Evaluation of Production Control Strategies for the Co-ordination of Work-Authorisations and Inventory Management in Lean Supply Chains

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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 (Ph.D.) in Engineering is entirely my own work, and 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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Walid Smew

DEDICATION

To My Mum and the Soul of My Dad,

My Beloved Wife Nadia and Children: Adam, Deena, and Leanne,

Who Generously Devoted Their Lives to My Success and Pictured

Their Own Happiness in My Achievements.

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ABSTRACT

A decision support framework is proposed for assisting managers and executives to possibly utilise lean production control strategies to coordinate work authorisations and inventory management in supply chains. The framework allows decision makers to evaluate and compare the suitability of various strategies to their system especially when considering conflicting objectives, such as maximising customer service levels while minimising Work in Process (WIP) in a business environment distressed by variabilities and uncertainties in demand stemmed from customer power. Also, the framework provides decision guidance in selecting and testing optimal solutions of selected policies control parameters.

The framework is demonstrated by application to a four-node serial supply-chain operating under three different pull-based supply chain strategies; namely CONWIP, Kanban, and Hybrid Kanban-CONWIP and exhibiting low, medium, and high variability in customer demand (i.e., coefficient of variation of 25%, 112.5%, and 200%). The framework consists of three phases; namely Modelling, Optimisation and Decision Support; and is applicable to both Simulation-Based and Metamodel-Based Optimisation. The Modelling phase includes conceptual modelling, discrete event simulation modelling and metamodels development. The Optimisation phase requires the application of multi-criteria optimisation methods to generate WIP-Service Level trade-off curves. The Curvature and Risk Analysis of the trade-off curves are utilised in the Decision Support phase to provide guidance to the decision maker in selecting and testing the best settings for the control parameters of the system. The inflection point of the curvature function indicates the point at which further increases in Service Level are only achievable by incurring an unacceptably higher cost in terms of average WIP. Risk analysis quantifies the risk associated with designing a supply chain system under specific environmental parameters.

This research contributes an efficient framework that is applicable to solve real supply chain problems and better understanding of the potential impacts and expected effectiveness of different pull control mechanisms, and offers valuable insights on future research opportunities in this field to production and supply chain managers.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

AKC_t^i	Available number of Kanban cards in node *i* in period *t*
APC_t	Available number of CONWIP cards in the SC in period *t*
B_t	Backlog of incoming orders in the SC in period *t*
D	Overall desirability function
D_t	Incoming orders to the SC at final node in period *t* (demand)
d_i	Individual desirability function
g	GP metamodel response variable
I_t^i	Input to the pipeline of the node *i* in period *t*
i	Node number
K^i	Total number of Kanban cards of node *i*
k	Number of independent variables
$\boldsymbol{k}$	The signed curvature of a function
L^i	Cycle time for a unit in pipeline to arrive to the FGI of the node *i*
$L(x_i)$	Lower limit of input variables x_i
M	Size of the vector of objectives space
m	Number of responses
MLP^i	Maximum number of units to be processed in the node *i* (capacity)
N	Size of the vector of decision variables
n	Number of experimental runs
n	The total number of nodes in the supply chain
n_c	Number of center points in the experimental design

O_t^i	Output from the pipeline of node *i* in period *t*
OP_t	Orders placed by the SC to the first node in period *t*
P_t^i	Pipeline (WIP) in node *i* in period *t*
p	Number of design factors
R	Spatial correlation function
R^2	Coefficient of determination
r	Response Weight
S_t^i	Shipments from node *i* to node *i+1* in period *t*
T	Total number of periods
T	Response target
TY_t^i	Available total FGI in node *i*, in period *t*
t	Period number
$U(x_i)$	Upper limit of the input variables x_i
WIP-Cap	Total number of CONWIP cards in the SC
X	Decision space
x_i	Independent variables
Y	Observed response
Y	Objectives space
Y_t^i	Finished Goods Inventory (FGI) in node *i*, in period *t*
y	Response variable
Z	GP dependent variable
α	Axial distance from the center point

α	Level of significance
α^2	Variance of random error
β	Independent variable coefficient
γ	GP metamodel coefficient
ΔWIP	Change in WIP between successive increments of Service Level
ε	Statistical random error
θ	Design factor
μ	GP metamodel coefficient (tatistical mean)
σ^2	Statistical variance
ψ	Tangent line angle with the positive *x*-axis
ω	Importance of the input factor (GP metamodel coefficient)

Abbreviation	***Description***
ANOVA	Analysis of Variance
ASL	Average Service Level
AWIP	Average Inventory in the System
BBD	Box and Behnken Design
BSCS	Basestock Control Strategy
BPR	Business Process Reengineering
CAO	Computer-Assisted-Ordering
CCD	Central Composite Design
cdf	Cumulative Density Function
CONWIP	Constant Work-In-Process Strategy

CRP	Continuous Replenishment Program
CV	Coefficient of Variation
DA	Desirability Function Approach
DFSCM	Design for Supply Chain Management
DOE	Design Of Experiment
SD	Standard Deviation of Demand
EDI	Electronic Data Interchange System
EDLP	Every Day Low Pricing Strategy
EKCS	Extended Kanban Control Strategy
GA	Genetic Algorithms
GKCS	Generalized Kanban Control Strategy
GKS	Generic Kanban System
GP	Gaussian Process Modeling
HIHPS	Horizontally Integrated Hybrid Production Systems
ICT	Information And Communication Technology
JIT	Just-In-Time Manufacturing
KCS	Kanban Control Strategy
LHD	Latin Hypercube Design
MDP	Markov Decision Process
MRP	Material Requirements Planning
MSE	Mean Square Error
NSGA	Non-dominated Sorting Genetic Algorithm
PCS	Production Control Strategy
POGA	Pareto Optimal Genetic Algorithm

POS	Point-of-Sale
PRESS	Prediction Error Sum of Squares
RSM	Response Surface Methodology
SC	Supply Chain
SCC	Supply Chain Council
SCM	Supply Chain Management
SNR	Signal-to-Noise Ratio
VMI	Vendor-Managed-Inventory
WIP	Work in Process

CHAPTER 1 INTRODUCTION

1.1 Motivation

Lean manufacturing (also known as Toyota Production System) can be defined as a philosophy of production that emphasises minimising the amount of all resources (including time) used in various enterprise activities. In its most basic form, lean Manufacturing is the systematic elimination of waste: overproduction, waiting, transportation, inventory, motion, over-processing, defective units and the implementation of the concepts of continuous flow and customer pull [1].

Manufacturing systems/production lines for repetitive manufacturing of discrete items are divided into stages where each stage may be seen as a production-inventory work centre consisting of a manufacturing process and an output buffer.

Material flow control aims to address the problems of when and how much to authorise parts to be processed at each stage. The control of materials flow through a manufacturing system is a major challenge to achieve high customer service levels while staying lean (e.g., holding less inventory). Difficulties in the control arise mainly due to production and demand variabilities and uncertainties. Since the 1980s, Japanese Just-In-Time (JIT) manufacturing approaches triggered various "lean/pull production control strategies" that react only to actual demand rather than future demand forecasts.

Similarly, supply chains consist of several stages representing suppliers, manufacturers, warehouses, distribution centres, and retail outlets, where raw materials are acquired and goods are manufactured, shipped to warehouses for storage, and then shipped to retailers or customers.

Supply Chain Management is a broad concept which includes many approaches and techniques to manage and integrate the entire supply chain stages from the suppliers at the first point to the customers at the end point. In a supply-chain network, the flow of product from initial raw-material convertors to the customer is complicated by variabilities and uncertainties in demand that ultimately are derived from customer power; for instance customer desires for enhanced or latest features, willingness (or lack thereof) to wait, reduced brand loyalty and price sensitivities. This leads to variations in orders, which in turn results in increased inventory levels across the entire supply-chain network if the members of the supply-chain utilise forecasting techniques to predict orders and plan production. This is the well-known bullwhip effect. The goal of supply chain (SC) integration is to co-ordinate activities across the whole stages to achieve global optimisation; that is improve performance, reduce system inventory levels and potential inventory cost, increase customer service level, better utilise resources, and effectively respond to changes in the market.

Quite recently, researchers have begun to investigate the potential of utilising the mechanisms of JIT/lean/pull production control strategies to co-ordinate the issuing of production authorisations and managing inventory across the entire SC to achieve global optimisation. So as a response to actual demand, the manufacturer should receive raw materials or parts from the upper stage (e.g., supplier) in a relatively short time before they will be used in production, and the output should then be shipped to the downstream stage (e.g., customer) as soon after completion as possible without holding a stock of either raw materials or finished goods if possible.

Much of the work in the literature is focused on optimising the parameters of a specific control policy under some given constraints and objectives but due to the dynamic nature of SCs and the conflicting objectives between the different stages involved, the control parameters have to be adjusted accordingly to respond to the changes in the demand patterns and objectives. Also, given the numerous control mechanisms introduced in recent years and the different conclusions, the determination of a proper pull mechanism is a major challenge to achieve high customer service levels while minimising Work-In-Process (WIP).

This research will review relevant literature on production and inventory control and will establish the conditions under which a given lean production control strategy (PCS) would be superior to others for the purpose of co-ordinating work authorisations and managing inventory in SCs while maintaining or improving service level. The aim is to propose a reliable and practical framework that could be used by decision makers at appropriate management level to assess and compare the suitability of various PCSs to their system through different phases of modeling, optimisation and decision making under different demand and production variabilities.

1.2 Thesis Structure

This research work is organised as follow. Supply Chain Management background and literature review is presented in chapter 2 along with a summery and research objectives; chapter 3 presents the details of the research methodologies employed in this research work; chapter 4 presents the development, validation, and optimisation of the simulation model and the Meta-models along with comprehensive analysis, comparisons, and discussions of the results; and finally chapter 5 provides the conclusions contributions, and directions for future research.

CHAPTER 2 SUPPLY CHAIN MANAGEMENT BACKGROUND & LITERATURE REVIEW

2.1 Introduction

Supply chain management can be defined as a set of approaches utilised to efficiently integrate suppliers, manufacturers, warehouses, and stores, so that merchandise is produced and distributed at the right quantities, to the right locations, and at the right time, in order to minimise systemwide costs while satisfying service level requirements [2, 3].

In today's highly competitive global markets, the introduction of products with shorter life cycles and the heightened expectations of customers have forced business enterprises to invest in and focus attention on their supply chains. This, together with the nonstop advance in communications and transportation technologies has motivated the continuous evolution of the supply chain and of the techniques to mange it.

A typical supply chain which is also referred as a *logistics network*, shown in Figure 2-1, consists of suppliers, manufacturers, warehouses, distribution centers, and retail outlets, where raw materials are procured and items are produced, shipped to warehouses for intermediate storage, and then shipped to retailers or customers. Consequently, to be efficient and cost effective across the entire supply chain; *total systemwide costs* from transportation and distribution to inventories of raw materials, work-in-process, and finished goods are to be minimised. It is challenging to design and operate a supply chain so that the total systemwide costs are minimised and *systemwide service levels* are maintained (supply chain global optimisation) for a variety reasons [2-10] of which:

1. The supply chain is a complex network of facilities scattered over a large geography and in many cases all over the globe, and that's make it difficult to deal with decisions regarding the number, location, and capacity of warehouses and plants and the flow of raw materials and finished goods through the entire network.
2. Different facilities in the supply chain frequently have different conflicting objectives. For instance, suppliers want manufacturers to commit themselves to purchasing large quantities in stable volumes with flexible delivery dates while the manufacturers need to be flexible to their customers' requirements and changing demands. Similarly, the manufacturers' objectives of making large production batches conflicts with the objectives of both warehouses and distribution centers to reduce inventory, which also implies an increase in transportation costs.

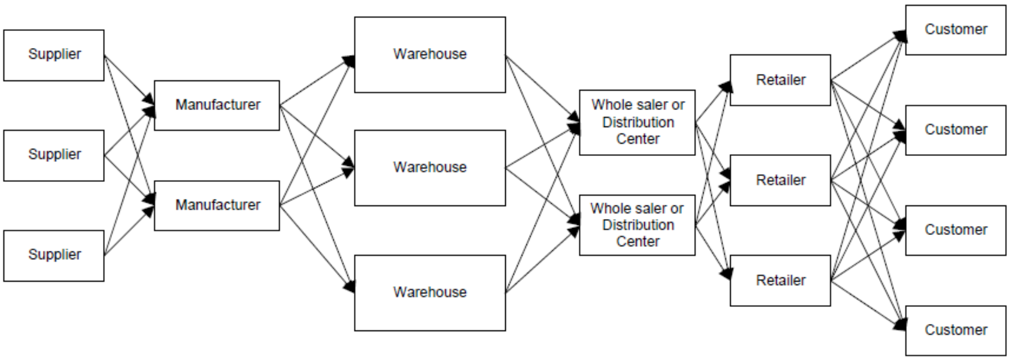


Figure 2-1: A typical supply chain network [3]

3. The supply chain is a dynamic system that evolves over time. The main and central concept in system dynamics is the understanding of how all the objects in a system interact with one another over time through what is called "*feedback loops*". For example, as the customer power increases, there is increased pressure placed on the manufacturers and suppliers to produce an enormous variety of high-quality products and ultimately to produce customised products. Demand and supply of custom products can be very dynamic and lead to variations in orders and inventory levels across the supply chain network and to the increase in the cost of units and throughout the Supply chain as well.

4. Managing uncertainty. Uncertainty is inherent in every supply chain; customer demand can never be forecast exactly, travel times will never be certain, machines and vehicles will breakdown, and natural and man-made disasters can never be expected as well. Supply chains need to be designed and managed to eliminate as much uncertainty as possible and to deal effectively with the uncertainty that remains.

Just a few years ago, most analysts would have said that to design and operate a supply chain so that the total systemwide costs are minimised and systemwide service levels are maintained could not be achieved at the same time. Indeed, traditional inventory theory tells us that to increase service level, the firm must increase inventory and therefore cost. Amazingly, recent development in manufacturing, information, and communications technologies together with a better understanding of production control strategies have led to innovative approaches that allow firms to achieve both objectives simultaneously (e.g. if lead times are reduced, customer service can then be increased without maintaining higher inventory levels). Strategies such as enterprise resource planning, just-in-time manufacturing, lean manufacturing, total quality management, Kaizen, and others become very popular and huge amount of resources were invested in implementing them by many companies all over the world; they discovered that effective *supply chain management* is the next step they need to take in order to achieve competitive advantage, reduce cost, increase profit, and market share [2, 11-15].

2.2 Activities and Key Issues in Supply Chain Management

Supply chain management (SCM) is a broad concept which includes so many activities to manage the entire supply chain from the suppliers at the point of origin to the customers at the end point. Basically, there are three categorical levels of SCM activities: *strategic*, *tactical*, and *operational* [2, 4, 12, 13, 16].

The activities at the *strategic level* deals with decisions and problems that have a long lasting effect on the supply chain, which might include the following:

- Strategic network optimisation, including the number, location, and capacity of the supply chain facilities such as warehouses, distribution centers, and manufacturing plants.
- Strategic partnership with suppliers, distributors, and customers by creating strong communication channels for important and critical information and by improving operations via direct shipping, cross docking, and third-party logistics.
- Product lifecycle management and design, so that new products can be easily integrated in to the supply chain alongside with the existing ones.
- Information Technology infrastructure, to support supply chain operations.
- Where-to-make and what-to-make-or-buy decisions.

The activities at the *tactical level* deals with decisions and problems that are typically updated anywhere between once every quarter and once every year and these might include the following:

- Sourcing contracts and other purchasing decisions.
- Production decisions, including contracting, scheduling, and planning.
- Inventory decisions, including quantity, location, and quality of stock.
- Transportation decisions, including contracting, routes, and frequency.
- Benchmarking of all operations against competitors and implementation of best practices throughout the enterprise.

The activities at the *operational level* refer to day-to-day decisions and problems such as Production Planning and scheduling for each manufacturing facility in the supply chain, Demand forecasting and lead time quotations, routing and truck loading, and coordinating and sharing information with all members in the supply chain.

Given the size, complexity, and dynamic nature of supply chains, next are key issues, questions, and trade-offs associated with major supply chain activities.

2.2.1 Logistics Network Configuration

Consider several plants manufacturing products to serve a set of geographically dispersed retailers where the current set of warehouses is deemed inappropriate and the management wants to reorganise or redesign the distribution network. This may be due to changing demand patterns or the termination of leasing contracts for a number of existing warehouses. In addition, changing demand patterns may require a change in plant production levels, a selection of new suppliers, and a new flow pattern of goods throughout the distribution network. How should the management select a set of warehouse locations and capacities, determine production levels for each product at each plant, and set transportation flows between facilities, in such a way to minimise total production, inventory, and transportation costs and satisfy service level requirements? This is a complex optimisation problem, and advanced technology and approaches are required to solve it [2, 17-19].

2.2.2 Inventory Management and Control

Matching supply and demand in supply chains is a critical challenge. To reduce cost and provide the required service level, it is important to take in to account inventory costs, lead time, and forecast demand. Consider a retailer who maintains an inventory of a particular product and uses historical data to predict customer demand. The retailer objective is to decide at which point to reorder a new patch of the product and how much to reorder so as to minimise inventory ordering and holding costs. What is the impact of the forecasting tool used to predict demand? Should the retailer order more than, less than, or exactly the demand forecast, and how to utilise the inventory turnover ratio? Why should the retailer hold inventory in the first place? Is it due to uncertainty in customer demand, uncertainty in the supply process, or some other reasons? If it is due to uncertainty in customer demand, is there anything that can be done to reduce it? Relationships between suppliers and buyers are established by means of supply contracts that specify pricing and volume discounts, delivery lead times, quality, returns, and so forth. How buyers and suppliers can use supply contracts to improve supply chain performance? [2, 20-22].

2.2.3 Procurement and Outsourcing Strategies

In the 90’s outsourcing the manufacturing of key components of certain products was the focus of many industrial manufacturers; it was one easy way to increase profit by reducing cost through strategic outsourcing, but how can a firm identify what manufacturing activities lie in its set of core competencies, and thus should be completed internally, and what product and components should be purchased from outside suppliers because theses manufacturing activities are not core competencies? What are the risks associated with outsourcing and how can they be minimised? When you do outsource and how can you ensure a timely supply of product? What is the impact of the internet on the procurement process? [2, 20, 23-25].

2.2.4 Distribution Strategies

Wal-Mart's success story highlights the importance of a particular distribution strategy referred to as cross-docking. This is a distribution strategy in which the stores are supplied by central warehouses called cross-dock points. They act as coordinators of the supply process and as transhipment points for incoming orders from outside vendors, but that do not keep stock themselves. How should a cross-docking strategy be implemented in practice? What are the savings achieved using a cross-docking strategy? Is the cross-docking strategy better than the classical distribution strategy in which inventory kept in warehouses, or direct shipping in which goods are shipped directly to stores? [2, 18, 19, 26].

2.2.5 Product Design

Effective product design is a critical issue in the supply chain where certain designs may increase inventory holding costs or transportation costs relative to their designs, while other may facilitate a shorter manufacturing lead time. Since product redesign is often expensive, when is it worthwhile to redesign products to reduce logistics costs or lead times? What changes should be made in the supply chain to take the advantages of the new product design? What role does SCM play to successfully implement new concepts such as mass customisation, delayed differentiation, design for logistics, and design for SCM (DFSCM)? What are the benefits from involving suppliers in the design process? [2, 27-30].

2.2.6 Information Technology and Decision Support Systems

Information technology is vital for effective SCM. In fact, much of the current interest in SCM is motivated by the opportunities that appeared due to the large quantity of data and the saving that can be achieved by the sophisticated analysis of these data. The primary issue in SCM is not whether data can be received, but what data should be transferred? Which data are significant for SCM and which data can safely be ignored? How should the data be analysed and used? What is the role of electronic commerce, and what infrastructure is required both internally and between supply chain partners? What is the impact of the internet and decision-support systems to achieve competitive advantage in the market? [2, 31-33].

2.2.7 Supply Chain Integration

Designing and implementing a globally optimal supply chain is quit difficult because of its dynamics and the conflicting objectives employed by different facilities and partners. Nevertheless, the Wal-Mart, National Semiconductor, and Procter & Gamble success stories demonstrate not only that an integrated and globally optimal supply chain is possible, but that it can have a huge impact on the company's performance and market share. One can argue that these examples are associated with companies that are among the biggest companies in the world; these companies can implement technologies and strategies that very few others can afford. However, in today's highly competitive markets most companies have no choice; they are forced to integrate their supply chain and engage in strategic partnering. How can integration be achieved successfully? Basically, sharing information and implementing a proper production control strategy are the keys to a globally integrated supply chain so, how does information affect the supply chain and what is the appropriate supply chain control strategy? Should the firm use a push, a pull, a push-pull, or any other strategy? What would be the cost to implement one of these strategies? What is a centralised and decentralised SCM? [2, 20, 26, 34-38]. As these issues are the main interest of this research work; they will be reviewed and discussed in details in section 2.4.

2.3 Supply Chain Performance Measures

An important component in supply chain design and analysis is the establishment of appropriate performance measures or metrics. These measures play important role in setting objectives, evaluating performance, and determining future options of actions. They can also provide us with necessary feedback information to show progress and diagnose problems. Available literature identified so many numbers of important performance measure(s) to evaluate supply chain effectiveness and efficiency (e.g. qualitative, quantitative, multiple, and SCOR metrics).

In general, performance measures can be classified into two broad categories; as either qualitative or quantitative in nature. A complete description of the qualitative and quantitative performance measures were reported in Chan et al. [14, 39] and Beamon [14, 39] as in following subsections:

2.3.1 Qualitative Performance Measures

Qualitative performance measures are those measures for which there is no single direct numerical measurement (although some aspects of them may be quantified) as follow:

- *Customer Satisfaction*: The degree to which customers are satisfied with the product and/or service received, and may apply to internal customers or external customers. Customer satisfaction is comprised of three elements as follows:
    1. Pre-Transaction Satisfaction: satisfaction associated with service elements occurring prior to product purchase.
    2. Transaction Satisfaction: satisfaction associated with service elements directly involved in the physical distribution of products.
    3. Post-Transaction Satisfaction: satisfaction associated with support provided for products while in use.
- *Flexibility*: The degree to which the supply chain can respond to random fluctuations in the demand pattern.
- *Information and Material Flow Integration*: The extent to which all functions within the supply chain communicate information and transport materials.
- *Effective Risk Management*: All of the relationships within the supply chain contain inherent risk. Effective risk management describes the degree to which the effects of these risks are minimised.
- *Supplier Performance*: With what consistency suppliers deliver raw materials to production facilities on time and in good condition.

2.3.2 Quantitative Performance Measures

Quantitative performance measures are those measures that may be directly described numerically. Quantitative supply chain performance measures may be categorised by: (i) objectives that are based directly on cost or profit, (ii) objectives that are based on some measure of customer responsiveness, and (iii) objectives that are based on productivity as follows:

<u>i- Measures Based on Cost</u>

- *Cost Minimisation*: Cost is typically minimised for an entire supply chain (total cost), or is minimised for particular business units or stages.
- *Sales Maximisation*: Maximise the amount of sales dollars or units sold.
- *Profit Maximisation*: Maximise revenues less costs.
- *Inventory Investment Minimisation*: Minimise the amount of inventory costs (including product costs and holding costs)
- *Return on Investment Maximisation*: Maximise the ratio of net profit to capital that was employed to produce that profit.

<u>ii- Measures Based on Customer Responsiveness</u>

- *Fill Rate Maximisation*: Maximise the fraction of customer orders filled on time.
- *Product Lateness Minimisation*: Minimise the amount of time between the promised product delivery date and the actual product delivery date.
- *Customer Response Time Minimisation*: Minimise the amount of time required from the time an order is placed until the time the order is received by the customer. Usually refers to external customers only.
- *Lead Time Minimisation*: Minimise the amount of time required from the time a product has begun its manufacture until the time it is completely processed.
- *Function Duplication Minimisation*: Minimise the number of business functions that are provided by more than one business entity.

<u>iii- Measures Based on Productivity</u>

- *Capacity utilisation maximization:* Maximise the capacity utilisation.
- *Resources utilisation maximisation*: Maximise the resources utilisation.

2.3.3 Multiple Performance Metrics

A supply chain performance measurement system that consists of a single performance measure is generally inadequate since it is not inclusive and ignores the interactions among important supply chain characteristics. It is important to find appropriate performance measures to determine if *all the efforts* in designing and operating a supply chain finally leads to an overall success or not. In most cases it is not suitable for a company to just improve function-specific or company-specific performance measures. Focusing on just one side can lead to a dramatically negative effect for the overall supply chain. To ensure an efficient supply chain, it is necessary to choose performance measures that control and improve the entire supply chain not just parts of it [40, 41].

Beamon [40] suggested a new framework for supply chain performance measurement that can be derived from the use of three vital types of measures: resources (generally cost), output (generally customer responsiveness), and flexibility (how well the system reacts to uncertainty). Each of the three types of performance measures has different goals and metrics. For overall performance success of the supply chain, it is important to include at least one individual metric from each of the three types.

Hausman [42] pointed out the importance of paying attention to different dimensions in setting up SCs performance measures and gave three dimensions that should be treated equally. Each SC should at least have one performance measure per dimension to report and control it. The three dimensions are *service*, *assets*, and *speed*. Hausman identified a fourth dimension which is *quality*, but regards it as natural and automatically given in modern industry. The service metrics will measure how well a supply chain serve its customers, using performance measures such as stock fill rate, percentage on-time delivery, lead time, or number of back orders. The assets metrics describes the inventory involvement in the chain. Appropriate measures would be the wok-in-process (WIP), the value of inventory, or the inventory changes. The speed metrics includes metrics which are time-related; they track responsiveness and velocity of execution. Adequate performance measures could be the total time of a product in the supply chain (throughput time), the response time to customers' orders, or the time necessary form buying the raw material or to getting paid by the customer for the finished product.

Kleijnen and Smits [43] emphasised the importance of multiple performance metrics in SCM and presented some supply chain metrics used in business practice by two large manufacturing companies. The first company evaluates the logistical performance of its supply chain management system through five key performance metrics. These metrics are measured each month for each specific product and were defined as follows [43]:

i. *Fill rate*: The percentage of orders delivered on time; that is, no later than the delivery day requested by the customer.
ii. *Confirmed fill rate*: The percentage of orders delivered as negotiated; that is, delivered no later than the day agreed between the customer and the supplier.
iii. *Response delay*: Is the difference between the requested delivery day (as in i) and the negotiated day (as in ii), expressed in working days.
iv. *Stock*: or total work in process (WIP) which can be expressed as a percentage of total sales over the number of preceding months. Obviously, the smaller this percentage is, the higher the financial metrics will be at least, in the short run. In the longer run, a small WIP may lead to low fill rates that affect customer's satisfaction.
v. *Delay*: Is the actual delivery day minus the confirmed delivery day. A fill rate (as in i) less than 100% implies some delay which can be measured by this metric.

The second company is Hewlett-Packard (HP) which put emphasis on the importance of shared performance metrics; that is, metrics shared by all companies in the supply chain. More specifically, in their supply chain management case study at HP, Calliloni and Billington [44] mention three metrics as follows:

i. *Fill rate*: Percentage of demand filled from available stock
ii. *Sales/Inventory ratio*. A higher ratio means there is less capital tied in inventory.
iii. *Product sales*.

2.3.4 The SCOR Model Performance Metrics

An initiative taken to improve supply chain performance and achieve global optimisation through measurement called "*supply chain operations reference model*" (SCOR). The SCOR model is a well-recognised supply chain (SC) model that has been successfully adopted by various industries around the world. It was introduced in 1996 and has been endorsed by the Supply Chain Council (SCC), a global not-for-profit organisation of firms interested in SCM. The SCOR model is a business process reference model attempts to integrate well-known concepts of business process reengineering (BPR), benchmarking, process measurement, and best practice analysis into a cross-functional framework and applies them to SCs. The model allows SC partners to "speak a common language" because it provides standardised definitions for processes, process elements, and metrics as follows [33, 45-49]:

- The SCOR model is founded on five distinct management processes: *Plan, Source, Make, Deliver* and *Return*. The SCOR modeling approach starts with the assumption that any supply chain can be represented as a combination of the five basic processes. The "plan process" deals with demand/supply planning; it balances the demand and supply to best meet the sourcing, production, and delivery requirements. The "source process" procures goods and services to meet planned or actual demand. The "make process" includes functions that transform goods to a finished state to meet planned or actual demand. The "deliver process" provides finished goods and services to meet planned or actual demand, typically including order management, transportation management, and distribution management. The "return process" is associated with returning or receiving returned products for any reason.
- As shown in Figure 2-2 the SCOR model contains three main hierarchical levels of process details. Level 1 is the *top level* that deals with the scope and content definitions of the supply chain using the five previously defined core processes. Level 2 is the *configuration level* and deals with process categories using the SCOR configuration *toolkit* shown in Figure 2-3.
- Each core process can now be further described by a process type (e.g. Planning, Execution, and Enable) as shown in Figure 2-4.

- Level 3 is the *process element level* which presents detailed process element information for each level 2 process category (e.g. process flow, inputs and outputs, source of inputs, and output destination) as shown in Figure 2-5.
- The *implementation level* (Level 4) is not in scope of the SCOR model where, companies further decompose process elements and start implementing specific supply chain management practices that are unique to their organisations.

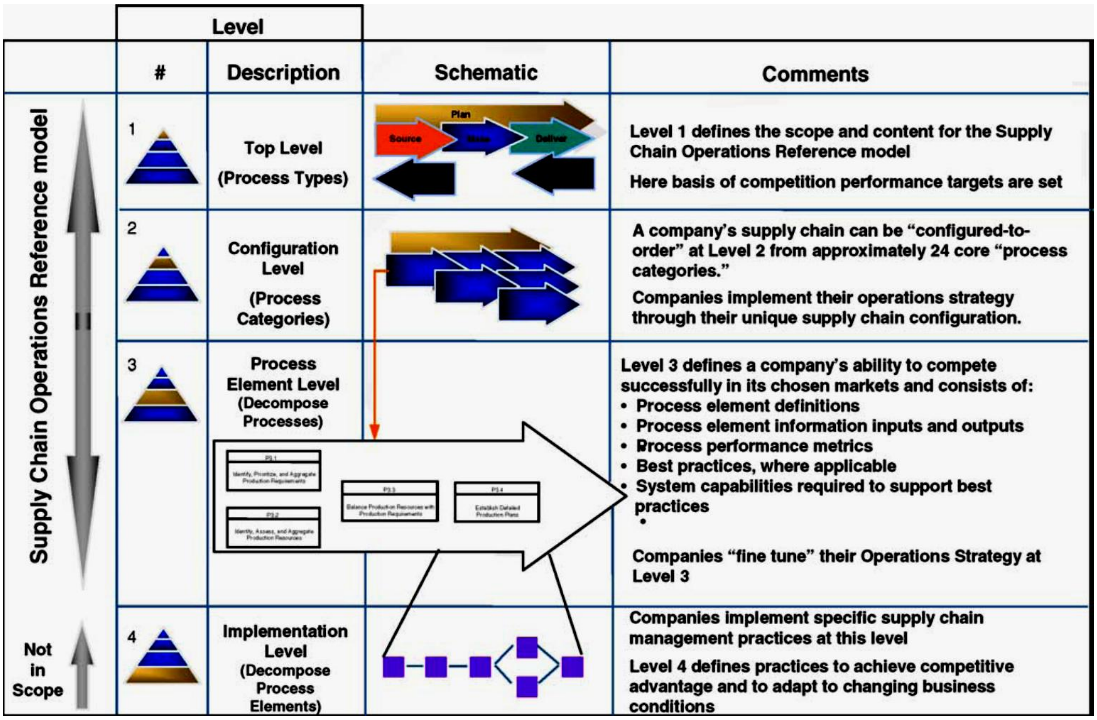


Figure 2-2: SCOR process levels [47]

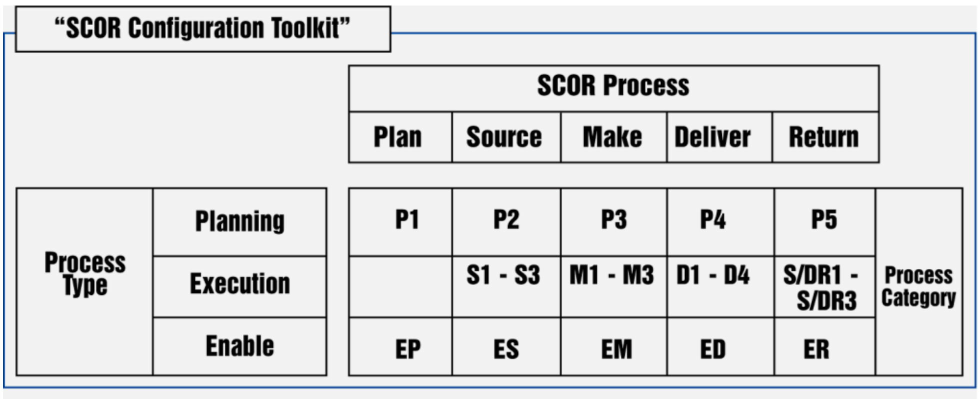


Figure 2-3: SCOR configuration toolkit [49]

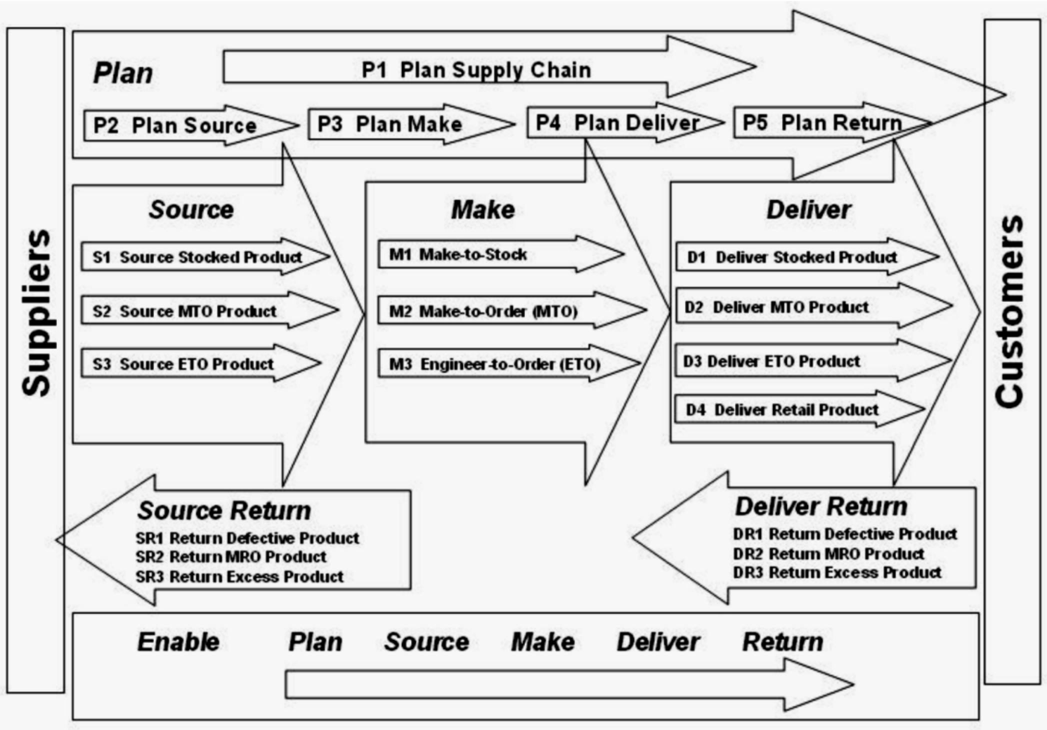


Figure 2-4: SCOR level 2 [33]

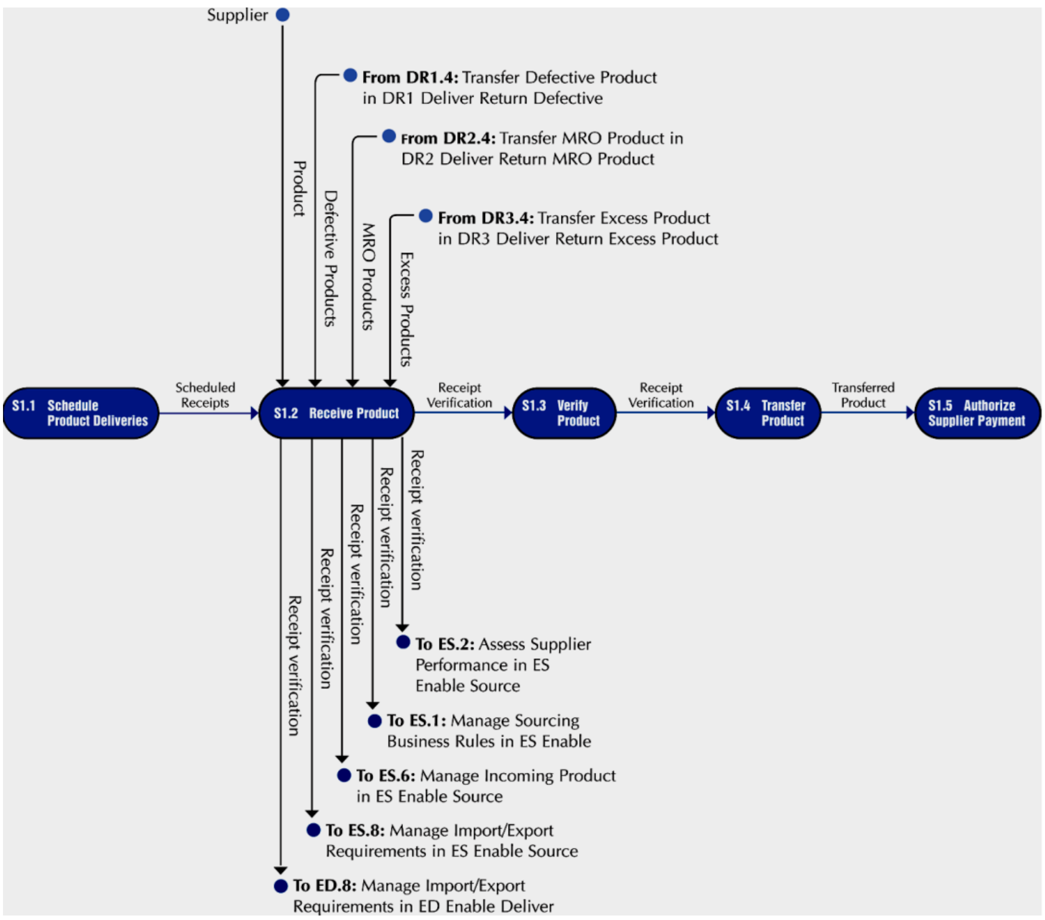


Figure 2-5: (S1.2) details for SCOR level 3 [49]

- As depicted in Figures 2-2 to 2-5, a set of standard notation is used throughout the Model. P describes Plan elements, S describes Source elements, M describes Make elements, D describes Deliver elements, and R describes Return elements. SR = Source Return and DR = Deliver Return. An E preceding any of the others (e.g., EP) indicates that the process element is an Enable element associated with the Planning or Execution element so; EP would be an Enable Planning element. As an example: (P1.1) is a notation that indicates a third level process element. In this case, it is a Plan (P – Level 1) element that is concerned with supply chain planning (1 – Level 2) and is specific to identifying, prioritising, and aggregating supply chain requirements (.1 – Level 3). Another example is (S1.2) which is a notation that indicates a third level process element as well and in this case, it is a Source (S = Level 1) element that is concerned with sourcing stocked product (1 = Level 2) and is specific to receiving product (.2 = Level 3).

The SCOR model promotes many metrics which are used in conjunction with five Performance Attributes: Reliability, Responsiveness, Flexibility, Cost, and Asset. These Performance Attributes are defined as follows [48]:

- *Reliability*: The performance of the supply chain in delivering the correct product, to the correct place, at the correct time, in the correct condition and packaging, in the correct quantity, with the correct documentation, to the correct customer.
- *Responsiveness*: The speed at which a supply chain provides products to the customer.
- *Agility*: The agility of a supply chain in responding to marketplace changes to gain or maintain competitive advantage.
- *Costs*: The costs associated with operating the supply chain.
- *Asset management*: The effectiveness of an organisation in managing assets to support demand satisfaction. This includes the management of all assets (e.g. fixed assets and working capital).

Performance Attributes are characteristics of the SC that permit it to be analysed and evaluated against other supply chains with competing strategies. Just as a physical object like a piece of wood would be described using standard characteristics (e.g., height, width, depth), a SC requires standard characteristics to be described. Without these characteristics it is extremely difficult to compare an organisation that chooses to be the low-cost provider against an organisation that chooses to compete on reliability and performance.

SCOR metrics are organised in a hierarchical structure, just as the process elements are hierarchical. Level 1 metrics are primary metrics designed to provide a view of overall supply chain performance. They are strategic and typically used by the top management to measure how successful they are in achieving their desired positioning within the competitive market space. SCOR Performance Attributes and associate level 1 metrics with there definitions are presented in Table 2.1. Level 2 and 3 metrics are supporting metrics and generally associated with a narrower subset of processes where, level 2 metrics are associated with process categories and level 3 metrics are associated with process elements. Further information and details regarding the SCOR model can be found at the Supply Chain Council website [49].

IBM China Research Laboratory developed supply chain simulation tool named SmartSCOR [33]. It is an On-Demand SCM problem-Solving software tool to help supply chain practitioners to model, simulate, analyse, and optimise their supply chains based on the SCOR model. Gunasekaran et al. [12, 50] have developed a supply chain performance measures framework, which is reminiscent of the SCOR model, in that its uses a variant of the entities: plan, source, make and deliver. The framework provides a set of supply chain performance measures based upon previous work, where they have been classified into operational, tactical and strategic so they can be best dealt with by the appropriate management level. The metrics were also distinguished as financial and non-financial so that a suitable costing method based on activity analysis can be applied.

2.4 Globally optimal Supply Chain Implementation

In recent years many companies all over the world have succeeded in improving performances, reducing costs, increasing service levels, reducing the so-called bullwhip effect, and responding to market changes by integrating their supply chains.

In many cases, this was mainly facilitated by *sharing information* and implementing an appropriate *supply chain strategy* as explained next.

Table 2-1: SCOR Performance Attributes and associate level 1 metrics and their definitions [48]

Performance Attributes	Level 1 Metrics	Metric Definition
Reliability	Perfect Order Fulfillment	The percentage of orders meeting delivery performance with complete and accurate documentation and no delivery damage
Responsiveness	Order Fulfillment Cycle Time	The average actual cycle time consistently achieved to fulfill customer orders
Agility	Upside Supply Chain Flexibility	The number of days to achieve an unplanned sustainable 20 percent increase in quantities delivered
	Upside Supply Chain Adaptability	The maximum sustainable percentage increase in quantity delivered that can be achieved in 30 days
	Downside Supply Chain Adaptability	The reduction in quantities ordered sustainable at 30 days prior to delivery with no inventory or cost fines
Cost	Supply Chain Management Cost	The sum of the costs associated with the SCOR Level 2 processes to Plan, Source, Deliver, and Return
	Cost of Goods Sold	The cost associated with buying raw materials and producing finished goods. This cost includes direct costs (labour, materials) and indirect costs (overhead)
Assets	Cash-to-Cash Cycle Time	The time it takes for an investment made to flow back into a company after it has been spent for raw materials
	Return on Supply Chain Fixed Assets	The return an organisation receives on its invested capital in SC fixed assets. This includes the fixed assets used in Plan, Source, Make, Deliver, and Return
	Return on Working Capital	A measurement which assesses the magnitude of investment relative to a company's working capital position verses the revenue generated from a SC

2.4.1 Information Sharing

A network or a SC of interconnected facilities (as in Figure 2.1) is generally characterised by a forward (downstream) flow of materials and a backward (upstream) flow of information. With appropriately information sharing and by coordinating replenishment and production decisions (especially under demand uncertainty) between the different members of the SC, it is possible to reduce systemwide costs, improve customer service levels, and maximise the SC performance. In most of the situations with no information sharing and coordination, these facilities are independent with individual preferences to be optimised "locally" without due respect to the impact of such policy on other partners in the SC. This policy which might be locally efficient can be inefficient from a global point of view to integrate and maximise the SC performance as pointed out in the previous sections. Many factors could influence the performance of a supply chain, among which is the *demand forecasting*. So, consider a series of companies in a supply chain, each of whom orders from its immediate upstream member and because the SC members do not communicate with each other and do not know their demand with certainty, they have to make their production planning and inventory decisions based on the orders history from the downstream member using forecasting. As the demand forecasting is not accurate and includes some uncertain terms (errors), which can be described as demand variability, the orders will not reflect the correct demand for the periods that they are supposed to cover and the forecasting error will travel up in the whole supply chain in a form of distorted orders that would misguide the upstream members in their production planning and inventory decisions [5, 6, 34, 38, 51-64].

An important phenomenon observed in supply chain practice is that the variability of an upstream member's demand is greater than that of the downstream member. Lee et al. [34, 38] reported that Hewlett-Packard (HP) had to rely on sales orders from the resellers to make product forecasts, plan capacity, control inventory, and schedule production and when their executives examined the sales of one of its printers at a major reseller, they found that there were some fluctuations over time, which is normal, but when they examined the orders from the reseller, they observed much bigger swings. Also, to their surprise, they discovered that the orders from the printer division to the company's integrated circuit division had even greater fluctuations. Lee et al. also reported that logistics executives at Procter & Gamble (P&G) examined the order patterns for one of their best-selling products, Pampers disposal diapers; they found that the sales at retail stores were fluctuating but the variability was certainly not excessive. However, as they examined the distributor's orders, the executives were surprised by the degree of variability. When these researchers looked at P&G's orders of materials to their suppliers, they discovered that the fluctuations were even greater. These variabilities did not make sense, while the consumers (in this case the babies) consumed diapers at a steady rate, the demand orders variability was amplified as they moved up in the supply chain. P&G called this phenomenon the *bullwhip effect* (in some industries it is known as the whiplash or the whipsaw effect). It was a major problem for HP's and P&G's executives, it forced upstream members to carry more safety stocks than downstream members to maintain higher capacities and be able to meet targeted service levels.

The bullwhip effect illustrated in Figure 2-6 is a new term but not a new phenomenon since it has been known to management scientists for some time as the "*Forrester effect*" after Jay Forrester (1958) at MIT, who came across the problem and afterwards demonstrated it by means of *DYNAMO* simulation [7-9]. The DYNAMO is a computer program used for simulating industrial dynamics models when mathematical analytical solutions were not possible.

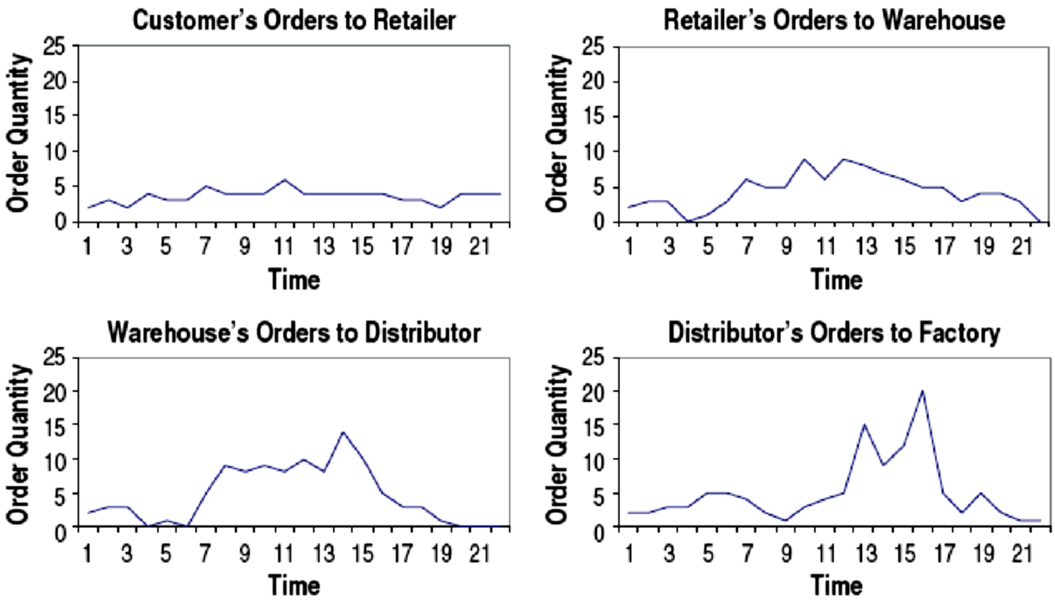


Figure 2-6: Increasing variability of orders up the supply chain (*the bullwhip effect*) [34]

The Forrester effect was also encompassed by Sterman [10]. His work was based on multiple observations of an experiment on stock management via the well known *Beer Distribution Game* which is a role-play simulation program that was originally developed in MIT during the 60s. The experiment involves an industrial production and distribution system (a SC) consists of four players who make independent inventory decisions relying only on orders from the neighbouring downstream player as the only source of communications. The experiment shows that the variances of orders amplify as one moves up in the system. Sterman interpreted the phenomenon as a consequence of players' systematic irrational behaviour or what he called "*misperceptions of informational feedback*".

The bullwhip effect is a major concern for many manufacturers, distributers, and retailers nowadays, the common symptoms of such distorted information could be [2, 34, 65, 66]: (i) poor product forecasts, (ii) excessive inventory, (iii) insufficient or excessive capacities, (iv) poor customer service due to unavailable products or long backlogs, (v) uncertain production planning (i.e., excessive revisions), (vi) increased costs due to overstocking and for corrections (i.e., for expedited shipments and overtime), and (vii) inefficient use of recourses such as labour and transportation due the fact that its not clear whether resource should be planned based on the average order or maximum order received.

It is clear that the bullwhip effect can lead to significant increases in costs and inventory levels throughout the supply chain, so it is necessary to understand the main factors contributing to it and to find out the proper techniques and tools that will help us to manage, control, or even eliminate it. Lee et al. [34, 38] analysed the demand variability along a supply chain and mathematically proved under different conditions that the demand variation was amplified when orders were passed up to the suppliers. Lee et al. made a significant contribution by identifying five main causes to the bullwhip effect and proposed some different suggestions to reduce and counter their impact on the performance of the SC as follow:

1. <u>Demand Forecast Updating</u>.

In a simple order-up-to level inventory policy practice, each member in the SC has to raise its inventory level up to a given target level when ever the inventory position drops below a given number, referred to as the reorder point. The reorder point is simply equal to the average demand during lead time plus a multiple of the standard deviation of demand during lead time (safety stock). In order to determine the target inventory level (i.e., the required amount to replenish the inventory to meet future demands and necessary safety stock), each member in the SC must now forecast both the expected demand and the standard deviation of demand using a proper forecasting technique such as moving average or exponential smoothing. As with most standard forecasting methods, future demands are updated each time a new demand is observed, therefore at the end of each period the downstream member will observe the most recent demand data, update the forecast and use it to update how much to reorder from the upstream member. The more data are observed the more the estimates of the average and the standard deviation of demand are modified and consequently increasing variability in the placed orders over time. This variability can be much greater than that in the demand data it self and as a result, the upstream member (e.g. manufacturer) loses sight of the true demand in the market and the distortion of demand information arises and gets amplified as moving up in the chain. One remedy to the repetitive processing of data in supply chains is demand information sharing. Making raw actual demand data available some how to all SC members will enable them to update their forecasts with more accuracy and less variability. Electronic data interchange systems (EDI) between SC partners are becoming fairly common nowadays. In the consumer products industry such as the grocery, nearly 60% of the placed orders were transmitted via EDI in 1995. In the computer industry, manufacturers such as IBM, HP, and Apple all request sell-through data on withdrawn stocks as part of their contract with resellers. Also in a more radical approach where the downstream site would become a passive partner in the SC, the upstream site could have access to demand and inventory information at the downstream site and update all necessary forecasts and resupply the downstream site. This practice is known as Continuous Replenishment Program (CRP) or Vendor-Managed-Inventory (VMI) [67-69]. Another approach is to get demand information about the downstream site by bypassing it (e.g. direct marketing, direct sales, and build-to-order production). The manufacturer in this instance will have complete information on the demand pattern and will not be subjected to the bullwhip effect created by demand repetitive processing. Dell Computer's "Dell Direct" program and the "Consumer Direct" program of Apple Computers are a good illustration of such policy (i.e., selling directly to consumers without going through the resellers and distribution channels) [70-73]. Access to a common data set for forecasting purposes is not the total solution. Differences in forecasting methodologies will still lead to higher fluctuations in ordering and demand distortion. So, to eliminate or reduce the impact of the bullwhip effect, having a single SC member to perform forecasting and ordering for other members would be a thought. This way the supply chain can implement centralised multi-echelon inventory control system. This philosophy was adopted by Clark and Scarf (1960) [74].

2. Lead Times

Lead time can add to the bullwhip effect by magnifying the increase in variability due to demand forecasting. To calculate safety stock levels and reorder points, estimates of the average and standard deviation of customer demand are multiplied by the lead time. So, with long replenishment lead time, a small change in the estimate of demand variability implies a significant change in safety stock and reorder level, leading to a significant change in ordered quantities [53, 66, 75]. Shortening the lead time is a direct and effective counter-measure to the bullwhip effect and this has long been the aim strategy in various companies and industries all over the world (e.g., Quick Response in the apparel industry [76], and product development in the Auto industry [77]). Effective information systems such as EDI can cut lead times by reducing that portion of the lead time linked to order processing, paperwork, stock picking, transportation delays, and so on. Often these can be a substantial portion of the lead time, especially if there are many different stages in the SC and this information is transmitted one stage at a time. Similarly, transferring Point-of-Sale (POS) data from the retailer to its supplier can help reduce lead times significantly because the supplier can anticipate an incoming order by reviewing the POS data [2]. Chen et al. [53] investigated the impact of both forecasting and lead time on the bullwhip effect and quantified it for simple two stages SC consisting of a single retailer and a single manufacturer. It was assumed that the retailer is using a simple order-up-to inventory policy to make inventory replenishment decisions and the moving average method to forecast demand. Under these assumptions, Chen et al. demonstrated that the variance of the orders was always higher than that of the demand and the magnitude of the variance was significantly influenced by the number of observations used in the moving average and the lead time between the retailer and the manufacturer. Chen et al. extended the analytical model to a multiple stage SC and found that the bullwhip effect could be reduced, but not completely eliminated. In another paper Chen et al. [75] examined the outcome of using the exponential smoothing forecasts on the bullwhip effect and compared the result with that using the moving average. It was found that the reduction in ordering lead time and using more demand information in constructing the demand forecast (a smoother forecast) could decrease the bullwhip effect.

3. Batch Ordering

In a SC, each member places orders with an upstream member using some inventory control policy. Demands come in, depleting inventory, but the member may not immediately place an order with its supplier. It might batches or accumulates demands before issuing an order. If the retailer uses batch ordering then the wholesaler will observe a large order followed by several periods of no orders, followed by another large order and so on. Thus, the wholesaler sees a distorted and highly variable pattern of orders. Caplin [78] considered the impact of batch ordering on the bullwhip effect. He proved that, for a retailer following an (s, S) inventory policy, the variance of replenishment orders placed by the retailer to the manufacturer exceeds the variance of customer demand observed by the retailer. Firms use batch ordering for several reasons such as the relatively high cost of placing an order, the quarterly or yearly sales quotas and incentives, and the high transportation costs where in this case they may order large quantities that allow them to take advantage of transportation discounts (e.g. full truck or container load quantities). To mitigate the batching effect, companies need to develop strategies that lead to more frequent replenishment in small batches, which in turn leads to less distortion of demand information and more efficient delivery and production schedules. EDI can reduce the cost and paperwork in generating an order. Companies using EDI such as the National Biscuit Company (Nabisco) perform paperless computer-assisted-ordering (CAO) which in return help the customers to order more frequently in small batches and in reducing the ordering costs. Also, Manufacturers can influence retailers batching decisions by allowing them to order a mixture of products to fill a truckload and offer them the same volume discount. Another approach is the use of third-party logistics companies which can make small batch replenishments more economical by combining loads from multiple suppliers. A company can realise full truckload savings without the batches coming from the same supplier. Also, *wholesalers* can introduce a degree of stabilisation to the SC. Baganha et al. [79] showed that, under certain conditions (e.g. periodic review inventory system, which implies ordering an amount equal to the previous up to level inventory in every review cycle), the variance of demand faced by a manufacturer is less when filtered through a distribution center than when the retailers submit their orders directly to the manufacturer.

4. <u>Rationing Games and Supply Shortages</u>

Inflated orders placed by retailers during shortage periods tend to magnify the bullwhip effect. Such orders are common when retailers and distributers suspect that a product will be in short supply and that the manufacturer will ration its product to customers (e.g. all customers receive 50% of what they order). When the period of shortage is over, the retailers go back to their standard orders, leading to all kind of distortions and variations in demand estimates. Moreover, due to generous return policies without a penalty that manufacturers offer, retailers continue to exaggerate their needs and cancel orders. On several occasions during the 1980s, the computer industry perceived a shortage of DRAM chips. Orders shot up, not because of the increase in consumption, but because of anticipation. Customers place duplicate orders with multiple suppliers and buy from the first one that can deliver, and then cancelled all other duplicate orders. To avoid this non-productive gaming during shortage situations, manufacturers can allocate products in proportion to past sales records instead of amount ordered and as a result, customers will have no incentive to exaggerate their orders. General Motors has long used this method of allocation in cases of short supply, and other companies, such as Texas Instruments and HP, are switching to it. A more efficient resolution comes in the form of a contract that restricts the buyer's flexibility, since an unrestricted choice of order quantities, free return and generous order cancellation policies all contribute to gaming. In addition, sharing of capacity and inventory information helps to reduce customer’s desire to engage in gaming, but if there is a genuine shortage then, sharing capacity information is insufficient and manufacturers have to work with their customers to place orders well in advance of the sales season so they can adjust production capacity more precisely with a better knowledge of the real product demand.

5. <u>Price Fluctuation</u>

If prices fluctuate, retailers often attempt to stock up when prices are lower. This is emphasised by the popular practice in many industries of offering drastic promotions and discounts at certain times or for certain quantities (high-low pricing strategy).

Estimates indicate that 80% of the transactions between manufacturers and distributors in the grocery industry were made in a "forward buy" arrangement in which items were bought in advance of requirements, usually because of a manufacturer's attractive price offer. Such promotions tend to magnify the bullwhip effect and can be costly to the SC. When a product's price is low (through direct discount or promotional schemes), a customer buys in bigger quantities than needed and when the price returns to normal, the customer stops buying until it has depleted its inventory. As a result, the customer's buying pattern does not reflect its real consumption pattern, and the variation of the buying quantities is much bigger than the variation of the consumption rate. This situation leads to all kind of distortions in demand estimates and the manufacturer will suffer from the uneven production schedules and the unnecessary inventory costs. The simplest way to manage the effect caused by forward buying is to reduce both the frequency and the level of wholesale price discounting. The manufacturer can reduce the incentives for retail forward buying by keeping wholesale prices constantly low, without resorting to a confusing array of price promotions. In the grocery industry, major manufacturers such as Kraft and P&G have moved to the Every Day Low Pricing (EDLP) strategy (i.e. maintaining low prices everyday and occasionally run sales without drastic discounts). P&G has reduced its list prices by up to 24 % and firmly slashed the promotions it offers to trade customers. In 1994, P&G reported its highest profit margins in twenty-one years and showed increases in market share. Another way to control the bullwhip effect due to price fluctuation is to synchronise purchase and delivery schedules. That is, the manufacturer may keep the high-low pricing practice, but the buyer has to sign a purchase contract, according to which he agrees to buy a large quantity of goods at a discount, yet the goods are delivered in multiple future time points evenly separated. This way, the manufacturer can plan production more efficiently, the buyer can enjoy his strategic buying practice, and both parties can save inventory carrying costs.

One of the most frequent suggestions for reducing the bullwhip effect is to *centralise demand information* within a SC. If demand information is centralised, then each stage of the SC can use the actual customer demand data to create more accurate forecasts rather than relying on the records of orders received from the previous stage which can vary significantly more than the actual customers demand. A centralised system is clearly the case when the whole network is owned by a single entity but it is also possible for a network that includes different organisations. From the previous sections, it has been seen that with the advance in information and communication technology (ICT), how information can be accessed from any where in the SC and how can be utilised to improve forecasts and reduce the bullwhip effect and systemwide costs. If the SC includes different organisations with different owners and different objectives and can not be centralised, then it is very important and helpful to form partnerships to approach the advantages of centralised systems [2, 55, 58, 60, 80, 81].

Chen [80] studied the value of centralised demand information in a serial inventory system for a single item with random customer demand. Each stage in the system controls its inventory position using a reorder point/order quantity policy (*R*, *nQ*). Two inventory system models were compared. The first one is based on *echelon stocks* that requires centralised demand and inventory information and in this case ordering decisions at a given stage are based on the echelon inventory position, which is the sum of the inventory position at the considered stage and at all the downstream stages. The second model is based on *installation stocks* requiring only local demand and inventory data (i.e. information from the immediate downstream stage only) and in this case the replenishment decisions are made for each stage in isolation without considering the state of the other stages. The relative cost difference between the two polices is called the value of centralised demand information. Chen's study [80] revealed that the centralised information system's costs are on average 1.75% lower than the decentralised information system, with a maximum of 9% savings. Cachon and Fisher [60] considered a single supplier and a number of identical retailers SC with stochastic customer demand under both a no-information-sharing scenario and an information-sharing scenario, in which the supplier has real-time access to the retailers' demand and inventory status. The retailers and the supplier use an (*R*, *nQ*) reorder point system in the no-information-sharing setting. Under full information sharing, retailers use the reorder point policy, while the supplier monitors echelon inventory levels at each retailer and utilise this information in determining the replenishment batch size and inventory allocation across retailers. Experimental results revealed that full information sharing provides an average 2.2% system cost reduction, with a maximum of 12.1% savings. Yu et al.

[55] illustrated the benefits of partnerships and information sharing in a decentralised SC model consisting of a single retailer and a single manufacturer and where both of them use the base stock policy of the (s, S) type to control their inventory. The bullwhip effect exists in this model because the manufacturer uses the retailer's ordering information to determine its inventory policy without any information about the real customer demand. The partnerships between the retailer and manufacturer were investigated under three levels of information sharing [55]:

- *Level1* and this is referred to as "decentralised control" where the inventories at different sites of the supply chain are controlled independently and there is neither information sharing nor any ordering coordination between the retailer and the manufacturer. Both the retailer and the manufacturer make their inventory decisions according to their own forecasting. The retailer uses the customer demand information and the manufacturer uses the retailer's ordering information.
- *Level2* and this is referred to as "coordinated control". The two neighbouring inventories are coordinated with sharing of the customer ordering information and in this situation, the manufacturer will obtain the customer demand information, together with the retailer's ordering information, and then make its inventory decision based on both the current customer demand information and the retailer's ordering information.
- *Level3* and this is referred to as "centralised control" where under this situation, the decentralised supply chain can obtain the optimal performance achievable by a SC utilising EDI and VMI. Based on EDI, both the retailer and the manufacturer can retrieve customer's demand information in a synchronised manner and by the adoption of VMI, the manufacturer takes the initiative to make major inventory replenishment decisions for the retailer in parallel with its own inventory decisions depending on customer's demand directly.

The authors proved quantitatively that partnerships and information sharing can not only help the members of a decentralised SC to confront the bullwhip effect, but also improve the overall performance of the SC in terms of inventory level reduction and cost savings. The study [55] also revealed that the manufacturer obtains more benefits than the retailer. Therefore, the manufacturer should take the initiative to establish information sharing-based partnerships and also give the retailer some incentives such as sharing logistics costs to induce the retailer's cooperation.

Li and Lin [81] empirically examined via field survey and statistical analysis the impact of environmental uncertainty, intra-organisational facilitators, and inter-organisational relationships on information sharing and information quality (e.g. accuracy, timeliness, adequacy, and credibility) in SCM. Environmental uncertainty refers to the unexpected changes in customer's demand and taste, supplier's product quality and delivery performance, and technology development. Intra-organisational facilitators refers to top management support (i.e., the degree of top manager's understanding of the specific benefits of and support for quality information sharing with SC partners) and IT enablers (i.e., the information technology used to facilitate information sharing and information quality in SCM). Inter-organisational relationship refers to the degree of trust, commitment, and shared vision between SC partners. The results of this study showed that supplier uncertainty and inter-organisational relationships, instead of top management and IT enablers, are the most critical factors in determining the level of information sharing and information quality and in distinguishing organisations with high levels of information sharing and information quality and those with low levels. Generally, organisations with high levels of information sharing and information quality are associated with low level of environmental uncertainty, high level of top management support and IT enablers, and high level of inter-organizational relationships.

While information sharing is important, the significance of its impact on a SC performance depends on what information is shared, when and how it is shared, and with whom. According to Huang et al. [6] "The debate is not about whether or not production information should be shared in the supply chain, but about how to share the right information at the right time in the right format by the right people under the right environment to maximise the mutual benefits of the supply chain as a whole as well as the individual business players". Lee and Whang [54] described the types of information that can be shared between SC partners and their associated benefits as follows:

- Inventory Levels. It is one of the most common data shared between SC partners. Access to inventory status can contribute to lowering the total inventory level in the SC as a whole. If a retailer and a manufacturer independently manage their respective inventories without sharing inventory status information, they may end up having duplicate safety inventories or stockouts at both locations. In practice to avoid this inefficiency, VMI is often employed to coordinate the management of inventories at neighbouring SC partners.
- Sales Data. In traditional SC partners exchange demand information and sales data in a form of "processed" orders. Theses orders serve as a critical source of information about future businesses but tend to be distorted and can misguide upstream partners in their inventory and production decisions (the bullwhip effect). To avoid this, actual sales data (along with inventory information) need to be shared through a proper technique (e.g. sell-through and/or POS data) to enable up stream partners make better demand forecast, develop better inventory and production plans, and lower costs.
- Order Status for Tracking/Tracing. A typical supply chain involves multiple functions and independent companies in the delivery of goods and services to the end consumer. As a result, it is difficult for a customer to find out the status of an order, since the customer does not know who else besides the retailer is involved or where in the supply chain the order is being processed. Recently, supply chain members started sharing their order status information (e.g. by hot-link their web sites or allow access to each others order databases). By calling the retailer or visiting its web site, the customer can find the order status no matter where and in which supply chain partners possession the order is. This one-stop inquiry is a big contrast to the traditional process in which a customer is referred several times to other chain partners or is called back hours or days later. The key benefit of this type of information sharing is the improvement of the quality of customer service, reduction in payment cycle, and savings in labour cost of manual operations.
- Production/Delivery Schedule. A manufacturer could make use of its supplier's production or delivery schedule to improve its own production

schedule. For example, US auto companies have access to the production schedule for their orders at steel suppliers. Such information helps the buyer to expand the planning horizon of his own production schedule and to quote more accurate due dates to his customers. Similarly, production schedules at a manufacturing site can be useful inputs to the supplier in ensuring reliable resupply. Motorola, for example, has used a program called "Scheduling Sharing" whereby computer and peripherals manufacturers that are the customers of Motorola's chip division would share their production schedules with Motorola. This enables Motorola to develop its own production plan, as well as to use the most cost-effective means to replenish customer's stockpiles so that their production schedule would not be disrupted by not having adequate chips.

- Performance metrics. By sharing performance metrics information such as product quality data, lead times, queuing delays at workstations and service performance, SC members can identify the bottlenecks of the chain and improve the overall performance. Chrysler, for example, shares the quality and on-time delivery performance data of all its suppliers across the supply chain. Each supplier can log on to the system to check its performance and its relative standing among the suppliers in the same category.
- Capacity information. Sharing capacity information can contribute to mitigating potential shortage gaming behaviour, thereby countering a potential source of the bullwhip effect. By sharing planned capacity information with the downstream partners well in advance, SC partners can coordinate and prepare against possible shortages. Semiconductor foundries, for example, routinely share their capacity status with the buyers to weather through peaks and valleys of volatile demand.

A supplier may get tremendous performance improvements if permitted to access POS data but the buyer may not gain significantly from this arrangement and in a case like this, one would expect a contract of some kind to ensure that the information is shared on a continuous basis, and that the value created is shared in a satisfactory manner. So when information is shared, an important issue is the level of information sharing. Seidmann and Sundarajan [82] identified the four levels shown in Figure 2-7 at which firms can share information and investigated how competition and contracting affect the generated value from sharing information at each level.

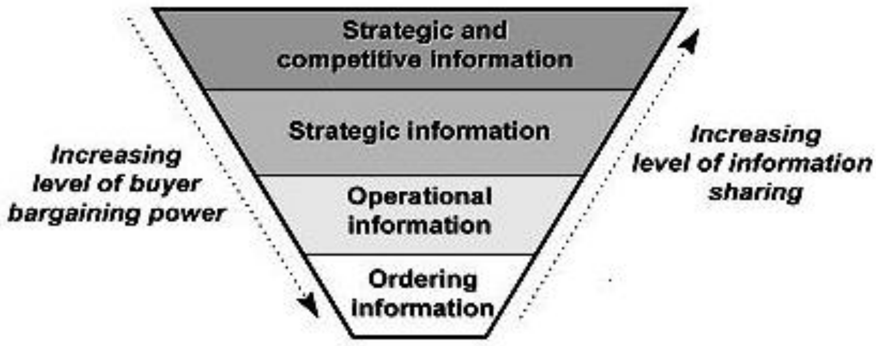


Figure 2-7: Levels of Information Sharing [82]

Within the first level (i.e., *exchanging order information*), order information such as order quantities and prices is shared through EDI and related technology. Both parties benefit from reduced transactions costs and order cycle times, which in turn reduce inventory levels. However, the benefit is not equal. Each party may improve efficiency independently, resulting in no value sharing issues, excluding information technology costs. One party may find it cost-effective to invest in an EDI system that enables these improvements; the other may not. However, both need to invest in the system in order to transact electronically. Wang and Seidmann [83] have analysed this situation where a subsidising policy is likely to be preferred when the buyer can derive a significant reduction of its operating expenses through the use of EDI and when the suppliers' EDI adoption costs are relatively high.

Within the second level (i.e., *sharing operational information*), selective operational information, such as inventory levels, is shared to utilise superior expertise across organizational boundaries and possibly to further improve efficiency. This occurs when one party owns valuable information while the other party is able to use this information more efficiently. An example of this is VMI, in which a buyer shares aggregate inventory position information with its suppliers, thus enabling suppliers to manage the inventory of their products at the buyer’s site. This reduces the supply-side uncertainty that a buyer normally encounters, which results in a lower average inventory for the buyer. If the supplier has comparable VMI arrangements with numerous buyers, it can exploit operational economies of scale. However, the buyer's ordering costs shift to the supplier, thus increasing the supplier's cost. As a result, the supplier's relative bargaining position for its other transactions with the buyer may improve.

With the superior knowledge of how well or badly the product is doing on regular basis, the supplier will be able to bargain for more favourable price schedules. Within the third level (i.e., *sharing strategic information*), the information shared has strategic value to the party that receives it. This occurs when an organisation possesses information that has no independent value, but from which another organisation can generate strategic benefits and, in turn, operational benefits for the other company. For example, a retailer may possess the POS information of all products it sells. Alone, this information is of little value; however, by analysing detailed transaction level POS information from many retailers, a supplier can make superior demand forecasts. This approach is applied extensively in the efficient customer response, continuous replenishment, and quick response systems models. Thus, through improved demand forecasting, this information can be applied to improve the internal efficiency of the supplier and s a result, the buyer receives improved operation efficiency and reduced transaction costs. When this POS information is available to the supplier; the relative bargaining power of the buyer decreases. For instance, with POS sharing, the supplier not only knows gross product movement figures, but also prices charged, local demand patterns, and promotion schedules. Pre-specification of supply terms may ease this limitation. Typically, this limitation management will be possible only when the buyer and the supplier enter into a long-term contract.

Finally at the highest level of information sharing, the fourth level (i.e., *sharing strategic and competitive information*), information adds both a strategic and competitive value to the partner that receives it. Again, this occurs when one organisation possesses information that it can derive little independent value from. However, the other organisation can derive internal strategic benefits as well as competitive benefits from this information. The competitive benefits are with respect to intra-industry rivals. This information does not give the supplier additional competitive advantage over the buyer, but over other suppliers in its own industry (e.g., category management). In category management, one buyer (the retailer) deals with numerous competing suppliers in a particular category. A buyer yields strategic benefits to a supplier in the form of improved demand forecasts and competitive benefits from sales and demand information regarding a competitor's products. Through inventory management, superiority over all products supplied within a specific category and receipt of relevant POS information, a supplier reaps superior inventory management and demand forecasts. Moreover, through dealing with only one supplier per category, the buyer's operating costs are reduced tremendously as order management and information technology costs are eliminated. Regarding competitive benefits, the supplier can track the sales of competing products and use this information to improve the sales strategy for its own products. Since there is an additional time lag between the category manager generating an order and a competing supplier receiving it, inventory costs of competing products tend to be higher, and hence, the category manager may gain a cost advantage as well as enable the buyer to reduce product costs. The trade off appears to increase transaction costs for the supplier who manages orders and monitors product movements of an entire product category.

As with information sharing, implementing a proper SC control strategy is a key to achieve successfully global integration. SCs are often categorised as a push-based supply chain, pull-based supply chain, or push-pull supply chain. That is probably stemmed from the manufacturing revolution of the 1980s, in which manufacturing systems were divided into these categories [2]. In order to review SC control strategies, it is necessary firstly to review and compare production control strategies (PCS) that have their origins in the control of manufacturing systems as follows:

2.4.2 Production and Inventory Control Strategies in Manufacturing Systems

Determination of the mechanism to control the flow of materials through a manufacturing system is one of the most important decisions. *Material flow control* is to addresses the problems of when and how much to authorise parts to be processed at each stage in order to achieve a specified service level while minimises WIP. Difficulties in the control arise due to production and demand variabilities.

Traditionally, *push control systems* such as MRP schedule periodic releases of raw materials into the system based on forecasted customer demands and hence control throughput and observe WIP from time to time, while *pull control systems* authorise parts to be processed in response to the actual demands and hence control WIP and observe throughput all the time. Hybrid push/pull control systems were relatively recently introduced. Those systems compromise the conflicting performance characteristics from both push and pull so that a better system performance can be anticipated. Pull systems are the easiest to implement and yet very efficient.

Since the 1980s, Japanese *Just-In-Time* (JIT) manufacturing approach has triggered the various pull production systems shown in Figure 2-8 which, emphasise the importance of production control that react to actual demand rather than future demand forecasts as in push control systems. JIT manufacturing systems have the primary goal of continuously reducing and ultimately eliminating all forms of wastes. Based on this principle, Japanese companies are operating with very low level of inventory and realising exceptionally high level of quality and productivity [84]. Fullerton et al. [85] have conducted a study in 253 firms in USA to evaluate empirically whether the degree with which a firm implements the JIT practices affects the firm financial performance. From their study, they found that JIT manufacturing systems outperforms the NON-JIT as measured by improved financial performance. Also, they studied the benefits of JIT implementation in 95 firms in USA and they have concluded that JIT implementation improves the performance of the system because of resultant quality benefits time based benefits, employees flexibility, accounting simplification, firms profitability and reduced inventory level.

Hopp et al. [86] identified four different reasons to choose pull over push systems: (i) Observability, WIP is directly observable, while capacity (with respect to which release rate must be set) is not, (ii) Efficiency, pull systems can achieve the same throughput rate as a push system with a smaller average WIP level, (iii) Variability, flow times are less variable in pull systems than in push systems because pull systems regulate the fluctuation of WIP level, while push systems do not, (iv) Robustness, pull systems are less sensitive to errors in WIP level than push systems are to errors in release rate. For advantages and disadvantages of the push and pull systems and other details see the literature [84, 86-92].

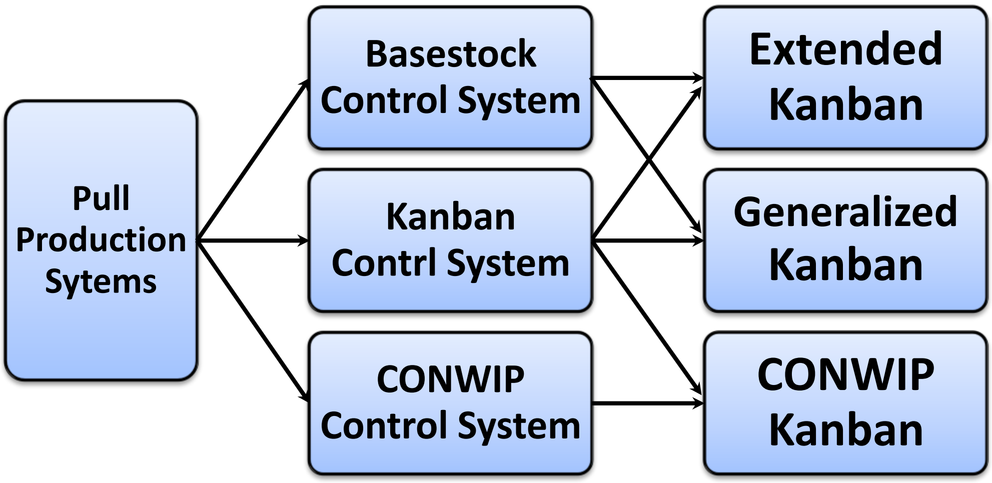


Figure 2-8: Pull Production Systems

Pull mechanisms can be implemented in many ways, the best known is the *Kanban Control Strategy* (KCS). The Kanban control was originally used in Toyota production lines during the 1970s and is often considered to be closely associated with the philosophy of the JIT approach [93]. In KCS, as shown in Figure 2-9, production authorisation cards called Kanbans, are used to control and limit the releases of parts into each production stage. In order for production to begin, a Kanban and a part must be present in the stages input buffer. The Kanban is attached to the part and travels downstream with the part to the stage's immediate successor. When the immediate successor begins production on the part, the Kanban is detached and sent back upstream to the production stage in order to authorise the production of a replacement part. Production in Kanban lines is controlled by actual customer demand, where only a demand event can remove a part from the finished-items inventory points. The advantage of this mechanism is that the number of parts in every stage is limited by the number of Kanbans of that stage. Its disadvantage is that the system may not respond quickly enough to changes in the demand especially in upstream stages of longer lines and when delays encountered at individual stages due to breakdown and repair time [94]. KCS requires inventories of semi-finished products to be maintained at each production stage. In multi-product environments the amount of semi-finished inventory maintained in the line could be prohibitively large.

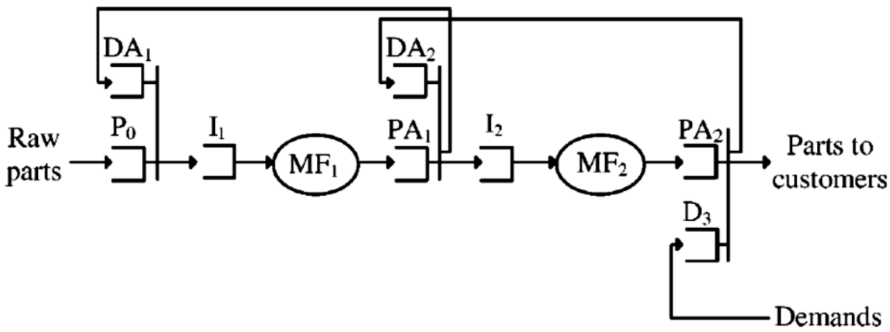


Figure 2-9: Kanban control mechanism in two stages series production line [94]

KCS has been the subject of numerous studies; a recent publication by Junior and Filho [95] reviewed the various Kanban systems and other alternatives proposed by several researchers, classified all the previous studies and presented suggestions for future research.

Chang and Yih [96] introduced a KCS named Generic Kanban System (GKS) that they hoped would be applicable to dynamic, multiproduct, non-repetitive manufacturing environments. GKS operates by providing a fixed number of Kanbans at each workstation that can be acquired by any product. A product / job can only enter the system if it acquires Kanbans from each of the workstations in the system.

Another pull control system originated from the inventory control techniques and considered to be the oldest pull-type control mechanism is the *Basestock Control Strategy* (BSCS) [74, 94]. The Basestock system was initially proposed for production/inventory systems with infinite production capacity and uses the idea of a safety stock for finished good inventory as well as safety buffers between stages for coordination. In BSCS, shown in Figure 2-10, every stage has a target inventory of finished parts, called basestocks, to control how much material is held in the line when waiting for another demand. When a demand for an end item arrives, demand cards are transmitted to each production stage. These demand cards are matched with a part in the stage's input buffer to authorise production and are destroyed once production begins. An advantage of this mechanism is that it avoids demand information blockage by transferring the demand information immediately to all production stages unlike the KCS where demand information passes slowly upstream. The down side is that it provides no limit on the number of parts in the system as every demand event authorises the release of new parts and to the loose coordination between stages. It was shown that this is an optimal control policy for an uncapacitated manufacturing system [74]. However, in a two-machine line with finite capacities and unreliable machines, Veatch at el. [97] demonstrated that the choice between BSCS and KCS depends on the location of the system bottleneck. If the upstream machine is slower, BSCS is preferred, otherwise KCS is better. This seems to be due to the difference in information flow in these two disciplines (i.e., global information flow in BSCS versus local information flow in KCS).

Combining the merits of Basestock and Kanban control mechanisms led to many potential benefits as, the Basestock mechanism faster reacts to demand and the Kanban mechanism achieves better coordination and limits WIP. Buzacott [98] proposed a hybrid control system, called *Generalized Kanban Control Strategy* (GKCS), which includes the Kanban and Basestock control system as special cases.

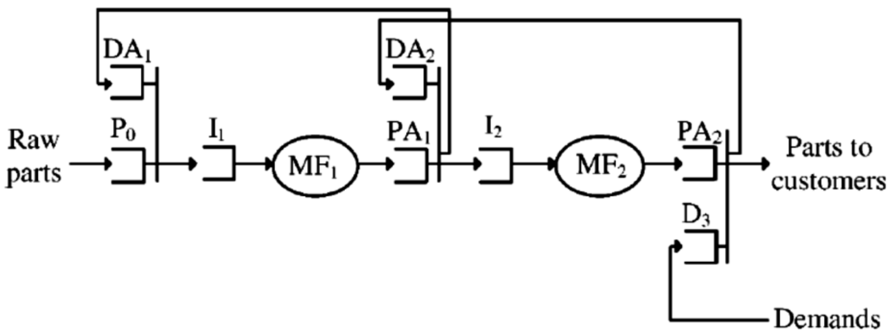


Figure 2-10: Basestock control mechanism in two stages series production line [94]

It is more versatile but also more complex than the Basestock and Kanban mechanisms individually. The complexity is due to that the demand information flow is relayed upstream rather than directly transferred upon arrival. GKCS, as shown in Figure 2-11, depends on two parameters per stage, (i) the amount of basestock of finished parts, and (ii) the number of Kanbans [94]. When a demand event takes place, information about the demand is communicated to the final stage in the form of demand cards. Each demand card must be matched with a free Kanban and when this match occurs, a demand card is sent to the stage's immediate predecessor and production at the stage is authorised if the demand-Kanban match can be matched with a part. Therefore, demand information is not necessarily transferred instantly to all production stages. The arrival of demand information at a stage can be delayed if downstream stages fail to match the demand cards with Kanbans instantly [99].

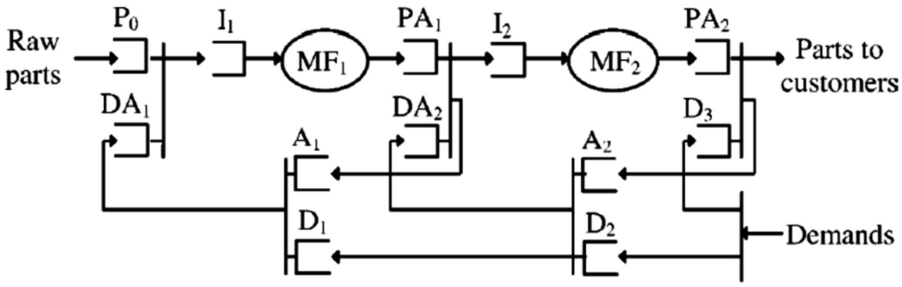


Figure 2-11: Generalized Kanban control mechanism in two stages series production line [94]

Similar framework shown in Figure 2-12 called *Extended Kanban Control Strategy* (EKCS), which also includes both the Basestock and Kanban systems as special cases [94, 99, 100]. In this control policy, production is authorised when a demand card, a Kanban and a part are available. The mechanism is conceptually less complicated than GKCS, since the demand information is now directly transferred to every stage as in the original Basestock system. In addition, unlike GKCS, the roles of Basestock and Kanban are completely separated thus; it is potentially easier to be implemented. Another difference is that the production capacity of EKCS depends only on the number of Kanbans at each stage, while the production capacity of GKCS depends on both the number of Kanbans and the basestock level at each stage. However, one drawback of EKCS compared with GKCS is that it requires the amount of Kanbans to be at least as large as the base stock level, which limits its configuration flexibility.

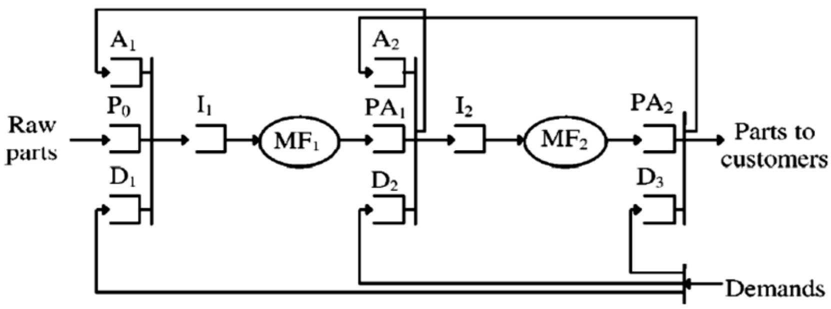


Figure 2-12: Extended Kanban control mechanism in two stages series production line [94]

Another pull system is the *Constant Work-In-Process* control policy, CONWIP, which was firstly proposed by Spearman et al. in 1990 [88]. The mechanism utilised by the CONWIP system shown in Figure 2-13 is very simple, a limit known as the work-in-process capacity (WIP Cap) is placed on the amount of inventory that may be in the system at any given period of time. Once this level of inventory has been achieved, inventory may not enter the system until a demand event removes a corresponding amount of inventory from the line. With only one parameter to control (i.e. the WIP Cap), CONWIP is easy to be implemented and maintained, and as it uses a single card to control the total amount of WIP permitted in the entire line, it can be viewed as a single stage system that uses Kanban control to release parts into and out of the system. In fact, the CONWIP control system is a pull system at the end of the line and a push system from the beginning of the line towards the end. The pushing part of the system can go through similar problems associated with a traditional push system (e.g. the inventory levels are not controlled at the individual stages, which can result in high inventory levels building up in front of bottleneck stages) [101].

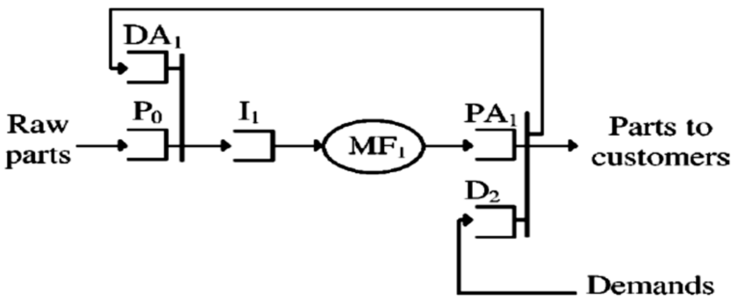


Figure 2-13: CONWIP control mechanism [94]

One more mixed pull control system is the hybrid *Kanban-CONWIP* control policy proposed by Bonvik in 1997 [101]. This control system, shown in Figure 2-14, combines a global inventory control using CONWIP and a WIP control mechanism using Kanbans in all stages except the last stage since any part that has progressed so far will replace a delivered finished part. In this policy, the demand information is transferred to the first stage to authorise processing of another part into the system (CONWIP mechanism) and then a Kanban will follow that part all the way out through the system (KCS mechanism). Bonvik developed a model based on an actual system in a Toyota assembly factory and showed that this hybrid system could achieve better performances than using some other control systems alone.

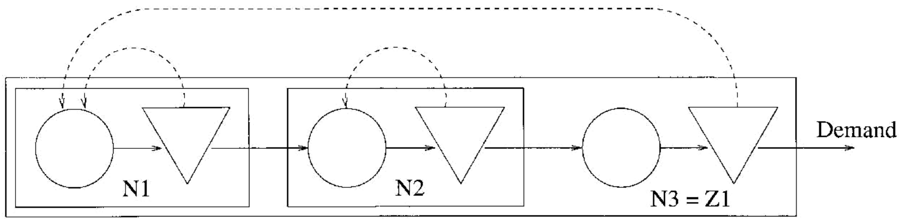


Figure 2-14: A production line controlled by hybrid Kanban-CONWIP policy [101]

2.4.3 Comparison of Performance of various Production Control Strategies

During the last two decades two research approaches have been followed in the selection, implementation and management of an appropriate PCS in organisations aiming to adopt a lean manufacturing philosophy. The first approach has been concerned with developing new, or combining existing pull-type production control strategies in order to maximise the benefits of pull control while increasing the ability of a production system to satisfy demand. The second approach has focused on how best to combine JIT and MRP philosophies in order to maximise the benefits of pull control. PCS that combine push and pull are commonly termed *hybrid Push/Pull* system. These research approaches are not mutually exclusive as there are intersections between these approaches. For instance, CONWIP is classified as a pull-type PCS, however CONWIP could also be considered as a hybrid Push/Pull PCS that utilises pull-type control to limit the amount of inventory in the line and a push-type control within the line to speed the progress of inventory toward the finished-goods buffer [102].

Spearman and Zazanis [90] compared the performance of pull and push strategies using queuing models and show that for serial lines manufacturing a single product pull strategy always results in less congestion and WIP. According to Hopp and Spearman [103], pull systems can attain the same throughput as push systems with less average WIP supporting the superiority of pull systems over push systems. However, Krishnamurthy et al. [104] concluded that push is superior to pull in multi-product environments. They compared the performance of MRP (push) and Kanban (pull) strategies in a multi-product manufacturing environment, in which a fabrication cell *S* supplies different products to several assembly cells. Those comparisons assume that the assembly cells fix their assembly schedules in advance and share this information with their supplier cell *S*. For different system loads and product mixes, they compared the average total inventory at cell *S* to guarantee certain service levels under push and pull systems and they found that push outperforms pull in terms of service levels and average inventories. Further, in the pull strategy, if the Kanban allocations are not set carefully, despite having high inventories the system could result in large average backorder delays and poor service levels. In comparison with CONWIP, GKS was favourable and shown to be more flexible. Gstettner and Kuhn [105] noted that GKS can be shown to reduce to segmented CONWIP with one workstation in each segment. This, however, is not completely true, as there is an overall cap on WIP caused by the requirement for jobs to acquire Kanbans from all the workstations before the job can enter the system. In traditional Kanban systems the number of cards in use is fixed and with the fluctuation of demand this may lead to either huge WIP or heavy backorders.

Tardif and Maaseidvaag [106] proposed an adaptive Kanban system where the number of cards in the system is dynamically readjusted based on current inventory and backorders levels. They investigated the performance of this adaptive system in single-stage system where demand arrives according to a Poisson distribution and processing times are Exponential and showed that this adaptive system outperforms the traditional Kanban even under stable conditions, while remaining easy to implement. They also presented simulation results and showed the benefits of this system under variable demand means. A comparison of KCS, minimal blocking

KCS, BSCS, CONWIP, and hybrid Kanban-CONWIP was presented in [101], these different pull PCS were compared in a four-stage tandem production line using simulation. Each of the control policies was compared using constant demand and demand that had a stepped increase/decrease. It was found that the hybrid Kanban-CONWIP strategy decreased inventories by 10% to 20% over KCS while maintaining the same service levels. The performance of BSCS and CONWIP strategies fell between those of KCS and hybrid Kanban-CONWIP.

Two publications proposed a generic pull model that as well as encapsulating the three basic pull control strategies, KCS, CONWIP and BSCS, also allows customised pull control strategies to be developed [107, 108]. Simulation and an evolutionary algorithm were used to study the generic model. Details of the evolutionary algorithm were given in [107] while results on extensive experimentation on the effect of factors (i.e., line imbalance, machine reliability) on the proposed generic pull model were given in [108].

Kleijnen and Gaury [109] noted that Operations Research techniques have traditionally concentrated on optimisation whereas practitioners find the robustness of the proposed solutions are more important. Kleijnen and Gaury presented a methodology that was a stage wise combination of four techniques: (i) simulation, (ii) optimisation, (iii) risk or uncertainty analysis, and (iv) bootstrapping. The methodology was illustrated through a production-control study for the four-stage, single product production line utilised by [101]. Robustness was defined as the capability to maintain short-term service in a variety of environments i.e. the probability of the short-term fill-rate (service level) remaining within a pre-specified range. Besides satisfying this probabilistic constraint, the system minimised expected long term WIP. In their research work they compared four systems, namely KCS, CONWIP, hybrid Kanban-CONWIP, and Generic. The optimal parameters found in [101] were used for KCS, CONWIP and hybrid Kanban-CONWIP and they used a Genetic Algorithm to determine the optimal parameters for the Generic pull system. For the risk analysis step, seventeen inputs were considered; the mean and variance of the processing time for each of the four production stages, mean time between failures and mean time to repair per production stage, and the demand rate. The inputs were varied over a range of ±5% around their base values. Kleijnen and Gaury concluded that in this particular example, hybrid Kanban-CONWIP was best when risk was not ignored; otherwise Generic was best and therefore, risk considerations can influence the selection of a PCS.

Each of the pull-type PCS discussed above, with the exception of GKCS, have one important advantage over KCS that ensures that they are more readily applicable to non-repetitive manufacturing environments. That advantage stems from the manner in which demand information is communicated in comparison to KCS. In KCS, demand information is not communicated directly to production stages that release parts/jobs into the system. Rather it is communicated sequentially up the line from the finished goods buffer as withdrawals are made by customer demands. This communication delay means that the pace of the production line is not adjusted automatically to account for changes in the demand rate. The arrival of demand information to the initial stages in a GKCS line might be delayed if the demand cards at a production stage in the line are not instantaneously matched with Kanban cards. BSCS, EKCS, CONWIP, GKCS and hybrid Kanban-CONWIP all, however, communicate the demand information instantaneously to the initial stages allowing the release rate to be paced to the actual demand rate. For instance, Bonvik et al. [101] showed that if the demand rate decreases unexpectedly the impact on a CONWIP strategy and hybrid Kanban-CONWIP strategy would be for the finished-goods buffer to increase toward the WIP Cap with all intermediate buffers tending toward empty. The impact, however, on a KCS line would be that all the intermediate buffers would increase toward their maximum permissible limits. Therefore, the KCS line would have semi-finished inventory distributed throughout the line. Another comparison study of pull control mechanisms for unreliable tandem transfer lines producing a single product observed that the hybrid mechanism always outperforms CONWIP and Kanban when storage space and inventory costs are considered explicitly [110]. However, hybrid was equivalent to CONWIP and both outperform KCS when storage space costs are not considered explicitly but aggregated with inventory costs in terms of holding costs.

Hybrid Push/Pull production systems can be classified into two categories: (1) vertically integrated hybrid systems (VIHS) consists of two levels, an upper level push-type production ordering system and a lower level pull-type production ordering system, and (2) horizontally integrated hybrid production systems (HIHPS) consists of one level which is a series of push stations followed by a series of pull stations with semi-finished product stored at a transition point [111, 112]. As an example on the implementation of vertically integrated hybrid systems, Lee [113] described a hybrid manufacturing system which incorporates the traditional MRP system and the Japanese JIT system in a single framework. The rationale was not whether MRP or JIT is better; it was how they complement each other in a hybrid system. He concluded that the vertically integrated hybrid system can provide better production planning, scheduling and control and can eliminates some of the inherent problems and drawbacks in both systems. The main disadvantage of VIHS is that MRP calculations must be performed for each stage in the production system and his makes it complex to implement and maintain and accounts for their relative lack of use in industry [114].

Hodgson and Wang [114, 115] developed a Markov Decision Process (MDP) model for a HIHS. The model was solved using both dynamic programming and simulation for several production strategies, including pure push and pure pull production strategies and strategies based on the integration of push and pull control. In this push/pull integration strategy each individual stage may push or pull. Hodgson and Wang denoted this type of control strategy as Hybrid Push/Pull. Initially in [114], the research was applied to a four-stage semi-continuous production iron and steel works as in Figure 2-15, with the first two stages in parallel and the remaining stages as serial production stages. In order to simplify the analysis the model assumes that the production process is a discrete time process and that demand per period and the amount of inventory are both integer multiples of a unit size. The research was later extended to a five-stage production system [115]. For both the four and five stage production systems, a strategy where production stages 1 and 2 (P1 and P2 in Figure 2-15) push and all other stages pull was demonstrated to result in the lowest average gain (average system cost). Hodgson and Wang [115] stated that they had observed similar results for an eight-stage system and concluded that this strategy would be the optimal hybrid integration strategy for a J-stage system. Subsequent papers that use the Hodgson and Wang model in or extensions of it are [89, 116, 117].

Deleersnyder et al. [89] considered that the complexity of the control structure required for the successful implementation of Synchro-MRP resulted in it being largely ignored by industry. The Synchro-MRP developed by Yamaha Motor Company combines a dual card Kanban system with an MRP system, it requires MRP control to be linked into every stage in the production line while utilising local Kanban control to authorise production at each stage [118]. Deleersnyder et al. developed a hybrid production strategy that limited the number of stages into which MRP type information is added in order to reduce the complexity of the hybrid strategy in comparison to Synchro-MRP, while realising the benefits of integrating push and pull type control strategies. The model developed by Deleersnyder et al. is similar to that presented in [114, 115] and comparable results were obtained for a serial production line.

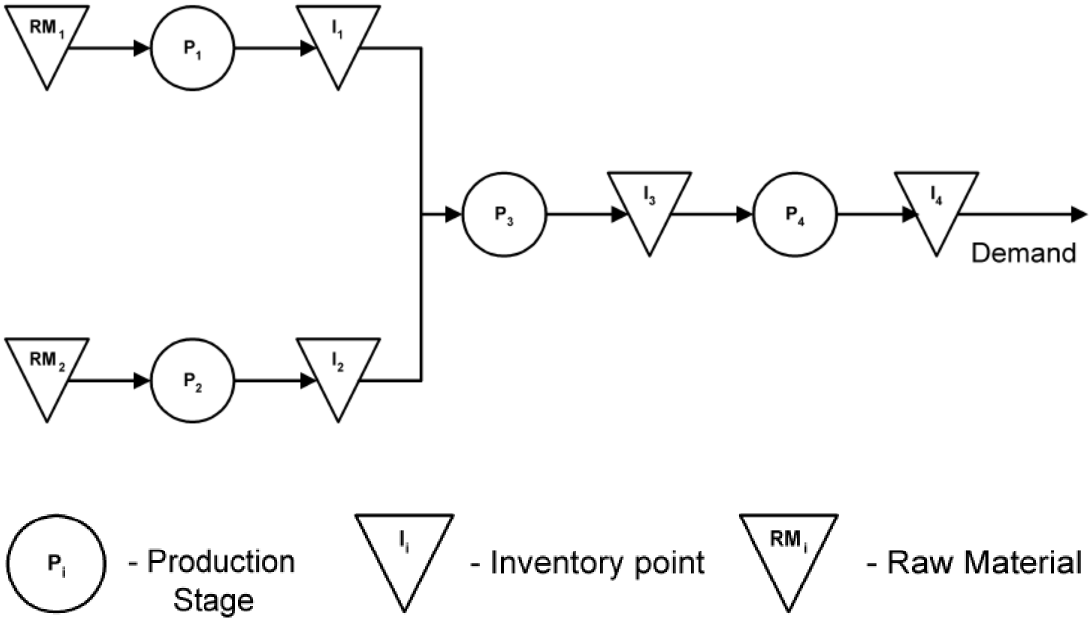


Figure 2-15: Parallel/Serial four stage production system modelled by Hodgson and Wang [114]

Pandey et al. [116] extended Hodgson and Wang's model to allow for the inclusion of raw material constraints at each stage. The modified model also allowed for a stage to require more than one item of inventory and/or more than one item of raw material to produce a part. They presented results from two sets of experiments. In the first set they modelled a four-stage parallel/serial production line similar to the system shown in Figure 2.15. The initial production stages P1 and P2 operated under raw material availability constraints had different order purchasing and delivery distributions but had identical production unreliability. Sixteen integration strategies were considered. In the second experimental set the authors applied the raw material availability constraint to all stages of the production line. The authors concluded that the hybrid strategy in which the initial stages (P1 and P2) operate under push control and the remaining stages operate under pull control is the best strategy when raw material constraints apply only to the initial stages. When the raw material availability constraint is applied to all stages the push strategy becomes the optimal control strategy.

For systems with large variability in demand none of the strategies dominated. Wang and Xu [117] presented an approach that facilitated the evaluation of a wide range of topologies that utilise hybrid push/pull. They used a structure model to describe a manufacturing system's topology. Their methodology was used to investigate four 45-stage manufacturing systems: (i) A single-material serial processing system; (ii) A multi-material serial processing system; (iii) A multi-part processing and assembly system, and (iv) A multi-part multi-component processing and assembly system. Wang and Xu compared pure pull and push strategies against the optimal hybrid strategy found in Hodgson and Wang, where the initial stages push and all other stages pull. Their results suggest that the optimal hybrid strategy out-performs pure push or pull strategies.

Geraghty and Heavey [119] showed that under certain conditions the Horizontally Integrated Hybrid Production Control Strategy, HIHPS, favoured by Hodgson and Wang is equivalent to the hybrid Kanban-CONWIP introduced by Bonvik et al. [101]. Cochran and Kim [111] presented a HIHPS with a movable junction point. The junction point is defined as the last push station that determines which stations are push systems and which stations are pull systems. The average queue size at the push stations and the average waiting time at the pull stations are stochastic and are determined by using a discrete event simulation technique. The objective function of their model is to minimise the cost of the integrated hybrid manufacturing system. The solutions include the location of the junction point, the safety stock level, and the number of Kanbans needed in the pull system. The trade-off between delivery lead time costs and inventory holding costs are to be resolved using Simulated Annealing. In their model, depending on the moving junction point, the system can be a pure push, a push/pull, or a pure pull production control system. This model was applied at a Phoenix company that makes transmitters. It shows that the company would save about 20–25% of the total late costs and inventory costs compared to the pure push approach, which was currently being used.

A simulation study by Taylor [120] showed that for the same system throughput, hybrid push-pull system had the lowest WIP inventory level, while pull system produced more and the push system had the highest WIP. Therefore, the study concluded that if management can learn to implement a hybrid push-pull inventory drive system effectively, it can reduce WIP inventory levels, increase cash flow, earn a greater return on investment and return higher net profits and argued that this alone would allow the company to be more competitive in the world market. Beamon and Bermudo [121] suggest a hybrid push/pull algorithm to reduce costs of inventory and at the same time, maintain a high level of customer service. The algorithm developed is for a multi-line, multi-stage assembly-type production system. The push control is applied from the raw material storage until the components complete processing and go to buffer storage at the end of each line. The pull stations start at this buffer storage down to the final packaging stations. Based on their study with computer-generated data, the results are in favour of the hybrid system.

Cochran and Kaylani [112] proposed a horizontally integrated hybrid production system with multiple part types that saves production costs compared to either pure push or pure pull. The main research question was whether each part type should have its own junction point or whether there should be one common junction point for the overall system. Genetic algorithm (GA) was used to optimise the hybrid production system by locating points of integration, and determining the optimal values of safety stocks for the push part and number of Kanbans for the pull part. Cochran and Kaylani tested the proposed model on a case study of a tube shop in an aerospace manufacturer (Boeing). From the results of their analyses, they draw a number of design conclusions: (i) horizontally integrated hybrid push/pull system can create considerable production cost savings when compared to either pure push or pure pull, (ii) if there is a bottleneck process then it is desirable to locate the junction point after that station (i.e. that process should be pushed), (iii) low variability in parts arrival leads to low safety stock, (iv) parts with higher production requirements need a larger number of Kanbans, and finally they recommend the use of a single junction point unless parts sharing the same resources have extremely different ratios of cost of being late on customer deliveries to holding inventory cost.

2.4.4 Supply Chains Control Strategies

So far, it has been observed that information sharing plays an important role in integrating and coordinating different activities across the entire SC in order to improve performance, reduce costs, and increase service level. Adopting and implementing a proper SC control strategy that make this information available and take the advantage of it is crucial to successfully achieve these goals. Similar to manufacturing systems, supply chains are often categorised as push-based, pull-based or push-pull supply chains.

In push-based supply chains, such as material requirements planning (MRP) systems, production and distribution decisions are based on long term demand forecast and products are pushed as quickly as possible through the network, from the production side upstream to retailers downstream. This characteristic may enable the system to reduce delivery lead time since many semi-finished or finished products are available but also, it will lead to the inability to meet changing demand patterns and to the bullwhip effect and all its inefficiencies [2, 36, 91].

In pull-based supply chains, such as Kanban systems, production and distribution decisions are based on true customer demand rather than forecasted demand and SC members do not hold any excess inventory and only respond to specific orders. Now days this is enabled by fast information flow mechanisms such as POS data to transfer information to the various SC participants. In pull-based supply chains, significant reductions in system inventory levels, reduced costs, and better response to market changes can usually be seen. However, this system may not work well in multi-product environments and in environments with large demand variations. This in turn may result in significant backorders, longer delivery lead times, and higher late penalty costs [2, 36, 91, 104].

In push-pull supply chains, some stages of the SC, typically the initial stages are operated in a push-based manner while the remaining stages are operated in pull-based manner and the interface between them is known as the push-pull boundary as illustrated in Figure 2-16. The hybrid system often compromises the conflicting performance characteristics of the push and the pull environments.

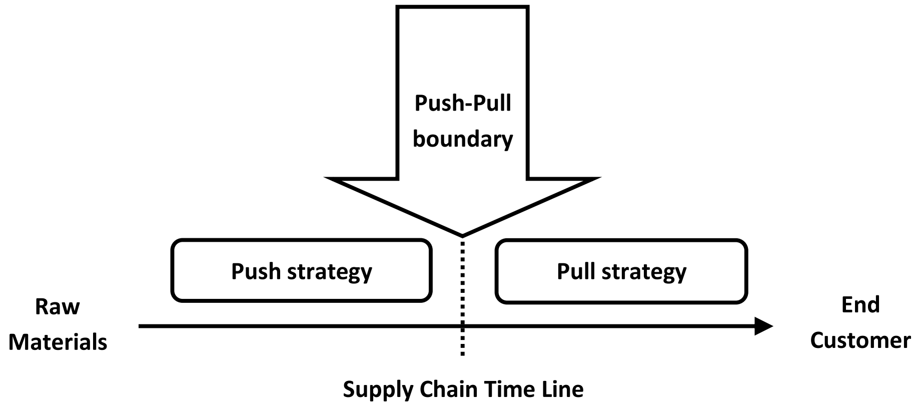


Figure 2-16: Push-pull supply Chains [2]

In the push type, high inventory cost is anticipated in the return of low delivery lead times. On the contrary, in the pull type, higher delivery lead time is expected in the return of low inventory cost. Dell Computers build to order supply chain would be an example for this push-pull strategy in which inventory levels of individual components are determined by demand forecasting, while final assembly is performed in response to actual customer request and the push-pull boundary would then be at the beginning of the assembly line. Another excellent example of push-pull SC strategy is delayed differentiation or product postponement where a firm designs and produces a generic product which then differentiated to a specific end product when demand is revealed. The portion of the SC prior to product differentiation is typically operated using a push-based strategy in which demand forecast for the generic product is based on the aggregation of demand for all its corresponding end product. Due to the fact that aggregate forecasts are more accurate this will leads to reduced inventory levels. The other portion of the SC starting from the time of differentiation is operated using a pull-based strategy. In this portion of the SC, customer demand for a specific end product has a high level of uncertainty thus, product differentiation occurs only in response to actual customer request [2, 36, 91, 122, 123].

The problem of determining optimally the number of raw material orders, Kanbans, finished goods shipments to the buyers, and the batch size for each shipment for a multi-stage KCS system with linear demand for products with short life cycles has been addressed in the literature [124]. This publication indicates that these parameters have to be considered together rather than separately in order to minimise the total cost of inventory. A cost function based on the costs incurred due to these parameters was developed. The optimal number of raw material orders that minimises the total cost was obtained and used to find the optimal number of Kanbans, finished goods shipments, and the batch sizes for shipments. In this KCS the number of cards in use is fixed and with the fluctuation of demand this may lead to either large WIP or backorders.

Two relatively recent papers have explored the possibility of utilising Pull-type PCS to manage inventory and production authorisations in a supply-chain. (i) Takahashi et al. [37] compared the performance of KCS with CONWIP and Synchronised CONWIP in a tiered supply chain. (ii) Ovalle and Marquez [35] compared the performance of CONWIP with MRP for managing inventory and authorising production in a serial supply chain. Both studies showed that CONWIP out performs the other strategy in terms of minimising WIP and achieve desired service levels. The only source of variation in both models was the demand event. Both models assumed that nodes in a supply-chain would produce the authorised quantity after a known lead-time had elapsed. Furthermore, the model presented in [37] assumes that there are no capacity constraints in place at a node in the supply chain also, the calculation of WIP in appears to exclude inventory in a node at the end of a production period and only considers inventory in the output buffers of nodes.

Takahashi and Nakamura [36] discussed the push, pull, and hybrid approaches to controlling a multi-stage supply chain. Their hybrid control system uses the pull controls during the distribution sections of the supply chain (warehouses, stockrooms, etc) and the push controls for the assembly or subassemblies of parts. The model assumes infinite capacity and mandatory transportation between processes and inventory stations. For the three control mechanisms, the variance of processing quantities at each process and the variance of inventory levels at each inventory station were analysed as performance measures. Using numerical calculations, the effect of the number of branches in each stage, the lead time of each transportation process, and the autocorrelation of demand, was investigated. Also, by comparing the total measure of the variances between the control mechanisms, it was shown that the proposed hybrid control mechanism is superior to both the push and the pull control mechanisms, especially under the condition of a small number of branches, short lead time, strong autocorrelation of demand, and high weight for the variances of inventory levels.

Ahn and Kaminsky [125] considered coordinating production and distribution simultaneously. They presented a two-stage stochastic model of a push-pull production-distribution system with non-linear transportation costs. Production at the first stage is completed and "pushed" to the second stage. The second stage is the pull stage where production is completed only once specific orders arrive. The orders arrive at stage 2 according to a Poisson process with rate λ. Two separate operations, which take place at different locations, are required to convert the raw materials into finished goods. They assumed that an infinite supply of raw material is available at stage 1. A single server whose processing time follows an exponential distribution is available at each of the two stages. Items are produced at stage 1, the push stage, and can then be either held as inventory at stage 1, or shipped to stage 2, in which case shipping costs are incurred. Based on some structural results and extensive numerical testing, the authors developed a heuristic for the proposed model, and computationally tested the performance of the heuristic. The results show that their heuristic is quite robust with respect to the changes in the maximum capacity of shipping (i.e., the size of the maximum shipment).

2.5 Summary and Research Objectives

Information sharing and the implementation of an appropriate production control strategy in SCs eager to adopt lean manufacturing principles is a key factor for success and to achieve competitive edge in the market. However, due to the dynamic nature of SCs arising partly from customer power, the conflicting objectives between the different members involved and given the numerous control mechanisms introduced in recent years and the different conclusions, the selection of a suitable pull mechanism is a major challenge to prospective users.

The author strongly feels that *it is a difficult task to evaluate which mechanism is best suited for a specific application under specific conditions using specific tools and approaches*; e.g.:

Pull systems usually have significant reductions in inventory levels and costs, and better response to market changes. However, they may not work well in multi-product environments and in environments with large demand variations resulting in significant backorders, longer delivery lead times, and higher late penalty costs [104]. KCS and CONWIP are mostly analysed and focused on however; Framinan et al. [126] reported that the comparison results in the literature seem to be contradictory. A comparison study of pull control mechanisms observed that the hybrid mechanism always outperforms CONWIP and KCS when storage space and inventory costs are considered explicitly [110]. However, hybrid was equivalent to CONWIP and both outperform KCS when storage space costs are not considered explicitly but aggregated with inventory costs in terms of holding costs. Takahashi et al. [37] compared the performance of KCS with CONWIP and Synchronised CONWIP in a tiered supply chain. Ovalle and Marquez [35] compared the performance of CONWIP with MRP in a serial supply chain. Both studies showed that CONWIP out performs the other strategies in terms of minimising WIP and achieve desired service levels. Kleijnen and Gaury [109] compared four systems (KCS, CONWIP, hybrid Kanban-CONWIP, and Generic -KCS) and concluded that hybrid Kanban-CONWIP was best when risk was not ignored; otherwise Generic was best and therefore, risk considerations can influence the selection of a PCS.

Simulation [122, 127-129] and several analytical techniques (e.g. Markov Time Chain Analysis [130]), Multiclass queuing network approximation technique [131, 132] and State Space representation approach [133, 134] have been applied in carrying out PCSs studies. Simulation is usually the preferred approach because of its ability to handle the dynamics that occur in real manufacturing/SC systems, where analytical methods have to make unrealistic assumptions to avoid intractability [135, 136].

Additionally, in comparing the performances of these strategies, researchers have used a wide variety of performance metrics. Average inventory and service level achieved (percentage of customer demands that are instantaneously satisfied) have been used in [107, 108]. Such performance metrics are conflicting in nature as the aim is to minimise WIP while maximising Service Level, but the Service Level achievable is determined by the amount of on-hand inventory. Therefore, the determination of the appropriate settings of the control parameters (e.g. number of cards to issue to each station in a manufacturing line controlled by a KCS) is a multi-criteria optimisation problem with conflicting objectives.

In order to solve such an optimisation problem any one of a variety of methods could be employed. For instance, Bonvik et al. [101] proposed the hybrid Kanban-CONWIP and compared the performance of this strategy to Kanban, Basestock and CONWIP on a four-stage serial production line. Bonvik et al. used a simulation model and complete enumeration of the decision space given lower and upper bounds for the control parameters to generate a trade-off curve depicting the minimum WIP requirements to meet targeted Service Levels. Using the same manufacturing line, Kleijnen and Gaury [109] used simulation in conjunction with a Genetic Algorithm to determine the control parameters that would minimise WIP for a pre-specified Service Level. Geraghty and Heavey [119] used simulation and Simulated Annealing to solve a cost function where WIP in the system incurred a unit holding cost and Service Level was represented by shortage cost.

Complete enumeration of a decision space is computationally expensive, especially as the number and/or ranges of control parameters increase. The approaches adopted by [109] and [119] have the disadvantage that a single solution emerges which is dictated by initial decisions, such as the service level to target or the relative weights of the costs in the objective function. Kernan and Geraghty [137] also leveraged the manufacturing system delineated in [101] and used simulation and a Pareto-Optimal Multi-Objective Genetic Algorithm to generate the WIP-Service Level Trade-off curves. This approach does not require the decision maker to use a priori knowledge to guide the solution, but rather can review the trade-off curve that emerges from the optimisation solution to finalise their decision.

All of the approaches discussed above used simulation to determine the optimal solution(s) which is a computationally expensive approach in comparison to optimisation of mathematical models. One further issue with these approaches such as [101] and [137] is how a decision maker should interpret the resulting trade-off curve in order to determine the control parameters. So in order to overcome these issues, the author is proposing a multi-objective optimisation framework that utilises Meta-modelling to develop a mathematical model that can be optimised to generate the trade-off curve. Then, to assist the decision maker in determining the optimal control parameters, we propose using information about the curvature of the trade-off curve to guide the decision making process.

2.5.1 Objectives

The objectives of this research is to provide a reliable and practical framework that could be used by decision makers and executives to: (i) possibly utilise lean production control strategies to coordinate work authorisations and inventory management at a supply-chain level, (ii) evaluate and compare their suitability to their system and help them understand the complex interactions between the many SC control parameters and utilise this understanding to achieve balance between conflicting objectives such as maximising service levels while minimising WIP, (iii) provide them with a decision guidance in selecting and testing the optimal solutions of the selected policies control parameters through different phases of modeling, optimisation and decision making under different demand variabilities and objectives. Such a decision support framework should prove very value to supply-chain managers and decision makers seeking to design robust inventory control and work authorisation strategies to respond to the power of the modern customer.

In this research work, of all existing pull control mechanisms, three Pull-based PCS will be considered: (i) Kanban, because it is the most commonly used pull mechanisms, (ii) CONWIP, because it has been shown to outperform Kanban and other mechanisms in many literatures and has the advantage of being easily optimised and (iii) Hybrid Kanban-CONWIP, because it has shown superiority and promising results in Bonvik et al. [101]. So through the proposed framework, Mathematical models applicable to a serial SC similar in structure to that presented [35] will be developed for these PCSs. The developed mathematical models will be different from the models presented in [35] and [37], they will include capacity constraints, production and demand unreliability, state variables, and performance measures. Inventory in the SC system will be calculated based on the sum of in-production inventory and finished goods inventory at each node. The performance measures for the SC will be the average inventory in the system and the average service level achieved by the system after *N* periods of time.

The mathematical models will then be translated into discrete event simulation model using ExtendSim software package. The simulation model will be used to explore the impact of some essential input factors such as the total number of production cards, the maximum production capacity of a node, and the standard deviation of demand on customer service level and WIP by means of Response Surface Methodology (RSM) and Gaussian Process Modeling (GP). Software packages, Design-Expert and JMP will be used to construct the experimental design matrices and analyse the data to develop a series of RSM and GP meta-models. A multi-objective optimisation using the developed meta-models, Metamodel-Based Optimisation, will be conducted by means of the Desirability Approach (DA). A Pareto-Optimal Genetic Algorithm (POGA) code for ExtendSim will be employed to conduct a Simulation-Based as well as a Metamodel-Based Optimisation for the multi-objective SC. Finally, the curvature and risk analysis of the trade-off curves will be utilised to provide guidance to the decision makers in selecting and testing the best optimal settings of the control parameters of the selected policies.

This research will establish the conditions under which a given lean SC control strategy would be superior to others for the purpose of co-ordinating work authorisations and managing inventory in SCs while maintaining or improving service level and will provides a discussion of the experimental results and implications for supply chain managers and offers insights on future research opportunities in this field.

CHAPTER 3 DECISION SUPPORT FRAMEWORK & RESEARCH METHODOLOGY

3.1 Introduction

To achieve the research aim, where a framework will be provided to decision makers at an appropriate level to assess the suitability of various SC strategies to their system and help them understand the complex interactions between the many SC factors and utilise this understanding to achieve balance between conflicting objectives that are ultimately derived from a need to address the influence of customer power on the effectiveness of the SC. The proposed framework utilises simulation, design of experiments, optimisation, and decision support tools to be implemented. An overview to the frame work and to the employed research tools and a detailed explanation of how they were applied is in the following sections.

The proposed framework is depicted in Figure 3-1 and is examined by considering the application of CONWIP, Kanban, and Hybrid Kanban-CONWIP control strategies to SC work authorisation and inventory control. The framework is proposing three main phases: (i) *Modelling phase,* (ii) *Optimisation phase*, and (iii) *Decision Support phase*. These phases can then be utilised by decision makers to assess different SC control strategies through the *Simulation-Based Approach* or the *Meta-Model Approach*. In the Modelling phase of the framework, the supply chain is analysed where key components and performance measures are identified and mathematical formulations are developed that are then translated into a Discrete Event Simulation model. Using Response Surface Methodology (RSM) and Gaussian Process Modeling (GP) to design experiments with the simulation, meta-models for the considered performance measures are developed. In the Optimisation phase of the framework, multi-objective optimisation approaches are used to determine a set of efficient (non-dominated) solutions for the conflicting performance measures. In the Decision Support phase of the framework, information about the curvature of the performance measures optimal trade-off curves is utilised to provide guidance to the decision maker in determining the best solution, from the set of non-dominated solutions, for their purpose and finally a risk analysis is conducted on these selected solutions to asses their robustness when the environmental (uncontrollable, noise) variables are altered.

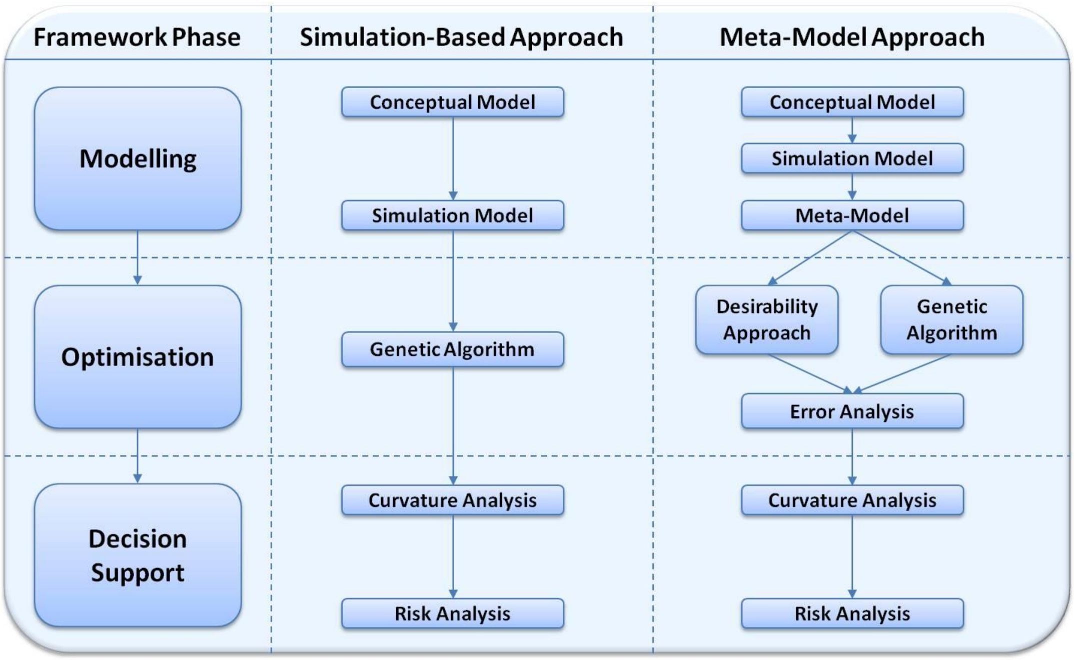


Figure 3-1: Proposed Decision Support Framework

3.2 Phase 1: Supply Chain Modelling

In the Modelling phase of the framework, the application of CONWIP, Kanban, and Hybrid Kanban-CONWIP control strategies to a SC system will be considered. The SC is analysed where key components such as the environmental conditions, the input variables and the performance measures are identified. Mathematical formulations for work authorisation and inventory control are developed that are then translated into a Discrete Event Simulation model. Using RSM and GP to design experiments with the developed simulation model, meta-models for the considered performance measures are developed.

3.2.1 Conceptual Model Development

The centralised SC in this research work is defined as a production–distribution system, in which the production line of each firm has a similarity to a "work center" being a part of a "global line" of supply and also in which a virtual center of control governs the SC and manages the information and parts flow and the inventories along the chain. The proposed SC consists of four nodes in series representing four different firms: a supplier, a manufacturer, a distributer, and a retailer as shown in Figure 3-2

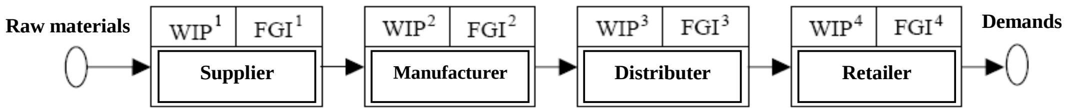


Figure 3-2: Conceptual model series supply chain

When the SC adopts the CONWIP PCS as shown in Figure 3-3, a WIP-Cap is assigned to the whole SC and once orders arrive at the final node it is assumed that these orders will be immediately shipped to final customers and if there is enough WIP-Cap in the system, the production orders and required materials are then released to the first node (considering its production capacity constraints) where they will be pushed through the SC till they are processed completely and leave the final node. When the supply of finished goods from the last node of the SC to final customers is limited, a portion of the orders will not be fulfilled and will accumulate as backlogs in the central control of the SC and can be considered as lost sales

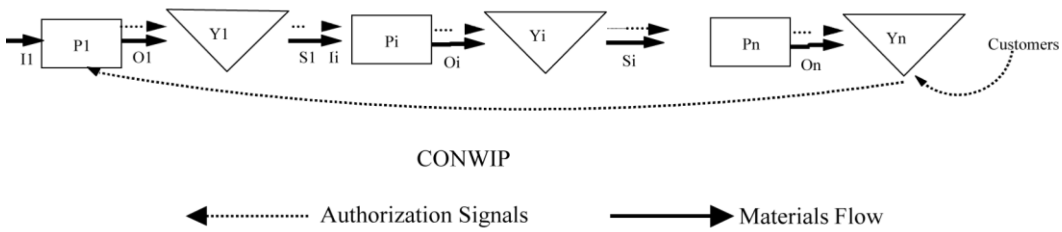


Figure 3-3: Conceptual model CONWIP control mechanism [35]

When the SC adopts the Kanbans PCS as shown in Figure 3-4, a number of Kanbans cards are assigned to each production stage in order to control and limit the releases of parts. In turn, for the production to begin, a Kanban and a part must be present in the stages input buffer. The Kanban is attached to the part when production starts and travels downstream with the part to the stage's immediate successor. When the immediate successor begins production on the part, the Kanban is detached and sent back upstream to the production stage in order to authorise the production of a replacement part. When the supply of finished goods from the last node of the SC to final customers is limited, a portion of the orders will not be fulfilled and will accumulate as backlogs in the central control of the SC and can be considered as lost sales.

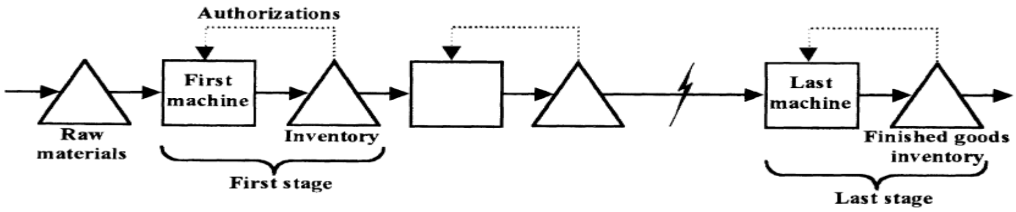


Figure 3-4: Conceptual model Kanban control mechanism [108]

When the SC adopts the Hybrid Kanban-CONWIP PCS as shown in Figure 3-5, a WIP-Cap is assigned to the entire SC in order to bound the amount of inventory that may be in the whole system at any given period of time by using CONWIP cards and a limit is allocated on the amount of inventory at each stage in the SC (excluding the last stage since the amount of parts in this stage can never exceed the inventory allowed in the entire SC) using Kanban cards. When orders arrive at the final node and there are enough finished goods they will be immediately shipped to final customers and production orders and required materials are then released to the first node considering its production capacity constraints, its on hand Kanban cards, and the WIP-Cap . The first node requires two authorisation cards: one from the second node (Kanban pattern) and another one from the last node (CONWIP pattern). Both cards are attached to the part and when at node 2 only the Kanban card is sent back to node 1; the CONWIP card remains attached to the part until it reaches the finished good inventory of the last node and is delivered. When the supply of finished goods from the last node of the SC to final customers is limited, a portion of the orders will not be fulfilled and will accumulate as backlogs in the central control of the SC and can be considered as lost sales.

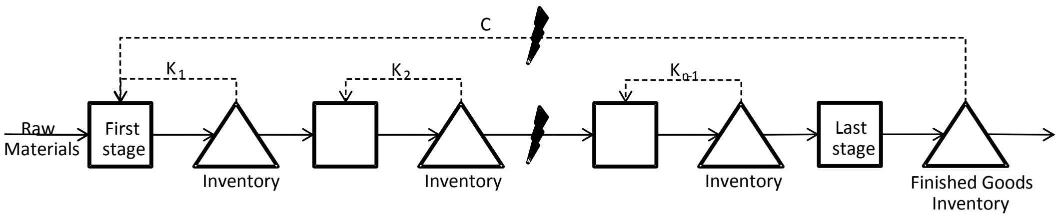


Figure 3-5: Conceptual model hybrid Kanban-CONWIP control mechanism [107]

3.2.1.1 Notations and Definitions

i- *Material flow variables*

P_t^i: Pipeline (WIP) in node *i* in period *t*, where *i*=1, 2, …, *n* (*n* is the total number of nodes in the SC)

Y_t^i: Finished Goods Inventory (FGI) in node *i*, in period *t*

S_t^i: Shipments from node *i* to node *i+1* in period *t*

O_t^i: Output from the pipeline of node *i* in period *t*

I_t^i: Input to the pipeline of the node *i* in period *t*

ii- *Information flow variables*

D_t: Incoming orders to the SC at final node in period *t* (demand)

OP_t: Orders placed by the SC to the first node in period *t*

B_t: Backlog of incoming orders in the SC in period *t*

APC_t: Available number of CONWIP cards in the SC in period *t*

AKC_t^i: Available number of Kanban cards in node *i* in period *t*

TY_t^i: Available total FGI in node *i*, in period *t* iii- *Model parameters*

L^i: Cycle (lead) time for a unit in the pipeline to arrive to the FGI of the node *i*

MLP^i: Maximum number of units to be processed in the node *i* (node capacity)

WIP-Cap: Total number of CONWIP cards in the SC

K^i: Total number of Kanban cards of node *i*

3.2.1.2 Mathematical Formulation

All the developed mathematical formulations for the Kanban, CONWIP, and Hybrid Kanban-CONWIP SC will be explained in terms of Shipments, Backlogs, Materials, Orders, and performance measures as follows:

i- Shipments

- It is assumed that the incoming orders to the final node (D_t), will be immediately shipped to customers as they are received but the inventory constraints may effect these shipments. The amount of units to be shipped to customers from the last node *n* in period *t*, S_t^n, is the minimum among the available total FGI in the final node, TY_t^n, and the incoming orders as follows for all SC production control polices:

$$S_t^n = min[TY_t^n, D_t] \tag{3-1}$$

- The shipments from any other node i in period t (S_t^i) depends on the available total FGI (TY_t^i) in node *i*, the maximum number of parts to be processed in node i+1 during its cycle time (MLP^{i+1}/L^{i+1}), and the available number of Kanban cards (if any) in node i+1. It is the minimum among them and will be centrally controlled as follows:

For the Kanban SC:

$$S_t^i = \begin{cases} \min\left[TY_t^i, \left(\frac{MLP^{i+1}}{L^{i+1}}\right), \left(K^{i+1} - [P_{t-1}^{i+1} + Y_{t-1}^{i+1}]\right)\right] & i = 1, i = n-2 \\ \min\left[TY_t^{n-1}, \left(\frac{MLP^n}{L^n}\right), (K^n - [P_{t-1}^n + Y_{t-1}^n - S_t^n])\right] & i = n-1 \end{cases} \tag{3-2}$$

For the CONWIP SC:

$$S_t^i = \min\left[TY_t^i, \frac{MLP^{i+1}}{L^{i+1}}\right] \qquad i = 1, i = n-1 \tag{3-3}$$

For the Hybrid SC:

$$S_t^i = \begin{cases} \min\left[TY_t^i, \left(\frac{MLP^{i+1}}{L^{i+1}}\right), \left(K^{i+1} - [P_{t-1}^{i+1} + Y_{t-1}^{i+1}]\right)\right] & i = 1, i = n-2 \\ \min\left[TY_t^i, \frac{MLP^{i+1}}{L^{i+1}}\right] & i = n-1 \end{cases} \tag{3-4}$$

ii- Backlogs (for all SC production control polices)

When the inventory constraints limit the supply of finished goods from the last node (*n*) of the SC to final customers in period *t*, a portion of the orders will not be fulfilled. These orders will be backlogged (B_t) in the central control of the SC as follows (It is presumed that backlogs must not be negative):

$$B_t = \max[(B_{t-1} + D_t - O_t^n) * (BL), 0] \tag{3-5}$$

where: $BL = \begin{cases} 0 & if\ backlogs\ considered\ lost\ sales \\ 1 & if\ backlogs\ have\ to\ be\ fulfilled \end{cases}$

iii- Materials flow, WIP, and inventory (for all SC production control polices)

- The WIP in the pipeline (P_t^i) and the FGI in the buffer (Y_t^i) for any node *i* in period *t*, fluctuate according to the input and output units and assuming that the initial conditions are known, then they can be calculated as follows:

$$P_t^i = P_{t-1}^i + I_t^i - O_t^i \tag{3-6}$$

$$Y_t^i = Y_{t-1}^i + O_t^i - S_t^i \tag{3-7}$$

- The available total FGI (TY_t^i) for node *i* in period *t* can be calculated as follows (It is presumed that TY_t^i must not be negative):

$$TY_t^i = \begin{cases} Y_{t-1}^i + O_t^i & i = 1, i = n-1 \\ \max[(Y_{t-1}^n + O_t^n - B_{t-1}), 0] & i = n \end{cases} \tag{3-8}$$

- The output from the pipeline (O_t^i) of any node i in period t is calculated as follows:

$$O_t^i = I_{t-L^i}^i \tag{3-9}$$

- The input to the pipeline (I_t^i) of the node i in period t can be calculated as follows:

$$I_t^i = \begin{cases} OP_t & for\ i = 1 \\ S_t^{i-1} & for\ i \neq 1 \end{cases} \tag{3-10}$$

<u>iv- Orders</u>

The orders (OP_t) placed by the SC to the first node in period t depends on the maximum number of parts to be processed in the first node during its cycle time (MLP^1/L^i), and the available number of Kanban and/or CONWIP cards in node 1. It is the minimum among them and will be centrally controlled as follows (It is presumed that OP_t must not be negative):

- For the Kanban SC:

$$OP_t = \max\left[min\left(\frac{MLP^1}{L^1}, [K^1 - (P_{t-1}^1 + Y_{t-1}^1)]\right), 0\right] \tag{3-11}$$

- For the CONWIP SC:

$$OP_t = \max\left[min\left(\frac{MLP^1}{L^1}, APC_t\right), 0\right] \tag{3-12}$$

- For the Hybrid SC:

$$OP_t = \max\left[min\left(\frac{MLP^1}{L^1}, [K^1 - (P_{t-1}^1 + Y_{t-1}^1)], APC_t\right), 0\right] \tag{3-13}$$

APC_t is the available number of CONWIP cards in the SC in period t and can be calculated as follows:

$$APC_t = \text{WIPCap} - \left[\left(\sum_{i=1}^{n} P_{t-1}^i + \sum_{i=1}^{n} Y_{t-1}^i\right) - S_t^n\right] \tag{3-14}$$

v- Performance measures

It is important to determine appropriate performance measures to find out if all the effort in designing and managing a SC finally leads to overall success or not. Inventory level is a key decision associated with SC performance since maintaining the right level of inventory at the right place and at the right time helps reducing costs and improves service levels. The SC performance measures that will be considered in this work will be the Average Inventory in the system and the Average Service Level (or fill rate) achieved by the system after T periods of time as follows:

- Average Inventory ($AWIP$) in the system in terms of the final product will be given by:

  $$AWIP(\mathrm{T}) = \frac{\sum_{t=1}^{\mathrm{T}}[Total\ WIP(t)]}{\mathrm{T}} \quad (3\text{-}15)$$

- Average Service Level (ASL) achieved by the system will be given by:

  $$ASL(\mathrm{T}) = \frac{\sum_{t=1}^{\mathrm{T}}[SL(t)]}{\mathrm{T}} \quad (3\text{-}16)$$

3.2.2 Simulation Model Development

Discrete Event Simulation modelling provides a virtual environment that looks, feels and behaves like a real workspace, which enable users to understand the overall SC processes and characteristics by graphics and animation techniques provided by simulation tools, while capturing the dynamics of the system by means of utilising the probability distributions and the use of unexpected events. The simulation model also gives the users freedom to make mistakes and learn the reactions of the system to certain actions by playing with the simulation model without interrupting the real system. It enables powerful "what-if" analyses to test several strategies and scenarios; on the other hand it permits the comparison of various operational alternatives leading to better future decision. [138]. The simulation modelling stage starts after the supply chain is analysed and the key components and performance measures are identified. ExtendSim, a multi purpose simulation package developed by Imagine That Inc., has been used to model the proposed SC system of this research work. The modeling approach proposed by ExtendSim is object oriented so; the translation of the conceptual model of the real system to a computer simulation model could be performed using library objects (or blocks) and the flow of items and information could be modelled by means of dynamic entities. In this research work an advanced modeling approach based on programming code, tables and an events generator is proposed. ExtendSim provides the user with a compiled programming language called Mod-L which can be used to write codes that helps to correctly translate conceptual models. The flow of dynamic entities, representing items and information, is substituted by information recorded in tables and simulation events are generated using event generator blocks (provided by the library). In correspondence of such events, the developed code elaborates and updates the information stored in theses tables.

The conceptual model described earlier has been implemented in a Periodic review simulation model as shown Figure 3-6. It is a generic simulation model that can simulate a centralised serial SC adopting one of the considered SC strategies (Kanban, CONWIP, or hybrid Kanban-CONWIP). In this simulation model, the Activity block (provided by the library) was modified using Mod-L to trigger the calculation of the mathematical model each period (1 time unit) a single entity entered the block. The 'entity' is a control command to instruct the model to perform the calculations for the next period. This single block effectively models the control structure of the entire SC. Information, such as the number of nodes in the SC, capacities of nodes, number of production cards assigned to nodes etc., is stored in global arrays which are accessed by the Activity block. This modelling approach provides a flexible, parametric and time efficient model.

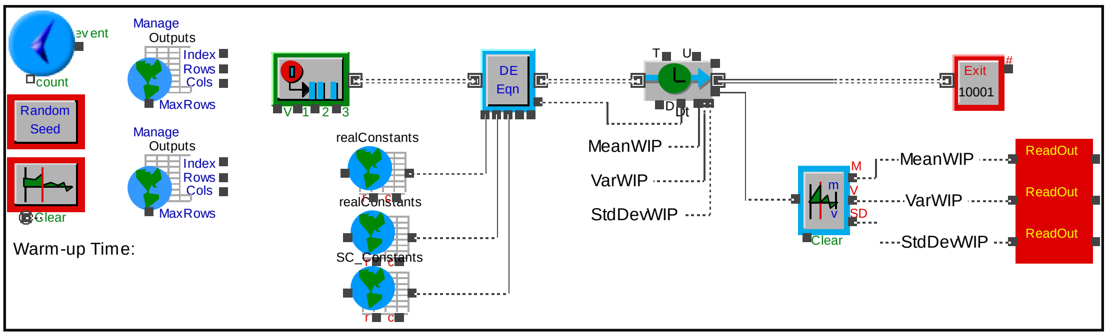


Figure 3-6: Periodic review simulation model

3.2.2.1 Simulation Model Validation

The SC modelled for this research work was similar in structure to that presented in Ovalle and Marquez [35], who compared the performances of CONWIP and MRP. Therefore, the CONWIP model could be validated by direct comparison of the results presented in [35] with the model developed here. Given that only summary results have been provided in [35], only visual inspection (as opposed to statistical comparisons of means e.g. paired t-test) was possible. The CONWIP model in [35] was analysed for 20 different configurations of MLP (maximum capacity) and demand SD and determined optimal settings of the WIP-Cap parameter as delineated by Table 3.1 below.

Table 3-1: Optimal WIP-Cap for given values of MLP and demand SD as determined by [35]

	Demand SD			
Max. Load	4	3	2	1
30	*68*	*60*	*39*	*44*
25	*68*	*60*	*39*	*44*
20	*69*	*60*	*39*	*44*
15	*75*	*62*	*39*	*44*
10	*85*	*85*	*52*	*45*

Table 3.2 below shows the total average inventory ($AWIP$) found by [35] when the CONWIP model was initialised with the appropriate WIP-Cap (see Table 3.1). Table 3.3 provides the results from the simulation model of CONWIP developed in ExtendSim.

Table 3-2: $AWIP$ (items) for given values of MLP and demand SD as determined by [35]

	Demand SD			
Max. Load	4	3	2	1
30	*59*	*53*	*31*	*38*
25	*59*	*53*	*32*	*38*
20	*59*	*53*	*31*	*38*
15	*60*	*53*	*31*	*38*
10	*51*	*59*	*36*	*38*

Table 3-3: $AWIP$ (items) for given values of MLP and demand SD from the devolved model

	Demand SD			
Max. Load	4	3	2	1
30	*60*	*54*	*33*	*38*
25	*60*	*54*	*33*	*38*
20	*61*	*54*	*33*	*38*
15	*64*	*54*	*33*	*38*
10	*60*	*67*	*41*	*39*

Similarly, results for average Service Level (ASL) are presented below in Tables 3.4 and 3.5.

Table 3-4: ASL (%) for given values of MLP and demand SD as determined by [35]

	Demand SD			
Max. Load	4	3	2	1
30	*100*	*100*	*100*	*100*
25	*100*	*100*	*100*	*100*
20	*100*	*100*	*100*	*100*
15	*100*	*100*	*100*	*100*
10	*91.5*	*99.7*	*100*	*99.5*

Table 3-5: ASL (%) for given values of MLP and demand SD from the devolved model

	Demand SD			
Max. Load	4	3	2	1
30	*100*	*100*	*96.9*	*100*
25	*100*	*100*	*96.9*	*100*
20	*100*	*100*	*96.9*	*100*
15	*100*	*100*	*96.9*	*100*
10	*99.9*	*100*	*99.5*	*100*

Some divergence from the results presented in [35] is noted, mainly in respect to ASL. Firstly, the ASL obtained when the standard deviation of demand was equal to 2 was never 100%; as obtained by [35]. Consequently, Some doubt exists over whether the results in [35] are accurate as it would be surprising that with a higher demand SD the WIP-Cap determined to be optimal would be lower than for SD=1. Therefore, it is believed that the results obtained from the ExtendSim model are more reflective of the true behaviour of the system under the prescribed settings of MLP at standard deviation of demand equal 2, than those presented in [35]. Secondly, [35] pre-set the amount of inventory in the system, sometimes to levels above the WIP-Cap and ran the model for 52 periods. The ExtendSim model was initialised with zero inventory and run for a warm-up period of 1,000 periods and statistics were collect over the next 10,000 periods. Finally, it is also apparent that there are a number of 'mistakes' in the equations presented in [35] that needed to be corrected in order to implement the CONWIP model in ExtendSim:

1. It is noted that [35] calculated the orders released to the first stage based on the following equation:

$$OP_t = \max\left[min\left(APC_t \times UC,\ DPO_t\ ,\ \frac{MLP^1}{L^1}\right), 0\right] \tag{3-17}$$

   Given that $DPO_t = D_t$, the customer demand in a period could potentially limit the entry of parts into the system where there are excess CONWIP cards. This is not generally a feature of CONWIP as normally the availability of CONWIP cards is the only limitation on entry into a system.

2. Also, it is noted that [35] presented the following equation to determine the number of available CONWIP cards at the start of a production period as:

$$APC_t = TNPC - \left[\ \left(\sum_{i=1}^{n} P_t^i + \sum_{i=1}^{n} Y_t^i\right)\ \right]/UC \tag{3-18}$$

   As presented, this equation would suggest that in order to determine the available number of CONWIP cards at the start of the production period t one would have to know the production volumes and pipe-line inventories at the end of the period t.

3. The total inventory available in the output buffer of a node for use by a successor node in period is defined by [35] as:

$$TY_t^i = Y_t^i + O_t^i \tag{3-19}$$

However, Y_t^i is unknown until the end of period t.

4. The point above also induces a circular reference in the model's calculations as follows:

$$Y_t^i = Y_{t-1}^i + O_t^i - S_t^i$$

$$\text{where: } S_t^i = \begin{cases} \min\left[TY_t^i, \left(\frac{MLP^{i+1}}{L^{i+1}}\right),\right] & for\ nodes\ i = 1, \dots, n-1 \\ \min[TY_t^n, D_t] & for\ final\ node\ i = n \end{cases} \tag{3-20}$$

Therefore, it is not possible to determine Y_t^i as it is dependent on knowing its value since $TY_t^i = Y_t^i + O_t^i$.

The equations to correctly represent a CONWIP-SC have been amended to account for these perceived inaccuracies and have been previously presented in Section 3.2.1.2.

Given the above discussion, it was not possible to completely validate the CONWIP model, but it is believed that the results from the ExtendSim model are representative of a CONWIP-SC. Furthermore, the logic of the ExtendSim model was verified to be correctly interpreted from the conceptual (mathematical) model by producing a trace file (event and system state log over time) and comparing the logical decisions to what would be expected by performing hand calculations from the conceptual model.

Finally, since [35] did not model Kanban-SC or the Hybrid-SC, it was not possible to validate these ExtendSim models. However, the logic of the ExtendSim models was verified as described above for the verification of the CONWIP-SC model.

3.2.3 Meta-Model Development

Meta-modelling is applicable to problems where the understanding of the process mechanism is limited and is difficult to be represented by a first-principles mathematical model. Depending on specific objectives in practice, meta-modelling techniques differ in the experimental design procedure, the choice of empirical models, and the mathematical formulation of the optimisation problem [139]. To assess the different SC control strategies of this research work through the Meta-Model Approach of the proposed framework, RSM and GP modeling techniques are used to build metamodels for the SC system being modelled by computer simulation. Although the most extensive applications of RSM are in the real industrial areas, RSM can be successfully applied to computer simulation models of physical systems. The assumption is that if the computer simulation model is a faithful representation of the real system, then RSM optimisation will result in adequate determination of the optimum conditions for that real system [140, 141]. Deterministic computer experiments present a challenge to RSM as there is no random error (or noise) to perform the lack-of-fit test [142, 143]. Vining [144] reported that traditional RSM tends to work better for simulations experiments which have noise than deterministic computer experiments. In RSM, quadratic polynomials are used to build the approximating metamodel however, if a more accurate representation is needed, the simulation modeller should consider other basis functions from which to build the metamodel [145]. GP models provide a good alternative approach as they have recently become popular and widely applied to diverse computer experiments [146-149] are among many others.

3.2.3.1 Response Surface Methodology

Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques that can be used for developing, improving, and optimising processes, products, and systems. When several input variables (factors) influence some performance measure or quality characteristic (response) of a process or a system, the relationship can be represented as [140, 150]:

$$y = f(x_1, x_2, \dots, x_k) + \varepsilon \qquad (3\text{-}21)$$

where k is the number of independent variables (x_i) and ε is the error observed in the response y.

In most RSM problems, the true form of the functional relationship f between the response and the selected independent variables is unknown, but can be reasonably approximated by a second-order polynomial model over a relatively small region of the independent variables space as follows [140, 150]:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i \ x_i + \sum_{i=1}^{k} \beta_{ii} \ x_{ii}^2 + \sum_{\substack{i,j=1 \\ i \neq j}} \beta_{ij} \ x_i x_j + \varepsilon, \quad \varepsilon \sim \text{NID}\,(0, \sigma^2) \qquad \text{(3-22)}$$

where β_0 is the intercept, $\beta_i \, x_i$ are the linear terms, $\beta_{ii} \, x_{ii}^2$ are the quadratic terms, $\beta_{ij} \, x_i x_j$ are the interaction terms, and ε represents a statistical error which is assumed to be normally and independently distributed.

Fitting and analysing this second-order polynomial model with data taken from the developed simulation model can be greatly facilitated by the choice of a proper RSM experimental design. Model (3-22) contains $1 + 2k + k(k-1)/2$ parameters, so the selected experimental design must have at least this number of distinct design points (scenarios or runs) and at least three levels for each selected independent variable [151]. Box and Wilson Central composite designs (CCD) and Box and Behnken three-level designs (BBD) [140, 150] are the most popular class of second-order designs. These designs are efficient while not involving large number of design points. CCD consist of two-level full or fractional factorial points (2^k or 2^{k-1}) contribute in the estimation of the linear and interactions terms, $2k$ axial or star points contribute in a large way in the estimation of quadratic terms, and $\mathrm{n_c}$ center points provide an internal estimation of the experimental error and contribute toward the estimation of quadratic terms. The areas of flexibility in the use of CCD reside in the selection of $\boldsymbol{\alpha}$, the axial distance from the center of the design, and n_c , the number of center runs. $\boldsymbol{\alpha}$ determines the location of the star points in CCD and its value generally varies from 1 to $\sqrt{k}$ depending on the region of operability and the region of interest to be investigated. BBD is a class of rotatable or nearly rotatable second-order designs which based on three-level fractional factorial design and consist of a total number of experiments that can be defined by $2k(k-1) + n_c$ where $k \geq 3$. For both the CCD and BBD, multiple center runs $\mathrm{n_c}$ are required in order to have sufficient number of degrees of freedom to estimate the experimental error and to manage the distribution and stability of the scaled prediction variance at different design regions (the property of rotatability) [151].

In this study, the incoming orders to the SC (customer demand) is assumed to be a random variable that follows a log-normal distribution with a mean demand considered to be fixed and equals to 4 items per period of time and a variable demand standard deviation, SD. The variability in demand (SD) will be considered at three different levels: a lower level of 1 item corresponding to a demand coefficient of variation (CV) of 25%, a medium level of 4.5 items corresponding to a CV of 112.5%, and a higher level of 8 items corresponding to a CV of 200%. Also, the cycle or lead time of any item in the pipeline to arrive to the FGI of any node in the SC will be considered as 2 periods of time.

A total of two independent variables ($k = 2$) will be considered for CONWIP SC: the maximum number of items to be processed in the node (node capacity), and the total number of production cards (WIP-Cap).

A total of five independent variables ($k = 5$) will be considered for Kanban SC: node capacity, total number of Kanban cards of node 1, total number of Kanban cards of node 2, total number of Kanban cards of node 3, and total number of Kanban cards of node 4.

A total of five independent variables ($k = 5$) will be considered for Hybrid Kanban-CONWIP SC: node capacity, WIP-Cap, total number of Kanban cards of node 1, total number of Kanban cards of node 2, and total number of Kanban cards of node 3

The working range of the selected input factors space represents the boundary of region from low to high to be searched and investigated in order to find an ideal or optimum response(s) settings. Therefore, each of the essential SC independent variables will be varied over a selected working range as per the selected experimental design in order to find their optimum settings and to investigate their impact on the conflicting SC performance measures (responses) namely, customer service level and average WIP.

The capacity of the different nodes in the SC will be considered at two levels: a minimum level of 8 items (corresponding to a mean demand of 4 items per period and a lead time of 2 periods) and a higher level of capacity of 24 items (corresponding to three times the minimum capacity)

Simulation runs shown in Appendix A were performed by changing the selected input factors one at a time (sensitivity analysis) in order to determine the best working range of the different production cards (WIP-Caps and Kanbans) for all SC policies that will enable us to extract as much information as possible from system considering (i) the selected level of demand standard deviation, (ii) service level range to be recognised, and (iii) a response max to min ratio of less than 3 (a ratio grater than 10 usually indicates that response variable transformation is required and for ratios less than 3 transformation has a little or no effect). Response variable transformation is known as power transformation and is discussed in more details by Box and Draper [152].

For the CONWIP SC, the selected range was decided to be from a minimum of 22 cards (so low service levels can be predicted at the best scenarios) to a maximum of 116 cards (so reasonably high service levels can be predicted at the worse scenarios).

For the Kanban SC, the selected ranges were decided to be from a minimum of 8 Kanban cards for nodes1-4 (so low service levels can be anticipated at best scenarios) to a maximum of 16 Kanban cards for nodes1 and 2, 20 Kanban cards for node 3 and 112 Kanban cards for node 4 (so reasonably high service levels can be anticipated at worse scenarios).

For the Hybrid Kanban-CONWIP SC, the selected ranges were decided to be from a minimum of 12 Kanban cards for nodes1-3 and 22 WIP-Cap cards (so low service levels can be predicted at the best scenarios) to a maximum of 20 Kanban cards for nodes1-3 and 136 WIP-Cap cards (so a reasonably high service levels can be predicted at the worse scenarios).

In this work the region of operability and the region of interest (region of experimentation) of the selected independent variables is the same and equals to the specified working ranges so, with five input variables ($k = 5$) to be varied in the Kanban and Hybrid Kanban-CONWIP SCs, BBD is selected. In this design each variable will have only three levels; low, middle, and high coded to the usual (-1, 0, 1) notation. The total number of experimental runs of all scenarios according to this design is 46; $[2k(k-1) = 40]$ augmented with 6 replicated center points $\mathrm{n_c}$ coded as (0, 0, 0).

With only two input variables ($k = 2$) to be varied in the CONWIP SC, CCD with $\alpha = 1.0$ is selected, as BBD is not applicable for two factors. This design is often called face-centered-CCD or simply FCD as the axial points take place at the centers of the cube faces rather than outside. In this design each variable will have three levels; low, middle, and high coded to the usual (-1, 0, 1) notations, the total number of experimental runs of all scenarios is 13; (2^k = 4) basic two-level full factorial points (or corner points) coded as (±1, ±1) augmented with ($2k = 4$) axial points coded as (±1, 0), (0, ±1), and 5 replicated center points n_c coded as (0, 0, 0).

Design-Expert, statistical software for Design Of Experiment (DOE) developed by Stat-Ease Inc., was used to apply RSM to the output simulation data; construct the different experimental design matrices, estimate the different terms of polynomial equation (3-22) using the method of least squares and the step-wise regression procedure [126] which will exclude al the non-significant terms at a level of significance 5% ($\alpha = 0.05$) in order to fit, build, and validate the performance measures meta-models of all SC policies according to summary Tables 3.9-3.17.

ExtendSim was used to conduct the simulation experiments according to the constructed design matrices of all SC policies. For all conducted experiments: (i) simulation run-length was 11000 periods with an excluded 1000 warm-up periods which was sufficient for deleting the influence of nodes initial conditions, (ii) the average out put of 50 replications was taken for each response variable, (iii) for all nodes, a fixed lead time of 2 periods, and (iv) for all nodes, same capacity and its value will be varied according the specified working range.

Table 3-6: CONWIP SC FCD Summary at SD = 1

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	WIP-Cap	Cards	22	44		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	77.5245	100.0000	1.2899	13
Y2	Average WIP	items	21.9914	44.0000	2.0008	13

Table 3-7: CONWIP SC FCD Summary at SD = 4.5

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	WIP-Cap	Cards	32	72		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	81.2536	99.1915	1.2208	13
Y2	Average WIP	items	30.2792	71.5940	2.3645	13

Table 3-8: CONWIP SC FCD Summary at SD = 8

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	WIP-Cap	Cards	48	116		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	81.9983	98.1522	1.1970	13
Y2	Average WIP	items	42.5925	114.2585	2.6826	13

Table 3-9: Kanban SC BBD Summary at SD = 1

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	Node1Kanbans	Cards	8	16		
C	Node2Kanbans	Cards	8	16		
D	Node3Kanbans	Cards	8	16		
E	Node4Kanbans	Cards	8	20		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	76.2018	100.000	1.3123	46
Y2	Average WIP	items	23.2941	49.1090	2.1082	46

Table 3-10: Kanban SC BBD Summary at SD = 4.5

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	Node1Kanbans	Cards	12	16		
C	Node2Kanbans	Cards	12	16		
D	Node3Kanbans	Cards	12	20		
E	Node4Kanbans	Cards	12	54		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	80.3918	99.3745	1.2361	46
Y2	Average WIP	items	42.7666	86.1303	2.0140	46

Table 3-11: Kanban SC BBD Summary at SD = 8

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	Node1Kanbans	Cards	12	16		
C	Node2Kanbans	Cards	12	16		
D	Node3Kanbans	Cards	12	20		
E	Node4Kanbans	Cards	28	112		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	82.4968	98.1125	1.1893	46
Y2	Average WIP	items	54.5277	133.5521	2.4493	46

Table 3-12: Hybrid Kanban-CONWIP SC BBD Summary at SD = 1

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	WIP-Cap	Cards	22	44		
C	Node1Kanbans	Cards	12	20		
D	Node2Kanbans	Cards	12	20		
E	Node3Kanbans	Cards	12	20		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	77.4458	100.0000	1.2912	46
Y2	Average WIP	items	21.9915	43.9996	2.0008	46

Table 3-13: Hybrid Kanban-CONWIP SC BBD Summary at SD = 4.5

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	WIP-Cap	Cards	32	76		
C	Node1Kanbans	Cards	12	20		
D	Node2Kanbans	Cards	12	20		
E	Node3Kanbans	Cards	12	20		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	81.2645	99.2231	1.2210	46
Y2	Average WIP	items	30.2680	73.8412	2.4396	46

Table 3-14: Hybrid Kanban-CONWIP SC BBD Summary at SD = 8

Factor	*Name*	*Units*	*Low Actual*	*High Actual*		
A	Node Capacity	items	8	24		
B	WIP-Cap	Cards	50	136		
C	Node1Kanbans	Cards	12	20		
D	Node2Kanbans	Cards	12	20		
E	Node3Kanbans	Cards	12	20		
Response	*Name*	*Units*	*Minimum*	*Maximum*	*Ratio*	*Runs*
Y1	Service Level	%	83.3175	98.4118	1.1812	46
Y2	Average WIP	items	44.1443	127.5539	2.8895	46

It is always necessary to examine the fitted metamodels to ensure that they provide an adequate approximation to the true system [140, 150]. The *coefficient of determination*, R^2, is a useful measure of how much is the variability in the response values that can be explained by the selected independent variables in the model. $0 \leq R^2 \geq 1$, however a large value of R^2 does not necessarily imply that the developed model is good one since adding more variables to the model will always increase the value of R^2 regardless of whether the additional variables are statistically significant or not. $Adjusted\ R^2$ corrects R^2 as it will decrease if un-necessary terms are added. When they differ dramatically, there is a good chance that non-significant terms have been included in the model.

$PRESS$ stands for "prediction error sum of squares" and was firstly proposed by Allen in 1971 [153]. To calculate $PRESS$ no new simulation runs are required, it can simply be done by applying the cross-validation criterion by eliminating one experimental run and then re-estimate the meta-model from the remaining runs and use it to predict the eliminated run. This predicted value and its corresponding simulation output can then be used to calculate the prediction error (i.e., $PRESS$ residual) of that eliminated run. This procedure is repeated for the remaining runs and then the $PRESS$ statistic is finally calculated as the sum of squares of all the calculated $PRESS$ residuals. Generally, a large difference between the ordinary residual sum of squares and $PRESS$ will indicate that the model fits the collected data well, but predicts poorly. Alternatively, one can covert $PRESS$ to an R^2 like statistic called $Predicted\ R^2$ which gives an indication on the amount of variation in predicting new observations by the fitted model. The $Adjusted\ R^2$ and

$Predicted\ R^2$ should be within approximately 0.20 of each other to be in a "reasonable agreement". If not, there may be a problem with either the data or the model [151].

3.2.3.2 Gaussian Process Modelling

Gaussian Process (GP) models are increasingly used as surrogate statistical models for predicting output of computer experiments [154]. Generally, GP models are both interpolators and smoothers of data and are effective predictors when the response surface of interest is a smooth function of the parameter space. GP prediction is simply a weighted linear combination of all output values already observed. The weights depend on the distance between the new input to be predicted and the *all* the old inputs so, it is assumed that the closer the inputs are, the more positively correlated their outputs are. A good introduction on GP emulators (metamodels), key steps in building them, and how to design the experiments are given in O'Hagan (2006) [155].

GP models, also known as *Kriging* and *Spatial Correlation*, are global rather than local (i.e., fitted to data that are obtained form larger experimental space than the small spaces used in law order polynomial regression models) [145, 156]. In 1989, Sacks et al. [157] developed the spatial correlation parametric regression modeling approach that predicts unknown values of deterministic simulation models where the predicted values at old inputs are exactly equal to the observed (simulated) outputs. In stochastic simulations, this property disappears and averages of replicated observations are obtained for each scenario. GP interpolates these averages which are still random however, GP still attractive because it may decrease the prediction bias and hence the mean square errors (MSE) at scenarios close together [158].

Mitchell and Morris in 1992 [159] described the spatial correlation model that is appropriate for stochastic simulation responses as follows:

Suppose an experiment with p design factors and n runs (n $\times$ $p\ matrix$) has been conducted, with simulation runs at factors settings $\theta^1, \theta^2, \dots, \theta^n$ and corresponding observed responses (averages of replications) of $y^1, y^2, \dots, y^n$. Let y represent the vector of responses then, the probability model can be expressed as:

$$Y(\theta) \;=\; Z(\theta) \;+\; \varepsilon \tag{3-23}$$

where ε represents the independent random error in each responses with mean zero and variance α^2 and $Z(\theta)$ represents a Gaussian process that accounts for the variation in the simulation outputs with mean $\mu(\theta)$ and variance σ^2 that exhibits spatial correlation function as:

$$Cov\;(Z(u), Z(v)) = \sigma^2 R(u, v) \tag{3-24}$$

where R describes the spatial correlation function between two points. Mitchell and Morris listed four different spatial correlation functions, the most commonly used is:

$$R(u, v) = \; \prod_{j=1}^{p} \exp\left(-\omega_j \left|u_j - v_j\right|^2\right) = \exp\left(-\sum_{j=1}^{p} \omega_j \left|u_j - v_j\right|^2\right) \tag{3-25}$$

wherr ω_j denotes the importance of the input factor j. For the prediction metamodel, estimates for ω_j , μ , σ^2, and α^2 were computed using the method of maximum likelihood estimation [154, 160] and used in the prediction equation as:

$$g(\theta) \;=\; \mu(\theta) \;+\; r'(\theta)C^{-1}(y \;-\; \mu 1) \tag{3-26}$$

where $r'(\theta)$ has components $\sigma^2 R(u, v)$, $C_{jk} = \sigma^2 R(\theta^i, \theta^k) + \alpha^2 I(i = k)$, and I is the indicator function. The matrix C_{jk} depends on θ^i but not on θ.

Using γ_i to represent the elements of the matrix-vector product $C^{-1}(y \;-\; \mu 1)$ makes the form of the basis functions of θ for the spatial correlation (or GP) metamodel clearer (with μ , γ_i , and ω_j as the fitted coefficients) as:

$$g(\theta) = \; \mu(\theta) \;+\; \sum_{i=1}^{\mathrm{n}} \gamma_i \times \exp\left(-\sum_{j=1}^{p} \omega_j \left|\theta_j \;-\; \theta_j^i\right|^2\right) \tag{3-27}$$

An important part of any computer experiment is the design of the experiment that is used to produce the training set for the production of the metamodel. The standard design for computer experiments is *space filling designs* [161]. These designs aim to fill the space with number of points (runs) so that the complete input parameter space is sampled. Such designs is intended to give a picture of what the simulator (the computer simulation model) is doing across the entire space of the parameters therefore, its needed (if possible) to span the full working range of the inputs with training set of runs. The usual space filling design for computer experiments is the *Latin Hypercube Design* (LHD) [162].

A LHD in n runs for k input variables is a $(\mathrm{n} \times k)$ matrix where each column is a random permutation of levels $1,2,\ldots,\mathrm{n}$. In LHD, the possible number of runs of the simulator has to be selected first; a common practice for an effective initial number is $\mathrm{n} = 10 \times k$ [163], and the range for each input variable is then divided into n equal sections or levels (this means a good marginal coverage of each variables). The maxi-min criterion that maximises the minimum Euclidean distance between points in the design is used to produce a LHD with good properties [164]. By permuting the combinations of the variables in a random manner (note that the randomisation is to produce a design with good properties rather than to randomise for external factors as it is used in field experiments), the simulator is evaluated once by considering the average of replications obtained for each scenario.

JMP, statistical and data analysis software developed by SAS Institute Inc., was used to apply GP modeling to the output simulation data; construct the different LHD matrices in accordance with $\mathrm{n} = 10k$ and provided that all the possible levels of each input factor is considered, estimate the different terms of the equation (3-27) using the method of maximum likelihood estimation in order to fit, build, and validate the performance measures meta-models of all SC policies according to the different input factors and working ranges presented in the summary Tables 3.9-3.17. ExtendSim was also used to conduct the simulation experiments according to the constructed LHDs and under the same general conditions in the previous RSM.

JMP generates a model report summarising the $Functional\ ANOVA$ and the estimated terms of the GP metamodel and also generates its actual by predicted plot. The $Functional\ ANOVA$ is an analysis of variance for the input factors according to their *main* and their *interactions* effects but, the variation is computed using a function-driven method and the total variation is the integrated variability over the entire experimental space [165, 166].

In this analysis, the functional main effect of input factor, (x), is the integrated total variation in the response due to (x) alone. The ratio of $(Functional\ x\ effect)/(Total\ Variation)$ is the value (%) listed as the main effect in the model report. A similar ratio exists for each input factor in the model and the functional interaction effects are computed in a similar way. Summing the value for main effect and all interaction terms gives the Total Sensitivity (i.e., the amount of influence a factor and all its two-way interactions have on the response variable).

It is necessary to examine the fitted metamodels to ensure that they provide an adequate approximation to the true system. The *jackknife* or *leave one out* procedure (a cross-validation technique in which no new simulation runs are required) is used to generate Actual by Predicted plots as a measure of goodness-of-fit. These plots depict the actual simulation outputs on the *y*-axis and the jackknife predicted values on the *x*-axis and how well or close the different points lie along a 45 degree diagonal line from the origin.

3.3 Phase 2: Supply Chain Optimisation

The purpose of this work is to propose and test a decision support framework for Supply-Chain optimisation problems with conflicting objectives. A multi-objective optimisation problem with conflicting objectives implies that there is no unique optimal solution to the problem. Instead, a set of solutions can be obtained that are indifferent to each other such that no improvement can be found in terms of any of the objectives without resulting in deterioration of the performance of at least one of the objectives so, decision makers must make a judgment and find good compromises (trade-offs) among them to arrive at a particular decision. A set of such optimal solutions is commonly known as the Pareto-frontier. These optimal solutions are non-inferior or non-dominated in the sense that there is no other solution in the search space superior than them when all the objectives are taken into consideration [137, 167-170]. In order to generate a set of such non-dominated solutions shown in Figure 3-7, two different multi-objective optimisation techniques are considered in this research work; an analytical optimisation called the Desirability Function Approach to perform a metamodel-based optimisation and a heuristic search called the Genetic Algorithms to carry out both a simulation-based and metamodel-based optimisation.

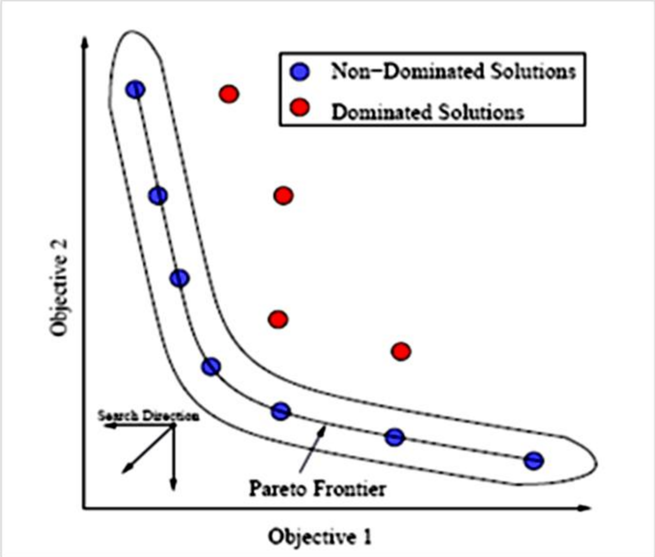


Figure 3-7: Pareto-frontier for two conflicting objectives [169]

3.3.1 The Desirability Function Approach

The Desirability Function Approach (DA) is a simultaneous optimisation of multiple responses technique popularised by Derringer and Suich [171] in the 1980s. In this technique, an objective is set to each response: a target value, maximise or/and minimise then, each estimated response is converted into a dimensionless measure of performance called the individual desirability function (d_i) which varies between 0 and 1. If the estimated response is at its goal or target value, then $d_i = 1$, if it is within an acceptable limit, then $(0 < d_i < 1)$, and if it is outside an acceptable limit, then $d_i = 0$. All individual desirability functions are then combined into an overall desirability function (D) by using the geometric mean. The objective is to choose an optimum setting for the input variables in order to maximise the overall desirability as:

$$\begin{aligned} &\max\ D = (d_i * d_2 * \ldots * d_m)^{1/m} \\ &\quad subject\ to{:}\quad L(x_i) \leq x_i \leq U(x_i) \end{aligned} \tag{3-28}$$

where:

m is the number of responses and

$L(x_i)$ and $U(x_i)$ are the Lower and Upper limits of the input variables x_i.

The single value of D gives the overall assessment of the desirability of the combined response levels so, if any $d_i = 0$ (that is, if one of the response variables is unacceptable) then, $D = 0$ which indicates an unacceptable overall product regardless of how desirable the other response variables might be. For more details, refer to Derringer and Suich [171].

In transforming y_i to d_i, two cases arise: the two-sided desirability and the one-sided transformations. The two-sided desirability function shown in Figure 3-8(c) assumes that the objective or target (T) for the response is located between the lower (L) and upper (U) limits considering the weight (r). If r = 1 the desirability function is linear and choosing r >1 places more emphasis on being close to the target value and the function is concave while choosing $0 < r < 1$ makes this less important and the function is convex. The two-sided desirability function can be defined as follows:

$$d = \begin{cases} 0 & y < L \\ \left(\frac{y-L}{T-L}\right)^{r_1} & L \le y \le T \\ \left(\frac{U-y}{U-T}\right)^{r_2} & T \le y \le U \\ 0 & y > U \end{cases} \tag{3-29}$$

For the one-sided case, if the target for the response is a maximum value as shown in Figure 3-8(a) then, the desirability function can be defined as follows:

$$d = \begin{cases} 0 & y < L \\ \left(\frac{y-L}{T-L}\right)^{r} & L \le y \le T \\ 1 & y > T \end{cases} \tag{3-30}$$

If the target for the response is a minimum value as shown in Figure 3-8(b) then, the desirability function can be defined as follows:

$$d = \begin{cases} 1 & y < T \\ \left(\frac{U-y}{U-T}\right)^{r} & T \le y \le U \\ 0 & y > U \end{cases} \tag{3-31}$$

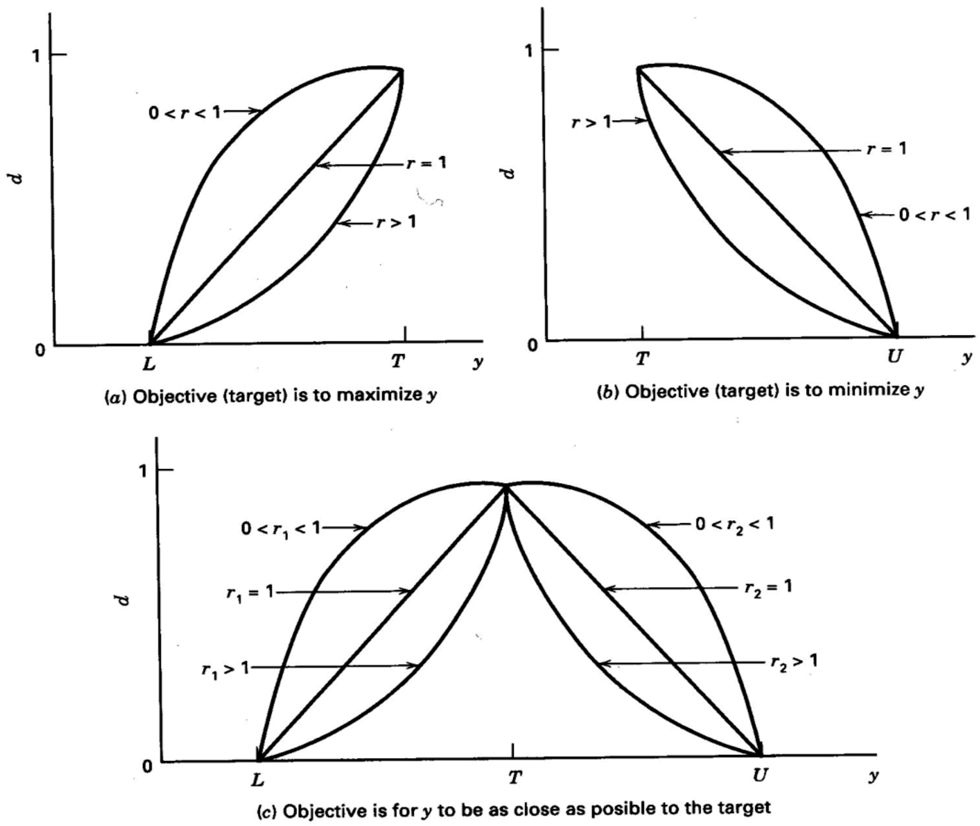


Figure 3-8: Desirability Functions for simultaneous optimisation [151]

For all SC polices, in order to build service level-average WIP trade-off curves (Pareto-frontier for two conflicting objectives) using DA, The service level at several possible targets and the average WIP are optimised simultaneously for each selected demand SD.

The possible targets of service level to be optimised and their limits for all SC polices are:

- 78±0.5, 80±0.5, ..., and 100 (for service level meta-models under SD=1)
- 82±0.5, 84±0.5, ..., and 98±0.5 (for service level meta-models under SD=4.5)
- 84±0.5, 86±0.5, ..., and 98±0.5 (for service level meta-models under SD=8)

The two-sided desirability function for each targeted service level will be defined as in the following example (CONWIP SC service level meta-model under SD=1):

$$d_1 = \begin{cases} 0 & service\ level < 77.5 \\ (0,1) & 77.5 \leq service\ level \leq 78 \\ (0,1) & 78 \leq service\ level \leq 78.5 \\ 0 & service\ level > 78.5 \end{cases} \tag{3-32}$$

Average WIP meta-models always have minimisation as an objective and their one-sided desirability function was defined as in the following example (CONWIP SC average WIP meta-model under SD=1):

$$d_2 = \begin{cases} 1 & average\ WIP < 21.99 \\ (0,1) & 21.99 \leq average\ WIP \leq 44.00 \\ 0 & average\ WIP > 44.00 \end{cases} \tag{3-33}$$

DA is implemented in Design-Expert and JMP software packages and will be applied directly to the meta-models. DA will search the input factors space of the fitted RSM or GP performance measures meta-models of any SC simultaneously and will generate a list of potential optimum factor settings (RSM-DA and GP-DA solutions) that meet the defined criteria. Optional fine-tuning called importance and weight can be applied to the search criteria. Importance specifies the relative importance of one response versus another. Some responses may be critical and can be assigned with five +'s, while some may be of medium importance and can be assigned with three +'s and some are of lowest importance and can be assigned with one +. Weight is a value ranges from 0.10 to 10. It fine-tunes how the optimisation process searches for the best solution. A low weight (near 0.10) will allow more solutions that don't quite meet the optimal goal. A high weight (close to 10) will cause the optimisation to seek a solution close to or beyond the stated goal.

3.3.2 Genetic Algorithms

In this research work, discrete event simulation modeling is employed to generate output values for multiple responses of a SC system, and due to the stochastic nature of the developed simulation model (that is getting different output values for the same run setting which requires replications to estimate the noise and create a confidence interval around the estimated responses) and the large search space in some cases (which implies long optimisation time), an efficient heuristic search algorithm is needed to optimise it. Among these algorithms, Genetic Algorithms (GA) is shown to be successful in optimising multi-response stochastic problems [137, 172].

GA is search algorithm for optimisation inspired by Darwin's theory about evolution. The mechanics of GA is simple; generally the search for the optimal solution begins from a set of randomly generated potential solutions (chromosomes) called the population. GA makes this initial population evolve through successive iterations (generations) towards a population that is expected to contain the optimum solution. Individuals from the current population are evaluated using the objective function and then selected with a given probability so that the fittest individuals have an increased chance of being selected. Selected individuals are subjected to mutation and to crossover (recombination). The process which contains selection, crossover, and mutation is called reproduction. The crossover mechanism allows for the mixing of parental information in passing it on to their descendants (offspring) while mutation introduces innovation into the population. From one generation to the next, the population tends to have a better fit [107, 168, 173, 174].

Generally, a multi-objective optimisation problem can be formulated as follows:

$$\begin{aligned} &Optimise\ \ y = f_i(x) \\ &subject\ to:\ x = \{x_1, x_2, \ldots, x_N\} \in X \\ &\quad where: y = \{f_1(x), f_2(x), \ldots, f_M(x)\} \in Y\ for\ \ i \in \{1, \ldots, M\} \end{aligned} \tag{3-34}$$

The vector of decision variables is x of size N, and X is the *decision space*. The vector of objectives is y of size M, and Y is called the *objective space*. The solution to a multi-objective problem is usually no unique; any two solutions x_1 and x_2 can have one of two possibilities: one dominates the other or none dominates the other. Mathematically (in the maximisation case), a solution x_1 dominates (superior to) x_2 *iff* the following condition is satisfied:

$$\forall i \in \{1, \ldots, M\}: y_i(x_1) \geq y_i(x_2) \wedge \exists j \in \{1, \ldots, M\}: y_j(x_1) > y_j(x_2) \tag{3-35}$$

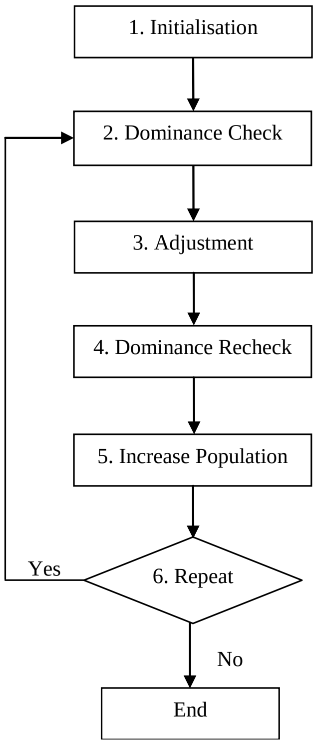
If any of the above conditions is violated, then x_1 does not dominate x_2. If x_1 dominates the solution x_2, then x_1 is called the non-dominated solution within the set $\{x_1, x_2\}$. The solutions that are non-dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal front.

Srinivas and Deb [175] proposed an algorithm called the Non-dominated Sorting Genetic Algorithm (NSGA) to generate the Pareto Frontier. Successful applications of multi-objective GA in optimising multi-response stochastic problems include [174, 176, 177]. Kernan and Geraghty [137] developed a Pareto-Optimal GA module (POGA) for ExtendSim. This code (optimiser) designed to find a set of non-dominated solutions in a decision space comprised of up to 8 decision variables that can be integer or real, for an objective vector comprised of up to 6 components. The procedure for the POGA code is shown in Figure 3-9.

The POGA code is applied directly to the developed simulation model and fitted RSM meta-models of this work. The interactions between this optimiser and the simulation model/meta-model can be illustrated in Figure 3-10 and the aim to find the set of non-dominated solutions (RSM-POGA and SIM-POGA) in a discrete decision space comprised of 2 decision variables for the CONWIP SC and 5 decision variables for the Kanban and Hybrid Kanban-CONWIP SC for an objective vector comprised of 2 components; the average service level to be *maximised* and the average WIP to be *minimised*.

For the CONWIP SC, the WIP-Cap takes values in the range 22 to 44 (e.g. for SD=1) while the node capacity takes values in the range 8 to 24. This gives a total of 391 cases (that is 391 discrete points in the decision space X).

For the Hybrid Kanban-CONWIP, the WIP-Cap takes values in the range 50 to 136 (e.g. for SD=8), nodes 1, 2 and 3 could take on Kanban values in the range 12 to 20, and node capacity takes values in the range 8 to 24. This gives a total of 1,078,191 cases (that is 1,078,191 discrete points in the decision space X).



1. Initialisation

An initial population of 5 individuals is created at random from the decision space.

2. Dominance Check

The current population is checked to see which individuals are non-dominated. Individuals who are non-dominated are assigned a Boolean value of true.

3. Adjustment

Any individuals in the current population, which are dominated, are replaced with an offspring created from two different non-dominated parents. The parents are obtained at random from the current population, with equal probability of being chosen. If there is only one non-dominated solution however (there will be at least one), then the second parent is obtained at random from the decision space. Because the decision space can be integer or real format, it was decided to use a hybrid recombination technique of discrete and intermediate recombination, which would be referred to as Triad-Based Recombination (TBR). With TBR, each chromosome that makes up the offspring can be obtained three different ways with equal probability: it can take on the value of the first parent's chromosome, the value of the second parent's chromosome, or it can take on a value in between, and including the two parents chromosome values. When each chromosome is created, *exo-parental mutation* can occur, with a probability of occurrence defined by the user.

4. Dominance Recheck

The adjusted population is rechecked, to see which solutions are non-dominated.

5. Increase Population

If all of the individuals of the current population are non-dominated, 5 new offspring are created (as described in step 3) and added to the population.

6. Repeat

The algorithm is repeated by going back to step 2. The algorithm can be terminated by the number of generations or the number of dead runs specified by the user. The algorithm will also end if the entire decision space has been searched (valid if decision space contains integer values only).

Figure 3-9: POGA Procedure for ExtendSim

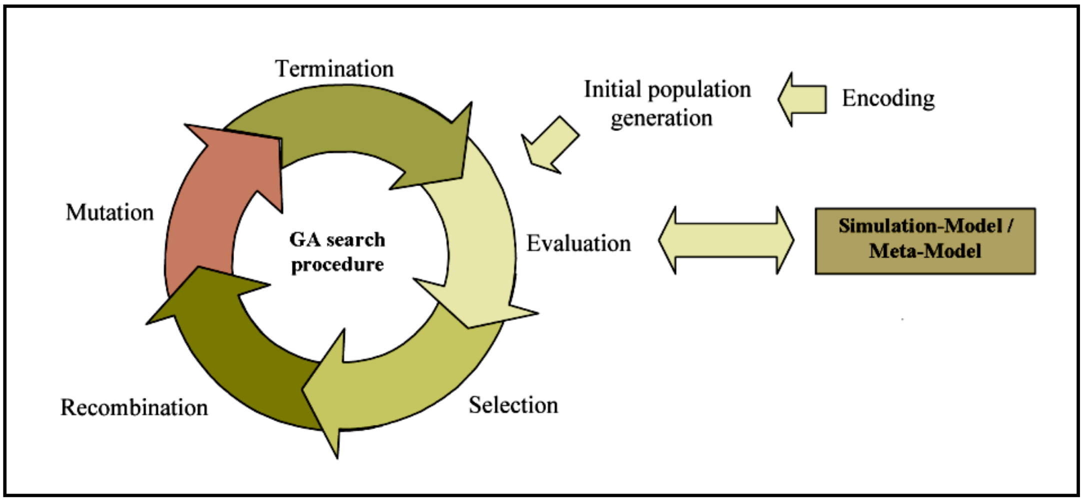


Figure 3-10: POGA and Simulation Model/Meta-Model Interactions (Adapted from [174])

The multi-objective genetic-algorithm therefore, seeks to obtain the set of pareto-optimal solutions so that:

$$\forall N_i, N_j \in X \neg\{S(N_i) \geq S(N_j) \wedge W(N_i) \leq W(N_j) \wedge [S(N_i) > S(N_j) \vee W(N_i) < W(N_j)]\} \quad (3\text{-}36)$$

where:

N (for CONWIP SC) = {Node Capacity, WIP-Cap}

N (for Kanban SC) = {Node Capacity, Node1Kanbans, Node2Kanbans, Node3Kanbans, Node4Kanbans}

N (for Hybrid SC) = {Node Capacity, WIP-Cap, Node1Kanbans, Node2Kanbans, Node3Kanbans}

S = Service Level

W = Average WIP

The critical parameters considered in this technique are the initial size of the population, crossover and mutation rate (probability of performing crossover and mutation), termination condition (e.g. maximum number of iterations or number of dead runs), and the number of replications.

3.3.3 Estimates Refinement (Error Analysis)

This step of the Optimisation phase applies only to the Meta-Model Approach. It, essentially, involves improving the accuracy of the estimates through experimentation with the simulation model under the parameters found to be "optimal" for given Service Level targets; SIM-RSM-DA, SIM-GP-DA and SIM-RSM-POGA.

3.4 Phase 3: Decision Support

Decision Support is the final phase of the proposed framework. Principally the aim of this phase is to provide guidance to decision makers in selecting the best optimal solutions (optimal settings of input parameters) and testing their robustness for the different SC strategies to best address the two conflicting objectives; namely Average WIP and Service Level. It is proposed that risk analysis and information about the curvature and stochastic dominance of the trade-off curves could provide such a tool.

3.4.1 Curvature Analysis

Curvature is a measure of how sharply a curve is turning as it is traversed or how quickly a tangent line turns on a curve [178, 179]. For example, consider the simple parabola shown in Figure 3-11. It is obvious, geometrically, that the tangent lines to this curve turn 'more quickly' between *P* and *Q* than along the curve from *Q* to *R*.

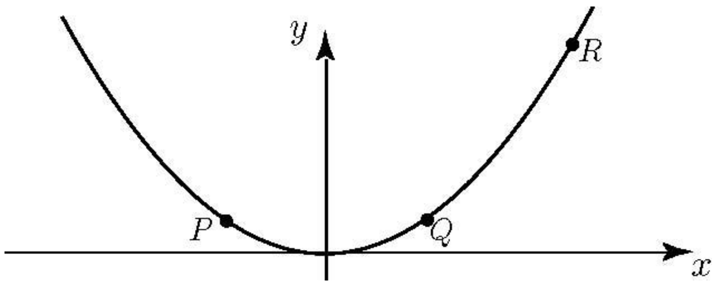


Figure 3-11: Simple parabola [178]

If the circle, (centred on the origin, of radius 1), shown in Figure 3-12 is considered, it is immediately clear that the circle has a constant value for the curvature, which is to be expected, as the tangent line to a circle turns equally quickly irrespective of the position on the circle. Therefore for every other curve, other than a circle, the curvature will depend upon position, changing its value as the curve twists and turns.

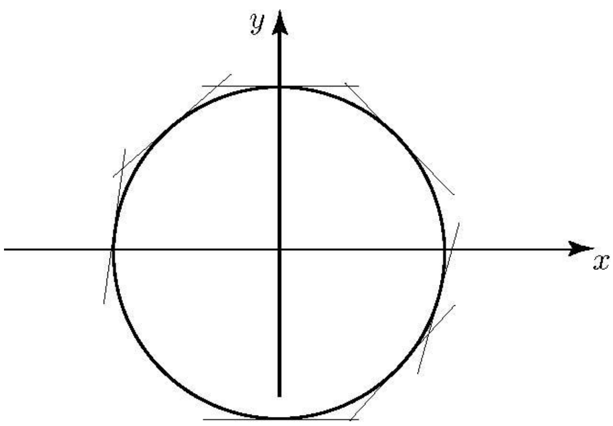


Figure 3-12: circle of radius 1 centred on the origin [178]

However, if the two circles (with the same centre but different radii) shown in Figure 3-13 are considered, it is again obvious that the smaller circle "bends" more tightly than the larger circle and it can be said that it has a larger curvature. Furthermore if tangent lines making an angle ψ with the positive x-axis are drawn on the two circles at P and P', and as moving from P to Q (inner circle) or from P' to Q' (outer circle) the angle ψ will change by the same amount. Nevertheless, the distance traversed on the inner circle is less than the distance traversed on the outer circle. This suggests that a measure of curvature is *the magnitude of the rate of change of ψ with respect to the distance moved along the curve*, that is [178, 179]:

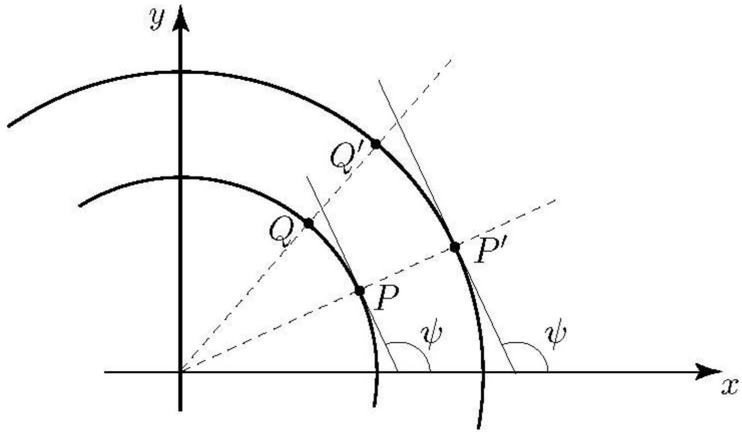


Figure 3-13: Two circles with the same centre and different radii [178]

$$Curvature\ (\boldsymbol{k}) = \frac{d\psi}{ds} \tag{3-37}$$

where s is the measure of arc-length along the curve

If the equation of the curve is given in the Cartesian form $y = f(x)$, then:

$$\frac{d\psi}{ds} = \frac{d\psi}{dx}\frac{dx}{ds} = \frac{d\psi}{dx} \Big/ \left(\frac{ds}{dx}\right) \tag{3-38}$$

To obtain expressions for the derivatives $\frac{d\psi}{ds}$ and $\frac{ds}{dx}$ in terms of the derivatives of $f(x)$, Figure 3-14 will be considered as follow:

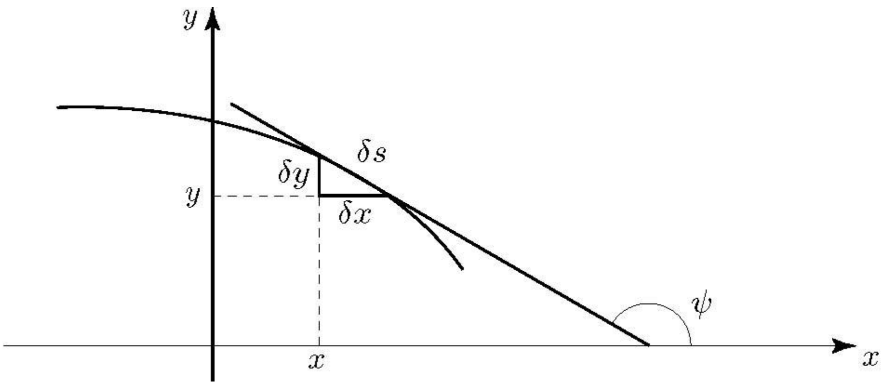


Figure 3-13: Two-dimensional curve with a tangent line making an angle ψ with the x-axis [178]

The small increments in the x and y directions have been denoted by δx and δy, respectively. The hypotenuse of the small triangle is δs, which is the change in arc-length along the curve.

From Pythagoras' theorem:

$$\delta s^2 = \delta x^2 + \delta y^2 \tag{3-39}$$

so

$$\frac{\delta s}{\delta x} = \sqrt{1 + \left(\frac{\delta y}{\delta x}\right)^2} \tag{3-40}$$

In the limit as the increments get smaller and smaller, this relation in derivative form becomes:

$$\frac{ds}{dx} = \sqrt{1 + \left(\frac{dy}{dx}\right)^2} \tag{3-41}$$

However, as $y = f(x)$ is the equation of the curve then:

$$\frac{ds}{dx} = \sqrt{1 + \left(\frac{df}{dx}\right)^2} = (1 + [f'(x)]^2)^{1/2} \tag{3-42}$$

The relation between the angle ψ and the derivative $\frac{df}{dx}$ is known as:

$$\frac{df}{dx} = \tan\psi \tag{3-43}$$

so differentiating again:

$$\frac{\mathrm{d}^2 f}{\mathrm{d}x^2} = \sec^2\psi \frac{\mathrm{d}\psi}{\mathrm{d}x} = (1+\tan^2\psi)\frac{\mathrm{d}\psi}{\mathrm{d}x} = (1+[f'(x)]^2)\frac{\mathrm{d}\psi}{\mathrm{d}x} \tag{3-44}$$

Inverting this relation:

$$\frac{\mathrm{d}\psi}{\mathrm{d}x} = \frac{f''(x)}{(1+[f'(x)]^2)} \tag{3-45}$$

and so, finally, The signed curvature of a two-dimensional curve, expressed in the Cartesian form $y = f(x)$, is obtained from:

$$\boldsymbol{k} = \frac{d\psi}{ds} = \frac{d\psi}{dx} \Big/ \left(\frac{ds}{dx}\right) = \frac{\boldsymbol{f''(x)}}{\left(\mathbf{1}+[\mathbf{f'(x)}]^{\mathbf{2}}\right)^{\mathbf{3/2}}} \tag{3-46}$$

The sign of the signed curvature $\boldsymbol{k}$ indicates the direction in which the unit tangent vector rotates along the curve. If the unit tangent rotates counter clockwise, then $\boldsymbol{k} > 0$ and if it rotates clockwise, then $\boldsymbol{k} < 0$.

This method will be illustrated by application to the trade-off curves of all SC polices generated from applying the POGA directly to the simulation model (SIM-POGA). So in order to obtain smoother curves (e.g., with higher R^2), a higher order (e.g., of power six) polynomial models will be fitted to the different SIM-POGA trade-off curves as ($Average\ WIP\ = f(Service\ Level\ )$). In addition, the change in WIP (ΔWIP) between successive increments of Service Level (e.g., at step of 0.1%) will be plotted also as ($\Delta WIP = f(Service\ Level\ )$) and the curvature formula (3-46) is then applied to the resulted curves and will be overlaid on them in order to determine the points of inflection and the correspondence service level to be achieved. The curvature analysis will be focused on Service Levels above 90% as industrial decision makers are usually more interested in these higher ranges for Service Level [103].

3.4.2 Risk Analysis

Robustness has become an important concern in systems design. In the 1980s, Taguchi introduced new ideas on robustness and quality improvement; he proposed various performance measures known as Signal-to-Noise ratios (SNR) for reducing variations and evaluating performance of products and processes [180-182]. Taguchi's principle of Robust Design (also known as robust parameter design) consists of searching for a process or product design that guarantees low variations in the performance level when the environment changes (that is insensitive to the effects of the uncontrollable or noise factors), instead of designing a process or product that is optimal for a specific environment. Although these measures generated considerable interest and gained usage in the industry, most of them are criticised in the literature, not with respect to the philosophy, but rather with regard to its implementation and the technical nature of data analysis [183-185]. Accordingly, Pignatiello and Ramberg [186] recommend differentiating between the strategic aspect (namely Taguchi's philosophy of robustness) and the tactical issues (e.g. SNR and the DOE technique). Many tactical alternatives are widely documented and can be found in the literature; [187-189] are among many others.

The environment in which the product/system will be used during the design process is not known with certainty. Moreover, the environment may vary during the product/system lifetime (e.g. the demand rate for a product may fluctuate) also, designing a product/system for specific environmental parameters does not guarantee a good performance for other environments: there is a risk associated with the chosen design; another design may lead to a lower risk [190]. Thus, Gaury and Kleijnen [109, 190] proposed the use of risk/uncertainty analysis techniques reported in [191] to quantify the risk associated with designing a product/system under specific environmental parameters and illustrated the approach through a comparison study of four different production control strategies.

Risk analysis for a designed product or system consists of sampling each environmental parameter (noise factor according to Taguchi's terminology) from statistical distribution functions, combining the sampled values into scenarios (factor combinations), and conducting a simulation experiment for each scenario as per the selected DOE (e.g. Latin Hypercube design). The outcome of this procedure is: (i) an estimated probability distribution of the performance measures and (ii) the choice between any two systems can be made by comparing these performance probability distributions using the theory of stochastic dominance [192].

Stochastic dominance is a form of stochastic ordering or ranking. The term is used in decision theory and decision analysis to refer to situations where one probability distribution over possible outcomes can statistically be ranked as superior to another one. There are two types (or orders) of such ranking known as first and second order stochastic dominance.

Consider two random variables called options A and B that have the cumulative density functions $FA(x)$ and $FB(x)$ and where it is desirable to maximise the value of x. option A *first-order stochastically dominates* option B if:

$$FA(x) \leq FB(x) \quad for\ all\ x \tag{3-47}$$

That amounts to saying that the cumulative density function (cdf) of option A is to the right of that of option B in an ascending plot shown in Figure 3-11. At another way, option A is superior to option B because for any cumulative probability value, it gives a higher profit.

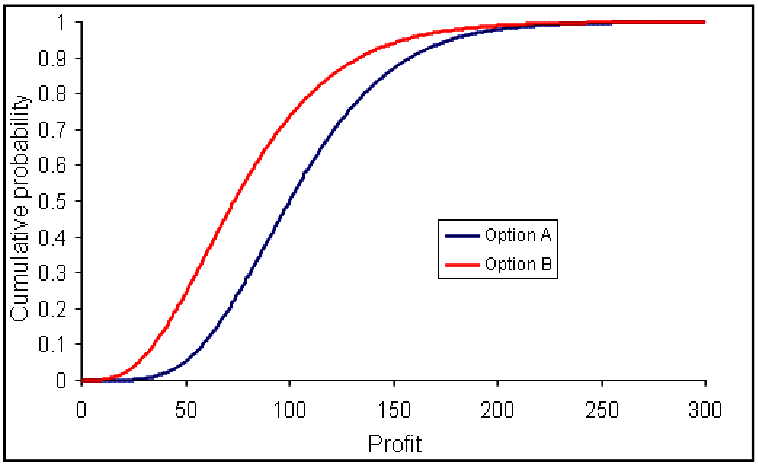


Figure 3-11: First order stochastic dominance [193]

Also, option A *second-order stochastically dominates* option B if:

$$D(z) = \int_{min}^{z} \big(FB(x) - FA(x)\big)\,dx \geq 0 \quad for\ all\ z \tag{3-48}$$

Figure 3-12(a) shows option A having second (but not first) order stochastic dominance over option B as the area under FA is less than or equal to that under

FB from min to for all z. The function $D(z)$ is also plotted to show it is always positive. However, in Figure 3-12(b) option A does not have second order stochastic dominance over option B as $D(z)$ dips below zero.

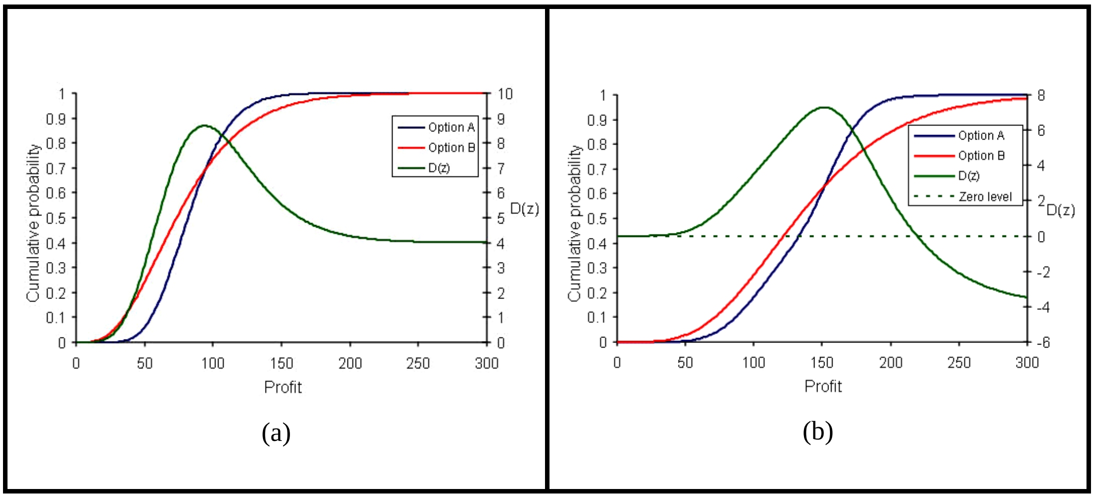


Figure 3-12: Second order stochastic dominance; (a) option A second-order stochastically dominates option B (b) option A does not have second order stochastic dominance over option B [193]

The environmental or noise parameters which are considered to optimise the proposed SC of this work and their base scenario (the set of values used for these parameters) are: (i) for all SCs, demand standard deviation of 1, 4.5, or 8 items, (ii) for all nodes, a fixed lead time of 2 periods, and (iii) for all nodes, same capacity with a value based on the working range.

So next to the curvature analysis, the robustness of the different SC optimal parameter settings (selected by decision makers) is performed taking into account the following environmental variations:

(i) a range of ±10% around the selected demand SD is chosen for the considered SC; that is 1 noise parameter to be varied (e.g. between 7.2 and 8.8 for SD=8)

(ii) a probability from 0% to 10% that the lead time of an item will be increased (delayed) by one period in each node of the considered SC; that is 4 noise parameters to be varied between 0 and 0.1.

(iii) a stochastic capacity in each node of the SC that follows a Log-normal distribution with a fixed mean equals to the capacity optimal setting and a varied standard deviation equals to a 0% to 20% of the mean; that is 4 noise parameters to be varied between 0 and 0.2.

For these nine parameters, JMP is used to generate a LHD with 33 environmental scenarios to test each selected optimal SC solution (i.e., the working range of each parameter will be divided into 33 levels which were found to provide a good marginal coverage for the design space). ExtendSim is used to execute the simulation experiments according to these scenarios and ModelRisk, a quantitative risk analysis package developed by Vose Software Company, is used to: (i) conduct a robustness analysis for the different POGA SCs at SD=8 optimal parameter settings selected by decision makers (e.g., generate the cdf plots of the performance measures), and (ii) conduct a stochastic dominance test for the different GP SCs targeting 95% service level. ModelRisk will produce a matrix of first and second order stochastic dominance test results of the simulation outcomes.

CHAPTER 4 RESULTS AND DISCUSSIONS

4.1 RSM Metamodels

To estimate the different terms of the RSM metamodels, a polynomial equation (3-22) was fitted to the simulation output data of the different experimental designs of all SCs (Table 4.1 is shown as an example for the CONWIP SC at SD=1) by using the method of least squares and the step-wise regression procedure which will exclude all the non-significant terms in the fitted metamodels at a level of significance of 5% ($\alpha = 0.05$).

Table 4-1: CONWIP SC FCD matrix and simulation outputs at SD=1

Run No.	Factor 1 A: WIP-Cap (Cards)	Factor 2 B:Node capacity (items)	Response 1 Service Level (%)	Response 2 Average WIP (items)
1	8	22	77.4716	21.9915
2	24	22	77.5009	22.0000
3	8	44	99.9991	43.3724
4	24	44	100.0000	44.0000
5	8	33	99.1738	32.5670
6	24	33	99.2945	33.0000
7	16	22	77.5098	22.0000
8	16	44	100.0000	43.9996
9	16	33	99.2901	32.9998
10	16	33	99.3024	32.9998
11	16	33	99.2851	32.9998
12	16	33	99.3095	32.9998
13	16	33	99.2728	32.9998

The resulted reduced RSM metamodels in terms of the actual significant variables are presented in Appendix B. As an example, the CONWIP SC RSM metamodels at demand SD = 1 were as follows:

$$Service\ Level = 29.17 + 0.03 \times \text{Node capacity} + 6.75 \times \text{WIPCap} - 0.001 \times \text{Node capacity}^2 - 0.09 \times \text{WIPCap}^2 \tag{4-1}$$

$$Average\ WIP = 0.22 + 0.05 \times \text{Node capacity} + 0.96 \times \text{WIPCap} + 0.002 \times \text{Node capacity} \times \text{WIPCap} - 0.003 \times \text{Node capacity}^2 \tag{4-2}$$

Although the simulation model is stochastic in nature as the incoming orders to the SC is assumed to be a random variable that follows a log-normal distribution (randomness in the simulation model was triggered by the common pseudo-random number generator), only a small variation between replications was observed in the simulation outputs which makes the simulation model appeared to be almost deterministic. Therefore, the conventional *lack-of-fit* test will not be considered to validate the fitted metamodels. Despite these circumstances, much of the standard analysis of variance tools remain relevant [142, 143].

Another traditional and very effective approach to test the validity of fitted models with respect to simulation models is by running new scenarios and then comparing the simulation outputs with the predictions of the developed meta-models. For this purpose, trade-off curves between service level and average WIP were generated form different new optimum scenarios for all the SCs policies as will be shown afterwards in Section 4.3 and Appendix E.

The $ANOVA$ results and the considered adequacy measures of all SC metamodels under different demand SD are presented in Appendix C. As an example, the $ANOVA$ results of the CONWIP SC RSM metamodels at SD = 1 are shown in Tables 4-2 and 4-3.

From the $ANOVAs$ (shown in Tables 4-2, 4-3, and Appendix C), it can be seen that all the models are quadratic, significant, and fit the data adequately at level of significance of 5%. Also R^2, $Adjusted\ R^2$, and $Predicted\ R^2$ show that a high percentage of the variability in the original and new observations are explained by the fitted models and that they are in a logical agreement, indicating that all models are adequate. It can also be seen that the differences between $PRESS$ and the ordinary residual sum of squares in all models are reasonable indicating that the fitted models are capable of making predictions for new scenarios with a tolerable amount of error.

Table 4-2: $ANOVA$ for CONWIP service level reduced quadratic model at SD=1

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	1757.87	4	439.47	356063.60	< 0.0001	significant
A- Node capacity	0.003	1	0.003	2.27	0.1557	
B- WIP-Cap	1266.50	1	1266.50	1026142.69	< 0.0001	
A^2	0.01	1	0.01	6.36	0.0255	
B^2	392.42	1	392.42	317941.74	< 0.0001	
Residual	0.02	13	0.00			
Total	1757.88	17				
R^2	1.0000		PRESS	0.03		
Adj R^2	1.0000					

Table 4-3: ANOVA for CONWIP average WIP reduced quadratic model at SD=1

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	1183.83	4	295.96	68256.78	< 0.0001	significant
A-Node capacity	0.344	1	0.344	79.23	< 0.0001	
B-WIP-Cap	1183.14	1	1183.14	272867.57	< 0.0001	
AB	0.19	1	0.19	43.42	< 0.0001	
A^2	0.13	1	0.13	30.90	< 0.0001	
Residual	0.06	13	0.00			
Total	1183.89	17				
R^2	1.0000		PRESS	0.11		
Adj R^2	0.9999					

In addition, by examining and comparing the service level and average WIP trade-off curves of the developed metamodels and the simulation model under the new different optimum scenarios of all the SCs policies, illustrated in Section 4.3 and Appendix E, it can be judged how accurately the fitted models predict simulation outputs based on how close the curves will lay on top of each other and if the deviation between the different points is acceptable.

According to these results, the fitted RSM metamodels are statistically significant and will be considered valid and can be used for further analysis.

4.1.1 Effect of input factor on the CONWIP SC performance measures

The effect of the selected input factors to be varied, node capacity (A) and WIP-Cap (B), on the performance measures of CONWIP SC, the *service level* and the *average WIP*, under different demand variability conditions, SD=1, SD=4.5, and SD=8, are shown in Figures 4-1and 4-2.

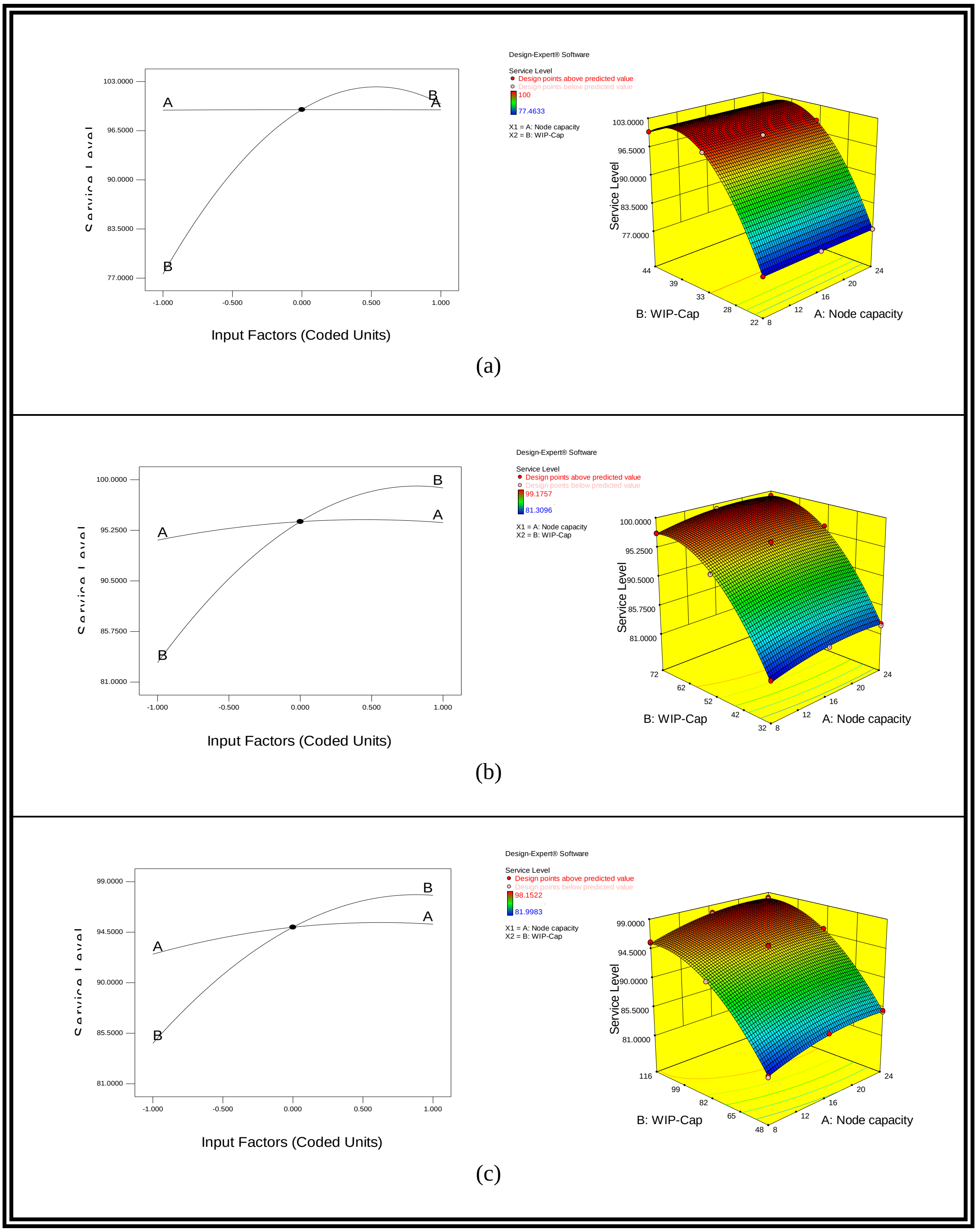


Figure 4-1: Effect of input factors on CONWIP SC service level at; (a) SD=1 (b) SD=4.5 (c) SD=8

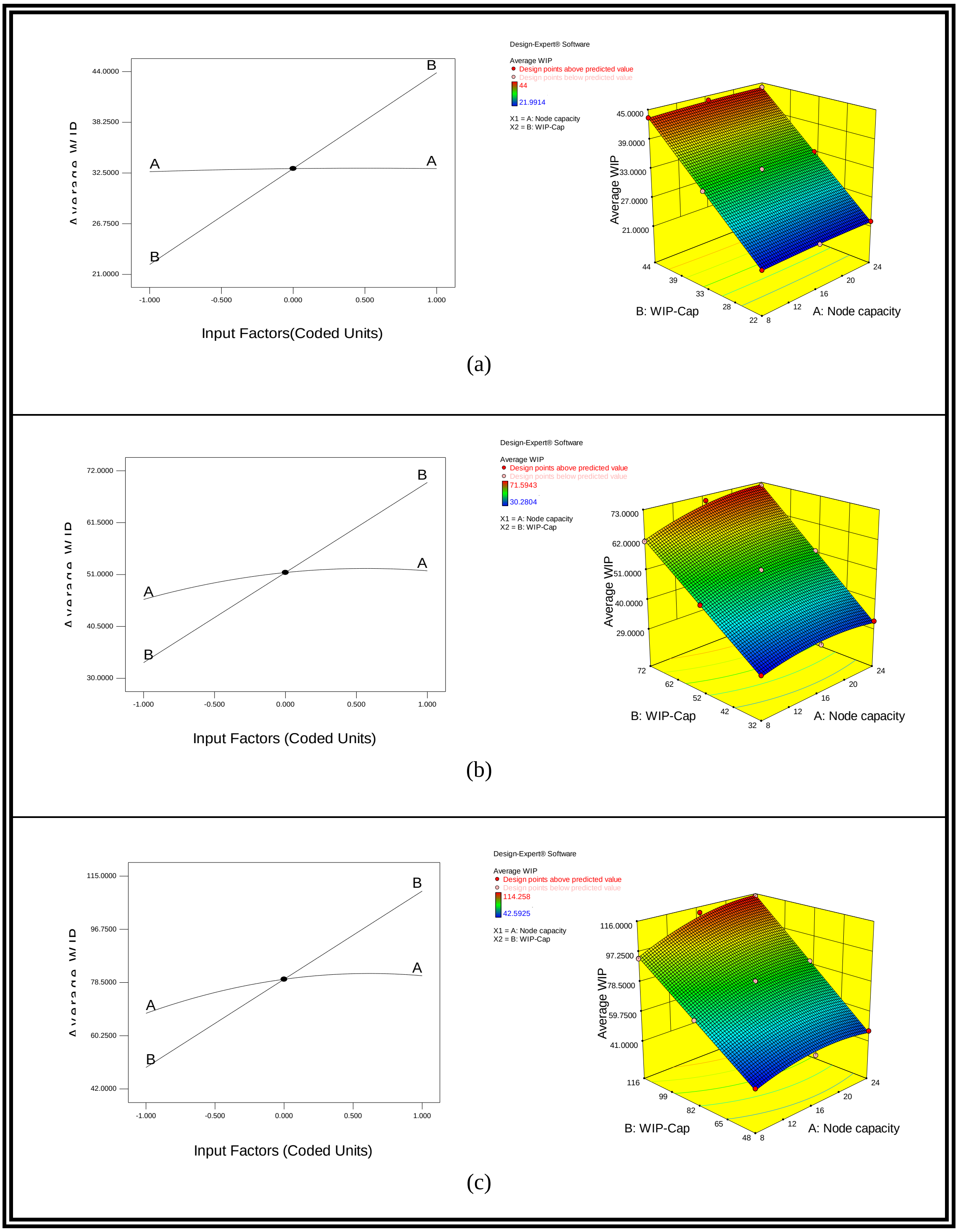


Figure 4-2: Effect of input factors on CONWIP SC average WIP at; (a) SD=1 (b) SD=4.5 (c) SD=8

Figures 4-1 and 4-2 show that the service level and WIP are directly related to the WIP-Cap and node capacity; both increase as the WIP-Cap and node capacity increase within their specified ranges. It can be seen that WIP-Cap has the most significant impact on both responses under all demand variability conditions; the larger the WIP-Cap the higher the service level and consequently the higher the WIP. It can also be seen that the positive effect of node capacity becomes more significant on both responses as the demand standard deviation increases.

4.1.2 Effect of input factor on the Kanban SC performance measures

The effect of the selected input factors to be varied, node capacity (A), Node 1 Kanban cards (B), Node 2 Kanban cards (C), Node 3 Kanban cards (D), and Node 4 Kanban cards (E) on the performance measures of the Kanban SC, the *service level* and the *average WIP*, under different demand variability conditions, SD=1, SD=4.5, and SD=8, are shown in Figures 4-3 and 4-4.

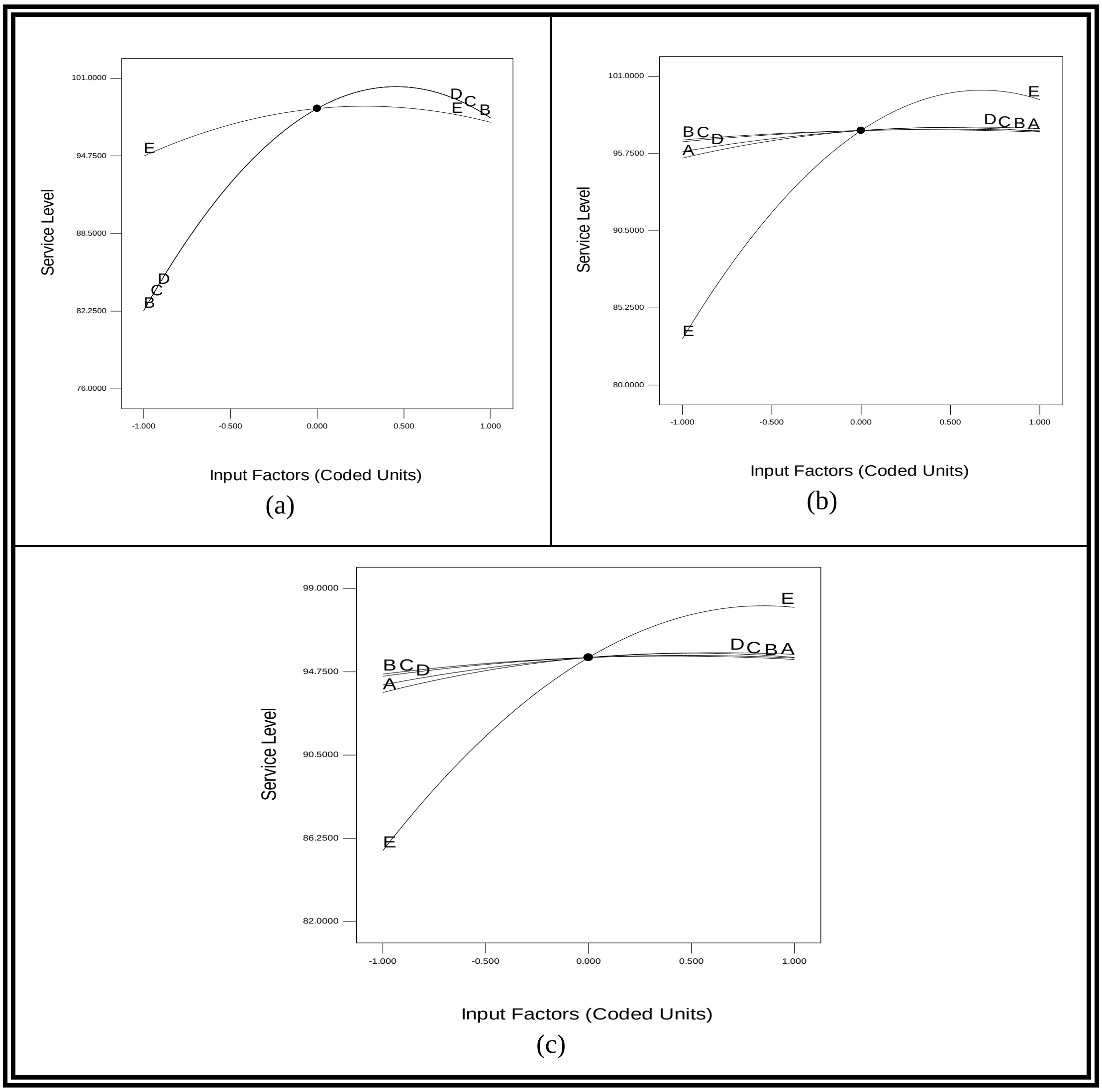


Figure 4-3: Effect of input factors on Kanban SC service level at; (a) SD=1 (b) SD=4.5 (c) SD=8

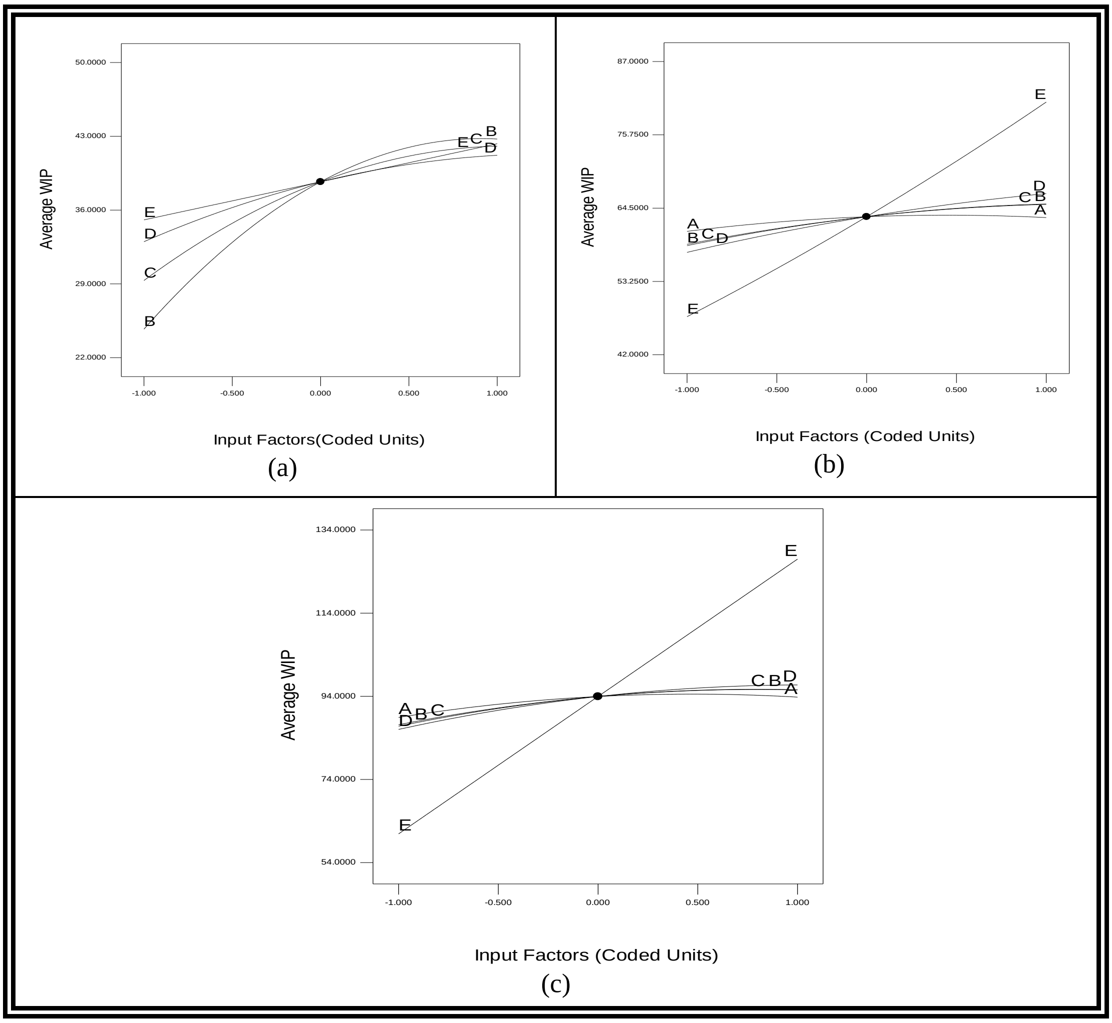


Figure 4-4: Effect of input factors on Kanban SC average WIP at; (a) SD=1 (b) SD=4.5 (c) SD=8

Figures 4-3 and 4-4 show that the service level and WIP are directly related to the node capacity, Node 1 Kanbans, Node 2 Kanbans, Node 3 Kanbans, and Node 4 Kanbans; both increase as these input parameters increase within their specified ranges from minimum to maximum. Under low demand variability condition (e.g., SD=1) for both response, it can be seen that the node capacity has no effect whatsoever and Node 1 Kanbans is the most significant whilst Node 4 Kanbans have the least effect. As the demand variability increases (e.g., SD= 4.5 and SD=8) Node 4 Kanbans become the most significant; the more the Node 4 Kanbans the higher the service level and accordingly the higher the WIP. It can also be seen that node capacity becomes slightly significant and affect both responses.

4.1.3 Effect of input factor on the Hybrid Kanban-CONWIP SC performance measures

The effect of the selected input factors to be varied, node capacity (A), WIP-Cap (B), Node 1 Kanban cards (C), Node 2 Kanban cards (D), and Node 3 Kanban cards (E) on the performance measures of the Hybrid Kanban-CONWIP SC, the *service level* and the *average WIP*, under different demand variability conditions, SD=1, SD=4.5, and SD=8, are shown in Figures 4-5 and 4-6.

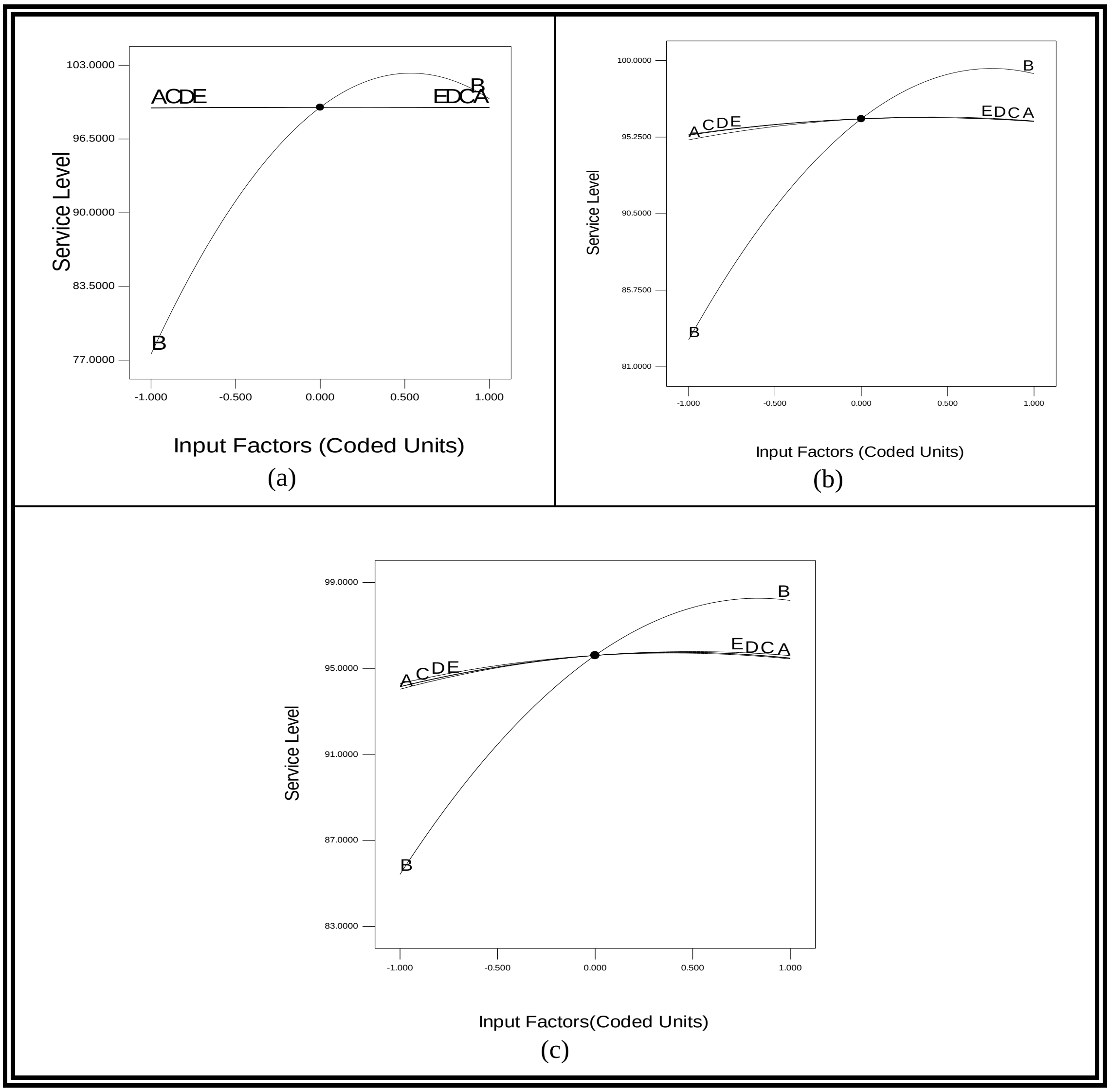


Figure 4-5: Effect of input factors on Hybrid SC service level at; (a) SD=1 (b) SD=4.5 (c) SD=8

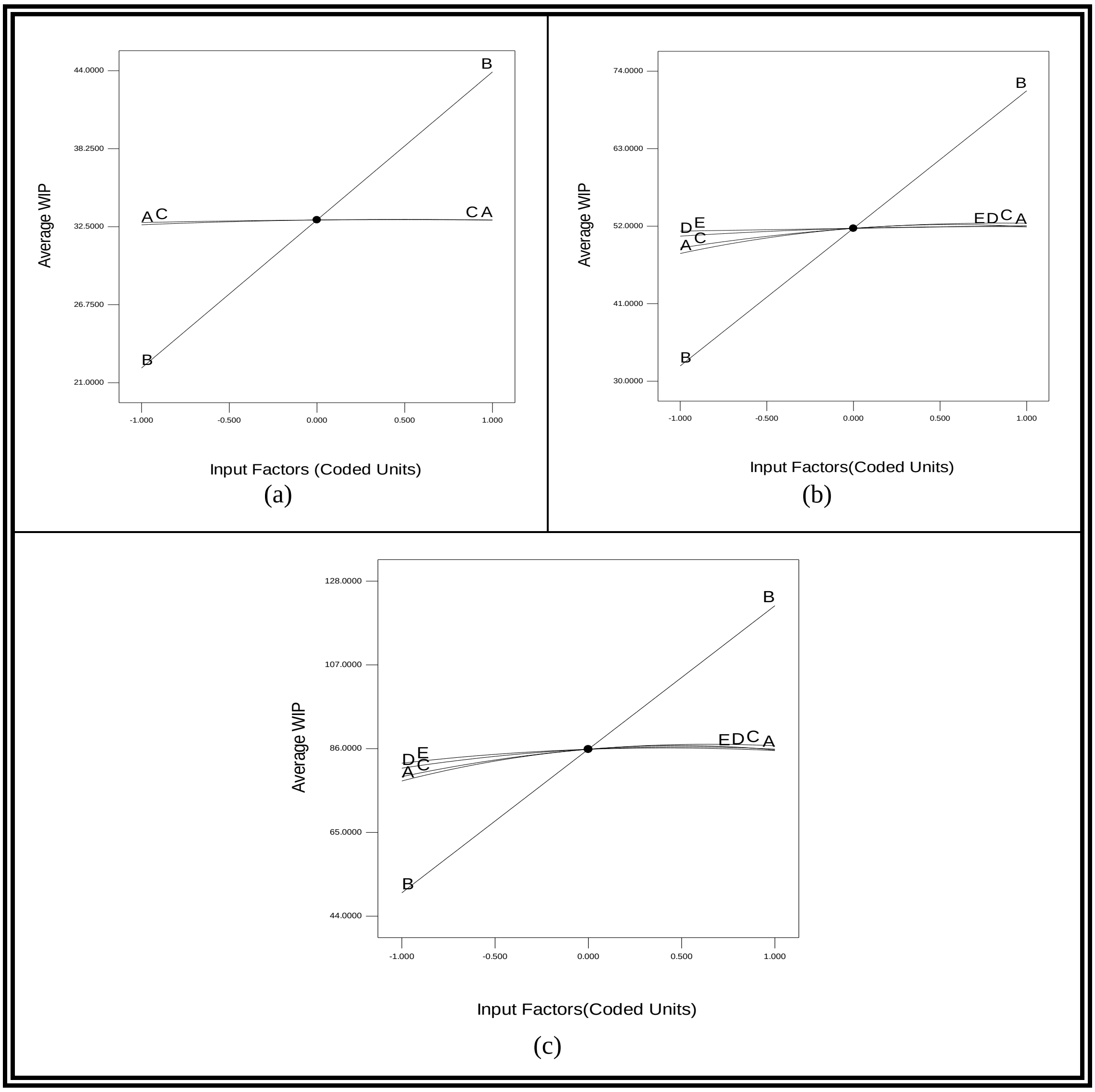


Figure 4-6: Effect of input factors on Hybrid SC average WIP at; (a) SD=1 (b) SD=4.5 (c) SD=8

Both Figures 4-5 and 4-6 show that the service level and WIP are directly related to the node capacity, WIP-Cap, Node 1 Kanbans, Node 2 Kanbans, and Node 3 Kanbans; both increase as these input parameters increase within their specified ranges from minimum to maximum. Under the low demand variability condition (e.g., SD=1), it can be seen that Node 2 Kanbans, and Node 3 Kanbans have no effect at all on the average WIP however, as the demand variability increases (e.g., SD= 4.5 and SD=8) they become slightly significant. The WIP-Cap has the most significant impact on both responses under all demand variability conditions; the larger the WIP-Cap the higher the service level and consequently the higher the WIP. It can also be seen that the rest of the input parameters become more significant on both responses as the demand standard deviation increases.

4.2 GP Metamodels

To estimate the different terms of the GP metamodels, $\mu, \sigma^2, \gamma_i, \omega_j$ (known as *Theta* in JMP) and the *Nugget* term which stands for the noise or randomness in the simulation model, equation (3-27) was fitted to the simulation output data of the different LHDs of all SCs by using the method of maximum likelihood estimation. Table 4-4 is shown as an example of a LHD matrix for the CONWIP SC at SD=1.

Table 4-4: CONWIP SC LHD matrix and simulation outputs at SD=1

	Factor 1	Factor 2	Response 1	Response 2
Run No.	A: WIP-Cap	B:Node capacity	Service Level	Average WIP
	(Cards)	(items)	(%)	(items)
1	8	33	99.1891	32.5679
2	22	29	95.4644	29.0000
3	11	38	99.9808	37.9370
4	13	32	98.7889	31.9932
5	18	31	97.9801	31.0000
6	18	35	99.8144	34.9999
7	9	40	99.9877	39.3793
8	19	22	77.4513	22.0000
9	19	28	93.6613	28.0000
10	21	34	99.6117	34.0000
11	17	43	99.9999	42.9996
12	20	30	96.8903	30.0000
13	22	23	80.6725	23.0000
14	12	26	89.2325	25.9994
15	24	41	99.9989	41.0000
16	15	42	99.9998	41.9980
17	14	39	99.9929	38.9981
18	10	44	99.9998	43.9348
19	16	36	99.9092	35.9997
20	17	24	83.6546	24.0000
21	23	37	99.9616	37.0000
22	16	27	91.5313	27.0000
23	24	25	86.5241	25.0000

JMP generates a model report, summarising the *Functional ANOVA* and the estimated terms of the GP metamodel, and also generates its actual by predicted plot. The resulted GP metamodels reports of all SCs at the different demand SD and their actual by predicted plots are presented in Appendix D. As an example, the CONWIP SC GP metamodel reports at Demand SD = 1 are shown in

Table 4-5 and Table 4-6 for the Service Level and the Average WIP GP metamodels, respectively. Figure 4-7 provides an example of the actual by predicted plots generated for the two GP metamodels.

Table 4-5: CONWIP service level GP metamodel report at SD=1

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP.Cap Interaction
Capacity	0.000015	0.0002508	7.8414e-5	.	0.0001724
WIP.Cap	0.0049178	0.9999216	0.9997492	0.0001724	.

μ	σ²	Nugget
86.147019	167.24539	0.0012046

Table 4-6: CONWIP average WIP GP metamodel report at SD=1

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP.Cap Interaction
Capacity	0.000015	0.0001073	0.0001061	.	0.0000012
WIP.Cap	0.0001539	0.9998939	0.9998927	0.0000012	.

μ	σ²	Nugget
31.349467	703.19682	0.0001474

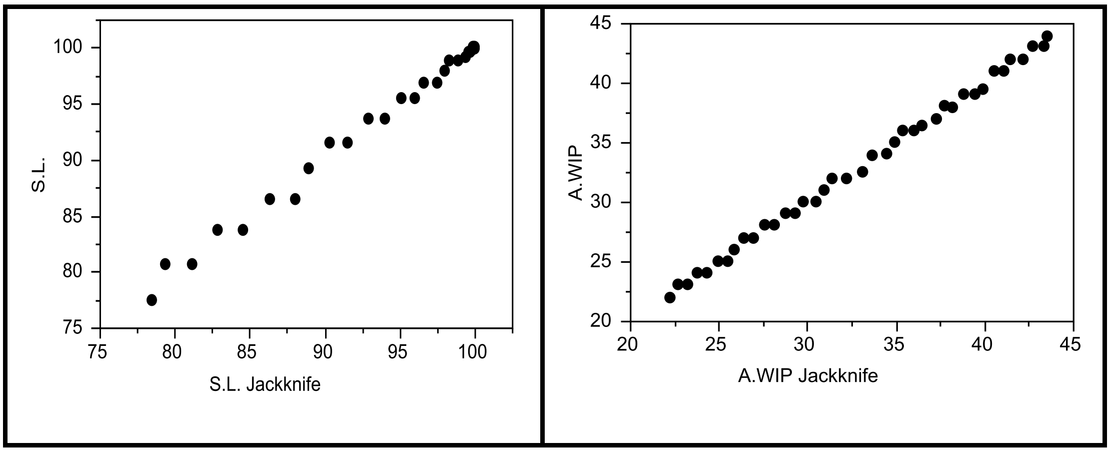


Figure 4-7: CONWIP SC GP metamodels actual by predicted plot at SD=1

The different metamodel reports (shown in Tables 4-5, 4-6, and Appendix D), show how the considered performance measures of all the SCs are affected by each of the input factors as a main and total sensitivity effect under different demand SD. This main and total sensitivity effect percentage (%), if it exists, reveals the amount of influence and importance an input factor has on the considered performance measure. Also, by looking at the different actual by predicted plots (shown in Figure 4-7 and Appendix D) it can be seen that the different points are scattered close the 45 degree diagonal line which reflects how accurately the models predict simulation outputs.

Furthermore, by examining and comparing the service level and average WIP trade-off curves of the fitted GP metamodels and the simulation model under the new optimum scenarios of all SCs policies, as will be shown afterwards in Section 4.4 and Appendix F, it can be seen that all the curves are laying close at the top of each other and the deviation between the different points is very reasonable which reflects the quality of making new predictions.

According to these results, the fitted GP metamodels are considered valid and can be used for further analysis.

4.3 RSM-DA Optimisation

For all SCs under different demand SD, the resulted optimal solutions from the desirability approach being applied to the developed RSM metamodels (RSM-DA) along with their actual simulation outputs as estimate refinements (SIM-RSM-DA) and their corresponding trade-off curves are presented in Appendix E. As an example, the results of the CONWIP SC at Demand SD = 1 are shown in Table 4-7 and Figure 4-8.

4.4 GP-DA Optimisation

For all SCs under different demand SD, the resulted optimal solutions from the desirability approach being applied to the developed GP metamodels (GP-DA) along with their actual simulation outputs as estimate refinements (SIM-GP-DA) and their corresponding trade-off curves are presented in Appendix F. As an example, the results of the CONWIP SC at Demand SD = 1 are shown in Table 4-8 and Figure 4-9.

Table 4-7: CONWIP SC RSM-DA and their SIM-RSM-DA results for SD=1

S.L. Target	Node Capacity	WIP-Cap	CONWIP RSM-DA			CONWIP SIM-RSM-DA	
			Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
78±0.5	8	22	77.9999	22.0997	0.9975	77.4989	21.9914
80±0.5	8	23	79.9998	22.7865	0.9818	80.4890	22.9839
82±0.5	8	24	81.9998	23.5051	0.9650	83.4903	23.9718
84±0.5	8	24	83.9998	24.3399	0.9451	83.4903	23.9718
86±0.5	8	25	85.9998	25.0578	0.9277	86.1996	24.9540
88±0.5	8	26	87.9998	25.9063	0.9067	89.0033	25.9281
90±0.5	8	27	89.9998	26.8169	0.8836	91.0887	26.8949
92±0.5	8	28	91.9998	27.8055	0.8578	93.1066	27.8518
94±0.5	8	29	93.9998	28.8964	0.8284	95.0752	28.8017
96±0.5	8	30	95.9998	30.1301	0.7939	96.1902	29.7469
98±0.5	8	32	97.9998	31.5838	0.7511	98.2109	31.6251
100	8	34	99.9998	33.4476	0.6924	99.8232	33.5183

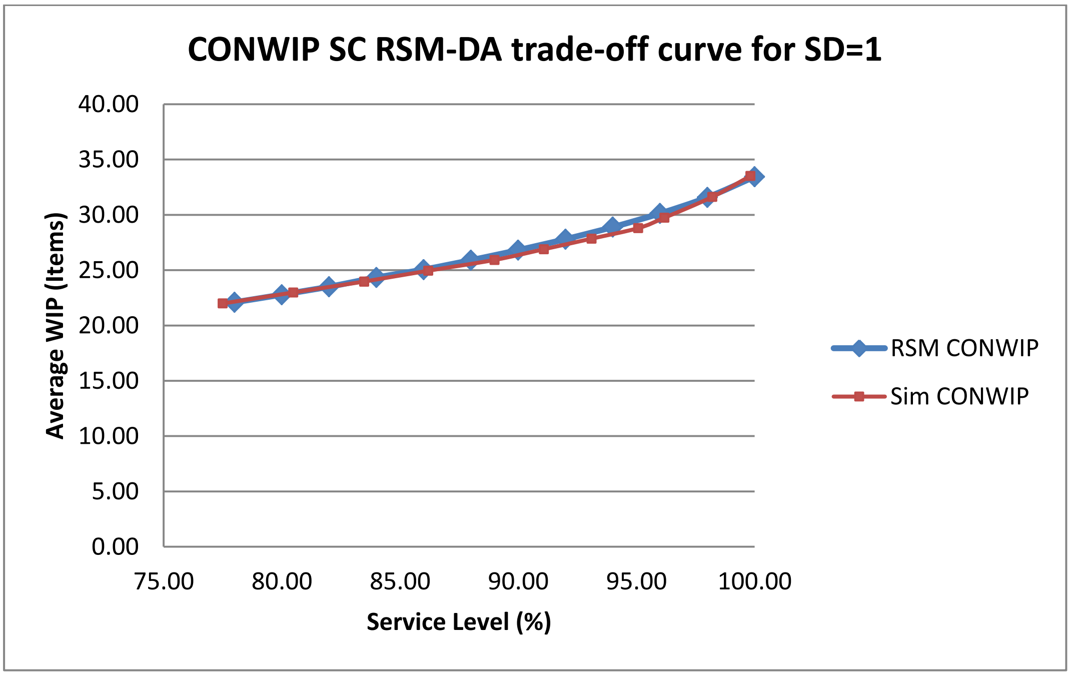


Figure 4-8: CONWIP SC RSM-DA trade-off curve for SD=1

Table 4-8: CONWIP SC GP-DA and their SIM-GP-DA results for SD=1

S.L. Target	Node Capacity	WIP-Cap	CONWIP GP-DA Service Level	CONWIP GP-DA Average WIP	CONWIP GP-DA Desirability	CONWIP SIM-GP-DA Actual Service Level	CONWIP SIM-GP-DA Actual Average WIP
78±0.5	19	22	78.0029	22.2026	0.9861	77.5089	22.0000
80±0.5	23	23	80.0035	22.8229	0.9714	80.6800	23.0000
82±0.5	21	23	82.0101	23.4784	0.9549	80.6398	23.0000
84±0.5	19	24	84.0031	24.1360	0.9392	83.6629	24.0000
86±0.5	16	25	85.9972	24.8187	0.9219	86.4742	25.0000
88±0.5	23	25	88.0046	25.5259	0.9035	86.5150	25.0000
90±0.5	19	26	89.9977	26.2988	0.8831	89.1512	26.0000
92±0.5	11	27	91.9974	27.1479	0.8601	91.5780	26.9889
94±0.5	12	28	93.9970	28.1199	0.8332	93.6901	27.9982
96±0.5	14	29	96.0025	29.3194	0.7994	95.4687	28.9997
98±0.5	9	31	97.9982	30.9889	0.7512	97.8516	30.6875
100	9	35	99.7284	34.2802	0.4304	99.7256	34.4699

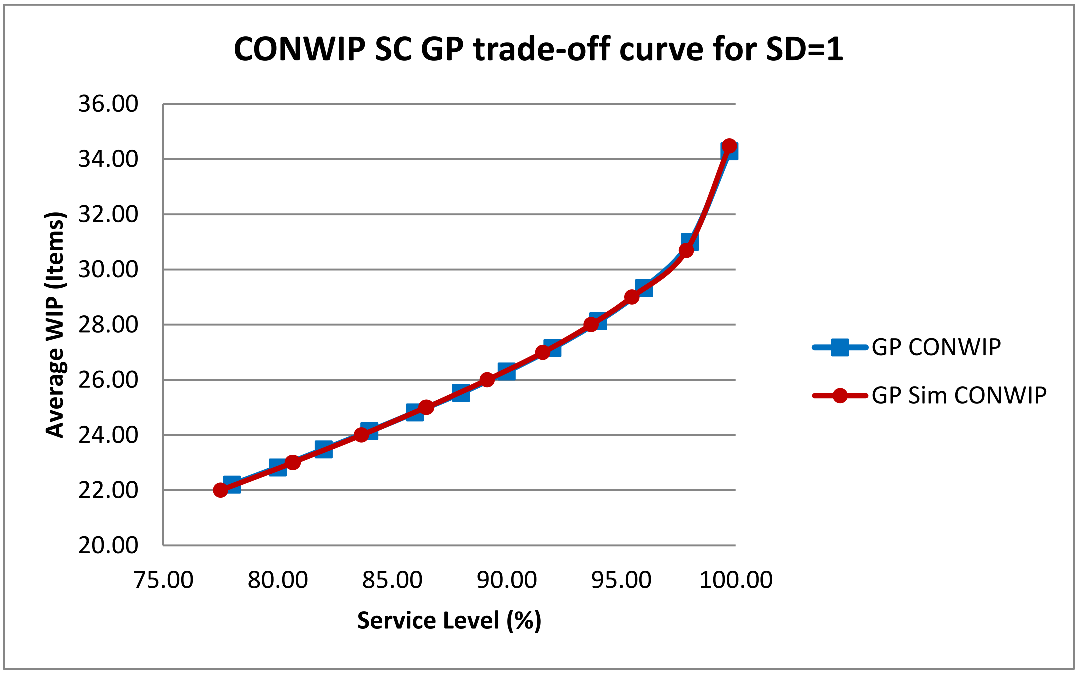


Figure 4-9: CONWIP SC GP trade-off curve for SD=1

4.5 RSM-POGA Optimisation

For all SCs under different demand SD, the resulted optimal solutions from the genetic algorithms technique being applied to the developed RSM metamodels (RSM-POGA) along with their actual simulation outputs as estimate refinements (SIM-RSM- POGA) and their corresponding trade-off curves are presented in

Appendix G. As an example, the results of the CONWIP SC at Demand SD = 1 are shown in Table 4-9 and Figure 4-10.

Table 4-9: CONWIP SC RSM-POGA and their SIM-RSM-POGA results for SD=1

S.L. Target	Node Capacity	WIP-Cap	CONWIP RSM-POGA Service Level	CONWIP RSM-POGA Average WIP	CONWIP SIM-RSM-POGA Actual Service Level	CONWIP SIM-RSM-POGA Actual Average WIP
78±0.5	17	22	77.531499	21.673557	77.4935	22.0000
80±0.5	8	23	80.311051	22.446913	80.6193	22.9840
82±0.5	*	*	*	*	*	*
84±0.5	*	*	*	*	*	*
86±0.5	17	25	85.545231	24.645305	86.6064	25.0000
88±0.5	17	26	87.869493	25.635887	89.2134	26.0000
90±0.5	12	27	89.99898	26.526315	91.5509	26.9989
92±0.5	17	28	91.997545	27.617052	93.6401	28.0000
94±0.5	17	29	93.801335	28.607635	95.4246	29.0000
96±0.5	*	*	*	*	*	*
98±0.5	8	32	98.106577	31.22095	98.6583	31.6292
100	8	34	100.15274	33.170736	99.5188	33.5154

* No Optimal Solution

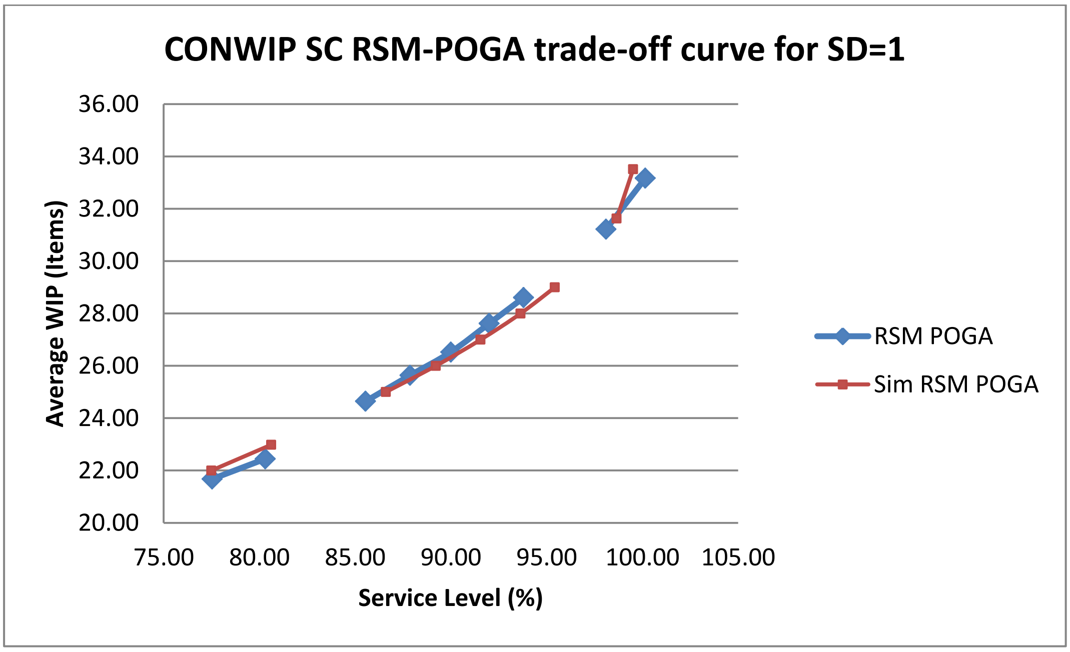


Figure 4-10: CONWIP SC RSM-POGA trade-off curve for SD=1

4.6 SIM-POGA Optimisation

For all SCs under different demand SD, the resulted optimal solutions from the genetic algorithms technique being applied directly to the SC simulation model of this research work (SIM-POGA) and their corresponding trade-off curves are presented in Appendix H. As an example, the results of the CONWIP SC at Demand SD = 1 are shown in Table 4-10 and Figure 4-11.

Table 4-10: CONWIP SC SIM-POGA results for SD=1

S.L. Target	Node Capacity	WIP-Cap	CONWIP SIM-POGA	
			Service Level	Average WIP
78±0.5	22	10	77.5107	21.9996
80±0.5	23	8	80.6596	22.9841
82±0.5	23	10	80.6626	22.9991
84±0.5	24	12	83.6783	23.9999
86±0.5	25	8	86.5198	24.9541
88±0.5	26	8	89.1473	25.9285
90±0.5	26	12	89.1739	25.9995
92±0.5	27	14	91.5733	26.9999
94±0.5	28	14	93.6814	27.9998
96±0.5	29	14	95.4682	28.9997
98±0.5	31	10	98.0066	30.9625
100	44	10	100	43.9363

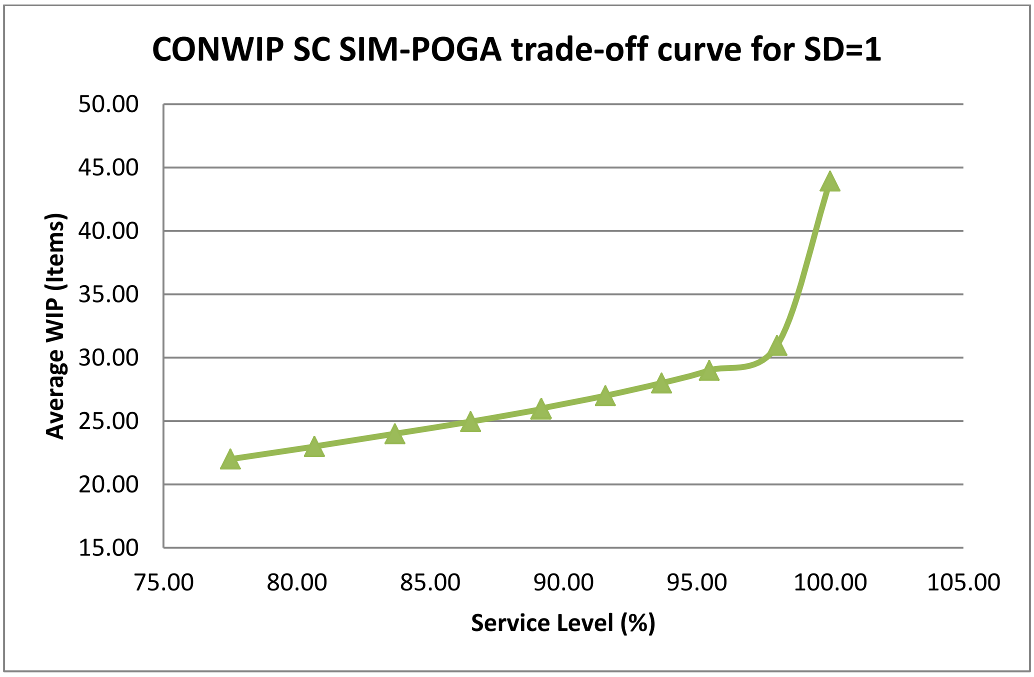


Figure 4-11: CONWIP SC SIM-POGA trade-off curve for SD=1

4.7 Discussion and Comparison of Results

To this stage of the optimisation phase, trade-off curves were generated using optimal solutions of four different methods; namely SIM-RSM-DA, SIM-GP-DA, SIM-RSM-POGA, and SIM-POGA. The trade-off curves generated from SIM-RSM-POGA will be discarded due to their inconsistency while the other three will be illustrated for each SC under different demand SD along with the percentage deviations (errors) between each of the metamodels based optimisation approaches (SIM-RSM-DA and SIM-GP-DA) and the simulation based approach (SIM-POGA; as the solutions from this method are the most accurate and generated from applying the POGA directly to the SC simulation model). The results are presented in Appendix I. As an example, the results of the CONWIP SC at Demand SD = 1 are shown in Figure 4-12, Table 4-7, Figure 4-13, and Figure 4-14 respectively.

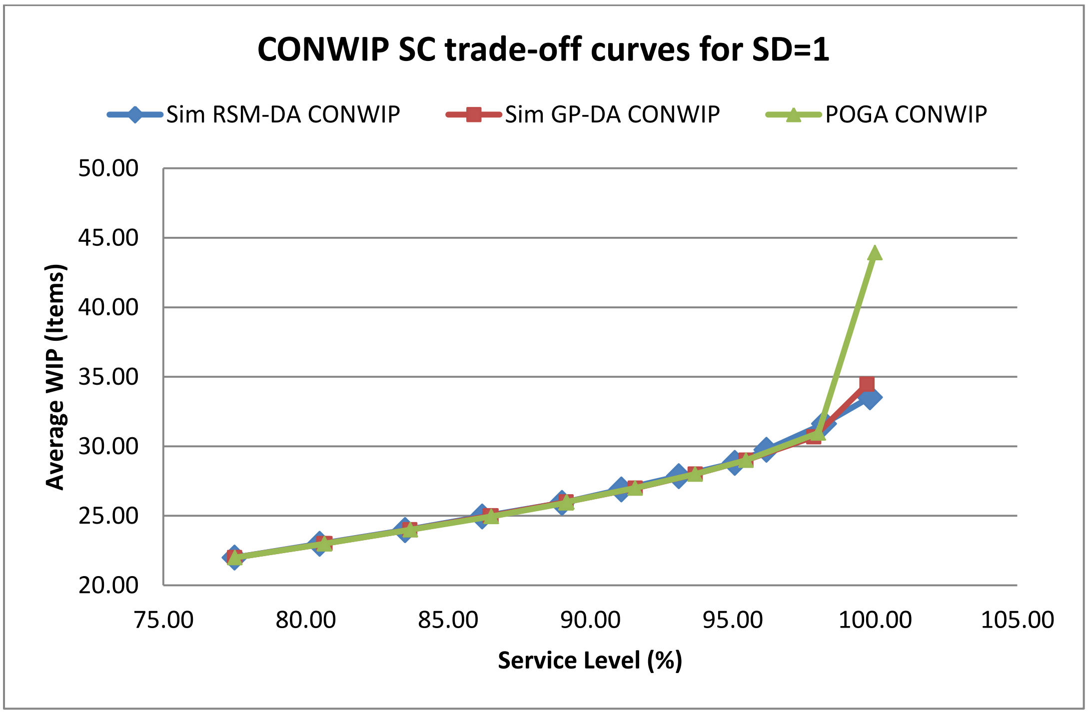


Figure 4-12: CONWIP SC trade-off curves for SD=1

Table 4-11: Percentage deviations from SIM-POGA of CONWIP SC for SD=1

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	78±0.5	0.015%	0.037%	0.002%	-0.002%
2	80±0.5	0.211%	0.001%	-0.025%	-0.069%
3	82±0.5	-3.506%	-4.229%	0.028%	-0.004%
4	84±0.5	0.225%	0.117%	0.018%	-0.001%
5	86±0.5	0.370%	0.000%	0.053%	-0.184%
6	88±0.5	0.161%	0.001%	2.953%	3.581%
7	90±0.5	-2.147%	-3.444%	0.025%	-0.002%
8	92±0.5	-1.674%	-3.155%	-0.005%	0.041%
9	94±0.5	-1.488%	-2.864%	-0.009%	0.006%
10	96±0.5	-0.756%	-2.577%	-0.001%	0.000%
11	98±0.5	-0.208%	-2.140%	0.158%	0.888%
12	100	0.177%	23.712%	0.274%	21.546%

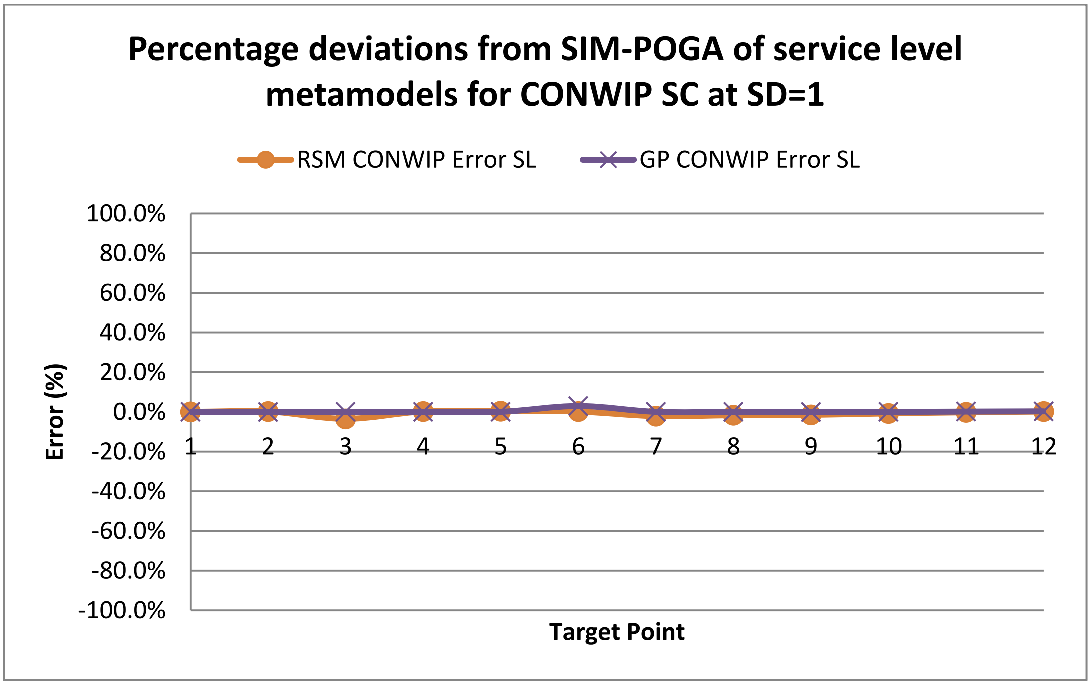


Figure 4-13: Percentage deviations from SIM-POGA of service level metamodels for CONWIP SC at SD=1

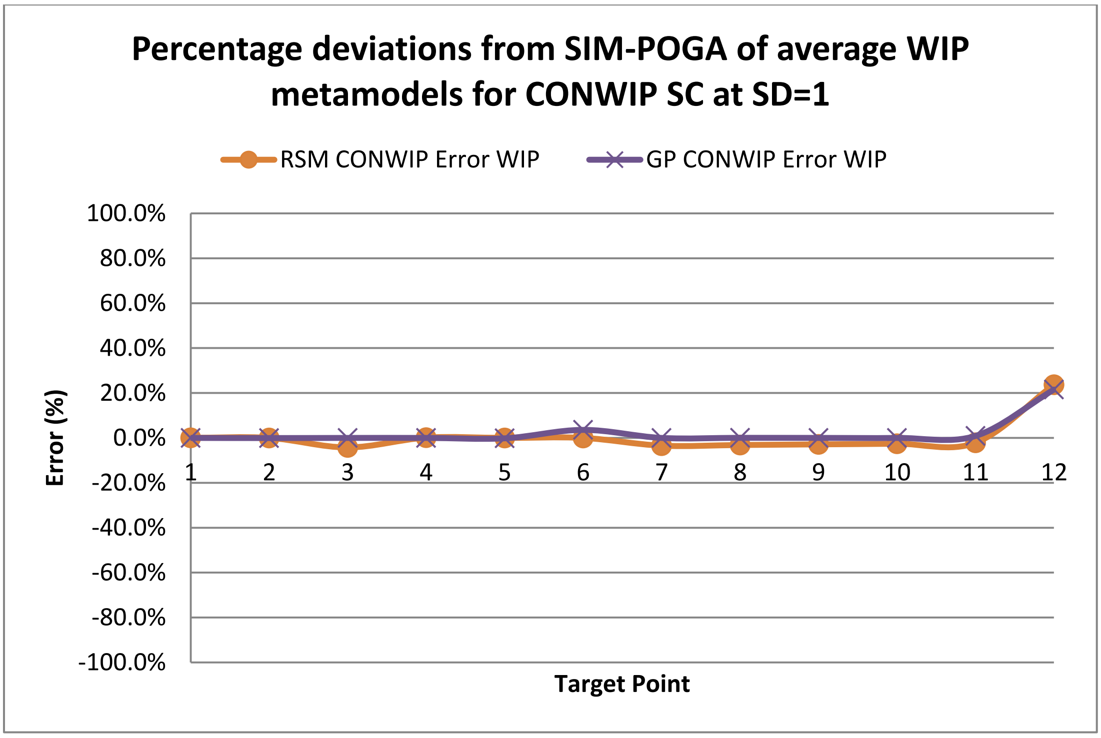


Figure 4-14: Percentage deviations from SIM-POGA of average WIP metamodels for CONWIP SC at SD=1

The Desirability Approach, implemented in Design-Expert and JMP software packages, was only capable of searching design spaces and generating optimal solutions comprised of real (continuous) numbers. As the different input factors of this research work are discrete (integer) numbers in nature, rounded figures of optimal solutions (not the actual continuous one) were simulated in order to validate and analyse the fitted metamodels. This condition could possibly add more to the existing error from experimenting with a stochastic simulation model.

For All SCs metamodels it can be seen that the main errors result from estimates of average WIP as opposed to service levels. However, SIM-RSM-DA tended to result in slightly higher errors for estimates of Average WIP than SIM-GP-DA in most of the time.

Generally, the GP metamodels can be considered more accurate and give better approximations to the SC simulation model under different demand SD than the RSM metamodels as the errors are less in both average WIP and service levels. This could be attributed to the fact that RSM uses the traditional experimental designs (e.g., FCD and BBD) which define each input variable at only three levels (low, middle, and high) over the entire region of experimentation to develop metamodels. These three levels seems to be not enough to acquire better quality metamodels that approximate the true functional relationship between the responses and input variables over the specified *large* domain.

Depending on specific objectives and conditions, an appropriate design of experiment is the pre-requisite for a successful meta-modelling study. The classical fractional factorial and central composite designs assign two or three predetermined levels for each input factor and perform experiments at the combination of these levels to explore the main and interactions effects of the input factors based on fitted polynomial models. Using a small number of levels may not have an optimal coverage of the entire design space especially if it's broad and large, and thus it may result in a less reliable metamodel [194]. The recognition of this disadvantage of classical DOE methods has motivated the concept of *space-filling designs* (e.g. Latin Hypercube Design, LHD) that allocate design points to be evenly distributed within the broad working range of each input factor [162, 195]. According to Kleijnen [196], when the experimental area covers the whole area in which the simulation model is valid, then other *global* metamodels become relevant. GP models (Kriging or Spatial Correlation), are global rather than local (i.e. fitted to data that are obtained form larger experimental space than the small spaces used in law order polynomial regression models), and more capable of approximating complex systems, thus provide great chances of identifying the optimum as opposed to the restrictive form of the polynomial models used in traditional RSM. In addition to prediction accuracy, GP models are also known for the capability of providing reliable prediction variance, which measures the uncertainty of the studied model (i.e. the degree to which the model is not sure about its prediction) [155].

Inventory is a common component throughout the SC either as raw material, work in progress or as finished goods and the levels of these inventories can often be viewed as the main warning sign in any SC. Therefore, how much inventory is being held to achieve targeted customer service levels at an acceptable price is very important issue to understand. Trade-off curves can effectively be used to understand and analyse this matter and help to attain sense of balance between conflicting objectives. The trade-off curves (Pareto-optimal fronts) of the CONWIP SC, the

Kanban SC, and Hybrid Kanban-CONWIP SC under the highly variable demand condition SD=8 resulted from applying the POGA are illustrated in Figure 4-15.

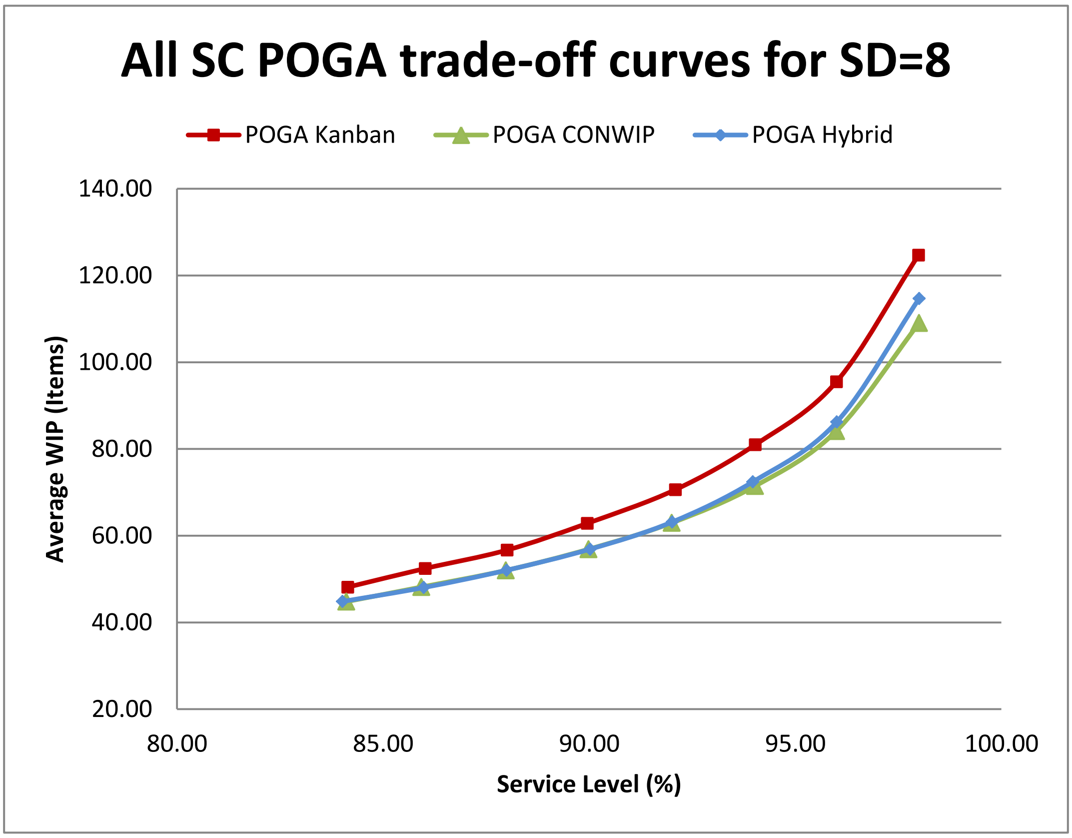


Figure 4-15: All SC POGA trade-off curves for SD=8

It can be seen that none of the solutions is best along the dimensions of both objectives; there is gain along one dimension and loss a long the other one. Furthermore, the relationship between this two conflicting objectives is not a straight line; increasing service level gives an exponential curve relationship in the extra stock to be carried. For example in all SCs under a highly variable demand environment, it can be seen that there is a huge increase of an average of 65% in WIP for an increase of 5% in service level (when moving from 93% towards a high 98% service level). It is clear that the increase in average service levels is coming at the cost of increase in average inventory levels. The decision of whether such a trade-off is acceptable depends on the cost of the inventory, cost of lost sales and several other aspects that need to be considered before making a decision by the supply chain managers.

With respect to SC performance evaluation, it can be seen that the Kanban SC strategy is consistently the worst performer in comparison with the CONWIP and the hybrid Kanban-CONWIP in terms of minimum WIP required to achieve a given service level (approximately ranging from 10% to 15% more inventory). In fact, several researchers have shown KCS to be the worst performer in a manufacturing system context, for example [94, 100-102] have shown that, in manufacturing systems, as variability in demand increases not only is KCS the worst performer, but the strategy degrades considerably in performance when compared to CONWIP and Hybrid Kanban CONWIP. Takahashi and Hirotani [37] compared the performance of KCS with CONWIP and Synchronised CONWIP in a tiered supply chain. They found KCS to be the worst performer, but did not examine whether the performance of KCS in relation to other strategies degrades in a supply-chain context as demand variability increases.

There is no difference between the performance of CONWIP and the hybrid Kanban-CONWIP for targeted service levels ranging from 84% to 93%. Afterwards, CONWIP outperforms the hybrid Kanban-CONWIP when moving from 93% towards the 98% service level. This, at first inspection, was a surprising result since many researchers have demonstrated that hybrid Kanban-CONWIP outperforms CONWIP in manufacturing systems [101, 102, 107]. However, given that the only source of variability in the system modelled here was the demand distribution, node capacity and lead times were known and constant, this result is perhaps not so surprising. CONWIP will utilise a push strategy in the line (system) from entry to Finished Goods Inventory (FGI) buffer. Inventory will naturally increase at bottlenecks [103] and, with no in-line variability to consider in the SC modelled, the majority of inventory will accumulate in the FGI buffer. Hybrid Kanban-CONWIP will delay the arrival of inventory to FGI buffer as it implements, local, pull control through Kanban cards at the nodes of the supply-chain. Hybrid Kanban-CONWIP may outperform CONWIP in the presence of one or more significant in-line bottlenecks as CONWIP will be incapable of locally controlling or limiting the build-up of WIP at these points.

4.8 Curvature Analysis

Application of the curvature analysis technique to trade-off curves generated based on using WIP achieved on the *y-axis* and Service Level on the *x-axis* tended to result in a lower inflection point (lower Service Level target) than application to trade-off curves generated based on using the incremental change in WIP (ΔWIP) required to achieve a 0.1% increase in Service Level. These two inflection points are referred to, hereinafter, as pessimistic and optimistic inflection points, respectively. It is worth noting that, the determination of a curvature function should be conducted based on normalising both axes to the same scale. Therefore, the *y-axis* has been normalised by calculating WIP as a percentage of the maximum WIP seen in the case of the pessimistic curve and ΔWIP as a percentage of the maximum increase in WIP required to achieve a 0.1% increase in Service Level in the case of the optimistic curve. Both the y and x axes are, therefore, in percentage with a maximum value of 100%.

The pessimistic and optimistic parameter settings derived from application of the curvature analysis technique to the trade-off curves generated from the simulation based optimisation approach, Sim-POGA, are summarised in Table 4-12 to

Table 4-14 for all values of SD and all PCS investigated.

Table 4-12: POGA CONWIP SC pessimistic and optimistic parameters settings

		chart SL	Chart WIP	WIP-Cap	Capacity	SL	WIP
SD=1	pes	96.500	28.591	30	8	96.796	29.745
	opt	100.000	38.135	44	10	100.000	43.936
SD=4.5	pes	95.500	48.520	49	24	95.471	48.756
	opt	98.900	67.081	67	24	98.905	66.622
SD=8	pes	95.500	48.520	49	24	95.471	48.756
	opt	98.900	67.081	67	24	98.905	66.622

Table 4-13: POGA Kanban SC pessimistic and optimistic parameters settings

		chart SL	Chart WIP	K1	K2	K3	K4	Capacity	SL	WIP
SD=1	pes	92.700	26.964	10	10	10	12	11	94.266	28.447
	opt	100.000	40.774	12	14	12	19	16	99.993	45.941
SD=4.5	pes	94.500	50.629	12	12	12	30	11	94.473	50.325
	opt	98.900	75.464	13	13	13	54	16	98.893	75.541
SD=8	pes	93.900	79.530	13	13	15	60	15	93.912	80.004
	opt	96.300	97.536	14	14	14	78	14	96.311	98.529

Table 4-14: POGA Hybrid Kanban-CONWIP SC pessimistic and optimistic parameters settings

		chart SL	Chart WIP	K1	K2	K3	WIP-Cap	Capacity	SL	WIP
SD=1	pes	97.200	29.563	15	16	16	30	13	96.860	29.995
	opt	100.000	37.340	29	29	28	46	9	100.000	45.373
SD=4.5	pes	93.300	43.934	16	21	20	46	12	93.338	44.178
	opt	100.000	77.906	22	24	20	76	16	99.291	74.638
SD=8	pes	93.600	71.307	17	17	19	76	16	93.596	71.415
	opt	97.200	101.524	19	19	18	108	15	97.197	101.663

Application of the curvature analysis procedure to the trade-off curves generated from applying the POGA directly to the simulation model (SIM-POGA) is illustrated in Figure 4-16 for the Kanban SC at Demand SD = 8. All other Figures are presented in Appendix J. In these Figures, the curvature of the polynomial trade-off curve (for average WIP and Service Level) and the curvature of the ΔWIP trade-off curve (for deviation in WIP and Service Level) which is overlaid on the polynomial trade-off curve as well, are depicted for each SC policy under different demand SD. While in these figures the y-axis presents the actual WIP or ΔWIP, the curvature function was determined based on a percentage axis, as described earlier. The reason that the *y-axis* has not been scaled as a percentage in the presentation of the figures is to ensure the decision maker can more easily translate the results to the performance metric of interest, i.e. WIP.

As an example, the curvature analysis of the Kanban SC under SD=8 is presented in Figure 4-16. The curvature analysis of the polynomial trade-off curve for the average WIP and Service Level suggests that the decision makers should set the parameters to achieve approximately 94% Service Level (where the curvature, $\boldsymbol{k}$, maximises) as a conservative or pessimistic decision. From this (inflection) point forward, there is evidence of diminishing returns (i.e., it is becoming more and more expensive in terms of WIP required to achieve an incremental improvement in Service Level). As a more optimistic decision, the curvature of the ΔWIP trade-off curve for the deviation in WIP and Service Level suggests that the decision makers should select the parameters to achieve approximately 96.5% Service Level also, where the curvature ($\boldsymbol{k}$) maximises at this value for Service Level.

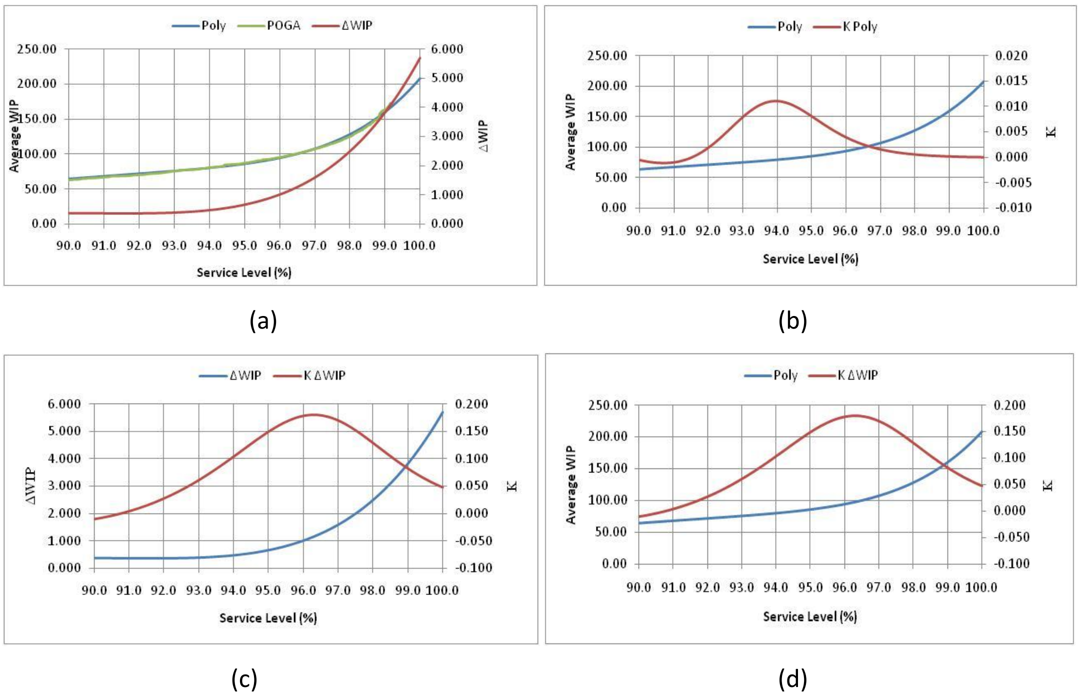


Figure 4-16: POGA Kanban SC curvature analysis for SD=8; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model

4.9 Risk Analysis

To test the robustness and quantify the risk associated with the different optimal parameter settings selected by the decision makers, the following LHD with 33 environmental scenarios can be used for different SCs under SD=8:

Table 4-15: LHD for robustness and risk analysis tests

	DS	Node1 L.T. Delay Prob.	Node2 L.T. Delay Prob.	Node3 L.T. Delay Prob.	Node4 L.T. Delay Prob.	Node1 Capacity Prob.	Node2 Capacity Prob.	Node3 Capacity Prob.	Node4 Capacity Prob.
1	8.1000	0.0688	0.0438	0.0375	0.0594	0.0438	0.0438	0.0125	0.0000
2	8.5500	0.0500	0.0844	0.0844	0.0031	0.1250	0.0313	0.0250	0.0438
3	8.6500	0.0844	0.0594	0.0219	0.0125	0.1313	0.1938	0.0438	0.1563
4	8.3000	0.0469	0.0625	0.0813	0.0781	0.0875	0.0250	0.0000	0.1625
5	7.3000	0.0781	0.0156	0.0063	0.0188	0.1188	0.1063	0.1000	0.1813
6	7.5500	0.0406	0.0500	0.0938	0.0625	0.1563	0.1688	0.1250	0.2000
7	7.7000	0.0563	0.0000	0.0625	0.0375	0.1000	0.1313	0.1813	0.0063
8	7.4000	0.0219	0.0406	0.0313	0.0688	0.0188	0.1000	0.0563	0.1938
9	7.9500	0.0594	0.0750	0.0125	0.0719	0.1750	0.0125	0.0750	0.1000
10	8.4000	0.0281	0.0094	0.0031	0.0438	0.0563	0.0188	0.0313	0.1500
11	8.4500	0.0000	0.1000	0.0250	0.0344	0.0688	0.0625	0.1063	0.0938
12	8.6000	0.0656	0.0563	0.0875	0.0906	0.1375	0.0375	0.1438	0.0563
13	7.6500	0.0250	0.0781	0.0906	0.0063	0.0375	0.0938	0.1875	0.1250
14	8.3500	0.0125	0.0281	0.0719	0.0844	0.0063	0.0563	0.1500	0.1313
15	8.1500	0.0813	0.0469	0.0531	0.0813	0.2000	0.1750	0.0875	0.0188
16	7.8000	0.0031	0.0188	0.0344	0.0969	0.1625	0.1125	0.1125	0.0875
17	7.5000	0.1000	0.0688	0.0781	0.0500	0.0938	0.0500	0.1188	0.1125
18	7.4500	0.0438	0.0875	0.0188	0.0281	0.0750	0.2000	0.1563	0.1750
19	7.3500	0.0188	0.0969	0.0438	0.0938	0.0625	0.0750	0.1938	0.1063
20	8.0000	0.0719	0.0375	0.0156	0.0531	0.0250	0.0000	0.2000	0.1188
21	8.5000	0.0313	0.0938	0.0500	0.0875	0.1813	0.1438	0.1625	0.1375
22	7.2500	0.0094	0.0250	0.0750	0.0094	0.1500	0.0063	0.0813	0.0813
23	7.2000	0.0156	0.0656	0.0656	0.0563	0.0500	0.1813	0.0688	0.0500
24	8.7500	0.0375	0.0125	0.0688	0.0469	0.1125	0.1375	0.0375	0.0688
25	8.2000	0.0875	0.0031	0.0469	0.0656	0.0125	0.1250	0.0938	0.1688
26	7.8500	0.0969	0.0063	0.0594	0.0313	0.1875	0.0688	0.0188	0.0750
27	8.7000	0.0344	0.0344	0.0094	0.0156	0.1688	0.0813	0.1750	0.0125
28	7.7500	0.0750	0.0906	0.0406	0.0000	0.1938	0.1500	0.1313	0.0250
29	7.9000	0.0906	0.0531	0.0969	0.0250	0.0813	0.1875	0.0500	0.0375
30	8.2500	0.0625	0.0813	0.1000	0.1000	0.0313	0.1563	0.0625	0.0625
31	8.0500	0.0063	0.0219	0.0000	0.0406	0.0000	0.1188	0.1375	0.0313
32	8.8000	0.0531	0.0313	0.0563	0.0219	0.1438	0.0875	0.1688	0.1875
33	7.6000	0.0938	0.0719	0.0281	0.0750	0.1063	0.1625	0.0063	0.1438

As an example, robustness test for the pessimistic and optimistic solutions of the POGA Kanban SC under the demand variability SD=8 (Table 4-13) was carried out by performing the simulation experiments as per the LHD (Table 4-15). The Cumulative Probability Density Function of the performance measures along with some supportive statistics were estimated for each solution as follows:

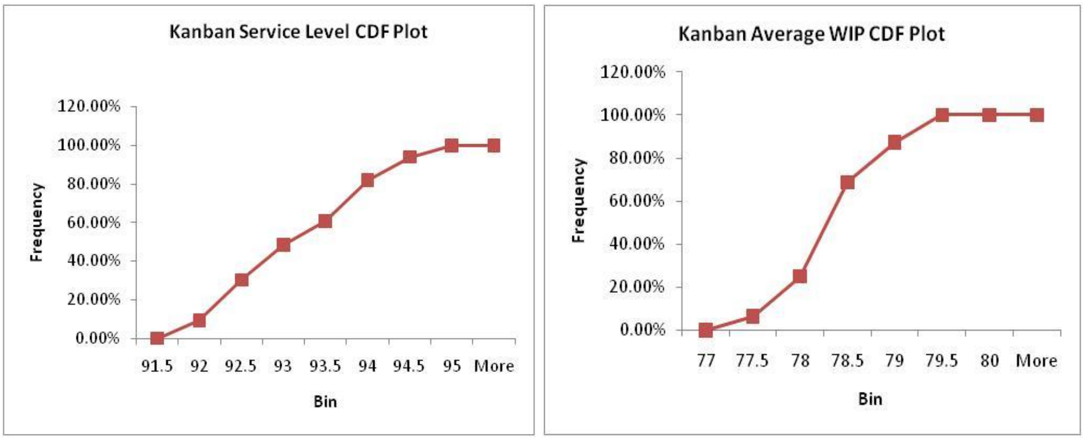


Figure 4-17: Pessimistic Kanban service level and Average WIP CDF Plot at SD=8

Table 4-16: Pessimistic Kanban service level and Average WIP statistics at SD=8

Statistic	S.L.	A.WIP
Mean	93.1672	78.2922
Standard Error	0.1582	0.0860
Median	93.0827	78.2773
Standard Deviation	0.9090	0.4938
Range	3.3806	1.8035
Minimum	91.5328	77.4080
Maximum	94.9134	79.2115
Confidence Level (95.0%)	0.3223	0.1751

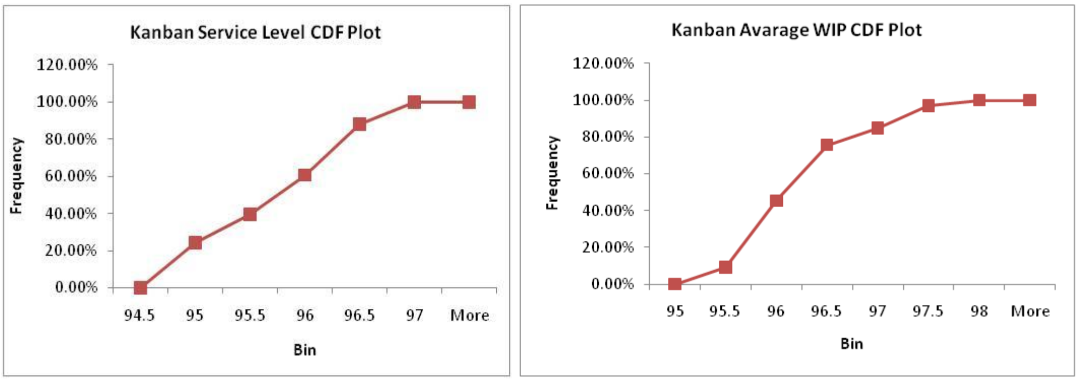


Figure 4-18: Optimistic Kanban service level and Average WIP CDF Plot at SD=8

Table 4-17: Optimistic Kanban service level and Average WIP statistics at SD=8

Statistic	S.L.	A.WIP
Mean	95.672087	96.19344
Standard Error	0.1241559	0.103509
Median	95.818127	96.15171
Standard Deviation	0.7132216	0.594616
Range	2.3274742	2.354946
Minimum	94.524359	95.15705
Maximum	96.851833	97.512
Confidence Level (95.0%)	0.2528974	0.210842

From the above CDF plots and the statistics tables, it can be seen that the variation in the environmental conditions causes the SC performance measurers to vary from the targeted service levels and their associated WIP. The service level of the pessimistic solution was varying from maximum to minimum with a range of 3.38% around the targeted 93.912% with a chance of approximately only 20% to achieve this target or higher. Whereas the service level of the optimistic solution was varying from maximum to minimum with a range of 2.32% around the targeted 96.311% with a chance of approximately 40% to achieve the target or more. It can also be noticed that the variations in the WIP for both solutions were less than the expected with a chance of 100% to hold less WIP than the targeted 80.0041 and 98.5285 items.

Risk analysis is used to make a choice between the selected SC systems (i.e., determining the superiority of on system over another to achieve a targeted or even better service level while holding less WIP) by comparing their performance probability distributions using the stochastic dominance.

The stochastic dominance analysis of the performance measures of the different GP SCs for SD=8 and targeting 95% service level (optimal settings are presented in Tables 4-18 to 4-20) was carried out by performing the simulation experiments as per the LHD in Table 4-15.

Table 4-18: GP CONWIP SC for SD=8 optimal setting for 95% service level

S.L. Target	Node Capacity	WIP-Cap	CONWIP GP-DA			CONWIP SIM-GP-DA	
			Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
95%	18	81	94.9973	78.7291	0.7198	95.0416	78.8482

Table 4-19: GP Kanban SC for SD=8 optimal setting for 95% service level

		Kanban Allocations				Kanban GP-DA			Kanban SIM-GP-DA	
S.L. Target	Capacity	Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
95%	16	13	15	14	71	94.9925	88.7008	0.7226	95.0208	89.7611

Table 4-19: GP Hybrid Kanban-CONWIP SC for SD=8 optimal setting for 95% service level

			Kanban Allocations			Hybrid GP-DA			Hybrid SIM-GP-DA	
S.L. Target	Capacity	WIP-Cap	Node 1	Node 2	Node 3	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
95%	16	84	18	18	18	94.9878	76.2592	0.7675	95.0316	79.3554

The Cumulative Probability Density Function of the performance measures (service level and Average WIP) along with their stochastic dominance results were estimated for each GP SC as shown in Figures 4-19 and 4-20 and Tables 4-21and 4-22 respectively.

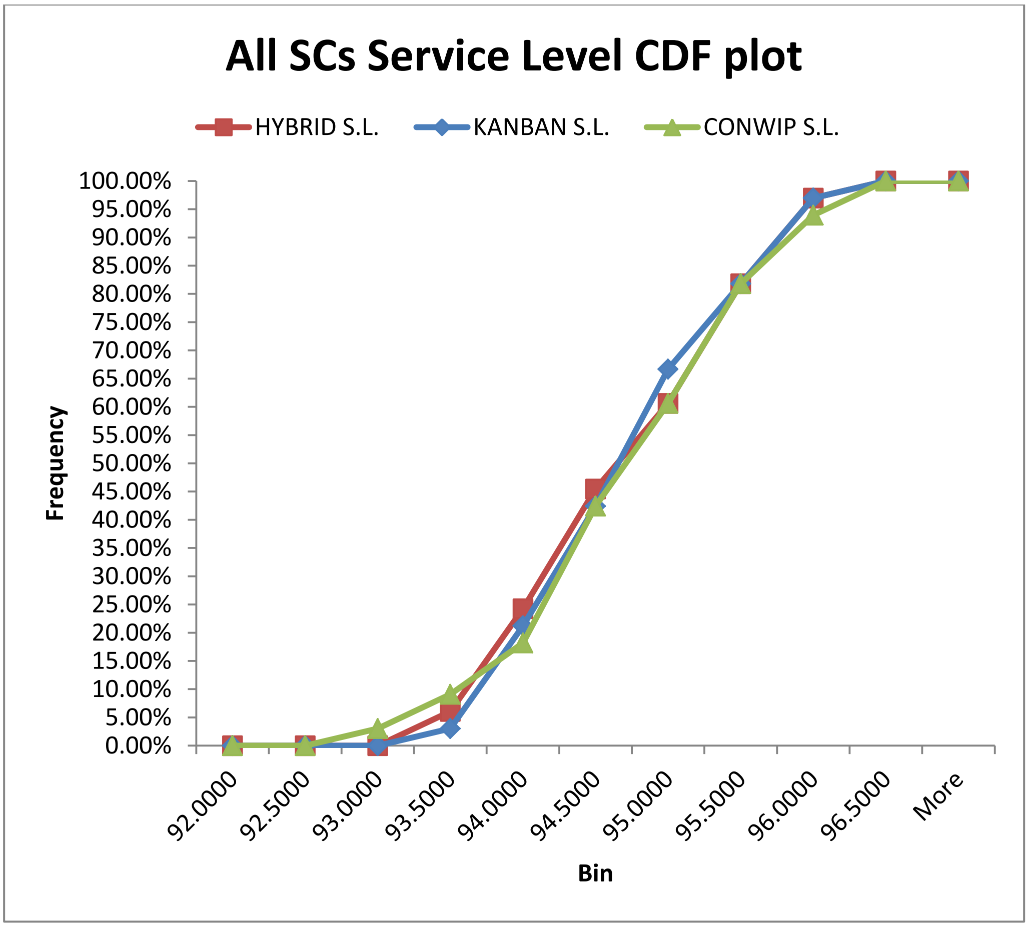


Figure 4-19: All GP SCs Service Level CDF plot at SD=8

Table 4-20: All GP SCs Service Level Stochastic Dominance at SD=8

Dominance	CONWIP S.L.	KANBAN S.L.	HYBRID S.L.
CONWIP S.L.		KANBAN S.L. is 2d over CONWIP S.L.	Inconclusive
KANBAN S.L.	KANBAN S.L. is 2d over CONWIP S.L.		KANBAN S.L. is 2d over HYBRID S.L.
HYBRID S.L.	Inconclusive	KANBAN S.L. is 2d over HYBRID S.L.	

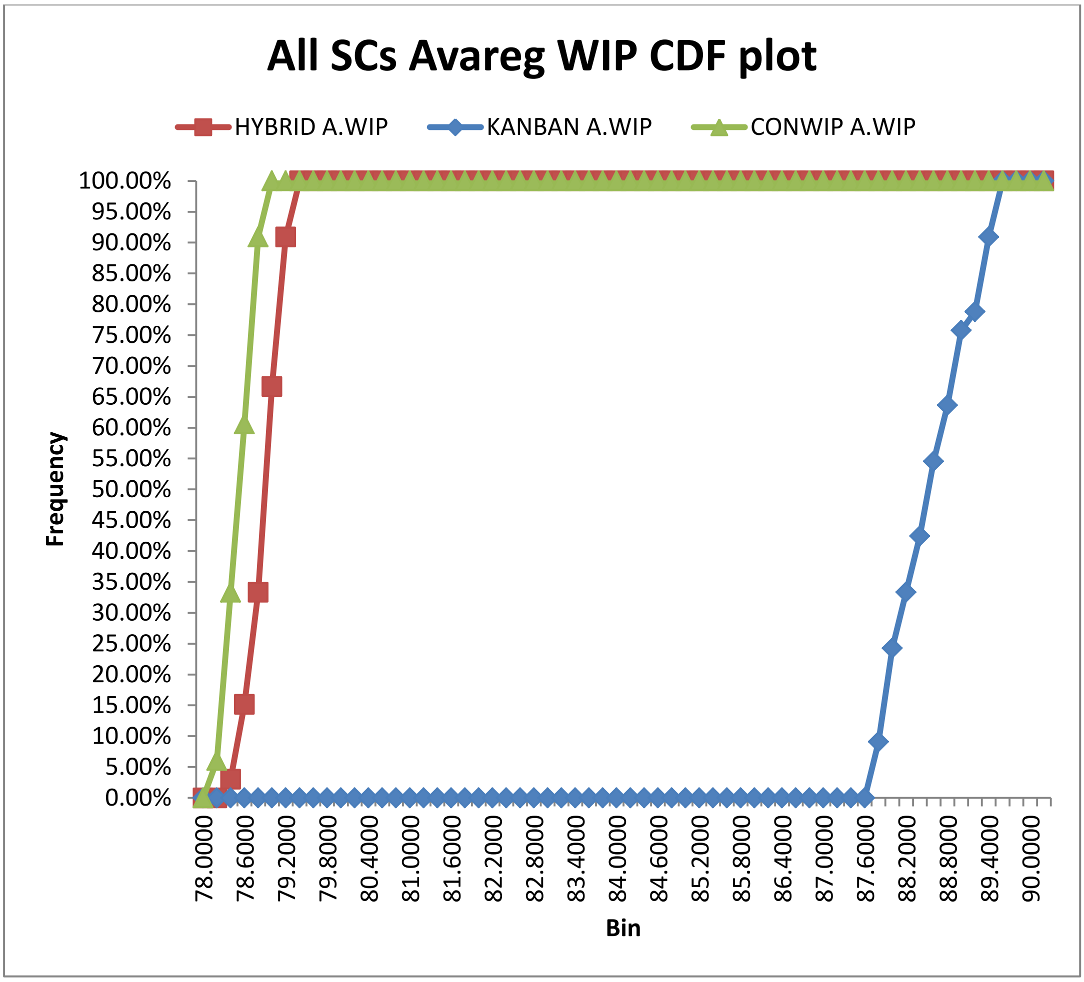


Figure 4-20: All GP SCs Average WIP CDF plot at SD=8

Table 4-21: All GP SCs Average WIP Stochastic Dominance at SD=8

Dominance	CONWIP A.WIP	KANBAN A.WIP	HYBRID A.WIP
CONWIP A.WIP		KANBAN A.WIP is 1d over CONWIP A.WIP	HYBRID A.WIP is 1d over CONWIP A.WIP
KANBAN A.WIP	KANBAN A.WIP is 1d over CONWIP A.WIP		KANBAN A.WIP is 1d over HYBRID A.WIP
HYBRID A.WIP	HYBRID A.WIP is 1d over CONWIP A.WIP	KANBAN A.WIP is 1d over HYBRID A.WIP	

In terms of achieving higher Service Levels, the analysis reveals that the Kanban SC has a second order stochastic dominance over the CONWIP and the Hybrid SCs thus, outperforms them because it is expected that it will generally give a higher service level for any cumulative probability value. The result of the test on the CONWIP and the Hybrid is inconclusive.

In terms of the holding the minimum WIP, the analysis reveals that the Kanban SC has a first order stochastic dominance over the Hybrid and CONWIP SCs therefore, it is the worst performer because for any cumulative probability value, it gives a higher WIP. Also, it can be seen that the Hybrid SC has a first order stochastic dominance over the CONWIP and as a result the CONWIP SC outperforms both the Hybrid and the Kanban in holding the minimum WIP.

From the above results, it can be seen that the achievement of Kanban SC with regards to service level comes at the expense of holding very high levels of inventory. The CONWIP SC on the other hand maintains the lowest inventory level but comes at the expense of prompt response to product demands and poorer service levels. The Hybrid SC in between, would offer a trade off between the two performance measures.

4.10 Discussion of the Developed Framework

Given the desire, and often requirement, to deliver lean operations, there is a need for supply-chain managers to effectively manage key performance metric trade-offs particularly between WIP inventory and Service Levels to the customer in both an optimal and robust fashion. In order to balance the performance interests of the producer (reducing the amount of investment capital tied up in inventory) with those of the customer (high Service Level) requires a means of efficiently exploring a complex and often large decision space. Therefore, this thesis has developed and investigated a decision support framework to address this issue.

Discrete-event simulation approaches are essential modelling tools to realistically capture and investigate the effect of the process phenomena relating level of WIP to Service Level. Other approaches, such as analytical techniques, would be too cumbersome and grossly incomplete to capture the dynamics of the system and provide a satisfactory analysis. However, simulation based optimisation is inherently unrealistic owing to the computation time required to derive a solution. The framework developed and investigated here further evidences this but also it has been shown that meta-modelling and optimisation, in particular GP meta-modelling, can provide solutions that are very reasonable in comparison to those provided by simulation based optimisation. Therefore, simulation models are best utilised within an optimisation problem to develop metamodels and assess and/or refine the results of the metamodel optimisation procedure. This approach considerably reduces the computational time required to provide solutions, deploying simulation analysis in a more effective and intelligent manner.

The utilisation of trade-off curves, either generated through complete/partial enumeration or multi-objective optimisation approaches such as POGA, is not novel in application to addressing the WIP – Service Level trade-off, e.g. [197]. However, they have not been utilised in a supply-chain management context before. The main power of such trade-off curves is that the decision maker does not have to make decisions prior to optimisation, such as weights for a fitness function that can affect the solution provided. Trade-off curves represent a series of competing solutions in a manner that allows the decision maker to visualise the trade-off without the need for a *priori* knowledge of the solution space. However, interpretation of the trade-off curve to select the solution that is *best* for the system is often difficult. Curvature analysis has been shown here to be a useful tool to assist the decision maker in this respect. It can, for instance, provide discussion or negotiation points for the producer and the customer to address the trade-off in their performance interests.

Finally, the framework developed here advocates the use of risk analysis to assess the robustness of an optimal solution to small variations in predictions of sources of variability. Risk analysis techniques, in particular stochastic dominance, have been demonstrated in this thesis to be valuable decision support tools when the decision maker wishes to compare competing solutions or compare production control strategies for application to their system.

CHAPTER 5 CONCLUSIONS, CONTRIBUTIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

5.1 Introduction

The selection and implementation of an appropriate production control strategy in supply chains aiming to adopt lean manufacturing principles is a key factor for success and to achieve competitive edge in the market. Given the numerous control mechanisms introduced in recent years and the different conclusions, it is a difficult task to evaluate which mechanism is best suited for a specific application under specific conditions. Pull systems are the easiest to implement and yet very efficient.

5.2 Research Contributions

The primary contribution of the research activity presented in this thesis has been towards the development, implementation and testing of a decision support framework for supply-chain mangers wishing to evaluate, optimise and determine the robustness of lean production control strategies to work-authorisation and inventory control in co-ordinated supply-chains. The framework provides an effective environment to allow stakeholders such as producers and customers to address trade-offs in their, often conflicting, key performance metrics/objectives. In this work it has been shown that:

1. Meta-model based optimisation approaches provide very accurate solutions for this class of problem with multiple, conflicting objectives.
2. The accuracy of meta-model based optimisation can be significantly enhanced through the use of space-filling designs (specifically LHD) and GP models (as the model uncertainty can be handled) in place of the traditional RSM and polynomial regression.
3. Multi-objective optimisation techniques that can provide information on the trade-offs between objectives are preferable to traditional optimisation

techniques that require a prior knowledge of the solution space and yield a single answer based on predetermined weights and fitness functions.

4. Decision makers require tools to aid in the analysis of optimisation output and this work provides two very useful tools; namely curvature analysis and robustness analysis.
5. Optimal solutions are not immediately useful to decision makers without a means to assess them in terms of their robustness to uncertainty in the operating environment.

5.3 Research Conclusions

A framework for the provision of decision support to supply-chain managers assessing the application of pull-based production control strategies to coordinate work authorisations and inventory management while maintaining or improving service level has been presented. The framework, which includes three phases; namely modelling, optimisation and decision support, has been tested by application to a four-stage serial supply-chain operating under three different pull-based PCS, namely Kanban, CONWIP, Hybrid Kanban-CONWIP. The elements of the framework have been presented and tested for both Simulation-based and Metamodel-based Optimisation approaches.

The first phase, *Modelling*, includes conceptual modelling, simulation modelling and meta-model development and provides the experimental platform for the second phase; *Optimisation* and through a series of designed experiments, the devolved simulation model was used to investigate the potential impact of the proposed PCS on the trade-off between the conflicting objectives of maximising customer service level and minimising average Work-In-Process (WIP).

In the *Optimisation* phase, two techniques of optimisation have been explored; namely the Desirability Function Approach and a Pareto-Optimal Genetic Algorithm. Employing the POGA to the simulation model required up to 4 hours of CPU time (on an INTEL 2.40 GHz Core 2 DUO CPU with 4.00GB RAM) for small problems such as two-factor CONWIP (where the CONWIP cap and Node Capacity were the only factors) and up to 30 hours of CPU time for larger problems such as the KCS-SC with high standard deviation of demand presented here. Application of the POGA to the RSM metamodels required between 2 and 8 hours of CPU time, depending on the size of the design-space. Whereas, the RSM-DA and the GP-DA results were almost instantaneously generated once the service level target was specified. For the metamodelling-based approach, the *Optimisation* phase also includes an estimates refinement step which utilises the simulation model to improve the solution estimates for the performance measures given the parameters of the Kanban, CONWIP, Hybrid Kanban-CONWIP found to be optimal for a targeted service level.

The final phase of the proposed framework is *Decision Support*. For this phase, the curvature of the Average WIP-Service Level and ∆WIP-Service Level Trade-off curves is employed to provide guidance to the decision maker in determining the parameters of the PCS that would best suit their system. The inflection point of these curves is used to indicate the point on the curve where there are diminishing returns to the supply-chain. That is to say that beyond this point it is becoming more and more expensive in terms of WIP to achieve an incremental improvement in Service Level. The curvature function of the Average WIP-Service Level trade-off curve has a lower inflection point than the curvature function of the ∆WIP-Service Level trade-off curve for all cases examined, which includes a variety of demand standard deviations (ranging from a CV of 25% to 200%). Therefore, the curvature function of the Average WIP-Service Level trade-off curve is a conservative decision support tool. Whereas, the curvature function of the ∆WIP-Service Level trade-off curve is a more optimistic decision support tool. The decision maker can utilise this information to make a decision for the parameters of the PCS and also use it in contractual negotiations with customers in determining a price premium for higher service level requirements and/or improvements in customer demand profile (especially variability of demand).

This framework, which involves the combined use of Simulation, RSM, Optimisation and Curvature Analysis for decision support, is potentially a valuable tool for decision makers to assess the suitability of various PCS to their systems and to understand the complex interactions between the different SC factors and utilise this understanding to achieve balance between conflicting objectives.

The influence of demand variability on the performance measures of the SC could be mitigated by optimising the number of CONWIP and Kanban cards in the system by applying the Desirability Approach to the meta-models or the POGA directly to the simulation model. The levels of inventory to be held in the SC is a critical decision based upon objective views to achieve targeted customer service levels at an acceptable expenditure; as higher service levels with higher demand variability mean proportionately far higher levels of WIP.

In this work the application of trade-off curves to the analysis of supply chain systems has been emphasised. Trade-off curves describe the relationship between conflicting performance measures and can be effectively used to analyse strategic objectives. Hence, a new SC system can be designed or redesign an existing one in such a way to reflect our decision of how to compete in the market. In order to build trade-off curves between the SC average service level and average WIP, optimisation problems of these confecting performance measures have been solved by applying algorithms known in the literature.

The combined use of Simulation, RSM/GP and Optimisation in SCM is potentially a valuable tool for decision makers. This work suggests that, if the initial effort for building metamodels is undertaken, then the process of finding an optimum, or at least a set of good solutions, can be made easier as the Metamodel-Based Optimisation can significantly speed-up the search for an optimum, given the initial overhead of developing these metamodels.

5.4 Recommendations for Future Research

This Research work could be an aid to go deeper and be extended to include and investigate:

- Other sources of variability, such as different lead-times and different nodes capacities. This would allow a fairer and more realistic comparison of CONWIP and hybrid CONWIP-Kanban.
- Longer serial SCs and other SC structures such as the Tiered-SCs.
- Multi-product environment.
- Inventory and logistics costs.

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List of Publications

1) Smew, Walid, Paul Young and John Geraghty. 2012. "Operational Design of Supply Chains using Simulation, GP, and Optimisation". Manuscript Submitted for publication to the *International Journal of Simulation Modeling* (IJSIMM)

2) Smew, Walid, Paul Young and John Geraghty. 2012. "A Decision Support Framework for Work Authorisation and Inventory Management in Lean Supply Chains", in *Simulation and Modelling in Supply Chains and Logistics*, Gerrit K. JANSSENS, Cathy MACHARIS And KENNETH SÖRENSEN (eds.), Cambridge Scholars: Newcastle upon Tyne, UK, Chapter 6.

3) Smew, Walid, Paul Young and John Geraghty. 2012. "Operational Design of Supply Chains using Simulation, GP, and Optimisation". In *Proceedings of the International Conference on Industrial Logistics* (ICIL2012). University of Zagreb, Zagreb, Croatia, 253-262.

4) Smew, Walid, Paul Young and John Geraghty. 2010. "A Practical Approach to Performance Improvement and Optimisation in Supply Chain Management". In *Proceedings of the 2010 European Simulation and Modelling Conference* (ESM2010). Hasselt University, Hasselt, Belgium, 391-395.

5) Smew, Walid, Paul Young and John Geraghty. 2010. "Exploring the Deployment of CONWIP in Serial Supply Chains Using Meta-Modeling". In *Proceedings of the 27th International Manufacturing Conference* (IMC27). Galway-Mayo Institute of Technology, Galway, Ireland, 13-24.

Notes:

Paper 1, has been invited for publication in the *International Journal of Simulation Modeling* (IJSIMM) after review of paper at ICIL2012 (paper 3) by the journal editor. Only two out of the 64 papers published in ICIL2012 were selected for publication by IJSIMM.

Paper 2, was invited for expansion and publication as a book chapter in the *Simulation and Modelling in Supply Chains and Logistics* book after review of presentation by the book editors. ESM2010 paper (paper 4) was selected on the basis that it was one of the fifteen best papers presented at ESM in the past 5 years in the field (over 100 papers were considered).

APPENDIX A ALL SCS SENSITIVITY ANALYSIS

A.1 CONWIP SC Sensitivity Analysis

Table A-1: CONWIP SC sensitivity analysis

Capacity	SD	WIP-CAP	S.L.	A.WIP	Capacity	SD	WIP-CAP	S.L.	A.WIP	Capacity	SD	WIP-CAP	S.L.	A.WIP
8	8	30	67.88	28.15	16	8	30	69.16	29.57	24	8	30	69.40	29.85
		60	87.05	51.47			60	89.82	58.12			60	90.22	59.16
		90	93.05	73.61			90	95.82	86.91			90	96.50	88.59
		120	95.59	95.85			120	97.86	116.01			120	98.06	118.16
		150	97.05	120.41			150	98.91	145.52			150	99.04	147.91
		180	97.81	143.66			180	99.37	175.30			180	99.40	177.74
		210	98.56	168.52			210	99.58	204.90			210	99.59	207.59
		240	99.12	195.77			240	99.70	234.70			240	99.67	237.56
	4.5	30	78.78	28.57		4.5	30	79.75	29.79		4.5	30	79.76	29.95
		60	95.96	52.17			60	97.93	59.03			60	97.92	59.65
		90	98.79	76.58			90	99.69	88.74			90	99.72	89.54
		120	99.56	103.94			120	99.95	118.63			120	99.96	119.51
		150	99.86	132.66			150	99.99	148.62			150	99.98	149.50
		180	99.96	161.23			180	99.98	178.61			180	100.00	179.48
		210	99.99	191.82			210	99.99	208.58			210	100.00	209.51
	1	20	70.90	20.00		1	20	70.95	20.00		1	20	70.90	20.00
		30	96.77	29.75			30	96.88	30.00			30	96.90	30.00
		60	100.00	59.38			60	100.00	60.00			60	100.00	60.00

A.2 Kanban SC Sensitivity Analysis

Table A-2: Kanban SC sensitivity analysis

All nodes capacity = 24					
Demand SD=1					
				S.L.	A.WIP
k1=8	k2=8	k3=8	k4=8	76.18808	21.52286
k1=12				76.16572	22.81441
k1=16				76.17595	23.28279
k1=20				76.19811	23.28343
k1=8	k2=8	k3=8	k4=8	76.18808	21.52286
	k2=12			76.19618	22.86661
	k2=16			76.18831	23.29079
	k2=20			76.16606	23.28967
k1=8	k2=8	k3=8	k4=8	76.18808	21.52286
		k3=12		76.24391	24.07575
		k3=16		76.20719	24.78182
		k3=20		76.22184	24.80598
k1=8	k2=8	k3=8	k4=8	76.18808	21.52286
			k4=12	76.15902	25.5268
			k4=16	76.17301	29.52087
			k4=20	76.15324	33.51658
k1=16	k2=16	k3=16	k4=16	99.99966	53.50095
			k4=20	100	57.49291
k1=16	k2=16	k3=16	k4=16	99.99966	53.50095
		k3=20		99.99971	57.49579
k1=16	k2=16	k3=16	k4=16	99.99966	53.50095
	k2=20			99.99977	57.49497
k1=16	k2=16	k3=16	k4=16	99.99966	53.50095
k1=20				99.99983	57.50122

All Capacity = 24			
K1=K2=K3=16			
SD	K4	S.L.	A.WIP
1	8	95.7043	45.9601
	16	99.9997	53.4946
4.5	8	70.3468	48.6099
	12	83.1677	51.1734
	20	93.1787	57.3642
	24	95.2113	60.7289
	28	96.6415	64.2466
	32	97.5798	67.8684
	36	98.2345	71.5006
	40	98.5321	75.2042
	44	99.0054	79.0731
8	16	76.5499	55.5831
	20	81.0748	58.5089
	24	84.2470	61.6649
	28	86.9568	64.8682
	32	88.3979	68.0302
	36	89.9906	71.2874
	40	90.9628	74.6341
	44	92.0434	78.0487
	48	93.2540	81.5512
	52	94.0597	85.0127
	56	94.8135	88.4475
	60	95.2143	92.0407
	64	95.5295	95.5153
	68	96.0519	99.1304
	72	96.2664	102.7222
	76	96.7762	106.3641
	80	96.9639	110.1191
	84	97.4485	113.8472
	88	97.4936	117.6152
	92	97.6774	121.1965
	96	97.9503	124.9679
	100	97.9887	128.8656
	104	98.1593	132.4857
	108	98.2468	136.0430
	112	98.3324	139.9315
	116	98.6836	143.7712
	120	98.8557	147.5964
	124	98.7481	151.4421

A.3 Kanban SC Sensitivity Analysis

Table -A-3: Hybrid Kanban-CONWIP SC sensitivity analysis

					WIP-Cap	S.L.	A.WIP
SD=8	Capacity=24	k1=32	k2=16	k3=16	30	69.1625	29.5546
SD=8	Capacity=24	k1=32	k2=16	k3=16	60	89.4394	56.8300
SD=8	Capacity=24	k1=32	k2=16	k3=16	100	96.3452	92.9153
SD=8	Capacity=24	k1=32	k2=16	k3=16	110	97.0864	102.1979
SD=8	Capacity=24	k1=32	k2=16	k3=16	120	97.8031	115.5926
SD=8	Capacity=24	k1=32	k2=16	k3=16	125	98.0506	116.2312
SD=8	Capacity=24	k1=32	k2=16	k3=16	130	98.1446	120.8625
SD=8	Capacity=24	k1=16	k2=16	k3=16	130	98.0916	120.6483
SD=8	Capacity=24	k1=32	k2=32	K3=32	130	98.4216	127.8497

All nodes capacity = 24											
K1=K2=K3=16											
SD	WIP-Cap	S.L.	A.WIP	SD	WIP-Cap	S.L.	A.WIP	SD	WIP-Cap	S.L.	A.WIP
1	20	70.9128	20.0000	4.5	29	78.3191	28.8167	8	30	69.2775	29.5569
	22	77.4808	22.0000		30	79.9187	29.7851		38	77.7050	37.0104
	24	83.6639	24.0000		35	85.9450	34.5624		40	79.0663	38.8273
	26	89.1510	26.0000		40	90.2721	39.2682		45	82.6035	43.4102
	28	93.6599	28.0000		45	93.1668	43.9541		50	85.4871	47.8977
	30	96.8579	29.9999		50	95.2864	48.6106		55	87.7552	52.3566
	32	98.7832	31.9995		55	96.7474	53.2734		60	89.4924	56.8648
	33	99.2747	32.9991		60	97.7040	58.0107		65	91.1434	61.2586
					65	98.2395	62.7027		70	92.4358	65.7271
					70	98.8469	67.4895		75	93.5407	70.3078
					75	99.1945	72.3427		80	94.1180	74.7196
									85	94.6720	79.2273
									90	95.3136	83.8584
									95	95.9119	88.3484
									100	96.2469	92.7118
									105	96.4388	97.3657
									110	97.3143	102.1190
									115	97.3122	106.7813
									120	97.7465	111.4321
									125	97.8388	116.2075
									130	97.9894	120.7356
									135	98.3771	125.6432
									140	98.3092	130.1735
									145	98.6581	135.0474
									150	98.7794	139.9030
									155	98.7630	144.5750

APPENDIX B RSM METAMODELS

B.1 CONWIP SC RSM metamodels at Demand SD = 4.5

$$Service\ Level = 35.37 + 0.56 \times Node\ capacity + 1.72 \times WIPCap - 0.01 \times Node\ capacity^2 - 0.01 \times WIPCap^2 \tag{B-1}$$

$$Average\ WIP = -1.17 + 0.967 \times \text{Node capacity} + 0.707 \times \text{WIPCap} + 0.017 \times \text{Node capacity} \times \text{WIPCap} - 0.04 \times \text{Node capacity}^2 \tag{B-2}$$

B.2 CONWIP SC RSM metamodels at Demand SD = 8

$$Service\ Level = 50.30 + 0.70 \times Node\ capacity + 0.73 \times WIPCap - 0.02 \times Node\ capacity^2 - 0.003 \times WIPCap^2 \tag{B-3}$$

$$Average\ WIP = -7.73 + 2.21 \times \text{Node capacity} + 0.65 \times \text{WIPCap} + 0.01 \times \text{Node capacity} \times \text{WIPCap} - 0.08 \times \text{Node capacity}^2 \tag{B-4}$$

B.3 Kanban SC RSM metamodels at Demand SD = 1

$$\begin{aligned} Service\ Level = {} & -57.35 + 5.81 \times \text{Node1Kanbans} + 5.81 * \text{Node2Kanbans} + \\ & 5.79 \times \text{Node3Kanbans} + 2.15 \times \text{Node4Kanbans} + \\ & 0.37 \times \text{Node1Kanbans} \times \text{Node2Kanbans} + \\ & 0.37 \times \text{Node1Kanbans} \times \text{Node3Kanbans} + \\ & 0.37 \times \text{Node2Kanbans} \times \text{Node3Kanbans} - \\ & 0.532 \times \text{Node1Kanbans}^2 - 0.53 \times \text{Node2Kanbans}^2 - \\ & 0.53 \times \text{Node3Kanbans}^2 - 0.07 \times \text{Node4Kanbans}^2 \end{aligned} \tag{B-5}$$

$$
\begin{aligned}
Average\ WIP \quad = \quad & 29.58 + 2.88 \times \text{Node1Kanbans} - 0.67 \times \text{Node2Kanbans} - \\
& 2.41 \times \text{Node3Kanbans} - 3.31 \times \text{Node4Kanbans} + \\
& 0.25 \times \text{Node1Kanbans} \times \text{Node2Kanbans} + \\
& 0.19 \times \text{Node1Kanbans} \times \text{Node3Kanbans} + \\
& 0.12 \times \text{Node1Kanbans} \times \text{Node4Kanbans} + \\
& 0.18 \times \text{Node2Kanbans} \times \text{Node3Kanbans} + \\
& 0.11 \times \text{Node2Kanbans} \times \text{Node4Kanbans} + \\
& 0.10 \times \text{Node3Kanbans} \times \text{Node4Kanbans} - \\
& 0.31 \times \text{Node1Kanbans}^2 - 0.19 \times \text{Node2Kanbans}^2 - \\
& 0.10 \times \text{Node3Kanbans}^2
\end{aligned}
\tag{B-6}
$$

B.4 Kanban SC RSM metamodels at Demand SD = 4.5

$$
\begin{aligned}
Service\ Level \quad = \quad & 41.08 - 0.003 \times \text{Node Capacity} + 1.70 \times \text{Node1Kanbans} + \\
& 0.88 * \text{Node2Kanbans} + 0.64 \times \text{Node3Kanbans} + \\
& 1.33 \times \text{Node4Kanbans} + \\
& 0.02 \times \text{Node Capacity} \times \text{Node2Kanbans} + \\
& 0.02 \times \text{Node Capacity} \times \text{Node3Kanbans} - \\
& 0.003 \times \text{Node Capacity} \times \text{Node4Kanbans} + \\
& 0.07 \times \text{Node1Kanbans} \times \text{Node2Kanbans} + \\
& 0.04 \times \text{Node2Kanbans} \times \text{Node3Kanbans} - \\
& 0.06 \times \text{Node Capacity}^2 - 0.10 \times \text{Node1Kanbans}^2 - \\
& 0.10 \times \text{Node2Kanbans}^2 - 0.04 \times \text{Node3Kanbans}^2 - \\
& 0.01 \times \text{Node4Kanbans}^2
\end{aligned}
\tag{B-7}
$$

$$
\begin{aligned}
Average\ WIP \quad = \quad & 17.19 - 1.07 \times \text{Node Capacity} + 1.80 \times \text{Node1Kanbans} + \\
& 1.73 \times \text{Node2Kanbans} - 0.69 \times \text{Node3Kanbans} - \\
& 0.57 \times \text{Node4Kanbans} + \\
& 0.06 \times \text{Node Capacity} \times \text{Node1Kanbans} + \\
& 0.05 \times \text{Node Capacity} \times \text{Node2Kanbans} + \\
& 0.01 \times \text{Node Capacity} \times \text{Node4Kanbans} + \\
& 0.32 \times \text{Node1Kanbans} \times \text{Node2Kanbans} + \\
& 0.13 \times \text{Node1Kanbans} \times \text{Node3Kanbans} + \\
& 0.03 \times \text{Node1Kanbans} \times \text{Node4Kanbans} + \\
& 0.11 \times \text{Node2Kanbans} \times \text{Node3Kanbans} + \\
& 0.03 \times \text{Node2Kanbans} \times \text{Node4Kanbans} + \\
& 0.01 \times \text{Node3Kanbans} \times \text{Node4Kanbans} - \\
& 0.09 \times \text{Node Capacity}^2 - 0.31 \times \text{Node1Kanbans}^2 - \\
& 0.29 \times \text{Node2Kanbans}^2 - 0.06 \times \text{Node3Kanbans}^2 + \\
& 0.006 \times \text{Node4Kanbans}^2
\end{aligned}
\tag{B-8}
$$

B.5 Kanban SC RSM metamodels at Demand SD = 8

$$\begin{aligned}
\mathit{Service\ Level} \quad = \quad & 4.13 + 0.31 \times \text{Node Capacity} + 3.50 \times \text{Node1Kanbans} + \\
& 3.69 * \text{Node2Kanbans} + 1.28 \times \text{Node3Kanbans} + \\
& 0.51 \times \text{Node4Kanbans} + \\
& 0.02 \times \text{Node Capacity} \times \text{Node3Kanbans} - \\
& 0.001 \times \text{Node Capacity} \times \text{Node4Kanbans} - \\
& 0.003 \times \text{Node3Kanbans} \times \text{Node4Kanbans} - \\
& 0.01 \times \text{Node Capacity}^2 - 0.12 \times \text{Node1Kanbans}^2 - \\
& 0.12 \times \text{Node2Kanbans}^2 - 0.04 \times \text{Node3Kanbans}^2 - \\
& 0.002 \times \text{Node4Kanbans}^2
\end{aligned} \tag{B-9}$$

$$\begin{aligned}
\mathit{Average\ WIP} \quad = \quad & -4.86 - 2.11 \times \text{Node Capacity} + 5.03 \times \text{Node1Kanbans} + \\
& 4.41 \times \text{Node2Kanbans} - 1.01 \times \text{Node3Kanbans} - \\
& 0.37 \times \text{Node4Kanbans} + \\
& 0.09 \times \text{Node Capacity} \times \text{Node1Kanbans} + \\
& 0.08 \times \text{Node Capacity} \times \text{Node2Kanbans} + \\
& 0.04 \times \text{Node Capacity} \times \text{Node3Kanbans} + \\
& 0.08 \times \text{Node Capacity} \times \text{Node4Kanbans} + \\
& 0.67 \times \text{Node1Kanbans} \times \text{Node2Kanbans} + \\
& 0.23 \times \text{Node1Kanbans} \times \text{Node3Kanbans} + \\
& 0.03 \times \text{Node1Kanbans} \times \text{Node4Kanbans} + \\
& 0.19 \times \text{Node2Kanbans} \times \text{Node3Kanbans} + \\
& 0.03 \times \text{Node2Kanbans} \times \text{Node4Kanbans} + \\
& 0.01 \times \text{Node3Kanbans} \times \text{Node4Kanbans} - \\
& 0.04 \times \text{Node Capacity}^2 - 0.69 \times \text{Node1Kanbans}^2 - \\
& 0.65 \times \text{Node2Kanbans}^2 - 0.16 \times \text{Node3Kanbans}^2
\end{aligned} \tag{B-10}$$

B.6 Hybrid Kanban-CONWIP SC RSM metamodels at Demand SD = 1

$$\begin{aligned}
\mathit{Service\ Level} \quad = \quad & -30.82 + 0.01 \times \text{Node Capacity} + 6.76 \times \text{WIPCap} + \\
& 0.06 \times \text{Node1Kanbans} + 0.07 \times \text{Node2Kanbans} + \\
& 0.06 \times \text{Node3Kanbans} + \\
& 0.0006 \times \text{Node Capacity} \times \text{Node1Kanbans} - \\
& 0.0006 \times \text{Node Capacity}^2 - 0.09 \times \text{WIPCap}^2 - \\
& 0.0020 \times \text{Node1Kanbans}^2 - 0.002 \times \text{Node2Kanbans}^2 - \\
& 0.001 \times \text{Node3Kanbans}^2
\end{aligned} \tag{B-11}$$

$$\begin{aligned}
Average\ WIP = & -0.17 + 0.02 \times \text{Node Capacity} + 0.93 \times \text{WIPCap} + \\
& 0.12 \times \text{Node1Kanbans} + 0.001 \times \text{Node Capacity} \times \text{WIPCap} + \\
& 0.001 \times \text{Node Capacity} \times \text{Node1Kanbans} + \\
& 0.002 \times \text{WIPCap} \times \text{Node1Kanbans} - 0.002 \times \text{Node Capacity}^2 - \\
& 0.006 \times \text{Node1Kanbans}^2
\end{aligned} \tag{B-12}$$

B.7 Hybrid Kanban-CONWIP SC RSM metamodels at Demand SD = 4.5

$$\begin{aligned}
Service\ Level = & -30.82 + 0.01 \times \text{Node Capacity} + 6.76 \times \text{WIPCap} + \\
& 0.06 \times \text{Node1Kanbans} + 0.07 \times \text{Node2Kanbans} + \\
& 0.06 \times \text{Node3Kanbans} + \\
& 0.0006 \times \text{Node Capacity} \times \text{Node1Kanbans} - \\
& 0.0006 \times \text{Node Capacity}^2 - 0.09 \times \text{WIPCap}^2 - \\
& 0.0020 \times \text{Node1Kanbans}^2 - 0.002 \times \text{Node2Kanbans}^2 - \\
& 0.001 \times \text{Node3Kanbans}^2
\end{aligned} \tag{B-13}$$

$$\begin{aligned}
Average\ WIP = & 41.74 - 0.24 \times \text{Node Capacity} + 1.52 \times \text{WIPCap} + \\
& 0.12 \times \text{Node1Kanbans} + 0.04 \times \text{Node2Kanbans} + \\
& 0.14 \times \text{Node3Kanbans} + \\
& 0.01 \times \text{Node Capacity} \times \text{Node1Kanbans} + \\
& 0.01 \times \text{Node Capacity} \times \text{Node2Kanbans} + \\
& 0.01 \times \text{Node Capacity} \times \text{Node3Kanbans} + \\
& 0.001 \times \text{WIPCap} \times \text{Node1Kanbans} + \\
& 0.001 \times \text{WIPCap} \times \text{Node2Kanbans} + \\
& 0.001 \times \text{WIPCap} \times \text{Node3Kanbans} + \\
& 0.03 \times \text{Node1Kanbans} \times \text{Node2Kanbans} + \\
& 0.03 \times \text{Node1Kanbans} \times \text{Node3Kanbans} + \\
& 0.03 \times \text{Node2Kanbans} \times \text{Node3Kanbans} - \\
& 0.01 \times \text{Node Capacity}^2 - 0.01 \times \text{WIPCap}^2 - \\
& 0.04 \times \text{Node1Kanbans}^2 - 0.03 \times \text{Node2Kanbans}^2 - \\
& 0.04 \times \text{Node3Kanbans}^2
\end{aligned} \tag{B-14}$$

B.8 Hybrid Kanban-CONWIP SC RSM metamodels at Demand SD = 8

$$\begin{aligned} Service\ Level \quad = \quad & 55.80 - 0.24 \times \text{Node Capacity} + 0.53 \times \text{WIPCap} + \\ & 0.28 \times \text{Node1Kanbans} + 0.32 \times \text{Node2Kanbans} + \\ & 0.08 \times \text{Node3Kanbans} + \\ & 0.01 \times \text{Node Capacity} \times \text{Node1Kanbans} + \\ & 0.01 \times \text{Node Capacity} \times \text{Node2Kanbans} + \\ & 0.01 \times \text{Node Capacity} \times \text{Node3Kanbans} + \\ & 0.03 \times \text{Node1Kanbans} \times \text{Node2Kanbans} + \\ & 0.05 \times \text{Node1Kanbans} \times \text{Node3Kanbans} + \\ & 0.03 \times \text{Node2Kanbans} \times \text{Node3Kanbans} - \\ & 0.01 \times \text{Node Capacity}^2 - 0.002 \times \text{WIPCap}^2 - \\ & 0.05 \times \text{Node1Kanbans}^2 - 0.05 \times \text{Node2Kanbans}^{\,2} - \\ & 0.05 \times \text{Node3Kanbans}^2 \end{aligned} \qquad \text{(B-15)}$$

$$\begin{aligned} Average\ WIP \quad = \quad & 0.40 - 0.80 \times \text{Node Capacity} - 0.23 \times \text{WIPCap} - \\ & 1.96 \times \text{Node1Kanbans} + 0.94 \times \text{Node2Kanbans} + \\ & 2.71 \times \text{Node3Kanbans} + \\ & 0.01 \times \text{Node Capacity} \times \text{WIPCap} + \\ & 0.08 \times \text{Node Capacity} \times \text{Node1Kanbans} + \\ & 0.06 \times \text{Node Capacity} \times \text{Node2Kanbans} + \\ & 0.02 \times \text{WIPCap} \times \text{Node1Kanbans} + \\ & 0.02 \times \text{WIPCap} \times \text{Node2Kanbans} + \\ & 0.02 \times \text{WIPCap} \times \text{Node3Kanbans} + \\ & 0.10 \times \text{Node1Kanbans} \times \text{Node2Kanbans} - \\ & 0.06 \times \text{Node Capacity}^2 - 0.19 \times \text{Node1Kanbans}^2 - \\ & 0.15 \times \text{Node2Kanbans}^2 - 0.12 \times \text{Node3Kanbans}^2 \end{aligned} \qquad \text{(B-16)}$$

APPENDIX C $ANOVA$ OF RSM METAMODELS

C.1 CONWIP SC RSM metamodels $ANOVA$ at Demand SD = 4.5

Table C-1: ANOVA for CONWIP service level reduced quadratic model at SD=4.5

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	851.23	4	212.81	3909.21	< 0.0001	significant
A-Node capacity	7.330	1	7.330	134.65	< 0.0001	
B-WIP-Cap	725.45	1	725.45	13326.44	< 0.0001	
A^2	3.34	1	3.34	61.27	< 0.0001	
B^2	100.78	1	100.78	1851.29	< 0.0001	
Residual	0.76	14	0.05			
Total	851.99	18				
R^2	0.9991		PRESS	1.55		
Adj R^2	0.9988					

Table C-2: ANOVA for CONWIP average WIP reduced quadratic model at SD=4.5

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	3861.07	4	965.27	1883.24	< 0.0001	significant
A-Node capacity	91.637	1	91.637	178.78	< 0.0001	
B-WIP-Cap	3614.65	1	3614.65	7052.20	< 0.0001	
AB	34.68	1	34.68	67.66	< 0.0001	
A^2	29.81	1	29.81	58.16	< 0.0001	
Residual	7.18	14	0.51			
Total	3868.24	18				
R^2	0.9981		PRESS	13.78		
Adj R^2	0.9976					

C.2 CONWIP SC RSM metamodels $ANOVA$ at Demand SD = 8

Table C-3: ANOVA for CONWIP service level reduced quadratic model at SD=8

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	562.39	4	140.60	4970.59	< 0.0001	significant
A-Node capacity	17.835	1	17.835	630.52	< 0.0001	
B-WIP-Cap	467.75	1	467.75	16536.62	< 0.0001	
A^2	4.06	1	4.06	143.38	< 0.0001	
B^2	48.34	1	48.34	1709.10	< 0.0001	
Residual	0.37	13	0.03			
Total	562.76	17				
R^2	0.9993		PRESS	0.70		
Adj R^2	0.9991					

Table C-4: ANOVA for CONWIP average WIP reduced quadratic model at SD=8

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	10858.75	4	2714.69	1462.25	< 0.0001	significant
A-Node capacity	415.507	1	415.507	223.81	< 0.0001	
B-WIP-Cap	9951.92	1	9951.92	5360.54	< 0.0001	
AB	130.10	1	130.10	70.08	< 0.0001	
A^2	120.97	1	120.97	65.16	< 0.0001	
Residual	24.13	13	1.86			
Total	562.76	17				
R^2	0.9978		PRESS	47.36		
Adj R^2	0.9971					

C.3 Kanban SC RSM metamodels ANOVA at Demand SD = 1

Table C-5: ANOVA for Kanban service level reduced quadratic model at SD=1

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	7166.7637	11	651.5240	51.8672	< 0.0001	significant
B-Node1Kanbans	1440.5680	1	1440.5680	114.6822	< 0.0001	
C-Node2Kanbans	1441.5829	1	1441.5829	114.7630	< 0.0001	
D-Node3Kanbans	1443.7339	1	1443.7339	114.9342	< 0.0001	
E-Node4Kanbans	29.4991	1	29.4991	2.3484	0.1323	
BC	281.0124	1	281.0124	22.3711	< 0.0001	
BD	283.6145	1	283.6145	22.5783	< 0.0001	
CD	283.6376	1	283.6376	22.5801	< 0.0001	
B^2	894.0016	1	894.0016	71.1706	< 0.0001	
C^2	893.8158	1	893.8158	71.1558	< 0.0001	
D^2	894.1620	1	894.1620	71.1834	< 0.0001	
E^2	58.2837	1	58.2837	4.6399	0.0365	
Residual	577.82	46	12.5614			
Total	7744.5877	57				
R^2	0.93		Adj R^2	0.91		
Pred R^2	0.88		PRESS	896.73		

Table C-6: ANOVA for Kanban average WIP reduced quadratic model at SD=1

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	4286.0173	13	329.69364	75.066646	< 0.0001	significant
B-Node1Kanbans	1951.4629	1	1951.4629	444.32089	< 0.0001	
C-Node2Kanbans	974.59335	1	974.59335	221.90132	< 0.0001	
D-Node3Kanbans	402.98129	1	402.98129	91.753222	< 0.0001	
E-Node4Kanbans	208.81383	1	208.81383	47.543998	< 0.0001	
BC	125.34706	1	125.34706	28.539778	< 0.0001	
BD	70.095144	1	70.095144	15.959687	0.0002	
BE	31.126067	1	31.126067	7.0869715	0.0108	
CD	69.719923	1	69.719923	15.874255	0.0003	
CE	28.698874	1	28.698874	6.5343335	0.0141	
DE	22.095104	1	22.095104	5.0307473	0.0300	
B^2	330.86774	1	330.86774	75.333973	< 0.0001	
C^2	120.21605	1	120.21605	27.371519	< 0.0001	
D^2	33.670579	1	33.670579	7.6663214	0.0082	
Residual	193.24855	44	4.3920124			
Total	4479.2658	57				
R^2	0.96		Adj R^2	0.95		
Pred R^2	0.92		PRESS	382.59		

C.4 Kanban SC RSM metamodels ANOVA at Demand SD = 4.5

Table C-7: ANOVA for Kanban service level reduced quadratic model at SD=4.5

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	1786.2153	15	119.08102	1447.3023	< 0.0001	significant
A-Node Capacity	14.931035	1	14.931035	181.47074	< 0.0001	
B-Node1Kanbans	1.1567582	1	1.1567582	14.059157	0.0006	
C-Node2Kanbans	2.2333713	1	2.2333713	27.144237	< 0.0001	
D-Node3Kanbans	11.27519	1	11.27519	137.03787	< 0.0001	
E-Node4Kanbans	1310.6619	1	1310.6619	15929.692	< 0.0001	
AC	0.6059472	1	0.6059472	7.3646399	0.0103	
AD	2.2919873	1	2.2919873	27.856651	< 0.0001	
AE	1.0296255	1	1.0296255	12.513996	0.0012	
BC	0.3560658	1	0.3560658	4.3275987	0.0449	
CD	0.3519933	1	0.3519933	4.2781022	0.0461	
A^2	8.8388951	1	8.8388951	107.42731	< 0.0001	
B^2	1.231953	1	1.231953	14.973069	0.0005	
C^2	1.3287676	1	1.3287676	16.149747	0.0003	
D^2	4.0544983	1	4.0544983	49.278086	< 0.0001	
E^2	348.30759	1	348.30759	4233.3057	< 0.0001	
Residual	2.8797272	35	0.0822779			
Total	1789.0951	50				
R^2	0.9984		Adj R^2	0.9977		
Pred R^2	0.9966		PRESS	6.1194		

Table C-8: ANOVA for Kanban average WIP reduced quadratic model at SD=4.5

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	6455.056	19	339.73979	876.16464	< 0.0001	significant
A-Node Capacity	20.773801	1	20.773801	53.574148	< 0.0001	
B-Node1Kanbans	163.50497	1	163.50497	421.66762	< 0.0001	
C-Node2Kanbans	149.59614	1	149.59614	385.79775	< 0.0001	
D-Node3Kanbans	377.00944	1	377.00944	972.28039	< 0.0001	
E-Node4Kanbans	5184.2326	1	5184.2326	13369.765	< 0.0001	
AB	3.5539941	1	3.5539941	9.1654969	0.0049	
AC	2.6492738	1	2.6492738	6.8322879	0.0137	
AE	10.043697	1	10.043697	25.901978	< 0.0001	
BC	6.6009377	1	6.6009377	17.023346	0.0003	
BD	4.0094896	1	4.0094896	10.340187	0.0030	
BE	6.9302247	1	6.9302247	17.872554	0.0002	
CD	3.0903988	1	3.0903988	7.9699175	0.0082	
CE	5.9074226	1	5.9074226	15.234821	0.0005	
DE	7.6502317	1	7.6502317	19.729401	0.0001	
A^2	13.264227	1	13.264227	34.207492	< 0.0001	
B^2	13.585621	1	13.585621	35.036345	< 0.0001	
C^2	12.184671	1	12.184671	31.423396	< 0.0001	
D^2	8.8309486	1	8.8309486	22.774385	< 0.0001	
E^2	12.195652	1	12.195652	31.451714	< 0.0001	
Residual	12.020496	31	0.3877579			
Total	6467.0765	50				
R^2	0.9981		Adj R^2	0.9970		
Pred R^2	0.9943		PRESS	36.6117		

C.5 Kanban SC RSM metamodels ANOVA at Demand SD = 8

Table C-9: ANOVA for Kanban service level reduced quadratic model at SD=8

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	1036.4256	13	79.725048	400.26549	< 0.0001	significant
A-Node Capacity	16.76753	1	16.76753	84.182622	< 0.0001	
B-Node1Kanbans	2.3739994	1	2.3739994	11.918839	0.0014	
C-Node2Kanbans	3.4777938	1	3.4777938	17.460521	0.0002	
D-Node3Kanbans	10.173585	1	10.173585	51.077233	< 0.0001	
E-Node4Kanbans	750.26229	1	750.26229	3766.7472	< 0.0001	
AD	2.3746431	1	2.3746431	11.922071	0.0014	
AE	1.8882144	1	1.8882144	9.4799201	0.0038	
DE	0.891997	1	0.891997	4.478337	0.0409	
A^2	7.8851475	1	7.8851475	39.587965	< 0.0001	
B^2	2.0325946	1	2.0325946	10.204791	0.0028	
C^2	2.1583298	1	2.1583298	10.836054	0.0022	
D^2	3.4760419	1	3.4760419	17.451725	0.0002	
E^2	127.65	1	127.65	640.87626	< 0.0001	
Residual	7.5688559	38	0.1991804			
Total	1043.9945	51				
R^2	0.9928		Adj R^2	0.9903		
Pred R^2	0.9853		PRESS	15.3738		

Table C-10: ANOVA for Kanban average WIP reduced quadratic model at SD=8

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	23564.159	19	1240.2189	822.41191	< 0.0001	significant
A-Node Capacity	123.14303	1	123.14303	81.658404	< 0.0001	
B-Node1Kanbans	319.72469	1	319.72469	212.01532	< 0.0001	
C-Node2Kanbans	281.80104	1	281.80104	186.86744	< 0.0001	
D-Node3Kanbans	477.6955	1	477.6955	316.76865	< 0.0001	
E-Node4Kanbans	21320.988	1	21320.988	14138.339	< 0.0001	
AB	10.728594	1	10.728594	7.114328	0.0119	
AC	7.9418454	1	7.9418454	5.2663835	0.0284	
AD	8.6151138	1	8.6151138	5.7128402	0.0229	
AE	44.210821	1	44.210821	29.317007	< 0.0001	
BC	28.447822	1	28.447822	18.864273	0.0001	
BD	13.132064	1	13.132064	8.7081129	0.0059	
BE	26.014152	1	26.014152	17.250462	0.0002	
CD	9.5829746	1	9.5829746	6.3546464	0.0169	
CE	23.710209	1	23.710209	15.722675	0.0004	
DE	19.647092	1	19.647092	13.028347	0.0010	
A^2	70.234643	1	70.234643	46.573882	< 0.0001	
B^2	78.011651	1	78.011651	51.730959	< 0.0001	
C^2	65.913432	1	65.913432	43.708407	< 0.0001	
D^2	66.471428	1	66.471428	44.078425	< 0.0001	
Residual	48.256845	32	1.5080264			
Total	23612.415	51				
R^2	0.9980		Adj R^2	0.9967		
Pred R^2	0.9940		PRESS	141.1130		

C.6 Hybrid Kanban-CONWIP SC RSM metamodels ANOVA at Demand SD = 1

Table C-11: ANOVA for Hybrid service level reduced quadratic model at SD=1

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	4589.9203	11	417.26548	574928.07	< 0.0001	significant
A-Node Capacity	0.0189	1	0.0188697	25.999603	< 0.0001	
B-WIP-Cap	3041.0955	1	3041.0955	4190164.9	< 0.0001	
C-Node1Kanbans	0.0005	1	0.0004897	0.6746853	0.4157	
D-Node2Kanbans	0.0033	1	0.0033099	4.5605121	0.0381	
E-Node3Kanbans	0.0018	1	0.0018366	2.5305114	0.1185	
AC	0.0030	1	0.0030327	4.1786561	0.0467	
A^2	0.0164	1	0.0163838	22.574334	< 0.0001	
B^2	1191.1223	1	1191.1223	1641184.5	< 0.0001	
C^2	0.0114	1	0.0113725	15.669632	0.0003	
D^2	0.0100	1	0.0099528	13.713477	0.0006	
E^2	0.0082	1	0.0082461	11.361892	0.0015	
Residual	0.0334	46	0.0007258			
Total	4589.9537	57				
R^2	0.99999		PRESS	0.0521545		
Adj R^2	0.99999					

Table C-12: ANOVA for Hybrid average WIP reduced quadratic model at SD=1

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	2860.36595	8	357.54574	124074.36	< 0.0001	significant
A-Node Capacity	0.75041	1	0.7504121	260.40554	< 0.0001	
B-WIP-Cap	2858.60191	1	2858.6019	991982.71	< 0.0001	
C-Node1Kanbans	0.20157	1	0.2015717	69.948757	< 0.0001	
AB	0.18717	1	0.1871668	64.949995	< 0.0001	
AC	0.02816	1	0.0281604	9.7721271	0.0030	
BC	0.08046	1	0.0804643	27.922449	< 0.0001	
A^2	0.43815	1	0.4381533	152.04654	< 0.0001	
C^2	0.13519	1	0.1351943	46.914688	< 0.0001	
Residual	0.14120	49	0.0028817			
Total	2860.50715	57				
R^2	0.99995		PRESS	0.208		
Adj R^2	0.99994					

C.7 Hybrid Kanban-CONWIP SC RSM metamodels ANOVA at Demand SD = 4.5

Table C-13: ANOVA for Hybrid service level reduced quadratic model at SD=4.5

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	1718.1741	19	90.430215	8183.6478	< 0.0001	significant
A-Node Capacity	6.7152	1	6.7151876	607.7032	< 0.0001	
B-WIP-Cap	1271.6412	1	1271.6412	115079.5	< 0.0001	
C-Node1Kanbans	3.1498	1	3.149799	285.04683	< 0.0001	
D-Node2Kanbans	2.8750	1	2.8749959	260.17802	< 0.0001	
E-Node3Kanbans	3.3920	1	3.3920349	306.9684	< 0.0001	
AC	1.1230	1	1.1229584	101.62418	< 0.0001	
AD	1.0896	1	1.0895643	98.602113	< 0.0001	
AE	0.7988	1	0.7988106	72.289825	< 0.0001	
BC	0.0928	1	0.0927983	8.3979498	0.0066	
BD	0.0837	1	0.0837313	7.5774174	0.0095	
BE	0.0919	1	0.0919388	8.3201671	0.0069	
CD	0.7661	1	0.7660715	69.327039	< 0.0001	
CE	0.6457	1	0.6456546	58.429692	< 0.0001	
DE	0.7243	1	0.7243332	65.54986	< 0.0001	
A^2	4.9353	1	4.9353313	446.63184	< 0.0001	
B^2	280.1218	1	280.12185	25350.139	< 0.0001	
C^2	3.1299	1	3.1298702	283.24333	< 0.0001	
D^2	2.8653	1	2.86531	259.30147	< 0.0001	
E^2	3.0752	1	3.0752292	278.2985	< 0.0001	
Residual	0.3647	33	0.0110501			
Total	1718.5387	52				
R^2	0.9998		PRESS	0.89		
Adj R^2	0.9997					

Table C-14: ANOVA for Hybrid average WIP reduced quadratic model at SD=4.5

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	7538.8077	13	579.90828	1260.7172	< 0.0001	significant
A-Node Capacity	71.3241	1	71.324121	155.05822	< 0.0001	
B-WIP-Cap	7054.7296	1	7054.7296	15336.941	< 0.0001	
C-Node1Kanbans	55.0047	1	55.004654	119.5798	< 0.0001	
D-Node2Kanbans	7.7695	1	7.7695049	16.890859	0.0002	
E-Node3Kanbans	2.7168	1	2.7168062	5.9063209	0.0198	
AB	14.6255	1	14.625503	31.795758	< 0.0001	
AC	8.0444	1	8.0443924	17.488462	0.0002	
BC	12.8094	1	12.809391	27.847542	< 0.0001	
BD	5.9667	1	5.9667149	12.971603	0.0009	
BE	3.6019	1	3.6019342	7.8305841	0.0079	
A^2	32.7818	1	32.781825	71.267497	< 0.0001	
C^2	11.5320	1	11.531979	25.070454	< 0.0001	
D^2	2.1420	1	2.1420161	4.6567305	0.0371	
Residual	17.9393	39	0.4599828			
Cor Total	7556.7470	52				
R^2	0.9976		PRESS	37.29		
Adj R^2	0.9968					

C.8 Hybrid Kanban-CONWIP SC RSM metamodels ANOVA at Demand SD = 8

Table C-15: ANOVA for Hybrid service level reduced quadratic model at SD=8

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	820.9058	16	51.306615	696.16423	< 0.0001	significant
A-Node Capacity	9.5171	1	9.5170548	129.13409	< 0.0001	
B-WIP-Cap	649.1731	1	649.17305	8808.4364	< 0.0001	
C-Node1Kanbans	7.9129	1	7.9129437	107.36838	< 0.0001	
D-Node2Kanbans	5.4722	1	5.4722312	74.251081	< 0.0001	
E-Node3Kanbans	8.4057	1	8.4057452	114.05506	< 0.0001	
AC	1.1654	1	1.16535	15.812289	0.0004	
AD	1.2696	1	1.2696294	17.227224	0.0002	
AE	1.1413	1	1.1412729	15.485594	0.0004	
CD	0.9275	1	0.9274918	12.584861	0.0012	
CE	2.2431	1	2.2431255	30.436304	< 0.0001	
DE	1.2185	1	1.2185197	16.533732	0.0003	
A^2	6.7691	1	6.769085	91.847706	< 0.0001	
B^2	127.7353	1	127.73528	1733.2021	< 0.0001	
C^2	5.6117	1	5.6117048	76.143557	< 0.0001	
D^2	4.8354	1	4.8353602	65.609567	< 0.0001	
E^2	4.7262	1	4.7261715	64.128018	< 0.0001	
Residual	2.3584	32	0.073699			
Total	823.2642	48				
R^2	0.9971		PRESS	5.29		
Adj R^2	0.9957					

Table C-16: ANOVA for Hybrid average WIP reduced quadratic model at SD=8

Source	*Sum of Squares*	*df*	*Mean Square*	*F Value*	*p-value Prob > F*	
Model	21951.9378	16	1371.9961	642.83105	< 0.0001	significant
A-Node Capacity	279.6282	1	279.62821	131.01618	< 0.0001	
B-WIP-Cap	20723.9030	1	20723.903	9709.9169	< 0.0001	
C-Node1Kanbans	266.9486	1	266.94856	125.0753	< 0.0001	
D-Node2Kanbans	95.1258	1	95.125756	44.569943	< 0.0001	
E-Node3Kanbans	40.2267	1	40.226666	18.847684	0.0001	
AB	52.1999	1	52.199931	24.457603	< 0.0001	
AC	39.9836	1	39.983599	18.733798	0.0001	
AD	19.1959	1	19.19592	8.994	0.0052	
BC	55.4111	1	55.411052	25.962132	< 0.0001	
BD	40.2795	1	40.279471	18.872426	0.0001	
BE	31.0116	1	31.011578	14.530074	0.0006	
CD	10.8402	1	10.840187	5.0790297	0.0312	
A^2	168.0608	1	168.06084	78.742736	< 0.0001	
C^2	89.1220	1	89.121959	41.756942	< 0.0001	
D^2	53.9561	1	53.956079	25.280424	< 0.0001	
E^2	34.4353	1	34.435335	16.134231	0.0003	
Residual	68.2977	32	2.1343028			
Total	22020.2355	48				
R^2	0.9969		PRESS	186.8		
Adj R^2	0.9953					

APPENDIX D GP METAMODELS REPORTS

D.1 CONWIP SC GP metamodels report at Demand SD = 4.5

Table D-1: CONWIP service level GP metamodel report at SD=4.5

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	CONWIP.Cap Interaction
Capacity	3.2777e-5	0.0080104	0.0076549	.	0.0003555
CONWIP.Cap	0.0011507	0.9923451	0.9919896	0.0003555	.

μ	σ²	Nugget
85.08765	129.40114	0.0014735

Table D-2: CONWIP average WIP GP metamodel report at SD=4.5

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	CONWIP.Cap Interaction
Capacity	0.0004176	0.0166785	0.0155922	.	0.0010864
CONWIP.Cap	7.8758e-5	0.9844078	0.9833215	0.0010864	.

μ	σ²	Nugget
35.090812	1644.7696	0.0003601

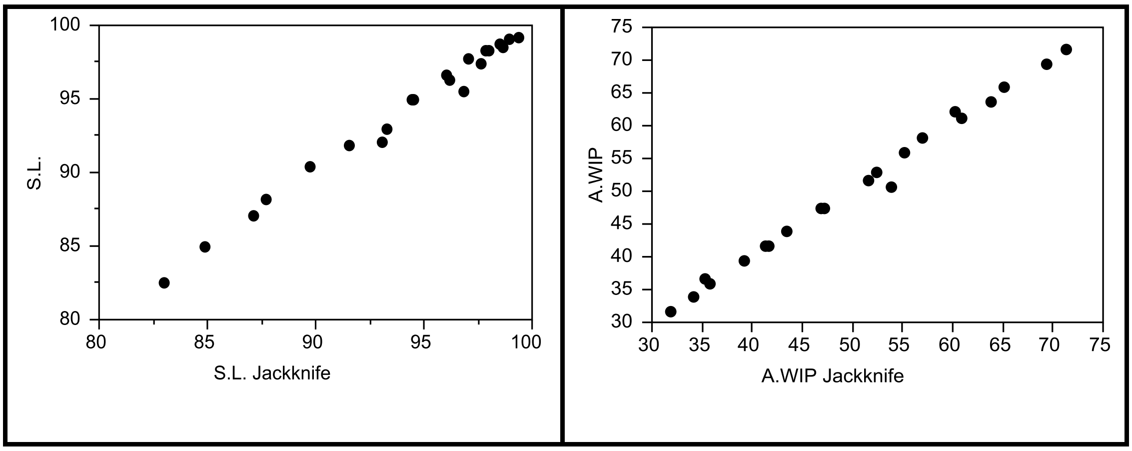


Figure D-1: CONWIP SC GP metamodels actual by predicted plot at SD=4.5

D.2 CONWIP SC GP metamodels report at Demand SD = 8

Table D-3: CONWIP service level GP metamodel report at SD=8

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP-Cap Interaction
Capacity	0.0005859	0.0501238	0.049691	.	0.0004329
WIP-Cap	0.0002417	0.950309	0.9498762	0.0004329	.

μ	σ²	Nugget
83.387613	98.373703	0.0042392

Table D-4: CONWIP average WIP GP metamodel report at SD=8

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP-Cap Interaction
Capacity	0.0026232	0.0517949	0.0423228	.	0.0094721
WIP-Cap	2.6549e-5	0.9576772	0.9482051	0.0094721	.

μ	σ²	Nugget
61.975395	4034.6316	0.0003837

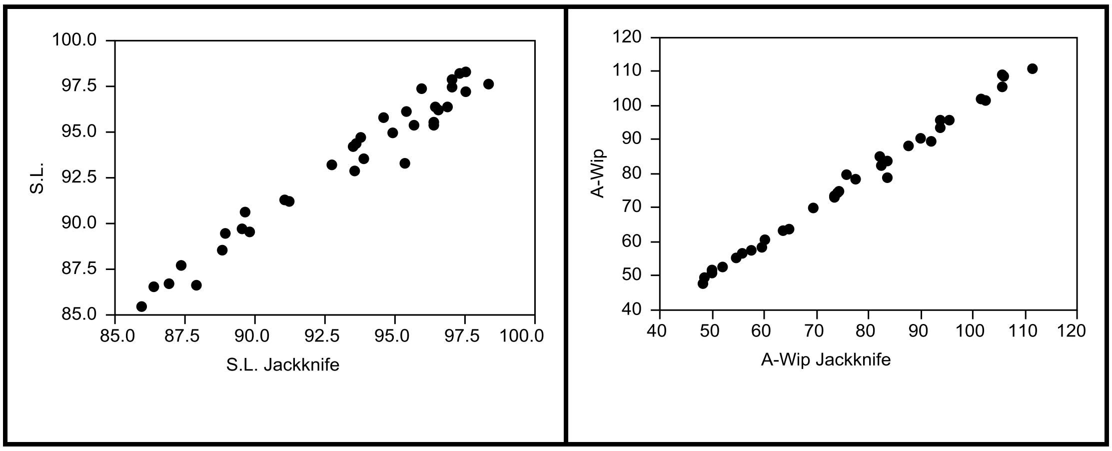


Figure D-2: CONWIP SC GP metamodels actual by predicted plot at SD=8

D.3 Kanban SC GP metamodels report at Demand SD = 1

Table D-5: Kanban service level GP metamodel report at SD=1

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	K1 Interaction	k2 Interaction	K3 Interaction	K4 Interaction
Capacity	0	0	0	.	0	0	0	0
K1	0.024141	0.3433207	0.2552299	0	.	0.0457378	0.042353	0
k2	0.0142982	0.3717617	0.2482606	0	0.0457378	.	0.0777633	0
K3	0.0140864	0.4503619	0.3302456	0	0.042353	0.0777633	.	0
K4	0	0	0	0	0	0	0	.

μ	σ²	Nugget
65.716233	370.70256	0.0262292

Table D-6: Kanban average WIP GP metamodel report at SD=1

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	K1 Interaction	k2 Interaction	K3 Interaction	K4 Interaction
Capacity	0.0001317	0.00189	0.0005601	.	0.0011542	1.9145e-5	0.0001563	3.7016e-7
K1	0.0383205	0.6378535	0.5161332	0.0011542	.	0.07608	0.0377447	0.0067415
k2	0.0218241	0.3135713	0.217602	1.9145e-5	0.07608	.	0.018366	0.0015042
K3	0.0080092	0.1565492	0.0995228	0.0001563	0.0377447	0.018366	.	0.0007595
K4	0.0010324	0.0271778	0.0181723	3.7016e-7	0.0067415	0.0015042	0.0007595	.

μ	σ²	Nugget
30.265871	74.499105	0.0405025

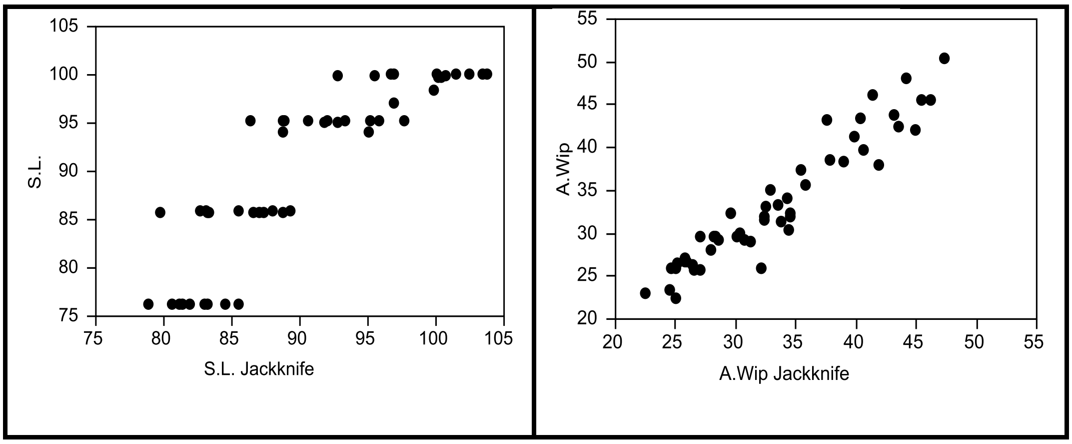


Figure D-3: Kanban SC GP metamodels actual by predicted plot at SD=1

D.4 Kanban SC GP metamodels report at Demand SD = 4.5

Table D-7: Kanban service level GP metamodel report at SD=1

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	K1 Interaction	K2 Interaction	K3 Interaction	K4 Interaction
Capacity	4.8502e-6	0.0061843	0.0055833	.	0	0	1.1448e-8	0.000601
K1	2.1107e-6	0.0000273	0.000024	0	.	0	0	3.2967e-6
K2	0	0	0	0	0	.	0	0
K3	3.4128e-5	0.0134495	0.0123942	1.1448e-8	0	0	.	0.0010553
K4	0.000822	0.9819985	0.9803389	0.000601	3.2967e-6	0	0.0010553	.

μ	σ²	Nugget
77.736936	476.92907	0.0008039

Table D-8: Kanban average WIP GP metamodel report at SD=1

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	K1 Interaction	K2 Interaction	K3 Interaction	K4 Interaction
Capacity	7.1576e-5	0.0027318	0.0016715	.	3.117e-5	1.0665e-6	0.0005041	0.0005239
K1	0.0091977	0.035003	0.0325959	3.117e-5	.	2.1383e-5	0.0017105	0.0006441
K2	0.0019084	0.0294969	0.0282096	1.0665e-6	2.1383e-5	.	0.0009598	0.0003051
K3	0.002374	0.0686089	0.0640565	0.0005041	0.0017105	0.0009598	.	0.001378
K4	0.0001937	0.8700365	0.8671854	0.0005239	0.0006441	0.0003051	0.001378	.

μ	σ²	Nugget
54.449993	454.96993	0.0021781

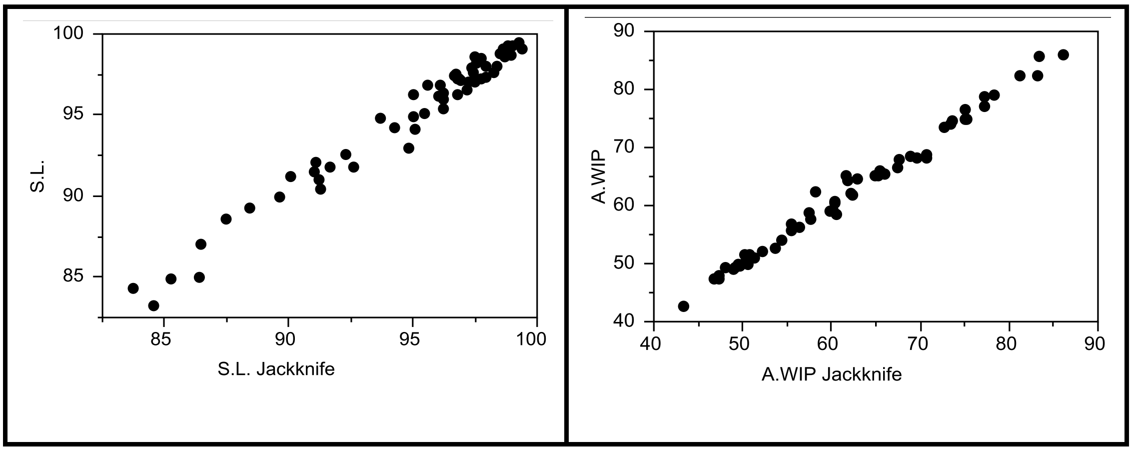


Figure D-4: Kanban SC GP metamodels actual by predicted plot at SD=4.5

D.5 Kanban SC GP metamodels report at Demand SD = 8

Table D-9: Kanban service level GP metamodel report at SD=8

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	K1 Interaction	K2 Interaction	K3 Interaction	K4 Interaction
Capacity	0.0004802	0.0131055	0.0105518	.	0.0002535	0.0001855	0.0007755	0.0013392
K1	0.0039087	0.0060454	0.0028291	0.0002535	.	0.0004656	0.0004045	0.0020926
K2	0.0025747	0.0156287	0.0140334	0.0001855	0.0004656	.	0.0002754	0.0006687
K3	0.0013574	0.01467	0.0113405	0.0007755	0.0004045	0.0002754	.	0.001874
K4	0.0002073	0.9585921	0.9526176	0.0013392	0.0020926	0.0006687	0.001874	.

μ	σ²	Nugget
77.805801	63.271246	0.0035204

Table D-10: Kanban average WIP GP metamodel report at SD=8

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	K1 Interaction	K2 Interaction	K3 Interaction	K4 Interaction
Capacity	1.4259e-6	0.0006734	0.0006723	.	5.3369e-9	2.9029e-7	4.964e-7	2.5692e-7
K1	0.0023508	0.0177888	0.0162496	5.3369e-9	.	0.0003662	0.000227	0.000946
K2	0.0016	0.0183865	0.0170083	2.9029e-7	0.0003662	.	0.0003036	0.000708
K3	0.0007926	0.0163029	0.0156576	4.964e-7	0.000227	0.0003036	.	0.0001142
K4	1.2984e-5	0.9495144	0.9477459	2.5692e-7	0.000946	0.000708	0.0001142	.

μ	σ²	Nugget
29.924326	5958.145	0.0009244

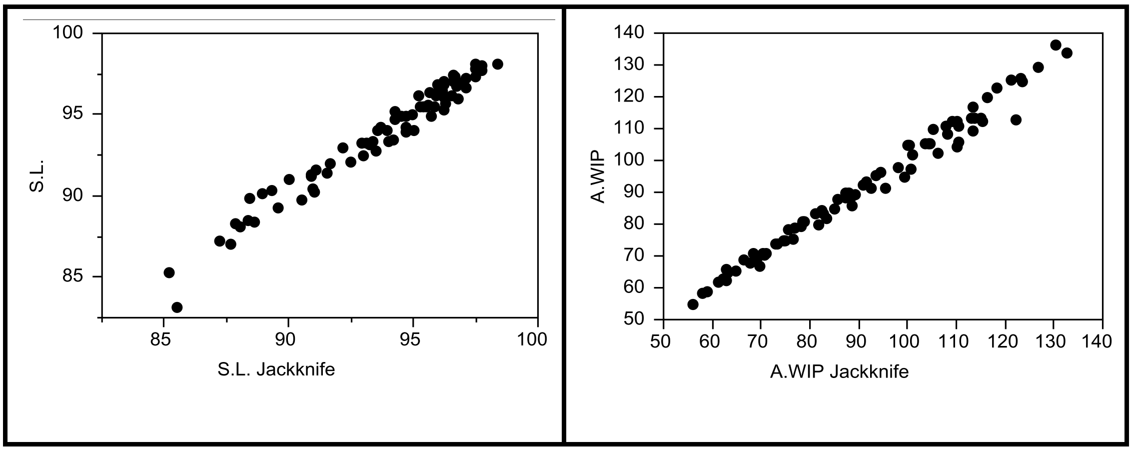


Figure D-5: Kanban SC GP metamodels actual by predicted plot at SD=8

D.6 Hybrid Kanban-CONWIP SC GP metamodels report at Demand SD = 1

Table D-11: Hybrid service level GP metamodel report at SD=1

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP.Cap Interaction	K1 Interaction	K2 Interaction	K3 Interaction
Capacity	0	0	0	.	0	0	0	0
WIP.Cap	0.0039999	0.9997932	0.9996172	0	.	0	0	0.000176
K1	0	0	0	0	0	.	0	0
K2	0	0	0	0	0	0	.	0
K3	1.0022e-5	0.0003828	0.0002068	0	0.000176	0	0	.

μ	σ²	Nugget
83.848626	315.65349	0.0006445

Table D-12: Hybrid average WIP GP metamodel report at SD=1

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP.Cap Interaction	K1 Interaction	K2 Interaction	K3 Interaction
Capacity	0	0	0	.	0	0	0	0
WIP.Cap	0.0000304	0.999975	0.999975	0	.	0	0	0
K1	0	0	0	0	0	.	0	0
K2	0	0	0	0	0	0	.	0
K3	3.6082e-9	2.499e-5	2.499e-5	0	0	0	0	.

μ	σ²	Nugget
32.033396	5755.2545	1.9326e-5

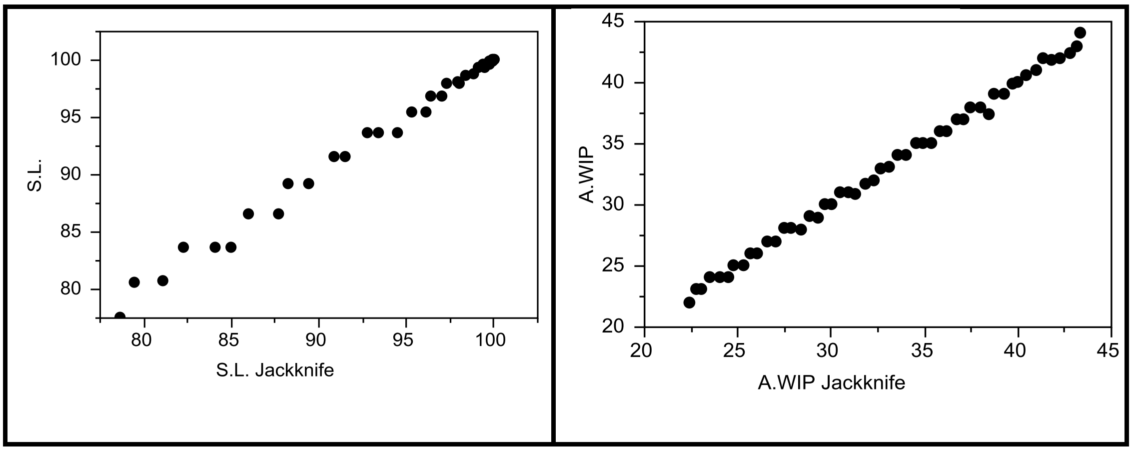


Figure D-6: Hybrid SC GP metamodels actual by predicted plot at SD=1

D.7 Hybrid Kanban-CONWIP SC GP metamodels report at Demand SD = 4.5

Table D-13: Hybrid service level GP metamodel report at SD=4.5

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP.Cap Interaction	K1 Interaction	K2 Interaction	K3 Interaction
Capacity	3.5866e-6	0.0030973	0.0030839	.	1.3383e-5	1.624e-10	0	0
WIP.Cap	0.0006883	0.9927472	0.9926042	1.3383e-5	.	4.5938e-5	7.7138e-5	6.521e-6
K1	8.0631e-6	0.0014388	0.0013929	1.624e-10	4.5938e-5	.	1.994e-10	0
K2	1.4329e-5	0.0024339	0.0023568	0	7.7138e-5	1.994e-10	.	0
K3	3.1663e-6	0.0004258	0.0004193	0	6.521e-6	0	0	.

μ	σ²	Nugget
79.529795	301.86541	0.0007346

Table D-14: Hybrid average WIP GP metamodel report at SD=4.5

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP.Cap Interaction	K1 Interaction	K2 Interaction	K3 Interaction
Capacity	0.0008143	0.0120761	0.0098472	.	0.0016324	0.0005963	2.9288e-7	0
WIP.Cap	0.000604	0.98396	0.9817754	0.0016324	.	0.0004895	6.2735e-5	0
K1	0.0005802	0.0054367	0.0043504	0.0005963	0.0004895	.	5.4196e-7	0
K2	4.0837e-5	0.0012788	0.0012153	2.9288e-7	6.2735e-5	5.4196e-7	.	0
K3	0	0	0	0	0	0	0	.

μ	σ²	Nugget
34.84074	335.10508	0.0029054

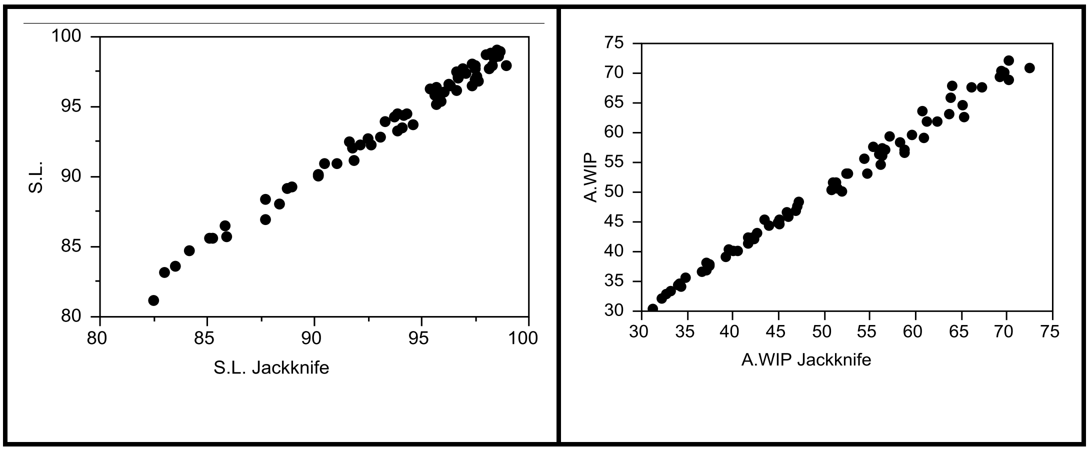


Figure D-7: Hybrid SC GP metamodels actual by predicted plot at SD=4.5

D.8 Hybrid Kanban-CONWIP SC GP metamodels report at Demand SD = 8

Table D-15: Hybrid service level GP metamodel report at SD=8

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP-Cap Interaction	K1 Interaction	K2 Interaction	K3 Interaction
Capacity	3.6653e-6	0.0026215	0.0025894	.	0.0000321	4.545e-11	3.155e-9	2.336e-10
WIP-Cap	9.0887e-5	0.9870593	0.9863538	0.0000321	.	6.7164e-5	0.0006043	1.9159e-6
K1	2.5773e-5	0.0057126	0.0056455	4.545e-11	6.7164e-5	.	3.244e-9	1.603e-9
K2	3.5456e-5	0.0040539	0.0034496	3.155e-9	0.0006043	3.244e-9	.	2.284e-10
K3	8.0732e-6	0.0012582	0.0012563	2.336e-10	1.9159e-6	1.603e-9	2.284e-10	.

μ	σ²	Nugget
83.809073	239.40506	0.0017624

Table D-16: Hybrid average WIP GP metamodel report at SD=8

Column	Theta	Total Sensitivity	Main Effect	Capacity Interaction	WIP-Cap Interaction	K1 Interaction	K2 Interaction	K3 Interaction
Capacity	0.000264	0.004328	0.004289	.	3.6922e-5	1.6939e-6	3.5928e-7	0
WIP-Cap	0.0000221	0.9877162	0.9873047	3.6922e-5	.	0.0003741	4.6183e-7	0
K1	0.0001384	0.0076774	0.0073017	1.6939e-6	0.0003741	.	9.379e-10	0
K2	0.0000099	0.0006918	0.000691	3.5928e-7	4.6183e-7	9.379e-10	.	0
K3	0	0	0	0	0	0	0	.

μ	σ²	Nugget
44.801934	4144.933	0.0020133

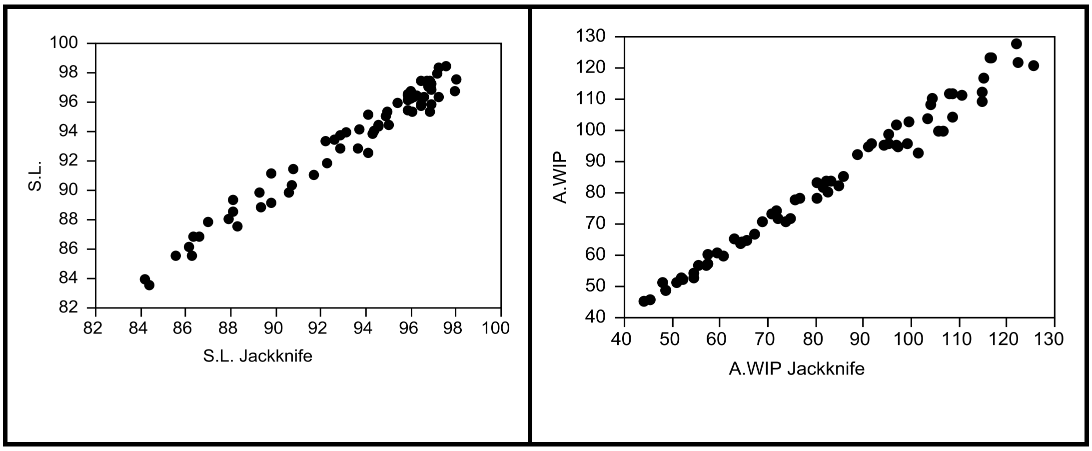


Figure D-8: Hybrid SC GP metamodels actual by predicted plot at SD=8

APPENDIX E RSM-DA OPTIMISATION RESULTS

E.1 CONWIP SC RSM-DA Optimisation Results at Demand SD = 4.5

Table E-1: CONWIP SC RSM-DA and their SIM-RSM-DA results for SD=4.5

S.L. Target	Node Capacity	WIP-Cap	CONWIP RSM-DA Service Level	CONWIP RSM-DA Average WIP	CONWIP RSM-DA Desirability	CONWIP SIM-RSM-DA Actual Service Level	CONWIP SIM-RSM-DA Actual Average WIP
82±0.5	8	33	81.9999	30.6305	0.9958	82.2532	31.1070
84±0.5	8	35	83.9999	32.5107	0.9726	84.4296	32.7696
86±0.5	8	38	85.9998	34.6261	0.9459	87.0438	35.1905
88±0.5	8	41	87.9998	36.7404	0.9185	89.0880	37.5916
90±0.5	8	44	89.9998	39.1892	0.8856	90.9416	39.8957
92±0.5	8	47	91.9998	41.9848	0.8466	92.1764	42.1560
94±0.5	8	51	93.9998	45.3899	0.7964	93.8316	45.2474
96±0.5	8	57	95.9998	49.8327	0.7258	95.6618	49.8737
98±0.5	14	59	97.9998	56.5129	0.6042	97.7948	57.6896

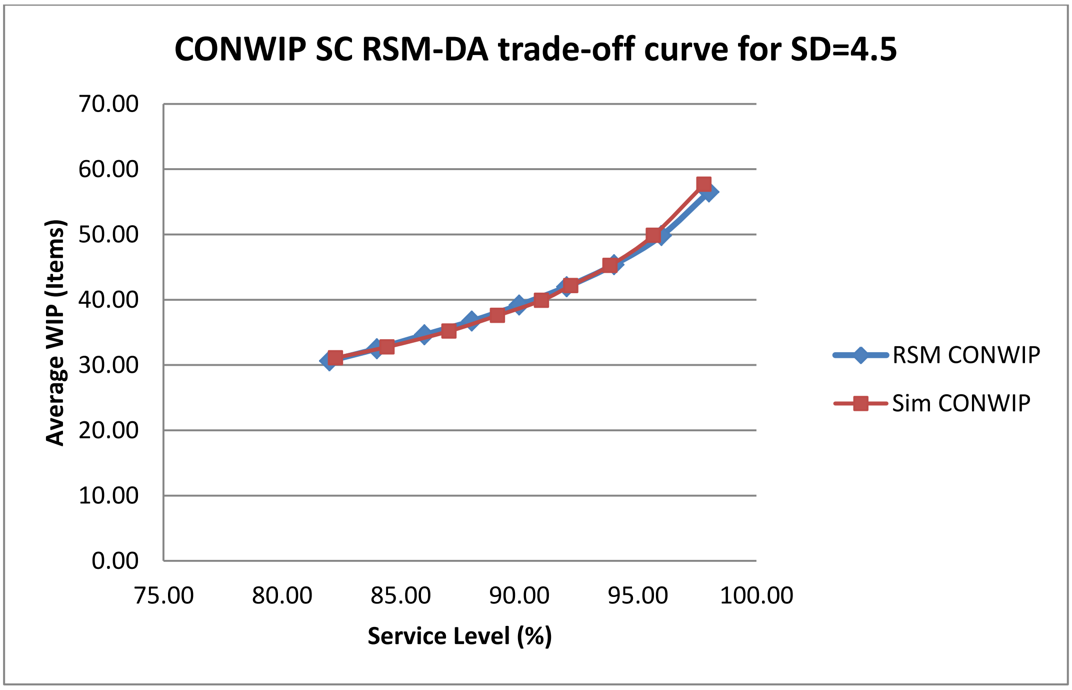


Figure E-1: CONWIP SC RSM-DA trade-off curve for SD=4.5

E.2 CONWIP SC RSM-DA Optimisation Results at Demand SD = 8

Table E-2: CONWIP SC RSM-DA and their SIM-RSM-DA results for SD=8

S.L. Target	Node Capacity	WIP-Cap	CONWIP RSM-DA			CONWIP SIM-RSM-DA	
			Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
84±0.5	8	53	83.9998	45.1848	0.9817	84.3948	46.3722
86±0.5	8	58	85.9998	49.3808	0.9515	86.3366	50.0670
88±0.5	8	64	87.9998	54.0504	0.9166	88.3356	54.4255
90±0.5	8	71	89.9998	59.4033	0.8749	89.7935	59.4966
92±0.5	8	79	91.9998	65.8726	0.8217	91.7219	65.4177
94±0.5	9	88	93.9998	74.6582	0.7433	92.9622	72.0663
96±0.5	19	86	95.9998	84.9328	0.6397	95.9177	83.7223
98±0.5	20	103	97.9998	101.7005	0.4186	97.4678	100.8730

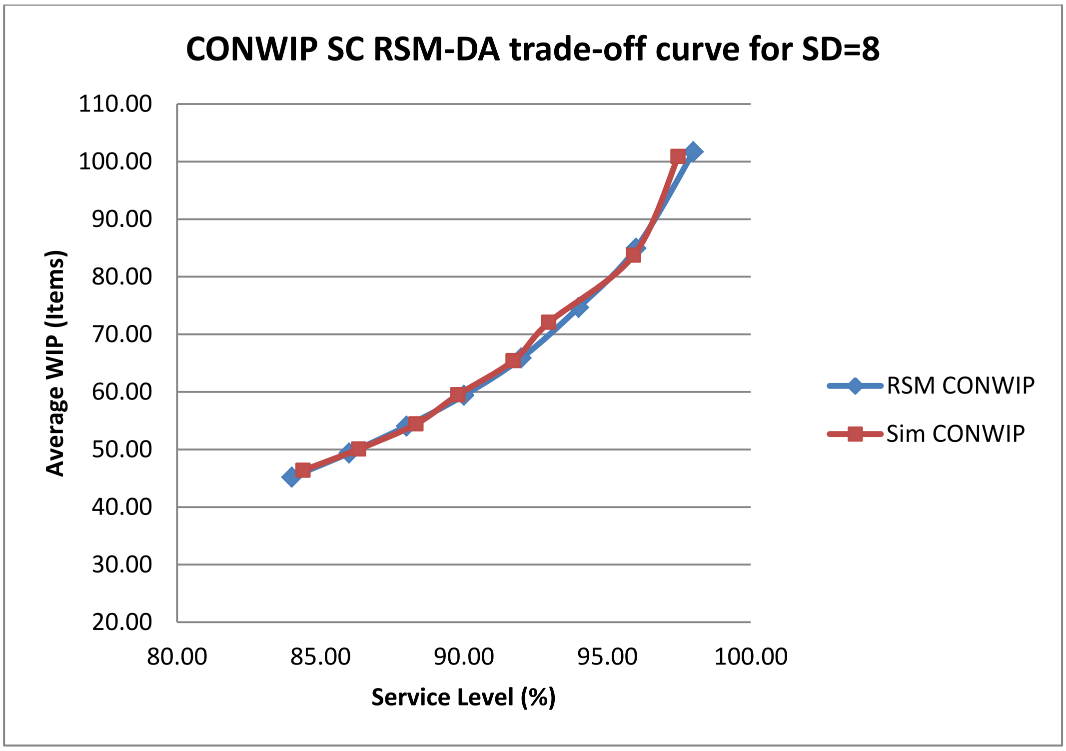


Figure E-2: CONWIP SC RSM-DA trade-off curve for SD=8

E.3 Kanban SC RSM-DA Optimisation Results at Demand SD = 1

Table E-3: Kanban SC RSM-DA and their SIM-RSM-DA results for SD=1

S.L. Target	Capacity	Kanban Allocations				Kanban RSM-DA			Kanban SIM-RSM-DA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
78±0.5	16	8	10	12	15	78.0001	21.9004	1.0000	76.1621	23.2819
80±0.5	16	8	10	12	15	79.9998	23.0685	0.9809	76.1621	23.2819
82±0.5	16	8	11	13	16	81.9998	25.0128	0.9435	76.2123	23.2833
84±0.5	16	8	13	12	15	83.9998	26.3672	0.9166	76.1081	23.2798
86±0.5	16	9	12	13	14	85.9998	27.7857	0.8876	85.7905	26.4698
88±0.5	16	9	12	13	12	87.9998	29.1535	0.8586	85.6668	26.4593
90±0.5	16	10	13	13	9	89.9998	30.6965	0.8247	95.0205	29.2197
92±0.5	16	10	13	13	10	91.9998	32.1207	0.7922	95.1070	29.0881
94±0.5	16	10	12	13	12	93.9998	33.8824	0.7500	95.0996	29.0715
96±0.5	16	11	13	12	9	95.9998	35.4057	0.7115	98.0730	33.9493
98±0.5	16	12	13	13	8	97.9998	36.4755	0.6831	95.7007	35.9436
100	16	12	13	14	9	99.9998	37.9538	0.6419	98.4021	37.5491

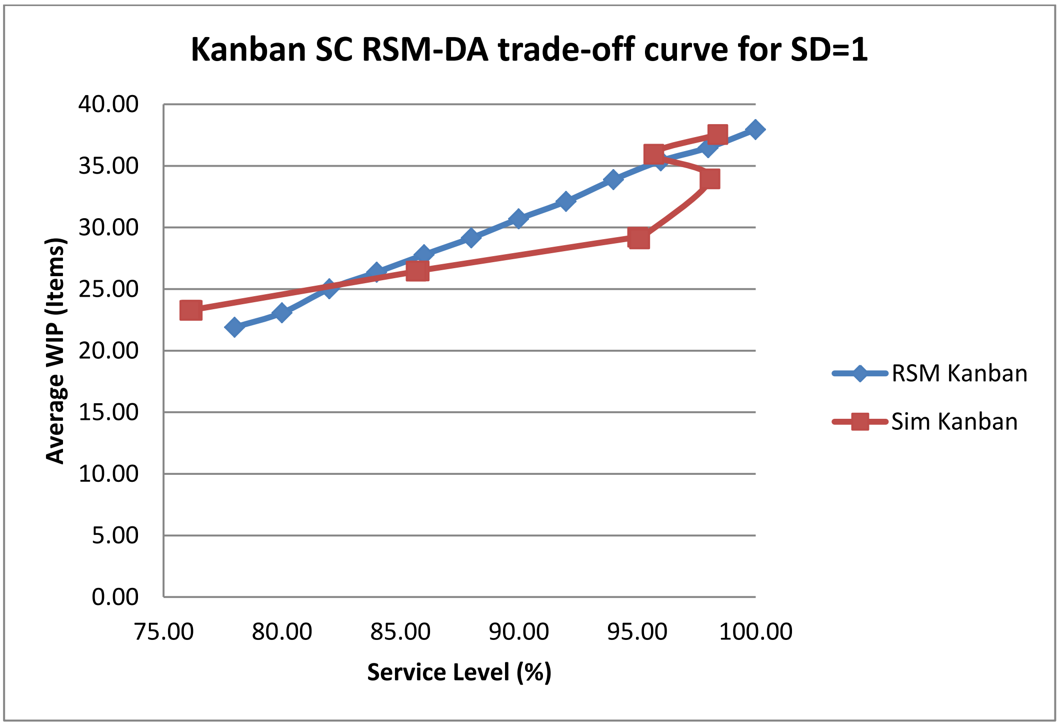


Figure E-3: Kanban SC RSM-DA trade-off curve for SD=1

E.4 Kanban SC RSM-DA Optimisation Results at Demand SD = 4.5

Table E-4: Kanban SC RSM-DA and their SIM-RSM-DA results for SD=4.5

S.L. Target	Capacity	Kanban Allocations				Kanban RSM-DA			Kanban SIM-RSM-DA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
82±0.5	23	13	12	14	12	81.9999	41.1182	1.0000	82.2538	41.4312
84±0.5	23	13	12	14	14	83.9999	42.7637	1.0000	85.2385	42.5628
86±0.5	24	12	14	14	16	85.9999	44.3482	0.9817	88.4767	44.6147
88±0.5	22	13	12	13	20	87.9999	45.2177	0.9714	90.5423	45.5521
90±0.5	24	12	13	12	24	89.9998	46.1931	0.9598	92.4213	47.4836
92±0.5	16	14	12	12	26	91.9999	49.9046	0.9142	93.1081	49.8163
94±0.5	22	12	12	15	28	93.9998	51.8461	0.8894	94.5822	51.5930
96±0.5	17	12	12	15	33	95.9998	55.1815	0.8452	95.9538	55.2601
98±0.5	16	12	12	16	38	97.9998	60.3810	0.7711	96.8903	59.6795

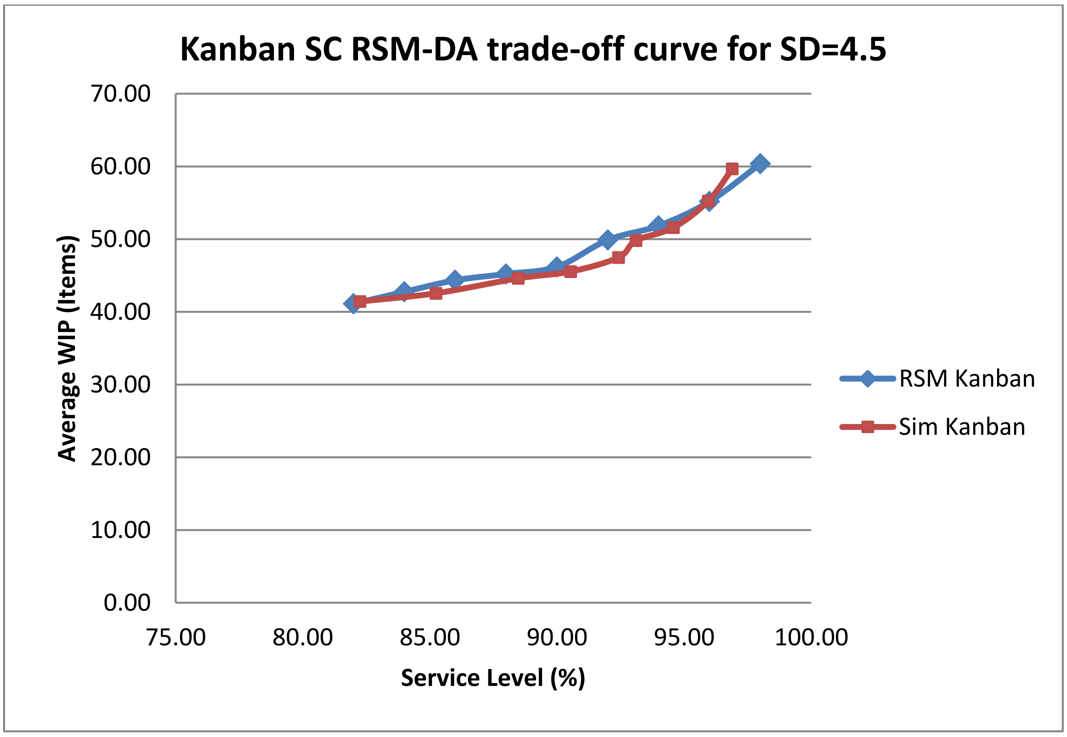


Figure E-4: Kanban SC RSM-DA trade-off curve for SD=4.5

E.5 Kanban SC RSM-DA Optimisation Results at Demand SD = 8

Table E-5: Kanban SC RSM-DA and their SIM-RSM-DA results for SD=8

S.L. Target	Capacity	Kanban Allocations				Kanban RSM-DA			Kanban SIM-RSM-DA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
84±0.5	17	13	15	12	28	83.9999	54.4996	1.0000	83.5410	54.4466
86±0.5	22	13	13	18	28	85.9998	55.2907	0.9952	86.0113	58.2085
88±0.5	23	12	14	19	33	87.9999	58.4008	0.9752	87.8853	60.7843
90±0.5	22	12	12	17	47	89.9998	65.6535	0.9269	90.3731	67.0539
92±0.5	23	12	16	18	50	91.9998	72.4181	0.8796	92.1224	73.2176
94±0.5	22	12	13	17	64	93.9998	81.6343	0.8105	93.8217	80.6036
96±0.5	22	13	13	19	74	95.9998	93.0951	0.7155	95.8970	94.4936
98±0.5	18	14	14	16	93	97.9998	114.2083	0.4948	97.4698	113.3928

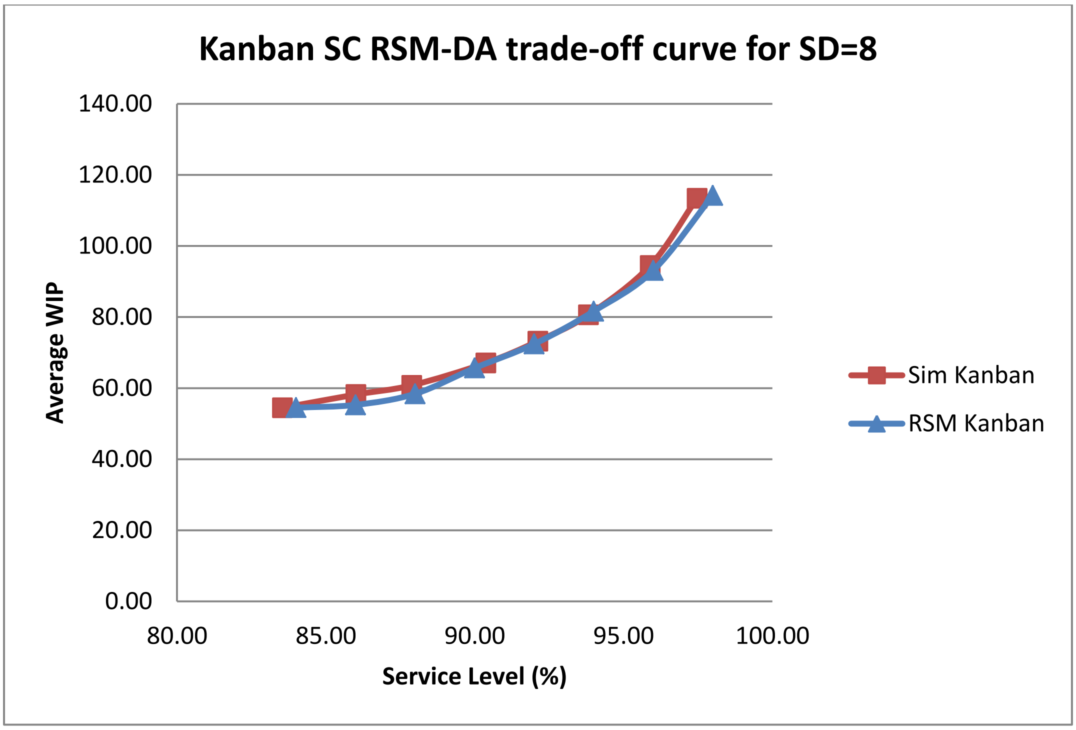


Figure E-5: Kanban SC RSM-DA trade-off curve for SD=8

E.6 Hybrid Kanban-CONWIP SC RSM-DA Optimisation Results at Demand SD = 1

Table E-6: Hybrid Kanban-CONWIP SC RSM-DA and their SIM-RSM-DA results for SD=1

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid RSM-DA			Hybrid SIM-RSM-DA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
78±0.5	10	22	10	22	19	78.0000	22.0531	0.9986	77.7966	21.9995
80±0.5	9	23	9	23	20	79.9999	22.6847	0.9841	80.3567	22.9837
82±0.5	9	24	9	24	13	81.9999	23.5148	0.9524	83.3774	23.7719
84±0.5	8	24	8	24	20	83.9998	24.1525	0.9496	83.9433	23.9922
86±0.5	10	25	10	25	19	85.9998	25.0368	0.9282	86.2116	24.9962
88±0.5	9	26	9	26	19	87.9998	25.8887	0.9071	89.0621	25.9285
90±0.5	9	27	9	27	18	89.9999	26.7907	0.8843	91.1643	26.8944
92±0.5	9	28	9	28	13	91.9999	27.7849	0.8583	93.2989	27.8523
94±0.5	9	29	9	29	13	93.9998	28.8735	0.8290	95.2479	28.8009
96±0.5	8	30	8	30	13	95.9998	30.0449	0.7963	96.3337	29.9443
98±0.5	8	32	8	32	12	97.9999	31.4661	0.7546	98.3212	31.6284
100	9	34	9	34	13	99.9998	33.3927	0.6942	99.7053	33.5126

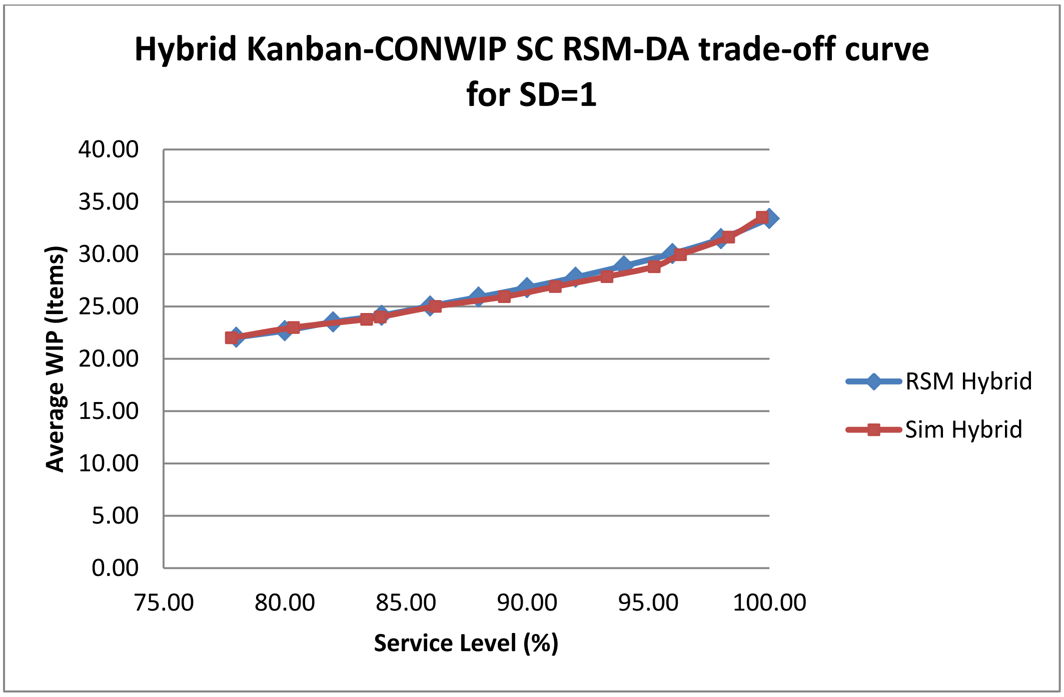


Figure E-6: Hybrid Kanban-CONWIP SC RSM-DA trade-off curve for SD=1

E.7 Hybrid Kanban-CONWIP SC RSM-DA Optimisation Results at Demand SD = 4.5

Table E-7: Hybrid Kanban-CONWIP SC RSM-DA and their SIM-RSM-DA results for SD=4.5

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid RSM-DA			Hybrid SIM-RSM-DA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
82±0.5	24	32	13	17	19	82.0001	28.8935	1.0000	82.0879	31.2664
84±0.5	23	33	18	19	15	83.9998	31.9100	0.9810	83.8494	32.7779
86±0.5	23	35	16	19	19	85.9998	33.6266	0.9607	85.9906	34.5439
88±0.5	23	37	19	19	19	87.9999	35.6629	0.9361	87.8800	36.6794
90±0.5	23	43	12	19	18	89.9998	38.9851	0.8944	90.7202	39.9563
92±0.5	22	43	17	19	18	91.9998	42.2241	0.8518	92.3739	42.2356
94±0.5	8	52	12	16	16	93.9998	45.7456	0.8029	94.1141	46.0188
96±0.5	9	58	12	15	15	95.9998	49.2980	0.7504	95.4601	50.5322
98±0.5	16	59	16	19	19	97.9998	56.4508	0.6316	97.5741	57.5172

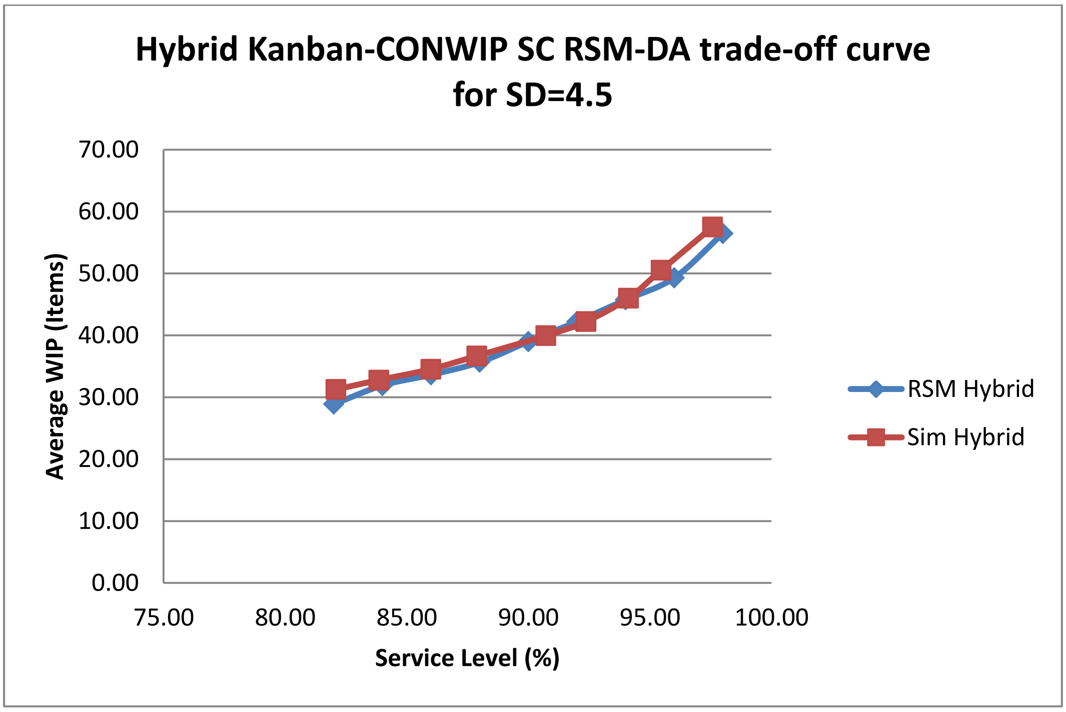


Figure E-7: Hybrid Kanban-CONWIP SC RSM-DA trade-off curve for SD=4.5

E.8 Hybrid Kanban-CONWIP SC RSM-DA Optimisation Results at Demand SD = 8

Table E-8: Hybrid SC RSM-DA and their SIM-RSM-DA results for SD=8

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid RSM-DA			Hybrid SIM-RSM-DA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
84±0.5	8	50	18	17	18	84.0001	41.3088	1.0000	83.4530	44.1255
86±0.5	24	51	16	17	17	85.9998	46.5160	0.9857	85.9919	48.8312
88±0.5	22	57	15	18	19	87.9998	51.6770	0.9538	88.2653	53.5887
90±0.5	20	61	17	18	19	89.9998	58.1706	0.9121	90.0335	58.0909
92±0.5	18	70	16	19	19	91.9998	65.7424	0.8608	92.1752	65.5702
94±0.5	23	80	16	16	19	93.9998	74.2016	0.7998	94.0773	74.6672
96±0.5	24	93	16	16	20	95.9998	85.5283	0.7957	95.6998	86.3500
98±0.5	21	103	16	19	19	97.9998	98.2617	0.5926	96.8361	95.4736

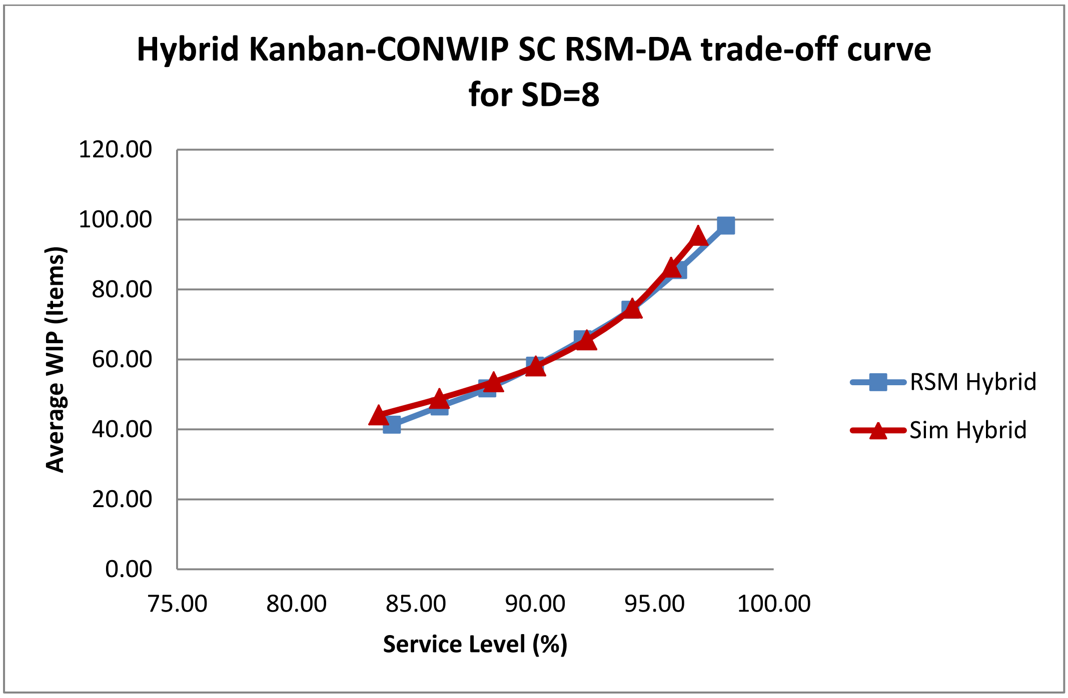


Figure E-8: Hybrid Kanban-CONWIP SC RSM-DA trade-off curve for SD=8

APPENDIX F GP-DA OPTIMISATION RESULTS

F.1 CONWIP SC GP-DA Optimisation Results at Demand SD = 4.5

Table F-1: CONWIP SC GP-DA and their SIM-GP-DA results for SD=4.5

S.L. Target	Node Capacity	WIP-Cap	CONWIP GP-DA			CONWIP SIM-GP-DA	
			Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
82±0.5	9	33	82.4617	30.8528	0.9836	82.4247	31.1180
84±0.5	8	34	83.9202	31.7963	0.9760	83.6978	31.9466
86±0.5	8	36	85.9981	32.9902	0.9578	85.6467	33.6014
88±0.5	8	39	88.0063	34.9998	0.9353	87.8302	35.7043
90±0.5	9	42	90.0014	37.7394	0.9083	89.8585	38.3592
92±0.5	10	43	91.9975	40.8405	0.8691	91.7845	41.0634
94±0.5	10	47	94.0063	44.4352	0.8203	93.7856	44.6852
96±0.5	24	50	95.9932	49.4294	0.7516	95.7423	49.7450
98±0.5	23	59	98.0060	57.9826	0.6267	97.8058	58.4253

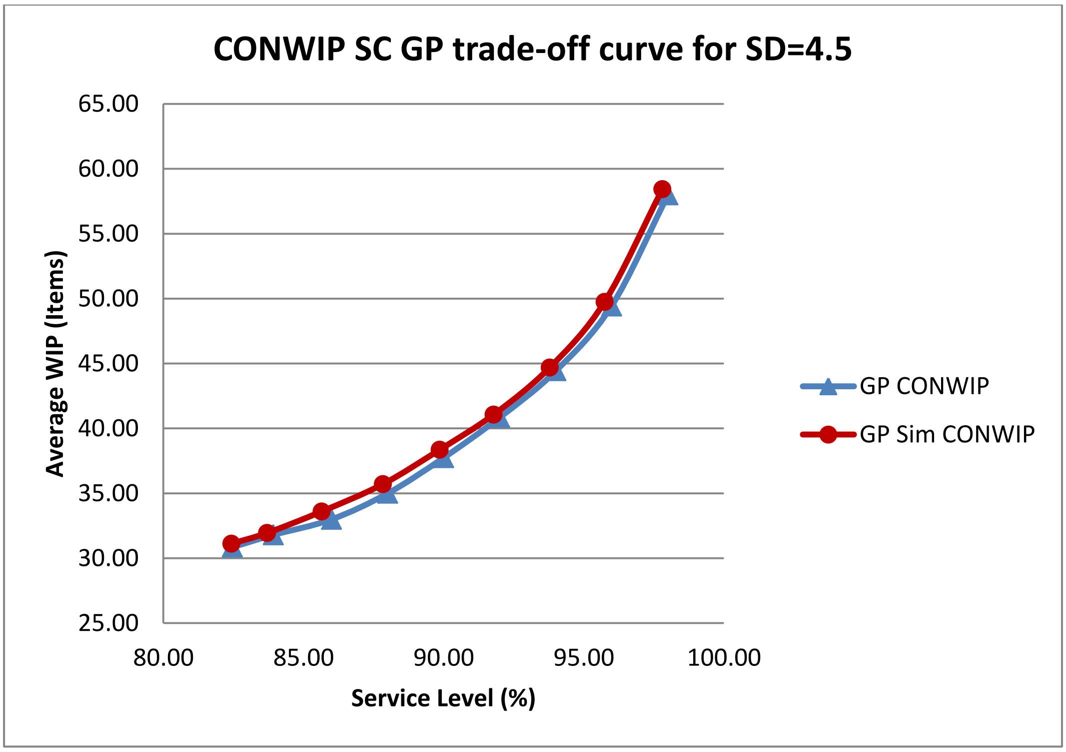


Figure F-1: CONWIP SC GP trade-off curve for SD=4.5

F.2 CONWIP SC GP-DA Optimisation Results at Demand SD = 8

Table F-2: CONWIP SC GP-DA and their SIM-GP-DA results for SD=8

S.L. Target	Node Capacity	WIP-Cap	CONWIP GP-DA			CONWIP SIM-GP-DA	
			Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
84±0.5	9	50	84.0090	45.4268	0.9565	83.9901	44.2228
86±0.5	19	49	85.9946	47.5816	0.9431	85.8202	47.9664
88±0.5	19	54	88.0095	52.3067	0.9115	88.0289	52.7726
90±0.5	19	60	90.0010	57.7436	0.8749	89.9830	58.5320
92±0.5	22	66	91.9835	64.6475	0.8236	91.9297	64.8130
94±0.5	21	74	93.9900	72.4677	0.7659	93.9544	72.4002
96±0.5	21	87	95.9823	84.9208	0.6650	95.9133	85.1361
98±0.5	21	111	97.9810	108.5586	0.4333	98.2048	108.6001

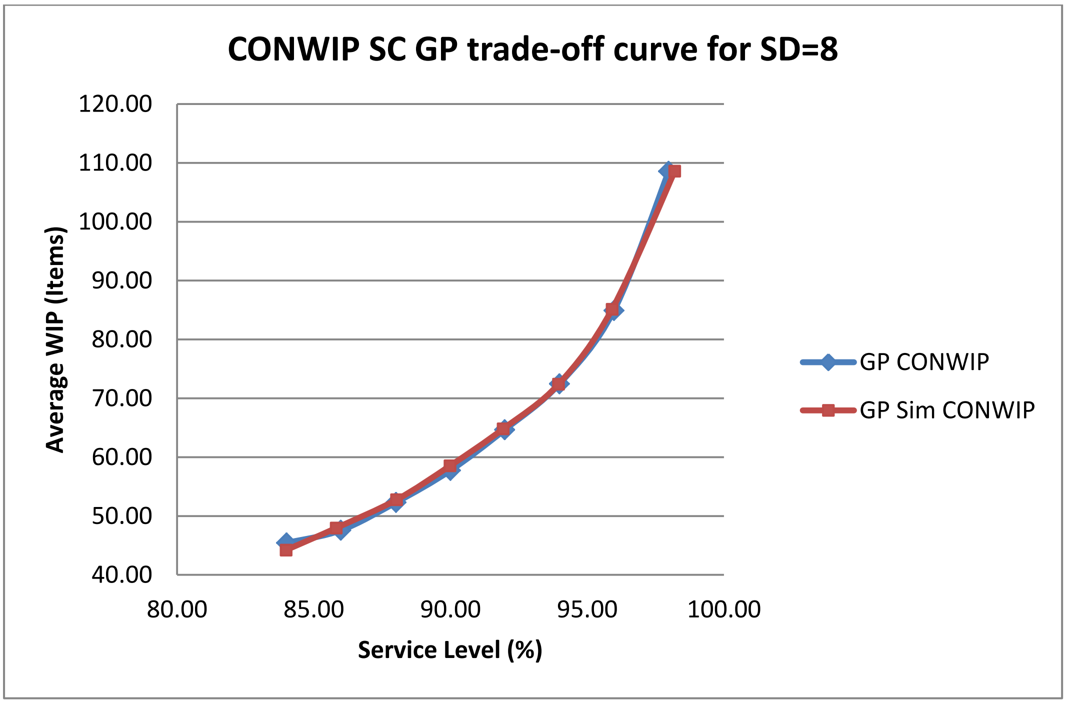


Figure F-2: CONWIP SC GP trade-off curve for SD=8

F.3 Kanban SC GP-DA Optimisation Results at Demand SD = 1

Table F-3: Kanban SC GP-DA and their SIM-GP-DA results for SD=1

S.L. Target	Capacity	Kanban Allocations				Kanban GP-DA			Kanban SIM-GP-DA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
78±0.5	8	8	14	15	20	77.9878	20.4400	0.9967	76.2125	22.0448
80±0.5	10	8	15	14	14	80.0160	21.5723	0.9940	76.1865	22.2993
82±0.5	13	8	15	12	19	82.0297	22.0130	0.9870	76.1822	22.6207
84±0.5	12	9	15	14	20	84.0025	23.2254	0.9760	85.7776	25.8015
86±0.5	12	9	14	13	19	86.0159	23.6953	0.9664	85.7134	25.7969
88±0.5	10	9	10	12	16	88.0019	25.0259	0.9465	85.6571	25.4744
90±0.5	9	10	10	12	9	90.0093	25.7079	0.9345	94.3613	28.4472
92±0.5	14	10	10	12	9	91.9806	26.8927	0.9122	94.4159	28.4694
94±0.5	9	10	14	13	10	93.9630	28.1323	0.8837	95.0876	29.1553
96±0.5	9	10	13	13	11	95.9626	29.3520	0.8621	95.1528	29.1001
98±0.5	17	11	13	12	9	98.0142	31.5452	0.8298	98.0786	33.9575
100	14	12	12	13	10	99.9708	33.8193	0.7812	99.4157	38.3052

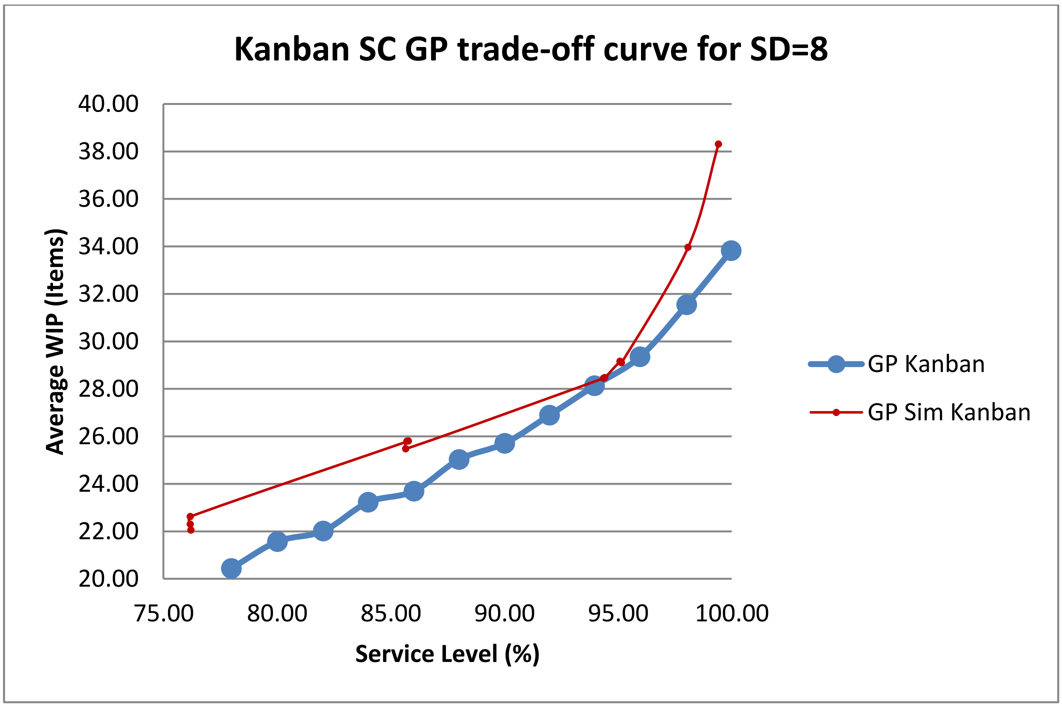


Figure F-3: Kanban SC GP trade-off curve for SD=8

F.4 Kanban SC GP-DA Optimisation Results at Demand SD = 4.5

Table F-4: Kanban SC GP-DA and their SIM-GP-DA results for SD=4.5

S.L. Target	Capacity	Kanban Allocations				Kanban GP-DA			Kanban SIM-GP-DA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
82±0.5	24	12	12	12	12	83.1773	37.8774	0.0000	81.6399	38.7883
84±0.5	20	12	13	13	13	84.0005	41.6552	0.9943	83.9935	41.1317
86±0.5	17	13	12	15	14	85.9910	43.7360	0.9778	86.0394	43.4408
88±0.5	22	14	13	13	16	88.0004	45.4004	0.9597	88.0693	45.5743
90±0.5	8	14	12	13	20	90.0001	46.6020	0.9459	89.8091	46.1536
92±0.5	16	12	13	16	20	91.9941	48.1305	0.9277	92.0172	47.7669
94±0.5	13	12	13	15	25	93.9814	49.6991	0.9088	93.9752	50.1174
96±0.5	17	12	12	15	31	95.9801	53.5258	0.8587	95.5691	53.7741
98±0.5	20	12	13	19	37	97.9855	61.9585	0.7492	97.2518	62.2753

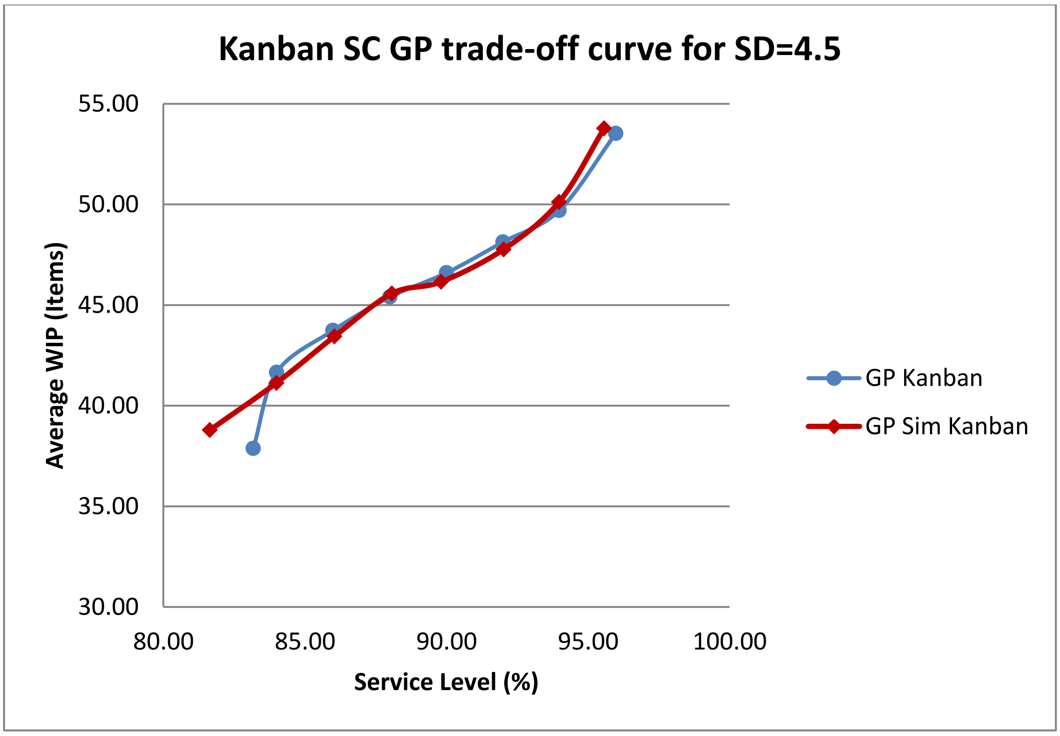


Figure F-4: Kanban SC GP trade-off curve for SD=4.5

F.5 Kanban SC GP-DA Optimisation Results at Demand SD = 8

Table F-5: Kanban SC GP-DA and their SIM-GP-DA results for SD=8

S.L. Target	Capacity	Kanban Allocations				Kanban GP-DA			Kanban SIM-GP-DA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
84±0.5	11	13	13	12	29	84.0046	52.6104	0.9765	84.0831	52.8191
86±0.5	23	12	13	13	31	86.0000	54.1456	0.9681	85.7521	54.2417
88±0.5	21	12	12	17	34	88.0205	58.9606	0.9377	87.8948	58.5283
90±0.5	21	12	13	14	44	90.0057	63.7317	0.9126	90.0224	63.9037
92±0.5	12	12	14	13	53	91.9770	70.2538	0.8694	91.7519	69.7868
94±0.5	15	13	15	16	59	93.9988	80.4318	0.8076	93.9631	81.6987
96±0.5	18	15	16	18	64	95.8726	93.7945	0.5317	95.7999	94.6957
98±0.5	19	14	15	16	103	97.9580	123.8226	0.4626	97.8591	124.3564

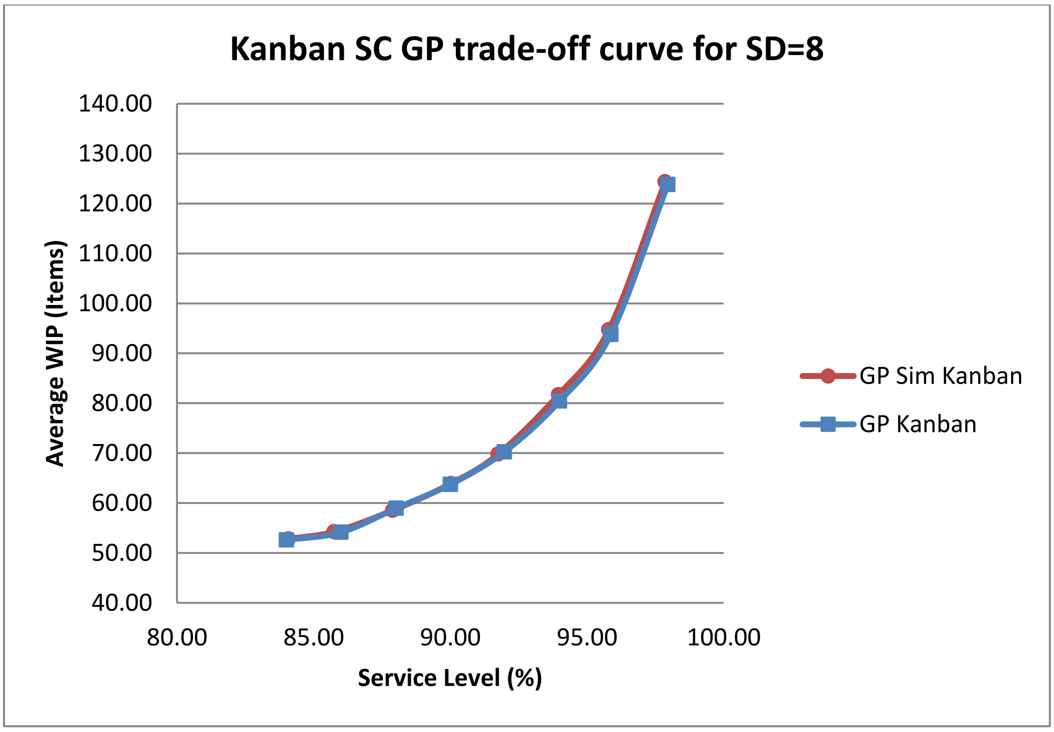


Figure F-5: Kanban SC GP trade-off curve for SD=8

F.6 Hybrid Kanban-CONWIP SC GP-DA Optimisation Results at Demand SD = 1

Table F-6: Hybrid Kanban-CONWIP SC GP-DA and their SIM-GP-DA results for SD=1

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid GP-DA			Hybrid SIM-GP-DA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
78±0.5	16	22	16	14	20	78.0052	22.0824	0.9888	77.5756	22.0000
80±0.5	18	23	13	13	20	79.9842	22.7126	0.9722	80.4557	22.8768
82±0.5	20	23	15	17	20	81.9914	23.3955	0.9572	80.6712	23.0000
84±0.5	17	24	16	13	19	83.9881	24.0211	0.9413	83.6651	24.0000
86±0.5	20	25	13	15	18	86.0126	24.7123	0.9238	86.4637	24.9997
88±0.5	23	25	16	18	19	87.9997	25.4543	0.9059	86.5110	25.0000
90±0.5	18	26	13	15	18	90.0038	26.2421	0.8851	89.1825	25.9990
92±0.5	22	27	16	16	20	91.9927	27.0475	0.8633	91.5512	27.0000
94±0.5	20	28	18	14	20	93.9844	28.0088	0.8356	93.7204	28.0000
96±0.5	20	29	18	13	19	95.9933	29.2214	0.7376	95.4899	29.0000
98±0.5	15	31	17	18	20	97.9956	30.8510	0.7559	97.9660	30.9993
100	9	35	19	18	20	99.8832	34.5452	0.6422	99.7396	34.4748

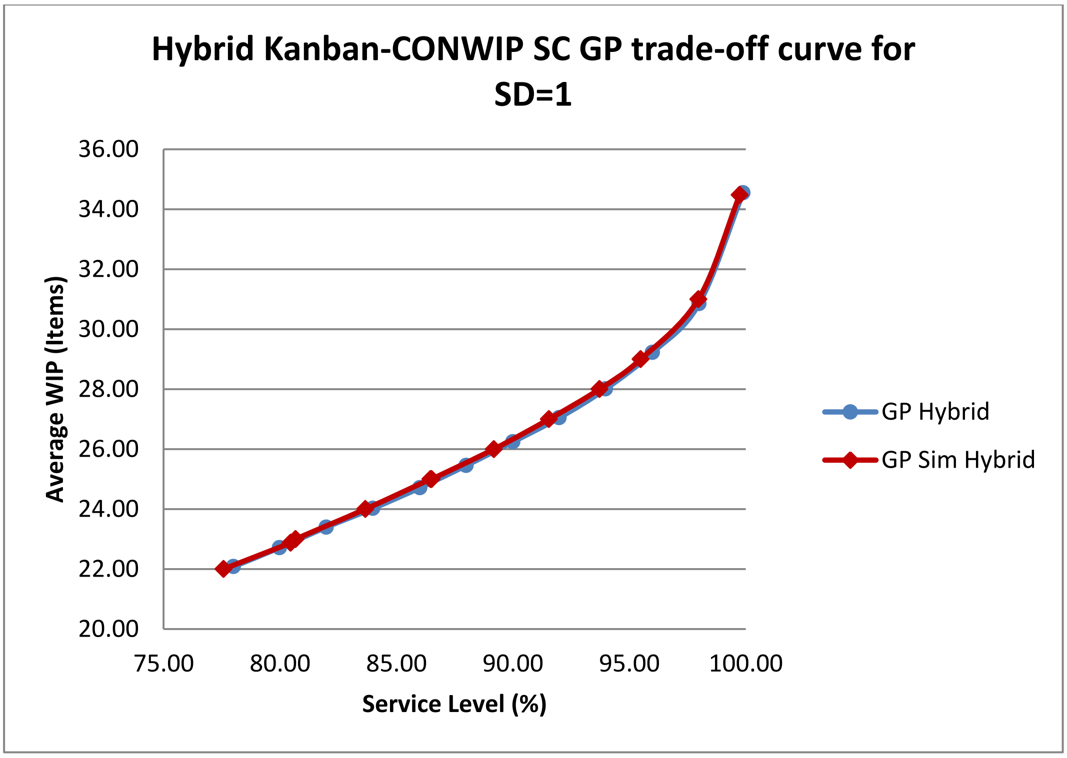


Figure F-6: Hybrid Kanban-CONWIP SC GP trade-off curve for SD=1

F.7 Hybrid Kanban-CONWIP SC GP-DA Optimisation Results at Demand SD = 4.5

Table F-7: Hybrid Kanban-CONWIP SC GP-DA and their SIM-GP-DA results for SD=4.5

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid GP-DA			Hybrid SIM-GP-DA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
82±0.5	10	32	15	13	17	82.0164	30.6611	0.9870	81.9949	31.0567
84±0.5	10	34	17	13	18	84.0000	32.4613	0.9713	84.0203	32.8989
86±0.5	8	37	19	13	15	86.0185	33.7790	0.9514	86.1559	34.3189
88±0.5	9	39	17	16	19	87.9774	36.0282	0.9241	87.9053	36.0089
90±0.5	9	42	20	16	20	89.9841	37.9575	0.9031	89.7435	38.1234
92±0.5	10	43	19	20	20	92.0081	41.0026	0.8670	91.7160	41.0360
94±0.5	23	49	12	16	14	93.9874	44.4858	0.8213	93.5378	44.6044
96±0.5	24	54	14	15	19	96.0151	50.1543	0.7445	96.0254	51.1048
98±0.5	23	64	13	19	18	97.9637	59.1210	0.5876	97.7397	59.3124

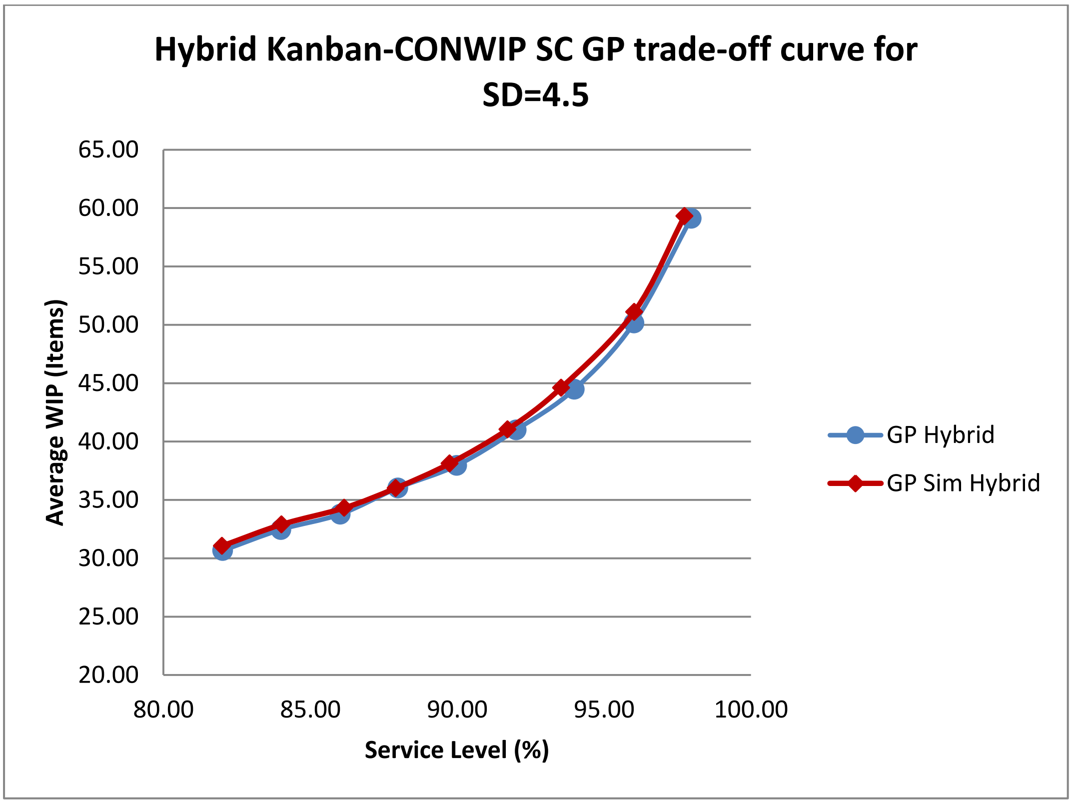


Figure F-7: Hybrid Kanban-CONWIP SC GP trade-off curve for SD=4.5

F.8 Hybrid Kanban-CONWIP SC GP-DA Optimisation Results at Demand SD = 8

Table F-8: Hybrid Kanban-CONWIP SC GP-DA and their SIM-GP-DA results for SD=8

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid GP-DA			Hybrid SIM-GP-DA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Desirability	Actual Service Level	Actual Average WIP
84±0.5	11	50	13	14	18	84.0118	43.4876	0.9713	84.1420	45.4131
86±0.5	8	56	17	12	16	86.0073	47.8898	0.9466	86.0439	48.6166
88±0.5	10	58	16	19	18	88.0103	52.2953	0.9208	88.2071	53.3941
90±0.5	9	69	15	18	20	90.0251	57.4404	0.8859	89.8185	58.0893
92±0.5	8	78	14	18	17	91.9800	64.9753	0.8405	91.5965	65.6146
94±0.5	23	84	14	19	18	94.0037	75.4566	0.8470	94.0106	75.5528
96±0.5	22	94	19	18	18	95.9535	88.5708	0.6695	95.8962	89.3552
98±0.5	21	123	19	19	19	97.7767	113.3916	0.2334	97.9600	117.1045

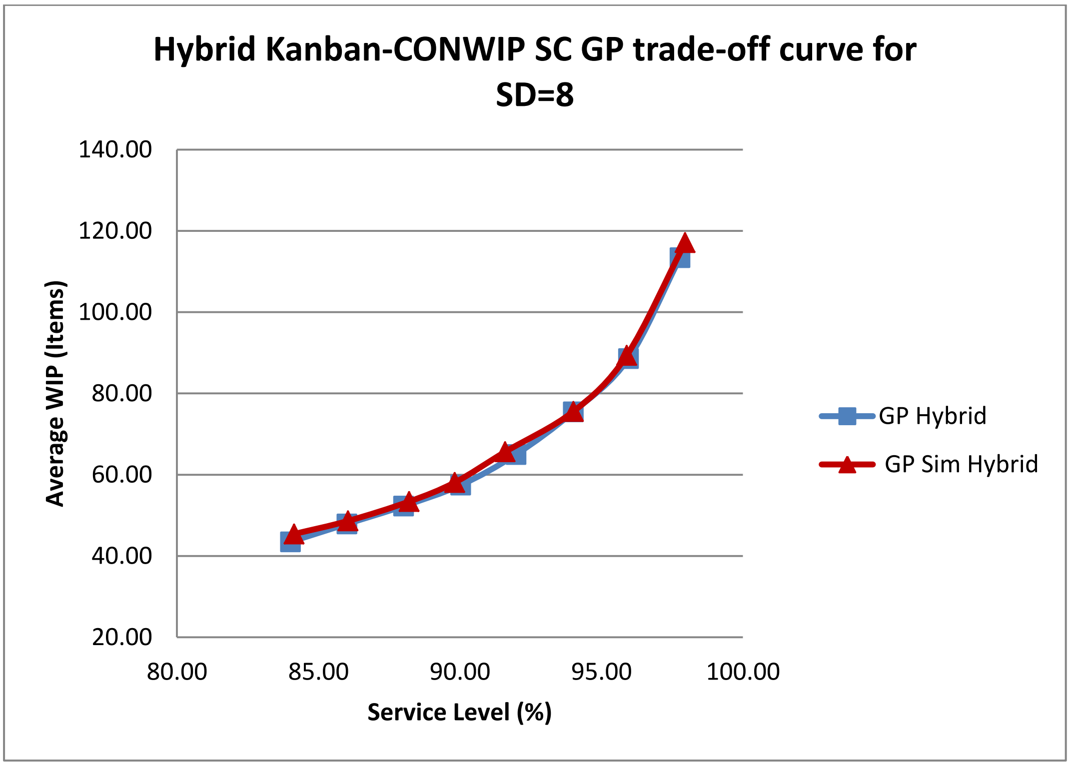


Figure F-8: Hybrid Kanban-CONWIP SC GP trade-off curve for SD=8

APPENDIX G RSM-POGA OPTIMISATION RESULTS

G.1 CONWIP SC RSM-POGA Optimisation Results at Demand SD = 4.5

Table G-1: CONWIP SC RSM-POGA and their SIM-RSM-POGA results for SD=4.5

S.L. Target	Node Capacity	WIP-Cap	CONWIP RSM-POGA		CONWIP SIM-RSM-POGA	
			Service Level	Average WIP	Actual Service Level	Actual Average WIP
82±0.5	8	33	81.98229	30.6145	82.3451	31.1226
84±0.5	9	35	84.0272	32.96811	84.4846	32.7705
86±0.5	8	38	86.11107	34.65183	87.0847	35.1865
88±0.5	9	40	87.90415	37.0705	88.6177	36.7909
90±0.5	8	44	90.23454	39.49663	90.8764	39.8590
92±0.5	8	47	91.95628	41.91903	92.2333	42.1794
94±0.5	8	51	93.89937	45.14889	93.5975	45.1977
96±0.5	8	57	96.05847	49.99369	95.3449	49.7990
98±0.5	15	58	97.95377	56.39362	97.5088	56.6950

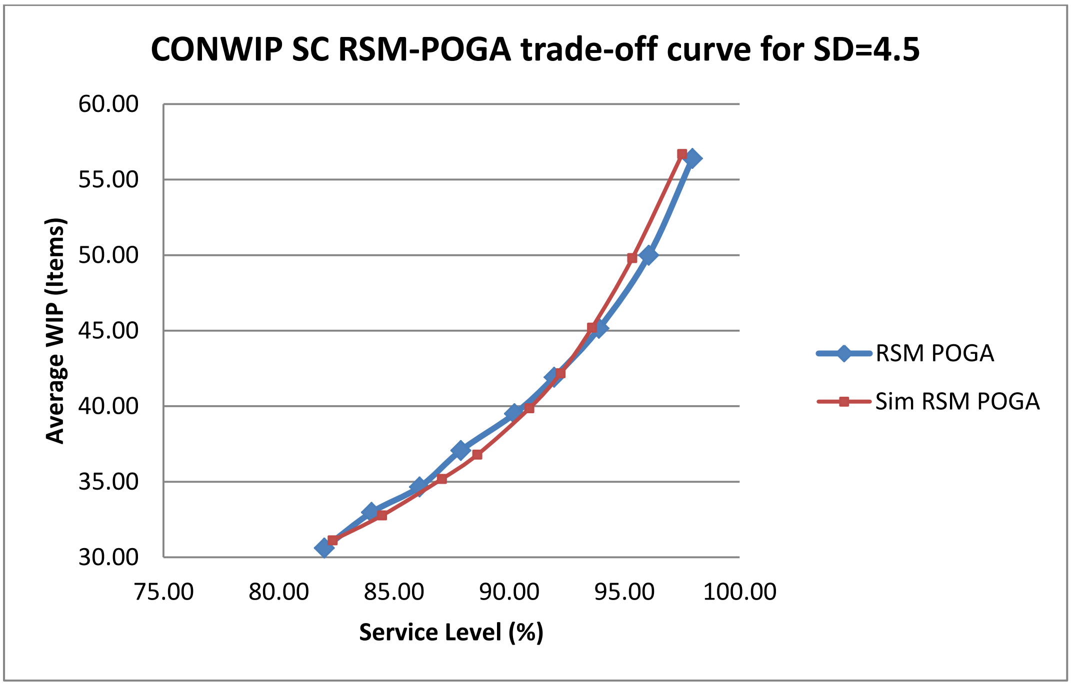


Figure G-1: CONWIP SC RSM-POGA trade-off curve for SD=4.5

G.2 CONWIP SC RSM-POGA Optimisation Results at Demand SD = 8

Table G-2: CONWIP SC RSM-POGA and their SIM-RSM-POGA results for SD=8

S.L. Target	Node Capacity	WIP-Cap	CONWIP RSM-POGA		CONWIP SIM-RSM-POGA	
			Service Level	Average WIP	Actual Service Level	Actual Average WIP
84±0.5	8	53	84.18892	45.56488	84.4750	46.3467
86±0.5	8	58	86.01788	49.4205	86.4628	50.0878
88±0.5	8	64	87.99857	54.04725	88.4907	54.4755
90±0.5	8	71	90.01424	59.44511	89.5977	59.4160
92±0.5	8	79	91.92866	65.61411	91.8223	65.6258
94±0.5	9	88	94.00319	74.67561	93.0113	72.3794
96±0.5	16	88	95.98868	84.94571	95.9219	85.0509
98±0.5	21	103	98.00143	101.8327	97.3881	100.7748

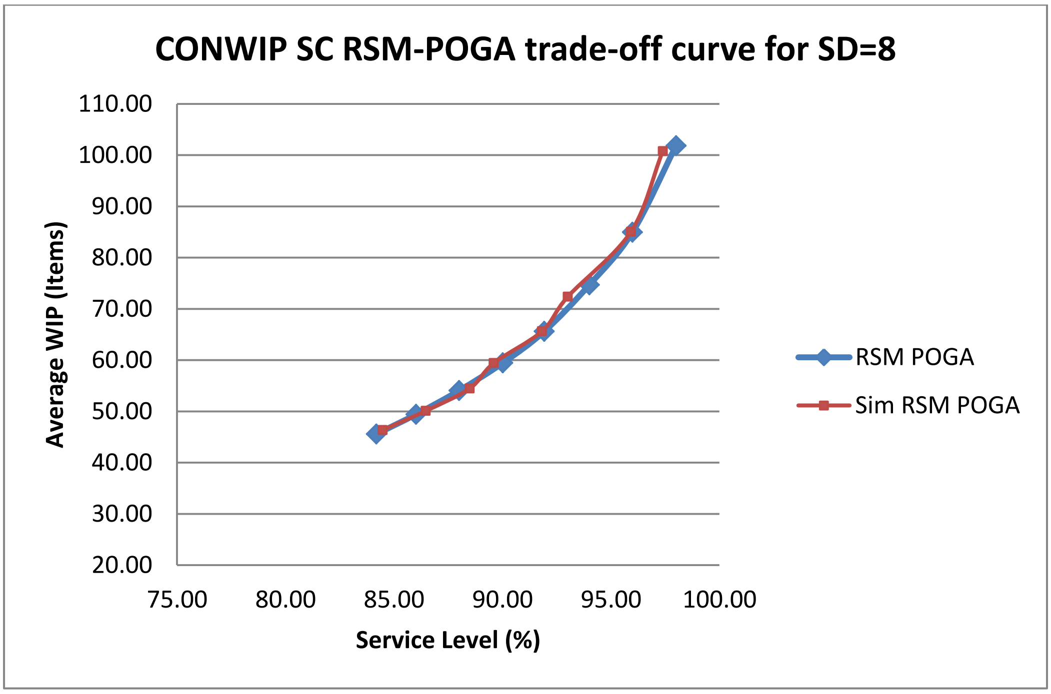


Figure G-2: CONWIP SC RSM-POGA trade-off curve for SD=8

G.3 Kanban SC RSM-POGA Optimisation Results at Demand SD = 1

Table G-3: Kanban SC RSM-POGA and their SIM-RSM-POGA results for SD=1

S.L. Target	Capacity	Kanban Allocations				Kanban RSM-POGA		Kanban SIM-RSM-POGA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Actual Service Level	Actual Average WIP
78±0.5	8	8	10	11	20	77.899671	21.631949	76.162081	22.044256
80±0.5	8	8	11	11	19	80.108747	23.353434	76.188159	22.041048
82±0.5	8	8	12	12	13	81.995645	24.567167	76.212451	22.042654
84±0.5	8	9	10	12	13	83.877838	26.648886	85.733595	24.92129
86±0.5	8	9	11	12	12	85.869647	27.806867	85.729986	24.926562
88±0.5	8	9	12	12	14	87.955285	29.128214	85.664049	24.922602
90±0.5	8	10	12	14	9	89.96847	31.018076	95.050492	29.272772
92±0.5	8	10	12	13	11	91.92112	32.085052	95.163858	29.056268
94±0.5	8	11	12	13	9	94.278233	33.937893	97.867149	33.939236
96±0.5	8	11	13	14	9	96.026213	34.960927	97.902287	35.911374
98±0.5	8	12	13	13	8	97.916537	36.327121	95.526562	35.88674
100	8	13	13	13	8	100.06341	38.006514	95.5291	36.88556

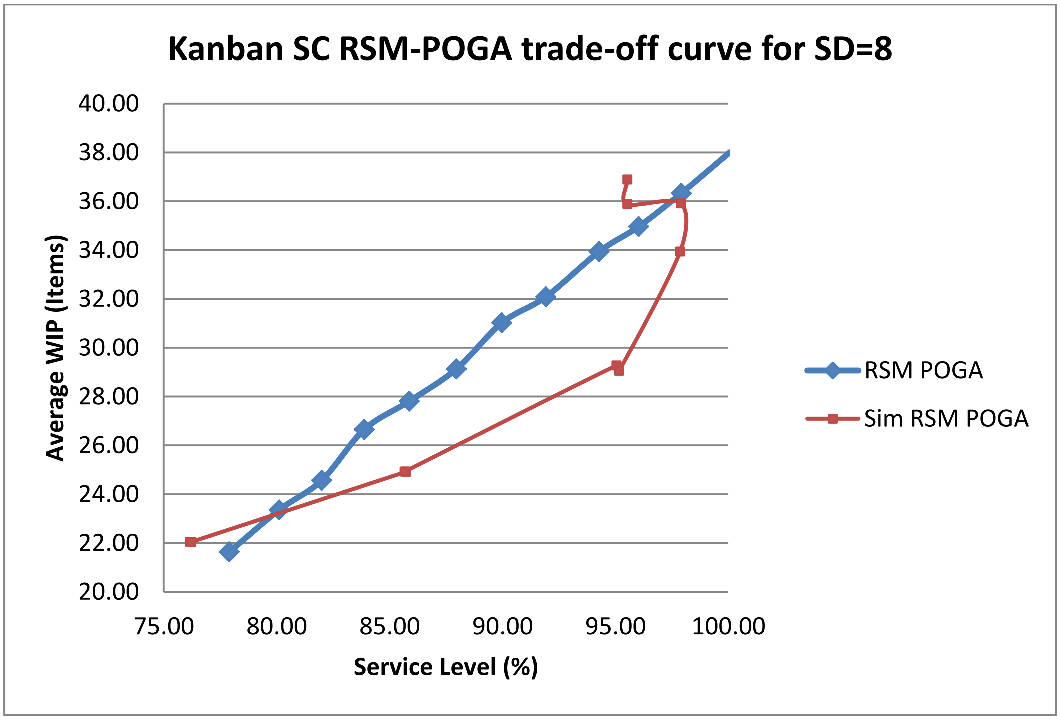


Figure G-3: Kanban SC RSM-POGA trade-off curve for SD=8

G.4 Kanban SC RSM-POGA Optimisation Results at Demand SD = 4.5

Table G-4: Kanban SC RSM-POGA and their SIM-RSM-POGA results for SD=4.5

S.L. Target	Capacity	Kanban Allocations				Kanban RSM-DA		Kanban SIM-RSM-POGA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Actual Service Level	Actual Average WIP
82±0.5	22	13	13	13	14	83.632011	43.063431	85.633131	43.23359
84±0.5	23	13	13	13	17	86.055872	44.639619	88.93822	45.223906
86±0.5	21	13	13	13	19	87.85703	46.587402	90.742141	46.66843
88±0.5	21	13	13	13	22	90.008157	48.56319	92.586051	48.841138
90±0.5	21	13	13	13	25	91.91288	50.585071	94.093727	51.158658
92±0.5	22	13	13	13	29	93.938718	53.138656	95.506794	54.25165
94±0.5	15	13	13	13	33	95.993568	56.514663	96.245924	57.208878
96±0.5	14	13	13	13	40	97.99946	61.230277	97.658544	63.133684
98±0.5	19	13	13	16	40	99.004089	65.029865	97.808113	65.892908

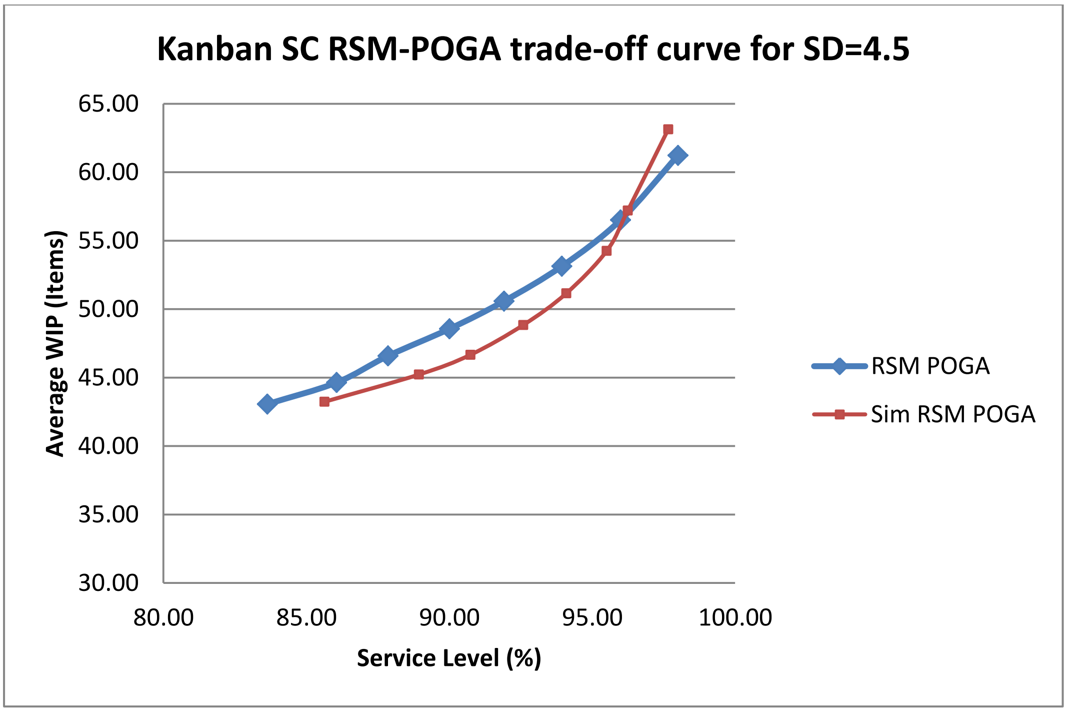


Figure G-4: Kanban SC RSM-POGA trade-off curve for SD=4.5

G.5 Kanban SC RSM-POGA Optimisation Results at Demand SD = 8

Table G-5: Kanban SC RSM-POGA and their SIM-RSM-POGA results for SD=8

S.L. Target	Capacity	Kanban Allocations				Kanban RSM-POGA		Kanban SIM-RSM-POGA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP	Actual Service Level	Actual Average WIP
84±0.5	*	*	*	*	*	*	*	*	*
86±0.5	9	15	15	13	31	85.931982	56.846876	84.190998	58.77055
88±0.5	9	15	13	13	39	87.959005	61.555935	87.228207	62.03233
90±0.5	9	15	13	13	46	89.923289	66.442509	89.171785	66.98788
92±0.5	9	15	13	13	54	91.919838	72.027165	91.294517	72.705748
94±0.5	9	15	13	13	64	94.043003	79.007986	92.749409	79.55632
96±0.5	9	15	13	13	76	96.044436	87.38497	93.799062	88.090618
98±0.5	9	15	13	13	95	97.9944	100.64853	95.332406	102.34901

* No Optimal Solution

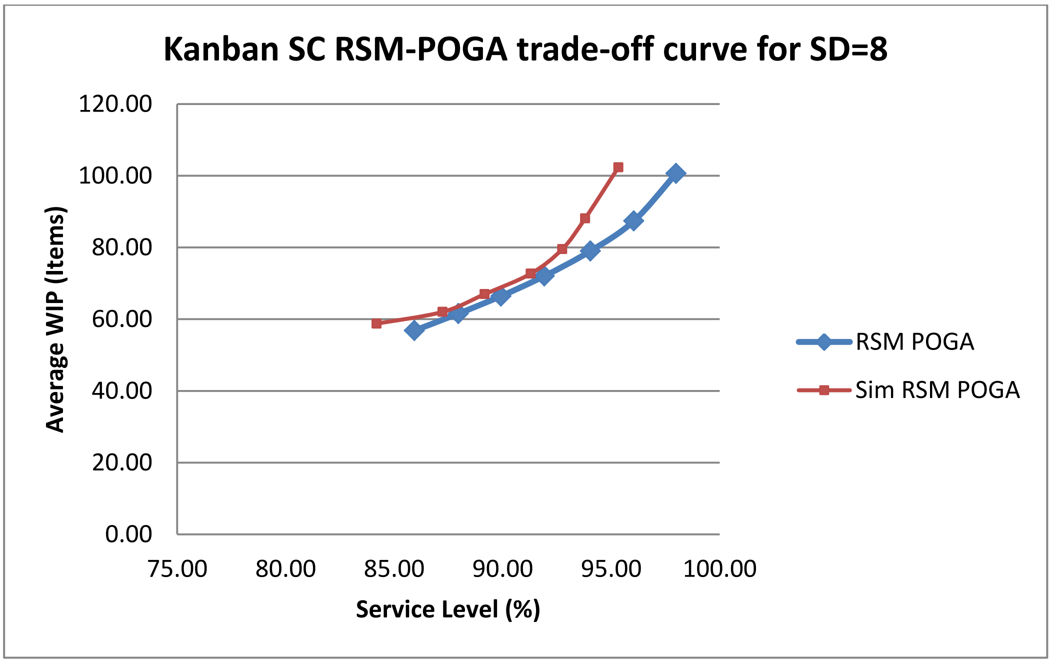


Figure G-5: Kanban SC RSM-POGA trade-off curve for SD=8

G.6 Hybrid Kanban-CONWIP SC RSM-POGA Optimisation Results at Demand SD = 1

Table G-6: Hybrid Kanban-CONWIP SC RSM-POGA and their SIM-RSM-POGA results for SD=1

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid RSM-POGA		Hybrid SIM-RSM-POGA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Actual Service Level	Actual Average WIP
78±0.5	*	*	*	*	*	*	*	*	*
80±0.5	9	23	19	17	17	80.2891	22.8091	80.6368	22.9834
82±0.5	*	*	*	*	*	*	*	*	*
84±0.5	*	*	*	*	*	*	*	*	*
86±0.5	19	25	17	17	17	85.5519	25.0607	86.4909	25.0000
88±0.5	19	26	17	17	17	87.8786	26.0603	89.1350	26.0000
90±0.5	23	27	14	17	17	90.0013	26.9175	91.5474	26.9997
92±0.5	23	28	16	17	17	91.9993	27.9910	93.6441	28.0000
94±0.5	19	29	17	17	17	93.8160	29.0592	95.4461	29.0000
96±0.5	*	*	*	*	*	*	*	*	*
98±0.5	9	32	13	17	17	98.1201	31.6446	98.6392	31.6295
100	9	34	13	17	17	100.1668	33.5908	99.5152	33.5172

* No Optimal Solution

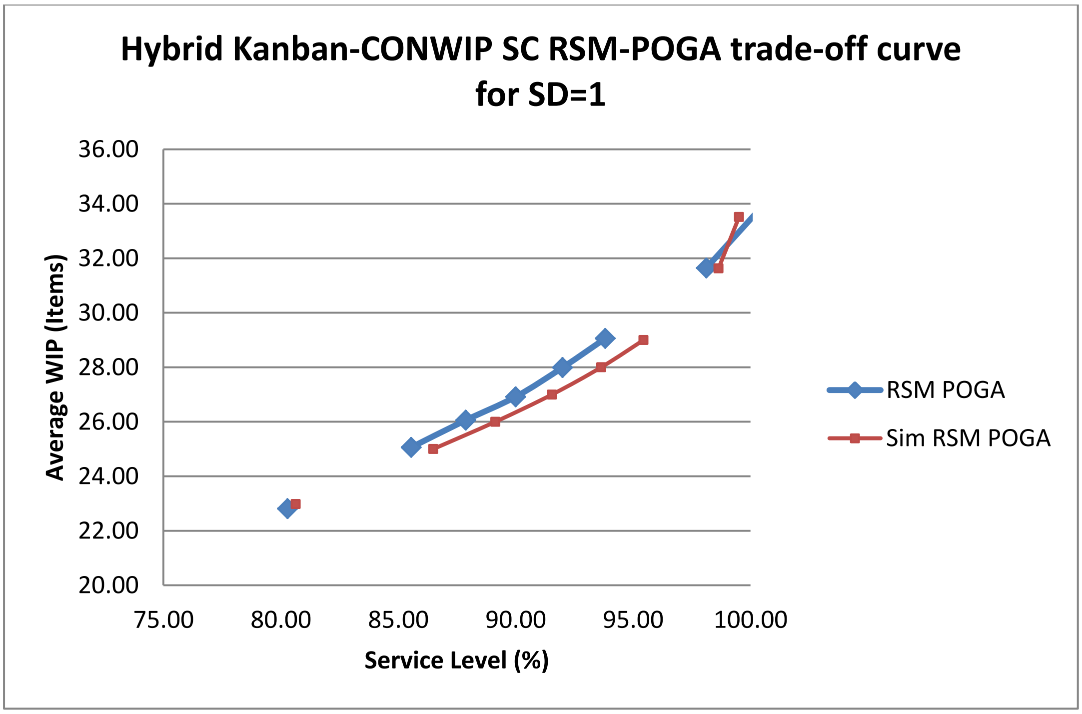


Figure G-6: Hybrid Kanban-CONWIP SC RSM-POGA trade-off curve for SD=1

G.7 Hybrid Kanban-CONWIP SC RSM-POGA Optimisation Results at Demand SD = 4.5

Table G-7: Hybrid Kanban-CONWIP SC RSM-POGA and their SIM-RSM-POGA results for SD=4.5

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid RSM-POGA		Hybrid SIM-RSM-POGA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Actual Service Level	Actual Average WIP
82±0.5	*	*	*	*	*	*	*	*	*
84±0.5	24	32	12	20	20	84.0471	27.0620	81.6767	30.9672
86±0.5	24	34	12	18	18	85.9621	29.7312	84.3276	32.7010
88±0.5	24	37	12	20	20	88.1505	31.9442	86.8008	35.1780
90±0.5	24	39	13	20	20	90.0488	34.7806	88.8980	37.4579
92±0.5	24	42	13	20	20	92.1102	37.7709	90.9293	40.0167
94±0.5	24	46	12	20	17	94.0134	40.6547	92.1511	42.2442
96±0.5	24	50	12	16	16	96.0384	44.3868	93.6611	45.3686
98±0.5	24	54	12	19	19	97.9709	48.4719	94.8056	48.4559

* No Optimal Solution

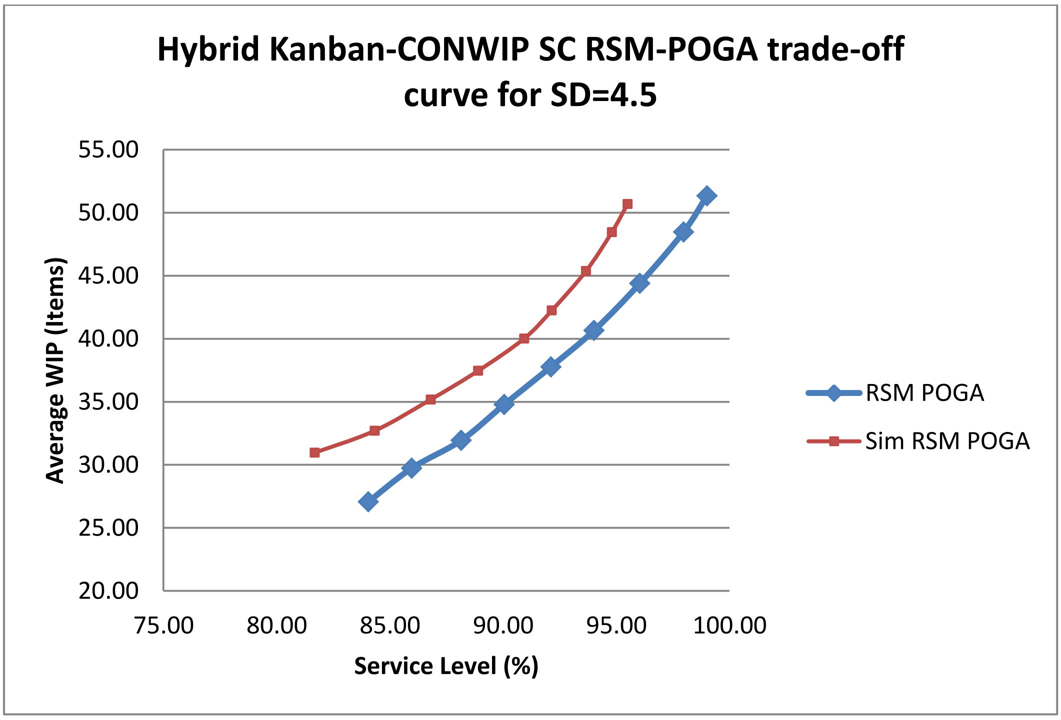


Figure G-7: Hybrid Kanban-CONWIP SC RSM-POGA trade-off curve for SD=4.5

G.8 Hybrid Kanban-CONWIP SC RSM-POGA Optimisation Results at Demand SD = 8

Table G-8: Hybrid Kanban-CONWIP SC RSM-POGA and their SIM-RSM-POGA results for SD=8

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid RSM-POGA		Hybrid SIM-RSM-POGA	
			Node 1	Node 2	Node 3	Service Level	Average WIP	Actual Service Level	Actual Average WIP
84±0.5	8	50	20	20	20	83.83865	33.40626	83.06284	44.0888
86±0.5	8	57	20	20	20	86.01598	40.25269	86.19685	49.34676
88±0.5	24	50	20	20	20	88.28258	43.29668	86.11693	48.74851
90±0.5	24	55	20	20	20	89.85844	49.0271	88.23962	53.46095
92±0.5	24	63	19	20	20	91.92031	58.10694	91.12052	60.72042
94±0.5	24	71	20	19	20	93.99939	67.29201	92.91384	68.37476
96±0.5	22	80	20	20	20	96.00923	77.58712	94.76146	76.90013
98±0.5	24	90	20	20	20	98.00238	89.14004	96.08039	86.4159

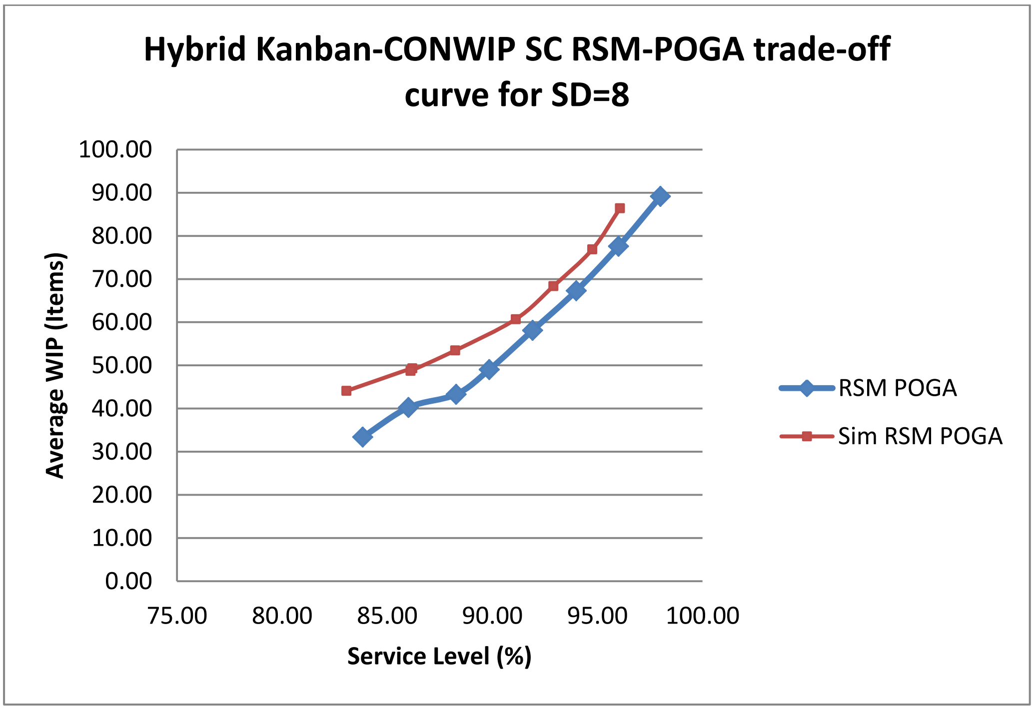


Figure G-8: Hybrid Kanban-CONWIP SC RSM-POGA trade-off curve for SD=8

APPENDIX H SIM-POGA OPTIMISATION RESULTS

H.1 CONWIP SC SIM-POGA Optimisation Results at Demand SD = 4.5

Table H-1: CONWIP SC SIM-POGA results for SD=4.5

S.L. Target	Node Capacity	WIP-Cap	CONWIP SIM-POGA Service Level	CONWIP SIM-POGA Average WIP
82±0.5	32	10	82.1957	31.0508
84±0.5	33	16	83.9012	32.7155
86±0.5	35	12	85.9025	34.2553
88±0.5	39	8	88.0151	36.0168
90±0.5	42	8	89.9566	38.3708
92±0.5	42	22	91.9977	41.7791
94±0.5	46	14	94.0059	45.0887
96±0.5	53	10	95.9814	50.1161
98±0.5	61	12	97.9956	58.9505

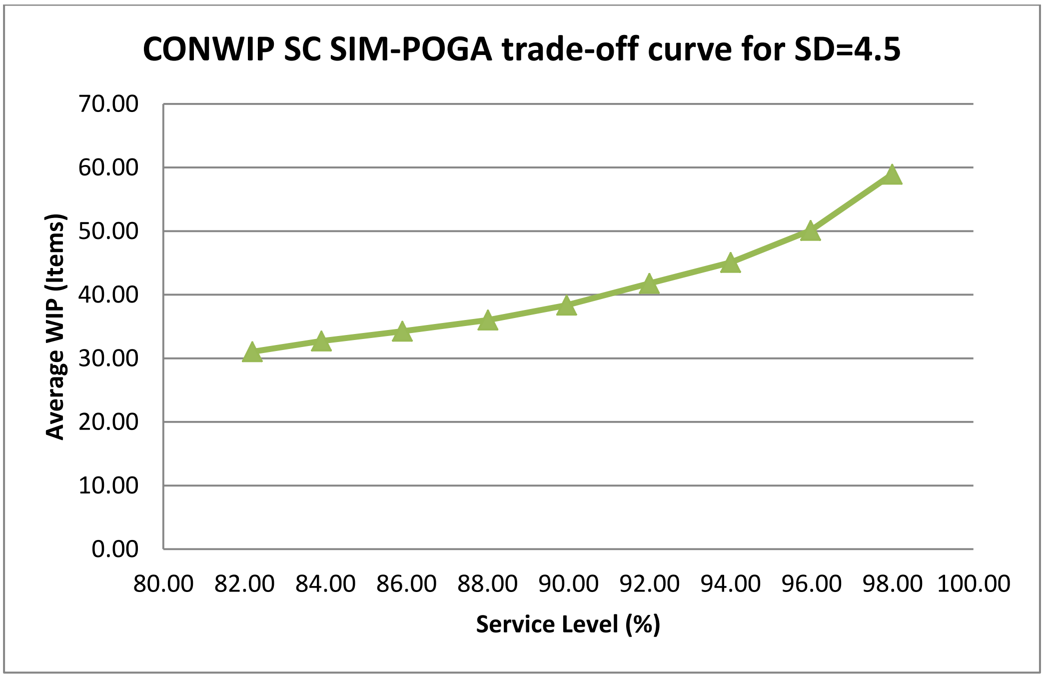


Figure H-1: CONWIP SC SIM-POGA trade-off curve for SD=4.5

H.2 CONWIP SC SIM-POGA Optimisation Results at Demand SD = 8

Table H-2: CONWIP SC SIM-POGA results for SD=8

S.L. Target	Node Capacity	WIP-Cap	CONWIP SIM-POGA Service Level	CONWIP SIM-POGA Average WIP
84±0.5	52	8	84.20153	45.6128
86±0.5	50	19	86.00413	48.89833
88±0.5	55	14	88.04149	52.92739
90±0.5	60	17	90.09375	58.16636
92±0.5	66	18	91.99323	64.31408
94±0.5	75	18	94.00594	72.96069
96±0.5	88	21	96.00413	86.02835
98±0.5	114	21	97.99761	111.5469

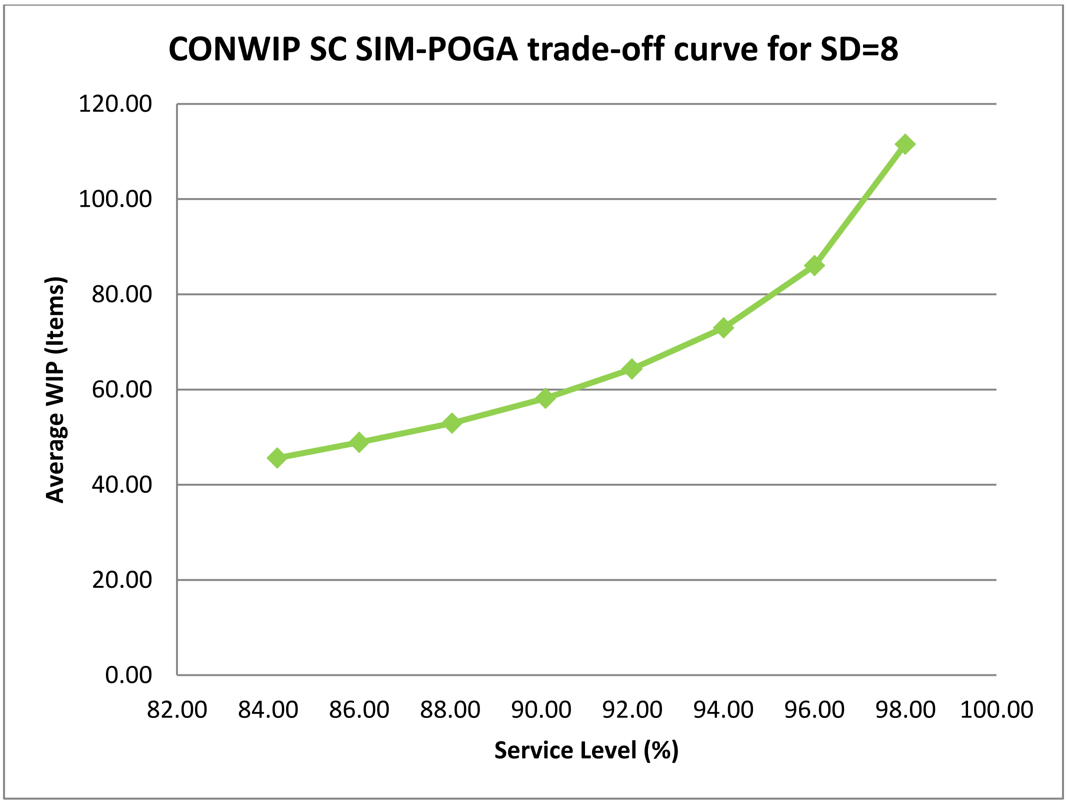


Figure H-2: CONWIP SC SIM-POGA trade-off curve for SD=8

H.3 Kanban SC SIM-POGA Optimisation Results at Demand SD = 1

Table H-3: Kanban SC SIM-POGA results for SD=1

S.L. Target	Capacity	Kanban Allocations				Kanban SIM-POGA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP
78±0.5	14	8	12	10	12	76.6300	23.3705
80±0.5	14	8	12	10	12	76.6300	23.3705
82±0.5	10	9	9	9	10	85.4461	24.4603
84±0.5	10	9	9	9	10	85.4461	24.4603
86±0.5	10	10	9	16	10	85.9603	26.8502
88±0.5	10	10	9	16	10	85.9603	26.8502
90±0.5	10	10	9	16	10	85.9603	26.8502
92±0.5	11	10	10	10	12	94.2660	28.4466
94±0.5	11	10	10	10	12	94.2660	28.4466
96±0.5	16	10	13	11	16	95.1453	29.3475
98±0.5	14	11	11	11	14	99.4088	34.8483
100	16	12	14	12	19	99.9930	45.9408

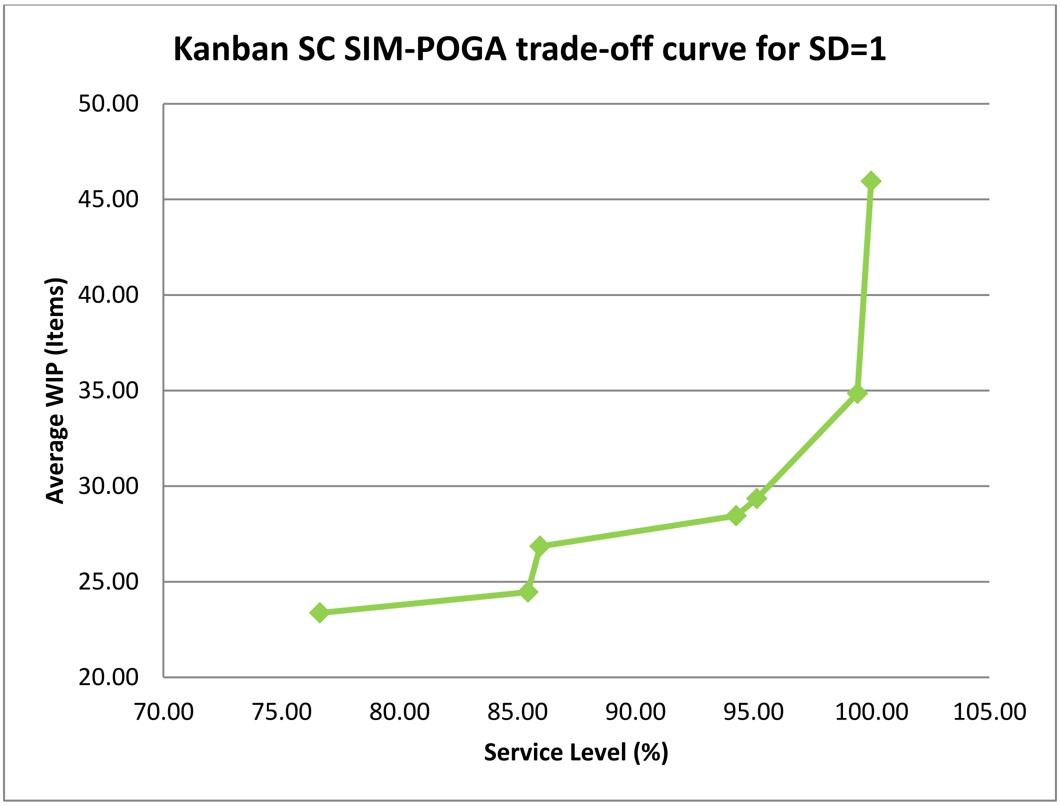


Figure H-3: Kanban SC SIM-POGA trade-off curve for SD=1

H.4 Kanban SC SIM-POGA Optimisation Results at Demand SD = 4.5

Table H-4: Kanban SC SIM-POGA results for SD=4.5

S.L. Target	Capacity	Kanban Allocations				Kanban SIM-DA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP
82±0.5	9	12	12	12	13	82.1481	38.8828
84±0.5	9	12	12	12	14	83.7592	39.4807
86±0.5	14	12	12	12	15	85.9210	40.4611
88±0.5	14	12	12	12	17	88.0104	41.7363
90±0.5	10	12	12	12	20	90.0282	43.3873
92±0.5	14	12	12	12	23	92.0484	45.8298
94±0.5	12	12	12	12	28	93.9835	49.1420
96±0.5	22	12	12	13	35	95.9990	55.2068
98±0.5	11	13	13	14	43	98.0053	66.0351

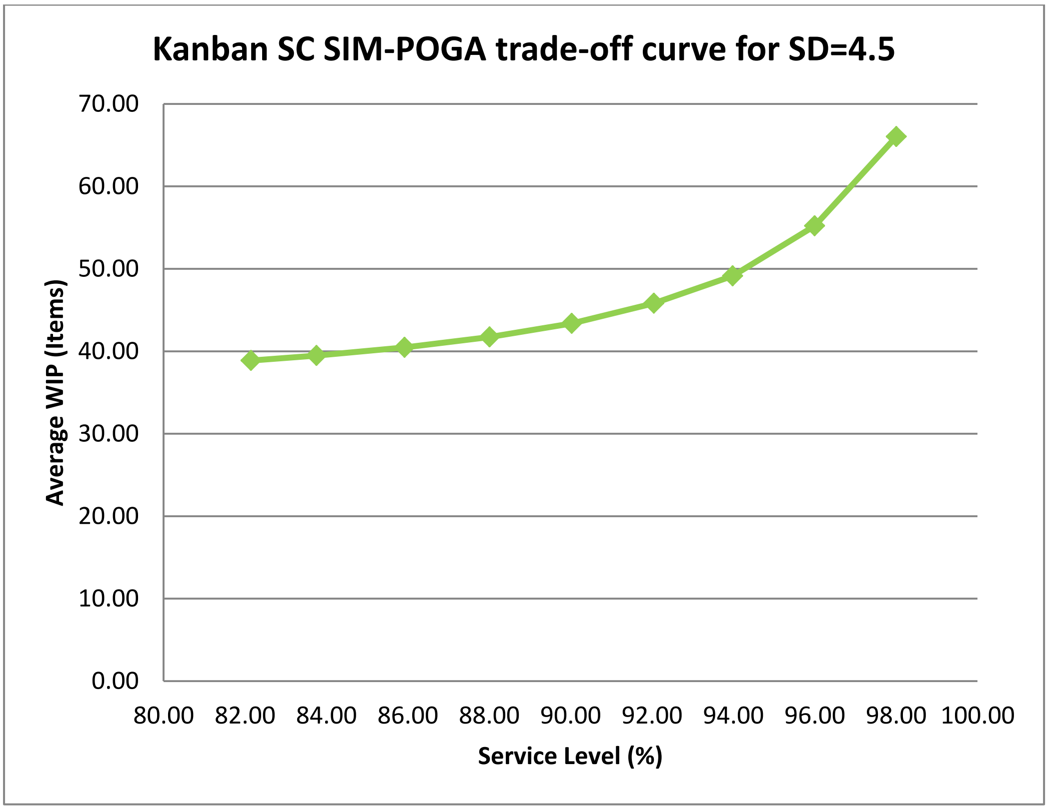


Figure H-4: Kanban SC SIM-POGA trade-off curve for SD=4.5

H.5 Kanban SC SIM-POGA Optimisation Results at Demand SD = 8

Table H-5: Kanban SC SIM-POGA results for SD=8

S.L. Target	Capacity	Kanban Allocations				Kanban SIM-POGA	
		Node 1	Node 2	Node 3	Node 4	Service Level	Average WIP
84±0.5	12	10	10	10	40	84.14374	48.14054
86±0.5	11	10	11	12	46	86.02318	52.4466
88±0.5	13	10	12	14	56	87.99994	58.62463
90±0.5	13	11	11	13	53	89.9529	62.84625
92±0.5	13	12	13	16	52	91.92884	70.71125
94±0.5	14	12	14	14	68	93.98663	81.66053
96±0.5	23	14	14	15	73	95.99852	95.50547
98±0.5	17	16	16	16	96	97.98846	124.6913

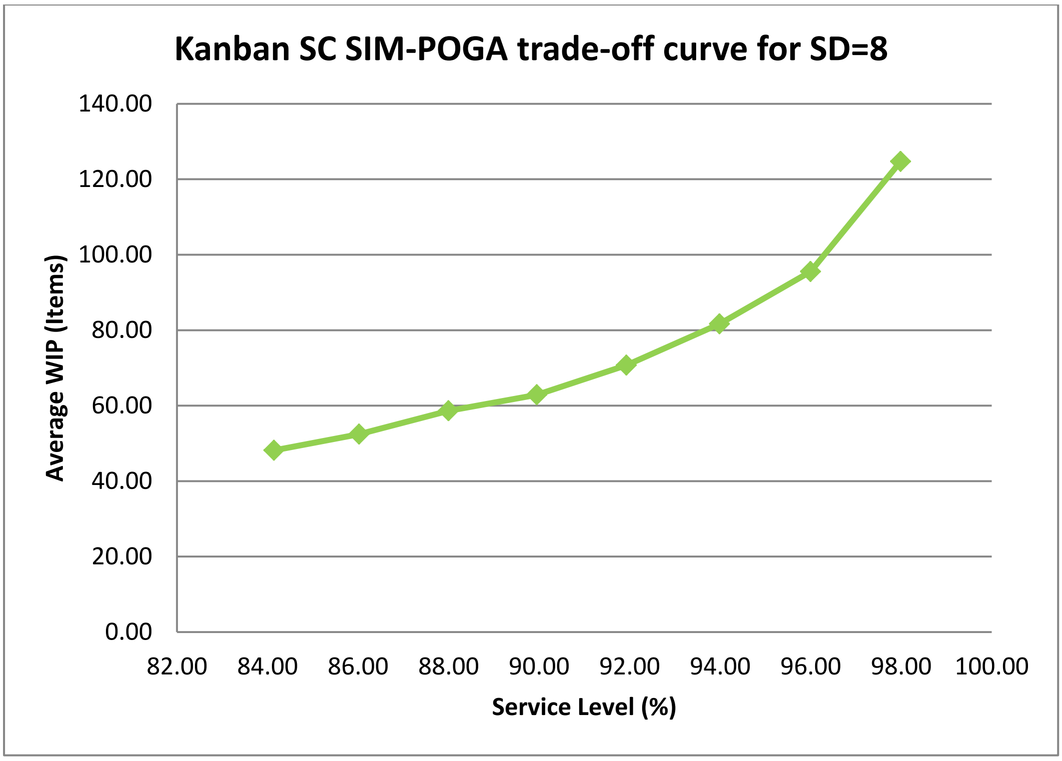


Figure H-5: Kanban SC SIM-POGA trade-off curve for SD=8

H.6 Hybrid Kanban-CONWIP SC SIM-POGA Optimisation Results at Demand SD = 1

Table H-6: Hybrid Kanban-CONWIP SC SIM-POGA results for SD=1

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid SIM-POGA	
			Node 1	Node 2	Node 3	Service Level	Average WIP
78±0.5	17	22	13	14	13	77.4500	21.9998
80±0.5	8	23	12	15	12	80.6028	22.9842
82±0.5	8	24	13	13	14	83.6220	23.9722
84±0.5	21	24	12	13	19	83.6279	23.9992
86±0.5	8	26	14	15	15	86.4822	24.9995
88±0.5	8	26	14	15	15	89.1026	25.9285
90±0.5	17	26	14	16	17	89.1275	25.9998
92±0.5	14	27	14	19	14	91.5261	26.9994
94±0.5	9	30	10	30	27	94.0543	28.0200
96±0.5	8	30	11	31	16	96.3039	29.4156
98±0.5	14	31	15	15	15	97.9623	30.9975
100	9	46	29	29	28	100.0000	45.3725

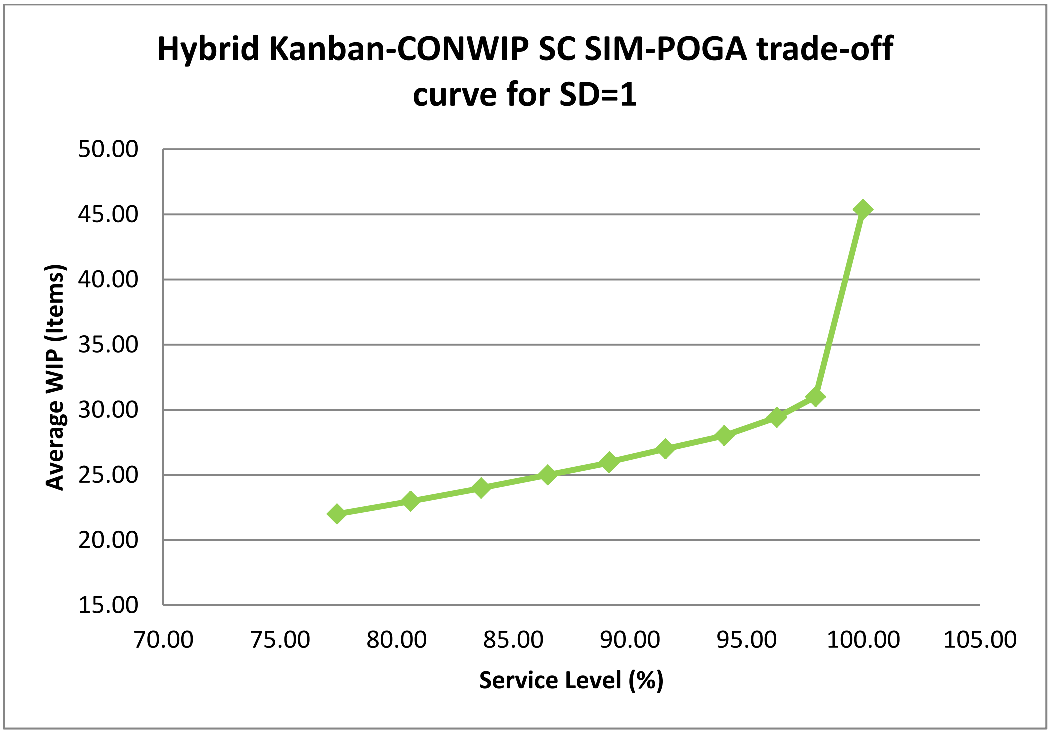


Figure H-6: Hybrid Kanban-CONWIP SC SIM-POGA trade-off curve for SD=1

H.7 Hybrid Kanban-CONWIP SC SIM-POGA Optimisation Results at Demand SD = 4.5

Table H-7: Hybrid Kanban-CONWIP SC SIM-POGA results for SD=4.5

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid SIM-POGA	
			Node 1	Node 2	Node 3	Service Level	Average WIP
82±0.5	9	33	20	22	20	82.0798	30.9926
84±0.5	8	37	10	12	15	83.9896	32.4543
86±0.5	9	37	12	19	15	86.0138	34.2935
88±0.5	10	39	12	24	22	88.0171	36.3503
90±0.5	11	42	12	29	18	89.9856	38.7514
92±0.5	11	44	22	23	15	91.9469	41.8565
94±0.5	11	48	24	16	17	94.0042	45.5005
96±0.5	16	52	23	21	20	96.0762	51.1478
98±0.5	16	62	24	24	24	98.1734	60.9810

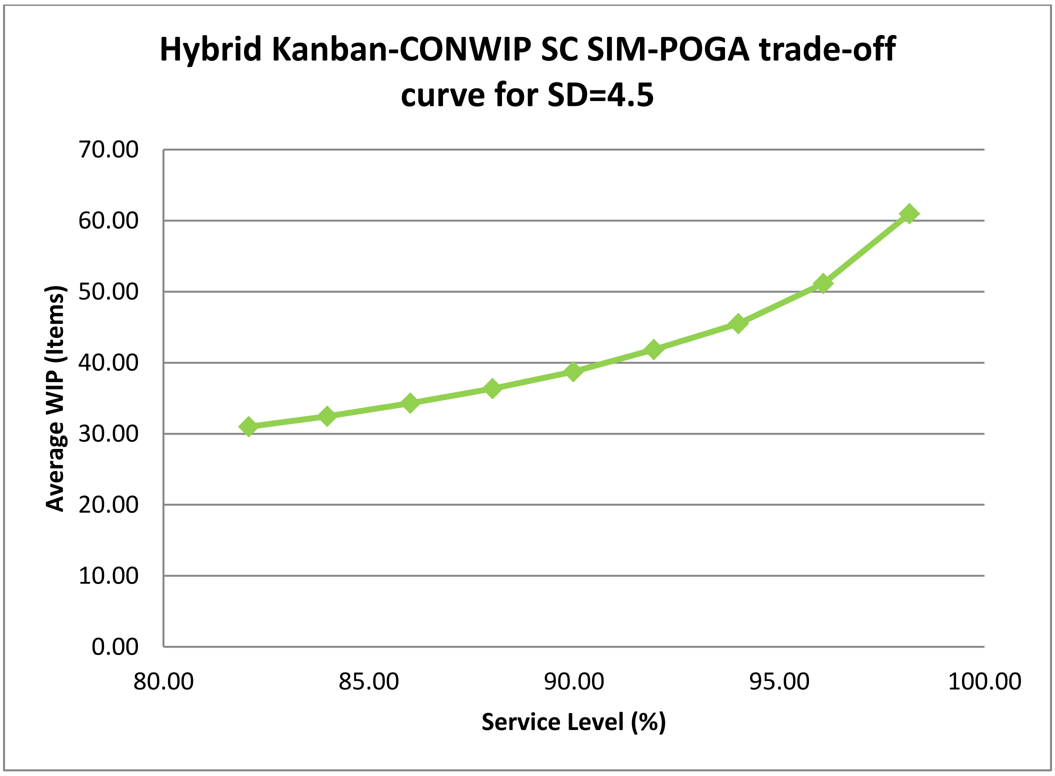


Figure H-7: Hybrid Kanban-CONWIP SC SIM-POGA trade-off curve for SD=4.5

H.8 Hybrid Kanban-CONWIP SC SIM-POGA Optimisation Results at Demand SD 8

Table H-8: Hybrid Kanban-CONWIP SC SIM-POGA results for SD=8

S.L. Target	Capacity	WIP-Cap	Kanban Allocations			Hybrid SIM-POGA	
			Node 1	Node 2	Node 3	Service Level	Average WIP
84±0.5	10	51	12	12	18	84.0145	45.2572
86±0.5	13	52	15	20	16	85.9980	48.5922
88±0.5	15	56	16	17	20	87.9996	52.7787
90±0.5	23	61	17	19	20	90.0236	56.8713
92±0.5	17	68	18	18	20	92.0084	64.4716
94±0.5	14	78	18	20	19	94.0182	73.4563
96±0.5	19	92	18	18	19	95.9675	86.9402
98±0.5	15	122	19	18	20	98.0003	115.0258

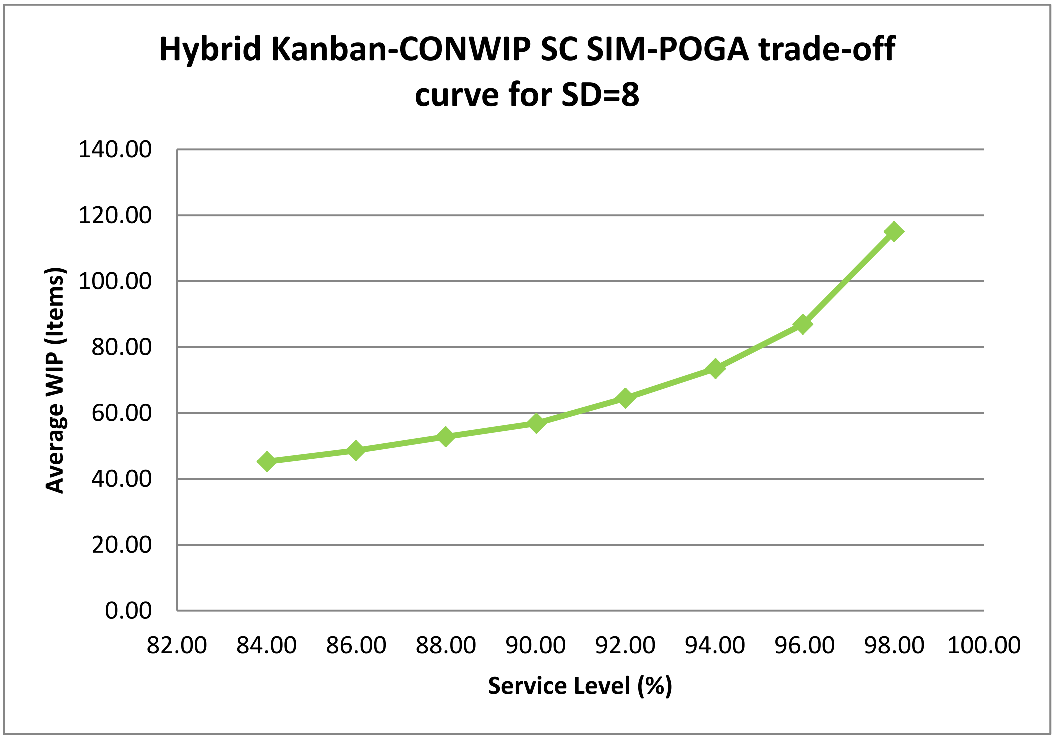


Figure H-8: Hybrid Kanban-CONWIP SC SIM-POGA trade-off curve for SD=8

APPENDIX I TRADE-OFF CURVES COMPARISON AND ERROR ANALYSIS

I.1 Trade-Off Curves Comparison and Error analysis of CONWIP SC at Demand SD = 4.5

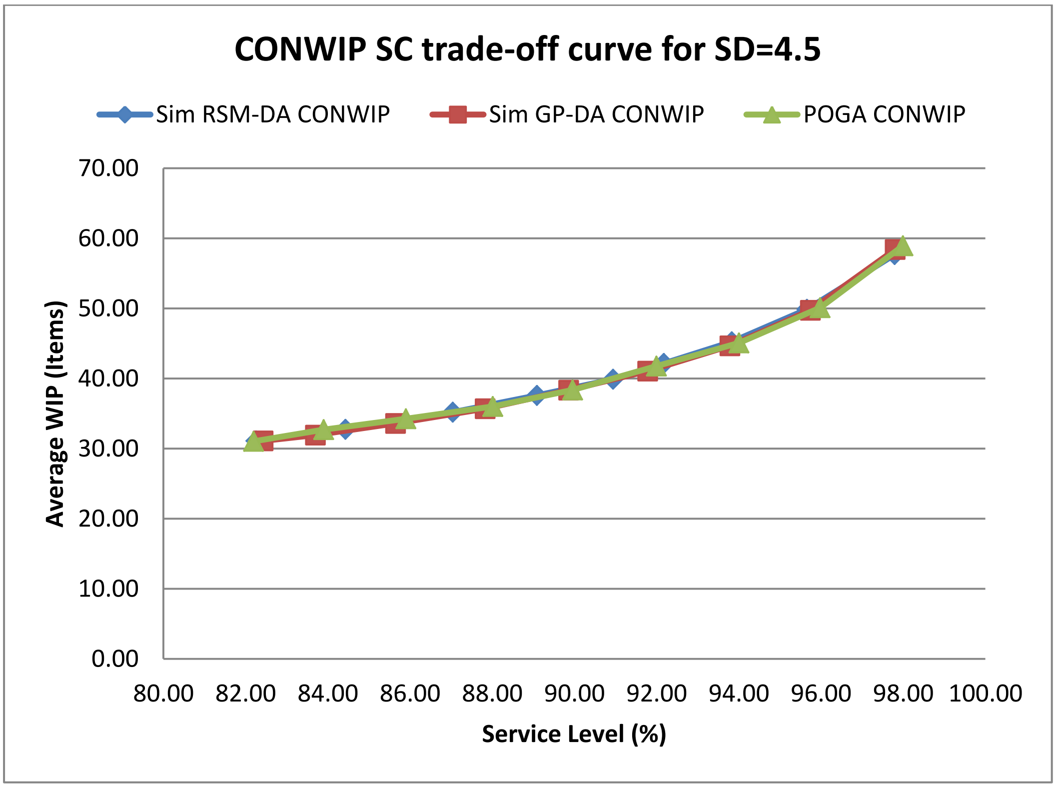


Figure I-1: CONWIP SC trade-off curve for SD=4.5

Table I-1: Percentage deviations from SIM-POGA of CONWIP SC for SD=4.5

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	82±0.5	-0.070%	-0.181%	-0.279%	-0.216%
2	84±0.5	-0.630%	-0.165%	0.242%	2.350%
3	86±0.5	-1.329%	-2.730%	0.298%	1.909%
4	88±0.5	-1.219%	-4.372%	0.210%	0.868%
5	90±0.5	-1.095%	-3.974%	0.109%	0.030%
6	92±0.5	-0.194%	-0.902%	0.232%	1.713%
7	94±0.5	0.185%	-0.352%	0.234%	0.895%
8	96±0.5	0.333%	0.484%	0.249%	0.740%
9	98±0.5	0.205%	2.139%	0.194%	0.891%

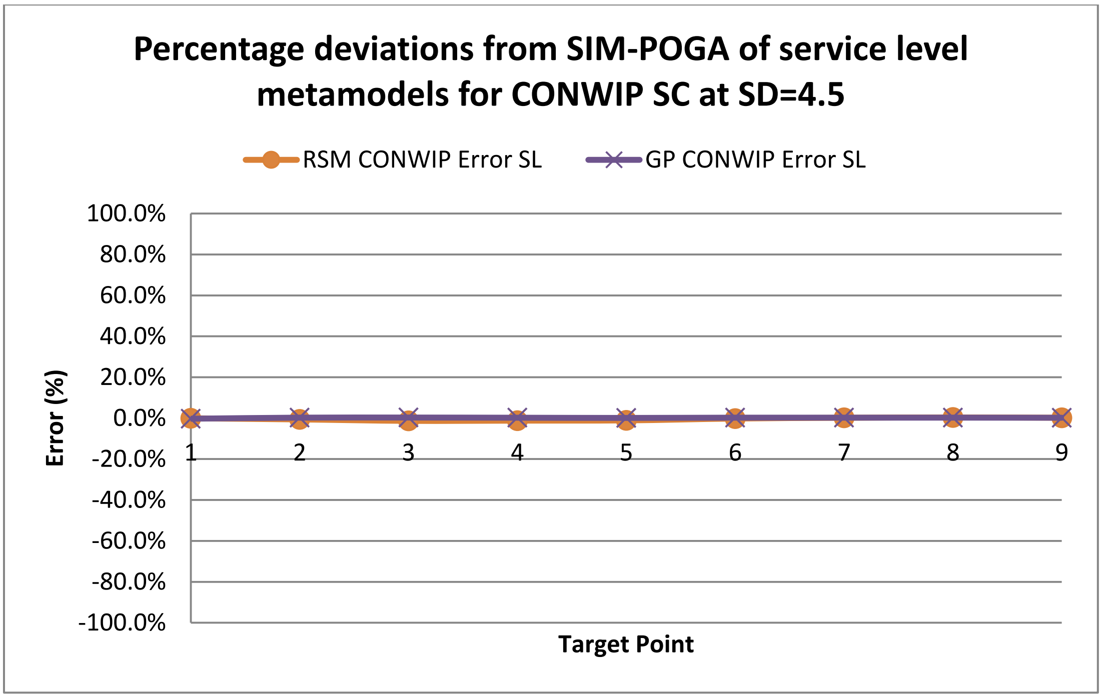


Figure I-2: Percentage deviations from SIM-POGA of service level metamodels for CONWIP SC at SD=4.5

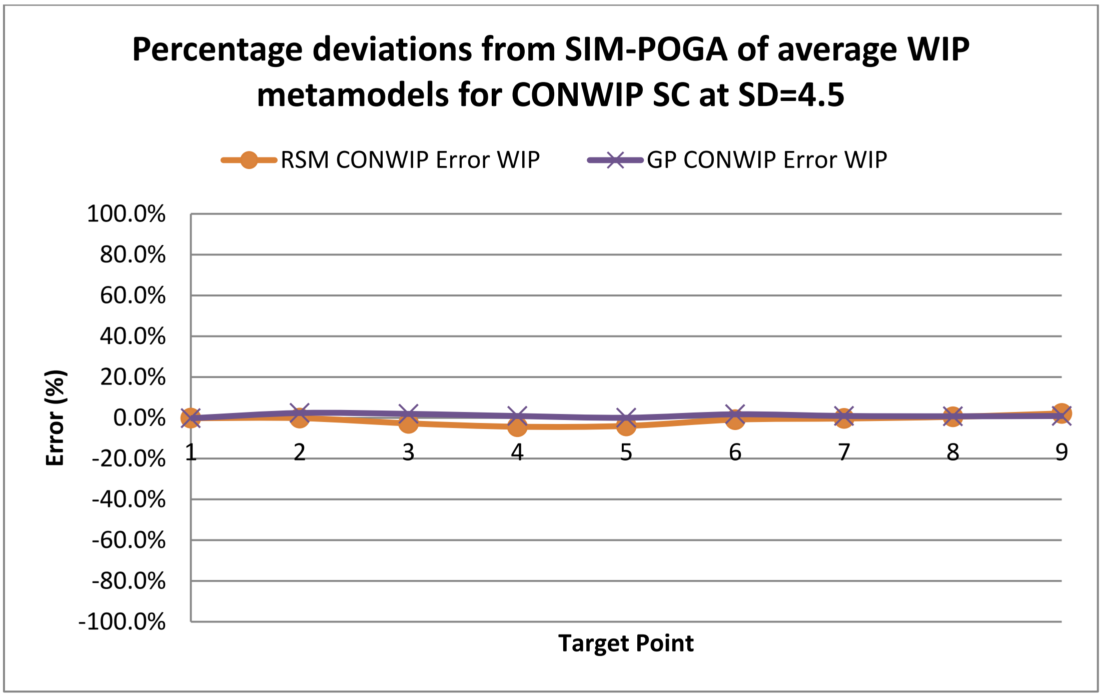


Figure I-3: Percentage deviations from SIM-POGA of average WIP metamodels for CONWIP SC at SD=4.5

I.2 Trade-Off Curves Comparison and Error analysis of CONWIP SC at Demand SD = 8

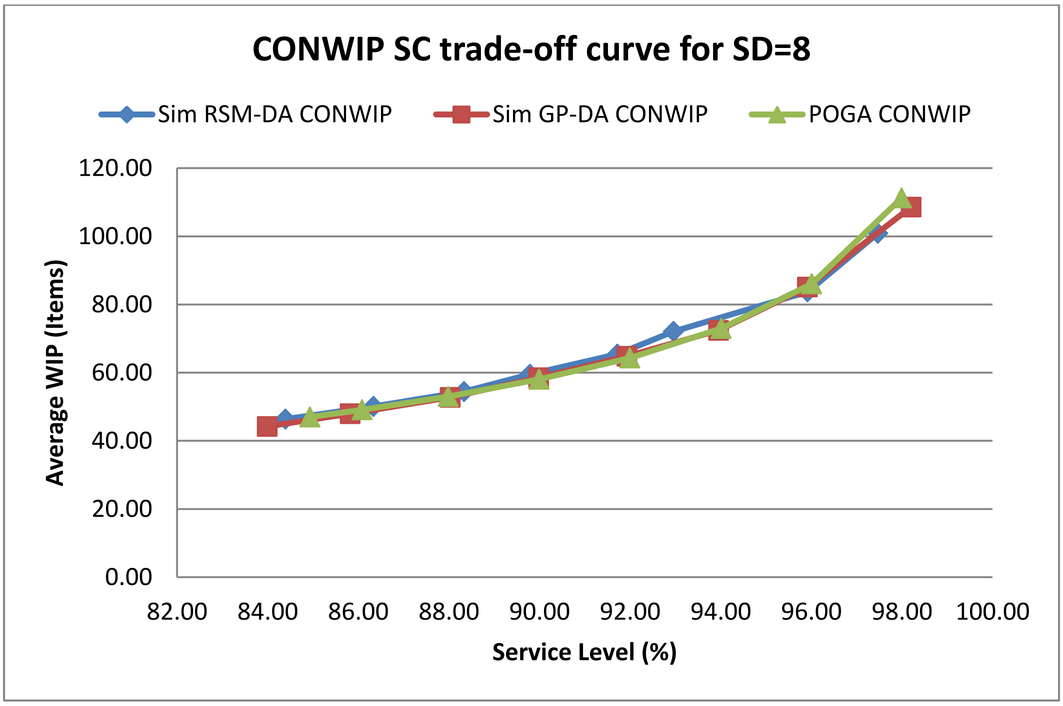


Figure I-4: CONWIP SC trade-off curve for SD=8

Table I-2: Percentage deviations from SIM-POGA of CONWIP SC for SD=8

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	84±0.5	0.633%	1.345%	1.110%	5.918%
2	86±0.5	-0.289%	-1.924%	0.311%	2.352%
3	88±0.5	-0.398%	-2.673%	-0.049%	0.445%
4	90±0.5	0.221%	-2.505%	0.011%	-0.844%
5	92±0.5	0.297%	-1.702%	0.071%	-0.762%
6	94±0.5	1.117%	1.262%	0.062%	0.805%
7	96±0.5	0.094%	2.707%	0.099%	1.064%
8	98±0.5	0.539%	9.330%	-0.213%	2.385%

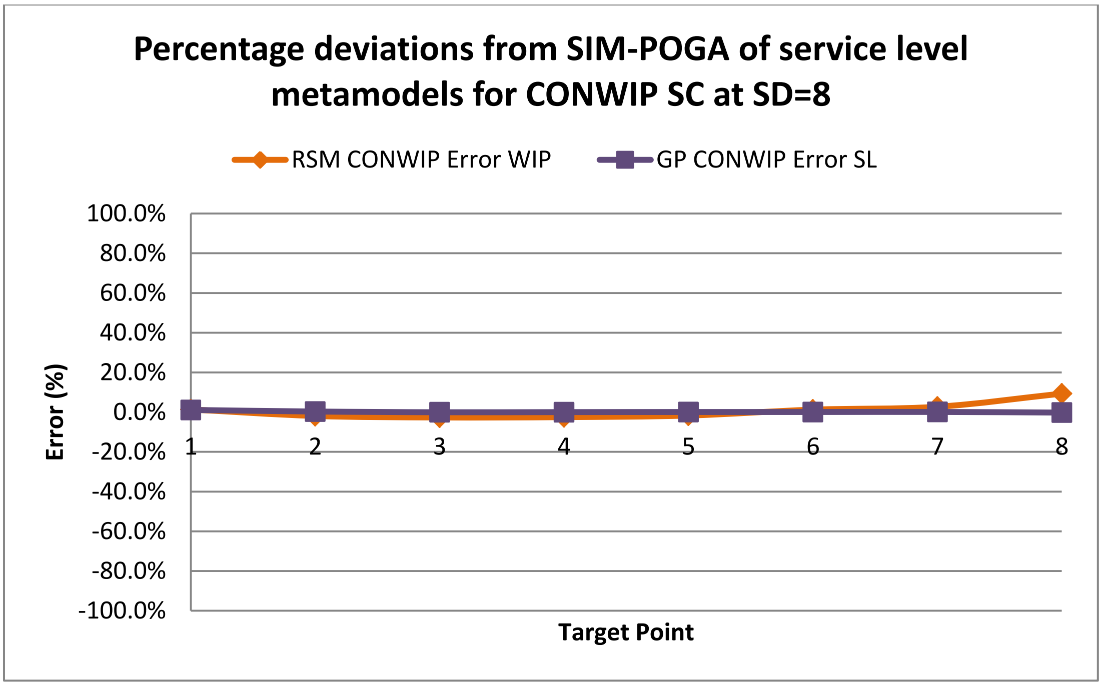


Figure I-5: Percentage deviations from SIM-POGA of service level metamodels for CONWIP SC at SD=8

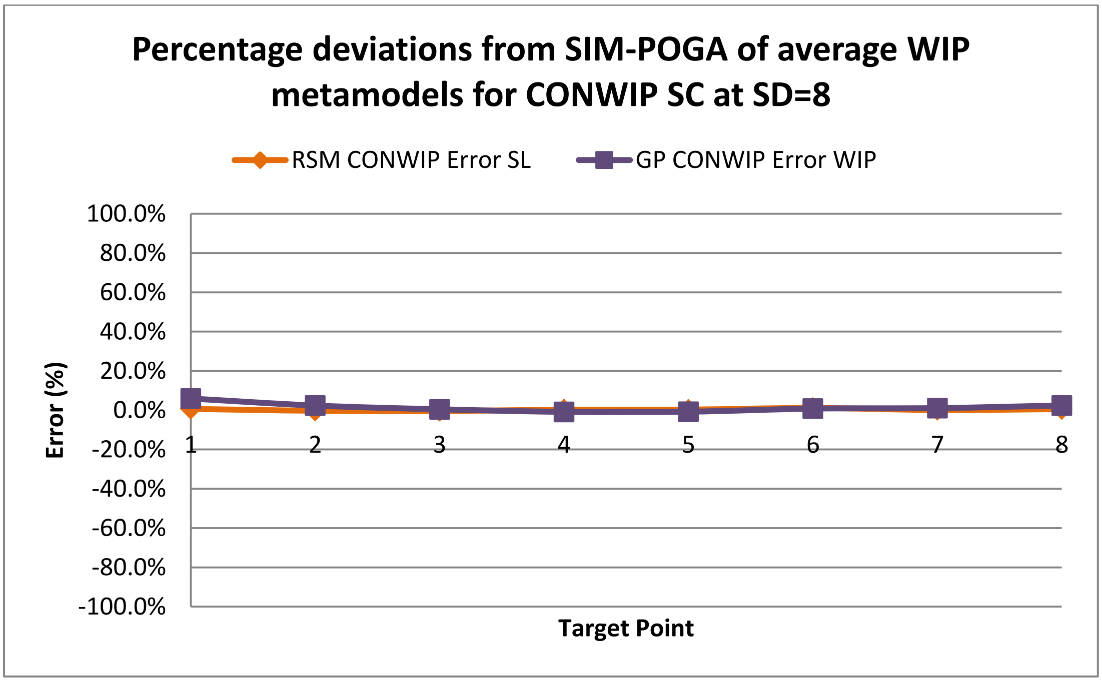


Figure I-6: Percentage deviations from SIM-POGA of average WIP metamodels for CONWIP SC at SD=8

I.3 Trade-Off Curves Comparison and Error analysis of Kanban SC at Demand SD = 1

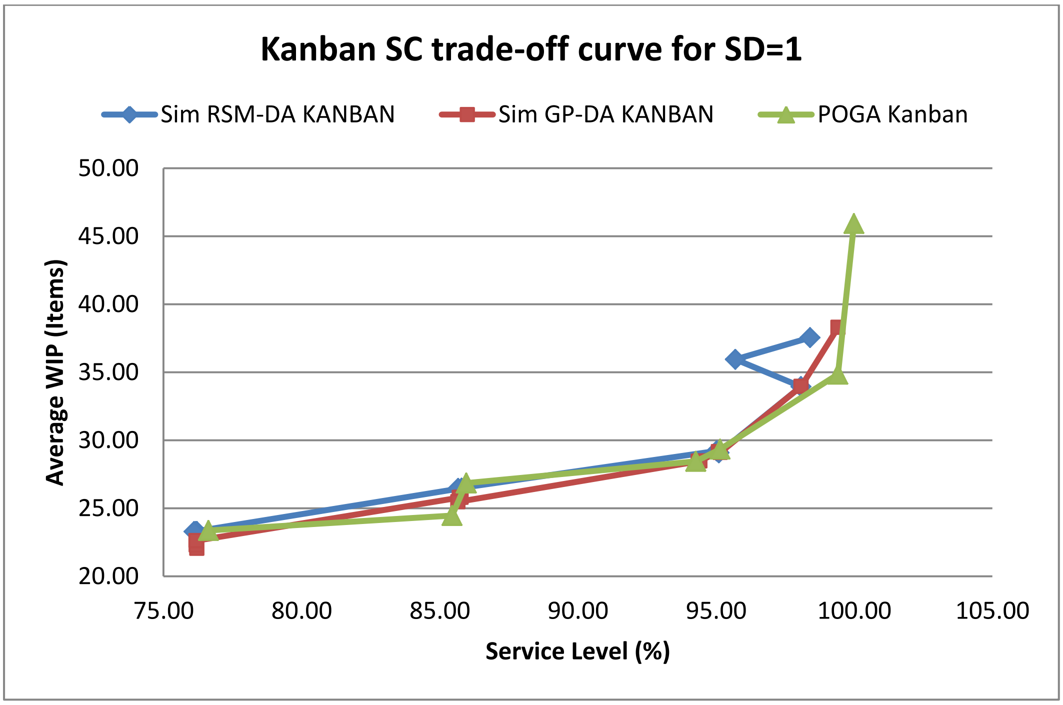


Figure I-7: Kanban SC trade-off curve for SD=1

Table I-3: Percentage deviations from SIM-POGA of Kanban SC for SD=1

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	78±0.5	0.611%	0.379%	0.545%	5.673%
2	80±0.5	0.611%	0.379%	0.579%	4.584%
3	82±0.5	10.807%	4.812%	10.842%	7.521%
4	84±0.5	10.929%	4.826%	-0.388%	-5.483%
5	86±0.5	0.198%	1.417%	0.287%	3.923%
6	88±0.5	0.341%	1.456%	0.353%	5.124%
7	90±0.5	-10.540%	-8.825%	-9.773%	-5.948%
8	92±0.5	-0.892%	-2.255%	-0.159%	-0.080%
9	94±0.5	-0.884%	-2.197%	-0.872%	-2.491%
10	96±0.5	-3.077%	-15.680%	-0.008%	0.843%
11	98±0.5	3.730%	-3.143%	1.338%	2.556%
12	100	1.591%	18.266%	0.577%	16.621%

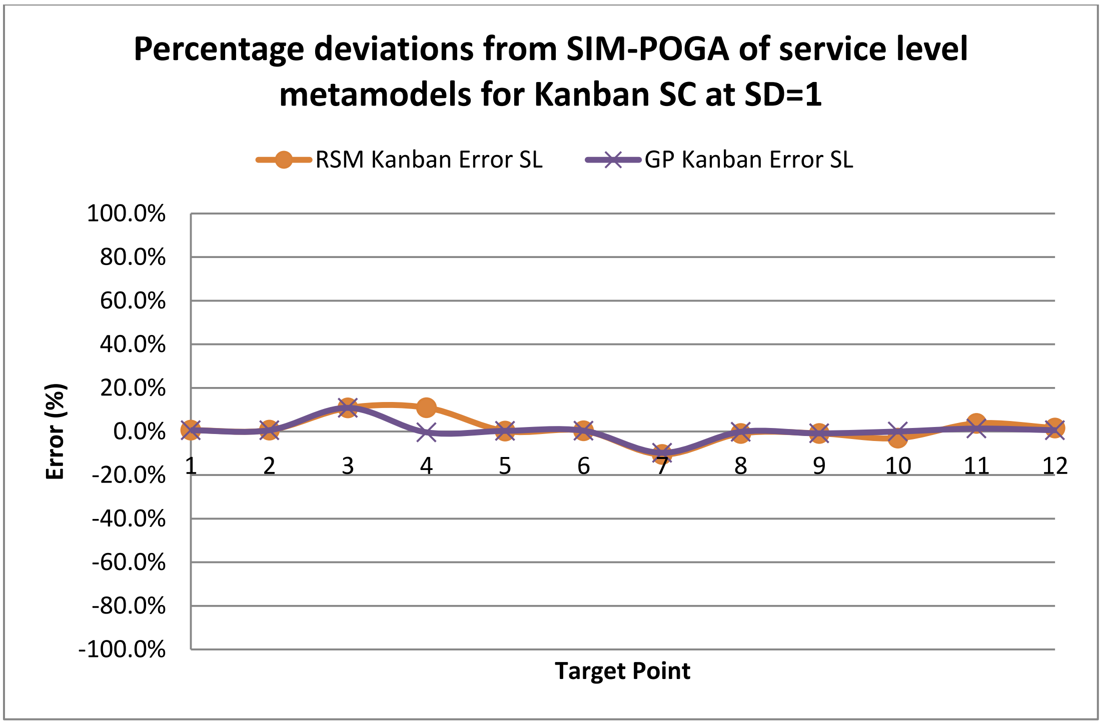


Figure I-8: Percentage deviations from SIM-POGA of service level metamodels for Kanban SC at SD=1

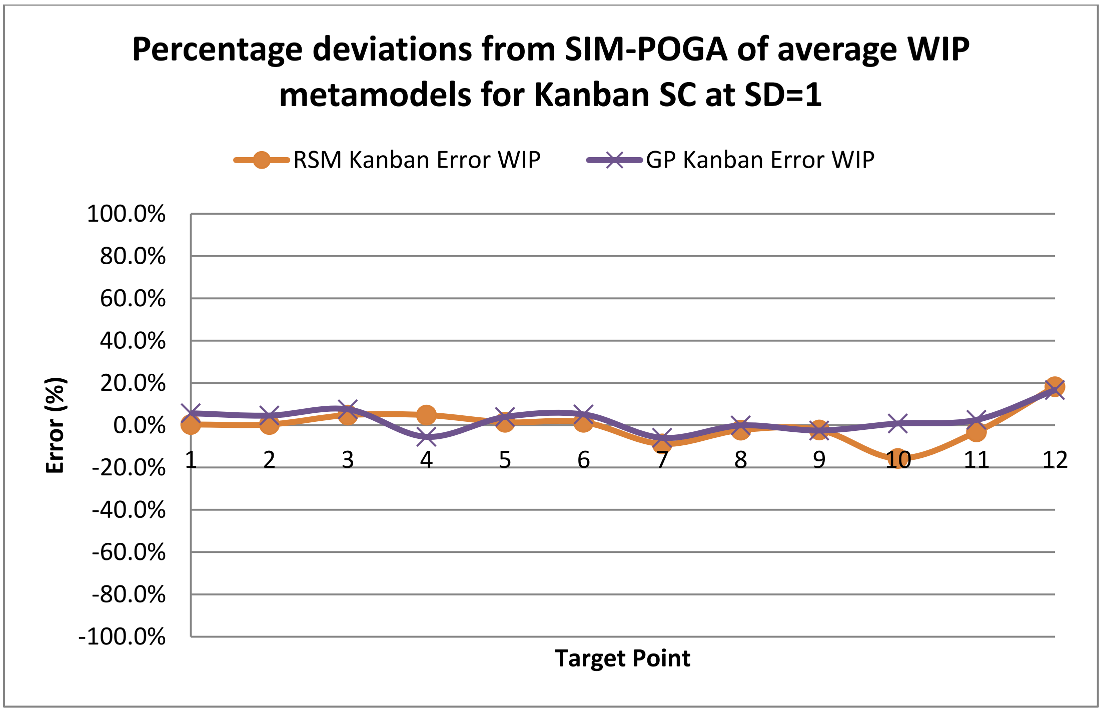


Figure I-9: Percentage deviations from SIM-POGA of average WIP metamodels for Kanban SC at SD=1

I.4 Trade-Off Curves Comparison and Error analysis of Kanban SC at Demand SD = 4.5

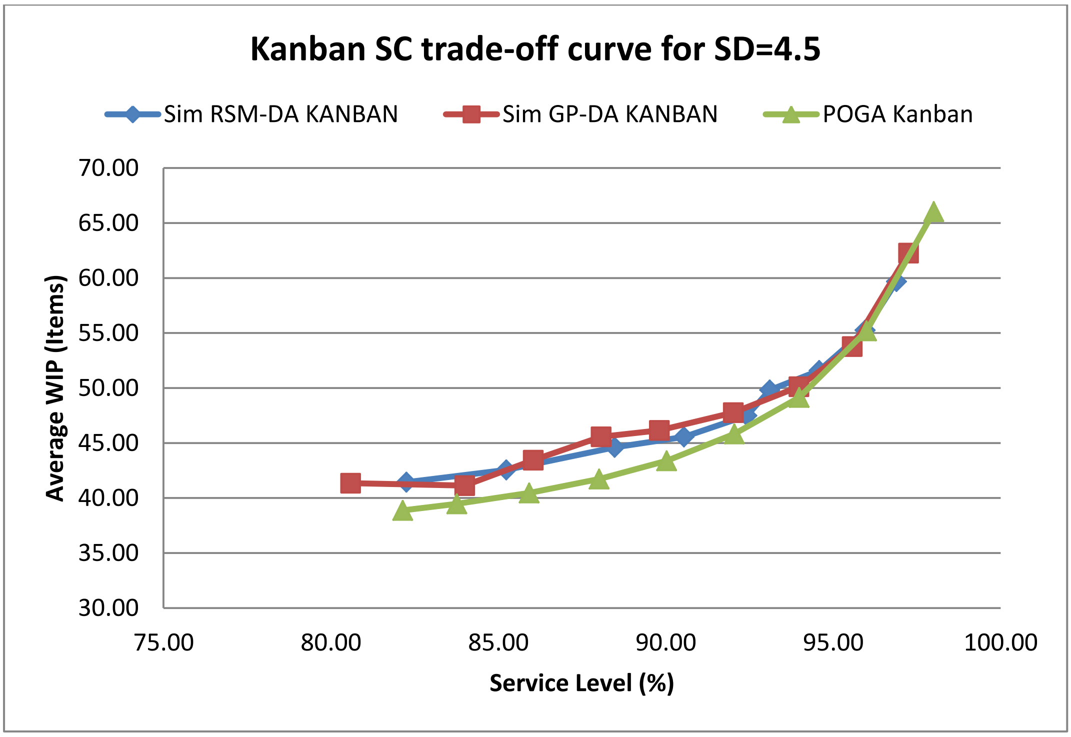


Figure I-10: Kanban SC trade-off curve for SD=4.5

Table I-4: Percentage deviations from SIM-POGA of Kanban SC for SD=4.5

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	82±0.5	-0.129%	-6.554%	1.898%	-6.355%
2	84±0.5	-1.766%	-7.807%	-0.280%	-4.182%
3	86±0.5	-2.974%	-10.266%	-0.138%	-7.364%
4	88±0.5	-2.877%	-9.143%	-0.067%	-9.196%
5	90±0.5	-2.658%	-9.441%	0.243%	-6.376%
6	92±0.5	-1.151%	-8.698%	0.034%	-4.227%
7	94±0.5	-0.637%	-4.988%	0.009%	-1.985%
8	96±0.5	0.047%	-0.097%	0.448%	2.595%
9	98±0.5	1.138%	9.625%	0.769%	5.694%

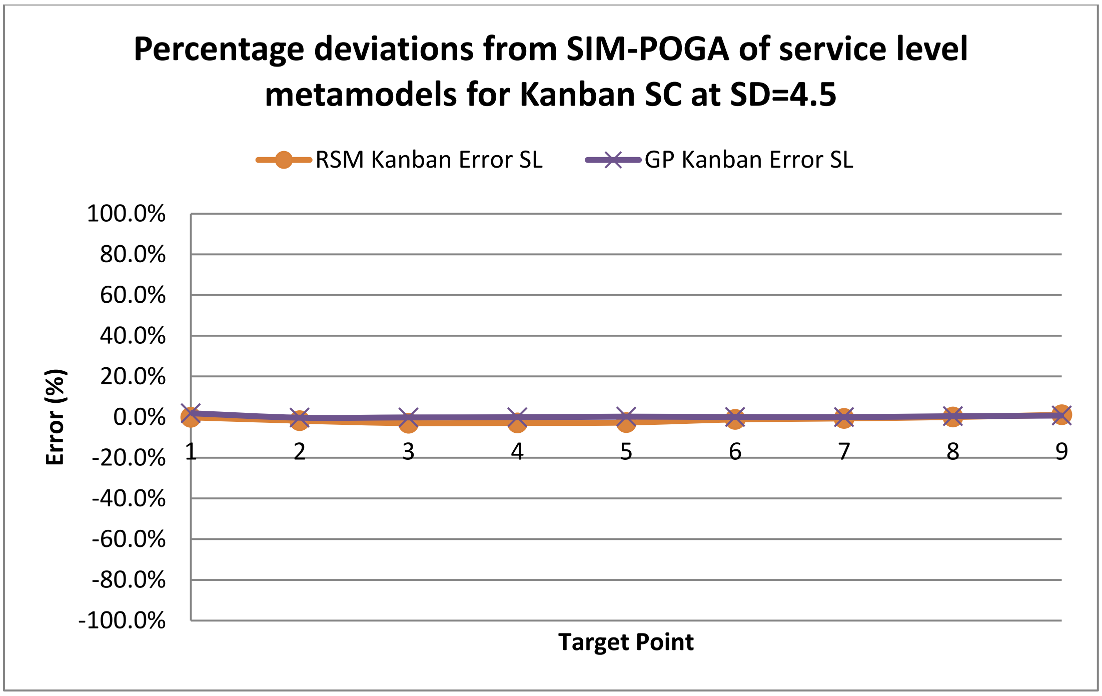


Figure I-11: Percentage deviations from SIM-POGA of service level metamodels for Kanban SC at SD=4.5

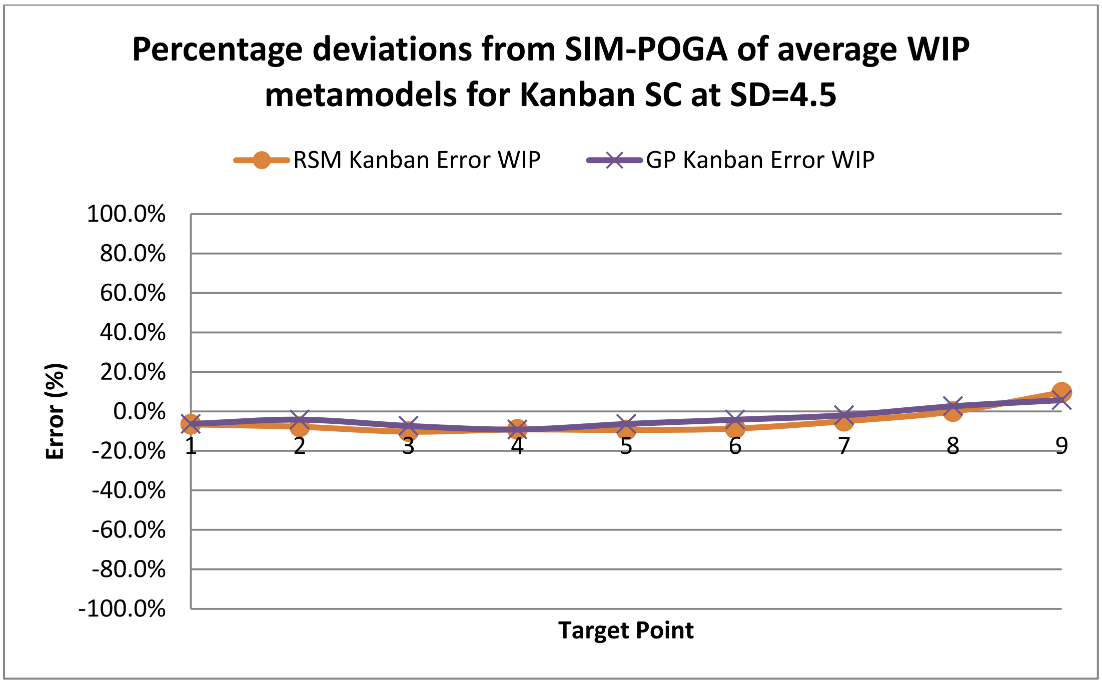


Figure I-12: Percentage deviations from SIM-POGA of average WIP metamodels for Kanban SC at SD=4.5

I.5 Trade-Off Curves Comparison and Error analysis of Kanban SC at Demand SD = 8

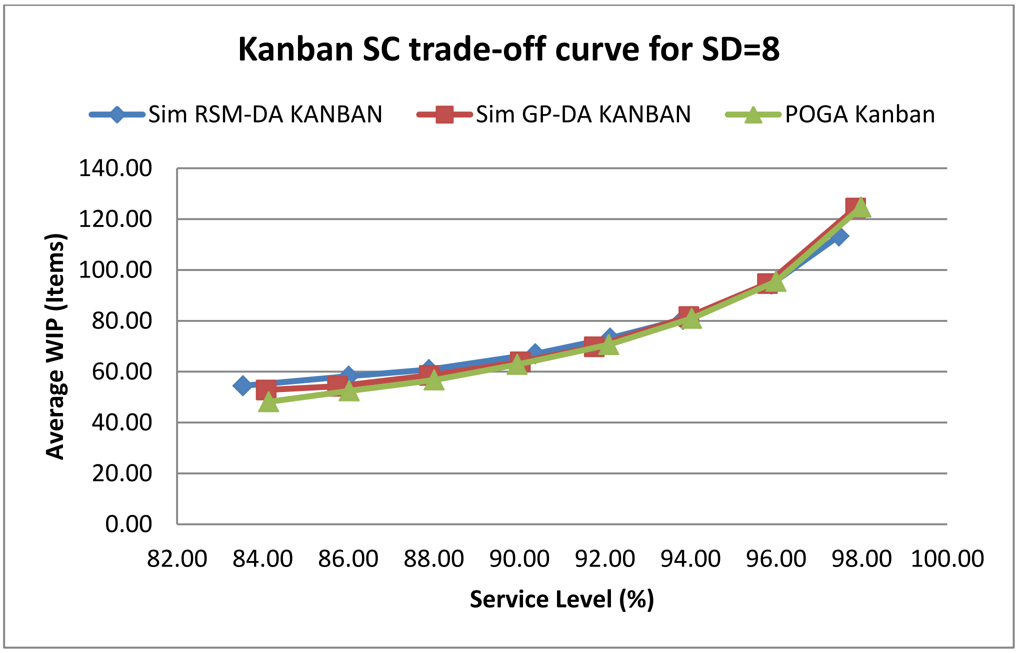


Figure I-13: Kanban SC trade-off curve for SD=8

Table I-5: Percentage deviations from SIM-POGA of Kanban SC for SD=8

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	84±0.5	-0.318%	-16.122%	0.072%	-9.719%
2	86±0.5	-1.014%	-13.865%	0.315%	-3.423%
3	88±0.5	-2.314%	-14.696%	0.129%	-3.243%
4	90±0.5	-1.257%	-10.514%	-0.077%	-1.683%
5	92±0.5	-0.468%	-4.384%	0.368%	1.173%
6	94±0.5	0.200%	-0.922%	0.069%	-0.897%
7	96±0.5	0.528%	1.878%	0.207%	0.848%
8	98±0.5	0.874%	9.951%	0.132%	0.269%

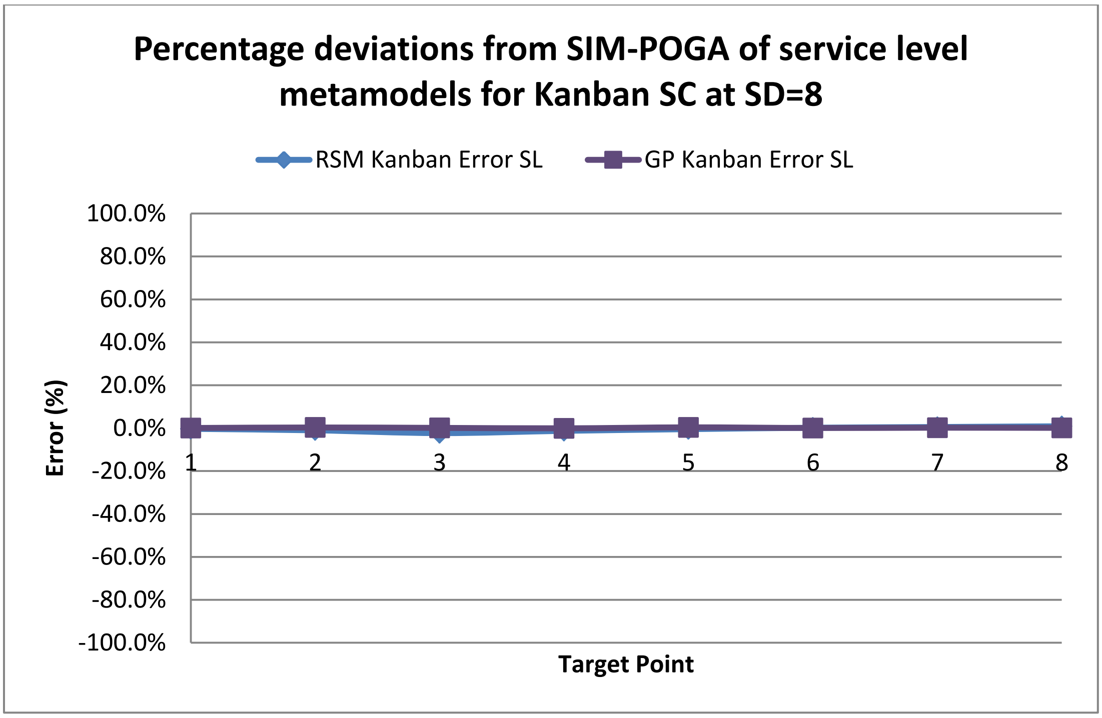


Figure I-14: Percentage deviations from SIM-POGA of service level metamodels for Kanban SC at SD=8

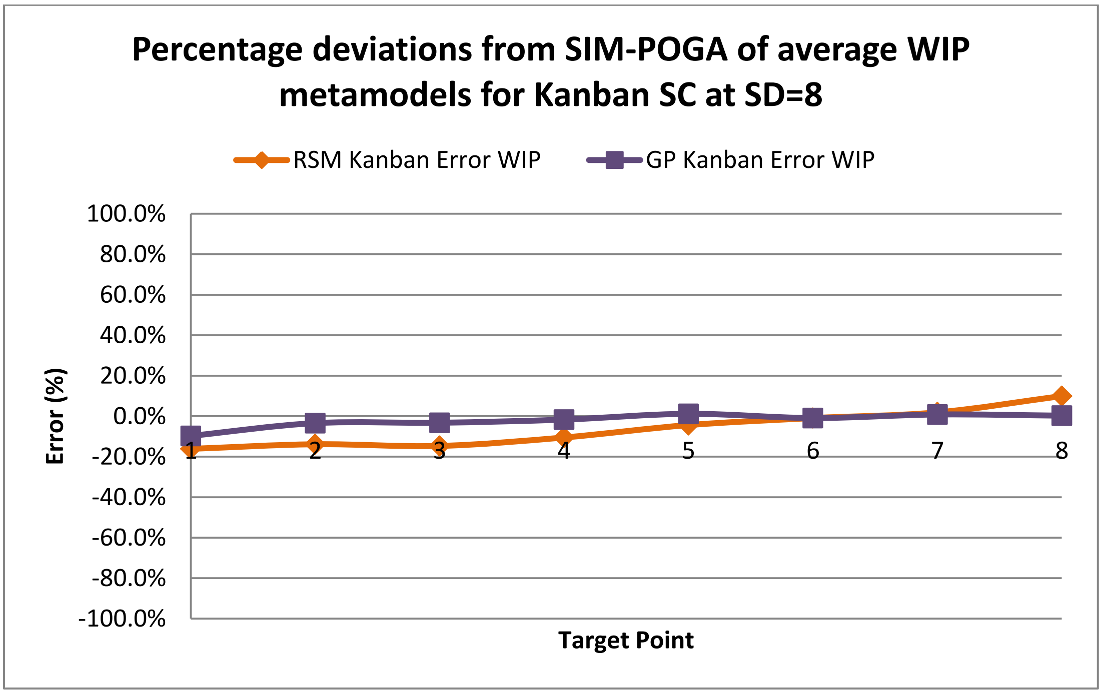


Figure I-15: Percentage deviations from SIM-POGA of average WIP metamodels for Kanban SC at SD=8

I.6 Trade-Off Curves Comparison and Error analysis of Hybrid Kanban-CONWIP SC at Demand SD = 1

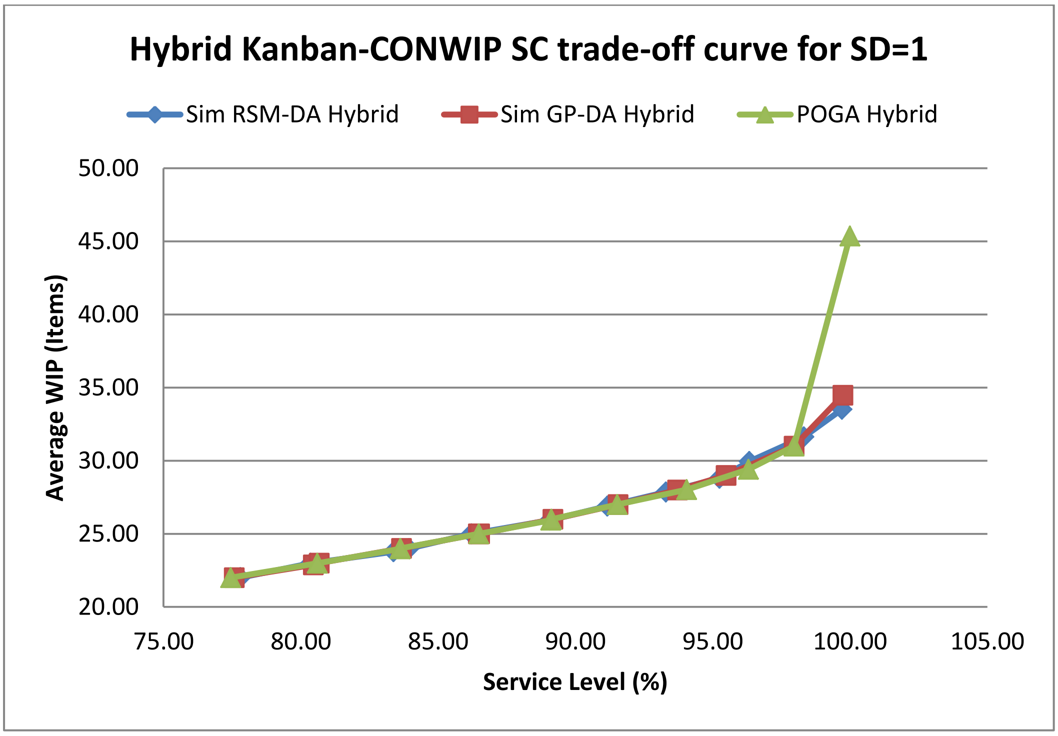


Figure I-16: Hybrid Kanban-CONWIP SC trade-off curve for SD=1

Table I-6: Percentage deviations from SIM-POGA of Hybrid Kanban-CONWIP SC for SD=1

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	78±0.5	-0.447%	0.002%	-0.162%	-0.001%
2	80±0.5	0.305%	0.002%	0.183%	0.467%
3	82±0.5	0.293%	0.836%	3.529%	4.056%
4	84±0.5	-0.377%	0.029%	-0.044%	-0.004%
5	86±0.5	0.313%	0.013%	0.021%	-0.001%
6	88±0.5	0.046%	0.000%	2.909%	3.581%
7	90±0.5	-2.285%	-3.441%	-0.062%	0.003%
8	92±0.5	-1.937%	-3.159%	-0.027%	-0.002%
9	94±0.5	-1.269%	-2.787%	0.355%	0.071%
10	96±0.5	-0.031%	-1.797%	0.845%	1.413%
11	98±0.5	-0.366%	-2.035%	-0.004%	-0.006%
12	100	0.295%	26.139%	0.260%	24.018%

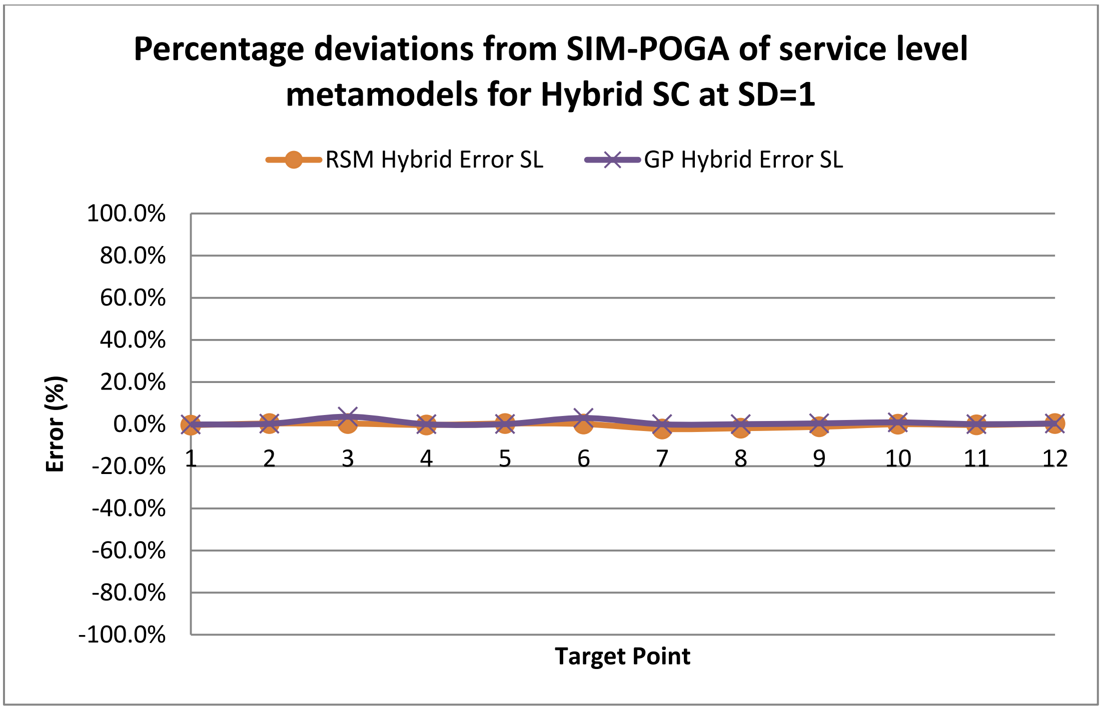


Figure I-17: Percentage deviations from SIM-POGA of service level metamodels for Hybrid SC at SD=1

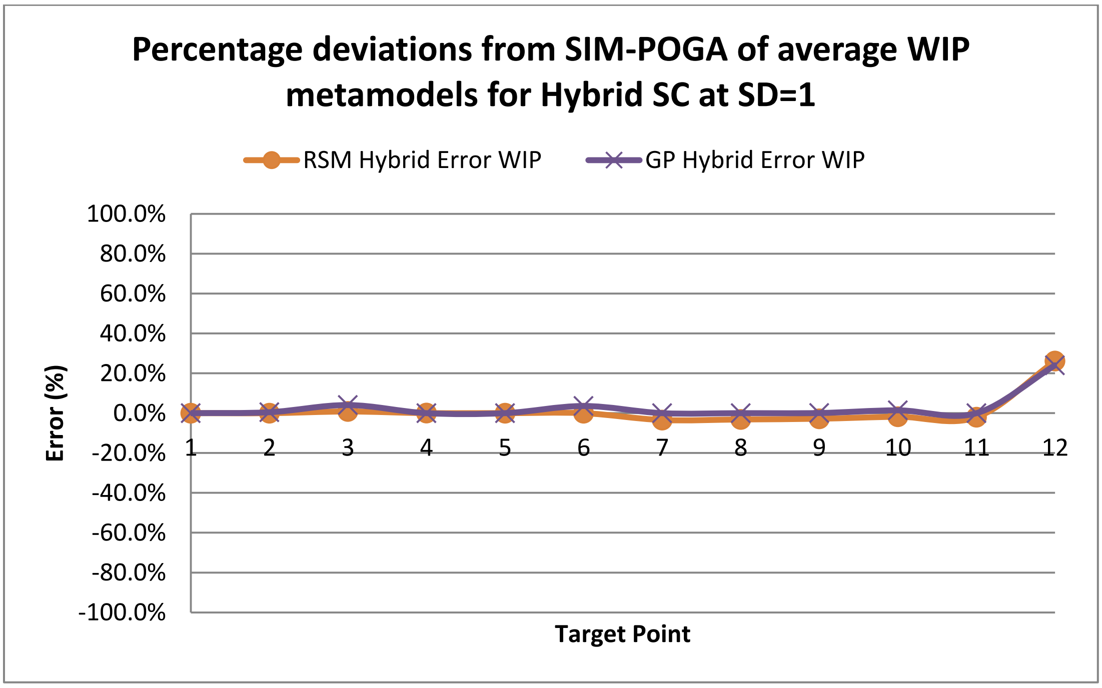


Figure I-18: Percentage deviations from SIM-POGA of average WIP metamodels for Hybrid SC at SD=1

I.7 Trade-Off Curves Comparison and Error analysis of Hybrid Kanban-CONWIP SC at Demand SD = 4.5

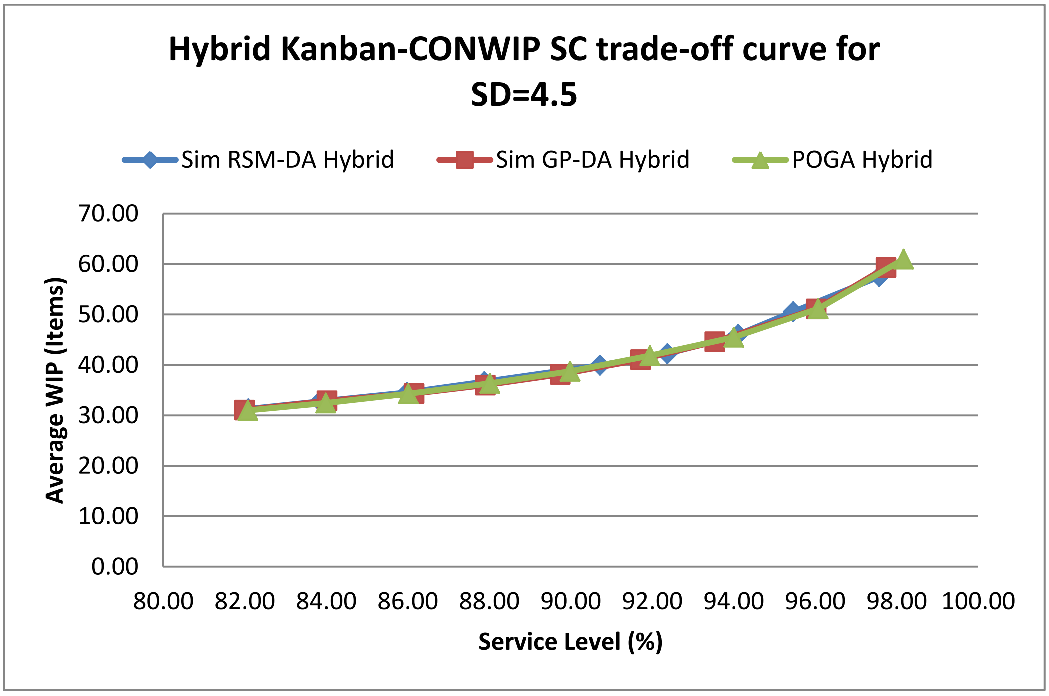


Figure I-19: Hybrid Kanban-CONWIP SC trade-off curve for SD=4.5

Table I-7: Percentage deviations from SIM-POGA of Hybrid Kanban-CONWIP SC for SD=4.5

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	82±0.5	-0.010%	-0.884%	0.103%	-0.207%
2	84±0.5	0.167%	-0.997%	-0.037%	-1.370%
3	86±0.5	0.027%	-0.730%	-0.165%	-0.074%
4	88±0.5	0.156%	-0.905%	0.127%	0.939%
5	90±0.5	-0.816%	-3.109%	0.269%	1.621%
6	92±0.5	-0.464%	-0.906%	0.251%	1.960%
7	94±0.5	-0.117%	-1.139%	0.496%	1.970%
8	96±0.5	0.641%	1.204%	0.053%	0.084%
9	98±0.5	0.610%	5.680%	0.442%	2.736%

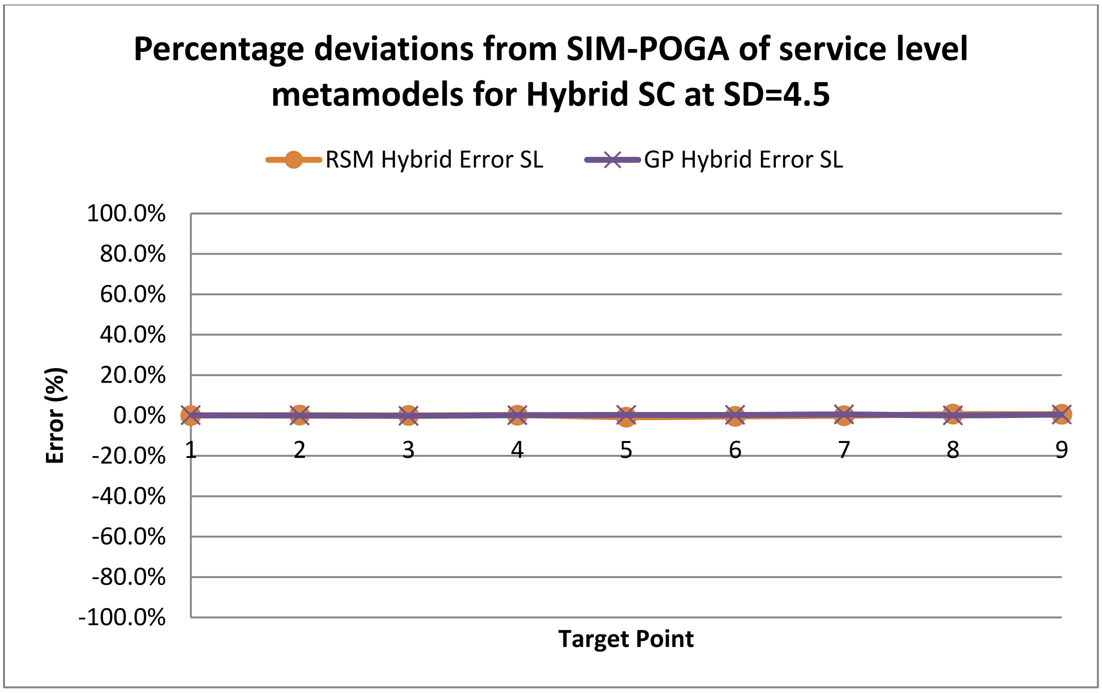


Figure I-20: Percentage deviations from SIM-POGA of service level metamodels for Hybrid SC at SD=4.5

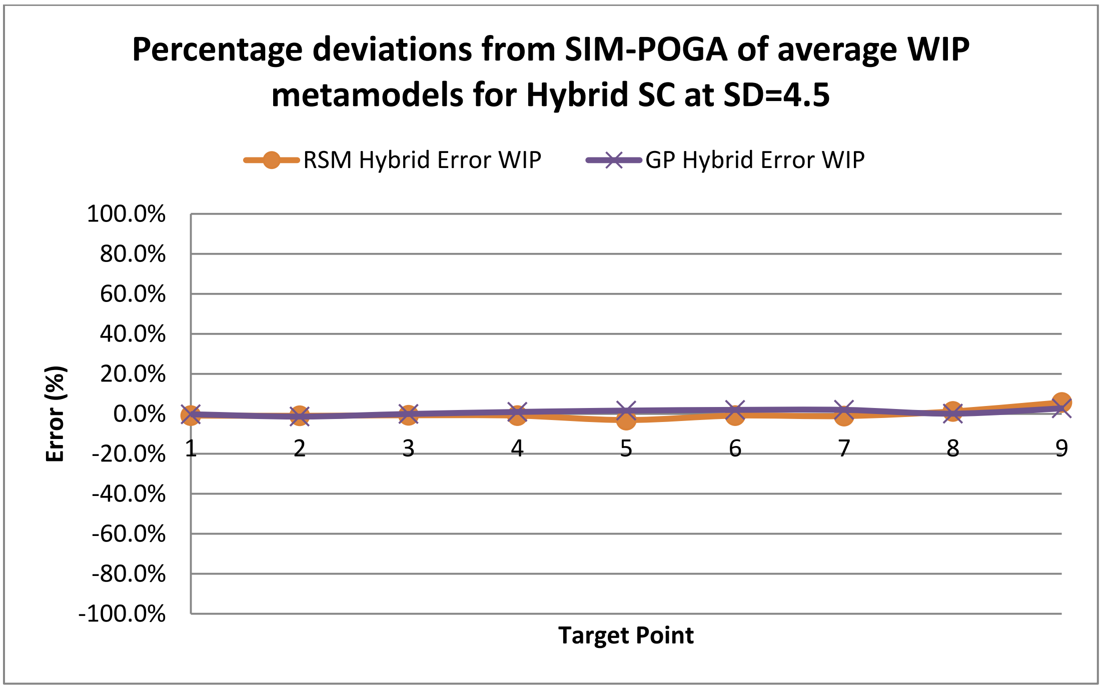


Figure I-21: Percentage deviations from SIM-POGA of average WIP metamodels for Hybrid SC at SD=4.5

I.8 Trade-Off Curves Comparison and Error analysis of Hybrid Kanban-CONWIP SC at Demand SD = 8

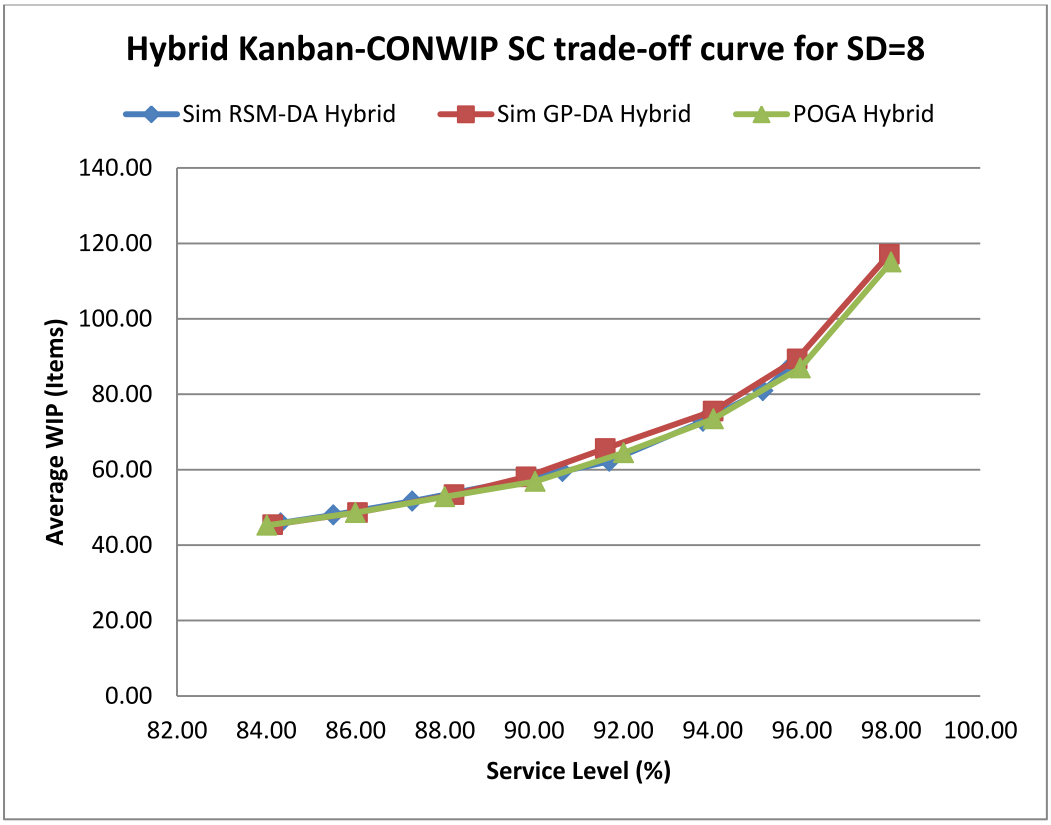


Figure I-22: Hybrid Kanban-CONWIP SC trade-off curve for SD=8

Table I-8: Percentage deviations from SIM-POGA of Hybrid Kanban-CONWIP SC for SD=8

		SIM-RSM-DA		SIM-GP-DA	
Number	SL Target	Error SL	Error WIP	Error SL	Error WIP
1	84±0.5	-0.366%	-1.412%	-0.152%	-0.344%
2	86±0.5	0.576%	1.236%	-0.053%	-0.050%
3	88±0.5	0.828%	2.166%	-0.236%	-1.166%
4	90±0.5	-0.682%	-4.626%	0.228%	-2.142%
5	92±0.5	0.348%	3.478%	0.448%	-1.773%
6	94±0.5	0.248%	0.878%	0.008%	-2.854%
7	96±0.5	0.874%	6.905%	0.074%	-2.778%
8	98±0.5	2.302%	24.109%	0.041%	-1.807%

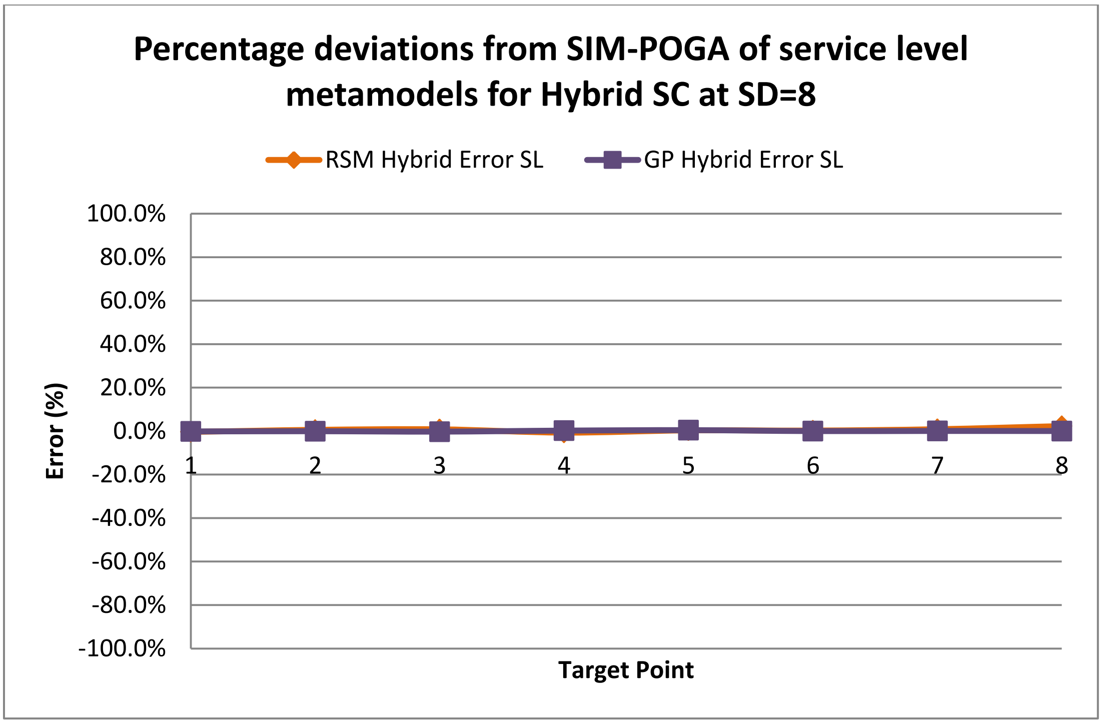


Figure I-23: Percentage deviations from SIM-POGA of service level metamodels for Hybrid SC at SD=8

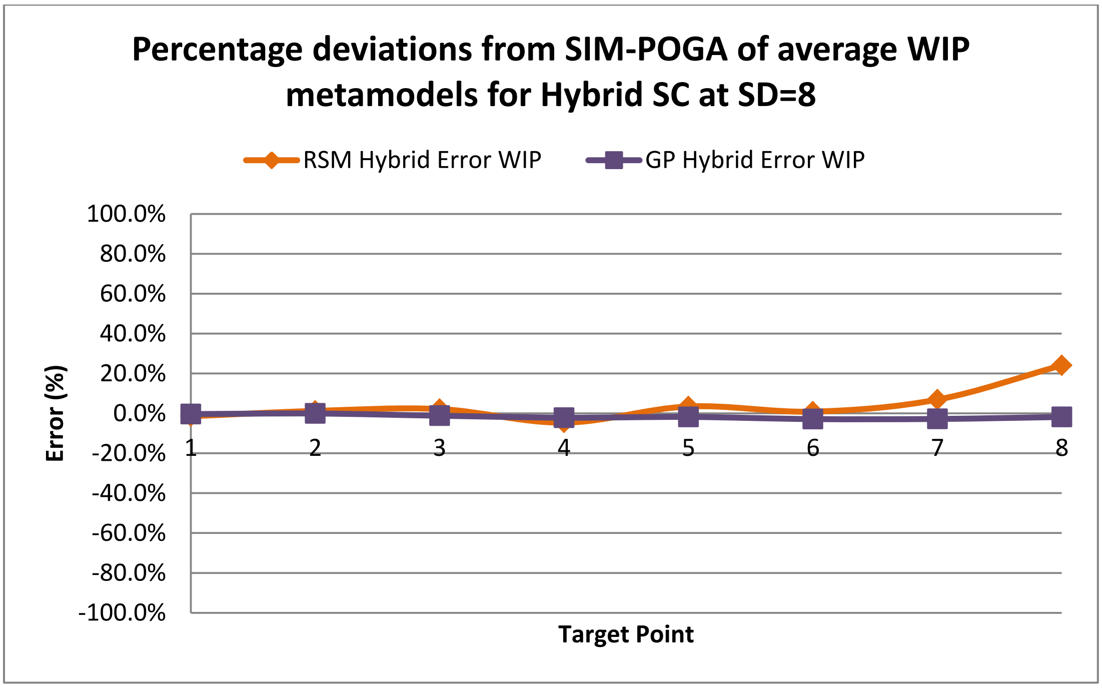
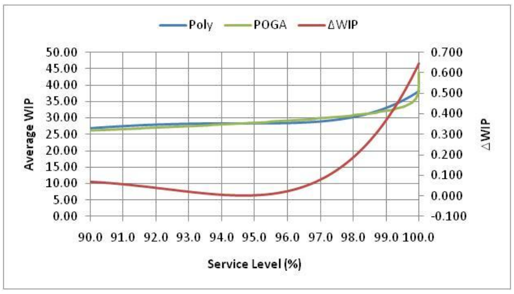


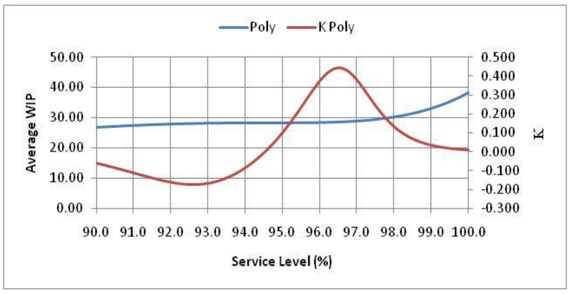
Figure I-24: Percentage deviations from SIM-POGA of average WIP metamodels for Hybrid SC at SD=8

APPENDIX J CURVATURE ANALYSIS RESULTS

J.1 CONWIP SC curvature analysis at Demand SD = 1

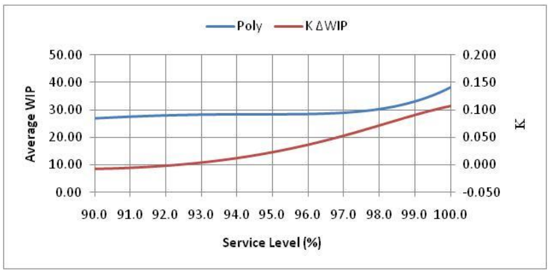


(a)



(b)

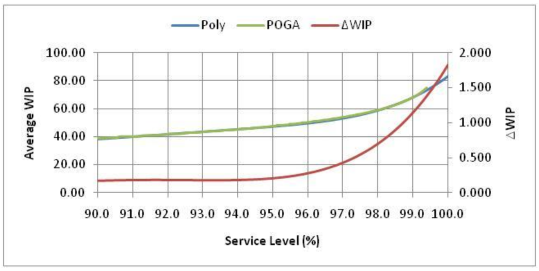
(c)



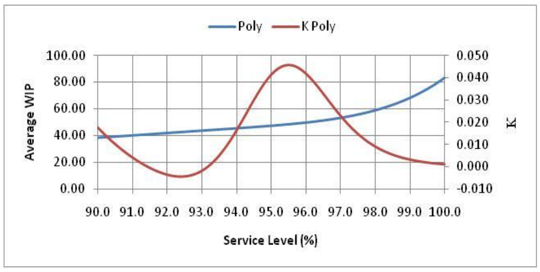
(d)

Figure J-1: POGA CONWIP SC curvature analysis for SD=1; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model

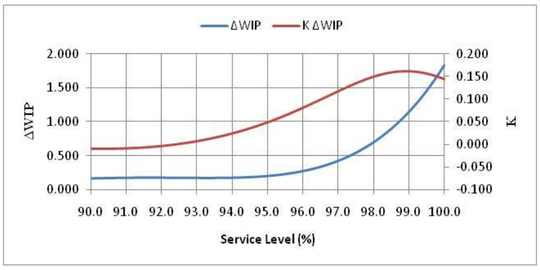
J.2 CONWIP SC curvature analysis at Demand SD = 4.5



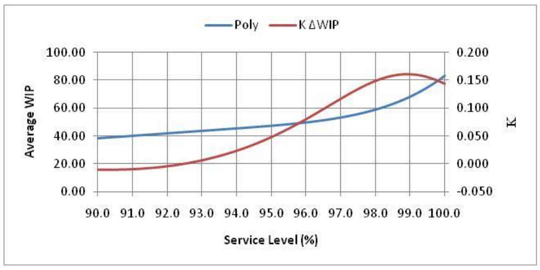
(a)



(b)



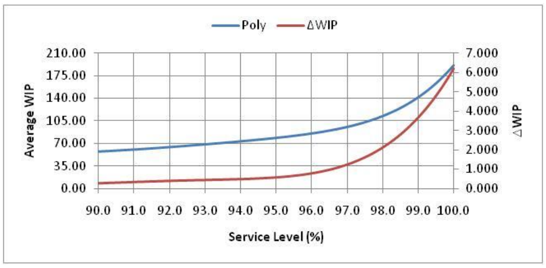
(c)



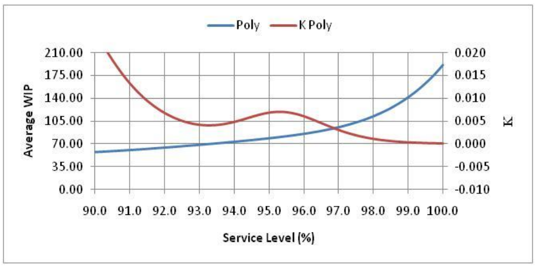
(d)

Figure J-2: POGA CONWIP SC curvature analysis for SD=4.5; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model

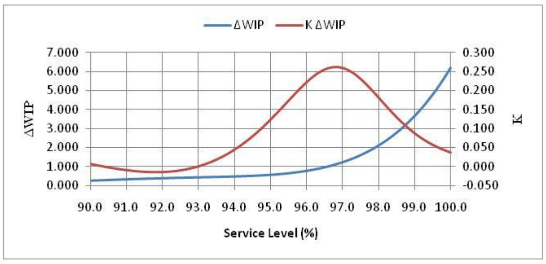
J.3 CONWIP SC curvature analysis at Demand SD = 8



(a)



(b)



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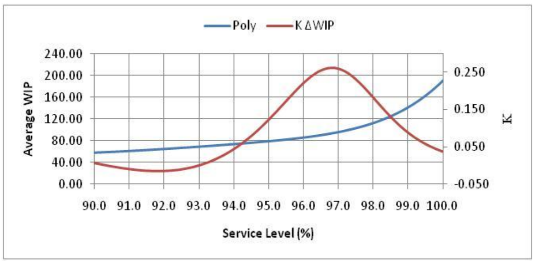
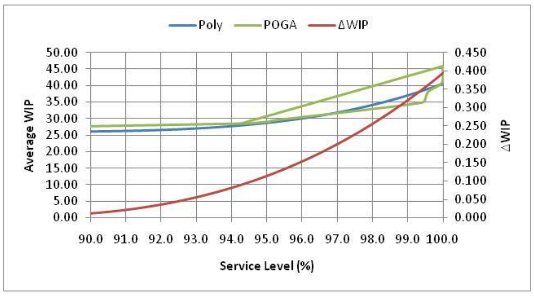


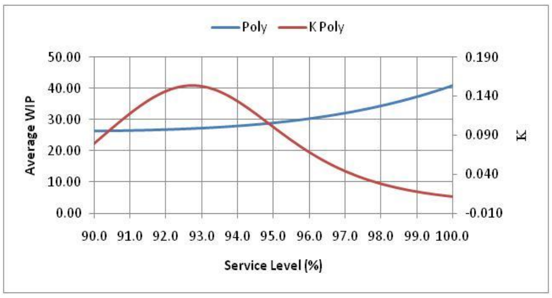
(d)

Figure J-3: POGA CONWIP SC curvature analysis for SD=8; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model

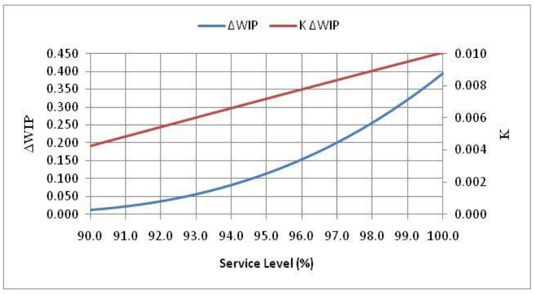
J.4 Kanban SC curvature analysis at Demand SD = 1



(a)



(b)



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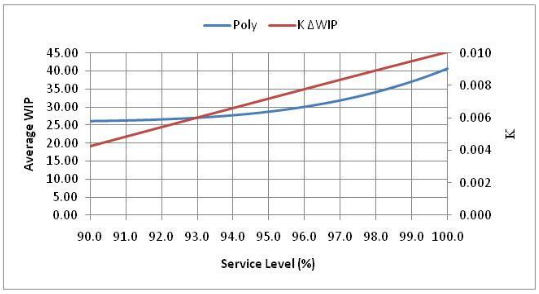
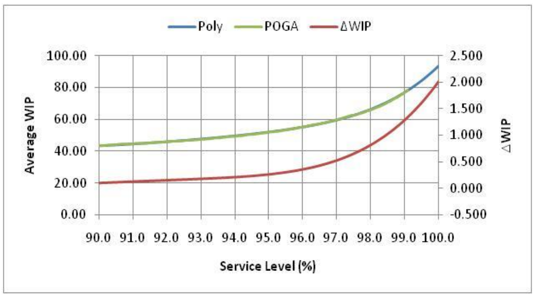


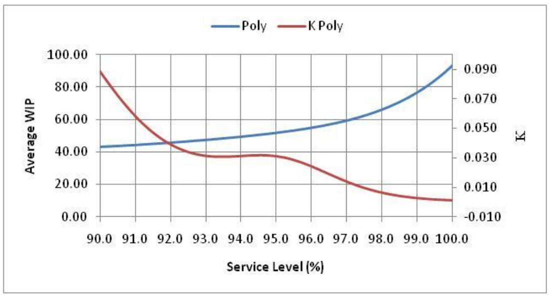
(d)

Figure J-4: POGA Kanban SC curvature analysis for SD=1; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model

J.5 Kanban SC curvature analysis at Demand SD = 4.5



(a)



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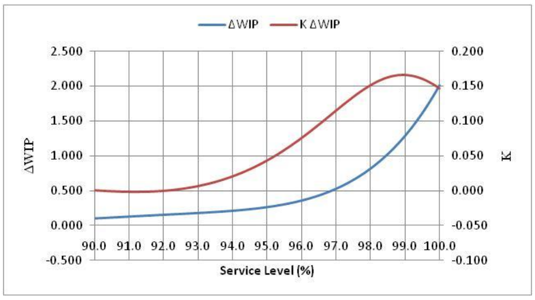

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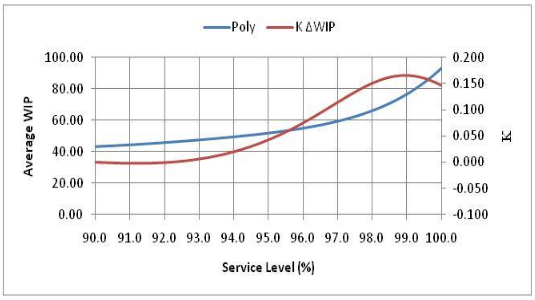
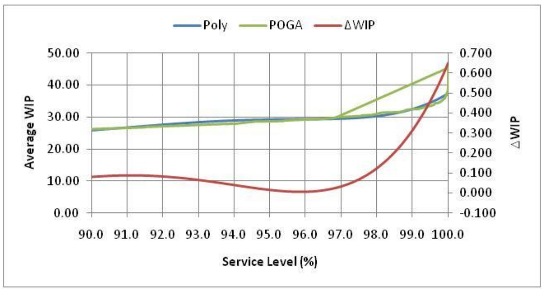
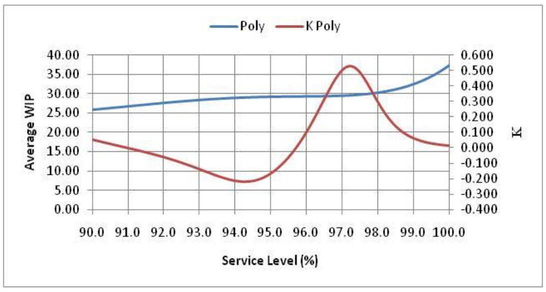


(d)

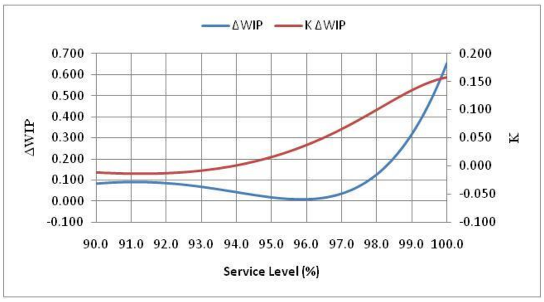
Figure J-5: POGA Kanban SC curvature analysis for SD=4.5; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model

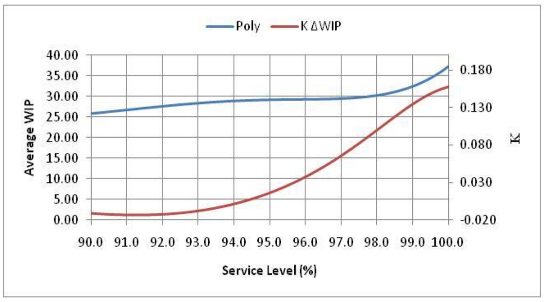
J.6 Hybrid Kanban-CONWIP SC curvature analysis at Demand SD = 1





(a) (b)

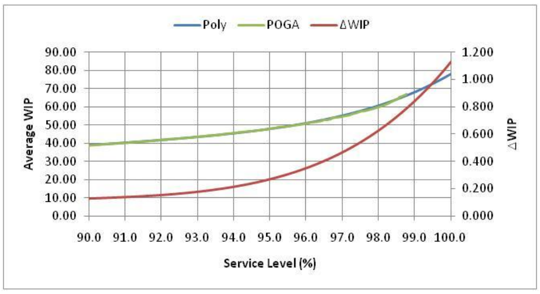




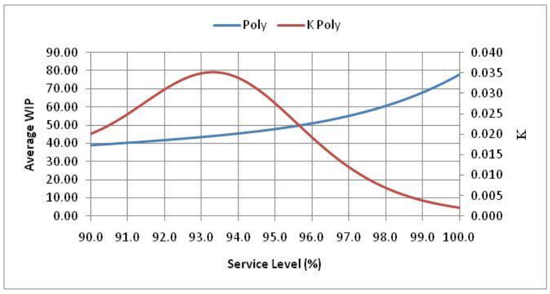
(c) (d)

Figure J-6: POGA Hybrid Kanban-CONWIP SC curvature analysis for SD=1; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model

J.7 Hybrid Kanban-CONWIP SC curvature analysis at Demand SD = 4.5



(a)



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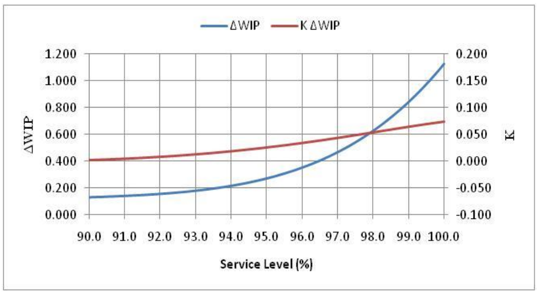
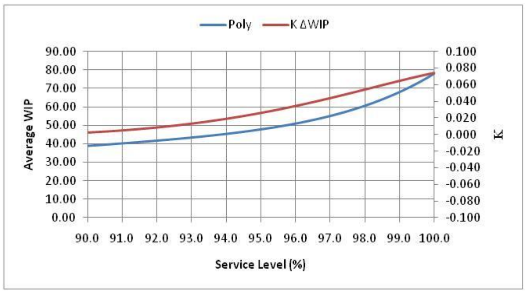


(c)

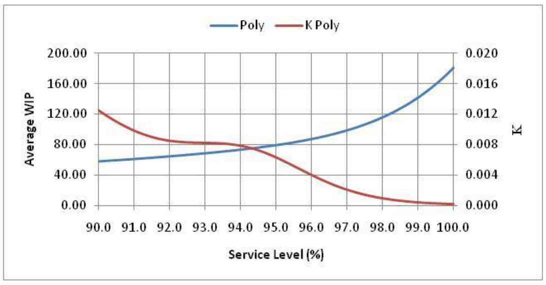


(d)

Figure J-7: POGA Hybrid Kanban-CONWIP SC curvature analysis for SD=4.5; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model

J.8 Hybrid Kanban-CONWIP SC curvature analysis at Demand SD = 8

(a)



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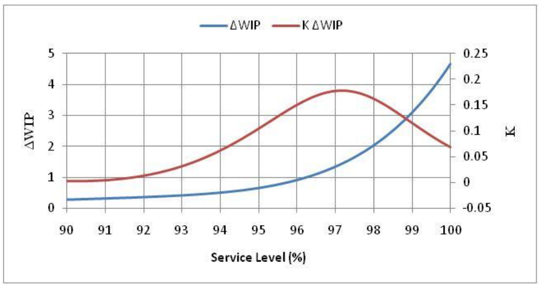

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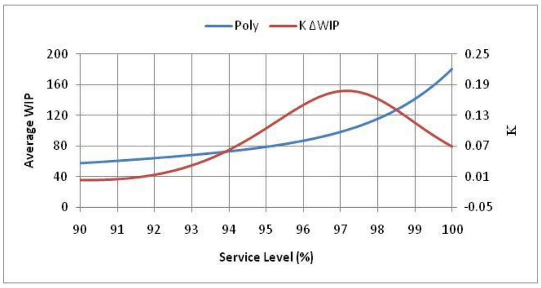

(d)

Figure J-8: POGA Hybrid Kanban-CONWIP SC curvature analysis for SD=8; (a) fitting the higher order polynomial model to POGA solutions and obtaining the ΔWIP curve (b) curvature analysis of the polynomial model (c) curvature analysis of the ΔWIP curve (d) curvature analysis of the ΔWIP curve overlaid on the polynomial model