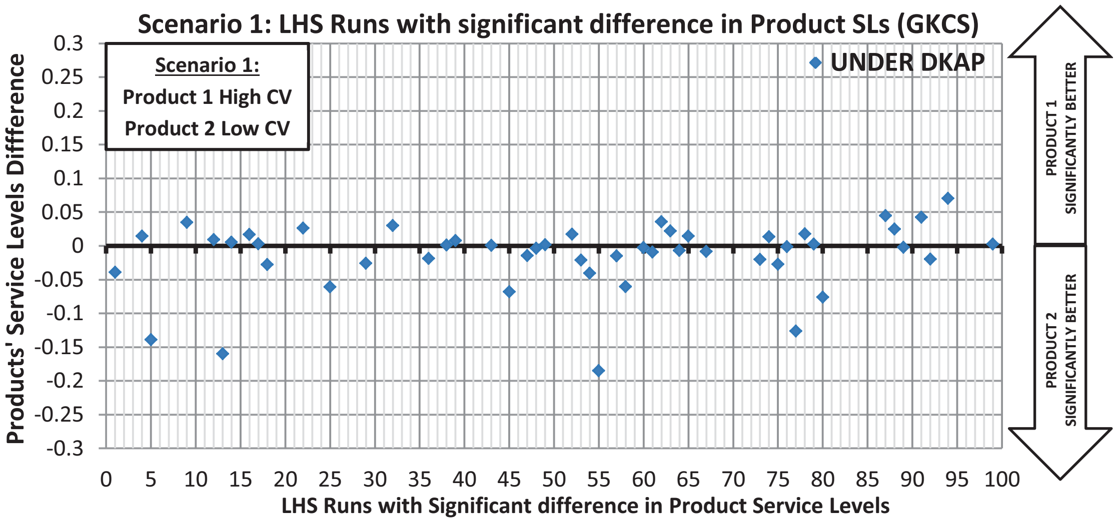


Figure B-2: Significant Differences in SL1 and SL2 GKCS (Scenario 1)

B.2 SCENARIO 2: LOW PRODUCT 1 CV – LOW PRODUCT 2 CV

B.2.1 EKCS

No single statistically significant difference in this scenario.

B.2.2 GKCS

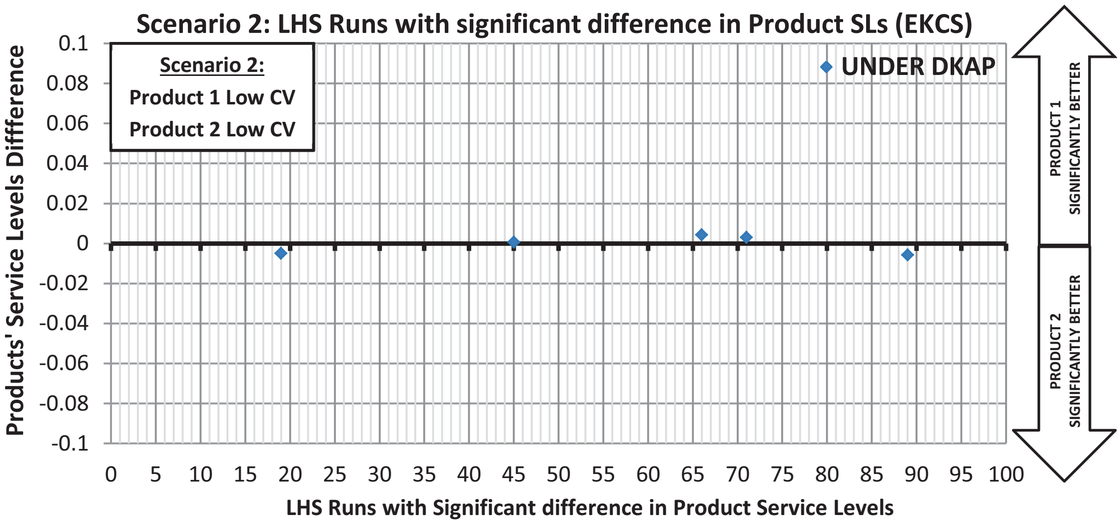


Figure B-3: Significant Differences in SL1 and SL2 GKCS (Scenario 2)

B.3 SCENARIO 3: LOW PRODUCT 1 CV – HIGH PRODUCT 2 CV

B.3.1 EKCS

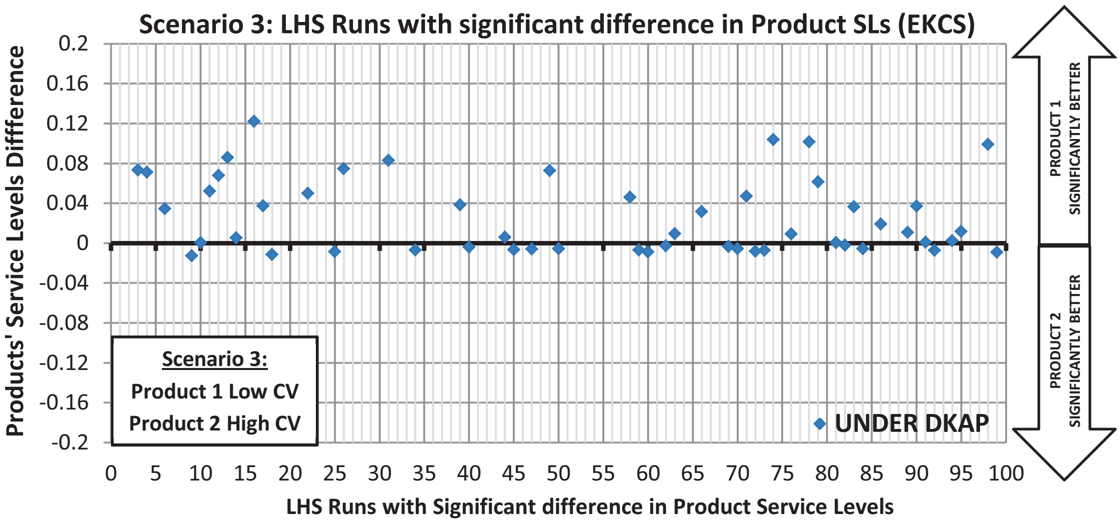


Figure B-4: Significant Differences in SL1 and SL2 EKCS (Scenario 3)

B.3.2 GKCS

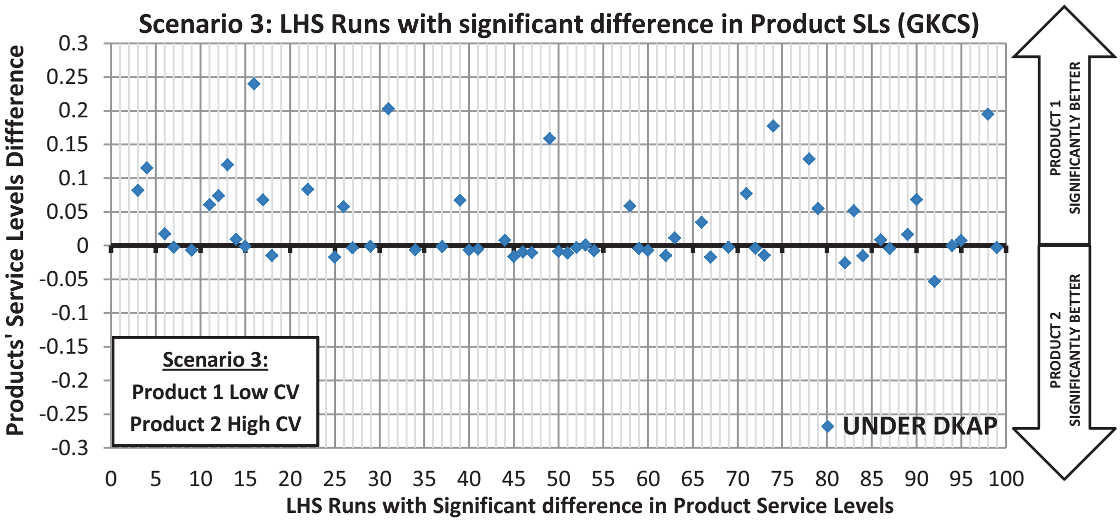


Figure B-5: Significant Differences in SL1 and SL2 GKCS (Scenario 3)

B.4 SCENARIO 4: HIGH PRODUCT 1 CV – HIGH PRODUCT 2 CV

B.4.1 EKCS

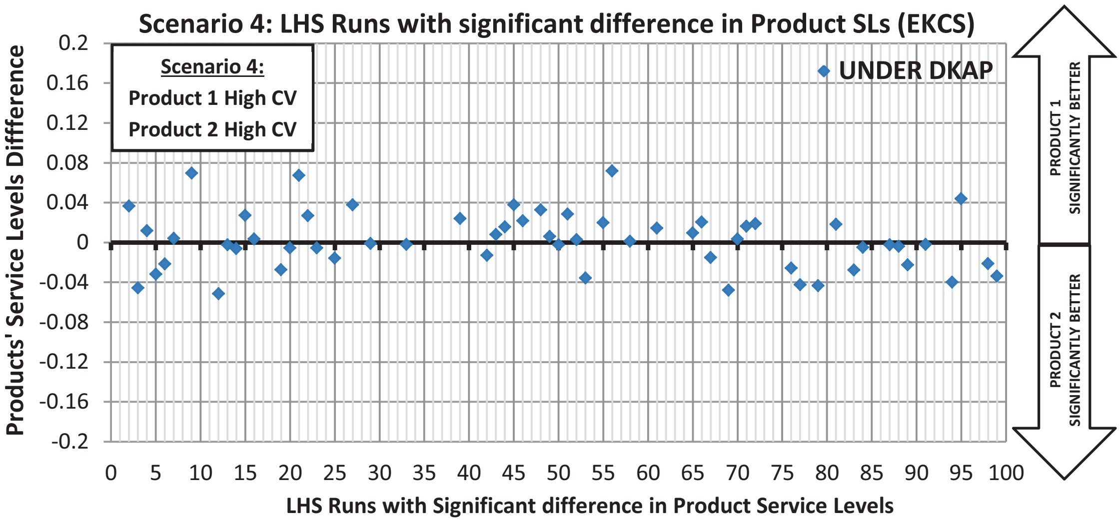


Figure B-6: Significant Differences in SL1 and SL2 EKCS (Scenario 4)

B.4.2 GKCS

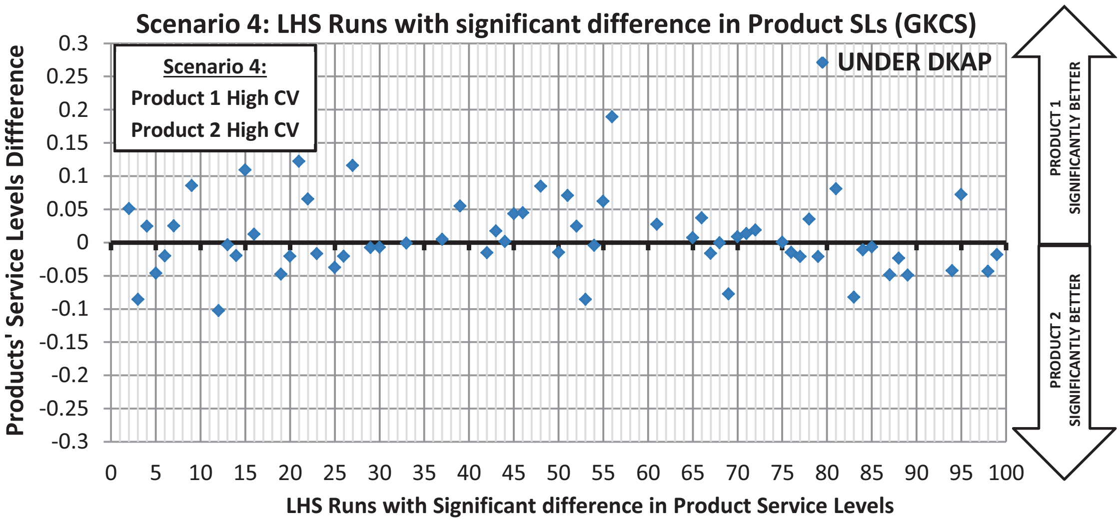


Figure B-7: Significant Differences in SL1 and SL2 GKCS (Scenario 4)

APPENDIX - C : ROBUSTNESS OF PRODUCT SERVICE LEVELS UNDER DKAP AND SKAP

TABLE OF CONTENTS

Page

C.1 SCENARIO 1: High Product 1 CV – Low Product 2 CV C-2

C.1.1 EKCS C-2
C.1.2 GKCS.. C-2

C.2 SCENARIO 2: Low Product 1 CV – Low Product 2 CV C-3

C.2.1 EKCS C-3
C.2.2 GKCS.. C-3

C.3 SCENARIO 3: Low Product 1 CV – High Product 2 CV C-4

C.3.1 EKCS C-4
C.3.2 GKCS.. C-5

C.4 SCENARIO 4: High Product 1 CV – High Product 2 CV C-6

C.4.1 EKCS C-6
C.4.2 GKCS.. C-7

LIST OF FIGURES

Page

Figure C-1: SLs under EKCS DKAP and SKAP (Scenario 1) C-2

Figure C-2: SLs under GKCS DKAP and SKAP (Scenario 1)....................................C-2

Figure C-3: SLs under EKCS DKAP and SKAP (Scenario 2) C-3

Figure C-4: SLs under GKCS DKAP and SKAP (Scenario 2)....................................C-3

Figure C-5: SLs under EKCS DKAP and SKAP (Scenario 3) C-4

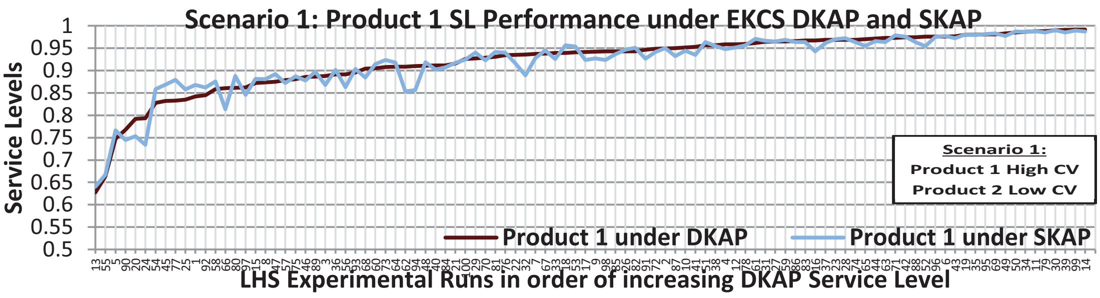
Figure C-6: SLs under GKCS DKAP and SKAP (Scenario 3)....................................C-5

Figure C-7: SLs under EKCS DKAP and SKAP (Scenario 4) C-6

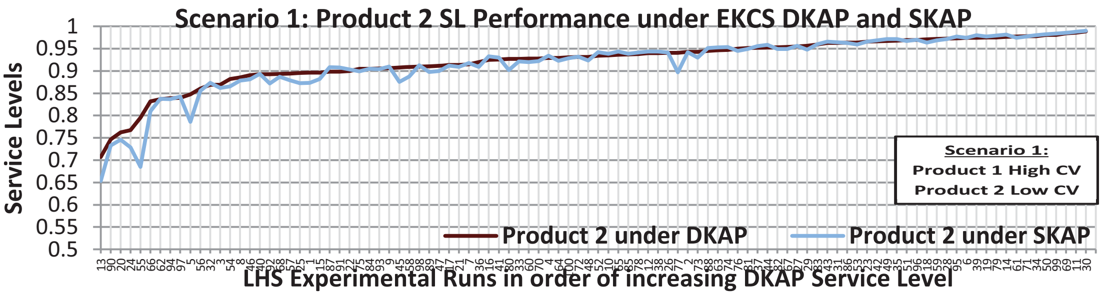
Figure C-8: SLs under GKCS DKAP and SKAP (Scenario 4)....................................C-7

C.1 SCENARIO 1: HIGH PRODUCT 1 CV – LOW PRODUCT 2 CV

C.1.1 EKCS



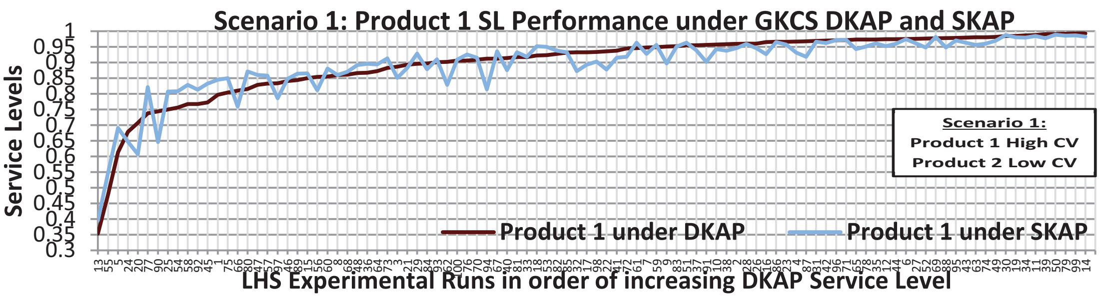
(a) Product 1 SL Performance under DKAP and SKAP



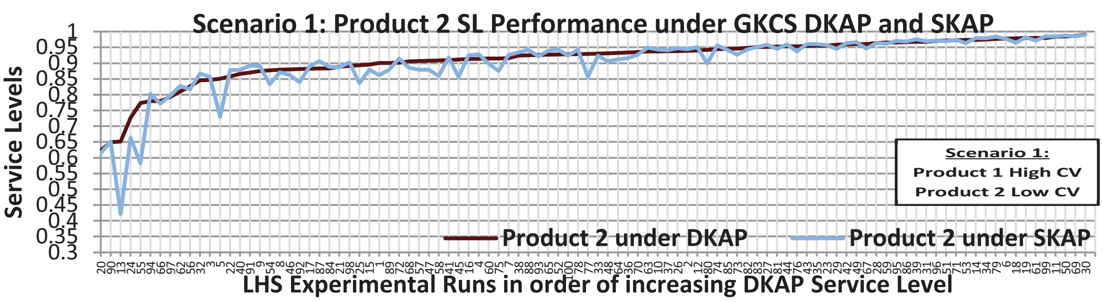
(b) Product 2 SL Performance under DKAP and SKAP

Figure C-1: SLs under EKCS DKAP and SKAP (Scenario 1)

C.1.2 GKCS



(a) Product 1 SL Performance under DKAP and SKAP

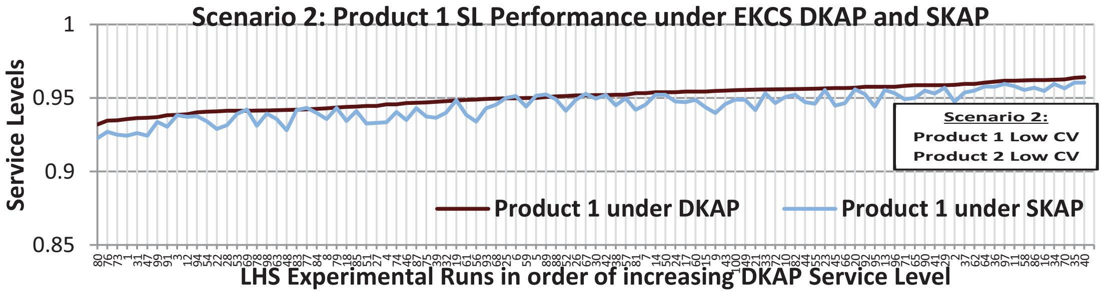


(b) Product 2 SL Performance under DKAP and SKAP

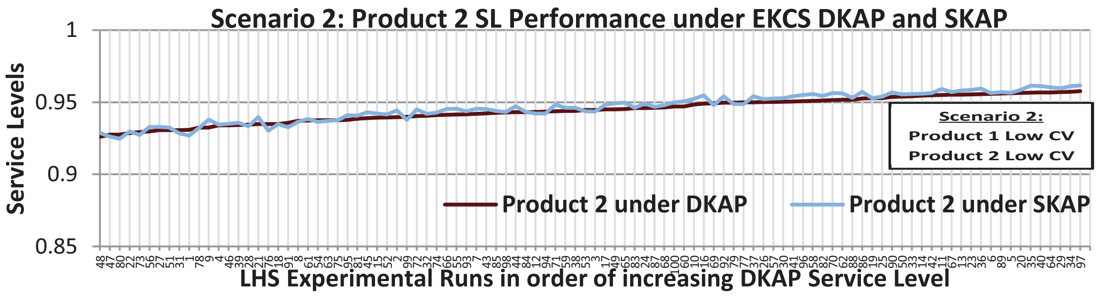
Figure C-2: SLs under GKCS DKAP and SKAP (Scenario 1)

C.2 SCENARIO 2: LOW PRODUCT 1 CV – LOW PRODUCT 2 CV

C.2.1 EKCS



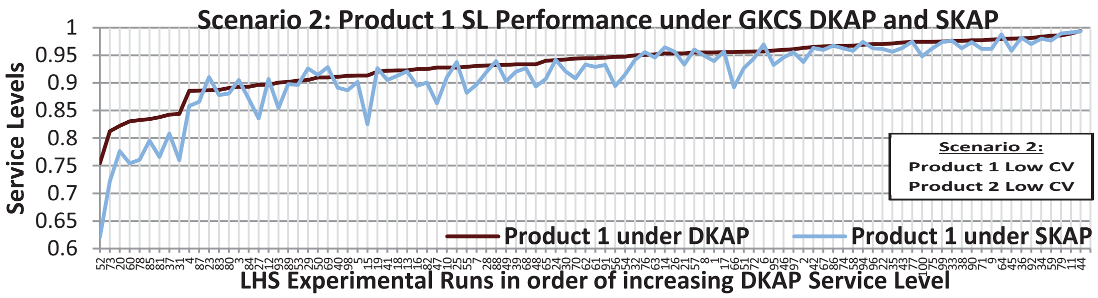
(a) Product 1 SL Performance under DKAP and SKAP



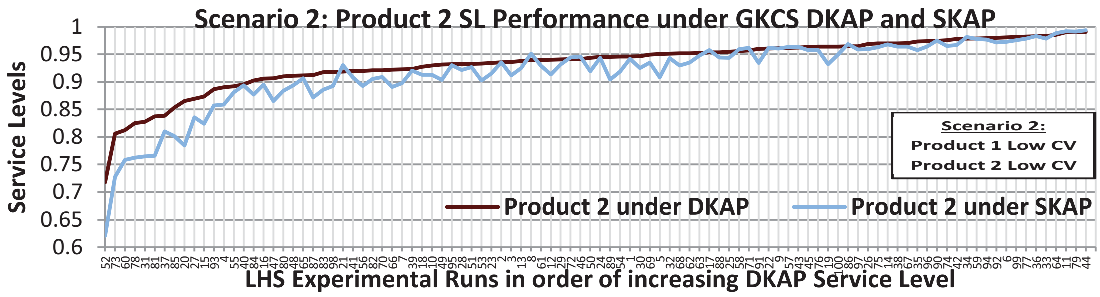
(b) Product 2 SL Performance under DKAP and SKAP

Figure C-3: SLs under EKCS DKAP and SKAP (Scenario 2)

C.2.2 GKCS



(a) Product 1 SL Performance under DKAP and SKAP

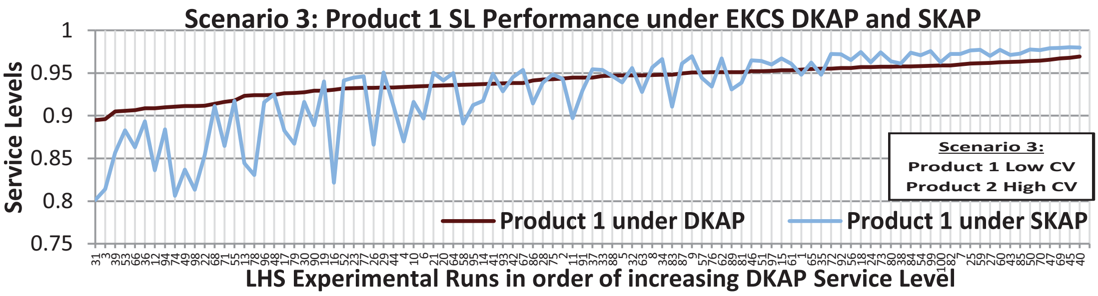


(b) Product 2 SL Performance under DKAP and SKAP

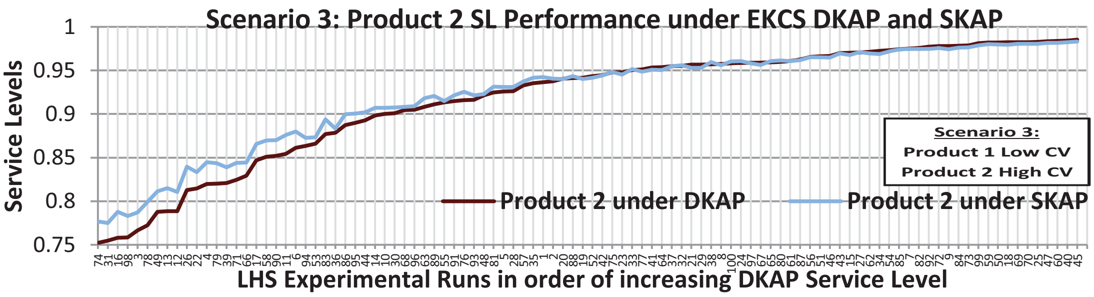
Figure C-4: SLs under GKCS DKAP and SKAP (Scenario 2)

C.3 SCENARIO 3: LOW PRODUCT 1 CV – HIGH PRODUCT 2 CV

C.3.1 EKCS



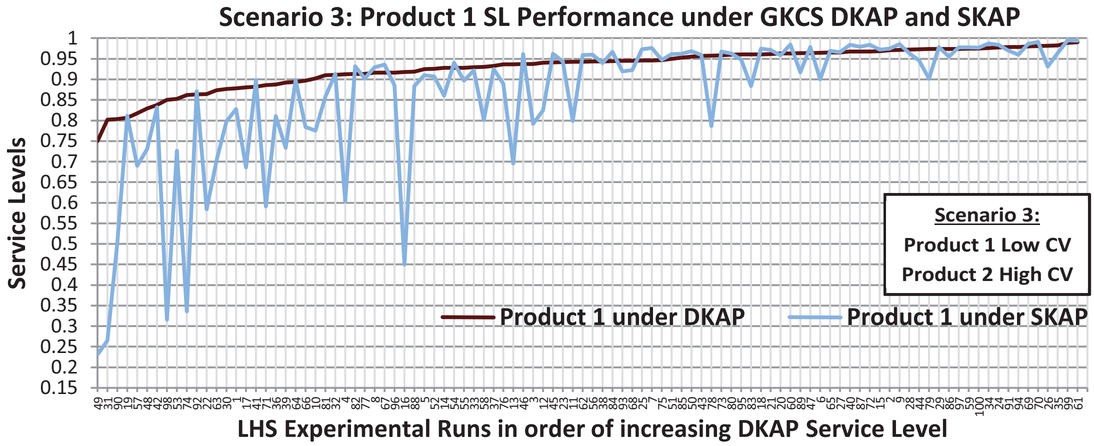
(a) Product 1 SL Performance under DKAP and SKAP



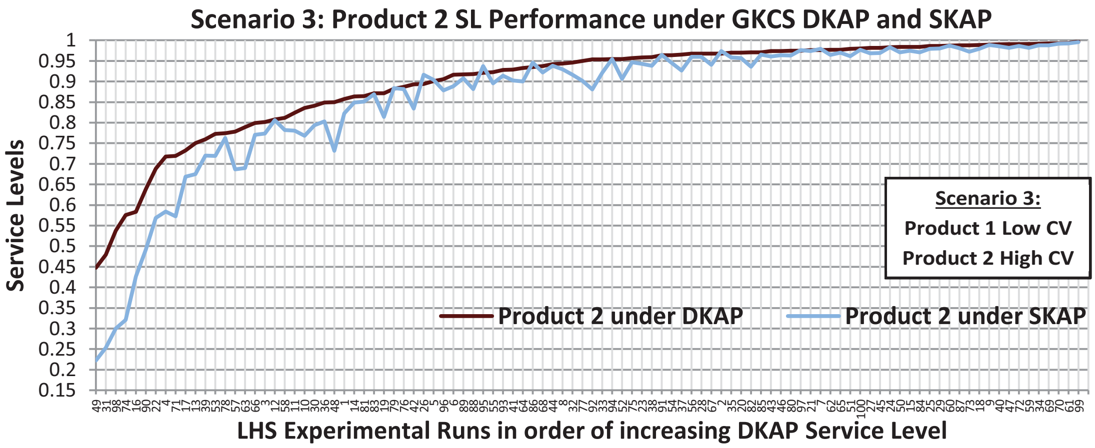
(b) Product 2 SL Performance under DKAP and SKAP

Figure C-5: SLs under EKCS DKAP and SKAP (Scenario 3)

C.3.2 GKCS



(a) Product 1 SL Performance under DKAP and SKAP

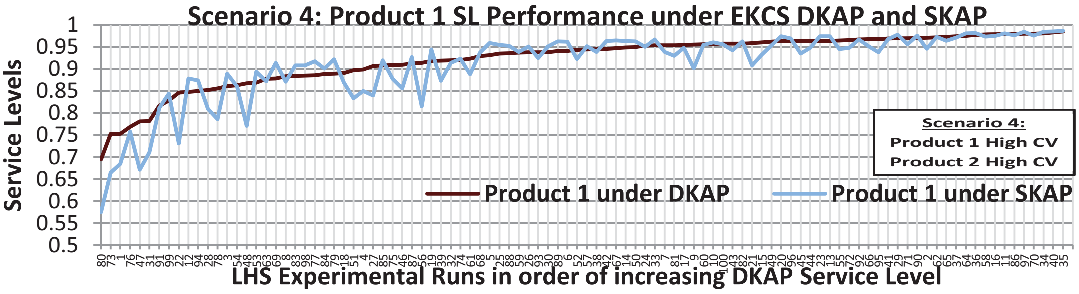


(b) Product 2 SL Performance under DKAP and SKAP

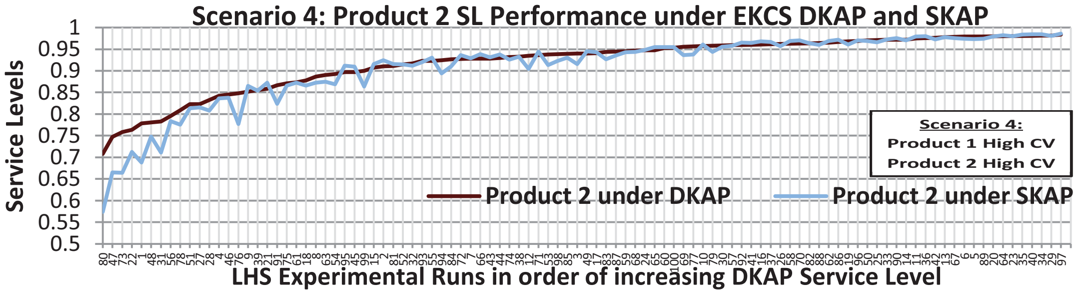
Figure C-6: SLs under GKCS DKAP and SKAP (Scenario 3)

C.4 SCENARIO 4: HIGH PRODUCT 1 CV – HIGH PRODUCT 2 CV

C.4.1 EKCS



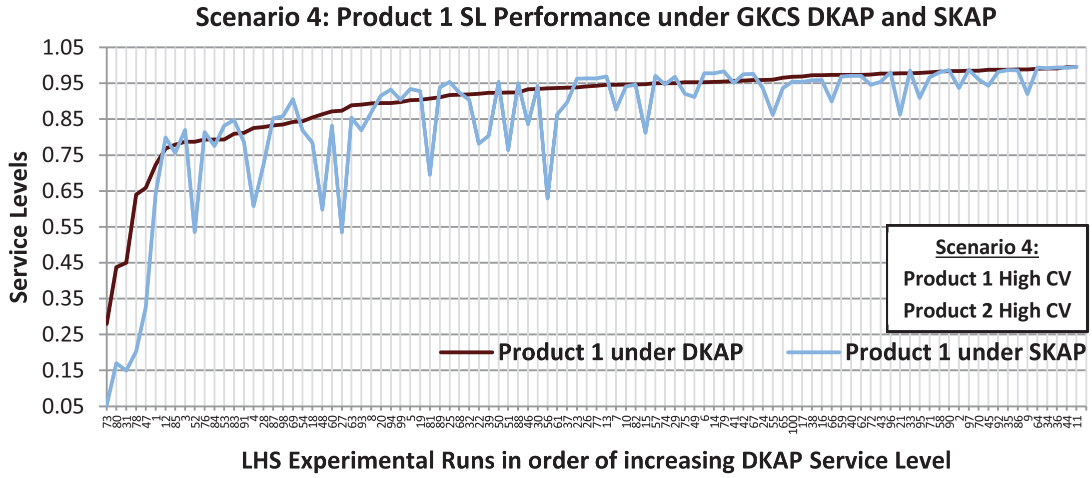
(a) Product 1 SL Performance under DKAP and SKAP



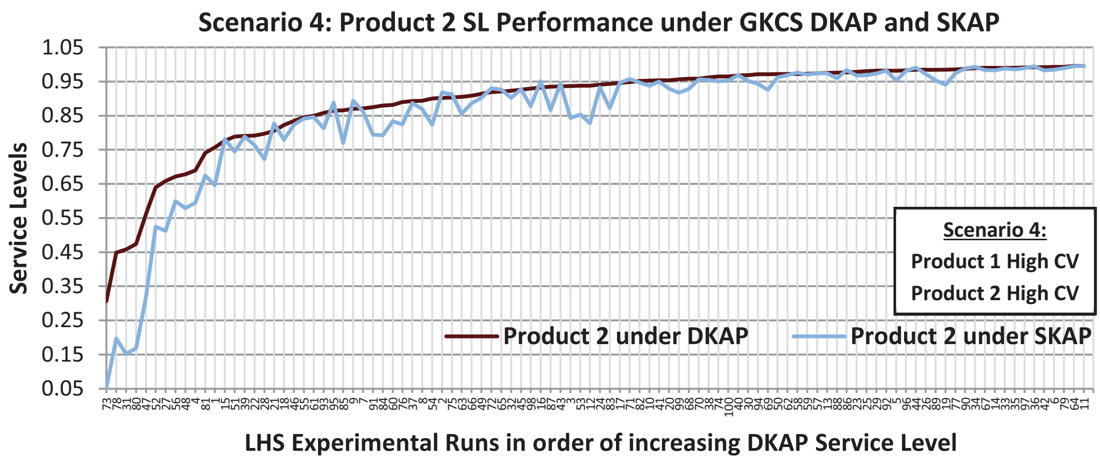
(b) Product 2 SL Performance under DKAP and SKAP

Figure C-7: SLs under EKCS DKAP and SKAP (Scenario 4)

C.4.2 GKCS



(a) Product 1 SL Performance under DKAP and SKAP



(b) Product 2 SL Performance under DKAP and SKAP

Figure C-8: SLs under GKCS DKAP and SKAP (Scenario 4)

APPENDIX - D : IMPACT OF VARIATION IN PRODUCTS' DEMAND VARIABILITY

TABLE OF CONTENTS

Page

D.1 Scenario 1: High Product 1 CV – Low Product 2 CV D-2

D.2 Scenario 2: Low Product 1 CV – Low Product 2 CV D-2

D.3 Scenario 3: Low Product 1 CV – High Product 2 CV D-3

D.4 Scenario 4: High Product 1 CV – High Product 2 CV D-3

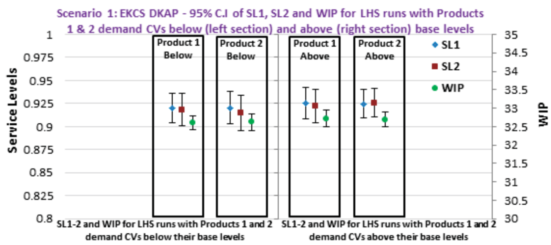
LIST OF FIGURES

Page

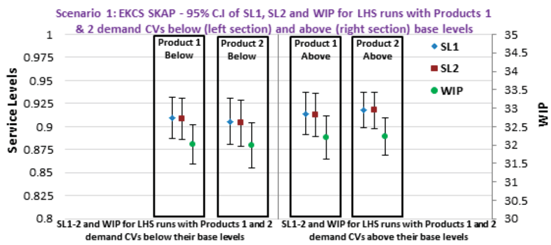
Figure D-1: Demand CV Impact on SLs and WIP EKCS (Scenario 1)........................D-2
Figure D-2: Demand CV Impact on SLs and WIP GKCS (Scenario 1) D-2
Figure D-3: Demand CV Impact on SLs and WIP EKCS (Scenario 2)........................D-2
Figure D-4: Demand CV Impact on SLs and WIP GKCS (Scenario 2) D-3
Figure D-5: Demand CV Impact on SLs and WIP EKCS (Scenario 3)........................D-3
Figure D-6: Demand CV Impact on SLs and WIP GKCS (Scenario 3) D-3
Figure D-7: Demand CV Impact on SLs and WIP EKCS (Scenario 4)........................D-3
Figure D-8: Demand CV Impact on SLs and WIP GKCS (Scenario 4) D-4

D.1 SCENARIO 1: HIGH PRODUCT 1 CV – LOW PRODUCT 2 CV

EKCS and GKCS

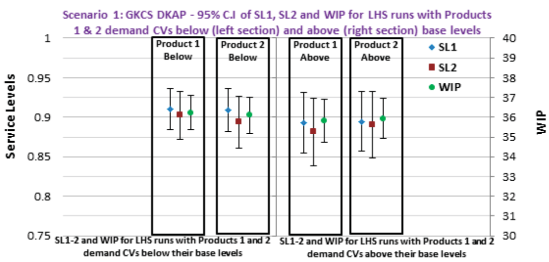


(a) DKAP

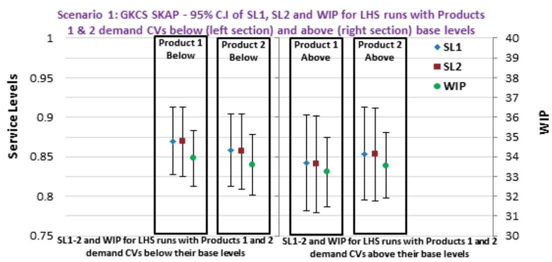


(b) SKAP

Figure D-1: Demand CV Impact on SLs and WIP EKCS (Scenario 1)



(a) DKAP

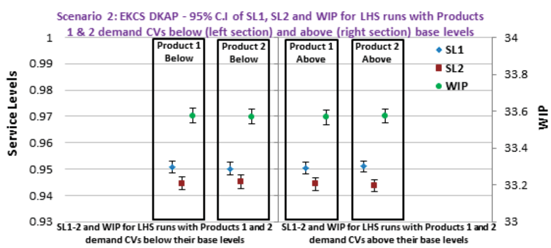


(b) SKAP

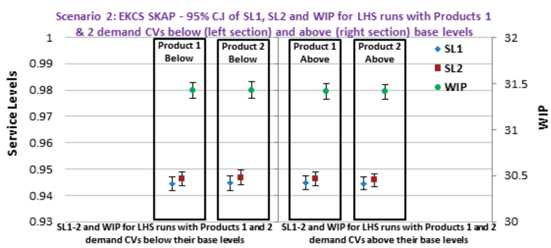
Figure D-2: Demand CV Impact on SLs and WIP GKCS (Scenario 1)

D.2 SCENARIO 2: LOW PRODUCT 1 CV – LOW PRODUCT 2 CV

EKCS and GKCS

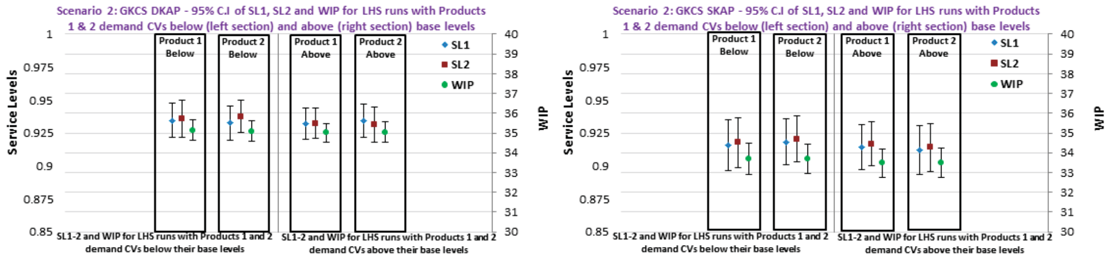


(a) DKAP



(b) SKAP

Figure D-3: Demand CV Impact on SLs and WIP EKCS (Scenario 2)

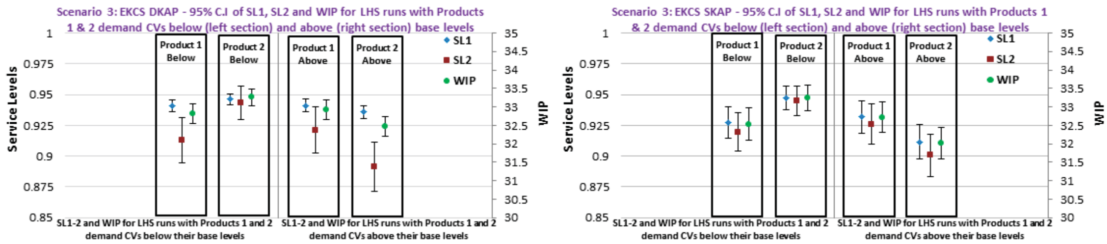


(a) DKAP (b) SKAP

Figure D-4: Demand CV Impact on SLs and WIP GKCS (Scenario 2)

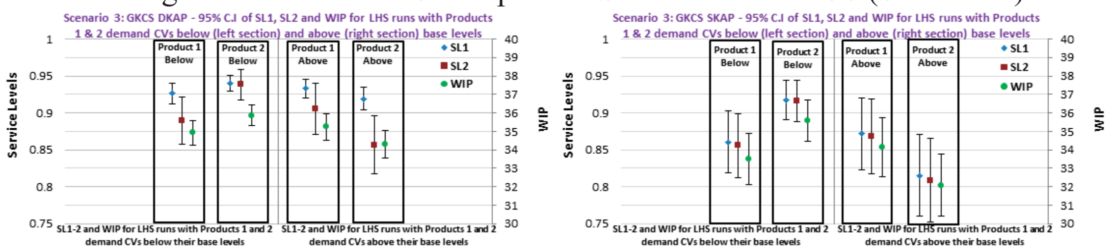
D.3 SCENARIO 3: LOW PRODUCT 1 CV – HIGH PRODUCT 2 CV

EKCS



(a) DKAP (b) SKAP

Figure D-5: Demand CV Impact on SLs and WIP EKCS (Scenario 3)

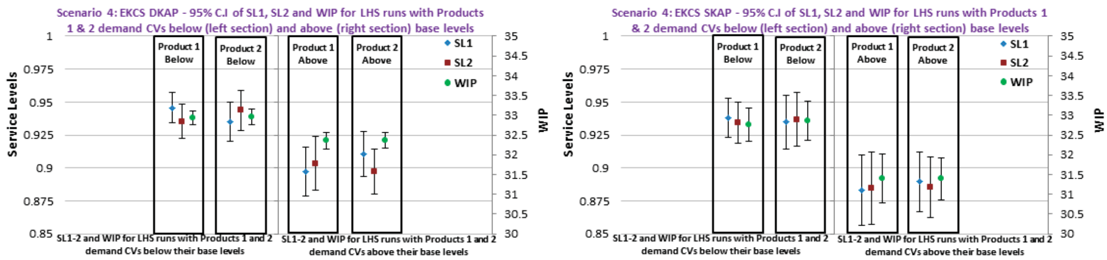


(a) DKAP (b) SKAP

Figure D-6: Demand CV Impact on SLs and WIP GKCS (Scenario 3)

D.4 SCENARIO 4: HIGH PRODUCT 1 CV – HIGH PRODUCT 2 CV

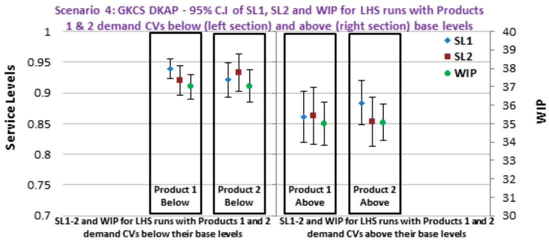
EKCS



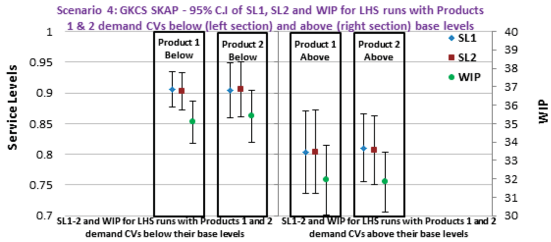
(a) DKAP (b) SKAP

Figure D-7: Demand CV Impact on SLs and WIP EKCS (Scenario 4)

GKCS



(a) DKAP



(b) SKAP

Figure D-8: Demand CV Impact on SLs and WIP GKCS (Scenario 4)

APPENDIX - E : IMPACT OF VARIATION IN PRODUCTS' MEAN TIME BETWEEN DEMANDS

TABLE OF CONTENTS

Page

E.1 Scenario 1: High Product 1 CV – Low Product 2 CV E-2

E.2 Scenario 2: Low Product 1 CV – Low Product 2 CV E-2

E.3 Scenario 3: Low Product 1 CV – High Product 2 CV E-3

E.4 Scenario 4: High Product 1 CV – High Product 2 CV E-4

LIST OF FIGURES

Page

Figure E-1: Mean Demand Impact on SLs and WIP EKCS (Scenario 1) E-2

Figure E-2: Mean Demand Impact on SLs and WIP GKCS (Scenario 1) E-2

Figure E-3: Mean Demand Impact on SLs and WIP EKCS (Scenario 2) E-2

Figure E-4: Mean Demand Impact on SLs and WIP GKCS (Scenario 2) E-3

Figure E-5: Mean Demand Impact on SLs and WIP EKCS (Scenario 3) E-3

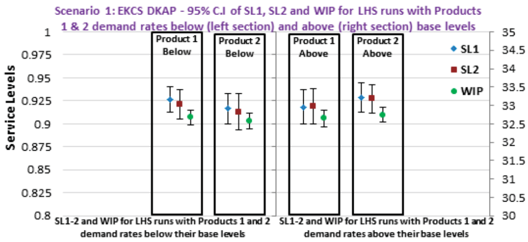
Figure E-6: Mean Demand Impact on SLs and WIP GKCS (Scenario 3) E-3

Figure E-7: Mean Demand Impact on SLs and WIP EKCS (Scenario 4) E-4

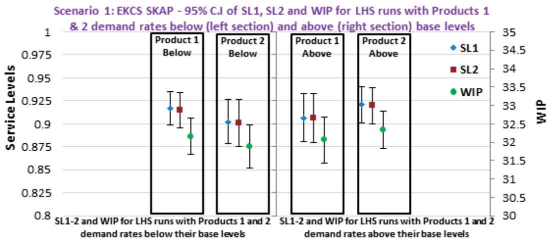
Figure E-8: Mean Demand Impact on SLs and WIP GKCS (Scenario 4) E-4

E.1 SCENARIO 1: HIGH PRODUCT 1 CV – LOW PRODUCT 2 CV

EKCS and GKCS

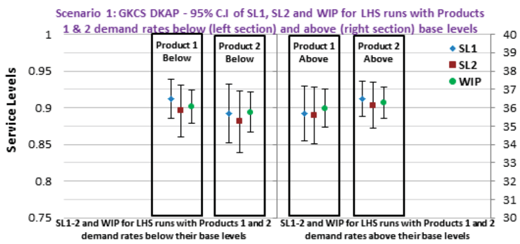


(a) DKAP

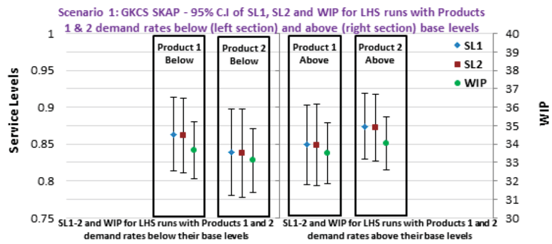


(b) SKAP

Figure E-1: Mean Demand Impact on SLs and WIP EKCS (Scenario 1)



(a) DKAP

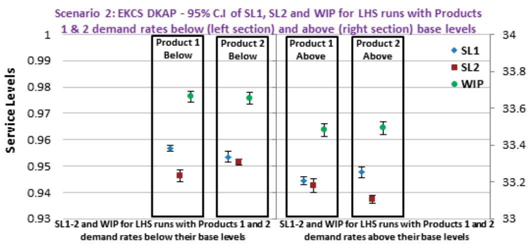


(b) SKAP

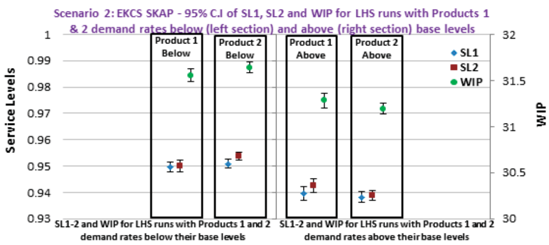
Figure E-2: Mean Demand Impact on SLs and WIP GKCS (Scenario 1)

E.2 SCENARIO 2: LOW PRODUCT 1 CV – LOW PRODUCT 2 CV

EKCS



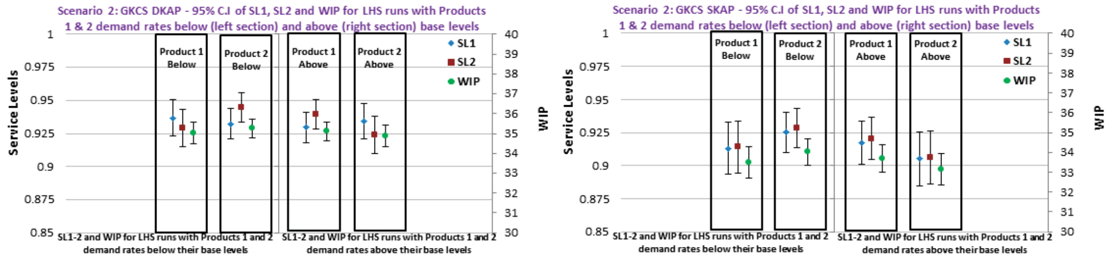
(a) DKAP



(b) SKAP

Figure E-3: Mean Demand Impact on SLs and WIP EKCS (Scenario 2)

GKCS

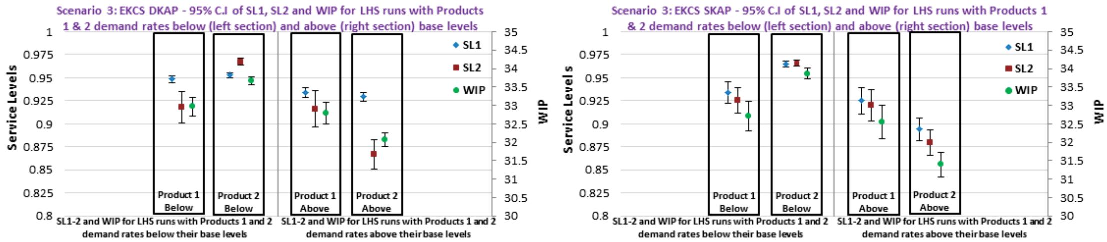


(a) DKAP (b) SKAP

Figure E-4: Mean Demand Impact on SLs and WIP GKCS (Scenario 2)

E.3 SCENARIO 3: LOW PRODUCT 1 CV – HIGH PRODUCT 2 CV

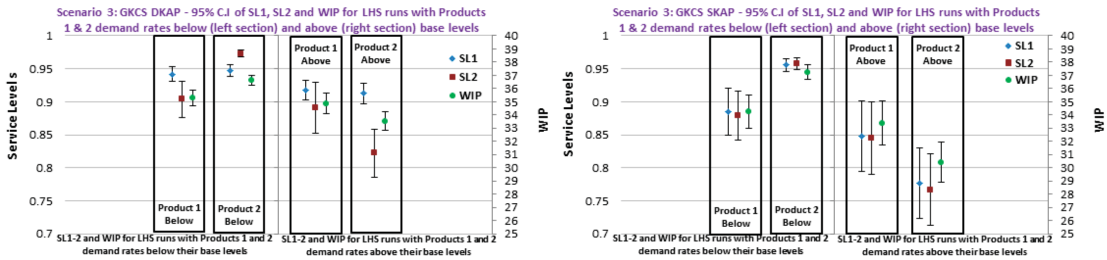
EKCS



(a) DKAP (b) SKAP

Figure E-5: Mean Demand Impact on SLs and WIP EKCS (Scenario 3)

GKCS

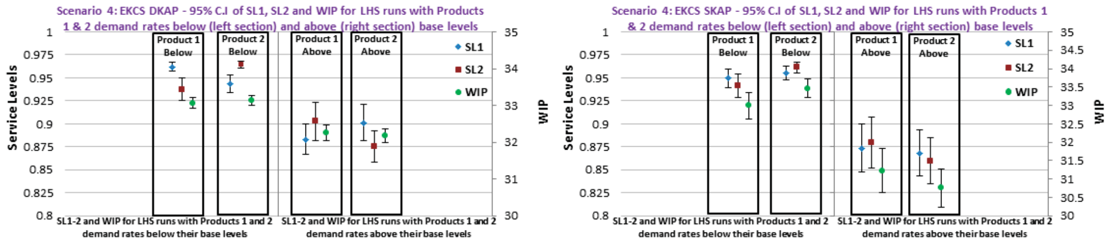


(a) DKAP (b) SKAP

Figure E-6: Mean Demand Impact on SLs and WIP GKCS (Scenario 3)

E.4 SCENARIO 4: HIGH PRODUCT 1 CV – HIGH PRODUCT 2 CV

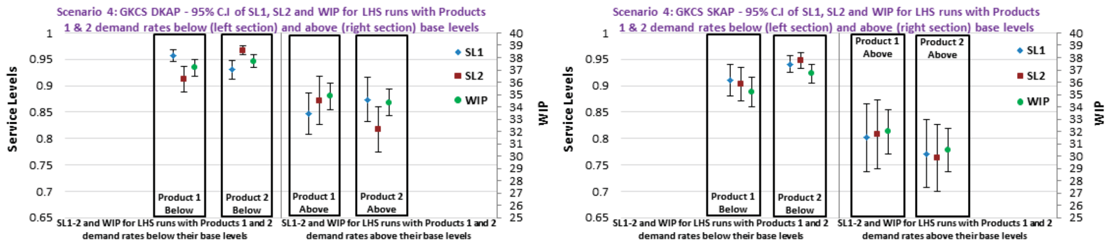
EKCS



(a) DKAP (b) SKAP

Figure E-7: Mean Demand Impact on SLs and WIP EKCS (Scenario 4)

GKCS



(a) DKAP (b) SKAP

Figure E-8: Mean Demand Impact on SLs and WIP GKCS (Scenario 4)

APPENDIX - F : IMPACT OF THE LEVEL OF AVAILABILITY OF STAGES

In this appendix, the charts used in determining the significance of the impact of the ±5% variation of the level of availability of multiple stages are presented.

TABLE OF CONTENTS

Page

F.1 Scenario 1: High Product 1 CV – Low Product 2 CV F-2

F.2 Scenario 2: Low Product 1 CV – Low Product 2 CV F-2

F.3 Scenario 3: Low Product 1 CV – High Product 2 CV F-3

F.4 Scenario 4: High Product 1 CV – High Product 2 CV F-4

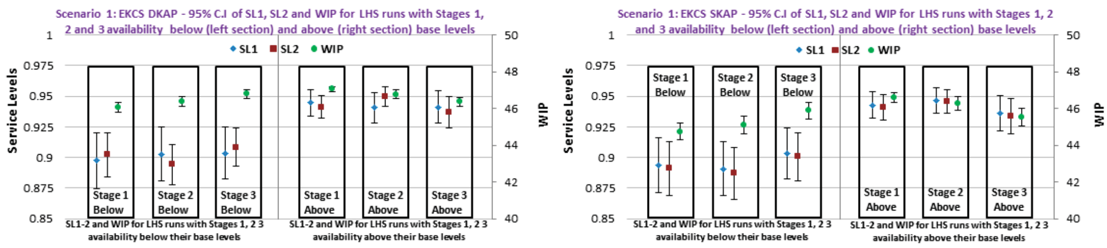
LIST OF FIGURES

Page

Figure F-1: Stage Avail. Impact on SLs and WIP EKCS (Scenario 1)......................... F-2
Figure F-2: Stage Avail. Impact on SLs and WIP GKCS (Scenario 1) F-2
Figure F-3: Stage Avail. Impact on SLs and WIP EKCS (Scenario 2)......................... F-2
Figure F-4: Stage Avail. Impact on SLs and WIP GKCS (Scenario 2) F-3
Figure F-5: Stage Avail. Impact on SLs and WIP EKCS (Scenario 3)......................... F-3
Figure F-6: Stage Avail. Impact on SLs and WIP GKCS (Scenario 3) F-3
Figure F-7: Stage Avail. Impact on SLs and WIP EKCS (Scenario 4)......................... F-4
Figure F-8: Stage Avail. Impact on SLs and WIP GKCS (Scenario 4) F-4

F.1 SCENARIO 1: HIGH PRODUCT 1 CV – LOW PRODUCT 2 CV

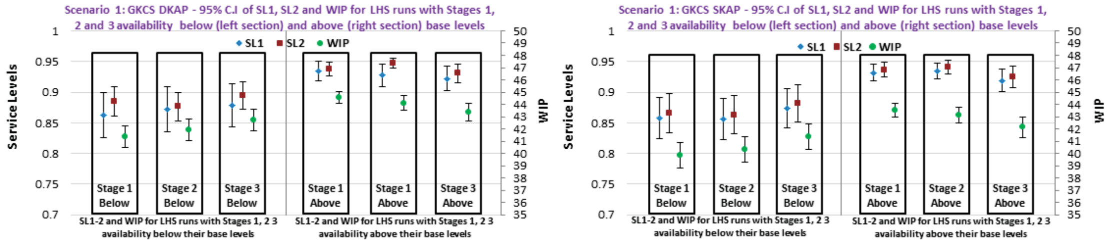
EKCS



(a) DKAP (b) SKAP

Figure F-1: Stage Avail. Impact on SLs and WIP EKCS (Scenario 1)

GKCS

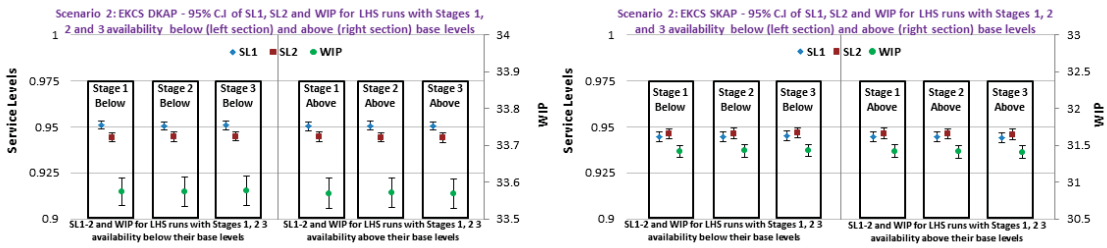


(a) DKAP (b) SKAP

Figure F-2: Stage Avail. Impact on SLs and WIP GKCS (Scenario 1)

F.2 SCENARIO 2: LOW PRODUCT 1 CV – LOW PRODUCT 2 CV

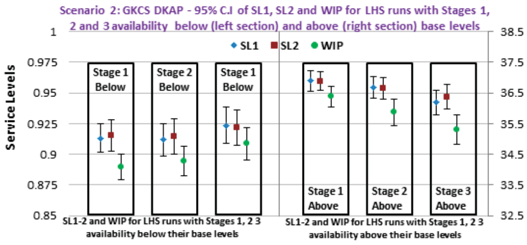
EKCS

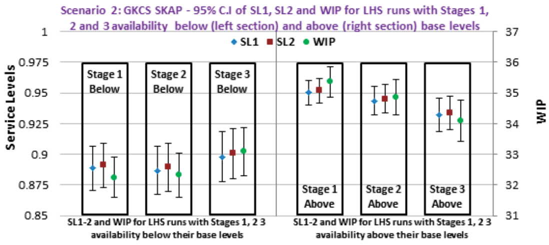


(a) DKAP (b) SKAP

Figure F-3: Stage Avail. Impact on SLs and WIP EKCS (Scenario 2)

GKCS



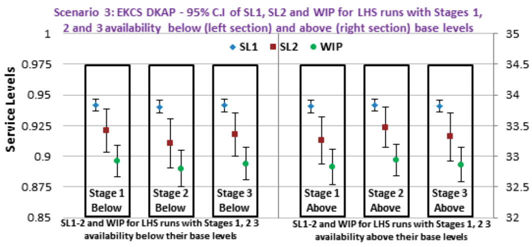


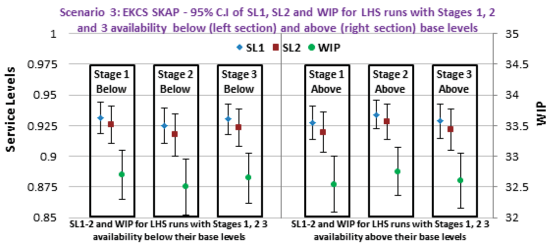
(a) DKAP (b) SKAP

Figure F-4: Stage Avail. Impact on SLs and WIP GKCS (Scenario 2)

F.3 SCENARIO 3: LOW PRODUCT 1 CV – HIGH PRODUCT 2 CV

EKCS

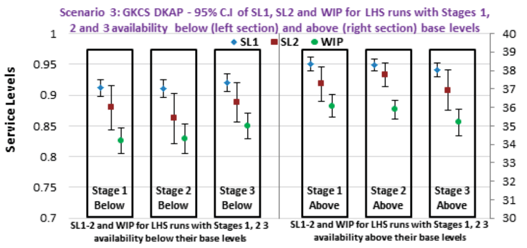


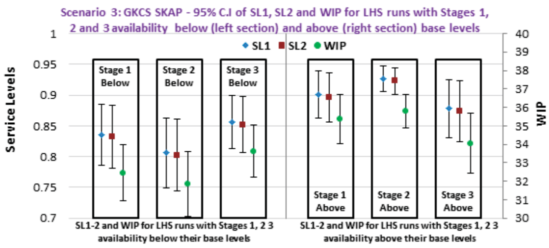


(a) DKAP (b) SKAP

Figure F-5: Stage Avail. Impact on SLs and WIP EKCS (Scenario 3)

GKCS



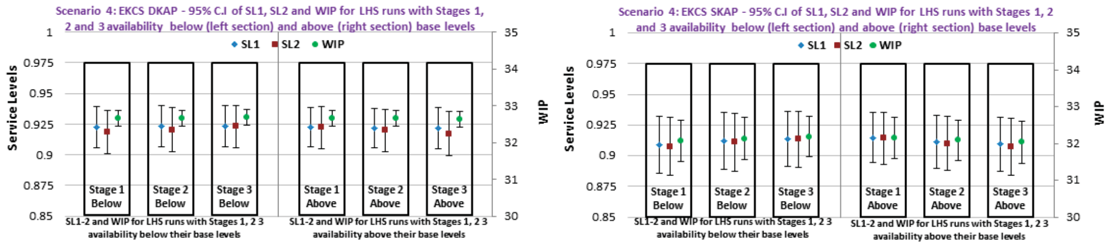


(a) DKAP (b) SKAP

Figure F-6: Stage Avail. Impact on SLs and WIP GKCS (Scenario 3)

F.4 SCENARIO 4: HIGH PRODUCT 1 CV – HIGH PRODUCT 2 CV

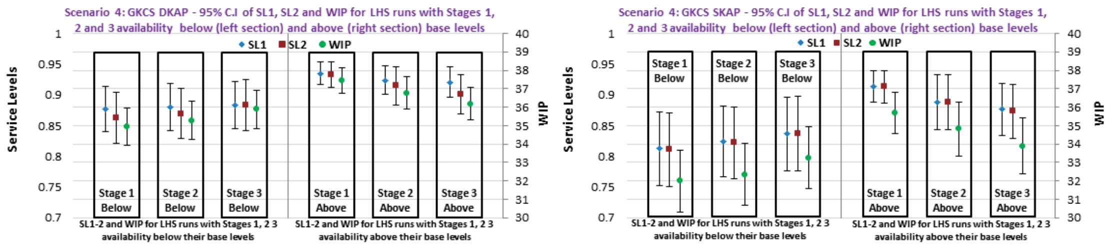
EKCS



(a) DKAP (b) SKAP

Figure F-7: Stage Avail. Impact on SLs and WIP EKCS (Scenario 4)

GKCS



(a) DKAP (b) SKAP

Figure F-8: Stage Avail. Impact on SLs and WIP GKCS (Scenario 4)

APPENDIX - G : EIGHT PRODUCT SYSTEM'S OPTIMISED SETTINGS AND LHS RUNS TABLES

In this appendix the optimised Kanban and basestock settings for the five scenarios of the second manufacturing system are presented.

TABLE OF CONTENTS

Page

G.1 OPTIMISED SETTINGS... G-2

G.2 EIGHT PRODUCT SYSTEM LHS RUNS TABLES..................................... G-6

G.2.1 50% Load level G-6
G.2.2 72.5% Load level G-12
G.2.3 95% Load level G-18

LIST OF TABLES

Page

Table G-1: EKCS DKAP Optimisation Settings for Eight Product System.................G-2

Table G-2: EKCS SKAP Optimisation Settings for Eight Product System.................G-3

Table G-3: EKCS HKAP Optimisation Settings for Eight Product System................G-4

Table G-4: Homogeneous Demand: Scenarios 1 and 3 ....G-6

Table G-5: Higher Group 2 Demand Arrival rate: Scenarios 2 and 5 ....G-8

Table G-6: Higher Group 1 Demand Arrival rate: Scenario 4...................................G-10

Table G-7: Homogeneous Demand: Scenarios 1 and 3 ....G-12

Table G-8: Higher Group 2 Demand Arrival rate: Scenarios 2 and 5 ....G-14

Table G-9: Higher Group 1 Demand Arrival rate: Scenario 4...................................G-16

Table G-10: Homogeneous Demand: Scenarios 1 and 3 ....G-18

Table G-11: Higher Group 2 Demand Arrival rate: Scenarios 2 and 5 ....G-20

Table G-12: Higher Group 1 Demand Arrival rate: Scenario 4.................................G-22

G.1 OPTIMISED SETTINGS

Table G-1: EKCS DKAP Optimisation Settings for Eight Product System

Load Level	Stage	GROUP 1 K	GROUP 1 AK	GROUP 1 S	GROUP 2 K	GROUP 2 AK	GROUP 2 S	RESULTS WIP	RESULTS SL G1	RESULTS SL G2
		Per Product			Per Product					
SCENARIO 1: HOMOGENEOUS PROCESSING TIME AND DEMAND										
95	**1**	7	6	1	4	4	0	83.4295± 0.259	0.98652± 0.009	0.98505± 0.007
	2	4	4	0	8	7	1			
	3	12	3	9	10	0	10			
72.5	**1**	1	0	1	1	0	1	31.6107± 0.009	0.98521± 0.002	0.98603± 0.001
	2	1	1	0	1	1	0			
	3	3	0	3	3	0	3			
50	**1**	1	1	0	1	1	0	23.9524± 0.001	0.99259± 0.001	0.99677± 0.0004
	2	2	1	1	2	2	0			
	3	5	3	2	3	0	3			
SCENARIO 2: HOMOGENEOUS PROCESSING TIME AND HETEROGENEOUS DEMAND										
95	**1**	1	1	0	2	1	1	87.5583± 0.9	0.99407± 0.0008	0.98611± 0.008
	2	5	4	1	7	4	3			
	3	5	1	4	14	0	14			
72.5	**1**	1	1	0	1	1	0	27.5411± 0.03	0.98551± 0.002	0.98873± 0.003
	2	1	1	0	1	0	1			
	3	2	0	2	6	2	4			
50	**1**	1	1	0	1	1	0	19.9281± 0.002	0.99657± 0.0008	0.98724± 0.0008
	2	1	1	0	1	1	0			
	3	4	2	2	4	1	3			
SCENARIO 3: HETEROGENEOUS PROCESSING TIME AND HOMOGENEOUS DEMAND										
95	**1**	1	1	0	2	2	0	78.8481± 1.36	0.98819± 0.01	0.9883±0 .004
	2	4	3	1	3	3	0			
	3	14	1	13	10	3	7			
72.5	**1**	1	1	0	1	1	0	31.5796± 0.04	0.98746± 0.002	0.99332± 0.0006
	2	1	1	0	1	0	1			
	3	4	0	4	4	1	3			
50	**1**	1	1	0	1	1	0	23.9304± 0.002	0.99157± 0.001	0.99481± 0.0005
	2	3	3	0	1	0	1			
	3	4	1	3	4	2	2			
SCENARIO 4: HIGHER PROCESSING TIME AND HIGHER DEMAND FOR GROUP 1										
95	**1**	7	6	1	6	5	1	79.5048± 0.1	0.98614± 0.009	0.99291± 0.006
	2	8	8	0	4	3	1			
	3	18	4	14	7	4	3			
72.5	**1**	1	0	1	1	1	0	27.4894± 0.02	0.9856±0 .001	0.99146± 0.001
	2	1	1	0	2	2	0			

	3	5	1	4	2	0	2			
50	**1**	1	1	0	1	1	0	19.9217± 0.003	0.98615± 0.001	0.99759± 0.0005
	2	1	1	0	1	1	0			
	3	3	0	3	2	0	2			
SCENARIO 5: HIGHER PROCESSING TIME AND LOWER DEMAND FOR GROUP 1										
95	**1**	1	1	0	6	5	1	93.329±1 .11	0.98667± 0.01	0.98585± 0.007
	2	1	0	1	7	4	3			
	3	8	0	8	14	3	11			
72.5	**1**	1	1	0	2	2	0	35.7657± 0.02	0.99022± 0.001	0.98701± 0.001
	2	1	1	0	2	0	2			
	3	4	1	3	5	1	4			
50	**1**	1	1	0	1	0	1	27.8312± 0.01	0.99543± 0.001	0.98899± 0.002
	2	3	2	1	1	1	0			
	3	2	0	2	3	0	3			

Table G-2: EKCS SKAP Optimisation Settings for Eight Product System

SCENARIO 1: HOMOGENEOUS PROCESSING TIME AND DEMAND								
Load Level	**Stage**	**SHARED**		**GROUP 1**	**GROUP 2**	**RESULTS**		
		Total K	**AK**	**S**	**S**	**WIP**	**SL G1**	**SL G2**
		For Stage		**Per Product**	**Per Product**			
95	**1**	1	1	0	0	68.6191± 0.8	0.98652± 0.004	0.98588± 0.007
	2	13	5	1	1			
	3	72	0	9	9			
72.5	**1**	1	1	0	0	30.8840± 0.04	0.99446± 0.0009	0.99298± 0.001
	2	8	4	0	1			
	3	29	1	4	3			
50	**1**	1	1	0	0	23.7136± 0.005	0.99225± 0.0008	0.99221± 0.0005
	2	9	1	1	1			
	3	19	3	2	2			
SCENARIO 2: HOMOGENEOUS PROCESSING TIME AND HETEROGENEOUS DEMAND								
95	**1**	2	2	0	0	73.3892± 1.3	0.98651± 0.005	0.98647± 0.004
	2	15	3	1	2			
	3	72	0	4	14			
72.5	**1**	1	1	0	0	30.8033± 0.03	0.99602± 0.001	0.99084± 0.0007
	2	8	0	1	1			
	3	24	0	2	4			
50	**1**	1	1	0	0	19.5397± 0.02	0.99616± 0.0007	0.98545± 0.001
	2	1	1	0	0			
	3	21	1	2	3			

SCENARIO 3: HETEROGENEOUS PROCESSING TIME AND HOMOGENEOUS DEMAND								
95	**1**	5	1	0	1	77.4693± 1.1	0.98907± 0.005	0.98873± 0.004
	2	12	4	0	2			
	3	77	1	11	8			
72.5	**1**	1	1	0	0	30.1618± 0.1	0.98644± 0.001	0.99138± 0.001
	2	5	1	0	1			
	3	28	0	4	3			
50	**1**	1	1	0	0	23.022±0 .04	0.9867±0 .002	0.99321± 0.0009
	2	1	1	0	0			
	3	24	0	3	3			
SCENARIO 4: HIGHER PROCESSING TIME AND HIGHER DEMAND FOR GROUP 1								
95	**1**	4	0	1	0	70.6213± 1.05	0.986±0. 01	0.99051± 0.004
	2	13	1	1	2			
	3	64	0	13	3			
72.5	**1**	1	1	0	0	26.813±0 .03	0.99165± 0.001	0.98894± 0.001
	2	5	1	1	0			
	3	24	0	4	2			
50	**1**	1	1	0	0	19.6397± 0.01	0.98577± 0.001	0.98715± 0.001
	2	5	1	0	1			
	3	19	3	3	1			
SCENARIO 5: HIGHER PROCESSING TIME AND LOWER DEMAND FOR GROUP 1								
95	**1**	5	1	0	1	90.0284± 2.5	0.98805± 0.004	0.98649± 0.004
	2	16	4	0	3			
	3	88	0	6	16			
72.5	**1**	1	1	0	0	34.2345± 0.1	0.992±0. 002	0.98709± 0.003
	2	9	1	0	2			
	3	28	0	3	4			
50	**1**	8	0	1	1	27.4931± 0.02	0.98949± 0.001	0.98517± 0.002
	2	1	1	0	0			
	3	20	0	2	3			

Table G-3: EKCS HKAP Optimisation Settings for Eight Product System

SCENARIO 1: HOMOGENEOUS PROCESSING TIME AND DEMAND										
Load Level	**Stage**	**GROUP 1** Total K (Per Group)	AK (Per Group)	S (Per Product)	**GROUP 2** Total K (Per Group)	AK (Per Group)	S (Per Product)	**RESULTS** WIP	SL G1	SL G2
95	**1**	4	0	1	4	0	1	85.5119± 1.62	0.98858± 0.01	0.98759± 0.01
	2	10	6	1	7	3	1			
	3	36	0	9	40	0	10			

72.5	**1**	1	1	0	1	1	0	30.9203± 0.02	0.99355± 0.0008	0.98941± 0.002
	2	6	2	1	1	1	0			
	3	12	0	3	17	1	4			
50	**1**	1	1	0	1	1	0	23.825±0 .004	0.99185± 0.0008	0.99183± 0.0007
	2	4	0	1	4	0	1			
	3	11	3	2	8	0	2			
SCENARIO 2: HOMOGENEOUS PROCESSING TIME AND HETEROGENEOUS DEMAND										
95	**1**	4	4	0	1	1	0	73.3552± 1.63	0.99028± 0.004	0.98552± 0.01
	2	4	0	1	13	1	3			
	3	15	3	3	56	0	14			
72.5	**1**	1	1	0	1	1	0	26.9335± 0.04	0.98698± 0.002	0.98989± 0.001
	2	1	1	0	4	0	1			
	3	8	0	2	16	0	4			
50	**1**	1	1	0	1	1	0	19.6671± 0.01	0.99688± 0.001	0.98654± 0.001
	2	2	2	0	1	1	0			
	3	9	1	2	15	3	3			
SCENARIO 3: HETEROGENEOUS PROCESSING TIME AND HOMOGENEOUS DEMAND										
95	**1**	4	0	1	3	3	0	73.2192± 1.58	0.98503± 0.02	0.98686± 0.009
	2	1	1	0	2	2	0			
	3	52	0	13	28	0	7			
72.5	**1**	1	1	0	1	1	0	30.9965± 0.04	0.98704± 0.001	0.99519± 0.001
	2	2	2	0	4	0	1			
	3	16	0	4	13	1	3			
50	**1**	1	1	0	1	1	0	23.7456± 0.008	0.99144± 0.0008	0.99585± 0.0002
	2	1	1	0	4	0	1			
	3	15	3	3	8	0	2			
SCENARIO 4: HIGHER PROCESSING TIME AND HIGHER DEMAND FOR GROUP 1										
95	**1**	4	0	1	1	1	0	66.9658± 1.7	0.98525± 0.01	0.99318± 0.002
	2	4	0	1	1	1	0			
	3	52	0	13	17	1	4			
72.5	**1**	1	1	0	1	1	0	27.0062± 0.03	0.99153± 0.002	0.99362± 0.001
	2	4	0	1	1	1	0			
	3	16	0	4	8	0	2			
50	**1**	1	1	0	1	1	0	19.6868± 0.006	0.98606± 0.0009	0.99858± 0.0004
	2	1	1	0	1	1	0			
	3	12	0	3	8	0	2			
SCENARIO 5: HIGHER PROCESSING TIME AND LOWER DEMAND FOR GROUP 1										
95	**1**	1	1	0	8	4	1	90.4811± 2.1	0.98621± 0.02	0.98877± 0.01
	2	4	0	1	14	2	3			
	3	35	3	8	45	1	11			

72.5	**1**	1	1	0	4	0	1	35.2179± 0.03	0.99022± 0.0007	0.98934± 0.002
	2	1	1	0	5	1	1			
	3	12	0	3	18	2	4			
50	**1**	1	1	0	4	0	1	27.6079± 0.01	0.99577± 0.0009	0.98842± 0.001
	2	5	1	1	1	1	0			
	3	8	0	2	12	0	3			

G.2 EIGHT PRODUCT SYSTEM LHS RUNS TABLES

G.2.1 50% Load level

Table G-4: Homogeneous Demand: Scenarios 1 and 3

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	15.960	15.313	16.154	15.313	15.426	15.216	15.281	16.493
2	15.992	15.297	15.943	15.976	16.687	15.345	16.073	15.814
3	15.620	15.927	16.428	15.717	15.265	16.444	15.539	15.556
4	16.558	16.428	16.380	16.444	16.283	15.265	16.057	16.331
5	15.523	15.895	16.331	16.331	16.105	16.671	16.089	15.798
6	15.717	16.752	15.426	16.315	16.752	15.459	15.507	15.846
7	16.137	15.717	16.315	16.347	15.362	16.655	16.541	15.362
8	15.653	15.523	15.927	15.943	15.475	15.572	16.590	16.574
9	15.701	15.248	15.556	16.784	16.154	15.588	16.574	15.685
10	16.461	16.558	16.444	15.960	15.782	16.396	15.846	15.265
11	15.491	16.590	16.089	16.040	16.719	16.089	15.976	16.267
12	15.216	15.701	16.347	16.137	15.911	15.248	15.895	16.234
13	15.556	15.830	15.620	15.232	15.232	15.313	15.992	16.299
14	15.895	16.574	15.281	15.507	16.574	16.606	16.251	16.202
15	15.636	16.251	16.784	15.410	15.798	15.717	16.525	16.105
16	16.089	15.992	15.216	16.089	16.331	15.410	16.461	16.251
17	16.703	15.442	16.509	15.911	16.784	16.024	15.523	16.186
18	15.782	15.943	15.459	16.800	15.620	16.202	15.572	15.442
19	16.299	16.606	16.606	16.752	15.669	15.733	15.248	16.444
20	15.265	16.170	15.588	16.121	16.057	15.604	16.735	15.749
21	16.638	15.653	16.525	15.863	16.137	15.749	15.733	15.216
22	16.057	16.105	16.364	15.281	15.491	16.752	16.380	15.475
23	16.509	16.218	15.378	15.442	16.186	15.943	15.814	15.572
24	15.345	15.410	15.895	15.329	15.879	15.766	15.459	15.588
25	15.297	15.572	16.024	16.509	15.572	16.477	15.362	16.057
26	16.364	15.491	16.283	16.735	15.830	15.378	16.186	15.313
27	15.362	15.604	16.574	15.846	16.703	15.556	16.008	16.687
28	16.412	16.299	15.798	16.364	16.622	16.137	16.154	16.768
29	16.315	15.879	16.170	15.475	16.234	15.329	16.784	16.137
30	16.251	16.493	15.475	16.687	16.477	15.653	16.299	15.232
31	16.574	16.347	16.396	15.491	15.329	15.669	16.170	16.396
32	16.671	16.461	15.717	15.766	16.638	16.154	16.687	15.863
33	15.588	16.040	15.830	16.057	15.410	15.701	15.426	15.879
34	15.943	16.267	15.491	16.008	15.378	15.475	16.234	15.329
35	15.911	16.735	15.879	16.461	15.927	16.121	16.267	15.911
36	15.572	16.380	15.701	15.459	16.315	15.442	15.911	15.701
37	15.879	16.719	16.477	16.396	16.671	15.232	15.766	15.636

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
38	16.493	15.863	16.105	16.412	15.216	15.491	15.329	16.073
39	16.170	16.477	16.461	15.378	16.380	15.523	15.636	16.606
40	16.347	16.073	15.265	15.345	15.701	15.394	15.265	16.784
41	16.784	15.814	16.267	16.638	15.749	15.895	16.703	16.541
42	15.669	16.008	15.846	16.768	15.539	15.620	15.669	16.703
43	16.331	15.846	15.297	15.636	16.735	16.331	16.477	16.671
44	16.073	15.766	16.735	16.622	15.556	15.362	16.105	16.800
45	15.976	16.655	16.137	15.798	16.218	15.863	15.216	15.733
46	16.121	15.378	15.523	15.556	15.313	16.267	15.927	16.364
47	16.008	15.636	16.412	15.200	16.008	15.992	15.943	15.992
48	15.442	16.412	15.572	15.539	15.814	16.428	15.491	15.604
49	16.218	15.345	15.313	16.477	15.248	15.927	16.428	15.507
50	15.459	16.444	15.394	16.283	15.297	16.768	16.364	15.653
51	16.752	16.089	16.202	15.297	15.442	15.911	15.653	15.523
52	16.444	16.622	15.636	15.588	15.943	16.105	15.410	16.412
53	16.590	15.475	15.992	15.749	15.523	15.685	16.719	15.345
54	15.232	16.509	16.251	16.024	15.636	16.073	15.960	15.281
55	15.733	15.281	15.329	15.604	15.976	16.525	15.313	16.638
56	16.186	16.154	16.800	16.105	15.588	15.636	15.879	15.782
57	15.798	16.186	16.218	15.216	15.846	16.622	16.024	16.752
58	16.040	15.749	15.345	16.154	16.170	15.814	15.442	16.477
59	15.378	16.671	15.863	16.493	16.299	16.590	15.200	15.960
60	16.687	15.426	16.234	15.814	15.459	16.509	15.782	15.410
61	16.525	16.784	16.719	16.525	16.364	16.638	16.558	15.491
62	16.477	16.283	16.703	15.992	16.509	16.412	15.830	15.976
63	16.800	15.265	15.960	16.234	15.766	16.800	16.396	16.154
64	16.428	15.216	16.186	15.927	15.863	15.782	15.749	16.509
65	16.606	16.687	15.669	15.523	16.040	15.200	16.331	15.717
66	16.234	15.232	15.604	15.426	16.444	16.170	15.588	15.927
67	16.735	15.394	15.653	16.170	16.412	16.687	15.556	15.426
68	15.281	16.364	16.073	16.541	16.024	16.364	16.752	16.735
69	15.604	15.798	16.493	15.782	15.992	16.057	16.493	15.248
70	15.426	16.396	15.507	16.655	16.461	16.493	16.040	15.378
71	15.927	15.362	15.782	16.590	16.590	16.735	16.768	15.297
72	15.410	15.782	16.008	16.380	16.347	15.846	15.620	15.459
73	15.685	16.137	16.622	16.719	15.200	16.251	16.121	16.121
74	16.024	16.541	16.057	15.248	16.428	16.719	15.717	15.895
75	15.539	15.911	16.558	15.733	16.525	16.299	15.345	16.170
76	16.105	16.057	15.749	16.299	15.717	16.703	16.622	16.380
77	15.766	15.588	15.976	15.620	16.251	16.461	16.638	16.024
78	16.622	16.331	15.442	16.671	16.073	16.186	15.604	15.943
79	15.200	16.638	16.655	15.265	16.267	16.380	16.137	16.283
80	15.394	16.525	15.200	15.830	15.960	16.283	15.232	16.590
81	16.719	16.703	15.539	15.362	15.394	16.008	16.202	15.830
82	15.475	15.669	16.590	15.701	15.281	15.830	15.798	16.461
83	16.202	16.315	16.040	16.703	15.345	15.297	16.444	16.008
84	16.768	15.507	15.410	16.267	15.507	15.281	16.315	16.428
85	15.846	16.234	16.638	16.574	16.396	15.879	16.412	15.669
86	15.814	15.960	16.299	16.558	16.541	15.539	15.378	16.347
87	16.380	15.539	16.752	15.685	15.653	16.315	16.655	16.040
88	16.541	16.202	16.768	15.653	16.606	15.960	16.800	15.394

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
89	16.396	16.121	15.911	16.073	16.800	16.347	15.297	15.620
90	15.248	15.200	15.814	16.606	16.558	16.040	16.218	16.655
91	15.329	15.620	15.362	15.895	16.768	16.218	15.685	15.766
92	16.267	15.329	15.248	16.218	16.089	16.234	16.283	16.089
93	15.863	15.459	16.671	16.251	16.121	15.976	16.606	16.525
94	15.749	15.556	15.685	15.669	15.733	16.541	15.863	15.539
95	16.655	15.976	16.121	15.879	15.685	16.558	15.701	16.315
96	16.283	15.685	15.766	16.428	16.655	16.784	15.475	16.558
97	15.313	15.733	16.687	15.394	16.202	16.574	16.671	16.622
98	16.154	16.024	15.232	16.186	16.493	15.798	15.394	15.200
99	15.830	16.768	15.733	15.572	15.604	15.507	16.509	16.218
100	15.507	16.800	16.541	16.202	15.895	15.426	16.347	16.719

Table G-5: Higher Group 2 Demand Arrival rate: Scenarios 2 and 5

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	47.879	45.939	48.461	45.939	9.256	9.130	9.168	9.896
2	47.976	45.891	47.830	47.927	10.012	9.207	9.644	9.488
3	46.861	47.782	49.285	47.152	9.159	9.867	9.324	9.333
4	49.673	49.285	49.139	49.333	9.770	9.159	9.634	9.799
5	46.570	47.685	48.994	48.994	9.663	10.002	9.653	9.479
6	47.152	50.255	46.279	48.945	10.051	9.275	9.304	9.508
7	48.412	47.152	48.945	49.042	9.217	9.993	9.925	9.217
8	46.958	46.570	47.782	47.830	9.285	9.343	9.954	9.944
9	47.103	45.745	46.667	50.352	9.692	9.353	9.944	9.411
10	49.382	49.673	49.333	47.879	9.469	9.838	9.508	9.159
11	46.473	49.770	48.267	48.121	10.032	9.653	9.585	9.760
12	45.648	47.103	49.042	48.412	9.547	9.149	9.537	9.741
13	46.667	47.491	46.861	45.697	9.139	9.188	9.595	9.779
14	47.685	49.721	45.842	46.521	9.944	9.964	9.750	9.721
15	46.909	48.752	50.352	46.230	9.479	9.430	9.915	9.663
16	48.267	47.976	45.648	48.267	9.799	9.246	9.876	9.750
17	50.109	46.327	49.527	47.733	10.070	9.615	9.314	9.712
18	47.345	47.830	46.376	50.400	9.372	9.721	9.343	9.265
19	48.897	49.818	49.818	50.255	9.401	9.440	9.149	9.867
20	45.794	48.509	46.764	48.364	9.634	9.362	10.041	9.450
21	49.915	46.958	49.576	47.588	9.682	9.450	9.440	9.130
22	48.170	48.315	49.091	45.842	9.295	10.051	9.828	9.285
23	49.527	48.655	46.133	46.327	9.712	9.566	9.488	9.343
24	46.036	46.230	47.685	45.988	9.527	9.459	9.275	9.353
25	45.891	46.715	48.073	49.527	9.343	9.886	9.217	9.634
26	49.091	46.473	48.848	50.206	9.498	9.227	9.712	9.188
27	46.085	46.812	49.721	47.539	10.022	9.333	9.605	10.012
28	49.236	48.897	47.394	49.091	9.973	9.682	9.692	10.061
29	48.945	47.636	48.509	46.424	9.741	9.198	10.070	9.682
30	48.752	49.479	46.424	50.061	9.886	9.392	9.779	9.139
31	49.721	49.042	49.188	46.473	9.198	9.401	9.702	9.838
32	50.012	49.382	47.152	47.297	9.983	9.692	10.012	9.518
33	46.764	48.121	47.491	48.170	9.246	9.421	9.256	9.527
34	47.830	48.800	46.473	48.024	9.227	9.285	9.741	9.198
35	47.733	50.206	47.636	49.382	9.556	9.673	9.760	9.547
36	46.715	49.139	47.103	46.376	9.789	9.265	9.547	9.421

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
37	47.636	50.158	49.430	49.188	10.002	9.139	9.459	9.382
38	49.479	47.588	48.315	49.236	9.130	9.295	9.198	9.644
39	48.509	49.430	49.382	46.133	9.828	9.314	9.382	9.964
40	49.042	48.218	45.794	46.036	9.421	9.236	9.159	10.070
41	50.352	47.442	48.800	49.915	9.450	9.537	10.022	9.925
42	47.006	48.024	47.539	50.303	9.324	9.372	9.401	10.022
43	48.994	47.539	45.891	46.909	10.041	9.799	9.886	10.002
44	48.218	47.297	50.206	49.867	9.333	9.217	9.663	10.080
45	47.927	49.964	48.412	47.394	9.731	9.518	9.130	9.440
46	48.364	46.133	46.570	46.667	9.188	9.760	9.556	9.818
47	48.024	46.909	49.236	45.600	9.605	9.595	9.566	9.595
48	46.327	49.236	46.715	46.618	9.488	9.857	9.295	9.362
49	48.655	46.036	45.939	49.430	9.149	9.556	9.857	9.304
50	46.376	49.333	46.182	48.848	9.178	10.061	9.818	9.392
51	50.255	48.267	48.606	45.891	9.265	9.547	9.392	9.314
52	49.333	49.867	46.909	46.764	9.566	9.663	9.246	9.847
53	49.770	46.424	47.976	47.248	9.314	9.411	10.032	9.207
54	45.697	49.527	48.752	48.073	9.382	9.644	9.576	9.168
55	47.200	45.842	45.988	46.812	9.585	9.915	9.188	9.983
56	48.558	48.461	50.400	48.315	9.353	9.382	9.527	9.469
57	47.394	48.558	48.655	45.648	9.508	9.973	9.615	10.051
58	48.121	47.248	46.036	48.461	9.702	9.488	9.265	9.886
59	46.133	50.012	47.588	49.479	9.779	9.954	9.120	9.576
60	50.061	46.279	48.703	47.442	9.275	9.905	9.469	9.246
61	49.576	50.352	50.158	49.576	9.818	9.983	9.935	9.295
62	49.430	48.848	50.109	47.976	9.905	9.847	9.498	9.585
63	50.400	45.794	47.879	48.703	9.459	10.080	9.838	9.692
64	49.285	45.648	48.558	47.782	9.518	9.469	9.450	9.905
65	49.818	50.061	47.006	46.570	9.624	9.120	9.799	9.430
66	48.703	45.697	46.812	46.279	9.867	9.702	9.353	9.556
67	50.206	46.182	46.958	48.509	9.847	10.012	9.333	9.256
68	45.842	49.091	48.218	49.624	9.615	9.818	10.051	10.041
69	46.812	47.394	49.479	47.345	9.595	9.634	9.896	9.149
70	46.279	49.188	46.521	49.964	9.876	9.896	9.624	9.227
71	47.782	46.085	47.345	49.770	9.954	10.041	10.061	9.178
72	46.230	47.345	48.024	49.139	9.808	9.508	9.372	9.275
73	47.055	48.412	49.867	50.158	9.120	9.750	9.673	9.673
74	48.073	49.624	48.170	45.745	9.857	10.032	9.430	9.537
75	46.618	47.733	49.673	47.200	9.915	9.779	9.207	9.702
76	48.315	48.170	47.248	48.897	9.430	10.022	9.973	9.828
77	47.297	46.764	47.927	46.861	9.750	9.876	9.983	9.615
78	49.867	48.994	46.327	50.012	9.644	9.712	9.362	9.566
79	45.600	49.915	49.964	45.794	9.760	9.828	9.682	9.770
80	46.182	49.576	45.600	47.491	9.576	9.770	9.139	9.954
81	50.158	50.109	46.618	46.085	9.236	9.605	9.721	9.498
82	46.424	47.006	49.770	47.103	9.168	9.498	9.479	9.876
83	48.606	48.945	48.121	50.109	9.207	9.178	9.867	9.605
84	50.303	46.521	46.230	48.800	9.304	9.168	9.789	9.857
85	47.539	48.703	49.915	49.721	9.838	9.527	9.847	9.401
86	47.442	47.879	48.897	49.673	9.925	9.324	9.227	9.808
87	49.139	46.618	50.255	47.055	9.392	9.789	9.993	9.624

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
88	49.624	48.606	50.303	46.958	9.964	9.576	10.080	9.236
89	49.188	48.364	47.733	48.218	10.080	9.808	9.178	9.372
90	45.745	45.600	47.442	49.818	9.935	9.624	9.731	9.993
91	45.988	46.861	46.085	47.685	10.061	9.731	9.411	9.459
92	48.800	45.988	45.745	48.655	9.653	9.741	9.770	9.653
93	47.588	46.376	50.012	48.752	9.673	9.585	9.964	9.915
94	47.248	46.667	47.055	47.006	9.440	9.925	9.518	9.324
95	49.964	47.927	48.364	47.636	9.411	9.935	9.421	9.789
96	48.848	47.055	47.297	49.285	9.993	10.070	9.285	9.935
97	45.939	47.200	50.061	46.182	9.721	9.944	10.002	9.973
98	48.461	48.073	45.697	48.558	9.896	9.479	9.236	9.120
99	47.491	50.303	47.200	46.715	9.362	9.304	9.905	9.731
100	46.521	50.400	49.624	48.606	9.537	9.256	9.808	10.032

Table G-6: Higher Group 1 Demand Arrival rate: Scenario 4

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	9.256	9.130	9.168	9.896	47.879	45.939	48.461	45.939
2	10.012	9.207	9.644	9.488	47.976	45.891	47.830	47.927
3	9.159	9.867	9.324	9.333	46.861	47.782	49.285	47.152
4	9.770	9.159	9.634	9.799	49.673	49.285	49.139	49.333
5	9.663	10.002	9.653	9.479	46.570	47.685	48.994	48.994
6	10.051	9.275	9.304	9.508	47.152	50.255	46.279	48.945
7	9.217	9.993	9.925	9.217	48.412	47.152	48.945	49.042
8	9.285	9.343	9.954	9.944	46.958	46.570	47.782	47.830
9	9.692	9.353	9.944	9.411	47.103	45.745	46.667	50.352
10	9.469	9.838	9.508	9.159	49.382	49.673	49.333	47.879
11	10.032	9.653	9.585	9.760	46.473	49.770	48.267	48.121
12	9.547	9.149	9.537	9.741	45.648	47.103	49.042	48.412
13	9.139	9.188	9.595	9.779	46.667	47.491	46.861	45.697
14	9.944	9.964	9.750	9.721	47.685	49.721	45.842	46.521
15	9.479	9.430	9.915	9.663	46.909	48.752	50.352	46.230
16	9.799	9.246	9.876	9.750	48.267	47.976	45.648	48.267
17	10.070	9.615	9.314	9.712	50.109	46.327	49.527	47.733
18	9.372	9.721	9.343	9.265	47.345	47.830	46.376	50.400
19	9.401	9.440	9.149	9.867	48.897	49.818	49.818	50.255
20	9.634	9.362	10.041	9.450	45.794	48.509	46.764	48.364
21	9.682	9.450	9.440	9.130	49.915	46.958	49.576	47.588
22	9.295	10.051	9.828	9.285	48.170	48.315	49.091	45.842
23	9.712	9.566	9.488	9.343	49.527	48.655	46.133	46.327
24	9.527	9.459	9.275	9.353	46.036	46.230	47.685	45.988
25	9.343	9.886	9.217	9.634	45.891	46.715	48.073	49.527
26	9.498	9.227	9.712	9.188	49.091	46.473	48.848	50.206
27	10.022	9.333	9.605	10.012	46.085	46.812	49.721	47.539
28	9.973	9.682	9.692	10.061	49.236	48.897	47.394	49.091
29	9.741	9.198	10.070	9.682	48.945	47.636	48.509	46.424
30	9.886	9.392	9.779	9.139	48.752	49.479	46.424	50.061
31	9.198	9.401	9.702	9.838	49.721	49.042	49.188	46.473
32	9.983	9.692	10.012	9.518	50.012	49.382	47.152	47.297
33	9.246	9.421	9.256	9.527	46.764	48.121	47.491	48.170
34	9.227	9.285	9.741	9.198	47.830	48.800	46.473	48.024
35	9.556	9.673	9.760	9.547	47.733	50.206	47.636	49.382

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
36	9.789	9.265	9.547	9.421	46.715	49.139	47.103	46.376
37	10.002	9.139	9.459	9.382	47.636	50.158	49.430	49.188
38	9.130	9.295	9.198	9.644	49.479	47.588	48.315	49.236
39	9.828	9.314	9.382	9.964	48.509	49.430	49.382	46.133
40	9.421	9.236	9.159	10.070	49.042	48.218	45.794	46.036
41	9.450	9.537	10.022	9.925	50.352	47.442	48.800	49.915
42	9.324	9.372	9.401	10.022	47.006	48.024	47.539	50.303
43	10.041	9.799	9.886	10.002	48.994	47.539	45.891	46.909
44	9.333	9.217	9.663	10.080	48.218	47.297	50.206	49.867
45	9.731	9.518	9.130	9.440	47.927	49.964	48.412	47.394
46	9.188	9.760	9.556	9.818	48.364	46.133	46.570	46.667
47	9.605	9.595	9.566	9.595	48.024	46.909	49.236	45.600
48	9.488	9.857	9.295	9.362	46.327	49.236	46.715	46.618
49	9.149	9.556	9.857	9.304	48.655	46.036	45.939	49.430
50	9.178	10.061	9.818	9.392	46.376	49.333	46.182	48.848
51	9.265	9.547	9.392	9.314	50.255	48.267	48.606	45.891
52	9.566	9.663	9.246	9.847	49.333	49.867	46.909	46.764
53	9.314	9.411	10.032	9.207	49.770	46.424	47.976	47.248
54	9.382	9.644	9.576	9.168	45.697	49.527	48.752	48.073
55	9.585	9.915	9.188	9.983	47.200	45.842	45.988	46.812
56	9.353	9.382	9.527	9.469	48.558	48.461	50.400	48.315
57	9.508	9.973	9.615	10.051	47.394	48.558	48.655	45.648
58	9.702	9.488	9.265	9.886	48.121	47.248	46.036	48.461
59	9.779	9.954	9.120	9.576	46.133	50.012	47.588	49.479
60	9.275	9.905	9.469	9.246	50.061	46.279	48.703	47.442
61	9.818	9.983	9.935	9.295	49.576	50.352	50.158	49.576
62	9.905	9.847	9.498	9.585	49.430	48.848	50.109	47.976
63	9.459	10.080	9.838	9.692	50.400	45.794	47.879	48.703
64	9.518	9.469	9.450	9.905	49.285	45.648	48.558	47.782
65	9.624	9.120	9.799	9.430	49.818	50.061	47.006	46.570
66	9.867	9.702	9.353	9.556	48.703	45.697	46.812	46.279
67	9.847	10.012	9.333	9.256	50.206	46.182	46.958	48.509
68	9.615	9.818	10.051	10.041	45.842	49.091	48.218	49.624
69	9.595	9.634	9.896	9.149	46.812	47.394	49.479	47.345
70	9.876	9.896	9.624	9.227	46.279	49.188	46.521	49.964
71	9.954	10.041	10.061	9.178	47.782	46.085	47.345	49.770
72	9.808	9.508	9.372	9.275	46.230	47.345	48.024	49.139
73	9.120	9.750	9.673	9.673	47.055	48.412	49.867	50.158
74	9.857	10.032	9.430	9.537	48.073	49.624	48.170	45.745
75	9.915	9.779	9.207	9.702	46.618	47.733	49.673	47.200
76	9.430	10.022	9.973	9.828	48.315	48.170	47.248	48.897
77	9.750	9.876	9.983	9.615	47.297	46.764	47.927	46.861
78	9.644	9.712	9.362	9.566	49.867	48.994	46.327	50.012
79	9.760	9.828	9.682	9.770	45.600	49.915	49.964	45.794
80	9.576	9.770	9.139	9.954	46.182	49.576	45.600	47.491
81	9.236	9.605	9.721	9.498	50.158	50.109	46.618	46.085
82	9.168	9.498	9.479	9.876	46.424	47.006	49.770	47.103
83	9.207	9.178	9.867	9.605	48.606	48.945	48.121	50.109
84	9.304	9.168	9.789	9.857	50.303	46.521	46.230	48.800
85	9.838	9.527	9.847	9.401	47.539	48.703	49.915	49.721
86	9.925	9.324	9.227	9.808	47.442	47.879	48.897	49.673

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
87	9.392	9.789	9.993	9.624	49.139	46.618	50.255	47.055
88	9.964	9.576	10.080	9.236	49.624	48.606	50.303	46.958
89	10.080	9.808	9.178	9.372	49.188	48.364	47.733	48.218
90	9.935	9.624	9.731	9.993	45.745	45.600	47.442	49.818
91	10.061	9.731	9.411	9.459	45.988	46.861	46.085	47.685
92	9.653	9.741	9.770	9.653	48.800	45.988	45.745	48.655
93	9.673	9.585	9.964	9.915	47.588	46.376	50.012	48.752
94	9.440	9.925	9.518	9.324	47.248	46.667	47.055	47.006
95	9.411	9.935	9.421	9.789	49.964	47.927	48.364	47.636
96	9.993	10.070	9.285	9.935	48.848	47.055	47.297	49.285
97	9.721	9.944	10.002	9.973	45.939	47.200	50.061	46.182
98	9.896	9.479	9.236	9.120	48.461	48.073	45.697	48.558
99	9.362	9.304	9.905	9.731	47.491	50.303	47.200	46.715
100	9.537	9.256	9.808	10.032	46.521	50.400	49.624	48.606

G.2.2 72.5% Load level

Table G-7: Homogeneous Demand: Scenarios 1 and 3

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	11.007	10.561	11.140	10.561	10.639	10.494	10.538	11.374
2	11.029	10.550	10.995	11.018	11.508	10.583	11.085	10.906
3	10.773	10.984	11.330	10.839	10.527	11.341	10.717	10.728
4	11.419	11.330	11.296	11.341	11.230	10.527	11.073	11.263
5	10.706	10.962	11.263	11.263	11.107	11.497	11.096	10.895
6	10.839	11.553	10.639	11.252	11.553	10.661	10.695	10.929
7	11.129	10.839	11.252	11.274	10.594	11.486	11.408	10.594
8	10.795	10.706	10.984	10.995	10.672	10.739	11.441	11.430
9	10.828	10.516	10.728	11.575	11.140	10.750	11.430	10.817
10	11.352	11.419	11.341	11.007	10.884	11.308	10.929	10.527
11	10.683	11.441	11.096	11.062	11.530	11.096	11.018	11.218
12	10.494	10.828	11.274	11.129	10.973	10.516	10.962	11.196
13	10.728	10.917	10.773	10.505	10.505	10.561	11.029	11.241
14	10.962	11.430	10.538	10.695	11.430	11.452	11.207	11.174
15	10.784	11.207	11.575	10.628	10.895	10.839	11.397	11.107
16	11.096	11.029	10.494	11.096	11.263	10.628	11.352	11.207
17	11.519	10.650	11.386	10.973	11.575	11.051	10.706	11.163
18	10.884	10.995	10.661	11.586	10.773	11.174	10.739	10.650
19	11.241	11.452	11.452	11.553	10.806	10.851	10.516	11.341
20	10.527	11.152	10.750	11.118	11.073	10.761	11.542	10.862
21	11.475	10.795	11.397	10.940	11.129	10.862	10.851	10.494
22	11.073	11.107	11.285	10.538	10.683	11.553	11.296	10.672
23	11.386	11.185	10.605	10.650	11.163	10.995	10.906	10.739
24	10.583	10.628	10.962	10.572	10.951	10.873	10.661	10.750
25	10.550	10.739	11.051	11.386	10.739	11.363	10.594	11.073
26	11.285	10.683	11.230	11.542	10.917	10.605	11.163	10.561
27	10.594	10.761	11.430	10.929	11.519	10.728	11.040	11.508
28	11.319	11.241	10.895	11.285	11.464	11.129	11.140	11.564
29	11.252	10.951	11.152	10.672	11.196	10.572	11.575	11.129
30	11.207	11.374	10.672	11.508	11.363	10.795	11.241	10.505
31	11.430	11.274	11.308	10.683	10.572	10.806	11.152	11.308

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
32	11.497	11.352	10.839	10.873	11.475	11.140	11.508	10.940
33	10.750	11.062	10.917	11.073	10.628	10.828	10.639	10.951
34	10.995	11.218	10.683	11.040	10.605	10.672	11.196	10.572
35	10.973	11.542	10.951	11.352	10.984	11.118	11.218	10.973
36	10.739	11.296	10.828	10.661	11.252	10.650	10.973	10.828
37	10.951	11.530	11.363	11.308	11.497	10.505	10.873	10.784
38	11.374	10.940	11.107	11.319	10.494	10.683	10.572	11.085
39	11.152	11.363	11.352	10.605	11.296	10.706	10.784	11.452
40	11.274	11.085	10.527	10.583	10.828	10.617	10.527	11.575
41	11.575	10.906	11.218	11.475	10.862	10.962	11.519	11.408
42	10.806	11.040	10.929	11.564	10.717	10.773	10.806	11.519
43	11.263	10.929	10.550	10.784	11.542	11.263	11.363	11.497
44	11.085	10.873	11.542	11.464	10.728	10.594	11.107	11.586
45	11.018	11.486	11.129	10.895	11.185	10.940	10.494	10.851
46	11.118	10.605	10.706	10.728	10.561	11.218	10.984	11.285
47	11.040	10.784	11.319	10.483	11.040	11.029	10.995	11.029
48	10.650	11.319	10.739	10.717	10.906	11.330	10.683	10.761
49	11.185	10.583	10.561	11.363	10.516	10.984	11.330	10.695
50	10.661	11.341	10.617	11.230	10.550	11.564	11.285	10.795
51	11.553	11.096	11.174	10.550	10.650	10.973	10.795	10.706
52	11.341	11.464	10.784	10.750	10.995	11.107	10.628	11.319
53	11.441	10.672	11.029	10.862	10.706	10.817	11.530	10.583
54	10.505	11.386	11.207	11.051	10.784	11.085	11.007	10.538
55	10.851	10.538	10.572	10.761	11.018	11.397	10.561	11.475
56	11.163	11.140	11.586	11.107	10.750	10.784	10.951	10.884
57	10.895	11.163	11.185	10.494	10.929	11.464	11.051	11.553
58	11.062	10.862	10.583	11.140	11.152	10.906	10.650	11.363
59	10.605	11.497	10.940	11.374	11.241	11.441	10.483	11.007
60	11.508	10.639	11.196	10.906	10.661	11.386	10.884	10.628
61	11.397	11.575	11.530	11.397	11.285	11.475	11.419	10.683
62	11.363	11.230	11.519	11.029	11.386	11.319	10.917	11.018
63	11.586	10.527	11.007	11.196	10.873	11.586	11.308	11.140
64	11.330	10.494	11.163	10.984	10.940	10.884	10.862	11.386
65	11.452	11.508	10.806	10.706	11.062	10.483	11.263	10.839
66	11.196	10.505	10.761	10.639	11.341	11.152	10.750	10.984
67	11.542	10.617	10.795	11.152	11.319	11.508	10.728	10.639
68	10.538	11.285	11.085	11.408	11.051	11.285	11.553	11.542
69	10.761	10.895	11.374	10.884	11.029	11.073	11.374	10.516
70	10.639	11.308	10.695	11.486	11.352	11.374	11.062	10.605
71	10.984	10.594	10.884	11.441	11.441	11.542	11.564	10.550
72	10.628	10.884	11.040	11.296	11.274	10.929	10.773	10.661
73	10.817	11.129	11.464	11.530	10.483	11.207	11.118	11.118
74	11.051	11.408	11.073	10.516	11.330	11.530	10.839	10.962
75	10.717	10.973	11.419	10.851	11.397	11.241	10.583	11.152
76	11.107	11.073	10.862	11.241	10.839	11.519	11.464	11.296
77	10.873	10.750	11.018	10.773	11.207	11.352	11.475	11.051
78	11.464	11.263	10.650	11.497	11.085	11.163	10.761	10.995
79	10.483	11.475	11.486	10.527	11.218	11.296	11.129	11.230
80	10.617	11.397	10.483	10.917	11.007	11.230	10.505	11.441
81	11.530	11.519	10.717	10.594	10.617	11.040	11.174	10.917
82	10.672	10.806	11.441	10.828	10.538	10.917	10.895	11.352

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
83	11.174	11.252	11.062	11.519	10.583	10.550	11.341	11.040
84	11.564	10.695	10.628	11.218	10.695	10.538	11.252	11.330
85	10.929	11.196	11.475	11.430	11.308	10.951	11.319	10.806
86	10.906	11.007	11.241	11.419	11.408	10.717	10.605	11.274
87	11.296	10.717	11.553	10.817	10.795	11.252	11.486	11.062
88	11.408	11.174	11.564	10.795	11.452	11.007	11.586	10.617
89	11.308	11.118	10.973	11.085	11.586	11.274	10.550	10.773
90	10.516	10.483	10.906	11.452	11.419	11.062	11.185	11.486
91	10.572	10.773	10.594	10.962	11.564	11.185	10.817	10.873
92	11.218	10.572	10.516	11.185	11.096	11.196	11.230	11.096
93	10.940	10.661	11.497	11.207	11.118	11.018	11.452	11.397
94	10.862	10.728	10.817	10.806	10.851	11.408	10.940	10.717
95	11.486	11.018	11.118	10.951	10.817	11.419	10.828	11.252
96	11.230	10.817	10.873	11.330	11.486	11.575	10.672	11.419
97	10.561	10.851	11.508	10.617	11.174	11.430	11.497	11.464
98	11.140	11.051	10.505	11.163	11.374	10.895	10.617	10.483
99	10.917	11.564	10.851	10.739	10.761	10.695	11.386	11.185
100	10.695	11.586	11.408	11.174	10.962	10.639	11.274	11.530

Table G-8: Higher Group 2 Demand Arrival rate: Scenarios 2 and 5

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	32.853	34.424	32.117	34.692	6.698	6.711	6.390	6.370
2	34.190	33.321	32.786	33.622	6.290	6.785	6.892	6.691
3	31.749	34.090	31.983	31.883	6.530	6.664	6.383	6.918
4	33.856	33.421	34.023	32.685	6.818	6.704	6.571	6.952
5	33.321	33.923	31.615	33.789	6.310	6.564	6.564	6.564
6	32.518	33.689	33.321	34.391	6.798	6.303	6.657	6.811
7	32.017	34.525	31.850	33.220	6.296	6.537	6.818	6.898
8	34.525	31.448	33.856	33.722	6.484	6.477	6.644	6.510
9	33.120	34.725	33.455	32.451	6.624	6.417	6.785	6.363
10	32.652	32.652	34.591	31.816	6.945	6.397	6.591	6.831
11	33.588	34.391	34.658	33.388	6.825	6.764	6.350	6.410
12	32.786	32.518	33.722	31.950	6.724	6.336	6.938	6.671
13	33.755	34.056	33.923	31.983	6.470	6.798	6.851	6.290
14	31.783	31.716	33.020	32.953	6.932	6.611	6.871	6.678
15	34.257	34.290	31.950	32.117	6.397	6.631	6.738	6.617
16	34.625	33.521	33.354	34.591	6.805	6.617	6.296	6.530
17	34.157	32.418	34.224	33.154	6.651	6.316	6.323	6.403
18	31.682	34.625	31.916	32.853	6.597	6.470	6.744	6.557
19	32.819	31.850	32.552	34.357	6.845	6.290	6.811	6.470
20	32.585	33.020	32.652	34.190	6.838	6.350	6.363	6.330
21	33.421	32.017	33.087	31.649	6.343	6.510	6.343	6.477
22	32.217	31.649	32.418	34.759	6.497	6.530	6.303	6.430
23	33.154	32.451	32.084	34.491	6.550	6.544	6.577	6.912
24	32.418	31.783	32.518	32.886	6.524	6.651	6.758	6.704
25	32.619	33.655	33.889	31.482	6.584	6.724	6.443	6.316
26	34.023	31.549	32.619	32.284	6.785	6.637	6.631	6.464
27	32.485	31.582	34.056	33.521	6.517	6.818	6.397	6.303
28	34.558	33.354	32.920	33.120	6.437	6.330	6.671	6.611
29	34.658	32.184	33.220	33.889	6.912	6.490	6.544	6.310
30	31.816	34.157	34.157	32.485	6.657	6.644	6.845	6.805

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
31	32.117	32.084	34.391	33.321	6.898	6.945	6.684	6.731
32	31.582	33.053	32.217	32.251	6.390	6.871	6.450	6.497
33	32.351	31.883	34.692	33.354	6.771	6.323	6.504	6.597
34	32.719	33.956	32.752	33.588	6.557	6.825	6.945	6.878
35	31.950	32.886	31.515	34.558	6.764	6.912	6.537	6.390
36	32.084	34.591	32.150	34.424	6.577	6.744	6.611	6.825
37	32.251	33.488	33.789	32.084	6.878	6.343	6.410	6.437
38	31.916	31.515	32.719	32.184	6.571	6.691	6.510	6.350
39	33.220	32.953	33.822	32.518	6.544	6.443	6.584	6.885
40	32.920	33.455	34.357	34.658	6.316	6.657	6.637	6.945
41	33.622	34.458	34.725	33.956	6.604	6.577	6.423	6.751
42	32.552	33.889	33.053	32.552	6.357	6.504	6.464	6.591
43	33.488	33.622	32.953	33.087	6.718	6.584	6.530	6.584
44	33.689	31.482	33.689	33.455	6.664	6.678	6.457	6.771
45	31.615	33.856	33.622	33.923	6.564	6.450	6.724	6.423
46	33.087	33.154	33.521	33.755	6.464	6.517	6.858	6.637
47	33.789	33.755	33.287	32.819	6.443	6.898	6.550	6.577
48	32.685	32.251	34.625	33.856	6.423	6.932	6.470	6.764
49	31.549	32.217	32.351	32.652	6.671	6.390	6.704	6.517
50	33.956	34.658	34.525	32.719	6.504	6.778	6.878	6.738
51	34.324	32.485	32.017	32.786	6.457	6.437	6.336	6.858
52	34.123	31.950	34.759	33.689	6.350	6.464	6.771	6.932
53	34.290	31.816	33.388	32.017	6.510	6.738	6.932	6.905
54	33.053	31.615	31.482	34.090	6.711	6.684	6.865	6.571
55	34.391	34.324	31.682	33.655	6.885	6.892	6.912	6.323
56	31.649	34.023	34.324	34.056	6.336	6.758	6.925	6.664
57	32.284	33.990	32.385	31.682	6.410	6.771	6.885	6.490
58	32.986	32.920	31.448	31.615	6.377	6.423	6.691	6.845
59	34.591	33.722	31.549	33.187	6.591	6.484	6.417	6.357
60	32.886	34.558	33.755	32.050	6.370	6.296	6.918	6.778
61	34.692	33.220	32.819	32.619	6.858	6.878	6.664	6.624
62	32.050	34.123	33.488	34.257	6.925	6.791	6.952	6.785
63	32.150	32.284	34.190	32.585	6.738	6.805	6.778	6.343
64	33.555	33.588	33.555	34.290	6.778	6.918	6.477	6.698
65	34.056	32.150	32.284	32.318	6.791	6.591	6.711	6.938
66	33.287	31.682	33.588	34.324	6.905	6.845	6.678	6.450
67	32.752	33.087	31.749	33.488	6.952	6.885	6.798	6.651
68	31.983	32.685	33.154	34.023	6.383	6.905	6.698	6.504
69	31.515	31.916	34.123	32.217	6.330	6.430	6.651	6.544
70	34.357	32.986	32.050	32.351	6.744	6.403	6.898	6.631
71	32.184	34.257	33.120	33.020	6.758	6.858	6.731	6.417
72	32.953	33.789	32.251	34.458	6.831	6.557	6.825	6.377
73	33.889	34.190	31.716	33.555	6.865	6.865	6.490	6.537
74	33.722	34.491	32.184	32.418	6.892	6.310	6.604	6.711
75	34.458	34.357	32.451	33.254	6.691	6.571	6.831	6.892
76	33.455	33.254	34.458	31.448	6.678	6.550	6.330	6.684
77	33.822	32.786	34.558	34.725	6.751	6.383	6.751	6.604
78	33.923	33.187	31.883	32.385	6.704	6.838	6.370	6.798
79	31.448	34.224	33.956	31.749	6.430	6.363	6.524	6.871
80	33.254	32.719	31.582	32.752	6.617	6.925	6.624	6.383
81	32.385	32.819	34.290	34.525	6.644	6.604	6.484	6.550

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
82	34.424	32.552	33.254	34.224	6.918	6.524	6.905	6.838
83	33.655	32.318	32.485	34.123	6.303	6.831	6.430	6.644
84	34.224	33.822	34.257	34.157	6.631	6.731	6.764	6.336
85	34.090	32.385	32.685	31.850	6.417	6.751	6.791	6.524
86	33.990	32.351	31.649	34.625	6.477	6.357	6.557	6.457
87	34.759	34.759	32.986	31.549	6.684	6.698	6.497	6.484
88	31.482	32.619	33.990	31.716	6.611	6.410	6.290	6.744
89	33.388	31.983	34.491	31.582	6.537	6.597	6.617	6.443
90	33.187	33.287	31.783	33.990	6.938	6.624	6.377	6.791
91	31.716	31.749	33.655	33.822	6.450	6.497	6.403	6.865
92	34.491	32.585	33.187	31.515	6.811	6.377	6.517	6.718
93	32.451	32.752	32.886	31.783	6.731	6.938	6.838	6.758
94	32.318	33.555	32.585	32.986	6.871	6.851	6.310	6.397
95	33.521	32.050	32.318	32.150	6.403	6.370	6.718	6.296
96	33.354	34.692	34.424	31.916	6.323	6.811	6.437	6.724
97	31.850	33.388	32.853	33.287	6.851	6.671	6.597	6.851
98	31.883	32.853	31.816	32.920	6.637	6.457	6.316	6.657
99	33.020	32.117	33.421	33.421	6.490	6.952	6.805	6.925
100	34.725	33.120	34.090	33.053	6.363	6.718	6.357	6.818

Table G-9: Higher Group 1 Demand Arrival rate: Scenario 4

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	6.698	6.711	6.390	6.370	32.853	34.424	32.117	34.692
2	6.290	6.785	6.892	6.691	34.190	33.321	32.786	33.622
3	6.530	6.664	6.383	6.918	31.749	34.090	31.983	31.883
4	6.818	6.704	6.571	6.952	33.856	33.421	34.023	32.685
5	6.310	6.564	6.564	6.564	33.321	33.923	31.615	33.789
6	6.798	6.303	6.657	6.811	32.518	33.689	33.321	34.391
7	6.296	6.537	6.818	6.898	32.017	34.525	31.850	33.220
8	6.484	6.477	6.644	6.510	34.525	31.448	33.856	33.722
9	6.624	6.417	6.785	6.363	33.120	34.725	33.455	32.451
10	6.945	6.397	6.591	6.831	32.652	32.652	34.591	31.816
11	6.825	6.764	6.350	6.410	33.588	34.391	34.658	33.388
12	6.724	6.336	6.938	6.671	32.786	32.518	33.722	31.950
13	6.470	6.798	6.851	6.290	33.755	34.056	33.923	31.983
14	6.932	6.611	6.871	6.678	31.783	31.716	33.020	32.953
15	6.397	6.631	6.738	6.617	34.257	34.290	31.950	32.117
16	6.805	6.617	6.296	6.530	34.625	33.521	33.354	34.591
17	6.651	6.316	6.323	6.403	34.157	32.418	34.224	33.154
18	6.597	6.470	6.744	6.557	31.682	34.625	31.916	32.853
19	6.845	6.290	6.811	6.470	32.819	31.850	32.552	34.357
20	6.838	6.350	6.363	6.330	32.585	33.020	32.652	34.190
21	6.343	6.510	6.343	6.477	33.421	32.017	33.087	31.649
22	6.497	6.530	6.303	6.430	32.217	31.649	32.418	34.759
23	6.550	6.544	6.577	6.912	33.154	32.451	32.084	34.491
24	6.524	6.651	6.758	6.704	32.418	31.783	32.518	32.886
25	6.584	6.724	6.443	6.316	32.619	33.655	33.889	31.482
26	6.785	6.637	6.631	6.464	34.023	31.549	32.619	32.284
27	6.517	6.818	6.397	6.303	32.485	31.582	34.056	33.521
28	6.437	6.330	6.671	6.611	34.558	33.354	32.920	33.120
29	6.912	6.490	6.544	6.310	34.658	32.184	33.220	33.889

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
30	6.657	6.644	6.845	6.805	31.816	34.157	34.157	32.485
31	6.898	6.945	6.684	6.731	32.117	32.084	34.391	33.321
32	6.390	6.871	6.450	6.497	31.582	33.053	32.217	32.251
33	6.771	6.323	6.504	6.597	32.351	31.883	34.692	33.354
34	6.557	6.825	6.945	6.878	32.719	33.956	32.752	33.588
35	6.764	6.912	6.537	6.390	31.950	32.886	31.515	34.558
36	6.577	6.744	6.611	6.825	32.084	34.591	32.150	34.424
37	6.878	6.343	6.410	6.437	32.251	33.488	33.789	32.084
38	6.571	6.691	6.510	6.350	31.916	31.515	32.719	32.184
39	6.544	6.443	6.584	6.885	33.220	32.953	33.822	32.518
40	6.316	6.657	6.637	6.945	32.920	33.455	34.357	34.658
41	6.604	6.577	6.423	6.751	33.622	34.458	34.725	33.956
42	6.357	6.504	6.464	6.591	32.552	33.889	33.053	32.552
43	6.718	6.584	6.530	6.584	33.488	33.622	32.953	33.087
44	6.664	6.678	6.457	6.771	33.689	31.482	33.689	33.455
45	6.564	6.450	6.724	6.423	31.615	33.856	33.622	33.923
46	6.464	6.517	6.858	6.637	33.087	33.154	33.521	33.755
47	6.443	6.898	6.550	6.577	33.789	33.755	33.287	32.819
48	6.423	6.932	6.470	6.764	32.685	32.251	34.625	33.856
49	6.671	6.390	6.704	6.517	31.549	32.217	32.351	32.652
50	6.504	6.778	6.878	6.738	33.956	34.658	34.525	32.719
51	6.457	6.437	6.336	6.858	34.324	32.485	32.017	32.786
52	6.350	6.464	6.771	6.932	34.123	31.950	34.759	33.689
53	6.510	6.738	6.932	6.905	34.290	31.816	33.388	32.017
54	6.711	6.684	6.865	6.571	33.053	31.615	31.482	34.090
55	6.885	6.892	6.912	6.323	34.391	34.324	31.682	33.655
56	6.336	6.758	6.925	6.664	31.649	34.023	34.324	34.056
57	6.410	6.771	6.885	6.490	32.284	33.990	32.385	31.682
58	6.377	6.423	6.691	6.845	32.986	32.920	31.448	31.615
59	6.591	6.484	6.417	6.357	34.591	33.722	31.549	33.187
60	6.370	6.296	6.918	6.778	32.886	34.558	33.755	32.050
61	6.858	6.878	6.664	6.624	34.692	33.220	32.819	32.619
62	6.925	6.791	6.952	6.785	32.050	34.123	33.488	34.257
63	6.738	6.805	6.778	6.343	32.150	32.284	34.190	32.585
64	6.778	6.918	6.477	6.698	33.555	33.588	33.555	34.290
65	6.791	6.591	6.711	6.938	34.056	32.150	32.284	32.318
66	6.905	6.845	6.678	6.450	33.287	31.682	33.588	34.324
67	6.952	6.885	6.798	6.651	32.752	33.087	31.749	33.488
68	6.383	6.905	6.698	6.504	31.983	32.685	33.154	34.023
69	6.330	6.430	6.651	6.544	31.515	31.916	34.123	32.217
70	6.744	6.403	6.898	6.631	34.357	32.986	32.050	32.351
71	6.758	6.858	6.731	6.417	32.184	34.257	33.120	33.020
72	6.831	6.557	6.825	6.377	32.953	33.789	32.251	34.458
73	6.865	6.865	6.490	6.537	33.889	34.190	31.716	33.555
74	6.892	6.310	6.604	6.711	33.722	34.491	32.184	32.418
75	6.691	6.571	6.831	6.892	34.458	34.357	32.451	33.254
76	6.678	6.550	6.330	6.684	33.455	33.254	34.458	31.448
77	6.751	6.383	6.751	6.604	33.822	32.786	34.558	34.725
78	6.704	6.838	6.370	6.798	33.923	33.187	31.883	32.385
79	6.430	6.363	6.524	6.871	31.448	34.224	33.956	31.749
80	6.617	6.925	6.624	6.383	33.254	32.719	31.582	32.752

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
81	6.644	6.604	6.484	6.550	32.385	32.819	34.290	34.525
82	6.918	6.524	6.905	6.838	34.424	32.552	33.254	34.224
83	6.303	6.831	6.430	6.644	33.655	32.318	32.485	34.123
84	6.631	6.731	6.764	6.336	34.224	33.822	34.257	34.157
85	6.417	6.751	6.791	6.524	34.090	32.385	32.685	31.850
86	6.477	6.357	6.557	6.457	33.990	32.351	31.649	34.625
87	6.684	6.698	6.497	6.484	34.759	34.759	32.986	31.549
88	6.611	6.410	6.290	6.744	31.482	32.619	33.990	31.716
89	6.537	6.597	6.617	6.443	33.388	31.983	34.491	31.582
90	6.938	6.624	6.377	6.791	33.187	33.287	31.783	33.990
91	6.450	6.497	6.403	6.865	31.716	31.749	33.655	33.822
92	6.811	6.377	6.517	6.718	34.491	32.585	33.187	31.515
93	6.731	6.938	6.838	6.758	32.451	32.752	32.886	31.783
94	6.871	6.851	6.310	6.397	32.318	33.555	32.585	32.986
95	6.403	6.370	6.718	6.296	33.521	32.050	32.318	32.150
96	6.323	6.811	6.437	6.724	33.354	34.692	34.424	31.916
97	6.851	6.671	6.597	6.851	31.850	33.388	32.853	33.287
98	6.637	6.457	6.316	6.657	31.883	32.853	31.816	32.920
99	6.490	6.952	6.805	6.925	33.020	32.117	33.421	33.421
100	6.363	6.718	6.357	6.818	34.725	33.120	34.090	33.053

G.2.3 95% Load level

Table G-10: Homogeneous Demand: Scenarios 1 and 3

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	8.689	8.612	8.306	8.349	8.655	8.255	8.145	8.111
2	8.791	8.196	8.009	8.485	8.391	8.485	8.000	8.272
3	8.187	8.510	8.145	8.766	8.357	8.434	8.604	8.230
4	8.374	8.094	8.332	8.374	8.672	8.459	8.170	8.060
5	8.298	8.238	8.834	8.680	8.340	8.732	8.544	8.391
6	8.766	8.698	8.519	8.400	8.272	8.170	8.723	8.740
7	8.621	8.043	8.323	8.757	8.213	8.340	8.187	8.519
8	8.408	8.230	8.825	8.638	8.442	8.306	8.468	8.825
9	8.519	8.128	8.179	8.196	8.638	8.153	8.026	8.425
10	8.383	8.502	8.723	8.595	8.842	8.349	8.442	8.068
11	8.136	8.842	8.570	8.204	8.791	8.646	8.272	8.732
12	8.247	8.621	8.187	8.077	8.493	8.060	8.085	8.774
13	8.740	8.366	8.621	8.706	8.238	8.468	8.332	8.170
14	8.680	8.306	8.774	8.043	8.715	8.221	8.655	8.179
15	8.196	8.281	8.578	8.468	8.698	8.119	8.111	8.476
16	8.051	8.357	8.706	8.289	8.408	8.689	8.221	8.281
17	8.068	8.578	8.068	8.323	8.153	8.196	8.077	8.442
18	8.281	8.425	8.170	8.264	8.026	8.502	8.808	8.298
19	8.077	8.374	8.536	8.332	8.612	8.800	8.774	8.145
20	8.272	8.680	8.238	8.791	8.706	8.442	8.417	8.817
21	8.672	8.434	8.221	8.391	8.374	8.051	8.306	8.493
22	8.817	8.732	8.213	8.094	8.740	8.638	8.680	8.842
23	8.578	8.723	8.272	8.783	8.663	8.774	8.051	8.698
24	8.476	8.715	8.629	8.145	8.009	8.238	8.757	8.349
25	8.332	8.808	8.434	8.723	8.102	8.570	8.009	8.663

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
26	8.213	8.587	8.732	8.570	8.281	8.017	8.408	8.153
27	8.128	8.077	8.000	8.655	8.255	8.400	8.289	8.102
28	8.536	8.757	8.017	8.476	8.230	8.842	8.578	8.561
29	8.085	8.655	8.451	8.298	8.774	8.604	8.825	8.638
30	8.434	8.417	8.374	8.383	8.136	8.315	8.034	8.680
31	8.264	8.604	8.817	8.629	8.536	8.698	8.238	8.749
32	8.255	8.221	8.808	8.663	8.349	8.272	8.043	8.043
33	8.230	8.783	8.646	8.808	8.017	8.476	8.425	8.221
34	8.017	8.068	8.060	8.519	8.485	8.417	8.740	8.485
35	8.349	8.315	8.842	8.000	8.808	8.230	8.340	8.587
36	8.808	8.766	8.476	8.315	8.170	8.834	8.800	8.417
37	8.221	8.162	8.357	8.340	8.179	8.672	8.400	8.655
38	8.783	8.264	8.672	8.621	8.077	8.527	8.715	8.621
39	8.757	8.026	8.485	8.179	8.723	8.621	8.349	8.791
40	8.238	8.272	8.264	8.612	8.034	8.162	8.553	8.459
41	8.732	8.119	8.612	8.561	8.825	8.383	8.391	8.383
42	8.485	8.774	8.289	8.060	8.425	8.247	8.476	8.289
43	8.357	8.400	8.663	8.111	8.094	8.749	8.612	8.213
44	8.544	8.629	8.698	8.689	8.519	8.391	8.749	8.451
45	8.510	8.485	8.783	8.502	8.400	8.825	8.834	8.808
46	8.663	8.145	8.425	8.247	8.561	8.655	8.842	8.553
47	8.145	8.111	8.510	8.051	8.817	8.612	8.281	8.468
48	8.009	8.791	8.502	8.442	8.570	8.425	8.060	8.366
49	8.638	8.383	8.128	8.834	8.544	8.187	8.017	8.510
50	8.026	8.136	8.638	8.451	8.646	8.408	8.766	8.570
51	8.587	8.638	8.527	8.128	8.732	8.179	8.689	8.629
52	8.000	8.527	8.749	8.272	8.060	8.204	8.255	8.527
53	8.162	8.349	8.026	8.366	8.553	8.451	8.196	8.408
54	8.715	8.451	8.102	8.213	8.749	8.289	8.638	8.196
55	8.595	8.408	8.587	8.068	8.145	8.578	8.527	8.706
56	8.723	8.740	8.680	8.281	8.468	8.536	8.510	8.094
57	8.749	8.060	8.595	8.136	8.451	8.085	8.783	8.544
58	8.340	8.009	8.400	8.434	8.247	8.519	8.698	8.238
59	8.366	8.536	8.655	8.817	8.834	8.077	8.587	8.766
60	8.604	8.247	8.544	8.408	8.578	8.510	8.817	8.026
61	8.111	8.519	8.442	8.672	8.111	8.629	8.663	8.578
62	8.102	8.689	8.408	8.842	8.119	8.102	8.068	8.323
63	8.289	8.672	8.043	8.170	8.417	8.561	8.706	8.800
64	8.612	8.298	8.247	8.527	8.204	8.757	8.536	8.357
65	8.306	8.825	8.391	8.187	8.000	8.128	8.247	8.162
66	8.060	8.153	8.417	8.825	8.510	8.026	8.485	8.119
67	8.774	8.051	8.153	8.715	8.366	8.366	8.502	8.077
68	8.391	8.468	8.111	8.604	8.051	8.544	8.094	8.204
69	8.502	8.179	8.791	8.085	8.196	8.587	8.162	8.340
70	8.825	8.459	8.119	8.162	8.085	8.094	8.646	8.502
71	8.800	8.289	8.553	8.749	8.783	8.009	8.732	8.034
72	8.400	8.570	8.459	8.230	8.434	8.817	8.102	8.672
73	8.204	8.323	8.230	8.238	8.298	8.264	8.451	8.128
74	8.834	8.544	8.766	8.646	8.043	8.766	8.179	8.757
75	8.629	8.800	8.162	8.740	8.766	8.323	8.595	8.085
76	8.315	8.170	8.740	8.425	8.383	8.043	8.672	8.374

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
77	8.034	8.663	8.366	8.544	8.502	8.136	8.459	8.536
78	8.094	8.204	8.715	8.221	8.323	8.791	8.791	8.612
79	8.442	8.706	8.468	8.732	8.459	8.298	8.230	8.315
80	8.493	8.834	8.757	8.119	8.527	8.068	8.128	8.255
81	8.655	8.595	8.051	8.417	8.315	8.595	8.434	8.000
82	8.527	8.561	8.034	8.578	8.221	8.332	8.493	8.715
83	8.706	8.442	8.085	8.102	8.289	8.680	8.315	8.604
84	8.119	8.085	8.077	8.017	8.306	8.723	8.561	8.332
85	8.459	8.255	8.493	8.255	8.476	8.000	8.383	8.834
86	8.043	8.391	8.204	8.774	8.264	8.357	8.213	8.689
87	8.646	8.187	8.383	8.026	8.162	8.281	8.374	8.306
88	8.553	8.646	8.340	8.536	8.587	8.783	8.264	8.247
89	8.179	8.102	8.298	8.698	8.332	8.808	8.119	8.434
90	8.561	8.213	8.136	8.587	8.629	8.706	8.519	8.783
91	8.425	8.476	8.281	8.034	8.604	8.740	8.570	8.187
92	8.323	8.332	8.315	8.800	8.757	8.553	8.298	8.400
93	8.570	8.017	8.689	8.306	8.128	8.213	8.204	8.646
94	8.468	8.000	8.604	8.553	8.068	8.111	8.357	8.136
95	8.417	8.493	8.349	8.459	8.595	8.034	8.629	8.264
96	8.153	8.553	8.196	8.153	8.187	8.663	8.136	8.017
97	8.170	8.340	8.561	8.009	8.680	8.145	8.366	8.051
98	8.842	8.749	8.255	8.510	8.689	8.374	8.323	8.723
99	8.698	8.817	8.800	8.357	8.621	8.493	8.153	8.595
100	8.451	8.034	8.094	8.493	8.800	8.715	8.621	8.009

Table G-11: Higher Group 2 Demand Arrival rate: Scenarios 2 and 5

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	25.633	24.868	24.689	25.837	5.035	5.300	4.892	5.086
2	24.332	24.817	24.715	25.761	5.086	5.213	5.116	5.111
3	25.123	25.684	25.761	24.255	4.948	5.208	5.254	4.938
4	24.102	24.919	24.817	24.383	5.070	5.188	5.019	4.943
5	24.230	26.475	25.097	26.348	4.958	5.142	4.856	5.091
6	25.276	25.812	25.455	25.633	5.076	5.035	4.866	4.820
7	24.766	24.561	24.791	25.939	5.157	5.203	4.933	4.815
8	25.378	24.612	25.939	26.322	4.856	5.173	4.907	4.897
9	24.204	26.501	25.710	25.123	4.968	4.826	5.055	4.907
10	24.715	24.102	24.077	24.051	5.270	5.055	4.928	5.055
11	25.965	24.638	25.888	26.118	5.224	5.234	5.004	4.928
12	24.306	26.093	24.179	25.046	5.305	4.953	4.994	5.173
13	26.501	24.408	25.863	26.169	5.025	4.938	5.076	4.999
14	24.868	24.766	24.638	24.281	4.887	5.122	5.305	5.142
15	25.786	24.128	25.990	24.791	5.065	4.928	4.831	4.953
16	25.455	26.016	26.271	25.072	5.111	5.132	4.805	5.101
17	26.093	26.067	25.633	25.276	4.815	4.871	5.234	4.902
18	24.051	25.046	25.735	26.195	5.173	4.836	5.127	5.070
19	24.459	24.485	25.965	24.128	4.989	5.065	4.922	5.152
20	25.608	26.297	26.144	26.450	5.234	4.815	5.142	5.270
21	24.663	25.097	25.148	25.786	4.882	4.897	5.229	4.989
22	25.506	24.740	26.195	25.710	4.943	5.127	4.984	5.254
23	25.557	25.174	24.102	25.225	4.892	4.851	5.101	5.147
24	24.408	25.939	26.041	25.199	4.984	5.290	4.963	4.984

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
25	25.250	24.306	24.510	25.250	5.208	4.912	4.810	4.851
26	24.740	25.837	25.837	24.434	5.244	4.831	4.902	5.040
27	24.179	24.510	24.230	24.740	4.851	5.295	4.999	5.219
28	24.791	24.255	26.322	26.041	4.912	4.820	5.152	5.208
29	24.128	24.689	24.919	25.506	4.871	5.004	4.871	5.030
30	25.327	26.169	24.128	24.689	4.979	5.050	4.877	5.065
31	26.041	26.373	25.174	24.179	5.040	5.081	5.106	5.305
32	24.536	24.077	24.587	25.097	5.132	4.974	5.270	4.810
33	26.169	25.990	25.812	25.965	4.917	4.892	4.948	5.127
34	25.174	24.434	25.072	24.153	5.116	4.933	5.096	5.096
35	25.046	25.123	25.250	26.526	4.846	4.979	5.014	5.183
36	24.689	26.424	25.429	25.352	4.963	4.958	5.025	5.264
37	26.220	24.204	24.612	25.021	4.836	5.275	5.035	5.188
38	25.582	25.531	24.153	24.995	5.249	5.244	4.958	5.290
39	26.118	25.633	25.914	25.429	5.254	5.137	5.147	5.285
40	24.587	24.970	26.297	25.404	5.259	5.239	4.938	4.979
41	24.944	25.021	25.046	25.812	4.861	5.152	5.244	5.275
42	25.684	26.399	25.276	25.301	5.014	5.086	5.295	5.167
43	24.434	25.225	25.123	24.944	5.096	4.902	5.259	5.213
44	25.735	24.230	25.404	24.510	5.178	5.264	5.290	4.861
45	24.485	26.144	26.067	24.970	5.213	5.254	5.188	5.234
46	25.301	25.301	25.531	24.868	4.805	4.922	4.851	5.122
47	24.995	25.480	24.561	24.638	5.203	5.183	5.275	5.116
48	26.373	25.888	25.786	24.893	5.264	4.948	4.897	4.856
49	24.638	26.118	26.526	26.246	5.019	5.076	5.162	5.050
50	26.399	25.352	24.893	25.990	5.239	5.111	4.882	5.162
51	24.919	26.220	24.536	25.480	4.866	5.045	5.086	4.892
52	25.531	24.663	24.868	25.863	4.907	4.810	4.968	4.846
53	24.153	25.378	24.970	26.501	5.183	5.116	4.917	5.300
54	24.817	25.557	25.684	24.715	4.810	5.270	5.009	5.259
55	24.842	24.995	24.000	24.561	4.933	4.999	5.091	4.877
56	25.148	26.526	24.766	26.093	5.081	4.856	4.820	5.076
57	24.561	25.455	24.408	26.271	5.162	5.229	5.300	4.917
58	24.255	24.536	26.475	24.817	5.229	5.014	5.167	4.974
59	25.990	24.459	24.204	26.475	5.152	4.963	5.065	5.178
60	26.450	26.322	26.450	25.735	4.922	5.198	5.040	5.198
61	26.016	25.863	24.255	25.608	4.902	5.305	5.198	5.106
62	25.429	25.404	25.301	25.378	5.127	4.841	5.045	5.025
63	26.067	26.246	25.659	24.587	5.142	5.147	5.060	5.004
64	24.357	25.608	26.501	24.357	4.953	5.030	5.178	5.244
65	25.659	25.965	26.220	25.659	4.800	5.193	5.249	5.019
66	26.475	25.072	24.944	24.332	5.060	5.162	4.800	5.137
67	26.195	25.761	26.348	24.230	5.030	4.917	5.208	4.933
68	24.077	26.041	24.995	25.557	5.295	4.882	4.943	4.841
69	24.510	25.199	26.118	24.026	5.004	4.907	5.239	4.831
70	25.914	24.383	24.026	24.842	5.188	5.249	5.030	4.912
71	25.863	25.506	26.373	24.102	4.897	5.224	4.953	4.963
72	24.383	25.786	24.051	26.297	5.193	4.994	5.264	5.203
73	25.888	24.281	24.485	26.016	4.877	5.259	5.183	4.922
74	26.348	25.250	24.281	25.914	5.101	4.866	4.826	5.014
75	25.021	24.357	25.608	24.306	5.280	5.157	4.974	5.229

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
76	25.710	24.332	26.424	24.077	5.009	5.040	5.111	4.968
77	26.526	25.327	24.663	25.327	4.826	4.968	4.912	4.994
78	26.424	26.195	26.399	25.531	4.999	5.101	5.173	4.805
79	26.144	25.710	24.383	26.424	4.928	4.943	5.213	4.948
80	25.939	25.735	25.021	24.919	5.219	4.989	5.280	4.866
81	25.404	26.348	25.378	26.220	5.290	5.091	5.122	4.887
82	25.761	24.893	25.327	24.766	4.831	5.060	5.070	4.800
83	24.000	24.587	25.225	24.459	5.055	4.800	4.861	4.882
84	25.352	24.842	25.506	24.204	5.167	5.178	4.846	4.871
85	24.970	24.000	25.480	24.408	4.938	5.280	5.137	5.295
86	24.612	26.271	26.169	26.399	4.820	5.070	4.979	4.826
87	24.281	24.944	24.332	25.888	5.050	4.805	4.989	5.060
88	26.322	24.153	26.016	25.582	5.122	5.285	4.887	5.224
89	25.072	25.914	24.842	26.373	5.275	5.219	4.841	5.045
90	26.271	24.026	24.740	24.536	4.994	5.025	5.203	5.035
91	24.026	25.659	24.306	24.612	4.841	4.984	5.081	5.132
92	25.480	24.179	24.434	25.148	4.974	5.019	4.815	5.157
93	25.225	25.148	25.352	25.455	5.106	4.887	4.836	5.280
94	26.297	25.276	25.582	24.485	5.285	4.861	5.050	5.193
95	25.812	24.715	25.199	25.174	5.045	5.009	5.193	5.249
96	24.893	25.429	25.557	24.000	5.300	4.877	5.219	5.009
97	25.837	26.450	24.459	24.663	5.091	4.846	5.224	5.081
98	25.199	24.791	26.246	26.144	5.137	5.096	5.285	4.958
99	25.097	24.051	26.093	25.684	5.198	5.106	5.157	5.239
100	26.246	25.582	24.357	26.067	5.147	5.167	5.132	4.836

Table G-12: Higher Group 1 Demand Arrival rate: Scenario 4

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
1	5.035	5.300	4.892	5.086	25.633	24.868	24.689	25.837
2	5.086	5.213	5.116	5.111	24.332	24.817	24.715	25.761
3	4.948	5.208	5.254	4.938	25.123	25.684	25.761	24.255
4	5.070	5.188	5.019	4.943	24.102	24.919	24.817	24.383
5	4.958	5.142	4.856	5.091	24.230	26.475	25.097	26.348
6	5.076	5.035	4.866	4.820	25.276	25.812	25.455	25.633
7	5.157	5.203	4.933	4.815	24.766	24.561	24.791	25.939
8	4.856	5.173	4.907	4.897	25.378	24.612	25.939	26.322
9	4.968	4.826	5.055	4.907	24.204	26.501	25.710	25.123
10	5.270	5.055	4.928	5.055	24.715	24.102	24.077	24.051
11	5.224	5.234	5.004	4.928	25.965	24.638	25.888	26.118
12	5.305	4.953	4.994	5.173	24.306	26.093	24.179	25.046
13	5.025	4.938	5.076	4.999	26.501	24.408	25.863	26.169
14	4.887	5.122	5.305	5.142	24.868	24.766	24.638	24.281
15	5.065	4.928	4.831	4.953	25.786	24.128	25.990	24.791
16	5.111	5.132	4.805	5.101	25.455	26.016	26.271	25.072
17	4.815	4.871	5.234	4.902	26.093	26.067	25.633	25.276
18	5.173	4.836	5.127	5.070	24.051	25.046	25.735	26.195
19	4.989	5.065	4.922	5.152	24.459	24.485	25.965	24.128
20	5.234	4.815	5.142	5.270	25.608	26.297	26.144	26.450
21	4.882	4.897	5.229	4.989	24.663	25.097	25.148	25.786
22	4.943	5.127	4.984	5.254	25.506	24.740	26.195	25.710
23	4.892	4.851	5.101	5.147	25.557	25.174	24.102	25.225

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
24	4.984	5.290	4.963	4.984	24.408	25.939	26.041	25.199
25	5.208	4.912	4.810	4.851	25.250	24.306	24.510	25.250
26	5.244	4.831	4.902	5.040	24.740	25.837	25.837	24.434
27	4.851	5.295	4.999	5.219	24.179	24.510	24.230	24.740
28	4.912	4.820	5.152	5.208	24.791	24.255	26.322	26.041
29	4.871	5.004	4.871	5.030	24.128	24.689	24.919	25.506
30	4.979	5.050	4.877	5.065	25.327	26.169	24.128	24.689
31	5.040	5.081	5.106	5.305	26.041	26.373	25.174	24.179
32	5.132	4.974	5.270	4.810	24.536	24.077	24.587	25.097
33	4.917	4.892	4.948	5.127	26.169	25.990	25.812	25.965
34	5.116	4.933	5.096	5.096	25.174	24.434	25.072	24.153
35	4.846	4.979	5.014	5.183	25.046	25.123	25.250	26.526
36	4.963	4.958	5.025	5.264	24.689	26.424	25.429	25.352
37	4.836	5.275	5.035	5.188	26.220	24.204	24.612	25.021
38	5.249	5.244	4.958	5.290	25.582	25.531	24.153	24.995
39	5.254	5.137	5.147	5.285	26.118	25.633	25.914	25.429
40	5.259	5.239	4.938	4.979	24.587	24.970	26.297	25.404
41	4.861	5.152	5.244	5.275	24.944	25.021	25.046	25.812
42	5.014	5.086	5.295	5.167	25.684	26.399	25.276	25.301
43	5.096	4.902	5.259	5.213	24.434	25.225	25.123	24.944
44	5.178	5.264	5.290	4.861	25.735	24.230	25.404	24.510
45	5.213	5.254	5.188	5.234	24.485	26.144	26.067	24.970
46	4.805	4.922	4.851	5.122	25.301	25.301	25.531	24.868
47	5.203	5.183	5.275	5.116	24.995	25.480	24.561	24.638
48	5.264	4.948	4.897	4.856	26.373	25.888	25.786	24.893
49	5.019	5.076	5.162	5.050	24.638	26.118	26.526	26.246
50	5.239	5.111	4.882	5.162	26.399	25.352	24.893	25.990
51	4.866	5.045	5.086	4.892	24.919	26.220	24.536	25.480
52	4.907	4.810	4.968	4.846	25.531	24.663	24.868	25.863
53	5.183	5.116	4.917	5.300	24.153	25.378	24.970	26.501
54	4.810	5.270	5.009	5.259	24.817	25.557	25.684	24.715
55	4.933	4.999	5.091	4.877	24.842	24.995	24.000	24.561
56	5.081	4.856	4.820	5.076	25.148	26.526	24.766	26.093
57	5.162	5.229	5.300	4.917	24.561	25.455	24.408	26.271
58	5.229	5.014	5.167	4.974	24.255	24.536	26.475	24.817
59	5.152	4.963	5.065	5.178	25.990	24.459	24.204	26.475
60	4.922	5.198	5.040	5.198	26.450	26.322	26.450	25.735
61	4.902	5.305	5.198	5.106	26.016	25.863	24.255	25.608
62	5.127	4.841	5.045	5.025	25.429	25.404	25.301	25.378
63	5.142	5.147	5.060	5.004	26.067	26.246	25.659	24.587
64	4.953	5.030	5.178	5.244	24.357	25.608	26.501	24.357
65	4.800	5.193	5.249	5.019	25.659	25.965	26.220	25.659
66	5.060	5.162	4.800	5.137	26.475	25.072	24.944	24.332
67	5.030	4.917	5.208	4.933	26.195	25.761	26.348	24.230
68	5.295	4.882	4.943	4.841	24.077	26.041	24.995	25.557
69	5.004	4.907	5.239	4.831	24.510	25.199	26.118	24.026
70	5.188	5.249	5.030	4.912	25.914	24.383	24.026	24.842
71	4.897	5.224	4.953	4.963	25.863	25.506	26.373	24.102
72	5.193	4.994	5.264	5.203	24.383	25.786	24.051	26.297
73	4.877	5.259	5.183	4.922	25.888	24.281	24.485	26.016
74	5.101	4.866	4.826	5.014	26.348	25.250	24.281	25.914

Run No.	MEAN 1	MEAN 2	MEAN 3	MEAN 4	MEAN 5	MEAN 6	MEAN 7	MEAN 8
75	5.280	5.157	4.974	5.229	25.021	24.357	25.608	24.306
76	5.009	5.040	5.111	4.968	25.710	24.332	26.424	24.077
77	4.826	4.968	4.912	4.994	26.526	25.327	24.663	25.327
78	4.999	5.101	5.173	4.805	26.424	26.195	26.399	25.531
79	4.928	4.943	5.213	4.948	26.144	25.710	24.383	26.424
80	5.219	4.989	5.280	4.866	25.939	25.735	25.021	24.919
81	5.290	5.091	5.122	4.887	25.404	26.348	25.378	26.220
82	4.831	5.060	5.070	4.800	25.761	24.893	25.327	24.766
83	5.055	4.800	4.861	4.882	24.000	24.587	25.225	24.459
84	5.167	5.178	4.846	4.871	25.352	24.842	25.506	24.204
85	4.938	5.280	5.137	5.295	24.970	24.000	25.480	24.408
86	4.820	5.070	4.979	4.826	24.612	26.271	26.169	26.399
87	5.050	4.805	4.989	5.060	24.281	24.944	24.332	25.888
88	5.122	5.285	4.887	5.224	26.322	24.153	26.016	25.582
89	5.275	5.219	4.841	5.045	25.072	25.914	24.842	26.373
90	4.994	5.025	5.203	5.035	26.271	24.026	24.740	24.536
91	4.841	4.984	5.081	5.132	24.026	25.659	24.306	24.612
92	4.974	5.019	4.815	5.157	25.480	24.179	24.434	25.148
93	5.106	4.887	4.836	5.280	25.225	25.148	25.352	25.455
94	5.285	4.861	5.050	5.193	26.297	25.276	25.582	24.485
95	5.045	5.009	5.193	5.249	25.812	24.715	25.199	25.174
96	5.300	4.877	5.219	5.009	24.893	25.429	25.557	24.000
97	5.091	4.846	5.224	5.081	25.837	26.450	24.459	24.663
98	5.137	5.096	5.285	4.958	25.199	24.791	26.246	26.144
99	5.198	5.106	5.157	5.239	25.097	24.051	26.093	25.684
100	5.147	5.167	5.132	4.836	26.246	25.582	24.357	26.067

APPENDIX - H : GROUP SERVICE LEVEL ROBUSTNESS

In this appendix the service level robustness charts for the two product groups in the eight product system are presented. It starts with those for the 50% load level in Section H.1, the 72.5% load level in Section H.2 and the 95% load level in Section H.3.

TABLE OF CONTENTS

Page

H.1 50% Load Level H-4

H.1.1 Scenario 1: Homogeneous Processing time and Demand H-4
H.1.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand....................H-4
H.1.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand....................H-5
H.1.4 Scenario 4: Higher Processing time and Higher Demand for Group 1 ....H-6
H.1.5 Scenario 5: Higher Processing time and Lower Demand for Group 1 ....H-6

H.2 72.5% Load Level H-7

H.2.1 Scenario 1: Homogeneous Processing time and Demand H-7
H.2.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand....................H-8
H.2.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand....................H-8
H.2.4 Scenario 4: Higher Processing time and Higher Demand for Group 1 ....H-9
H.2.5 Scenario 5: Higher Processing time and Lower Demand for Group 1 ....H-10

H.3 95% Load Level H-10

H.3.1 Scenario 1: Homogeneous Processing time and Demand H-10
H.3.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand....................H-11
H.3.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand....................H-12
H.3.4 Scenario 4: Higher Processing time and Higher Demand for Group 1 ....H-12

H.3.5 Scenario 5: Higher Processing time and Lower Demand for Group 1 ....H-13

LIST OF FIGURES

Page

Figure H-1: SLG1 Robustness – 50% Load Level Scenario 1....................H-4
Figure H-2: SLG2 Robustness – 50% Load Level Scenario 1....................H-4
Figure H-3: SLG1 Robustness – 50% Load Level Scenario 2....................H-4
Figure H-4: SLG2 Robustness – 50% Load Level Scenario 2....................H-5
Figure H-5: SLG1 Robustness – 50% Load Level Scenario 3....................H-5
Figure H-6: SLG2 Robustness – 50% Load Level Scenario 3....................H-5
Figure H-7: SLG1 Robustness – 50% Load Level Scenario 4....................H-6
Figure H-8: SLG2 Robustness – 50% Load Level Scenario 4....................H-6
Figure H-9: SLG1 Robustness – 50% Load Level Scenario 5....................H-6
Figure H-10: SLG2 Robustness – 50% Load Level Scenario 5....................H-7
Figure H-11: SLG1 Robustness – 72.5% Load Level Scenario 1....................H-7
Figure H-12: SLG2 Robustness – 72.5% Load Level Scenario 1....................H-7
Figure H-13: SLG1 Robustness – 72.5% Load Level Scenario 2....................H-8
Figure H-14: SLG2 Robustness – 72.5% Load Level Scenario 2....................H-8
Figure H-15: SLG1 Robustness – 72.5% Load Level Scenario 3....................H-8
Figure H-16: SLG2 Robustness – 72.5% Load Level Scenario 3....................H-9
Figure H-17: SLG1 Robustness – 72.5% Load Level Scenario 4....................H-9
Figure H-18: SLG2 Robustness – 72.5% Load Level Scenario 4....................H-9
Figure H-19: SLG1 Robustness – 72.5% Load Level Scenario 5....................H-10
Figure H-20: SLG2 Robustness –72.5% Load Level Scenario 5....................H-10
Figure H-21: SLG1 Robustness – 95% Load Level Scenario 1....................H-10
Figure H-22: SLG2 Robustness – 95% Load Level Scenario 1....................H-11
Figure H-23: SLG1 Robustness – 95% Load Level Scenario 2....................H-11
Figure H-24: SLG2 Robustness – 95% Load Level Scenario 2....................H-11
Figure H-25: SLG1 Robustness – 95% Load Level Scenario 3....................H-12

Figure H-26: SLG2 Robustness – 95% Load Level Scenario 3..................................H-12
Figure H-27: SLG1 Robustness – 95% Load Level Scenario 4..................................H-12
Figure H-28: SLG2 Robustness – 95% Load Level Scenario 4..................................H-13
Figure H-29: SLG1 Robustness – 95% Load Level Scenario 5..................................H-13
Figure H-30: SLG2 Robustness – 95% Load Level Scenario 5..................................H-13

H.1 50% LOAD LEVEL

H.1.1 Scenario 1: Homogeneous Processing time and Demand

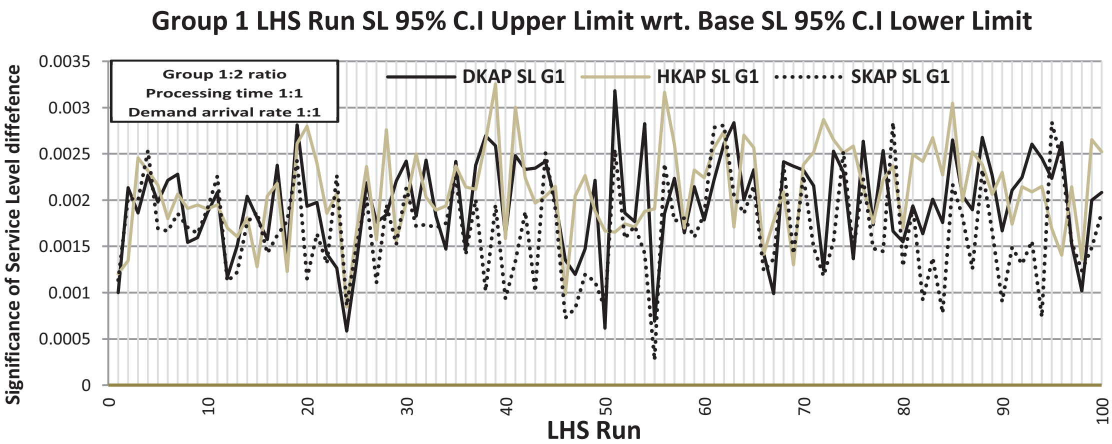


Figure H-1: SLG1 Robustness – 50% Load Level Scenario 1

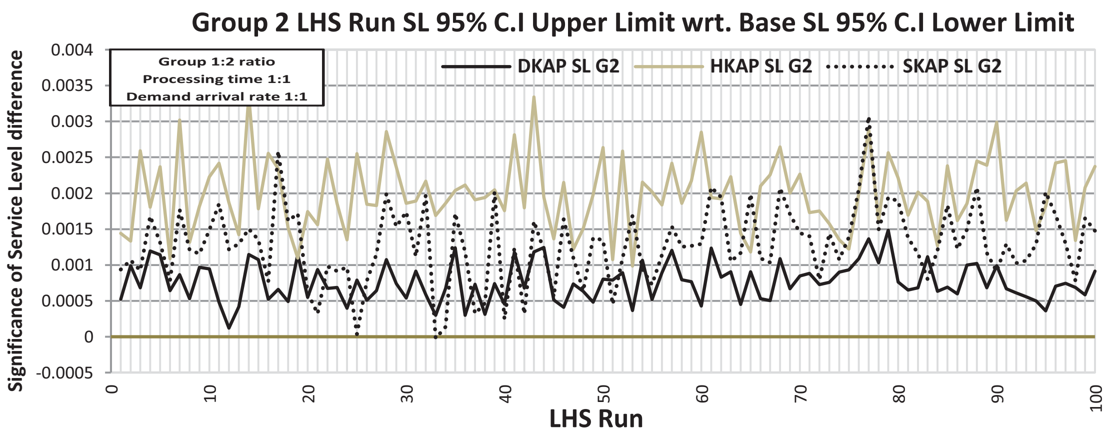


Figure H-2: SLG2 Robustness – 50% Load Level Scenario 1

H.1.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand

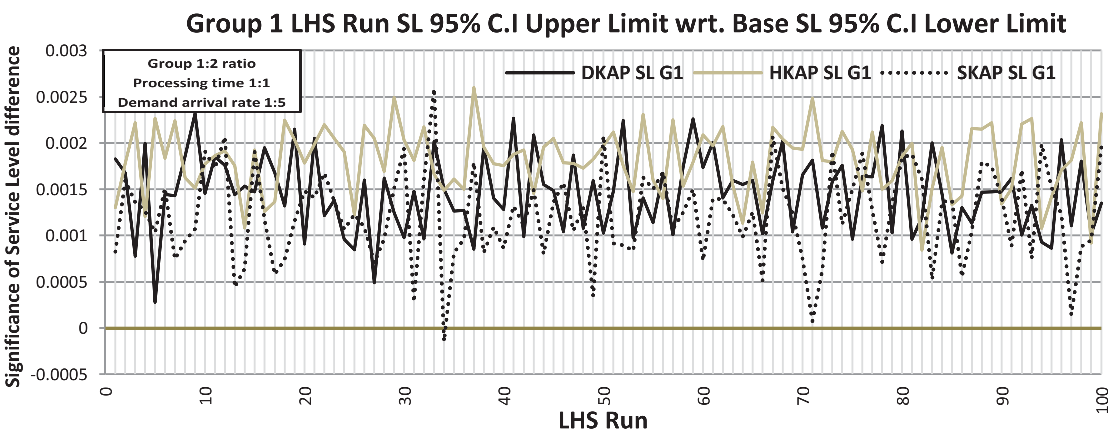


Figure H-3: SLG1 Robustness – 50% Load Level Scenario 2

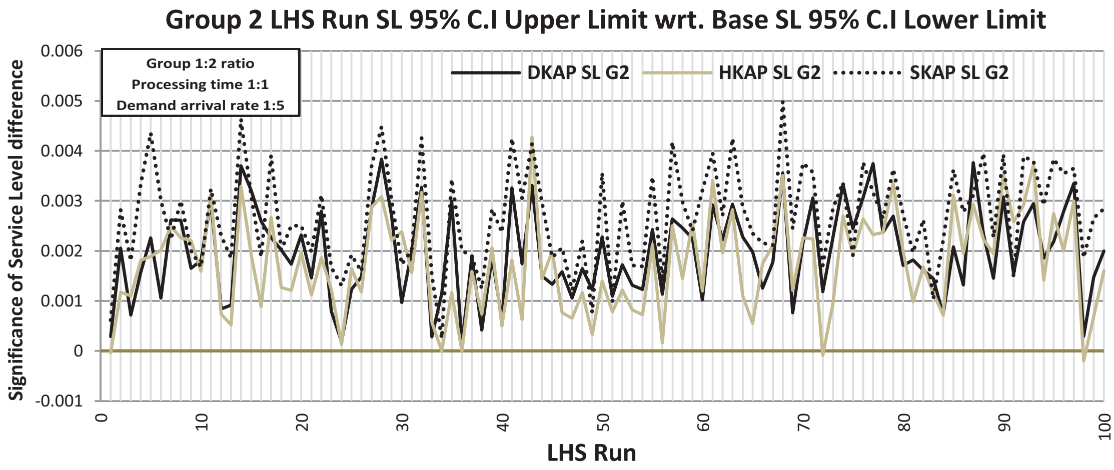


Figure H-4: SLG2 Robustness – 50% Load Level Scenario 2

H.1.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand

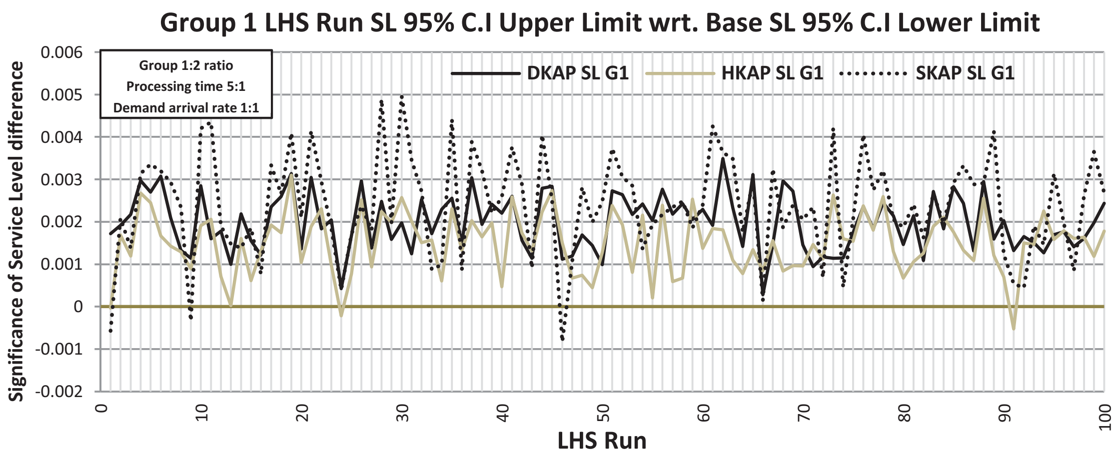


Figure H-5: SLG1 Robustness – 50% Load Level Scenario 3

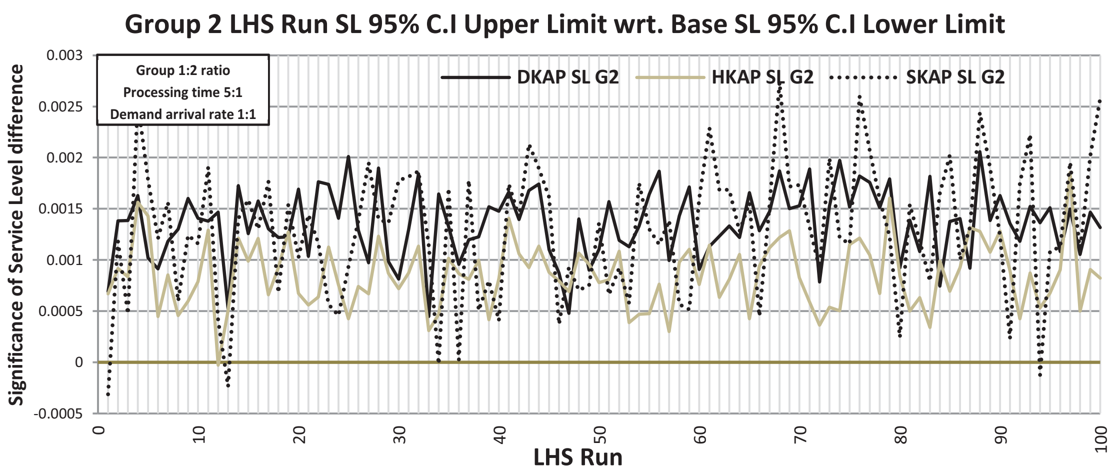


Figure H-6: SLG2 Robustness – 50% Load Level Scenario 3

H.1.4 Scenario 4: Higher Processing time and Higher Demand for Group 1

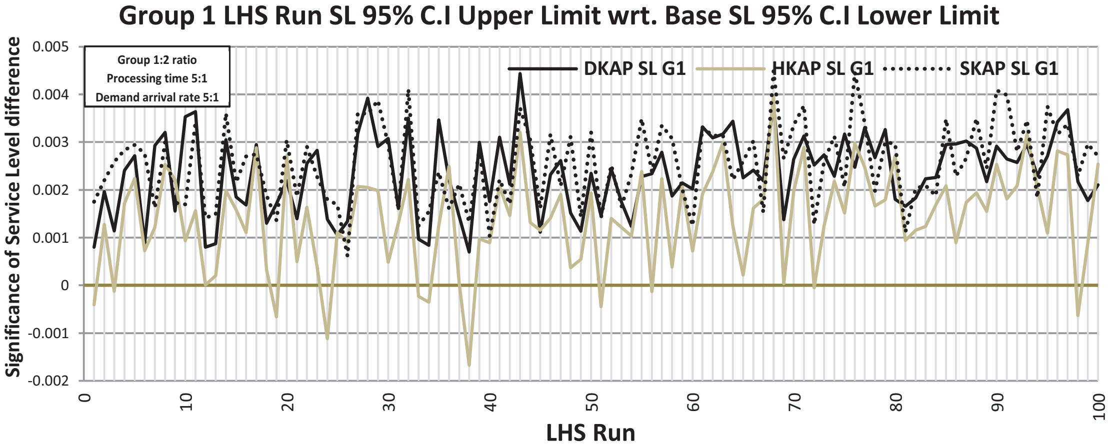


Figure H-7: SLG1 Robustness – 50% Load Level Scenario 4

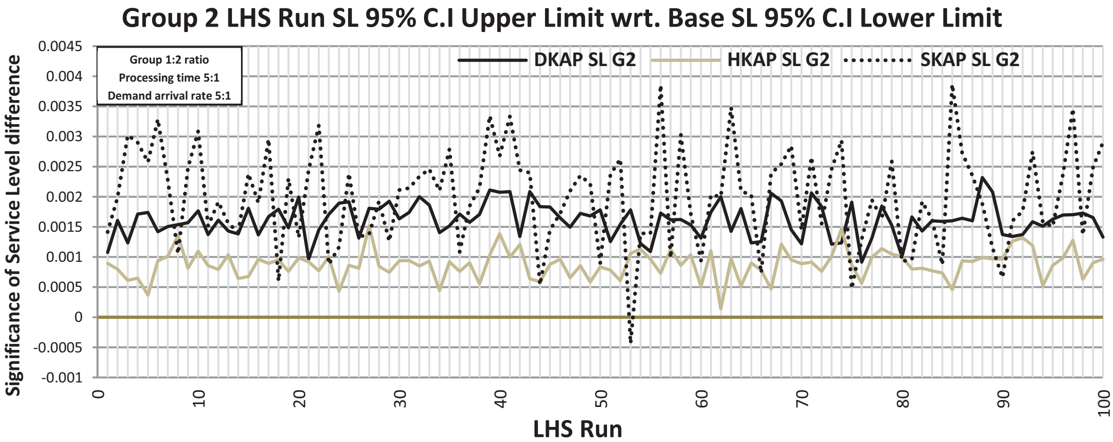


Figure H-8: SLG2 Robustness – 50% Load Level Scenario 4

H.1.5 Scenario 5: Higher Processing time and Lower Demand for Group 1

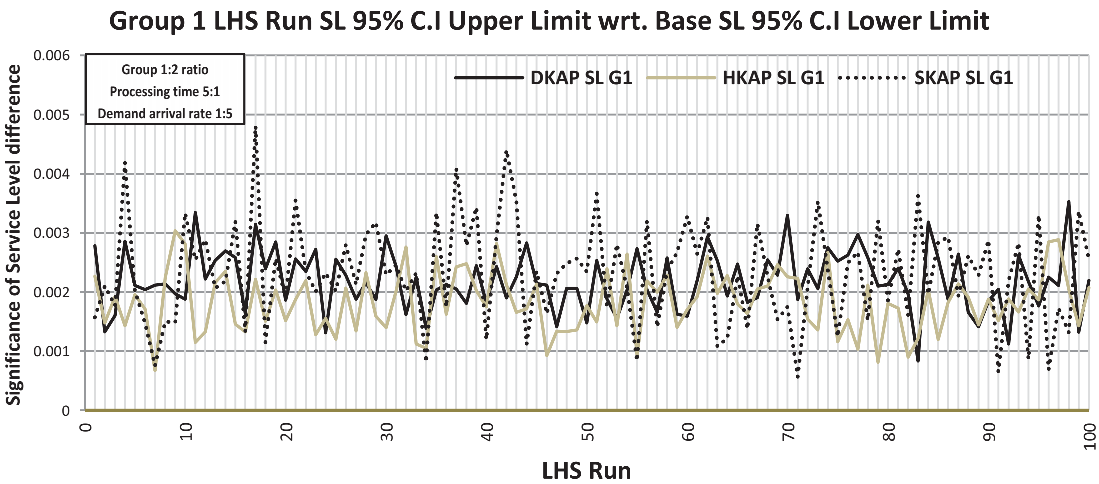


Figure H-9: SLG1 Robustness – 50% Load Level Scenario 5

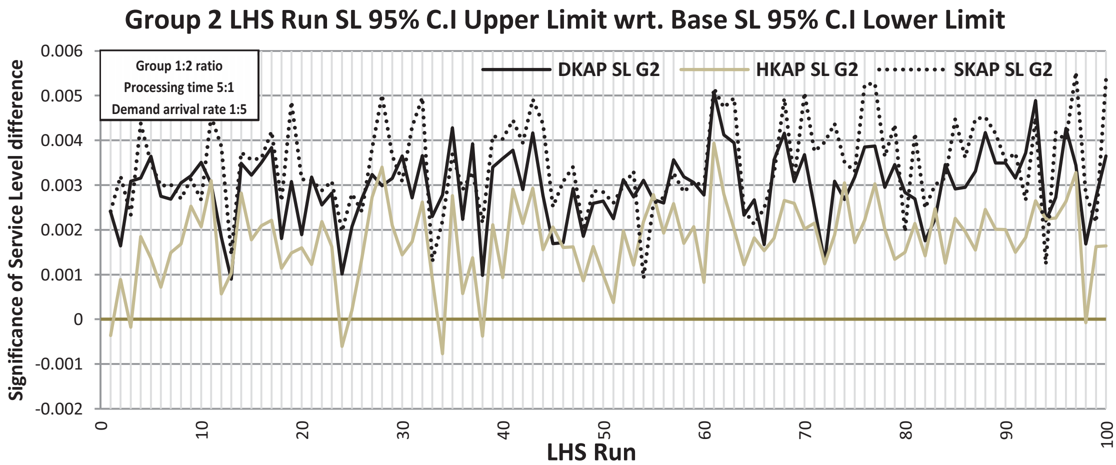


Figure H-10: SLG2 Robustness – 50% Load Level Scenario 5

H.2 72.5% LOAD LEVEL

H.2.1 Scenario 1: Homogeneous Processing time and Demand

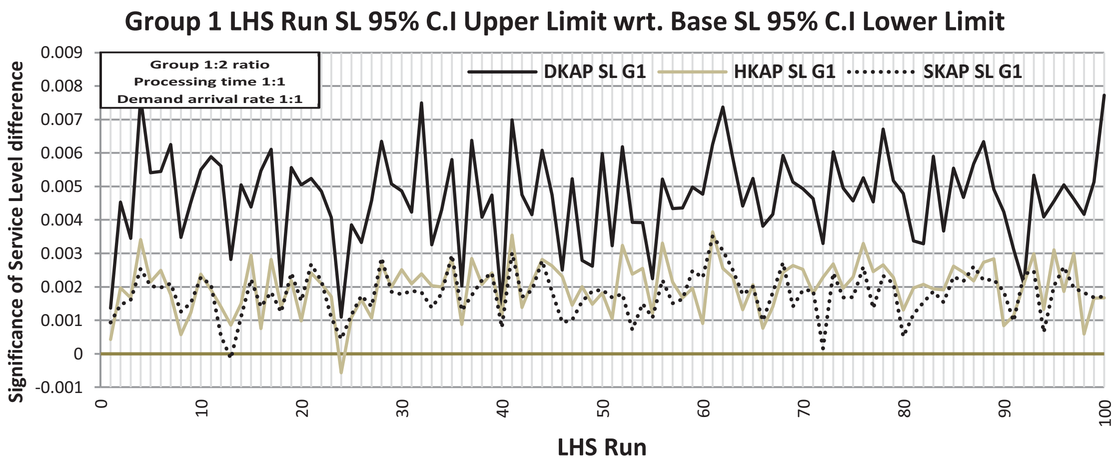


Figure H-11: SLG1 Robustness – 72.5% Load Level Scenario 1

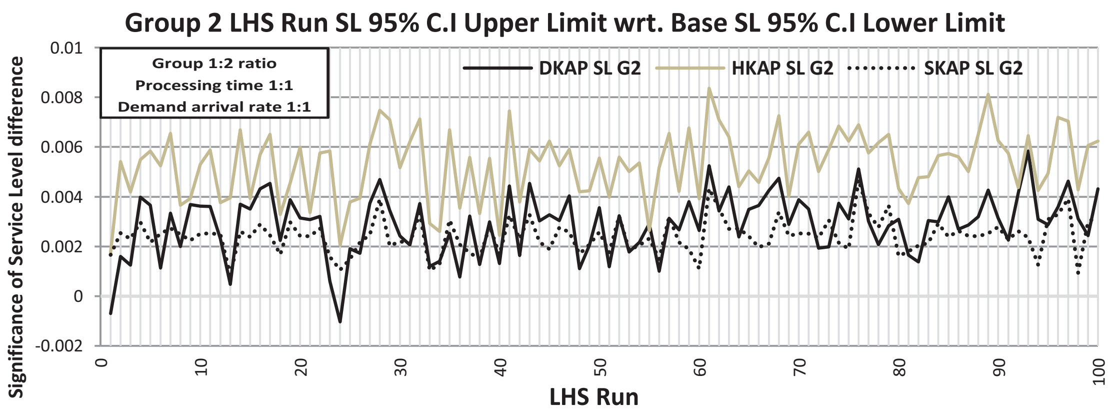


Figure H-12: SLG2 Robustness – 72.5% Load Level Scenario 1

H.2.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand

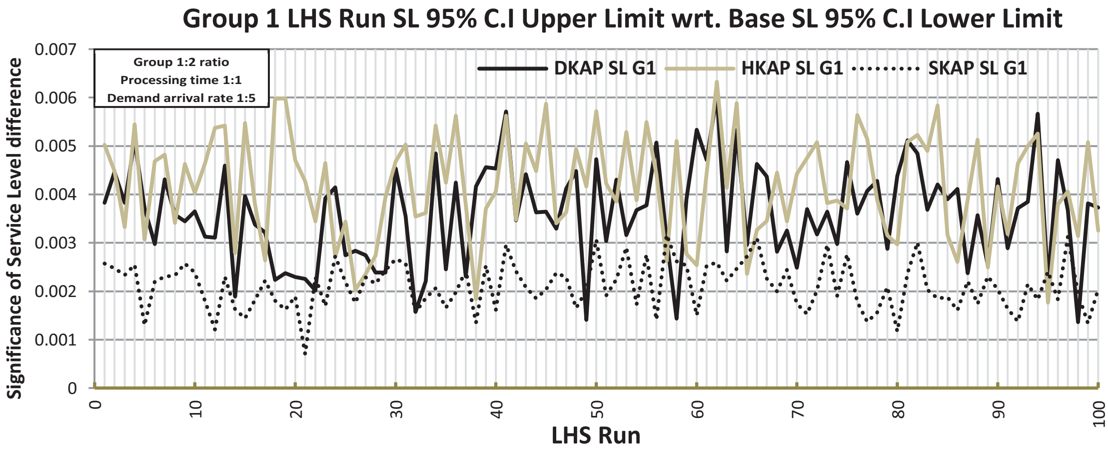


Figure H-13: SLG1 Robustness – 72.5% Load Level Scenario 2

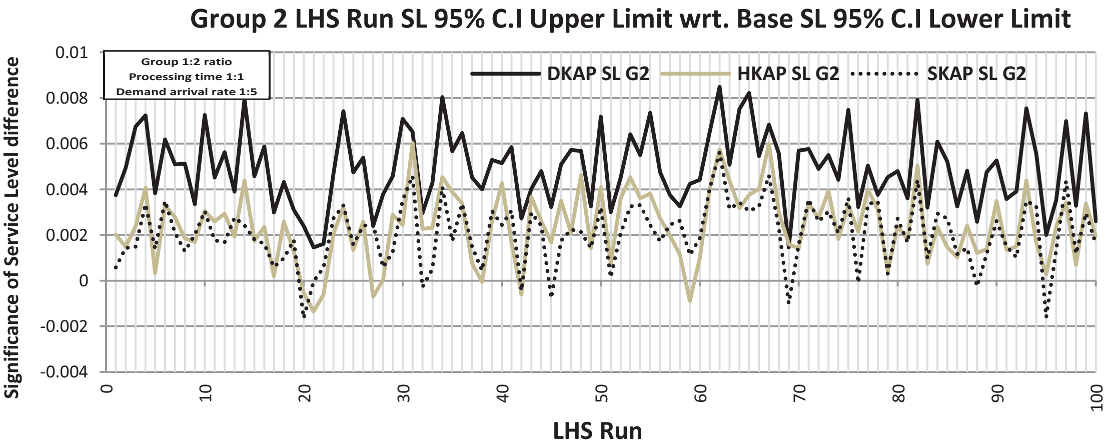


Figure H-14: SLG2 Robustness – 72.5% Load Level Scenario 2

H.2.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand

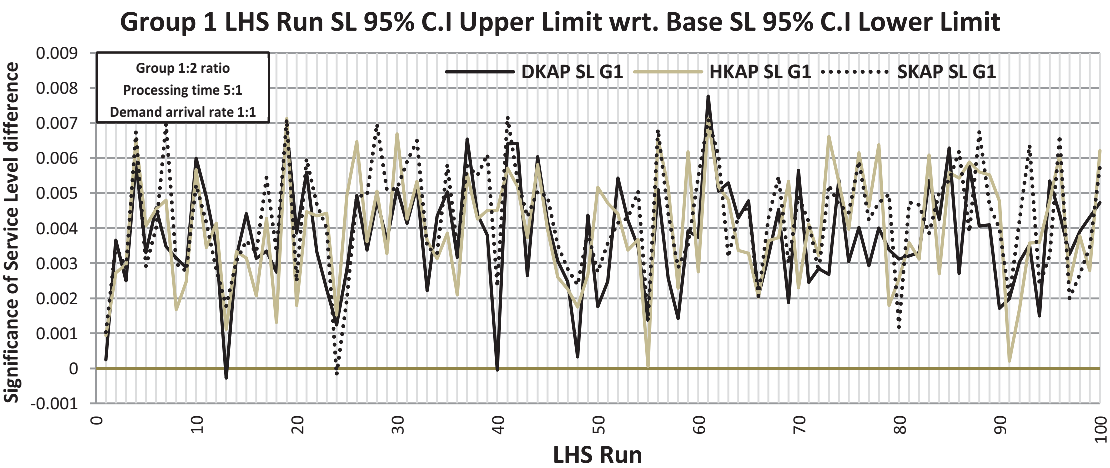


Figure H-15: SLG1 Robustness – 72.5% Load Level Scenario 3

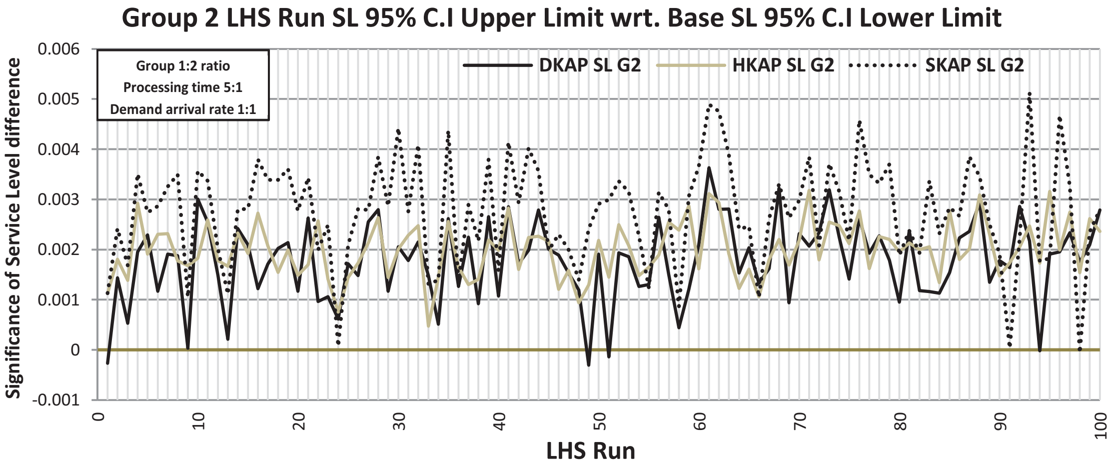


Figure H-16: SLG2 Robustness – 72.5% Load Level Scenario 3

H.2.4 Scenario 4: Higher Processing time and Higher Demand for Group 1

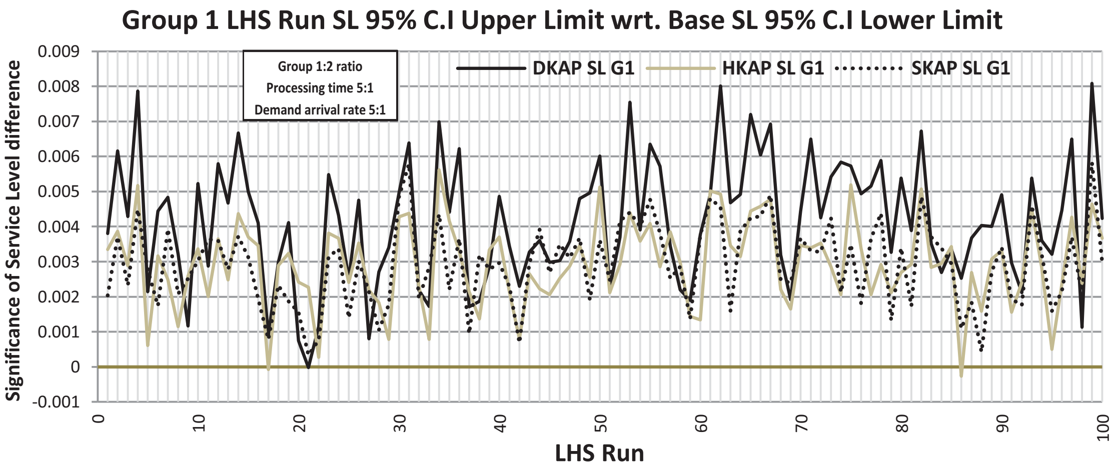


Figure H-17: SLG1 Robustness – 72.5% Load Level Scenario 4

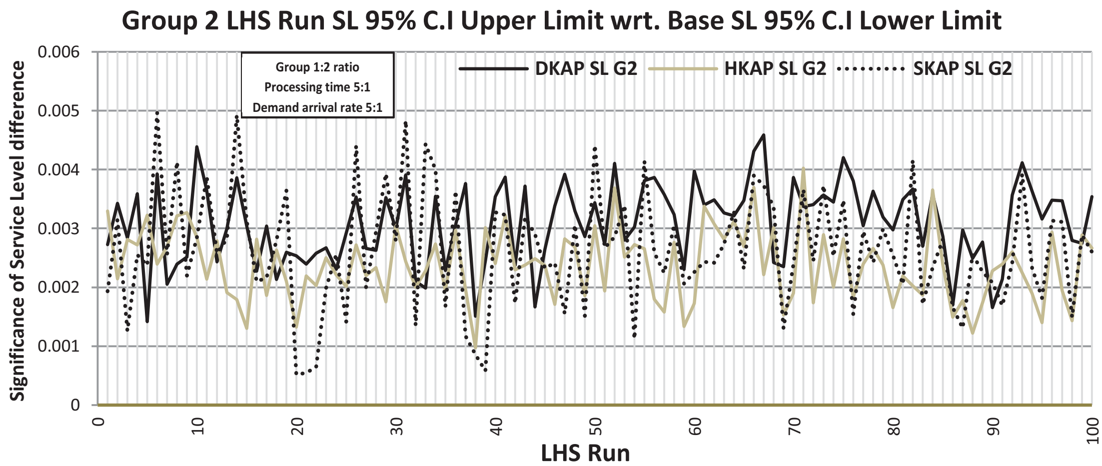


Figure H-18: SLG2 Robustness – 72.5% Load Level Scenario 4

H.2.5 Scenario 5: Higher Processing time and Lower Demand for Group 1

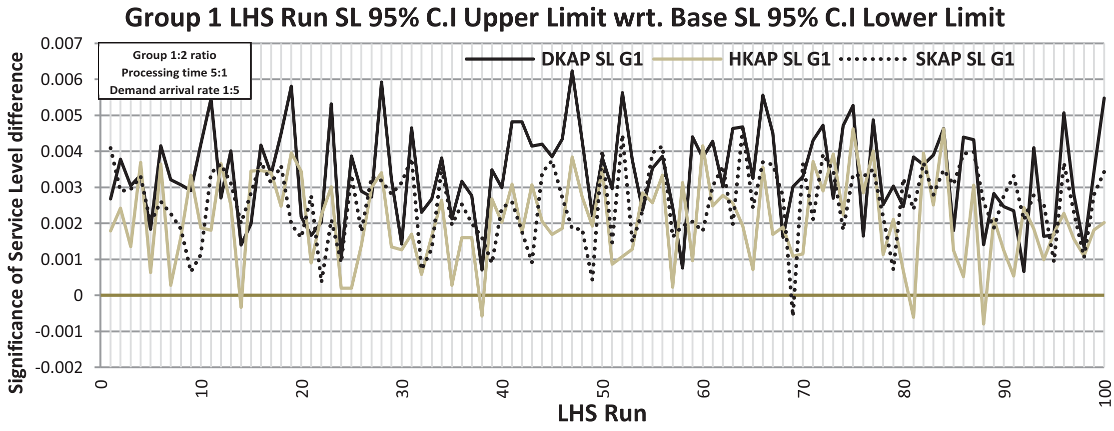


Figure H-19: SLG1 Robustness – 72.5% Load Level Scenario 5

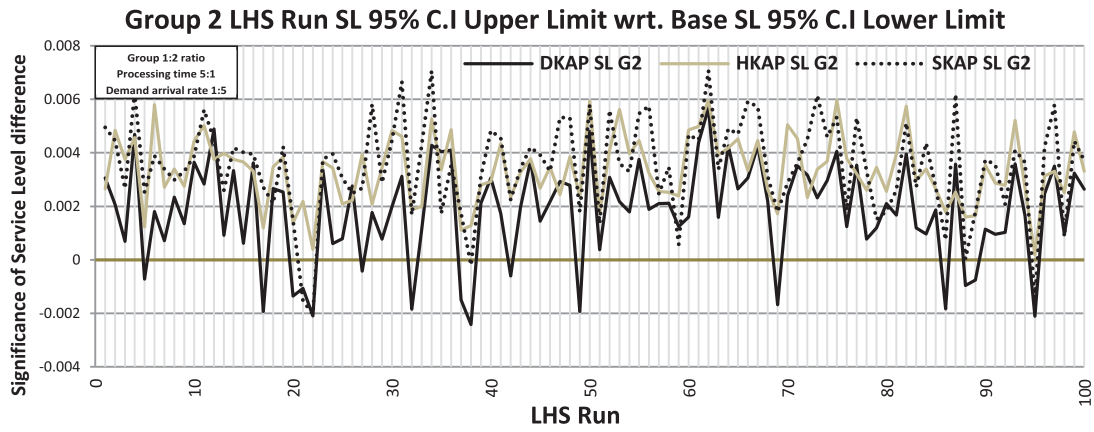


Figure H-20: SLG2 Robustness –72.5% Load Level Scenario 5

H.3 <u>95% LOAD LEVEL</u>

H.3.1 Scenario 1: Homogeneous Processing time and Demand

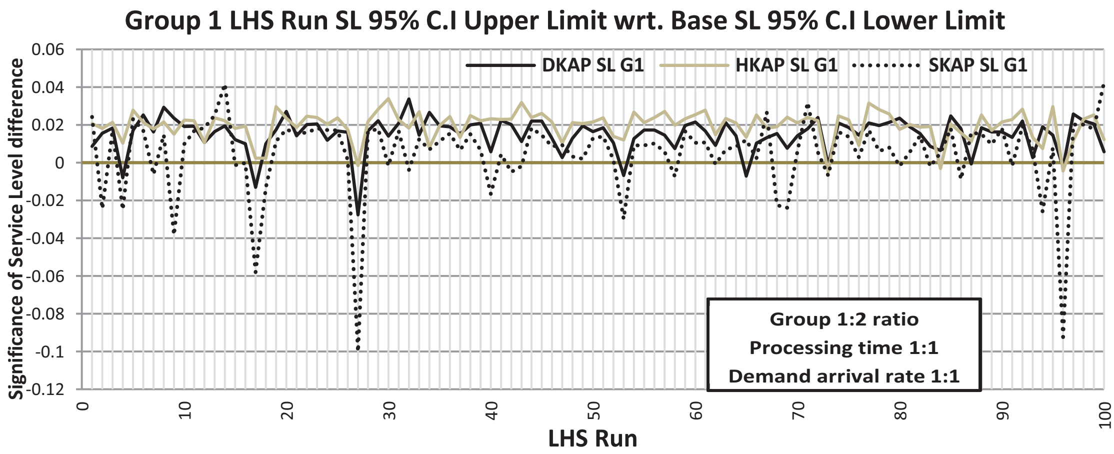


Figure H-21: SLG1 Robustness – 95% Load Level Scenario 1

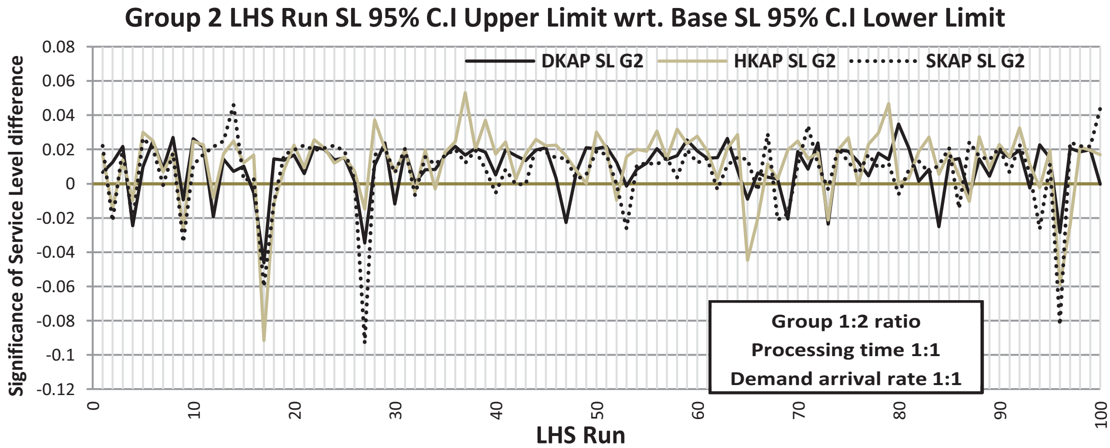


Figure H-22: SLG2 Robustness – 95% Load Level Scenario 1

H.3.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand

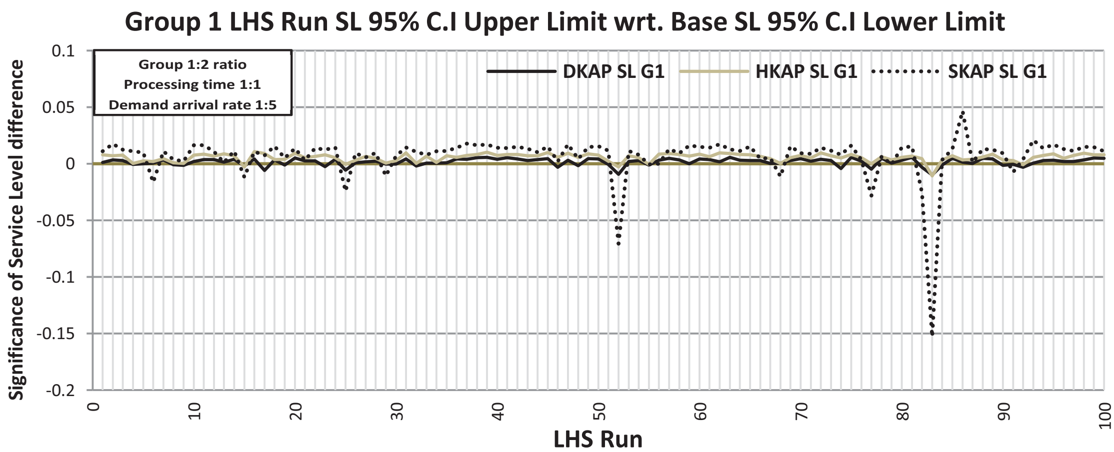


Figure H-23: SLG1 Robustness – 95% Load Level Scenario 2

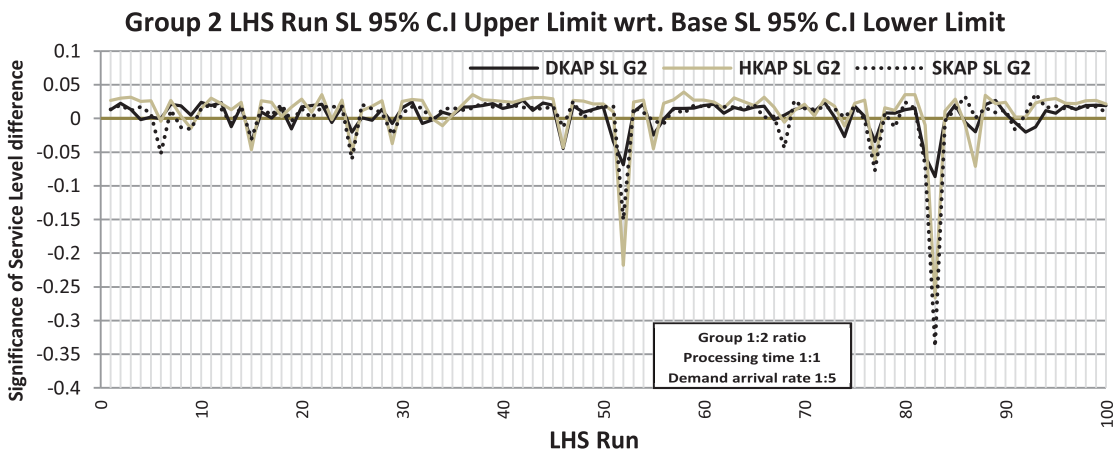


Figure H-24: SLG2 Robustness – 95% Load Level Scenario 2

H.3.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand

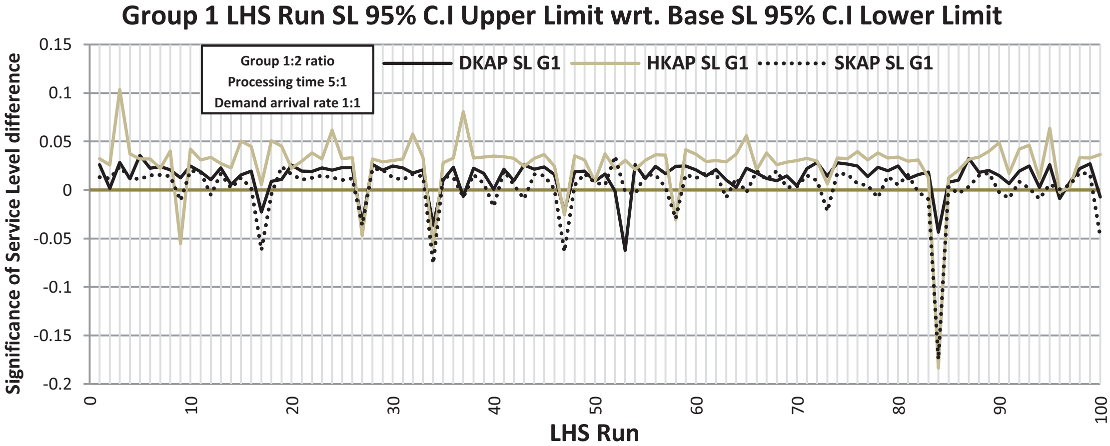


Figure H-25: SLG1 Robustness – 95% Load Level Scenario 3

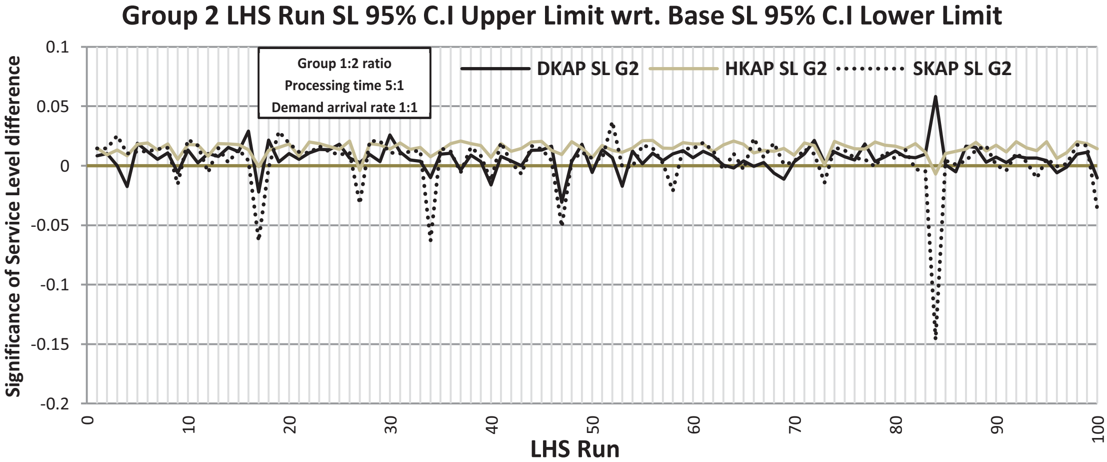


Figure H-26: SLG2 Robustness – 95% Load Level Scenario 3

H.3.4 Scenario 4: Higher Processing time and Higher Demand for Group 1

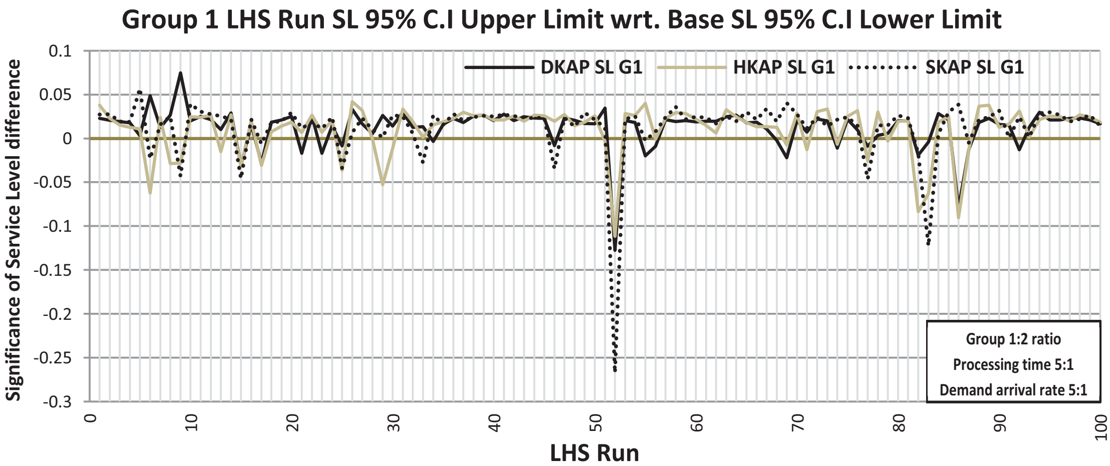


Figure H-27: SLG1 Robustness – 95% Load Level Scenario 4

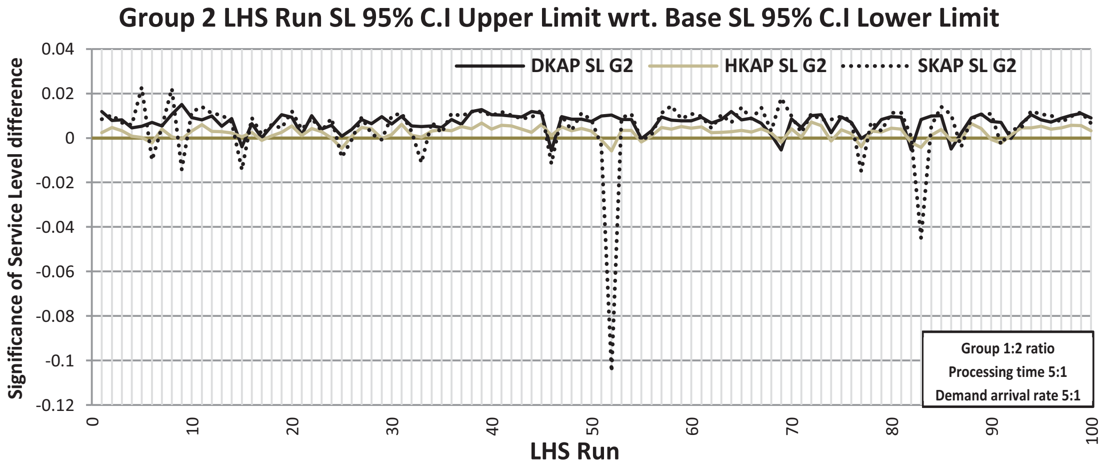


Figure H-28: SLG2 Robustness – 95% Load Level Scenario 4

H.3.5 Scenario 5: Higher Processing time and Lower Demand for Group 1

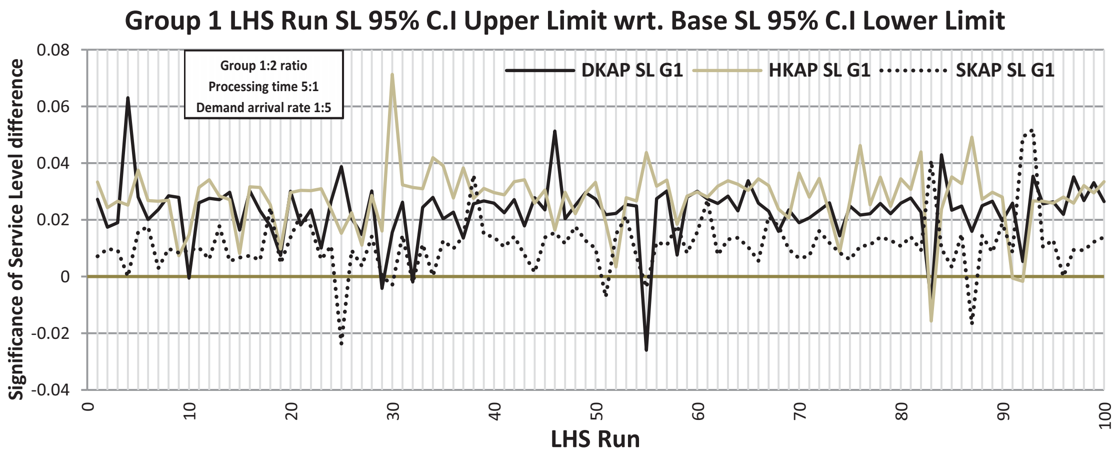


Figure H-29: SLG1 Robustness – 95% Load Level Scenario 5

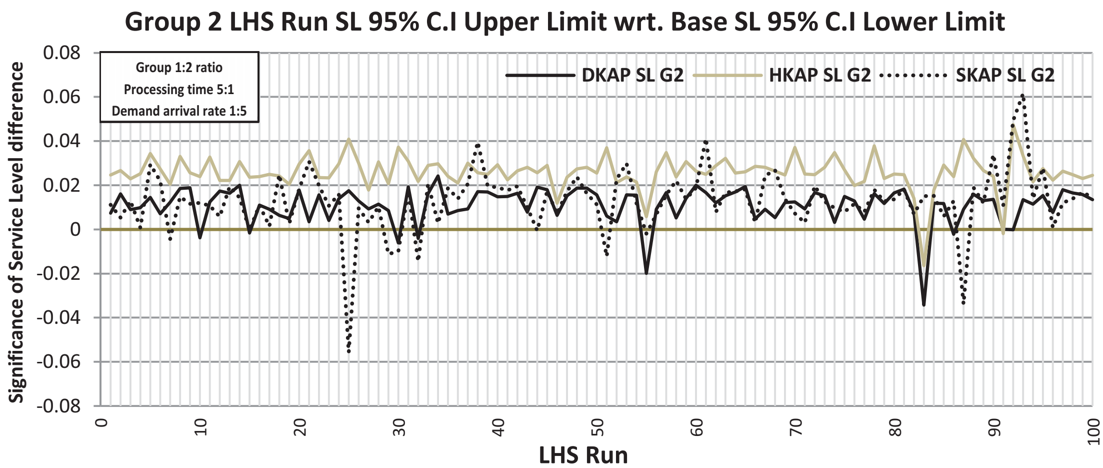


Figure H-30: SLG2 Robustness – 95% Load Level Scenario 5

APPENDIX - I : IMPACTS OF MEAN DEMAND ARRIVAL RATES

The charts in this appendix have been used to estimate the impact of the products' mean demand arrival rates on their service levels. For instance, the chart in Figure I-1 has been used to identify the products whose service levels are significantly affected by the mean demand arrival rate of each of the Products 1-4.

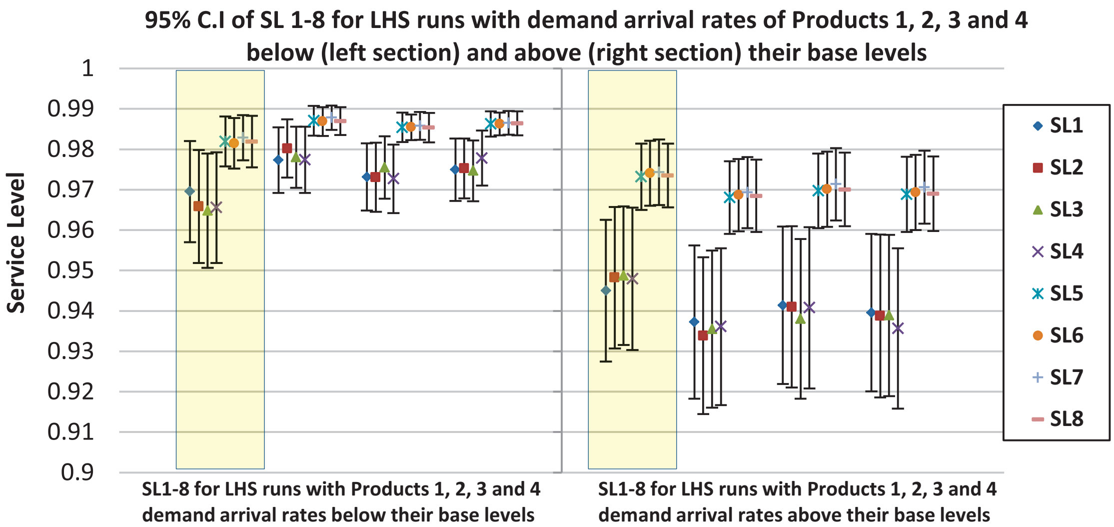


Figure I-1: Impact of Products (1-4) Demand Arrival rates on SL(1-8)

The two sets of plots highlighted in the chart in Figure I-1 are the confidence intervals for SL1-8 for the sets of runs in which Product 1 had demand arrival rates below and above its base level respectively. Two corresponding plots on the left and the right side will thus be used to compare the service level confidence intervals of a specific product's service level under the influence of the demand arrival rate of a product.

TABLE OF CONTENTS

Page

I.1 Impacts on Products' Service Levels I-4

I.1.1 Scenario 1: Homogeneous Processing time and Demand I-4
I.1.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand I-5
I.1.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand I-5
I.1.4 Scenario 4: Higher Processing time and Higher Demand for Group 1 .... I-6
I.1.5 Scenario 5: Higher Processing time and Lower Demand for Group 1 .... I-7

I.2 Impacts on Average System WIP I-8

I.2.1 Scenario 1: Homogeneous Processing time and Demand I-8
I.2.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand I-9
I.2.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand I-10
I.2.4 Scenario 4: Higher Processing time and Higher Demand for Group 1 .... I-11
I.2.5 Scenario 5: Higher Processing time and Lower Demand for Group 1 .... I-12

LIST OF FIGURES

Page

Figure I-1: Impact of Products (1-4) Demand Arrival rates on SL(1-8) I-1

Figure I-2: Products' Demand Arrival rate impact on SLs Scenario 1 DKAP I-4

Figure I-3: Products' Demand Arrival rate impact on SLs Scenario 1 HKAP I-4

Figure I-4: Products' Demand Arrival rate impact on SLs Scenario 1 SKAP I-4

Figure I-5: Products' Demand Arrival rate impact on SLs Scenario 2 DKAP I-5

Figure I-6: Products' Demand Arrival rate impact on SLs Scenario 2 HKAP I-5

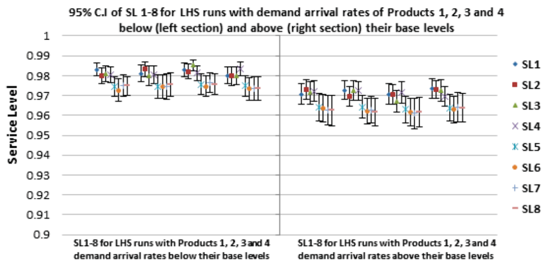
Figure I-7: Products' Demand Arrival rate impact on SLs Scenario 2 SKAP I-5

Figure I-8: Products' Demand Arrival rate impact on SLs Scenario 3 DKAP I-5

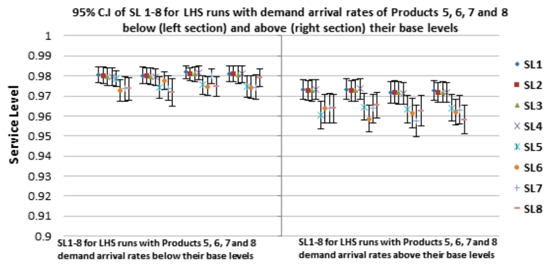
Figure I-9: Products' Demand Arrival rate impact on SLs Scenario 3 HKAP I-6
Figure I-10: Products' Demand Arrival rate impact on SLs Scenario 3 SKAP............ I-6
Figure I-11: Products' Demand Arrival rate impact on SLs Scenario 4 DKAP I-6
Figure I-12: Products' Demand Arrival rate impact on SLs Scenario 4 HKAP I-6
Figure I-13: Products' Demand Arrival rate impact on SLs Scenario 4 SKAP............ I-7
Figure I-14: Products' Demand Arrival rate impact on SLs Scenario 5 DKAP I-7
Figure I-15: Products' Demand Arrival rate impact on SLs Scenario 5 HKAP I-7
Figure I-16: Products Demand Arrival rate impact on SLs Scenario 5 SKAP I-7
Figure I-17: Products' Demand Arrival rate impact on WIP Scenario 1 DKAP I-8
Figure I-18: Products' Demand Arrival rate impact on WIP Scenario 1 HKAP I-8
Figure I-19: Products' Demand Arrival rate impact on WIP Scenario 1 SKAP........... I-8
Figure I-20: Products' Demand Arrival rate impact on WIP Scenario 2 DKAP I-9
Figure I-21: Products' Demand Arrival rate impact on WIP Scenario 2 HKAP I-9
Figure I-22: Products' Demand Arrival rate impact on WIP Scenario 2 SKAP........... I-9
Figure I-23: Products' Demand Arrival rate impact on WIP Scenario 3 DKAP I-10
Figure I-24: Products' Demand Arrival rate impact on WIP Scenario 3 HKAP I-10
Figure I-25: Products' Demand Arrival rate impact on WIP Scenario 3 SKAP.......... I-10
Figure I-26: Products' Demand Arrival rate impact on WIP Scenario 4 DKAP I-11
Figure I-27: Products' Demand Arrival rate impact on WIP Scenario 4 HKAP I-11
Figure I-28: Products' Demand Arrival rate impact on WIP Scenario 4 SKAP.......... I-11
Figure I-29: Products' Demand Arrival rate impact on WIP Scenario 5 DKAP I-12
Figure I-30: Products' Demand Arrival rate impact on WIP Scenario 5 HKAP I-12
Figure I-31: Products' Demand Arrival rate impact on WIP Scenario 5 SKAP.......... I-12

I.1 IMPACTS ON PRODUCTS' SERVICE LEVELS

I.1.1 Scenario 1: Homogeneous Processing time and Demand

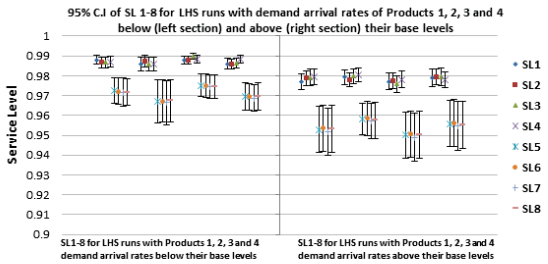


(a) Group 1 Products

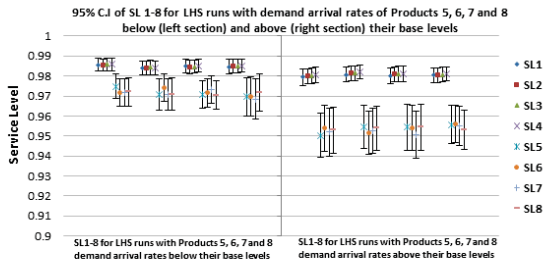


(b) Group 2 Products

Figure I-2: Products' Demand Arrival rate impact on SLs Scenario 1 DKAP

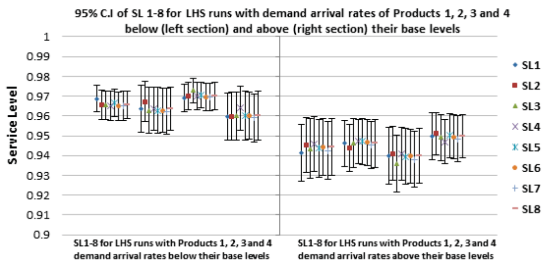


(a) Group 1 Products

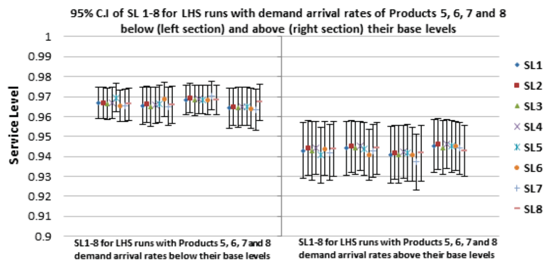


(b) Group 2 Products

Figure I-3: Products' Demand Arrival rate impact on SLs Scenario 1 HKAP



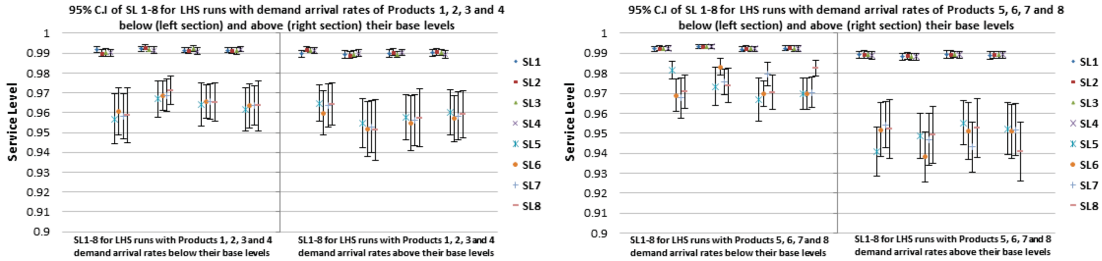
(a) Group 1 Products



(b) Group 2 Products

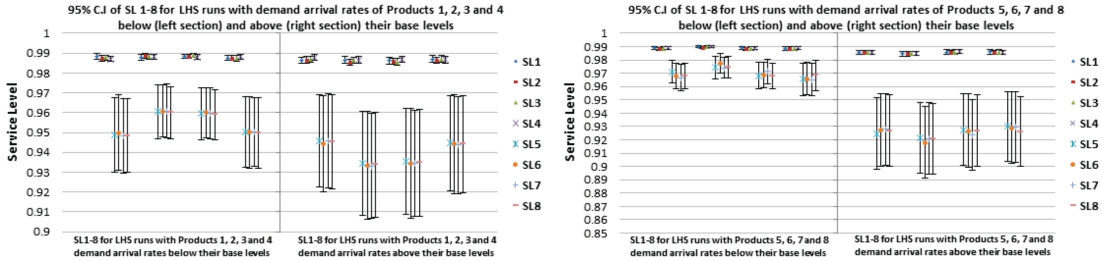
Figure I-4: Products' Demand Arrival rate impact on SLs Scenario 1 SKAP

I.1.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand



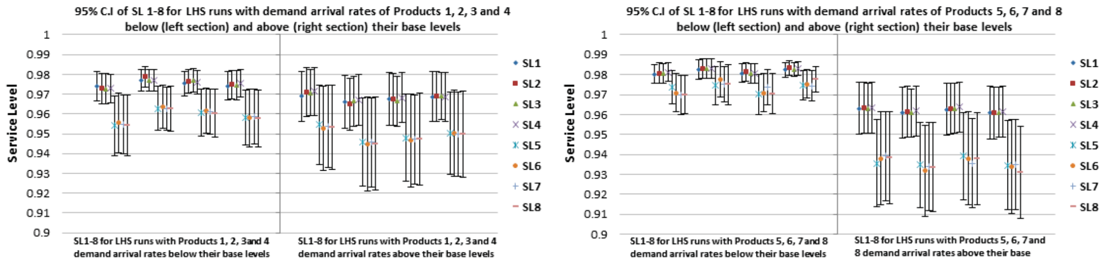
(a) Group 1 Products (b) Group 2 Products

Figure I-5: Products' Demand Arrival rate impact on SLs Scenario 2 DKAP



(a) Group 1 Products (b) Group 2 Products

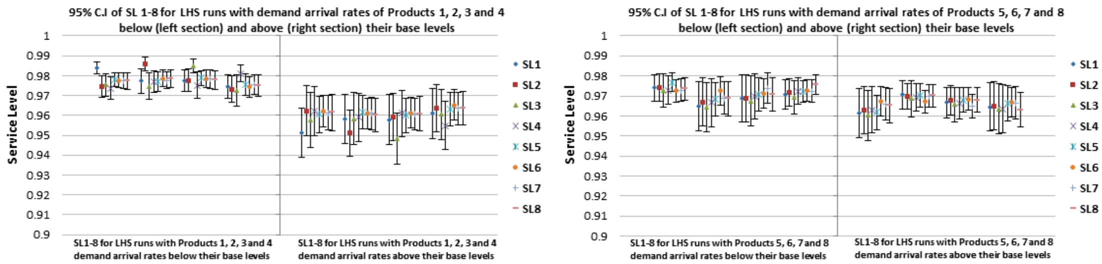
Figure I-6: Products' Demand Arrival rate impact on SLs Scenario 2 HKAP



(a) Group 1 Products (b) Group 2 Products

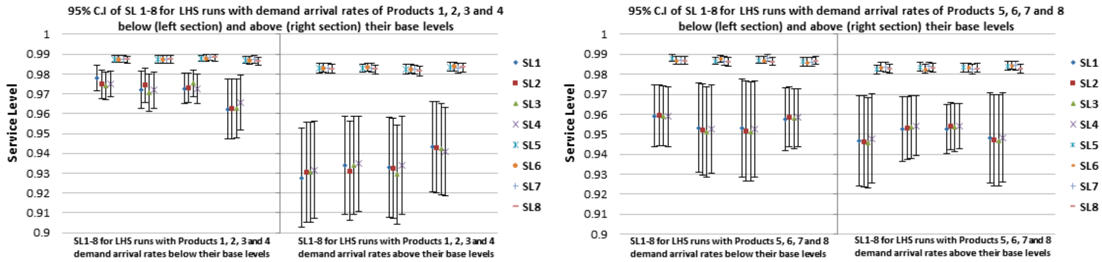
Figure I-7: Products' Demand Arrival rate impact on SLs Scenario 2 SKAP

I.1.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand



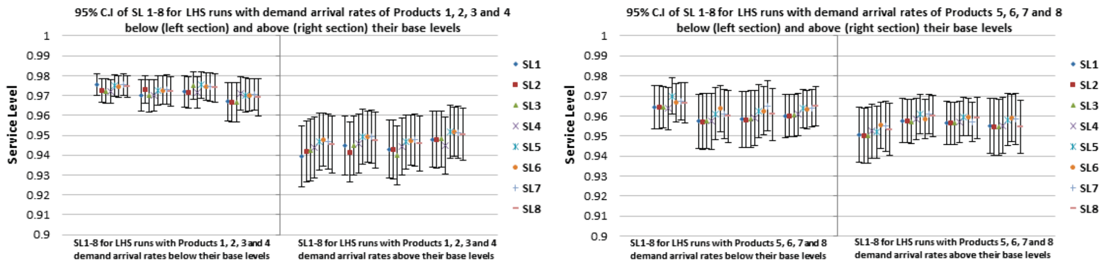
(a) Group 1 Products (b) Group 2 Products

Figure I-8: Products' Demand Arrival rate impact on SLs Scenario 3 DKAP



(a) Group 1 Products (b) Group 2 Products

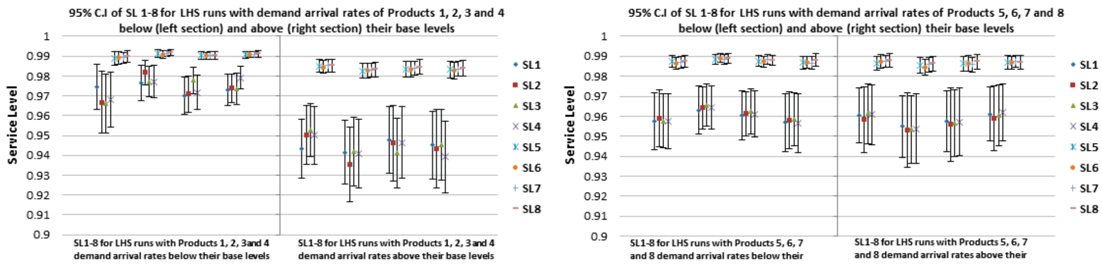
Figure I-9: Products' Demand Arrival rate impact on SLs Scenario 3 HKAP



(a) Group 1 Products (b) Group 2 Products

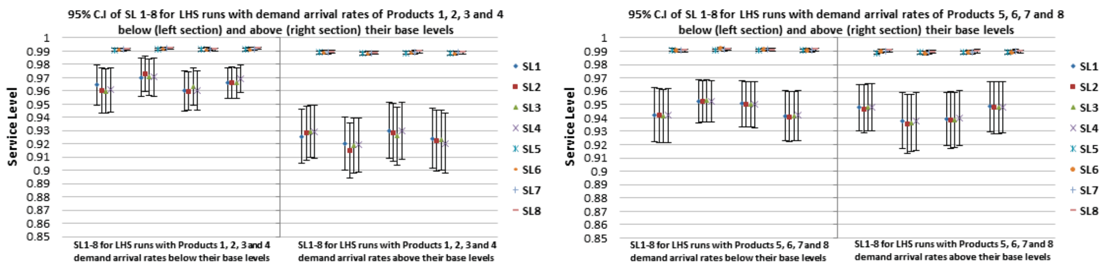
Figure I-10: Products' Demand Arrival rate impact on SLs Scenario 3 SKAP

I.1.4 Scenario 4: Higher Processing time and Higher Demand for Group 1



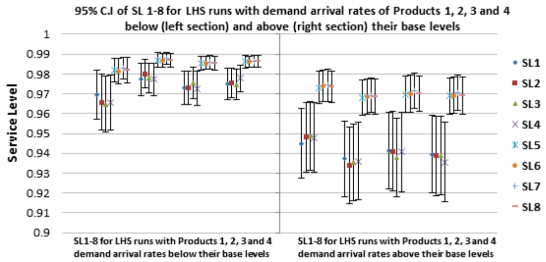
(a) Group 1 Products (b) Group 2 Products

Figure I-11: Products' Demand Arrival rate impact on SLs Scenario 4 DKAP

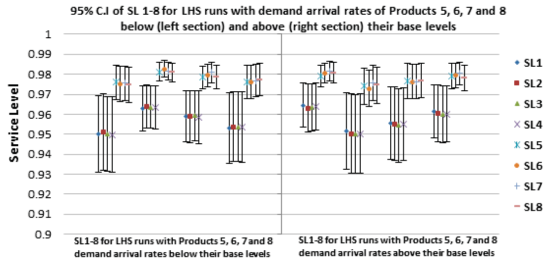


(a) Group 1 Products (b) Group 2 Products

Figure I-12: Products' Demand Arrival rate impact on SLs Scenario 4 HKAP



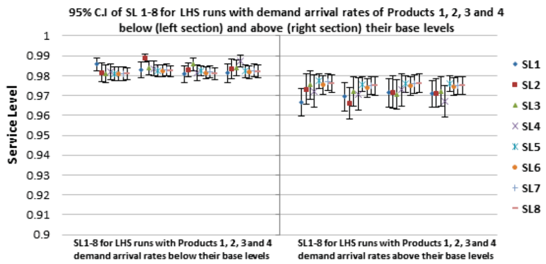
(a) Group 1 Products



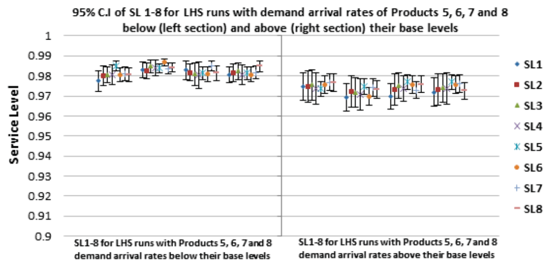
(b) Group 2 Products

Figure I-13: Products' Demand Arrival rate impact on SLs Scenario 4 SKAP

I.1.5 Scenario 5: Higher Processing time and Lower Demand for Group 1

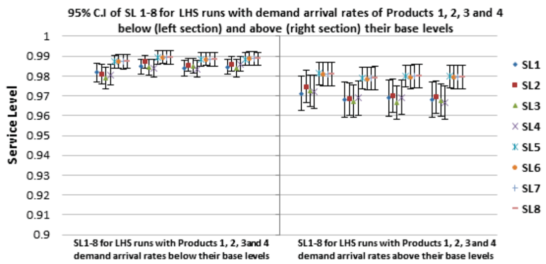


(a) Group 1 Products

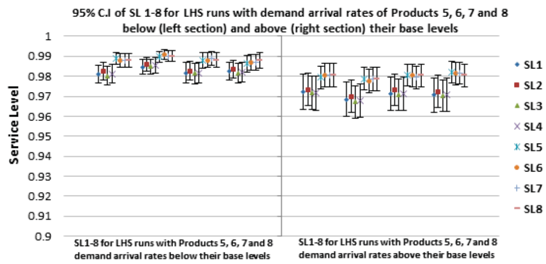


(b) Group 2 Products

Figure I-14: Products' Demand Arrival rate impact on SLs Scenario 5 DKAP

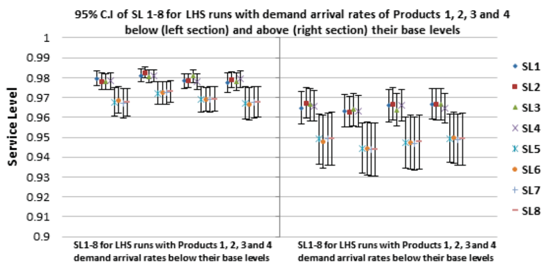


(a) Group 1 Products

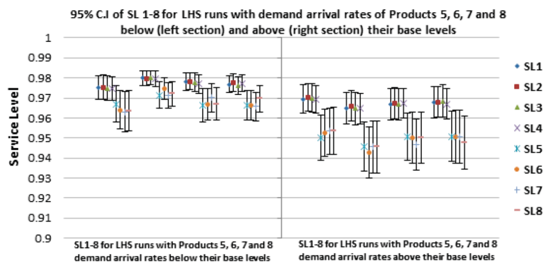


(b) Group 2 Products

Figure I-15: Products' Demand Arrival rate impact on SLs Scenario 5 HKAP



(a) Group 1 Products



(b) Group 2 Products

Figure I-16: Products Demand Arrival rate impact on SLs Scenario 5 SKAP

I.2 IMPACTS ON AVERAGE SYSTEM WIP

I.2.1 Scenario 1: Homogeneous Processing time and Demand

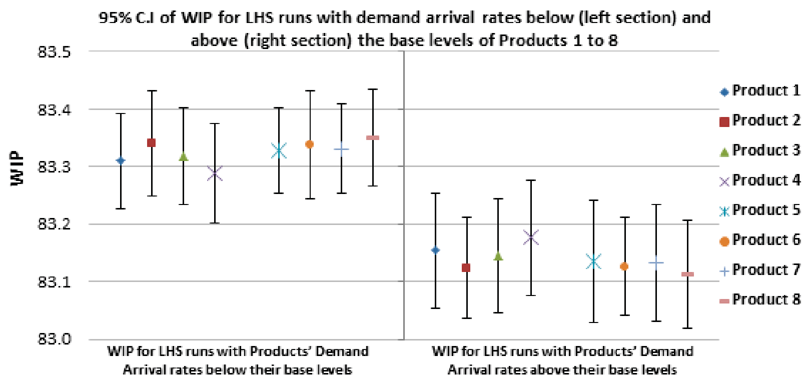


Figure I-17: Products' Demand Arrival rate impact on WIP Scenario 1 DKAP

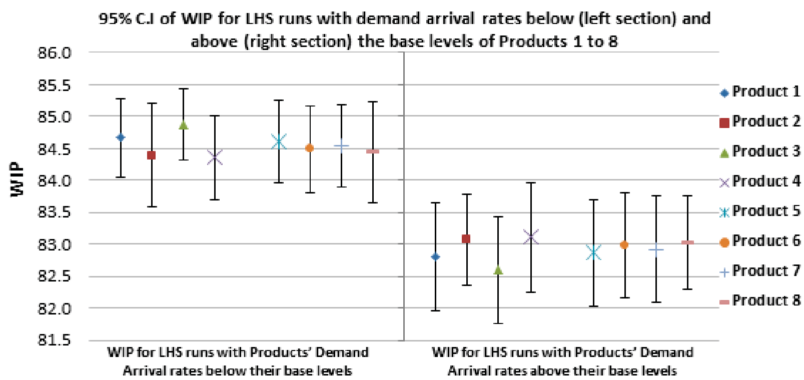


Figure I-18: Products' Demand Arrival rate impact on WIP Scenario 1 HKAP

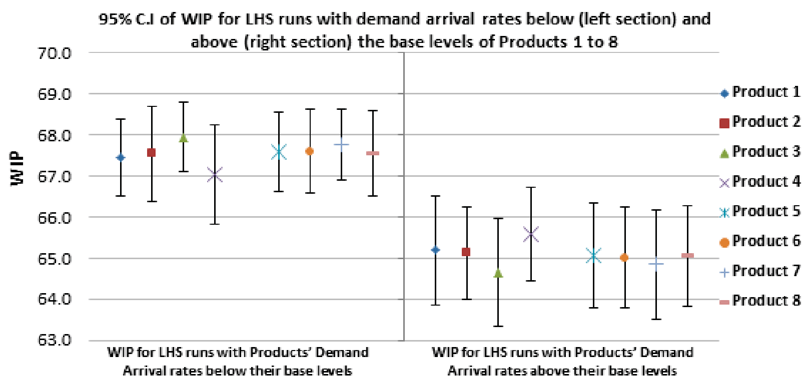


Figure I-19: Products' Demand Arrival rate impact on WIP Scenario 1 SKAP

I.2.2 Scenario 2: Homogeneous Processing time & Heterogeneous Demand

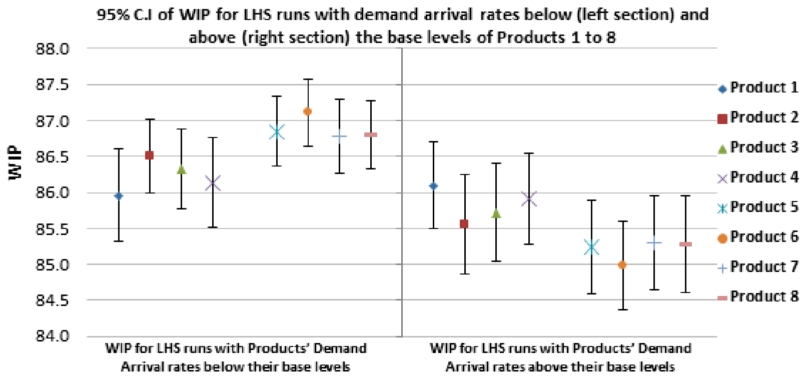


Figure I-20: Products' Demand Arrival rate impact on WIP Scenario 2 DKAP

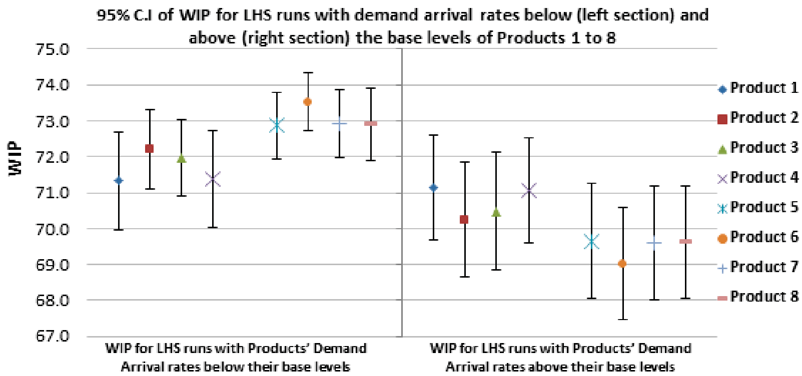


Figure I-21: Products' Demand Arrival rate impact on WIP Scenario 2 HKAP

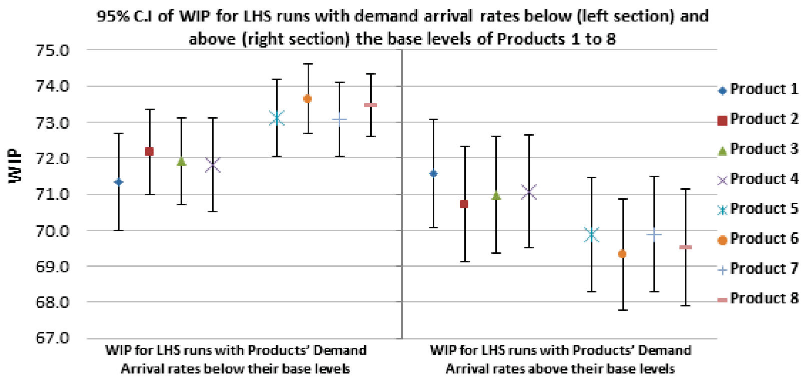


Figure I-22: Products' Demand Arrival rate impact on WIP Scenario 2 SKAP

I.2.3 Scenario 3: Heterogeneous Processing time & Homogeneous Demand

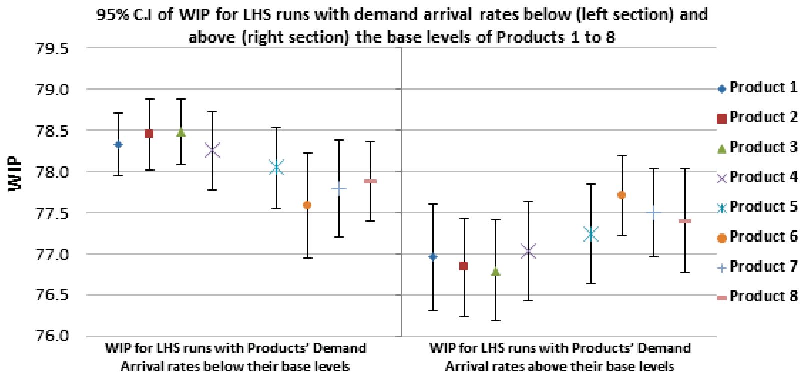


Figure I-23: Products' Demand Arrival rate impact on WIP Scenario 3 DKAP

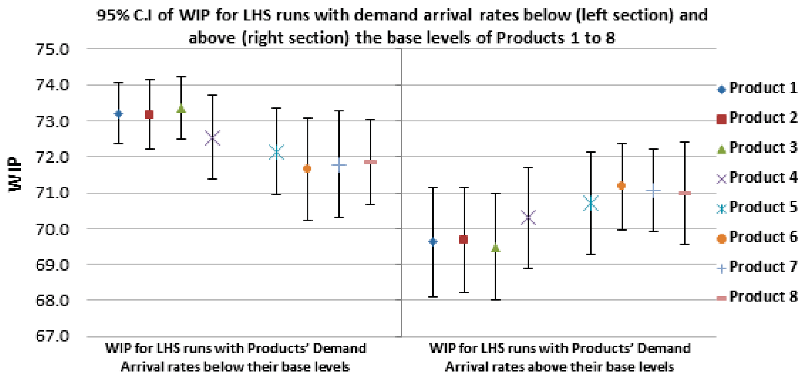


Figure I-24: Products' Demand Arrival rate impact on WIP Scenario 3 HKAP

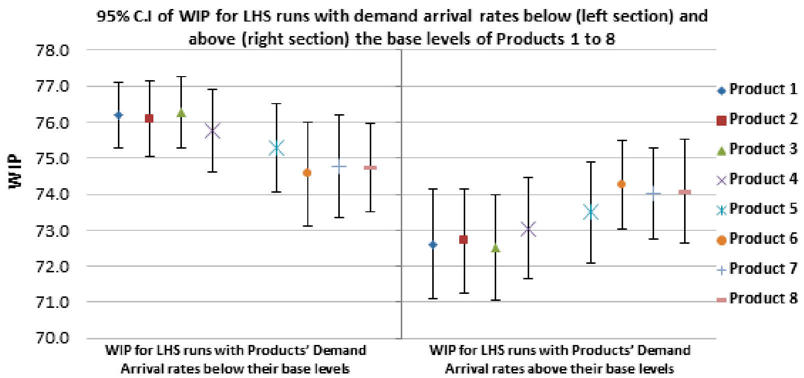


Figure I-25: Products' Demand Arrival rate impact on WIP Scenario 3 SKAP

I.2.4 Scenario 4: Higher Processing time and Higher Demand for Group 1

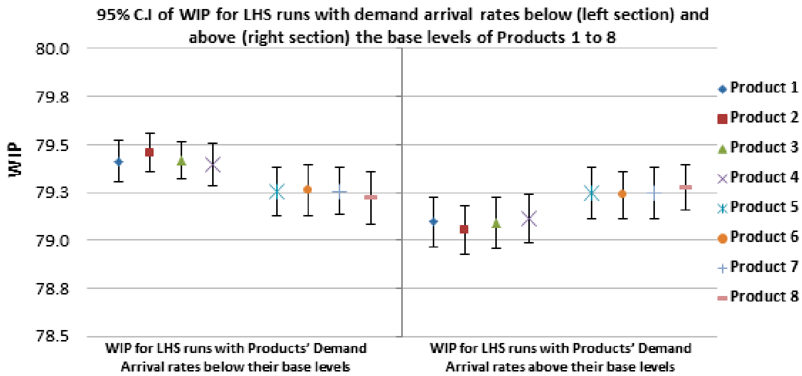


Figure I-26: Products' Demand Arrival rate impact on WIP Scenario 4 DKAP

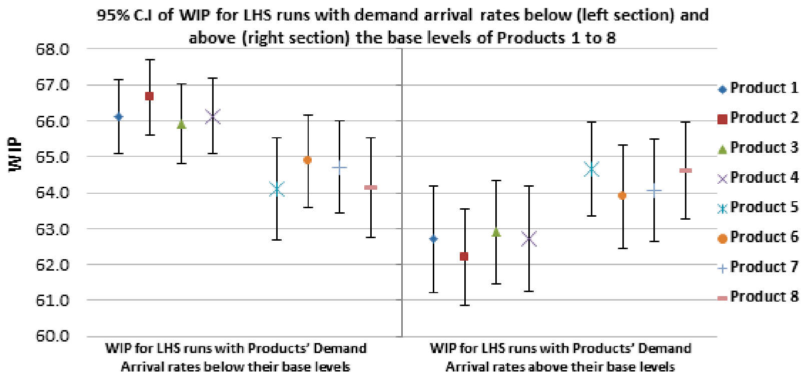


Figure I-27: Products' Demand Arrival rate impact on WIP Scenario 4 HKAP

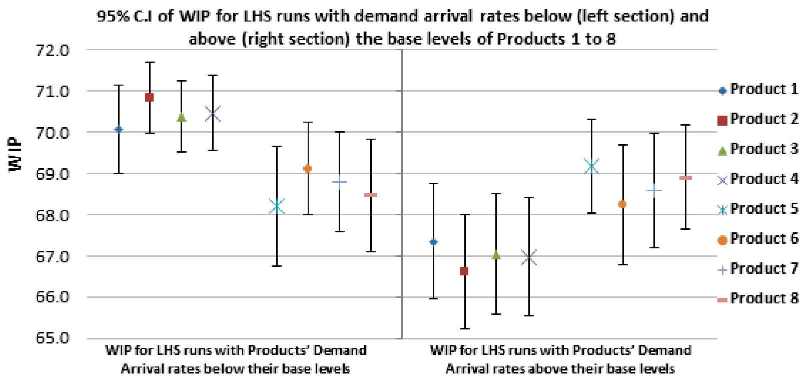


Figure I-28: Products' Demand Arrival rate impact on WIP Scenario 4 SKAP

I.2.5 Scenario 5: Higher Processing time and Lower Demand for Group 1

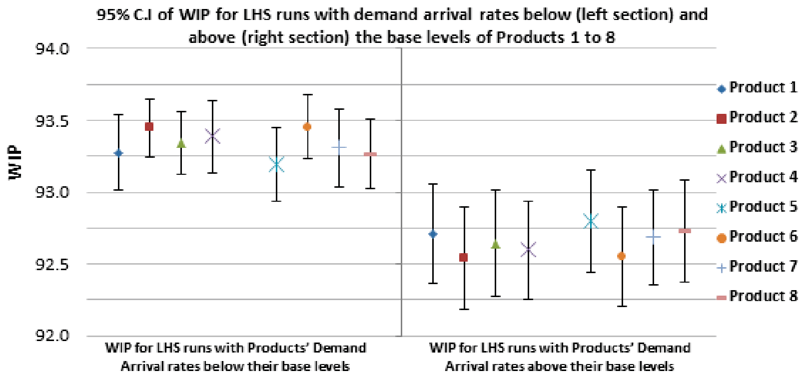


Figure I-29: Products' Demand Arrival rate impact on WIP Scenario 5 DKAP

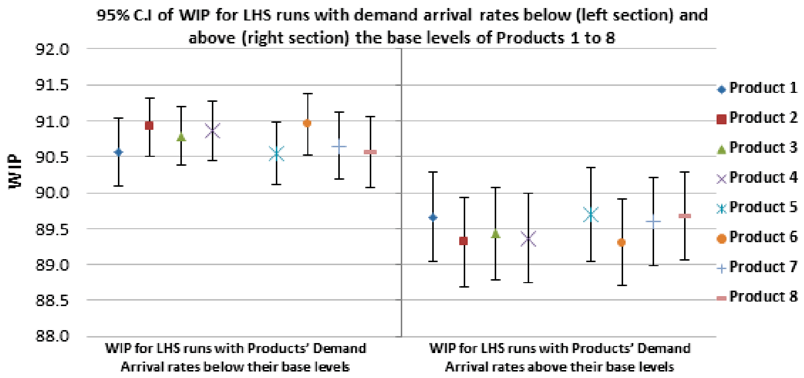


Figure I-30: Products' Demand Arrival rate impact on WIP Scenario 5 HKAP

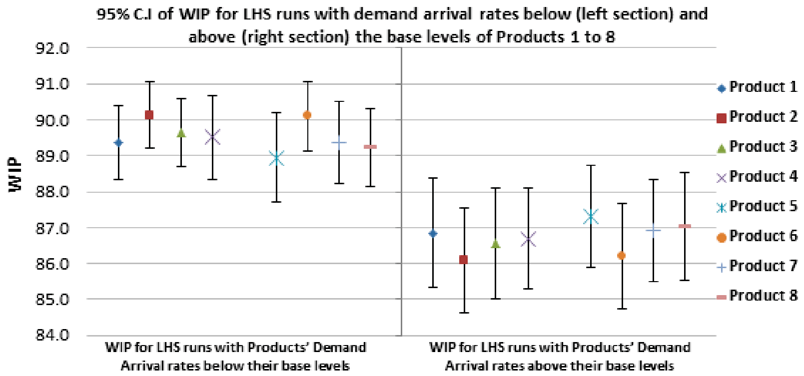


Figure I-31: Products' Demand Arrival rate impact on WIP Scenario 5 SKAP