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Designing a robust production system for erratic demand environments.

Joseph Elias El-Khoury 1963-
University of Louisville

DESIGNING A ROBUST PRODUCTION SYSTEM FOR ERRATIC DEMAND ENVIRONMENTS

By

Joseph Elias El-Khoury
Speed School of Engineering, 2013

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Joseph Elias El Khoury
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by the following Dissertation Committee:

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Dissertation Director
Dr Sunderesh S. Heragu

____

Dr Gail W. DePuy

____

Dr Gerald Evans

____

Dr John Usher

____

Dr Mahesh Gupta

DEDICATION

This dissertation is dedicated to my parents, Elias and Vania El Khoury, both of whom believed in diligence, perseverance, and the pursuit of academic excellence. Their life was a testament to me that I am able to achieve whatever goals I sought to pursue, no matter what the challenge, if I believe in myself. There is no doubt in my mind that without their continued support and counsel I could not have completed this process.

I would also like to dedicate this dissertation to my brother Rony for all his encouragement, support, and patience.

Also, I would like to thank my daughters, Vania, Sharlymar, Alyssar and Adael, my pride and joy, my legacy. Thank you for the unconditional love and support throughout the course of this thesis.

Last but certainly not least, I would like to dedicate this dissertation to my wife Silvia. I will be forever grateful for her understanding and patience.

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ABSTRACT

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Joseph E. El-Khoury

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Production systems must have the right type of material in the right quantities when required for production. They must minimize the work in progress while ensuring no stock-outstock-out occurs. While these twin opposing goals are achievable when demand is stable, they are difficult to realize under an erratic demand pattern. This dissertation aims to develop a production system that can meet erratic demands with minimal costs or errors. After a detailed introduction to the problem considered, we review the relevant literature. We then conduct a numerical analysis of current production systems, identify their deficiencies, and then present our solution to address these deficiencies via the ARK (Automated Replenishment System) technique. This technique is applied to a real-world problem at Methode Engineering ©. We conclude by detailing the scientific benefit of our technique and proposing ideas for future research.

TABLE OF CONTENTS

PAGE

LIST OF TABLES

TABLE **PAGE**

LIST OF FIGURES

FIGURE **PAGE**

LIST OF EQUATIONS

EQUATION **PAGE**

CHAPTER 1

INTRODUCTION AND WORK MOTIVATION

The set of resources and procedures involved in converting raw material into products and delivering them to customers defines a production system (Askin et al, 2002). This definition of a production system is a simplified description of a complex organism. The micro and macro connections and relationships involved in all stages of a product supply chain make the production planning and control stages challenging.

Our goal is to generate an optimized production control strategy that reduces inventory while meeting customer demand. One line of research in this area focuses on generating accurate forecasts of customer demand and developing a production schedule to meet this forecast. These studies assume a rather stable demand and would generate results accordingly (Willemain et al, 1994). This assumption is not always seen in practice. In fact, in most industries, the demand is highly unpredictable and characterized by a high degree of uncertainty. Another line of research has proposed alternate production systems that attempt to absorb forecast errors by building up inventory or by waiting until demand builds up to a threshold to release the production order. Some even presented adaptive approaches that integrated customer demand, inventory and backorders to release production requests (Tardif et al, 2001).

Each manufacturing enterprise is unique. Produced goods can be standardized or highly variable. Demand can be accurately forecasted or erratic and completely unpredictable. Production processes can be well defined and fixed or must be completely reset to suit the job order. The cultural environment also has an impact. The robustness of a production system should be assessed under well-defined conditions in well-defined environments. While a kanban system might work well in stable demand environments, it might not work well when operating in non-stable environments. Push systems such as materials requirement planning (MRP) may also fail in such environments because they were designed to work in a deterministic and stable demand, and constant processing time environment (Gupta and Al-Turki, 1997). Moreover, they require intensive standardization and thus are not suitable for highly customized products (Krishnamurthy et al, 2004).

Motivated by the lack of methods available to tackle the types of demand faced by automotive suppliers supplying to multiple automobile manufacturers such as Methode[1] industries, this research aims to develop and implement a robust production system, which will be capable of coping with the complexity of unpredictable and highly variable demand patterns witnessed in automobile industries. Erratic demand is characterized by its infrequent occurrence and highly variable demand (Silver and Peterson, 1985). This type of demand is considered a challenge for inventory control due to the fact that the variability in demand is greater than the mean. Demand occurs intermittently, with some time periods having no demand at all. Moreover, when a demand is made, it is highly variable. In the academic literature, intermittent demand is often referred to as lumpy,

[1] Methode Electronics International GmbH, Rheinstr. 48 55435 Gau-Algesheim, Germany

sporadic or erratic demand (Syntetos et al., 2010). Our goal is to develop alternate versions of Kanban systems that will be functional under erratic demand scenarios in order for inventory stock-outstock-outs to be minimized.

This thesis is organized into six chapters. The first chapter is an introduction to the problem and the motive for this study. It presents the goal of our work as well as the industrial motivation behind it. A problem arises where supplier shortage and short shipments are constantly increasing and currently available production system control strategies appear to be inadequate.

The second chapter reviews the extensive literature in this field. It presents an extensive review of production systems followed by a survey of forecasting and simulation techniques. At first, the main production systems are presented and explained with focus on MRP, CONWIP (CONstant Work-In-Process), Theory of Constraints and Kanban systems. Hybrid compositions are also reviewed. We first define the production systems variables and use these to compare the different control strategies. Then, a second section elaborates on forecasting studies and their inadequacy under erratic conditions. Both parametric and non-parametric forecasting techniques are investigated.

Numerical analysis of current production systems and their expected behavior are discussed in Chapter 3. Using simulation techniques, it investigates the effectiveness of existing production control systems in an erratic demand environment. The three systems that are investigated are push, Kanban and ConWIP. At first the manufacturing system is presented with its five stages. Then, the models used for simulation are developed followed by the presentation of the modeling tool. Third, modeling description and building blocks are set as well as initial states leading to the selection of control parameters. The chapter ends with experimental results and a first conclusion on demand pattern effect on optimal production system selection.

A new production planning system (ARK Production system) is fully described and developed in Chapter 4. It presents a generalized scheme of the proposed production system **ARK**. The latter is adapted from Kanflow as presented in (Louis et al, 2005). The new production system is specifically designed to handle erratic demand. It also enables manufacturing industries facing erratic demands to reduce stock-outs and inventories. The system is rather stable. Once a trigger is issued there is no more change, creating a stable supply chain and accurate supplier performance management for continuous improvement. **ARK** first applies the conventional Kanban formula in determining a preliminary Kanban lot size. It is then tested via simulation and the final Kanban lot size ensuring no stock-out is determined.

The implementation at an automobile parts supplier - Methode© is presented in chapter 5. Several case studies with diverse control parameters are detailed. Several demand patterns are compared coupled with lead times and product variance. Improvements in stock-outs and inventory costs are reported. Also, operator numbers were reduced affecting current cost of labor hours.

The sixth and final chapter presents an elaborate conclusion on our work as well as a perspective section detailing further potential enhancements that can be added to the system. The main contributions of our work are thoroughly detailed: Cultural impact, cost reduction, buyer intervention and the forecast hub.

CHAPTER 2

LITERATURE REVIEW

Production systems have been described extensively in scientific literature. Numerous references are found to cover each system as well as the integration/combination of different ones. While it is impossible to provide a complete review of production systems, this chapter shows that applying traditional production systems would fail when demand is erratic. To achieve this, a bibliographical review of three main production systems is presented at first: MRP (Materials Requirements Planning), Kanban and CONWIP (Constant work in progress). The behavior of these systems facing erratic demand is investigated as well hybrid compositions of control strategies. (Silver et al, 1981) draws attention to the serious gap that exists between theory and practice. For future purposes, the main variables identifying production systems are listed. Other production systems or strategy concepts such as Basestock and Starving avoidance (Glassey et al 1, 1988) (Glassey et al 2, 1998) are not investigated. A part addresses the Theory of Constraints (Goldratt et al, 1986) (Kayton et al, 1998) and its optimization benefits. While TOC is rather an optimization technique than a production control strategy, it is discussed in the first part of production systems investigation. A second section presents parametric and non-parametric forecasting techniques: the former addresses distribution under normal distribution and the latter deals with intermittent demand. Finally, a conclusion on our literature review is presentedwith the main findings, mainly the failure of current production system strategies to deal with erratic demand.Production Systems

Ordering when a part/material should flow within a manufacturing system represents the core of production control systems. Manufacturing facilities function with typically conflicting objectives of meeting demands while keeping minimal inventory. The desired solution is a suitable inventory control policy that will guarantee a satisfactory service level without keeping unnecessarily large inventories that are costly and difficult to handle (Nenes et al, 2010). Some references proposed sharing inventory costs between the vendor and the customer (Panda et al, 2006). The authors developed a join lot size model under the assumption that customer demand and the stock level of the vendor are to be identically distributed continuous random variables.

The problem arises from the variability of customer demand. The latter is affected by a multitude of inter-connected factors and although forecasting sciences are well advanced, demand remains highly unpredictable. Additionally, production systems will address time and quantity values: when will a part move to a second processing stage as well as what is its quantity.

MATERIAL REQUIREMENTS PLANNING (PUSH SYSTEMS)

MRP is still regarded as one of the most commonly used production planning and control systems (Mohan et al, 1998). Push systems (such as MRP) schedule periodic releases of raw materials into the system based on forecasted customer demands (Krishnamurthy et al., 2004). Figure 1 shows an example of a push system where upstream information generates the job order. Traditional research in MRP assumed the demand to be deterministic (De Bodt et al, 1982) (Brennan et al, 1993). (De Bodt et al 1982) highlighted the need to investigate lot sizing and safety stock decisions under conditions of uncertain demand. They state that usually in industrial situations uncertainties in demand have considerable influences on the efficiency of MRP systems. (Brennan et al, 1993) also built a computerized simulation of a multi-level product environment to evaluate the influence of these combined uncertainties in a rolling planning horizon. Forecasting errors significantly impacts all major performance features of MRP systems. (Lee et al, 1986) built a computerized simulation to examine the impact of forecasting errors on the MRP system inventory cost and shortage. They concluded that the greater the forecast error the greater the shortages.

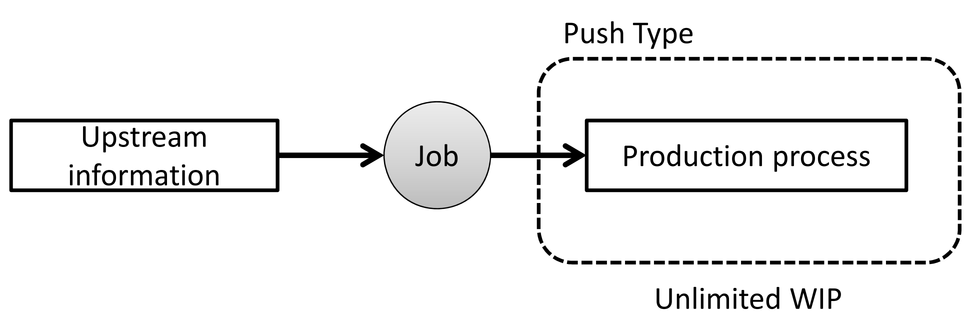


Figure 1. Push Control System.

Push systems operate without a feedback loop to communicate the current work in progress status. The replenishment system based on push concept is hindered by two factors: Capacity infeasibility and Lead times. The assumption of fixed lead time to compute the schedule is erroneous: in the setup of real manufacturing facilities, the line loading heavily influences the lead time. It has long been recognized that workflow is heavily influenced by both planned lead times and lot sizes, yet prescriptive ways of setting either have not been adequately developed (Enns et al, 2001). Additionally, MRP systems do not account for machine downtime that can render production schedules infeasible when product levels are at or near maximum capacity (Hopp and Spearman, 2008).

Most of the literature confirms the limitations of MRP under uncertain demand, and recommend several approaches to deal with demand uncertainty, in particular, safety stocks. (Anderson et al, 1989) considered the problem of predicting customer service levels in a single-stage MRP environment. Their proposition was to implement generalized period review policies. Eventually, policy rules and relationships were set in place and simulation was used to verify priority allocation. Demand uncertainty is defined as demand that exhibits no discernible pattern and high day-to-day variability (Kulonda et al, 2002). Several references attempted to review and categorize uncertainty under MRP Planned manufacture. (Koh et al, 2002) reports the underperformance of industries with adapted MRP systems that are supposedly able to handle uncertainty. They carried an extensive literature review on uncertainty under MRP-planned production. Uncertainty was categorized into input and process. A complete categorization was identified and it was claimed that a structured and systematic approach is required to cope with uncertainty holistically within MRP-Planned manufacture. (Guide et al, 2010) presents a detailed review of techniques for buffering against uncertainty with MRP Systems. The results of their review are reported in the table below.

Table 1

Review result of Guide et al

Research Issue	Gap/Limitation
Integrated approach for multi-stage system	Only up to two stages
Realistic reflection of practice	No benchmarking of research with industrial data
Interaction with other subsystems in production and planning control	Virtually ignored
Robustness of model/findings	Not evaluated
General solution methodologies/guidelines	Note available
Type of buffer to be used	No agreement in literature, conflicting results
Size of buffer to be used	No resolution of issue
Impact of other managerial issues	Not evaluated

One of the most highlighted deficiencies is the limited amount of realism in the models and approaches: None of the works reviewed benchmarks the parameters used in the study with any industrial data. Given the widespread use of MRP systems, such data to ground models could and should be used. Some literature suggests that advanced MRP concepts handle uncertainties by incorporating safety stocks and scrap allowances into release order calculations. However, (Inderfurth et al, 2009) states that these concepts fail to address how these measures of risk protection might interact. The authors further address the weakness of traditional MRP systems, mainly the disregard of uncertainties like those referring to demand and supply quantities.

(Wijngaard et al, 1985) proposes the distribution of the safety stock across different production stages depending on peculiar situations. Their approach splits the system into three levels of control. They do not derive general rules for slack distribution but rather state that the distribution has to depend on flexibility and uncertainty with respect to manufacturing purchasing and sales. (Yeung et al, 1998) highlights that most of the previous research dealt with one kind of uncertainty: demand uncertainty. In the real-world, there are many other uncertainties facing MRP users, such as incoming quality, delivery time, process yield, production downtime and many other factors. Further study on various uncertainties is recommended.

In summary, implementing MRP under non-linear demand can only be possible with high levels of safety stocks and inventories.

KANBAN AND JUST IN TIME SYSTEMS (PULL SYSTEMS)

Pull control systems function backwards: actual demands will generate a processing request sent to the production process. Pull systems control work in progress and observe the constant fluctuations throughout.

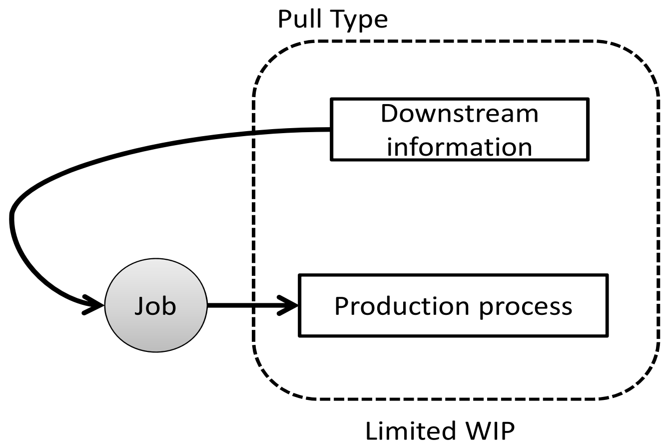


Figure 2. Pull Control System.

Figure 2 shows an example of pull systems functionality: A user makes a demand, the latter is recorded and the information is sent to the processing center where a job is released. In general, pull systems make sure that no goods are produced unless demanded, but this requires that minimum inventory is held at the output of every processing unit. The pull system eliminates under or over production by limiting production to those parts demanded by the next downstream process (TPS Handbook). Additionally, pull systems require intensive standardization and thus are not suitable for highly customized products (Krishnamurthy et al., 2004).

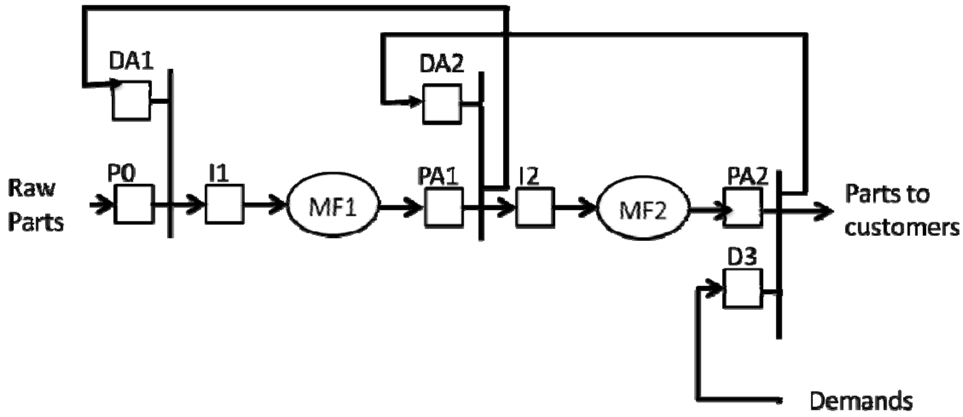


Figure 3. Kanban Control Strategy.

The figure above details the Kanban control strategy:

First, the Kanban card issues the authorization for production

Next, the actual production begins when a part is available in the station input buffer

Following this, the Kanban sticks to the part and travels with the part to the next station: when the immediate successor begins manufacturing the kanban is detached and sent back upstream to the production stage in order to authorize the production of a replacement part.

This enables the system to be controlled by actual demand.

Kanban and JIT systems originated from Japanese industries in the 1950's. Adaptations to US firms started early and in different environments (i.e. Semiconductors manufacturing (Otenti et al, 1991)). Kanban is a Japanese word for card. Kanban systems are based on the concept of issuing a different card for every Production/Move/Supplier, thus initiating an action. Then, using several variables (mainly lead time and safety stock) the number of cards is recalculated and adjusted by adding or retracting cards. (Huang et al, 1983) attributed the success of JIT to the production environment that is receptive of the zero inventory policy. They simulated adapting kanban methodologies to a US firm production line with positive feedback. However the authors highlighted that importing the kanban process in total is risky without assessing the differences between American and Japanese operating conditions and production system characteristics. They provided a mean to analyze the kanban process given US local operating conditions. (Groenevelt et al, 1988) generated a dynamic kanban study for a rural US manufacturer. The system was forecast dependent. This permitted the reduction of inventories over a purely reactive scheme. The system added a push element to the kanban approach by adjusting the number of cards in the system as a function of changes in the average level and variability of demand over lead time. (Buzacott et al, 1989) showed that backordered Kanban systems for multiple stages are equivalent to Kanban systems of fewer stages. Surplus Kanbans are recognized through release rules at each stage. Thus, their removal will have no impact on the system performance. The authors considered that both conventional Kanban and MRP controlled production systems are both special cases of a general approach to production control. (Akturk et al, 1999) presents an overview of the kanban system design parameters. They analyzed the impact of operational issues, such as kanban sequences and actual lead times, on the design parameters of the withdrawal cycle length, kanban size and number of Kanbans. Moreover, they state that scheduling algorithms should be further developed to enhance the effectiveness of the kanban system. In more recent development, electronic kanban systems were introduced. They give possibilities to solve some of the limitations of kanban system, like the model mix change management and failure recovery (Kouri et al, 2008). (Muckstadt et al, 1993) identified and studied four main sources of variability: processing time variation, rework requirement, machine breakdowns and yield losses. Through models adaptation, the authors showed that most structural results carry over to more realistic settings. Further publications by the same authors proved their concepts through simulation. (Andijani et al, 1998) proposed a multi-criterion approach with three conflicting objectives: the average throughput rate (to be maximized), the average work-in-process (to be minimized), and the average flow time (to be minimized). A sensitivity analysis is also conducted to examine the trade-off between the three objectives. Other studies attempted to reduce constraint sets. (Mitwazi et al, 1994) provided a non-linear integer mathematical model for the multi-item, single stage, capacitated kanban system. The modification was easily implemented. They investigated the use of Kanban control at work centers which produce multiple items with dynamic, random demand. The authors indicated that the dynamic aspects of demand may cause temporary capacity shortages. They advised that the Kanban control system must quickly react to the random changes of the demand, and by selecting different numbers of Kanbans, the dynamic aspects can be accommodated.

The analytical intractability of Kanban systems makes simulation and heuristics essential when studying them. (Tayur et al, 1993) studied heuristics. They presented two factors, reversibility and dominance, that characterize Kanban dynamics, provide insight into their behavior and help greatly to reduce the simulation effort needed to study them. Reversibility deals with certain permutations of the machines; dominance deals with the allocation of Kanbans to cells. (Baykok et al, 1998) used simulation to explicitly examine the performance of a multi-item, multi-line, multi-stage JIT system and to show how this system reacts under different factor settings. The study results were that output rate and utilization are increased as the number of Kanbans increase. However this also led to a striking increase in waiting time and WIP length. For the studied system, they set the value of 2 Kanbans as the preferred.

Kanban generic hybrid systems are well developed i.e. the generalized kanban control strategy (with Basestock control). The merits of joining Kanban and Basestock systems are clear in the sense that the Basestock mechanism offers the ability to react faster to demand. (Frein et al, 1995) discuss the complexity of the generalized kanban control strategy system (GKCS) and present results that can be useful for designing multistage GKCS. Another mechanism for the coordination of multi-stage manufacturing systems is presented by (Dallery et al, 2000): the Extended Kanban Control System (EKCS). (Chang et al, 1994)(Chang et al 2, 1994) present a generic kanban system that is adaptable to dynamic environments. The approach optimizes the system performance by determining the number of Kanbans at each station and lot sizes of job types.

Finally, different studies attempt to overcome certain system deficiencies or to enhance kanban systems in regard to a particular need through the development of tailored algorithms. (Duenyas et al 1997) addresses quotas from the perspective of the supplier plant. It generates based on what the manufacturer has to abide by for deliveries. They formulated two models for determining an inventory control policy for production systems with stochastic production and demand. They integrated this quota-setting issue with the problem of using safety capacity. (Gupta et al, 1997) dynamically adjust the number of Kanbans in stochastic processing times. The Flexible Kanban system (FKS) offsets the blocking and starvation caused by the said uncertainties during a production cycle. The main objective was to introduce a systematic methodology to manipulate the number of kanban in FKS in order to compensate for the variation in processing times and anticipated surge in demand. (Tardiff et al, 2001) allow the number of Kanban cards to change with respect to the inventory and backorder levels.

CONWIP

(Spearman et al, 1990) present a pull alternative to kanban: CONWIP. CONWIP stands for **CON**stant **W**ork **I**n **P**rogress. The model allows a certain level of inventory within a production system. The processing will take place after a demand consumes a part of the inventory. This consumption allows production to be reinstated and so on. This limit on the WIP assumes that all the jobs are identical and that the production line is a single route. The figure below shows an example of how a CONWIP system functions.

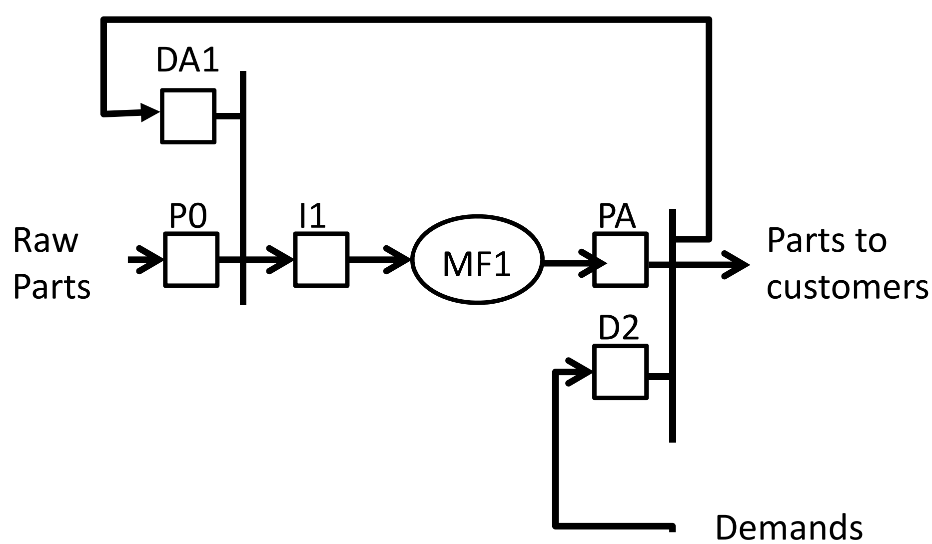


Figure 4. CONWIP model.

CONWIP models require major conditions to operate smoothly with respect to the loop length, part routing and the measure of WIP. (Duenyas et al, 1993) propose a closed queuing network. They assume there are an infinite number of jobs awaiting the WIP level to drop to enter the production state. They modeled a CONWIP production line with deterministic processing times and exponential failure and repair times as a closed queuing network. The suggestion was to give computable conditions under which a proposed approximation performs well. (Heragu et al, Article In Press) demonstrate that closed queuing networks provide inaccurate estimates of some critical performance measures, mainly due to the false assumption of infinite job queuse. It is therefore important to model these systems as semi-open queuing networks. (Herer et al, 1997) developed a mathematical programming technique to support the order of the backlog list as well as to set the amount of regular time and overtime to be used daily. The mathematical programming formulation of CONWIP based on production control systems allowed the determination of the order of the backlog list. This led to setting up the amount of regular/over time to be used daily. (Cao et al, 2005) propose a nonlinear mixed integer programming model. The system was tested on an assembly station fed by two parallel fabrication lines. The total setup time and the work load balance were identified as performance measurement items. Finally, it is logical to generate an overall measurement of WIP in the system with respect to the processing time required (better for product variety). (Framinan et al, 2006) propose a new procedure for card controlling. The method obtains a given throughput rate for make to order environments or a given service level for make to stock environments. The new procedure was computationally verified in a numerical experimental setup.

CONWIP system remains a hybrid system combining the push advantages/disadvantages at the end of a production system and the pull advantages/disadvantages at the start. The system attempts to put some constraint on the acceptable inventory level. Determining this acceptable level is still challenging. (Ryan et al, 2000) formulated an optimization problem using the open queuing network model. They proposed a heuristic to find the minimum total WIP and WIP mix that would optimize the operating throughput. They extended the CONWIP concept to a job shop setting in which multiple production with distinct routings compete for the same set of resources.

CONWIP methodology presents the following challenges: CONWIP system inherits from push systems being the high inventory levels building in front of bottleneck stages (Bonvik et al, 1997). Solutions included using tandem CONWIP loops. (Yang et al, 2007) presented multi-CONWIP on an industrial case study. However, they indicate that the theoretical merits were offset by the tremendous amount of time and experience required to build a simulation model to address the case study. The experimentation was performed on an international integrated circuit (IC) packaging company. All the used data were physically collected from the company's shop floor. The method detailed a WIP cap that was verified through extensive preliminary numerical analysis. (Li et al, 2010) presented a different case study: modeling a semi-conductor facility. A series of numerical experiments were conducted to examine the accuracy of their evaluation method. Results showed that most cases are quite acceptable, although the throughput errors for systems with smaller throughput rate are more than for systems with larger throughput rate.

The high number of shared resources complicated both the control and forecasting of CONWIP line progress.

The total workload in the line and the homogenization between the different amounts of processing on the machines. A solution proposed by Hopp and Spearman (2008) would be to adjust standard times according to critical resources.

Finally, several literatures proposed to enhance CONWIP model for one of the above stated deficiencies. (Rose et al, 1999) presented CONLOAD. The system overcomes performance problems of traditional lot release rules. It keeps bottleneck utilization at a desired level and provides a smooth evolution of the WIP. CONLOAD is perceived as a simple extension of CONWORK. A case study was presented. (Takahashi et al, 2004) presented syncho-CONWIP. The system had different lead times in its branches and was found to reduce inventories. The invented PCS was constructed on CONWIP system by taking different lead times for synchronization into consideration. Detailed results of simulation experiments are presented for multiple scenarios.

THEORY OF CONSTRAINTS

TOC is frequently suggested to be an appropriate paradigm to evaluate the economic consequences of production-related decisions on the short term (Kee et al, 2000). TOC proposes to use throughput (T), inventory (I) and operating expense (OE) all together to generate a reliable prediction. (Watson et al, 2007) present an extensive review of the TOC, from the early 1979 developmental phase (labeled as era 1: the secret algorithm) and the first publication on the issue (Goldratt et al, 1984) till the recent era acclaimed as the critical chain/project management. The review concluded on the importance of TOC as reported by (Mabin et al). Findings included massive reduction percentages when it comes to order-to-delivery lead time (70%), manufacturing cycle time (65%), inventory (49%) and high increase percentages of throughput (63%) and due date (44%). Different strategies for TOC are available: Drum Buffer Rope, Starvation Avoidance, Pull from Bottleneck, workload regulation, CONLOAD release amongst others. These different strategies mainly regulated the issue of bottleneck. Some strategies are found to be similar to CONWIP production systems (specifically when it comes to implementation details).

(Wang et al) proposed a TOC solution that is integrated with Kanban/CONWIP. The authors mainly highlighted that this integration will tackle the production line control problems relevant to bottleneck resources. The hybrid system generated overall better performance values. (Linhares et al, 2009) studied the process of selecting the preferred product mix under the theory of constraint procedure. They illustrated several forms where TOC failed even in the case of one simple bottleneck. The authors concluded that the failure did not result from a problem in deficiency but rather from the problem of suitability and the non-adaptability of TOC. To conclude our primary investigation of TOC, we can identify that the latter's managerial and operational philosophy has been proven somewhat successful, mainly when it comes to resolving bottleneck issues. However, some found that TOC is not suitable to specific production systems.

At Methode Engineering, bottleneck problems are controlled and few processes exhibit this inconvenience. The main issues revolve around the supplier or lead time. Moreover, we have KanBan that is already employed and operational. For the previous mentioned reasons, we will attempt to solve our problem of 'coping with erratic demand' through the enhancement of the currently deployed Kanban production system, rather than moving towards other production strategies such as TOC.

LITERATURE HANDLING ENHANCEMENT, INTEGRATION, COMBINATION OR COMPARISON OF DIFFERENT PRODUCTION CONTROL STRATEGIES

(Krajewski et al, 1987) present a first extensive detailed comparison between MRP, ROP and Kanban systems. The authors concluded that applying kanban in US firms is not crucial to improving performance. Integrated JIT into MRP systems, or merged JIT and MRP systems are abundantly studied in scientific literature. They identified several experimental factor clusters such as customer influence, vender influence, buffer mechanisms, production structure, facility design, process, inventory and other factors. (Flapper et al, 1991) forward a three step framework for embedding JIT into MRP with few changes needed on the level of the MRP database. (Ding et al, 1991) discuss the co-existence of MRP and Kanban as separate entities in the same manufacturing environment. MRP is modified through two lot-sizing rules to be used in part explosion. Since, as the authors state, kanban parts are not reordered until parts are withdrawn, accumulation of demand generally determines order releases. In the new system, an order release of a kanban part is to be entered in its MRP whenever the gross requirement accumulates and reaches the container size. (Hodgson et al 1, 1991)(Hodgson et al 2, 1991) propose to use MRP at all initial stages of the system and JIP strategies at all other downstream stages. They first present a particular casestudy on an iron and steel manufacturing company in (Hodgson et al 1, 1991). Then, in (Hodgson et al 2, 1991), they generalize the scenario to other types of industries. Furthermore, (Deleersnyder et al, 1992) use a markovian model to develop a general N-stage hybrid push/pull system. Lower inventory levels and better response to demand changes were reported.

(Veatch et al, 1994) propose a methodology to control production rates and exponential service times through dynamic programming. Results were compared with kanban, Basestock and buffer control mechanisms. (Gstettner et al, 1996) investigate the difference between Kanban and CONWIP. Presented results are based on unlimited demand at the end of the production line. They noted that kanban would reach a given production rate with less WIP than in a CONWIP system. A combination of pull systems is laid out: Segmented CONWIP system, combination between kanban and CONWIP system and a segmented base stock system. (Bonvik et al, 1997) study the performance of kanban, minimal blocking, Basestock, CONWIP and hybrid kanban-CONWIP control policies. The adopted performance measures were the service level and the amount of work in progress. The authors report that the hybrid policies were 10% to 20% better in regard to inventory over the major kanban policy. (Benton et al, 1998) present a first of a kind of taxonomy for MRP/JIT Literature.

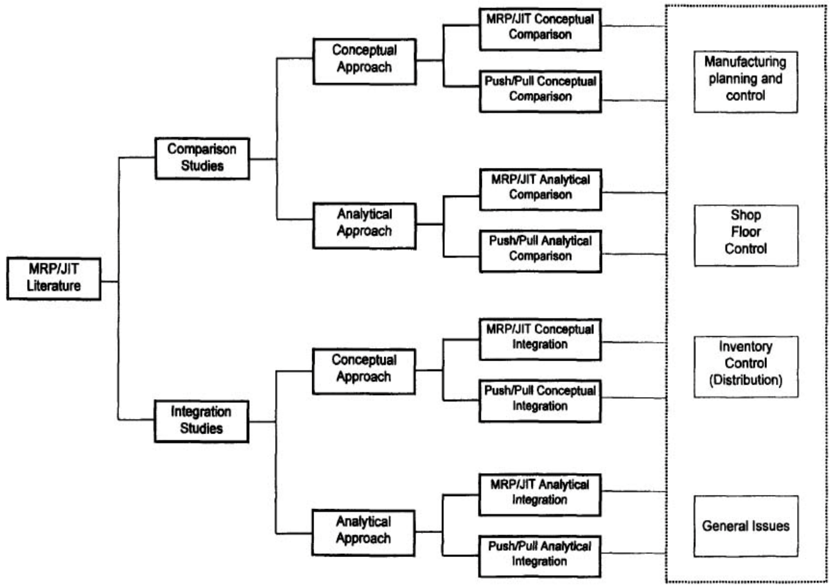


Figure 5. MRP/JIT Literature taxonomy (Benton et al, 1998).

(Gaury et al, 1998) generalize the way CONWIP has evolved from kanban in order to generate new hybrid species. The authors illustrate their approach through an example of a production line with four stages making a single part type. The authors further develop their concepts in (Gaury et al, 2000) and (Gaury et al, 2001) where they push the boundary and enable users to customize their system. In fact, they use a generic model that connects each stage of a given production line with each preceding stage.

Consequently, each loop will have its own kanban, CONWIP or Basestock system. (Beamon et al, 2000) also propose a hybrid push/pull system. The latter is primarily based on dependent demand aspects of manufacturing resources planning to manage intermediate inventories. (Krishnamurthy et al, 2004) re-examine the performance of MRP and Kanban material control strategies for multi-product flexible manufacturing systems. They analyze the system performance under different product mixes and observe that in certain environments with advance demand information, kanban-based pull strategies can lead to significant inefficiencies. Furthermore, in these environments, MRP-type push strategies yield better performance in terms of inventories and service levels. (Geraghty et al, 2005) state that literature has followed two approaches to developing production control strategies to overcome the disadvantages of kanban in non-repetitive manufacturing environments. The first approach has been to develop new or combine existing Pull-type systems while the second approach has been to develop hybrid systems based on combining elements of Push and Pull systems. A comparative study of kanban, CONWIP, hybrid Kanban-CONWIP, Basestock and Extended-Kanban was carried out. The criterion used in the study was the Service Level vs. WIP trade-off. Details are elaborated in the article. (Cheraghi et al, 2008) use simulation to compare control strategies. The computer simulation confirms that no single production control system is functional under all conditions.

(Selvaraj et al, 2008) propose another hybrid kanban system joining extended kanban with CONWIP in a single line and multistage environment. The authors report better performance through simulation of their proposition. (Pettersen et al, 2008) present a restricted work in process system. With the same WIP amount, CONWIP presented a higher throughput rate and less time between job outs. Even though theoretically CONWIP outperformed kanban, the authors state that in practice, the lack of CONWIP installation guidelines makes kanban more favorable. (Cochran et al, 2008) propose an optimization technique, based on genetic algorithms, to design a hybrid push/pull serial manufacturing system with multiple parts. They proposed a genetic algorithm optimization based on extensive numerical studies. a discrete-event simulation model estimates the stochastic performance measures needed to assess the fitness value.

(Wang et al, 2009) integrated the theory of constraints as the optimizer for kanban/CONWIP integration. They conclude that this integration rendered the production system more effective. (Khojasteh et al, 2009) gave a detailed comparison between Kanban and CONWIP: Both systems were highly affected by the card release policy and the card distribution. The latter in a kanban system, and the number of circulating cards in a CONWIP system affected the system performance such that WIP might rise by increasing the number of cards. (Kabardurmus et al, 2009) compared POLCA, with kanban/CONWIP. . The comparison was made under different hypothetical scenarios. Different key parameters were used to assess differences: coefficient of variation, batch size, downtime ratio, interarrival times and product mix. Finally, (Sun et al, 2011) used simulation to study differences between dynamic risk-based scheduling methods with MRP. This study will be further detailed in the next chapter where we attempt to use simulation and other numerical analysis tools to prove the need for a new production system at industries with erratic demand.

PRODUCTION SYSTEMS EVALUATION PARAMETERS

This section lists and defines the evaluation parameters of production systems. A detailed system to system comparison is presented in Appendix A (page 128).

Table 2

List of Parameters

	Parameter	Definition
1	Upstream information	Forecasting studies are required to set what is identified as upstream information or Demand. Several systems rely on demand to communicate production requirements. Demand can intervene at several stages of the production cycles as shows in the different systems. It can be transferred to the last production stage which in its turn informs the one preceding it, or it can be transmitted to inform all production stages.
2	Actual Demands	Actual demand presents the actual demands that are occurring and not the forecasted (expected ones). This factor plays a correction role to correct calculations based on forecast.
3	Work in Progress (WIP)	Work in progress represents the information about the current status of the production schedule. It relays information on the number of parts currently undergoing manufacturing as well as the manufacturing system capacity.
4	Lead Time	Lead time is the time required to setup a certain manufacturing procedure. It participates as a parameter due to the fact that some systems make the assumption of a fixed lead time to compute their schedule and this does not take into account that in real life manufacturing facilities the line loading heavily influences the calculation of the lead time.
5	Machine Downtime	Machine downtime can render manufacturing schedules infeasible and must be accounted for especially when product levels are near or at maximum capacity.
6	Inventory	Production systems have a main constraint: Keeping the inventory at the lowest level while meeting demand. Inventory levels could be a key parameter to minimize storage.
7	Standardization	Some production systems require heavy standardization and cannot operate in a flexible manner. It is imperative to measure the customization ability of a production system. This measure is of importance to manufacturers offering different production alternatives.
8	Throughput	Throughput represents the actual manufacturing data. It tracks the number of goods produced during a day.

9	Implementation	The implementation parameters deal with the complexity to install a certain production system or to maintain. This parameter is influenced by the size of the production facility as well as by the duration of the manufacturing procedure. If not suitable, a less complex system should be opted for.
10	Production Line	Some production systems are generated for linear manufacturing layouts. Systems where a production operation requires the completion of two parallel lines have their own complications and cannot be studied accordingly.
11	Control Parameters	The number of control parameters affecting the functionality system is another parameter to put on the watch list. The number of the control parameter can be a measure of the production system complexity.
12	Loop Length	A production system loop length should be controlled for some systems as not to surpass the operation length.
13	Information Flow	Information flow can be local or global, and this can affect the desirable production system.
14	Capacity	The ability of a system to perform is restrained by the capacity limit.

FORECASTING

The need for forecasts of individual products most frequently arises because of an inventory control system, or a production scheduling system, consisting of decision rules which specify when to produce or order more of a particular item (triggers or order points) and how much to produce or order (Winter et al, 1960). The unpredictable variations in demand complicate the job of forecasting the future demands and increase the chance for significant forecasting errors (Kohan et al, 2002). This variation in demand is particularly present for spare parts (Syntetos et al, 2010). (Wemmerlov et al, 1986) state that the dramatic differences between environments with and without demand uncertainty suggest that research findings achieved under deterministic conditions may have little relevance in more realistic stochastic environments. (Watson et al, 1987) studied the effects of demand-forecast fluctuations on customer service and inventory under erratic demand. The study showed that fluctuations between the desired customer service level and that actually achieved is not coherent (can be either positive or negative).

The literature on erratic demand divides the forecasting approaches into two main categories: parametric and non-parametric. We will show in the subsequent sections that both fall short in accurately estimating erratic demand. Detailed investigation is found in Appendix B (Page 136).

PARAMETRIC FORECASTING

While traditionally literature accepted to approximate a non-normal D_L distribution by a normal one (Bookbinder et al, 1989), recent works have showed that the system-cost penalty is large when using the normal approximation. (Naddor et al, 1978) presented decisions and costs of several inventory systems with the (s, S) policy showing how they are affected by different distributions of demand, different shortage costs and different lead times. The numerical results indicated that the Normal-D_L approximation is robust only when the D_L's coefficient of variation (c_w) is small. (Tadikamalla et al, 1984) compared several distributions for approximating D_L; in particular, normal, logistic, lognormal, gamma, and weibull. The results indicated that the normal approximation is inadequate when c_w is large. (Tyworth et al, 1997) tested the normal and empirical approximations and showed that the normal one is only appropriate when $c_w < 0.45$. (Lau et al, 2003) assumed the real D_L follows a beta distribution, and proved that even when the lead time is deterministic and the "correct" D_L is restricted to be beta distributed with low c_w (< 0.3), there are many situations in which a wrong (Q^*, R^*) computed by the normal-D_L approximation can lead to a substantial cost penalty. The authors concluded with the recommendation that instead of trying to search for an inevitably complex "rule" to determine whether the normal approximation is appropriate, maybe it is better and faster to estimate more accurately the actual D_L distribution and use it to compute (Q^*, R^*).

NON-PARAMETRIC FORECASTING

Traditional statistical forecasting methods work well when product demand is normal or smooth, but they do not give accurate results with non-linear data. Demand for slow-moving products frequently consists of a small number of large orders so that classical techniques are not applicable (Williams et al, 1982). (Smart et al, 2002) indicated that both exponential smoothing and a variant of exponential smoothing, developed by (Croston et al, 1972) and re-evaluated by (Willemain et al, 1994), are effective in forecasting mean (average) demand per period when demand is intermittent. However, neither Croston's method nor exponential smoothing accurately forecasts the entire distribution of demand values, especially customer service level inventory requirements for satisfying total demand over a lead time. Most of the literature on forecasting erratic demand refers to exponential smoothing as the most popular method. (Teunter et al, 2009) show that Croston's method clearly outperforms moving average and single exponential smoothing. They also show that the performance of Croston's can be significantly improved by taking into account that an order in a period is triggered by a demand in that period.

SUMMARY OF FINDINGS

This section highlights the main findings from our review of the literature. Initially, we studied production systems and forecasting techniques to investigate typical solutions for current demand pattern related problems at automotive suppliers supplying to multiple automobile manufacturers. We will refer to these industries as ASAM for compactness.

The problem and/or work constraints reported at ASAM can be summarized as follow:

- highly nonlinear, erratic and frequent shift in demand
- too many part numbers to be feasible to calculate manually to follow high demand fluctuation
- a part number may fit a normal distribution curve today and not fit in the next planning period
- short shipments to overcome shortage and supplier shortage are increasingly reported
- production planning administered by several personnel
- suppliers dissatisfied as they were not receiving acceptable forecasted demands
- failure of kanban implementation mainly due to the demand nature
- difficulty to measure supplier performance since baseline is moving all the time (MRP moves supplier schedule in and out continuously)

In order to solve the main constraint of typical ASAM production systems we reviewed the existing literature on production systems and forecasting techniques. Below we will summarize the main points of our findings:

- MRP uses forecasting and the latter is not reliable under erratic demand
- Implementing MRP under uncertain/non-linear demand can only be possible with the expense of high levels of safety stocks and inventories
- MRP systems operates without a feedback loop to communicate the current work in progress status
- JIT production control systems are appropriate under repetitive environments with stable (non-erratic) market demands
- Kanban is usually not suitable for dynamic environments with variable demands and processing times
- MRP/JIT integration is better than either of the two systems alone
- MRP/JIT hybrid systems (such as CONWIP) are still not appropriate under erratic demand due to the limitation of the forecasting that drives MRP and the need to recalculate kanban lot sizes
- CONWIP is a particular Push/Pull integration with high inventory levels building up in front of bottleneck stages (especially under erratic demand)
- Forecasting is not reliable when it comes to nonlinear demand: both parametric and non-parametric methods lead to high levels of inventories and excessive stock-outs
- The normality assumption for parametric forecasting is inappropriate and lead to high stock-out costs

- Exponential smoothing fails to accurately forecast the entire distribution of demand values, especially customer service level inventory requirements for satisfying total demand over a lead time

Following our conclusion of the literature, we propose that any new proposed system should:

- Calculate the order point directly from real demand where applicable
- Determine the degree of safety stock required through simulation
- Be independent from the demand pattern and be able to stabilize the latter
- Concentrate on main statistic variables that are average demand, lead time and desired service level
- Verify stock-outstock-out conditions on a periodical base

In the next chapters we will propose a robust production system derived from the above findings: **ARK**. The new system was successfully implemented at a peculiar ASAM. **ARK** is capable of handling non-linear demand patterns with the objective of reducing stock-outs and inventory costs. It uses simulation to generate better inventory parameters. Chapter 3 will present a numerical analysis proving the failure of production systems and of statistical means to meet demand variability and abrupt changes. Chapter 4 presents ARK and its generalization to other industrial setups. Chapter 5 forwards a case study and presents the suitability at a particular AS.

CHAPTER 3

NUMERICAL ANALYSIS OF PRODUCTION SYSTEMS AND STATISTICAL TOOLS

This chapter uses simulation techniques to test the effectiveness of production control systems in a stable, moderate variance and high variance (erratic demand) demand environment. The three systems that are investigated are push, Kanban and ConWIP. The study is focused on a multi-product manufacturing environment and assumes demand is stochastic. Firstly, a manufacturing system of an automotive parts supplier is presented with its five stages. The simulation models are then presented. The statistically generated 3 different demand profiles and the parameters are specified. The chapter ends by showcasing the simulation results. It concludes that, for the system under consideration, CONWIP outperforms Kanban, while Kanban outperforms Push system. Also when demand variation is moderate to high, the three PCS's perform poorly relative to minimize work in progress (WIP), inventory and backlog. The results and findings will be used to develop a new Production system in Chapter 5.

DESCRIPTION OF THE MANUFACTURING SYSTEM

As mentioned previously, l an automotive supplier manufacturing system model is composed of 5 stages:

- [P0] Winding Bobbin (Serving as a component flow unit rather than an actual stage)
- [P1] KIS Assembly
- [P2] Ultrasonic Welding
- [P3] ISS Assembly
- [P4] Electrical Test
- [P5] Visual Inspection

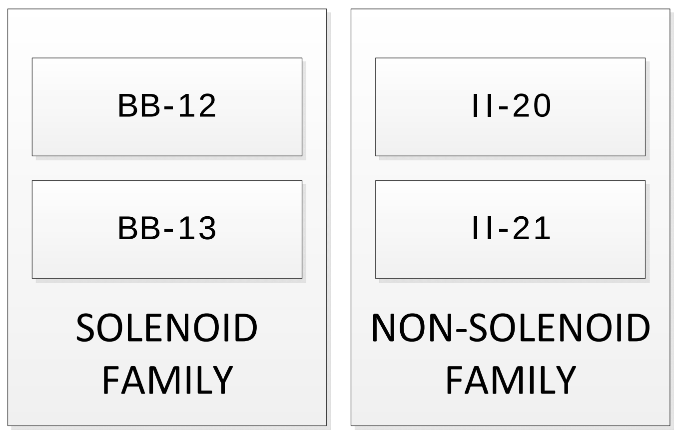


Figure 6. Products Families.

A total of 4 products are manufactured on this line: two families each consisting of two production varieties.

The solenoid family begins its process on P1. The component and other raw materials are assembled. Then the component is transferred to P1. The component is consumed by only the solenoid family. The second production stage for the solenoid family is called Ultra Sonic Welding (P2) which performs a welding operation. After welding, these products are packed into boxes containing exactly 90 units and transferred on a pallet of 16 boxes to the next assembly stage, ISS Assembly (P3). There are 10 pallets in the system that can be used for this product family.

Products of the non-solenoid family enter the line at workstation P3. These products enter the system on pallets of 16 boxes but each box contains 120 items. There are five pallets in the system that can be used for this product family. ISS Assembly operation is followed by an automated electrical test stage P4 and then a visual inspection stage P5. The output from P5 is then transferred to a supermarket area where a 'shopper' checks every two hours for finished goods to match with current weekly demand. If there is a sufficient quantity of finished goods, they are transferred to shipping and dispatched to customers at the end of the production week.

The manufacturing system operates three 8-hour shifts, five days per week and is idle for the weekend unless there is a request to do more bases bottleneck. Operators are provided with a 30 minute break after 3.75 hours. Products from the first family are given priority on P3 stage for the first, second and fourth day of each production week. Products from the second family are given priority on P3 stage on the third day of each production week. The product families have equal priority on P3 stage on the final day of each production week.

Processing times for an item on a machine are identical and constant across products, but vary for production stages. Setups are only significant for the section of the assembly line beginning at P3. When a set-up is conducted on P3, production (electrical test) at P4 and (visual inspection) P5 cannot occur. The set-up time includes line clearance time. The machines are unreliable. When a failure occurs on either P1 or P2, production on the other stage is stopped. Similarly if one of the other three stages (P3, P4 and P5) fails, the other two stages cease production immediately. A pictorial representation of the manufacturing system is shown in figures 7 through 12.

Figure 7. [P0] Winding Bobbin.

<u>Figure 8.</u> [P1] KIS Assembly.

<u>Figure 9.</u> [P2] Ultrasonic Welding.

Figure 10. [P3] ISS Assembly.

Figure 11. [P4] Electrical Test.

Figure 12. [P5] Visual Inspection.

SOFTWARE SELECTION, DESCRIPTION AND MODELING

In this paragraph we present the software we opted to build our simulation models. We will first justify our selection and then proceed through the description of the software and the modeling technology.

SOFTWARE SELECTION

Various factors influence the choice of the simulation software. These factors affect the techniques used in simulating the system. The latter influences the outcome of the simulation. Proper selection of software for simulation increases the efficiency and productivity of a user. Law and Kelton (2000) analyze the main features. They state the main points:

- The compatibility of the simulation software with the existing software
- Statistical features to aid user to input data
- Quality of output reports and plots to help in validation and evaluation of the system
- Support and documentation from vendors
- Animation features and efficiency

Of several systems we reviewed, ExtendSim simulation software was selected. ExtendSim is found to meet all the important features as listed above. The software was also selected because of its ability to model complex systems.

SOFTWARE DESCRIPTION

ExtendSim is powerful simulation software developed by Image That Incorporated (USA). Its graphical user interface is similar to those seen in other Microsoft Windows software. David Khral (2001) identified some of the main features of ExtendSim as follows:

- Drag and drop modeling features
- Real time communications with third party software including Microsoft excel
- Hierarchical modeling capabilities
- Optimization block that performs evolutionary optimization
- Opportunity for alteration of existing block or development of new blocks for addressing user needs

In this study, some of the features that were helpful during the modeling stage were:

- Animation of entities based on attributes was useful in showing various product types, stages, processes and the sequence in the system.
- Hierarchical modeling feature was helpful in developing workstations and complex sections such as the demand and supply sections and reuse such hierarchical blocks through the entire modeling process.
- Optimization block uses Genetic Algorithms which was suitable for carrying out the authorization cards and setting up the minimization parameters' optimization.
- Library feature of classifying blocks to area of specification made the model building easy. For instance, in the manufacturing library; the resource pool and resource pool release combined with the batching block was useful in modeling the authorization cards, part and demand.

SOFTWARE MODELING

ExtendSim has modeling block libraries assigned to various modeling applications: A manufacturing library is assigned for modeling manufacturing systems. This does not prevent the usage of other libraries.

Hierarchical blocks can be developed. They represent a combination of blocks that are joined together. Hierarchical blocks carry out specific functions which may not be represented by a single block. ExtendSim blocks have items and values connectors for events and collecting statistical information about items or events in a system. In each of these PCS models, the entities perform a similar set of events and interaction. However, the time and sequence of occurrence of these events vary. The variations could be the determining factor for the differences between the different PCS. Some of the important events to capture during modeling include:

- The release and entry of parts into the system
- The arrival of customer demands
- The closed loop sequence of authorization cards at a stage
- The transmission of demand information to stages
- The transfer of parts downstream
- The synchronization with demand and Kanban information at stage
- The authorization of parts release downstream
- The breakdown and repair of machines

MODELING

MODEL DESCRIPTION

This section describes the model we developed to undertake our comparison. In developing models for the three PCS, the raw materials for production are considered as being always available, including the winding bobbin which is consumed by products BB-12 and BB-13. The winding bobbin is distributed to the two solenoid products without starvation of any of the products at any time. It is the availability of the dedicated Kanban, dedicated CONWIP or the production capacity that delays the authorization of any of the products.

The KIS Assembly (P1) stage is considered to have a production unit of one pallet. Production of products BB-12 and BB-13 are considered to start in P1. In order to begin production on P1, raw materials including winding bobbin are attached to either of the two products and the part is thereafter attached to an appropriate Kanban card or CONWIP card. If the appropriate Kanban or CONWIP card is not available, the part will not be processed. Also in P2 the production unit is considered as one pallet. There is a buffer space between P1 and P2 for one pallet. In P2 stage, the production unit of one pallet (16 boxes) is modeled. The output from this machine is a pallet, which contains 16 boxes of the same product-type. If a pallet is not available for the 16 boxes, P2 is blocked. After this stage, the production unit becomes one box. There is no set-up modeled in stages P1 and P2. However, there is a preventive maintenance in stages P1 and P2, such that both stages are modeled to shut down at the same time and restart at the same time.

The production unit of stages P3, P4 and P5is one box (a pallet arriving to P3 will be split into 16 boxes). To begin production at P3, a box with one Kanban card or CONWIP card for the appropriate product-type attached must be available. P3 will exclusively produce solenoid products on days 1, 2, 4 of each production week and exclusively produce non-solenoid products on day 3. On the final day of a production week, either the solenoid or non-solenoid family could be produced. There is a set-up in stage P3, P4 and P5 which is normally distributed with a mean of 19.6 minutes and standard deviation of 6.528 minutes. The set-up time includes the line clearance period. The set-up occurs such that all the three stages go down at same time and recover at same time. There is also a preventive or routine maintenance in all the stages P3, P4 and P5.

Finished goods are held in the supermarket area in box quantities. On a two-hour interval, the 'shopper' will seek to obtain as many of the four product-types as there is demand for. If the shopper selects a box, the Kanban or CONWIP is released. A pictorial representation of the model structure is shown in Figure 13.

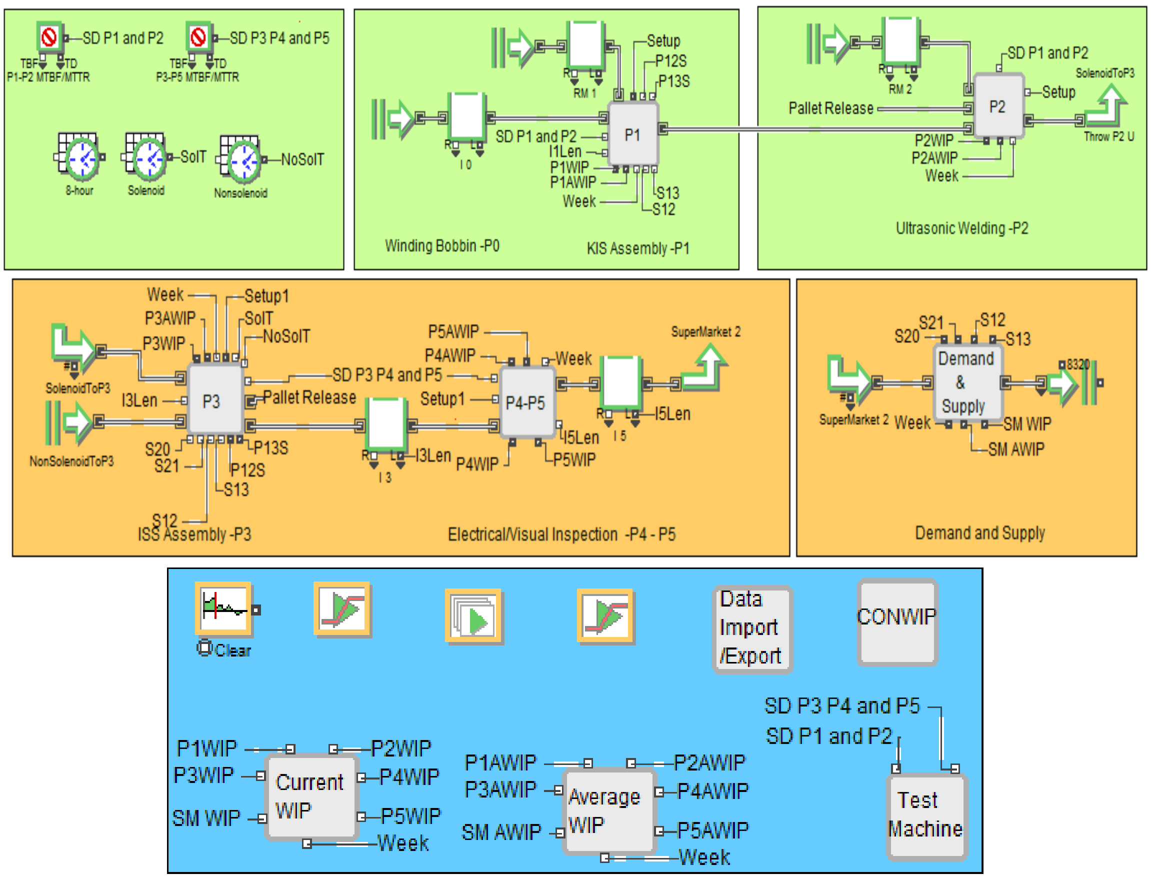


Figure 13. Model Structure.

MODEL BUILDING

A manufacturing system refers to a set of inter-linked or connected entities which interact in order to accomplish specified objectives or goals. The first step in building the model described in this study is to create a simple representation of the system entities and their interactions such that it can easily be developed using a simulation programme. The level of accuracy of a model in representing entities, events and interactions in a system influences the level of accuracy the model could predict or define the system. In this study the entities of interest include the WIP, Machines, Buffers, Customers, Operators, finished goods and the authorisation cards, while the events of interest are Customer demand arrival, starting and finishing of part-type processing, workstation failures and repairs. Modelling requires the ability to distinguish vital, critical and relevant entities and events to be able to make assumptions that would simplify yet produce a good representation of the system. The entities distinguished as important for modelling in this study are the part-types, production authorisation cards, buffer, demand information and the production stages. Production stage is characterised by a manufacturing process, an input and an output buffer for the stage production of part-type. The authorisation cards control the release of parts into a stage of the system.

Production authorisation cards are modelled as resource items from resource pools which are interconnected to queue blocks (queue blocks represent the system buffer). The demand item information read from the ExtendSim database is synchronized with the production authorisation cards (for Kanban) and raw materials or semi-finished parts using a batch block. Resource pool release authorisation cards from part-types and send them back to their initial state. The activity block is used in modelling a manufacturing process in the system. It represents a set of machines, operations or a machine. When queue blocks are interlinked with the activity block, as input and output buffers, it is considered as a manufacturing stage. A statistical block is used to collect the WIP level of a stage in the system. A shutdown block is used in modelling the systems mean time between failure and repair. The set-up is modelled using a combination of blocks; queue equation block for ranking the part-types in order to minimise set-up or switching times, equation block for determining and defining the set-up time for a part-type and an activity block to implement the delay on the part-type in order to observe the set-up.

Part-types generation are modelled using a create block which creates items as raw materials or part-types. The created items or part-types are assigned part-type attributes using a set block. The assigned attribute items are sent to a queue block to wait for authorisation for further processing or release to a customer.

DETERMINATION OF THE WARM UP PERIOD USING WELCH – DELETION APPROACH

It is important to reduce to a minimum the effect of the initial state of a system in order to make unbiased judgements about the systems. Three approaches are found in literature for reducing the influence of initial state of a system are (1) the deletion of initial set of data, considered to have been affected by transitory state of a system, (2) use of a very long simulation run length approach such that the transitory state of the system would be reduced (3) setting simulation into steady state approach at the beginning of the experiment (Law et al, 2000).

The deletion of initial set of data approach is widely used in simulation studies. The Welch graphical technique of deletion of initial set of data approach is found relatively simple in detecting and finding a warm period for a simulation. (Chung et al, 2003) and (Goldsman et al, 2000) suggested that the Welch technique is sometimes conventional, like other deletion approaches in estimating the warm up period. However several studies that compared Welch's technique and other deletion techniques often recommend it for warm up analysis (Goldsman et al, 2000 and Alexopoulos et al, 2001).

In this study, the Welch graphical technique was used by applying it to the WIP of the system for Push, kanban and CONWIP because these three models behave differently and accepting a warm up period of one could affect the data from the other two either because of under-estimation (collecting biased data) or over-estimation (wasting steady state data) of the warm up period.

7 replications of 9 weeks period run length was used in determining the warm up period of the system. The "change over" parameters of Push, KANBAN and CONWIP strategies were set based on the knowledge (based on a simulation that will be presented in following chapters) to 6, 4, 5 and 4 for product 1, 2, 3 and 4 respectively. The Kanbans setting for the two stages referred to as K1 and K2 Kanbans of KANBAN were set to K1 for product 1 = 8, K1 for product 2 = 3, K1 Kanban is not applicable to product 3 and 4. K2 Kanbans are set as 81, 62, 74 and 47 for product 1, 2, 3 and 4 respectively. The CONWIP cards for CONWIP strategy are 121, 89, 89, and 68 for products 1, 2, 3 and 4 respectively. The WIP of the system was collected for every 24 hour time frame for the 9 weeks' period for each of the 7 runs. The mean of the outcome of the 7 runs were determined by summation outcome of the entire 7 runs and dividing it by 7. Two smoothing window sizes 30 and 40 were used in the warm–up analysis. KANBAN and CONWIP, as observed from the graphs, show that around 2.7 and 2.7 week-period they both became steady while the Push strategy became consistent around 3.7 week-period.

We adopted the suggestion of Law and Kelton (2000) that significant numbers of irregular events should be considered in selecting a final warm up period; for instance, the need for a manufacturing stage to undergo significant number of shutting down for maintenance and commencing production again, the changing over or set up periods for switch to various part-types and restarting work, affects our choice of selection of a warm-up period such that a 4 week-period was selected as sufficient enough to eliminate biased data. This implies that data before the 4 week-period is deleted for all the models. Figures 14 to 16 below show the Welch graphical representation of the three models.

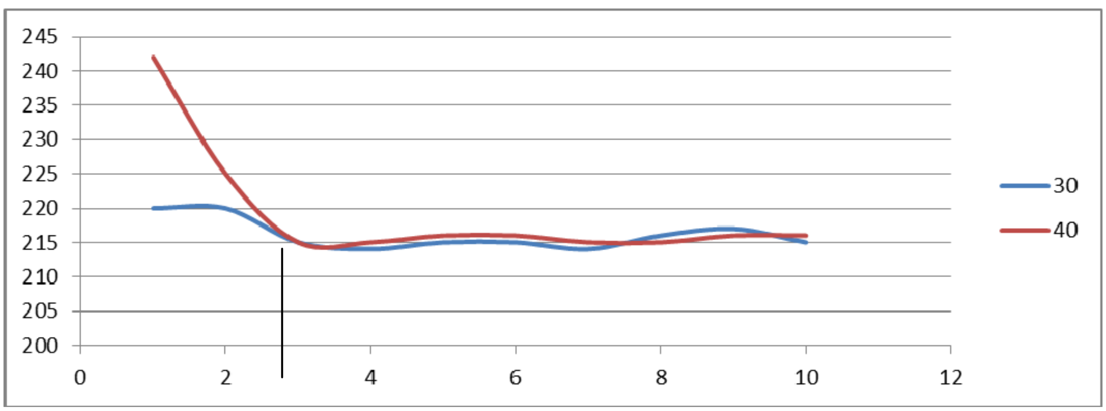


Figure 14. Welch graph for CONWIP model with Window Sizes of 30 and 40.

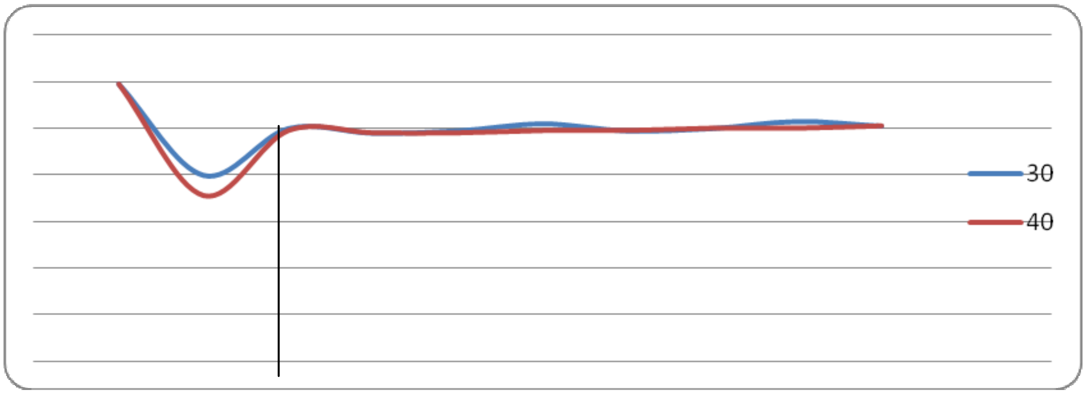


Figure 15. Welch graph for KANBAN model with Window Sizes of 30 and 40.

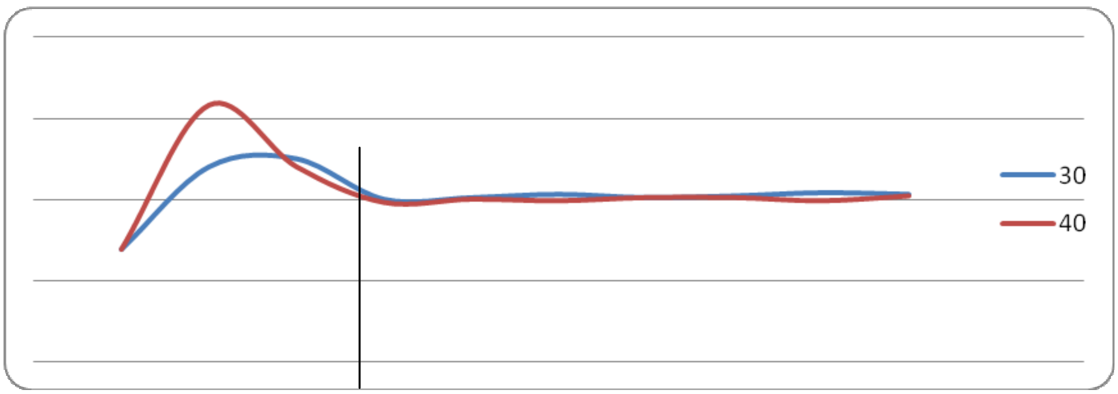


Figure 16. Welch graph for Push model with Window Sizes of 30 and 40.

Run Length And Number Of Replications Selection

Simulation run length has a significant effect on the level of accuracy of simulation results. Confidence Interval is often used in measuring the accuracy of simulation outcomes. It is also used in determining the appropriateness of a selected run length. Reducing the confidence interval and performing several replications of experiments is a means of increasing the precision of the simulation results. One of the widely used methods is the sequential technique which involves using a pilot number of replications and measuring the confidence interval to determine if it is within a suitable range depending on the level of accuracy needed in such an experiment.

The push, KANBAN and CONWIP models used in determining the Warm Up period of the simulation were also used for determining the number of replications. The run length of 10 weeks was selected in consideration of the 4 weeks warm up period deleted. 8 and 10 numbers of replications were performed. The backlog and total WIP recorded were used to determine their confidence intervals. The confidence intervals of the two replications are presented in **Table 3**. It was observed that at 10 replications, the confidence intervals have significant precision for our study.

Table 3

Confidence Intervals from different replications numbers

Number of	PUSH		KANBAN		CONWIP	
	WIP	Backlo	WIP	Backlog	WIP	Backlog
8 / Confidence	0.93	0.027	0.56	0.24	0.49	0.014
10 / Confidence	0.44	0.015	0.31	0.011	0.28	0.007

SELECTION OF CONTROL PARAMETERS

The control parameters have significant influence on the performance of a pull control strategy. In order to select appropriate control settings for the model, several trial runs were performed for each Pull PCS. The best values obtained from these runs were selected and used for the experiments.

ExtendSim simulation software was used in conducting the trial runs and selecting the appropriate values for the control mechanism of each Pull PCS. Moreover the change-over parameter were varied during the trial runs for both Push and Pull PCS in order to determine the best setting for change-over of part-type in stage 3. The trial test carried out was only for week 20 demand profile because this is the view for configuration of the system for production.

Three levels of probability demand variability were considered in this study in order to compare their performances against the actual demand simulation result. The following demand variability was investigated: Steady demand variation, moderate demand variation and high demand variations.

Due to the nature of the market and the manufacturing environment, the demands are ordered in batch sizes and the demand interval is once a week. This corresponded to a mean time between demands of one week period and the demand sizes are intermittent. The mean of demand size for each part-type over a six week period was determined. **Table 4** presents a detailed description of the mean of the three levels of demand variability studied and the best values selected for experiments are presented in Tables 5-9.

Normal distribution was used to model steady demand profile with mean for demand size as the mean of the sample size of the part-type during a six week period and a standard deviation of one. This is because normal distribution represents and models a combination of natural occurring events such as in the case of customer demand. Furthermore, using a standard deviation of one makes the events or demand sizes occur in an unvarying or uniform pattern.

Exponential distribution was used for modelling moderated demand variability, because it is useful in modelling events which happen independently, for instance: arrival time and downtime. It also has 100% variability with same value for mean and standard deviation which has memory-less property.

Lognormal was selected for high demand variability due to its ability to model events that are skewed or irregular in nature. If the distribution tends to concentrate towards the mean, normal distribution would be a good option, however as the distribution is intermittent and skewed, Lognormal was selected as suitable for the model with a standard deviation of 50% of the mean of the demand size.

Table 4

Mean of the Demand Size and Parameters of the three Distributions for Models

Period	Part-Type	Mean of demand sizes	Steady Variability Parameter Normal Distribution with Sigma = 1	Moderate Variability Parameter Exponential Distribution Sigma = Mean	High Variability Parameter Lognormal Distribution Sigma=50% of Mean
Week 20	II-20	146	~*N*(146, 1)	~*Expo*(146)	~*Log .N*(146, 73)
	II-21	94.33	~*N*(94.33, 1)	~*Expo* (94.33)	~*Log .N* (94.33, 47.17)
	BB-12	438.5	~*N*(438.5, 1)	~*Expo* (438.5)	~*Log .N* (438.5, 219.25)
	BB-13	142.83	~*N*(142.83, 1)	~*Expo* (142.83)	~*Log .N* (142.83, 71.42)
Week 21	II-20	147.67	~*N*(147, 1)	~*Expo* (147)	~*Log .N* (147, 73.83)
	II-21	97.33	~*N*(97.33, 1)	~*Expo* (97.33)	~*Log .N* (97.33, 48.67)
	BB-12	418	~*N*(418, 1)	~*Expo* (418)	~*Log .N* (418, 209)
	BB-13	145	~*N*(145, 1)	~*Expo* (145)	~*Log .N* (145, 72.5)
Week 22	II-20	131.5	~*N*(131.5, 1)	~*Expo* (131.5)	~*Log .N* (131.5, 65.75)
	II-21	99.17	~*N*(99.17, 1)	~*Expo* (99.17)	~*Log .N* (99.17, 49.58)
	BB-12	440.5	~*N*(440.5, 1)	~*Expo* (440.5)	~*Log .N* (440.5, 220.25)
	BB-13	142.17	~*N*(142.17, 1)	~*N*(142.17)	~*Log .N* (142.17, 71.08)
Week 23	II-20	120.5	~*N*(120.5, 1)	~*Expo* (120.5)	~*Log .N* (120.5, 60.25)
	II-21	109.67	~*N*(109.67, 1)	~*Expo* (109.67)	~*Log .N* (109.67, 54.83)
	BB-12	440.33	~*N*(440.33, 1)	~*Expo* (440.33)	~*Log .N* (440.33, 220.17)
	BB-13	157.33	~*N*(157.33, 1)	~*Expo* (157.33)	~*Log .N* (157.33, 78.67)
Week 24	II-20	120.5	~*N*(120.5, 1)	~*Expo* (120.5)	~*Log .N* (120.5, 60.25)
	II-21	99.5	~*N*(99.5, 1)	~*Expo* (99.5)	~*Log .N* (99.5, 49.75)
	BB-12	561.5	~*N*(561, 1)	~*Expo* (561)	~*Log .N* (561, 280.75)
	BB-13	172.67	~*N*(172.67, 1)	~*Expo* (172.67)	~*Log .N* (172.67, 86.33)
Week 25	II-20	96.17	~*N*(96.17, 1)	~*Expo* (96.17)	~*Log .N* (96.17, 48.08)
	II-21	70.33	~*N*(70.33, 1)	~*Expo* (70.33)	~*Log .N* (70.33, 35.17)
	BB-12	464.67	~*N*(464.67, 1)	~*Expo* (464.67)	~*Log .N* (464.67, 232.33)
	BB-13	183.17	~*N*(183.17, 1)	~*Expo* (183.17)	~*Log .N* (183.17, 91.58)

Table 5

Push Model Change over for the 3 Distributions

Part–Type	**Steady** Variability Best Value after 30 Pilot tests (Pallet Quantity)	**Moderate** Variability Best Value after 30 Pilot tests (Pallet Quantity)	**High** Variability Best Value after 30 Pilot tests (Pallet Quantity)
Product BB-12	6	7	7
Product BB-13	5	5	5
Product II-20	6	6	6
Product II-21	3	5	5

Table 6

KANBAN Model Change over for the 3 Distributions

Part–Type	**Steady** Variability Best Value after 30 Pilot tests (Pallet Quantity)	**Moderate** Variability Best Value after 30 Pilot tests (Pallet Quantity)	**High** Variability Best Value after 30 Pilot tests (Pallet Quantity)
Product BB-12	5	6	6
Product BB-13	5	4	4
Product II-20	5	5	5
Product II-21	5	4	4

Table 7

CONWIP Model Change over for the 3 Distributions

Part–Type	**Steady** Variability Best Value after 30 Pilot tests (Pallet Quantity)	**Moderate** Variability Best Value after 30 Pilot tests (Pallet Quantity)	**High** Variability Best Value after 30 Pilot tests (Pallet Quantity)
Product BB-12	5	6	6
Product BB-13	5	5	4
Product II-20	3	5	5
Product II-21	4	3	4

Table 8

Kanban card Configuration

Part–Type	**Steady** Variability Best K1 Value after 30 Pilot tests (Pallet Quantity)	**Steady** Variability Best K2 Value after 30 Pilot tests (Box Quantity)	**Moderate** Variability Best K1 Value after 30 Pilot tests (Pallet Quantity)	**Moderate** Variability Best K2 Value after 30 Pilot tests (Box Quantity)	**High** Variability Best K1 Value after 30 Pilot tests (Pallet Quantity)	**High** Variability Best K2 Value after 30 Pilot tests (Box Quantity)
Product BB-12	6	84	9	105	5	75
Product BB-13	3	43	3	85	4	69
Product II-20	N/A	49	N/A	70	N/A	81
Product II-21	N/A	25	N/A	68	N/A	53

Table 9

CONWIP card Configuration

Part–Type	**Steady** Variability Best Value after 30 Pilot tests (Box Quantity)	**Moderate** Variability Best Value after 30 Pilot tests (Box Quantity)	**High** Variability Best K2 Value after 30 Pilot tests (Box Quantity)
Product BB-12	97	80	129
Product BB-13	93	80	84
Product II-20	97	62	88
Product II-21	77	75	69

Experimental Results

The weekly WIP level versus the Backlog is examined. The Total weekly WIP and Backlog of each PCS are documented. The results of the WIP and Backlog for Push, KANBAN and CONWIP PCS are recorded in Tables 10 to 27.

Table 10

Steady Variability WIP and Backlog Results for Week 20

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	241	238.4	247.3	246.6	238	282.7
	Total Backlog	0.5	0.6	0.2	0	0.4	0.3
CONWIP	Total WIP	214.4	201.1	204.3	206.1	222.7	293.7
	Total Backlog	0.3	0.5	0	0.3	0.2	0.7
Push	Total WIP	391.6	379.7	368.7	352.2	337.9	488.4
	Total Backlog	140.8	277.5	424.1	568.9	711.3	850.7

Table 11

Steady Variability WIP and Backlog Results for Week 21

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	244.9	241.1	236.4	240.4	239.1	308.3
	Total Backlog	0.6	0.2	0.2	0.1	0.5	0.5
CONWIP	Total WIP	190.9	202.2	221.1	229.4	204.8	271.2
	Total Backlog	0.2	0	0.2	0.2	0.3	0.4
Push	Total WIP	347.8	380.3	379.2	354.1	357.5	462.7
	Total Backlog	127	250	373.2	499.2	623.7	743.6

Table 12

Steady Variability WIP and Backlog Results for Week 22

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	270	251	261	207	213	298
	Total Backlog	1.3	0	0.4	0	0.1	1.7
CONWIP	Total WIP	233.3	213.2	206.8	218.1	206.5	291.8
	Total Backlog	0.3	0	0	0.1	0.4	0
Push	Total WIP	375.6	411.7	401.1	395.1	394.2	466.5
	Total Backlog	131.7	266	394.3	522.3	657.9	791.7

Table 13

Steady Variability WIP and Backlog Results for Week 23

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	251	263	260	261	262	278
	Total Backlog	4.3	2	0.4	1.3	1.8	0.5
CONWIP	Total WIP	231.4	230.5	244.9	230.2	219.2	287.8
	Total Backlog	1.3	0.7	0.4	2.4	0.4	1.5
Push	Total WIP	362.1	350	344.2	327.9	353	484.1
	Total Backlog	123.2	238.5	360.3	481.7	596.4	716.1

Table 14

Steady Variability WIP and Backlog Results for Week 24

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	205	202	192	196	193	286
	Total Backlog	99.7	188.5	284.8	388.9	470.9	585.4
CONWIP	Total WIP	217.6	206.8	193.2	194	196.3	202.4
	Total Backlog	97	187.6	263.7	351	438.8	532.5
Push	Total WIP	329.3	319.5	362.9	341.1	339.6	483.4
	Total Backlog	243.3	480.1	719.4	958.5	1195.8	1440.6

Table 15

Steady Variability WIP and Backlog Results for Week 25

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	227	180	224	216	225	162
	Total Backlog	15.4	19.6	38.3	52	74.9	92.9
CONWIP	Total WIP	237.1	227.1	222.7	216.8	213.8	257.8
	Total Backlog	15.2	21.2	28.1	26.9	39.1	65.9
Push	Total WIP	370	335.2	341.3	364.8	372.8	508
	Total Backlog	140.9	277	416.8	557.9	697.9	834.4

Table 16

Moderate Variability WIP and Backlog Results for Week 20

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	266.8	266.7	233.9	232.4	228.6	239
	Total Backlog	512.4	715.9	851.6	865.3	1005.5	1194.5
CONWIP	Total WIP	175.5	212	183	181.1	192.4	211.9
	Total Backlog	260.7	365.6	716.1	732.4	874	1123.2
Push	Total WIP	535.7	507.2	477.3	569.4	530.9	725.1
	Total Backlog	206.1	276.3	333.8	451.2	489.5	659.3

Table 17

Moderate Variability WIP and Backlog Results for Week 21

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	268.9	263.6	251.6	239.3	227.9	244
	Total Backlog	391	690	810.2	871.8	974.9	1192.1
CONWIP	Total WIP	200.4	185.4	189.2	199.9	196.5	204.9
	Total Backlog	419.3	629.9	1038.2	1015.5	1241.8	1276.5
Push	Total WIP	556.9	680.4	567.8	569.5	497	756.3
	Total Backlog	251.4	173	220.1	244.8	447.1	638.2

Table 18

Moderate Variability WIP and Backlog Results for Week 22

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	259.6	237.9	230.1	241.5	252.4	265.2
	Total Backlog	205.7	489.1	689.3	812.8	814.6	923.9
CONWIP	Total WIP	189.7	192.9	200.3	180.6	191.2	203.9
	Total Backlog	449.1	834.3	845	818.2	1009.3	1328.2
Push	Total WIP	498	598.4	486.7	550.1	513.3	765.1
	Total Backlog	249.1	229	349.2	749.6	832	649.4

Table 19

Moderate Variability WIP and Backlog Results for Week 23

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	243.4	253.3	254.4	245.5	239.3	243.7
	Total Backlog	286.2	600	652.4	1075.9	1088.6	1352.6
CONWIP	Total WIP	169.3	186.9	179.3	195	200.3	221.6
	Total Backlog	360.1	592	751.6	964.4	818.6	1043.3
Push	Total WIP	606.3	642.1	577.9	500.3	415.8	658.8
	Total Backlog	236.4	360.5	381.3	479.7	729	1066

Table 20

Moderate Variability WIP and Backlog Results for Week 24

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	249.9	241.7	241.7	245	238.9	242.1
	Total Backlog	468.2	896.2	1091.8	1046.9	1130.6	1274.6
CONWIP	Total WIP	179	183.8	185.4	191.2	204.4	202.6
	Total Backlog	399.5	622.4	852.5	1308.9	1588.2	1807.1
Push	Total WIP	510.7	565.7	534.6	489.4	533.5	685.6
	Total Backlog	303.8	405.7	630.5	864.5	1075.4	1182.8

Table 21

Moderate Variability WIP and Backlog Results for Week 25

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	262.7	249.1	249.9	232.6	230.8	231.2
	Total Backlog	496.9	759.3	1071.2	1085.9	1232.7	1249.7
CONWIP	Total WIP	194.7	207.2	184.8	194.1	191.5	207.3
	Total Backlog	468.6	637.8	736.2	933.5	1288.8	1401.1
Push	Total WIP	595.3	594.1	605	579.1	578.3	810.8
	Total Backlog	534.6	532.7	826.7	810.6	1128.6	1352.5

Table 22

High Variability WIP and Backlog Results for Week 20

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	247.9	238	230.9	232	231.2	225.4
	Total Backlog	121	272.5	431.5	672.9	738.1	806.7
CONWIP	Total WIP	220.4	217.6	233.8	236.7	218.1	252.4
	Total Backlog	139.9	276.3	303.1	405	389.2	560
Push	Total WIP	391.9	326.5	344.6	364	315.5	413.6
	Total Backlog	242.3	375.7	476.9	628.6	848.8	1016.4

Table 23

High Variability WIP and Backlog Results for Week 21

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	240.1	229.8	210.5	217.6	223.7	227.6
	Total Backlog	158.6	147.8	378.5	395	407.2	401.5
CONWIP	Total WIP	212.9	195.5	229.7	218.7	215.8	233.8
	Total Backlog	132.7	181.7	327.3	397.9	570	673.4
Push	Total WIP	304.8	322.4	338.2	331.9	333.5	397.1
	Total Backlog	218.8	310.6	406.4	644.6	751.2	851

Table 24

High Variability WIP and Backlog Results for Week 22

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	238.1	225.6	224.9	235.4	233.1	237.9
	Total Backlog	97.5	122.9	104.1	256.2	344	442.2
CONWIP	Total WIP	211.4	222.6	227.7	234.8	223.8	245.5
	Total Backlog	231.8	404.8	524.9	660.9	648.1	700.7
Push	Total WIP	328.1	346.2	390.4	372.8	415.6	518.5
	Total Backlog	226.9	450.1	580	688.1	746.6	845

Table 25

High Variability WIP and Backlog Results for Week 23

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	249.2	210.4	203.7	210.7	216.9	226.1
	Total Backlog	201.4	380.5	464.9	452.9	525.1	553.3
CONWIP	Total WIP	230.5	212.5	242.4	229.7	221.9	228.8
	Total Backlog	366.7	433.4	486.7	527.3	605.6	724.9
Push	Total WIP	324.7	330.8	296.9	328.2	364.5	427
	Total Backlog	208.2	262.4	338.2	450.2	558.1	590.7

Table 26

High Variability WIP and Backlog Results for Week 24

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	235.8	228.5	199.9	198.1	198.6	212.5
	Total Backlog	135.8	348.2	502.7	653	767	974.1
CONWIP	Total WIP	235.7	230	223.5	232.8	225.5	233.9
	Total Backlog	250.6	424.4	654.5	809.7	923.6	984.7
Push	Total WIP	320	335.7	301.6	319	348	451
	Total Backlog	267.1	430.5	648.6	809.6	944.8	1271.4

Table 27

High Variability WIP and Backlog Results for Week 25

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	234.7	230.6	215.8	221.7	213.1	241
	Total Backlog	119.2	276.2	297.9	466	590.9	672.7
CONWIP	Total WIP	227.5	223.1	226.7	222.6	205.1	223.7
	Total Backlog	181.2	323	377.7	321.9	483	593.6
Push	Total WIP	302.6	305.9	359.3	326.1	326.4	377.8
	Total Backlog	97.5	205.1	196	305.3	500.9	607.8

Conclusion

Using simulation modeling, this chapter compared three main production control strategies and their performance in 3 different demand environments (stable, moderate variability and high variability/erratic). A sample manufacturing system and its different stages were presented first. We then highlighted the main reasons that lead to the selection of ExtendSim as a simulation tool. Then we described the model, the demand profile and the settings of the control parameters. Finally we showed the experimental results of WIP vs backlog.

From the results the following observations were made:

1. In steady demand variability:

   - CONWIP outperformed KANBAN and Push PCS with respect to lower WIP and backlog.

   - CONWIP has a higher rate of change-overs than KANBAN and Push as shown in the change-factor configuration in Tables 5 to 7; however, it has superior performance when compared to KANBAN and Push PCS.

2. In moderate demand variability: Exponential distribution was used. It is important to state that exponential distribution has memory-less property. This implies that the demand size distribution has 100% variability. From the moderate variability results, Week 20 demand profile result shows that CONWIP outperformed KANBAN and Push PCS in terms of lower WIP and backlog. Week 21 results show CONWIP has the highest backlog when compared with other PCS (KANBAN and Push). However, in all the

weeks' results, CONWIP maintained lower WIP over the rest PCS (KANBAN and Push) but has higher backlog than KANBAN in other weeks except in weeks 20, 23 and 25. In weeks 21 to 25, Push PCS outperformed CONWIP and KANBAN in terms of lower level backlog. The inconsistencies in performances of the PCS found in moderate demand variability are largely attributed to the nature and behaviour of the exponential distribution used in modelling it.

3. In high demand variability:

   a. KANBAN was shown to have superior performance over the other PCS.

   b. KANBAN has lower backlog and has WIP relatively low as that of CONWIP. CONWIP outperformed Push PCS.

CONWIP was shown to have lower card configuration and higher changeover settings in this study. The results suggest that CONWIP is superior to KANBAN and

Push in steady demand variability; also, under moderate demand variability (with exponential distribution) Push PCS was found to outperform CONWIP and KANBAN with respect to backlog. Finally, in high demand variability KANBAN outperformed CONWIP and Push.

CHAPTER 4

PRESENTATION OF THE PROPOSED AUTOMATED REPLENISHMENT KANBAN SYSTEM (ARK)

This section presents a new production control strategy (PCS) for the problems faced by typical suppliers that deliver components to automotive assembly lines. It is called the Automated Replenishment Kanban (ARK) strategy. The latter will enable automotive suppliers to optimize their performance. Particularly, it will allow production to cope with erratic demand.

This chapter reviews first the functionality of Kanban systems: both manual and automated systems are described. This review discusses the functionality of such systems. In a second stage, we discuss customer demand. The long-term accuracy of forecasts hinders the performance of existing production control strategies (PCS). In a third stage, an overview of the ARK system is provided. ARK, being a computerized system that interfaces current MRP systems, will generate a full 52 week demand sizing for multiple Kanban computations. Then, in the fourth section, the building blocks of the ARK solution are presented: Control screen, calculation grid, data scrubber/load reports and process preferences. In the fifth section we detail the kanban calculations. Multiple scenarios are considered to determine the kanban lot size. Finally, a brief conclusion in the sixth section outlines our contributions and potential enhancements.

KANBAN SYSTEMS

In chapter 2 we reviewed the scientific literature on production systems. In our review, we highlighted the major publications that investigated kanban production systems. In this section, we present the functionality of Kanban system and traditional replenishment systems.

MANUAL KANBAN SYSTEMS

Traditional Kanban Systems utilize manually calculated kanban lot sizes and physical kanban cards. The latter serve as a tool for providing information for the replenishment of parts only as demanded, or to replenish those taken from a storage location or supermarket. Kanban systems are designed to reduce the level of inventory and improve the synchronization of material flow with customer consumption. Several studies have shown that pull systems - the production of items only as demanded by consumption - such as Kanban systems, significantly outperform push systems - the production of items at times as required by a given schedule planned in advance - such as MRP, relative to minimizing inventory levels and maximizing delivery performance, especially when demand is variable. However pull systems such as kanban systems have their limitations.

Two conditions must be present for the Traditional Kanban to operate effectively:

- Demand must be level for a reasonably long time
- The final assembly has potentially different root parts

These conditions are not present in environments with erratic demand patterns and consequently the kanban lot sizes have to be frequently re-calculated and manual kanban cards replaced.

Manually calculating kanban lot sizes is time consuming. Also, it does not occur as often as it should in environments with no linear demand, demand shift and erratic demand patterns. This is due to the sheer amount of resources of time and people required. In environments with erratic demand a manual application of the simple kanban formula is difficult especially when a large number of parts are manufactured. Circulated physical kanban cards are often missed, lost or destroyed. The negative effect of this disruption to product flow can be significant. In manual kanban systems, the information flow is restricted between up-stream and down-stream units, and consumption or replenishment information and performance cannot be easily and efficiently shared across related functions.

In summary, for a manual kanban system to operate in a stable and effective manner, much time and resources must be allocated to the production site. Still, due to the high manual input, the working efficiency could be low, whilst the chance of errors remains relatively high. Consequently, the use of Electronic Kanban has been highly promoted in recent times especially with the increasing rapid development of information and communication technology.

ELECTRONIC OR AUTOMATED KANBAN SYSTEMS

Automated Kanban Systems utilize a computerized system to address the inherent weaknesses of manual systems. Currently, most electronic systems continue to apply the traditional formula in an automated manner using computers.

Equation 1. Traditional Kanban Formula

$$\boldsymbol{Kanban\ Lot\ Size} \\ = \boldsymbol{Average\ Demand} \\ \times (\boldsymbol{Replenishment\ Lead\ time} + \boldsymbol{Safety\ Stock})$$

Electronic kanban systems automated the pull-based replenishment methodology without foresaking lean manufacturing's focus on simplicity (Drickhamer, 2005).

The benefits of e-kanban are numerous. It:

1. Eliminates lost cards and reduces manual card handling and order-entry activities
2. Clarifies communication with suppliers and speeds analysis of supplier performance
3. Enables real-time visibility of demand signals and allows efficient analysis and adjustment of kanban quantities
4. Uses information technology to rapidly and efficiently recalculate the kanban lot sizes as frequently as necessary.
5. Eliminates human and manual input cognitive errors, mainly relevant to calculations.

Even though e-kanban still exhibits significant higher performance in inventory and delivery performance, it still has stock-outstock-outs. Therefore, its abilities are shadowed by the addition of safety stocks to compensate for erratic demand. Consequently, other authors and organizations have attempted to include safety stock as a compensation for this non-linearity in demand patterns. Such authors and organizations utilize MRP to calculate safety stock. However the statistical calculation is based on a pre-determined production level. During the actual production processes, the non-level production can seldom be avoided, leading again to stock-outstock-outs and delivery performance issues. This happens when the erratic demand pattern challenges the deterministic approach of the statistically calculated safety stock.

We present a summary of a new PCS we develop. The PCS:

- Uses information technology for automating the Kanban calculating process and for creating the replenishment signals, capturing all the advantages of the electronic or automated Kanban system previously discussed.
- Employs "Step Logic" for calculating Kanban lot size to compensate for erratic demand which does not depend on statistically predicted safety stock levels.
- Develops a new method of alerting the Kanban user when the degree of change in demand might generate potential stock-outstock-outs. This novel alert mechanism will be detailed in Chapter 6.
- Generates its own forecast of anticipated demands to create a full 52 week demand for the kanban calculation filling the gaps that exist in the demand patterns available through other sources such as customer EDI schedules or

forecasts which normally do not always cover a sufficiently long forward planning horizon that covers all the component lead times present in the supply chain.

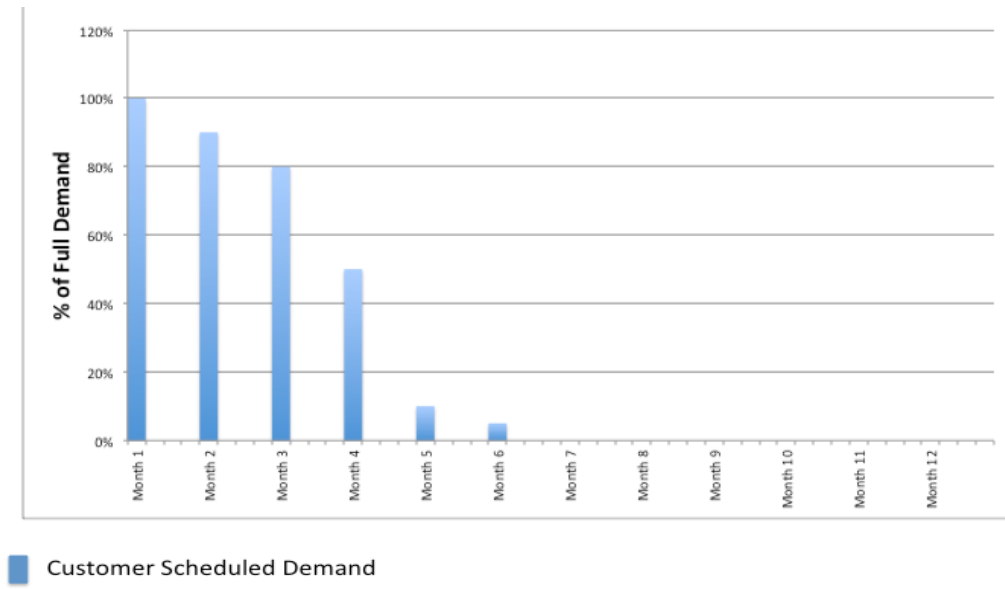
- Utilizes critical information about consumption and replenishment performance and distributes to other related functions to drive educated decision making and continuous improvement effort.

CUSTOMER DEMAND

Any production control strategy must have demand as one of the main input parameters. The high variability and randomness of demand will prevent the production system to optimize its performance in accordance to most performance criterions. In this section, we will first showcase current demand patterns and their problems, and then we will propose how to build a proper demand forecast for the ARK system.

INVESTIGATING DEMAND PATTERN

Currently, most OEM customers provide a schedule of forecast demands for periods ranging from one to four months. The forecast typically depends on three parameters: the customer, the market characteristics and the industry. These forecast demands are then superseded by customer orders for deliveries in the subsequent 1- 4 week periods. However, in most cases, demand created by these customer forecast demands is seldom a full rack of demand. In other words, the first 1-2 months are normally a close representation of the actual firm customer orders that will follow. However as the forecasting horizon begins to extend, the accuracy of the customer forecast decreases rapidly and by the 3rd or 4th month, the accuracy can drop below 50%. Very often no usable forecast is given beyond the 5th month (check figure below).



<u>Figure 17.</u> Typical customer scheduled/forecasted demand.

Notwithstanding this incomplete demand over an extended planning horizon, it is common within the external supply chain to have certain components, such as electronic components, which exhibit lead times in the region of 5-6 months or more. Consequently, unless a full rack of demand is utilized over the entire planning horizon, production systems will be misguided on the correct lot sizes to calculate and what kanban signals to trigger for replenishment to cover demand of long lead-time components. Eventually this leads to stock-outs. Additionally, in the absence of a sufficiently long forecast having a full rack of demand, staffing and capacity considerations for the medium term are challenging. Occasionally, no customer forecast is provided at all which compounds the situation even further.

52 WEEKS DEMAND FORECAST

Before presenting our solution to demand uncertainty, a proper forecast is critical to generate an internal forecast of demand to fill the gaps from the Customer Forecast/Orders that guarantees a full rack of demand over a sufficiently long planning horizon.

The forecast will facilitate the:

- Calculation of kanban lot size based on a full rack of anticipated demand
- Triggering of kanban signals for replenishment
- Determination of required manual interventions to support demand within Lead time
- Performance of Load Reporting for an extended planning horizon based on a full rack of demand for staffing and capacity considerations for the long term.

Figure 18 below represents the functionality of our system. It fills the gap highlighted previously in figure 17.

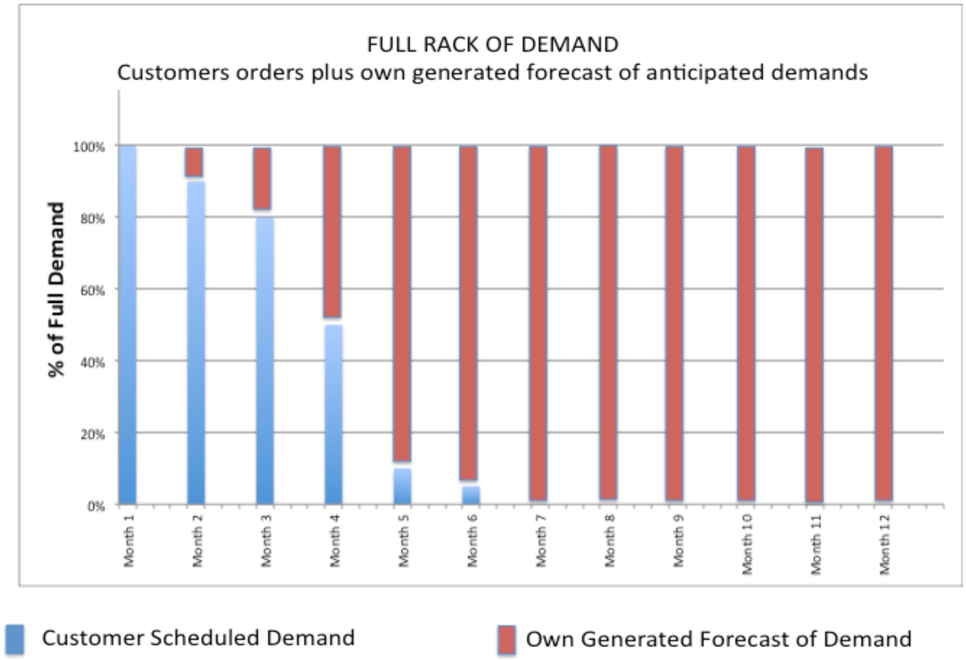


Figure 18. Typical customer scheduled/forecast demand.

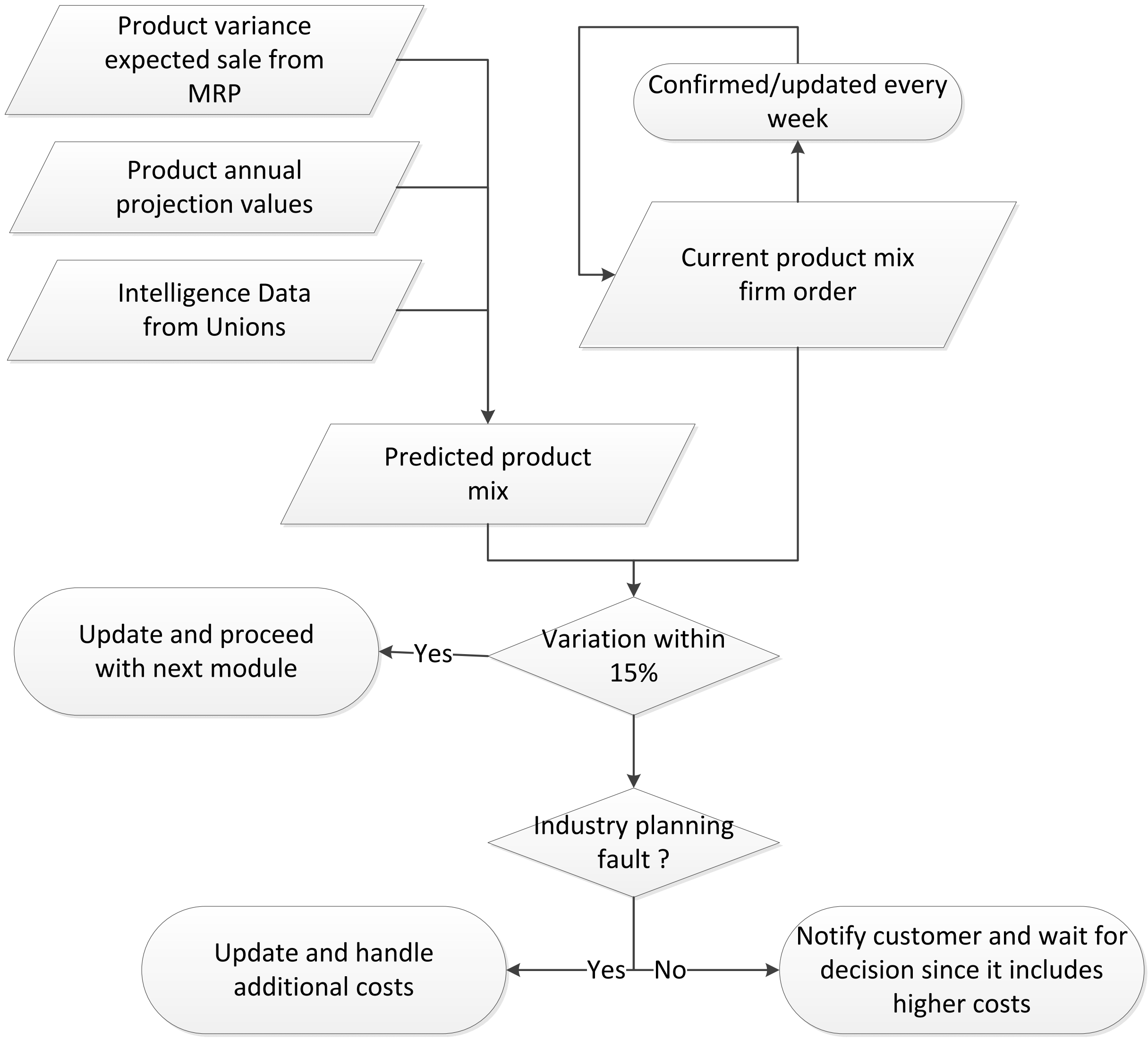
FORECAST CALCULATOR

The forecast calculator will use 7 parameters to compute. These parameters were identified and tested through a real industrial setup. The own generated forecast is an essential step for the performance of our system.

The parameters are:

1. (**TAS10**) Total annual sales dating back 10 years. If we have a new product at hand the system will subdivide sales equally and will automatically adjust itself as we go through time. In the scenario where we are handling a new customer whose product has a minor variance with regards to a pre-existing product, the later product data is loaded onto the system. The parameter is product-based. It includes all the potential variances.

2. (**TPS2**) Total projected sales for 2 years forward. The projection is usually received 5 years forward and is based on investment capacity. However only the first year is important and the second year will serve to alert suppliers not to face stock-outs.
3. (**PM8**) The product mix of current actual customer orders for the next 8 weeks. This is an actual firm demand that should be satisfied. It is updated weekly (weeks 2 through 8 are updated and week 9 is added).
4. (**SP**) Selling price of each product
5. (**ER**) The exchange rates
6. (**ID**) Intelligence Data. This allows the industry to angle internal data to confirm demand. Even though the industry sets clear variation rules (demand is allowed to be reduced a maximum of X %), they use internal reporting data to adapt its master production schedule. A typical example would be an upcoming union strike.
7. (**DFO**) Customer demand forecast and firm orders form MRP



<u>Figure 19.</u> Overview of Forecast Calculator.

It will generate a 52 week sales forecast of anticipated demand:

- TAS10 will be used to establish the percentage of annual sales per calendar month, which is subsequently used to apportion the annual sales by month to create a 52wk forecast of anticipated sales per calendar month (Figure below, starting from May similar to the fiscal year)

MAY	7.200	JUN	9.500	JUL	6.600
AUG	7.300	SEP	10.200	OCT	8.100
NOV	8.100	DEC	7.500	JAN	7.700
FEB	8.500	MAR	10.400	APR	8.700

Figure 20. % of Annual Sales apportioned by calendar month based on historic Sales Performance.

- TPS2 is used to establish the monetary value of the 52wk forecast of anticipated sales per calendar month using the monthly % allocations established in step 1 above.

Fiscal Year:	2012	Fiscal Year:	2013
Sales Forecast €:	86920434	Sales Forecast €:	86920434

Figure 21. Total Annual Sales for current Fiscal Year and subsequent Fiscal Year.

- PM8 is used to create a product mix ratio based on current demand, subsequently used to apportion the monetary values for each calendar month established in the 52wk forecast of anticipated sales in step 2, into individual product forecast.

- SP is used to quantify the monetary values for each calendar month established in the 52wk forecast of anticipated sales in step 3 for each individual product.
- ER is used to convert all sales orders into the base currency (i.e. Euro or USD).
- ID from the Sales and Marketing team relative to any known initiatives such as Sales Offers, Sales Incentives, Customer Shutdowns, Product Launches or end of life.

The forecast can be included in the finished builds schedule from any week as desired, depending on the forecast provided by the customer, its accuracy and the length of the planning horizon. The shorter an accurate customer forecast goes out the sooner the internally generated forecast should be released. A condition is included whereby if a sales order is already attached to the product number and is greater than the forecast quantity, then the sales order will take precedence and no forecast is included. If the sales order is less than the forecast quantity, then only the difference between the sales order and the forecast quantity is posted in the production build grid.

ARK OVERVIEW

This section presents our solution for production systems malfunctioning facing erratic demand: ARK.

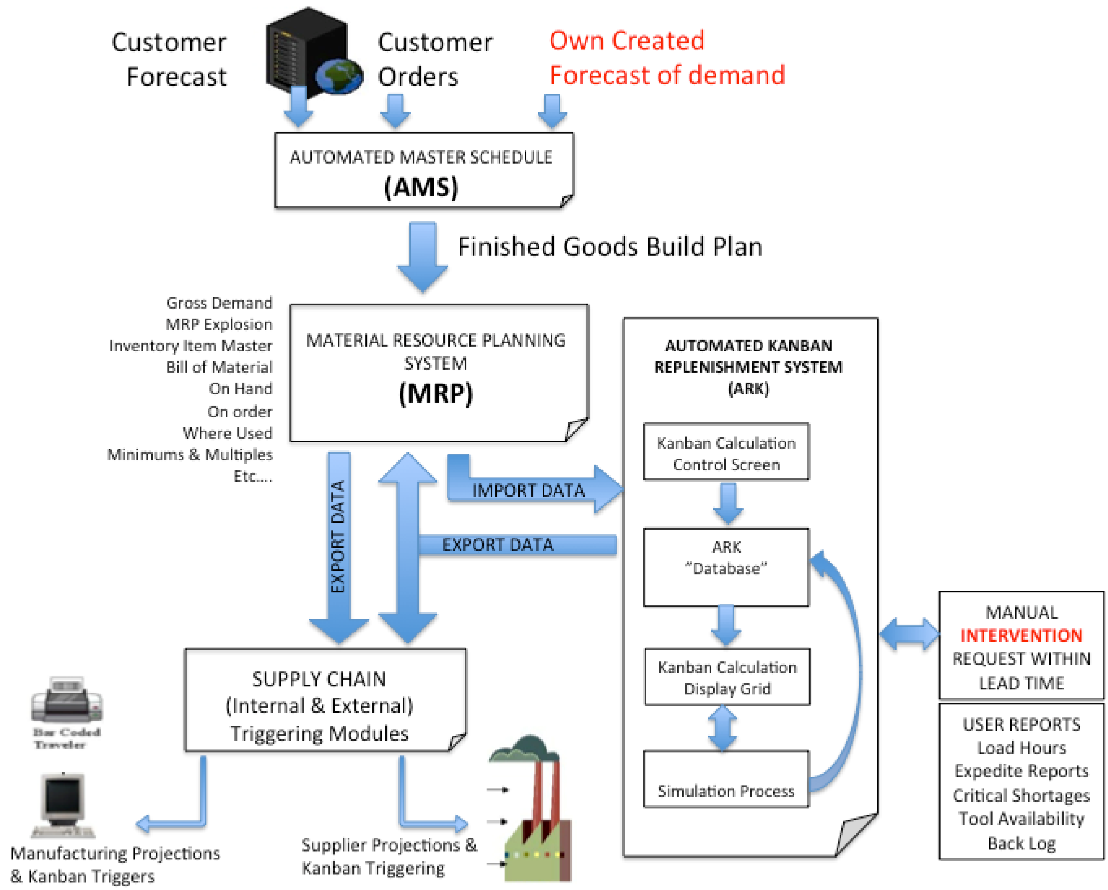


Figure 22. ARK overview.

The figure above shows an overview of the ARK system; connections between ARK and other industrial modules within the management systems are highlighted. ARK is completely electronic with potential manual intervention. It is fully integrated within existing MRP systems. It uses the previously defined Forecast Calculator. It is also integrated within the supply chain holonic recognition (Traveler cards, barcodes, and web portals). All signals can be received/ transmitted from internal and external suppliers.

This computerized mechanism allows an organization to create a pull system that is highly responsive to uncertain demand. Also, organizations can significantly reduce inventory and improve customer delivery. The system allows for a constant realignment to changing customer demand and does away with the excess inventory inherently carried in a manual kanban system. The latter does not recalculate wastes leading to high inventory of unneeded components, stock-outs of needed components and low delivery performance. ARK will prevent building inventory of unneeded components whilst preventing stock out of needed components. Also, ARK gives the flexibility for management to determine mechanisms to handle specific items (Kanban or MRP). This is especially important because kanban is gradually implemented whilst internal/external suppliers are adapting to the new ARK system.

The table below represents the main features of the ARK system along the main parameters it computes. The next section will detail the building blocks of the ARK System.

Table 28

Main ARK Performance Parameters

Feature	**Description**
Kanban Lot Size Computation	Calculates kanban lot sizes using data such as gross demand, lead time, safety stock, minimum & multiple settings and current on-hand inventory levels from the existing MRP system, whilst taking into consideration non-linear demand, demand shift and erratic demand patterns
52 Weeks Forecast	Generates an internal forecast of anticipated demands to ensure a full 52-week demand rack is available for the kanban calculation

	which is especially critical for long lead time components within the external supply chain.
Demand Simulation	Performs a demand simulation using the initially calculated kanban lot size over a pre-specified planning horizon to determine if stock-outs will occur as a result of erratic demand.
Kanban size adjustment	Automatically adjusts the initial kanban lot size upward to avert any stock-outs outside lead-time.
Alerts	Alerts purchasing and manufacturing of potential stock-outs within lead-time by providing an automated manual intervention request report if the kanban simulation fails as a result of a stock-out within lead-time whilst still automatically establishing the appropriate simulated kanban triggers and the adjusted kanban lot size to satisfy all demand outside lead-time.
Reloading / Automation	Automatically reloads the adjusted permanent kanban lot sizes into the database for subsequent replenishment
Continuous improvement	Utilizes triggering and replenishment performance information across the organization to drive decision making and continuous improvement using reports such as critical shortage lists, expedite reports, load hours reporting, tool/equipment availability, actual production lead time, backlog status and

	planning horizon demand visibility.

ARK BUILDING BLOCKS

In this section we present the ARK building blocks. Figure 21 below shows the blocks: Kanban calculation control screen, ARK Database, Kanban calculation display grid, the simulation process and calculation.

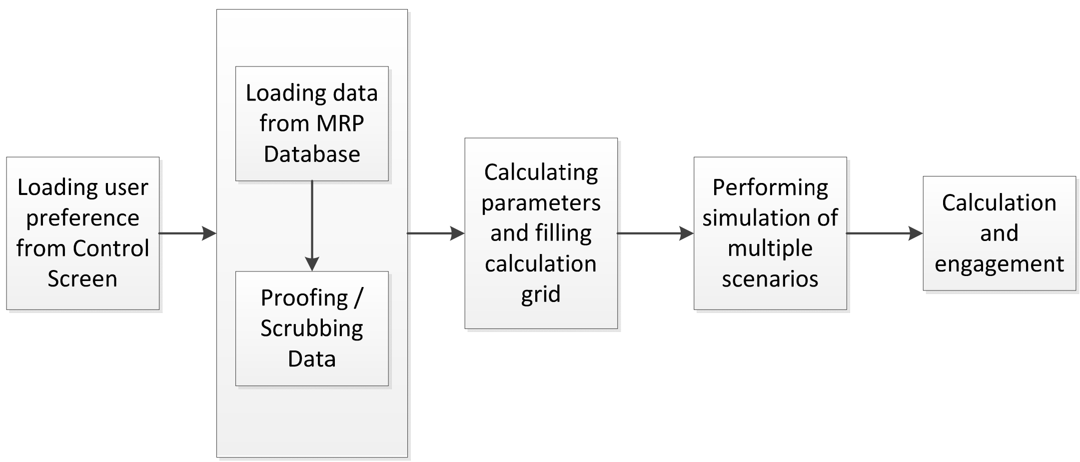
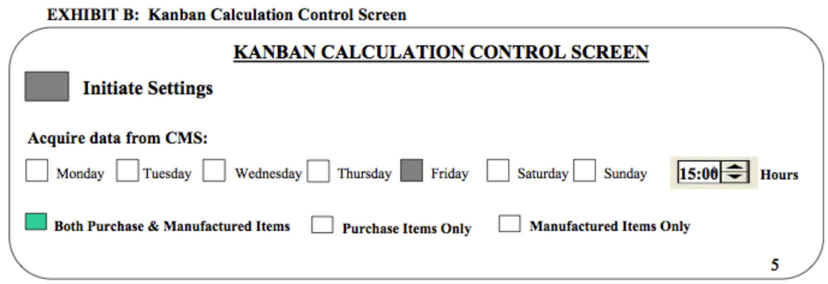


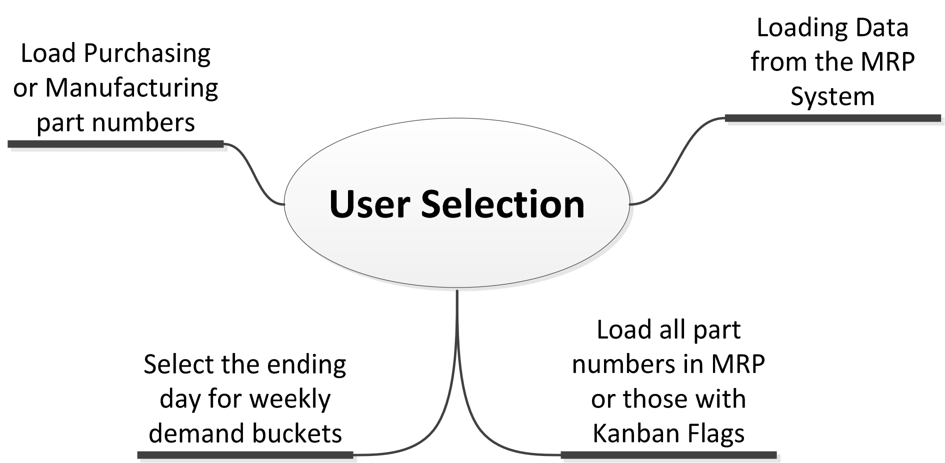
Figure 23. ARK overview.

THE KANBAN CALCULATION CONTROL SCREEN

The control screen shown in figure 24 is available for the user to load and initiate a new Kanban calculation grid. The user selection alternatives are presented in figure 25.



<u>Figure 24.</u> Kanban Calculation Control Screen.



<u>Figure 25.</u> User Selection.

ARK DATABASE

After the user selects his or her preferences (as set in the figure above), the second module ARK Database is accessed. The module performs two main steps: data extraction and data verification/validation. The data extracted from the MRP system is placed in the ARK database and used to calculate kanban lot sizes and is run after the MRP explosion takes place. Prior to loading the ARK database all previously loaded data is erased and replaced by the extracted data. Table 29 lists the data extracted to populate the kanban calculation grid.

Table 29

Parameters Loaded into ARK

Part Number	Description	Part Type	Safety Stock Weeks
Replenishment Lead Time	Supplier Transportation Time	Minimum Quantity	Multiple Quantity
Kanban Container Option	Current Quantity of Kanban containers	Old Kanban Lot Size	Cell/Line number
Unit Cost	Planner Code	Buyer Code	Vendor Number
On Hand Balance	Period 1 (MRP) Gross	Period 1 (MRP) Triggered	

Before loading the data into the Kanban Calculation Grid, a data validation check is performed. The software does not correct data but rather identifies outliers and enables the production system analyst to input new values. The solution however is not permanent. Future calculations of the same part use the original data values and not the manually correct ones.

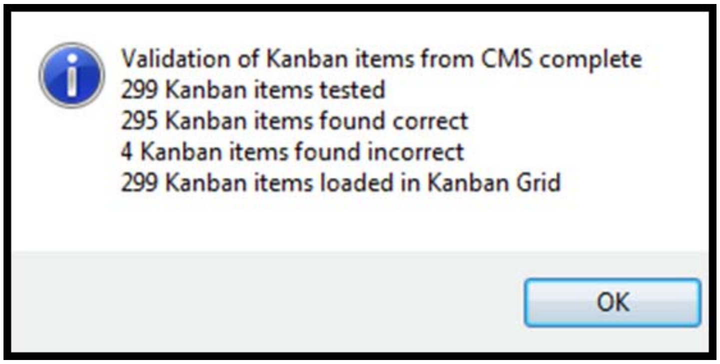


Figure 26. Load Dialogue Box.

Figure 26 shows the output of the data verification step. It provides a load statistics dialog box showing the number of part numbers acquired and the number of part numbers with errors. If the supervisor wishes to further investigate incorrect kanban items, a load error report can be extracted from the report sections showing the details of the said errors for user intervention.

KANBAN CALCULATION GRID

The Kanban Calculation Grid contains both data fields and calculated fields. At this point the grid is loaded with imported data placed into the data fields. There are 6 calculated fields in the grid, which are still empty, and as ARK performs its calculations it will post the results to these calculated fields. The user can intervene and modify any data field or calculated field on the grid prior to the calculation process. The user also has the ability to hide/unhide columns and rows for ease of work and right click on any row producing menu options such as expanding the gross demand patterns loaded from MRP for each part number.

Week Date	Gross Requirements	Orders
05/09/2012	36	0
12/09/2012	0	100
19/09/2012	24	0
26/09/2012	12	0
03/10/2012	12	0
10/10/2012	12	0
17/10/2012	48	0
24/10/2012	36	0
31/10/2012	48	0
07/11/2012	48	0
14/11/2012	36	0
21/11/2012	84	0
28/11/2012	36	0
05/12/2012	24	0
12/12/2012	12	0
19/12/2012	36	0
26/12/2012	0	0

Figure 27. Snap shot of calculation grid.

Simulation Process

In this section, the user selects the simulation preferences relevant to trials (**mtp**) and percentage increase (**pit**). Figure 28 shows the visual interface for this step. It also shows the option to generate reports for retries.

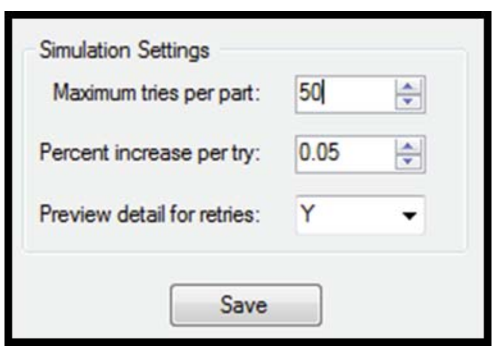


Figure 28. Simulation preferences Dialogue Box.

The maximum tries per part (MTP) functions as in the figure below.

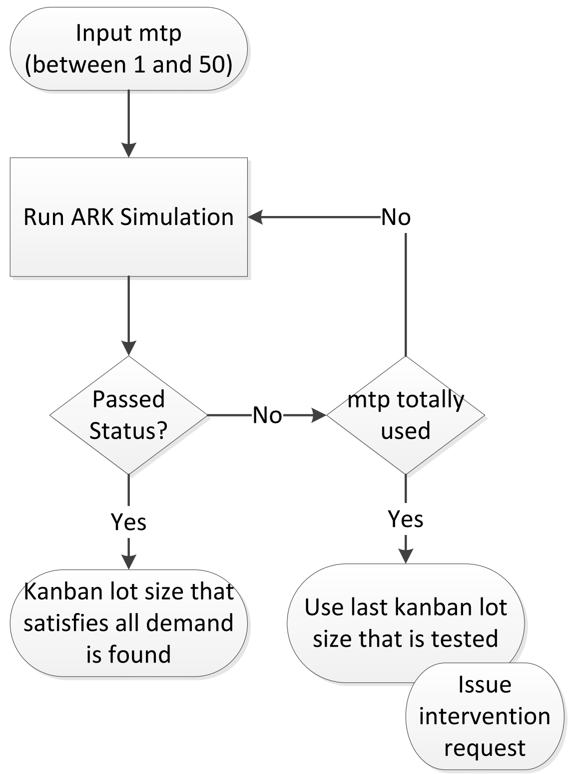


Figure 29. mtp parameter.

The **pit** parameter is the % by which ARK will increase the kanban lot size each time the simulation fails and then rounds it off to the multiple. It will continue to increase in such steps until the kanban lots size satisfies all demand that are found or if the maximum number of tries is reached.

Calculate and Engage

The final building block is to calculate and engage. The interface is presented below.

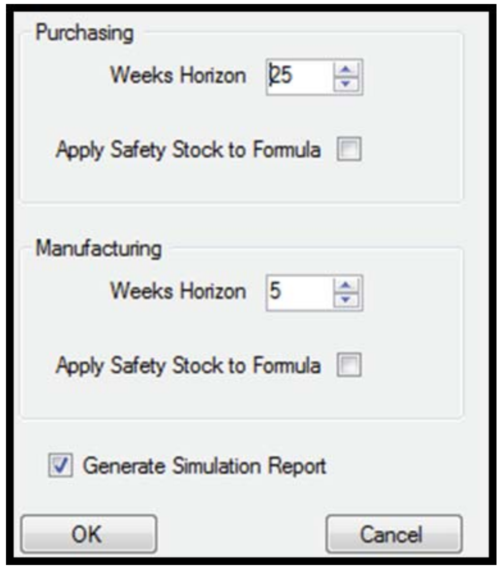


Figure 30. Kanban calculation Formula Modifier Dialogue Box.

The user is prompted to select three major components. The first component (planning horizon selection) tells ARK how much further into the future it should extract gross demand of part numbers. Then we determine the average demand per period (using the number of periods). The selections are detailed in the figure below.

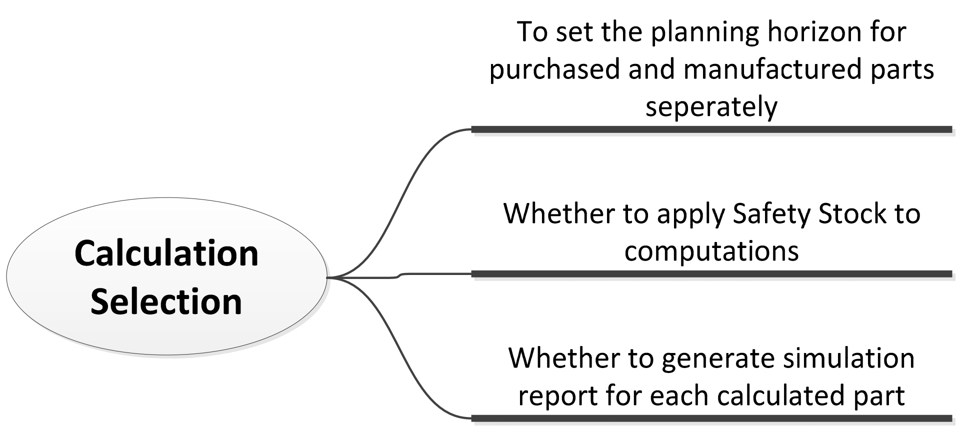


Figure 31. Calculation selection.

Once these settings are completed the User will initiate the kanban calculation process, the results of which are posted in the calculated fields of the Kanban Calculation Grid as previously defined. The new number of containers field in the Kanban Calculation Grid is also calculated and updated. Following any needed human intervention or validation, the engage command is used to Load the calculated data back into the MRP system and into the Kanflow Database. The user has the option to select all part numbers or select specific part numbers for the engage process. Upon engaging, an archive copy of the Kanban Calculation Grid is stored which can only be viewed but not modified subsequently.

KANBAN CALCULATIONS

This section details how the ARK solution computes the Permanent Kanban Lot Size for each Part Number. The algorithm functions in three sequential steps:

1. Calculate an average demand per period for each part number and generate an initial kanban lot size for each part number based on the basic kanban formula
2. Determine the permanent kanban lot size for each part number based on a simulation process to test the initial kanban lot size against non-linear demand patterns.
3. Alerts and options in case of stock-out within lead time.

The complete logical flow is represented in the figure below.

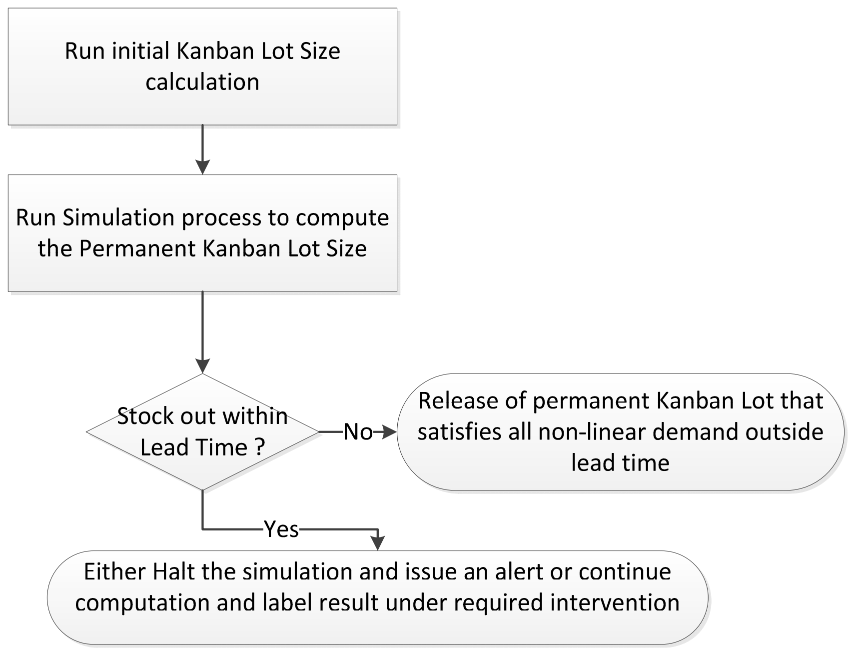


Figure 32. Computations logical flow.

COMPUTATION OF INITIAL KANBAN LOT SIZE

ARK first applies the basic kanban lot size computation (see figure 31).

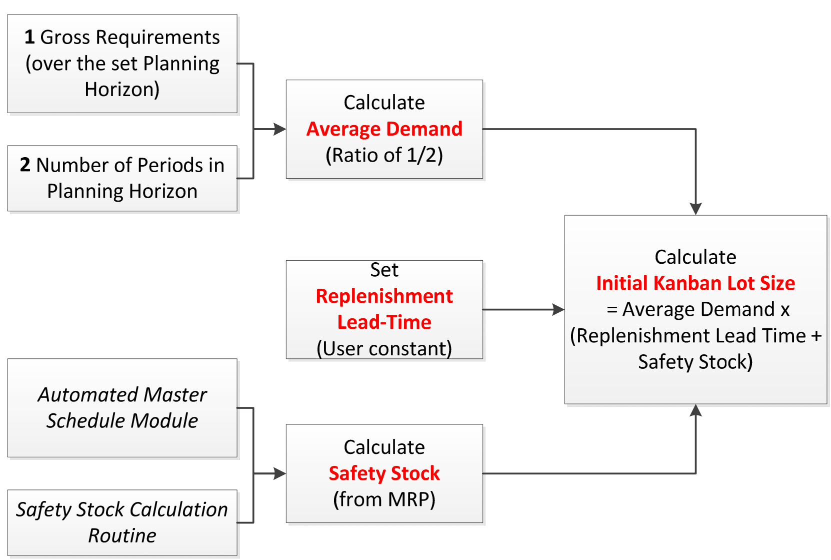


Figure 33. Computation of Initial Kanban Lot Size.

Following this basic computation, ARK considers minimums and multiples. Minimums are used where a supplier requires a minimum buy quantity or the manufacturing has a setup time issue wherein minimum runs become feasible. Multiples are used when a supplier or manufacturer packages items in specific quantities (Standard Packs, e.g. 5,000 per box) or a specific number of standard packs are moved/stored together (Standard Pallets, e.g. 5,000 per box and 10 boxes per pallet means a multiple of 50,000).

Once the minimums and multiples are applied to the result of the kanban formula, this becomes the **initial kanban lot size**.

Application of the minimums and multiples is dependent on the kanban container option selected.

- Single Discrete - Minimums and Multiples do not apply.
- Single Full and Dual Container – Minimums and Multiples apply.
- Multiple Containers – Minimums do not apply but Multiples apply.

Computation of the permanent Kanban Lot Size

At this stage, the initial kanban lot size is set and the ARK uses it to generate the permanent kanban lot size that emulates the real manufacturing environment. Logically, the system adjusts the lot size upwards to avert stock-outs that are due to erratic demand.

The simulation simply loops the process ensuring that on hand inventory remains positive at the end of the suggested period. If the inventory on hand is negative, then

ARK increases the initial lot size by the previously defined % set (rounding it off to the multiple) and re-running the simulation.

As soon as a kanban lot size is found which with the existing on hand and on order inventory condition passes all planning periods with the projected on hand inventory being positive, this is frozen as the **permanent kanban lot size**.

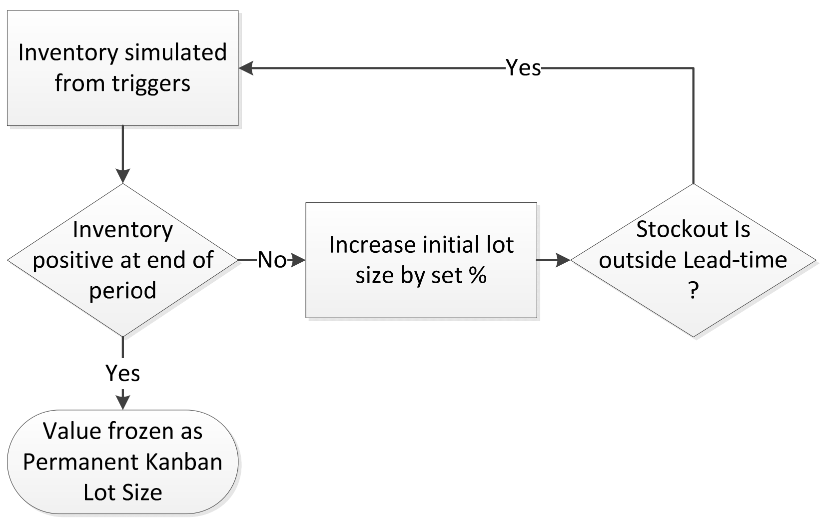


Figure 34. Computation of Permanent Kanban Lot Size.

DECIDING ON THE BUYER OR PLANNER INTERVENTION

A stock-out within lead-time implies that if the normal logistic and production routes are allowed to take place, the required material will not become available in time to satisfy the demand and a stock-out will occur. If whilst performing the simulation process, ARK encounters a stock-out within Lead time, the analysis uses a different approach to overcome the situation, with two different alternatives:

- Halt the simulation process, issue an alert and depend on a buyer or planner to correct the situation in a very timely manner and rerun the entire kanban calculation process. This freezes the complete process.
- The ARK Solution.

In the ARK Solution, the kanban calculation process and simulation process continues even when identifying a stock-out within lead-time. The unsatisfied demand is posted by ARK in the ‘Intervention required’ field in the simulation grid. The simulation will still continue to create simulated triggers and increment the initial kanban lot size as per previous rules until a kanban lot size is found that satisfies all demand outside Lead Time. This value is then set as the Permanent Kanban Lot Size.

For the unsatisfied demand posted under the ‘Intervention required’ field no action is taken by ARK. A manual intervention by the Buyer or Planner is now required since there is not sufficient lead time to procure or manufacture the parts through the usual channels. Hence the buyer or planner needs to generate a manual trigger for these parts under expedite conditions.

This innovative routine within ARK is a protection routine that does not jeopardize all future requirements due to safety stock problems. Instead ARK takes care of itself to adjust for future demand whilst issuing an alert in the form of the intervention required report for parts with unsatisfied demand within lead-time.

The advantages of this routine are reported as follows:

- The continued operation of the majority of parts in the entire supply chain is never jeopardized because of the few constraints within lead time.
- Buyers and planner can focus on the intervention reports and expediting these requirements, knowing that ARK is taking care of the rest. This also reduces the indirect cost of material planners and buyers, who are now required to primarily deal with the expedite requirements where constraints exists within lead-time and not with the entire supply chain.

CONCLUSION

This chapter is intended to show the approach to an automated kanban system using a new method of kanban lot size calculation. The method adapts to erratic demand patterns without depending on a deterministic prediction of safety stocks. At first we reviewed Kanban systems and noted the advancement from the manual application of Kanban systems to the current electronic processing. In a second stage, we investigated customer demand and presented our forecast calculator: tool to be used later in determining variable values needed for the proper function of ARK. The latter overview and main parameters were then thoroughly presented. Next the ARK building blocks permitting the computation of primary parameters and the underlying logic were detailed. The chapter ends with an extensive case study depicting in detail the application of ARK. The case study is benchmarked against other production systems whose performance was evaluated in the previous chapter. This study validates with preliminary results why ARK is superior to existing methods demonstrating how under demand with different types of distributions, the ARK solution for Kanban Lot Sizing allows environments with non-linear demand, demand shift and erratic demands to perform with significantly reduced inventory levels and no stock-outs. The latter improvements were noted whilst carrying a lower managerial cost in the form of Buyers and / or material planners using the referenced Buyer or Planner Intervention protection routine in the ARK solution.

CHAPTER 5

DEPLOYMENT OF ARK AT METHODE ENGINEERING

Methode Electronics Malta Limited has shown great interest in the performance measurement of the Production Control Strategies (PCS) and their applicability in complex manufacturing systems. Methode had MRP installed in its premises for over 10 years. The company was suffering massive losses coming from stock-outs and air shipments. Following kanban was installed; however the main parameters did not improve. The company then decided to investigate in an in-house system that was tailored to optimize preferred variables.

This chapter presents the implementation of ARK at Methode Electronics. We will run simulations and report results of the ARK benchmarked with Pull, Push and CONWIP. The comparison will take an actual demand profile. Another case study is reported in Appendix D.

MANUFACTURING SYSTEM DESCRIPTION

To show the flexibility of ARK, we decided to use a different manufacturing line. Methode has POWER division using different assembly techniques and material flow. The selected manufacturing system is a seven-stage serial flow line similar to a job shop. The demand profile is intermittent and occurs weekly. The system which produces one product has capacity constraints such that the weekly demand is hardly met with, within one-week time frame. The job scheduling is processed on FIFO (First in, First out) policy. The stages are non-identical having different activities, process times and preventive maintenance schedules. There are significant factors which influence the performance of each stage in the system, i.e.: transporting parts, processing times, loading and unloading. Stage performance is also affected by a set-up operation in stage.

The sequence of operations could be described as follows: The raw materials come in trolley loads of 300 pieces then loaded onto a punching machine by an operator. Punching is performed on the raw materials at this stage using different punching tools necessitating change-overs. Next, parts are offloaded to a trolley and transported to the second stage. Scheduled maintenance operations are performed when due. In the second stage the semi-finished parts are loaded to a de-burring machine by an operator to de-burr them. Operations and activities such as preventive maintenance, offloading semi-finished parts and transporting these parts to the next stage are performed as scheduled. The third stage performs plating operations and similar operations/activities scheduled maintenance, loading, unloading and transporting are carried out. The latter differ from stage to stage due to probability distribution in use or the time frame used. The next stage involves lamination (stage 4). The semi-finished parts are transported to this stage in a trolley size of 300 parts. At this stage, various activities are carried out such as cutting of laminating films or materials to required sizes and heat treatment processes. After these manufacturing shaping processes are performed, the parts are offloaded to three trolleys of 100 parts size. The trolley (with 300 parts size) which brought semi-finished parts will be held until the three trollies (100 parts size) are transported out. Only then the previous trolley (with 300 parts size) is returned to the first stage for further production. The fifth stage is the bending stage. Similar operations are performed in the bending stage (loading, unloading, transporting and maintenance), however a trolley load of 100 semi-finished parts are transport to and from this stage. The sixth stage is metal insertion along with testing and quality check-up. Finished parts which passed the test are transported to the supermarket section to the final goods inventory section.

In the supermarket area, a 'shopper' checks every two hours for finished goods to match with current weekly demand. If the shopper finds finished goods, they are transferred to Shipping and dispatched to customers at the end of the production week.

There are various production scheduled shifts which are referred to as DAY shift, 1shift and 3 shift. The system operates five days per week and is idle for the weekend unless on-request. Operators are provided with a 45 minute break for the DAY shift, 30 minutes for 1 and 3 shifts.

Processing times are identical and relatively constant at each stage, but vary at different production stages. Setups are only significant for stage 1. Machines are unreliable: when a failure occurs in one stage it does not stop subsequent processes. Figure 35 shows a schematic diagram of the manufacturing system under investigation.

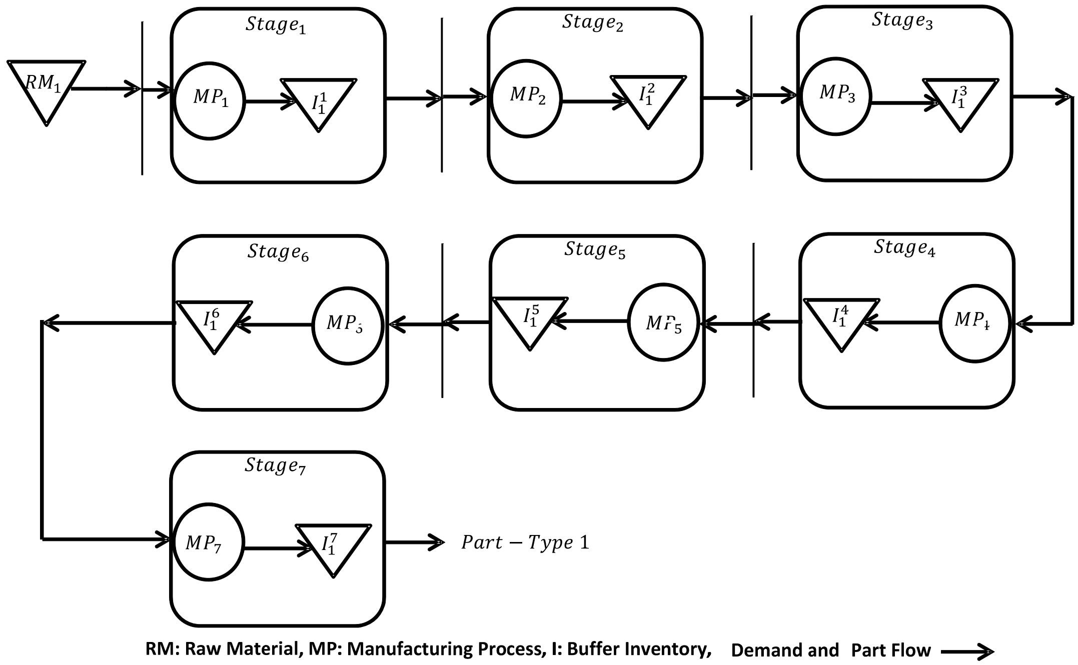


Figure 35. One Product Seven Stages Manufacturing System.

MODEL DESCRIPTION

In developing the models for the three PCS, the following assumptions were made to eliminate insignificant factors in the system and simplify it for modelling:

- The system produces one product type in a serial manufacturing/assembly line configuration.
- Raw materials are readily available.
- The system consists of seven manufacturing stages and a supermarket area.
- Parts are processed in FIFO job scheduling policy.
- Products are available in trolley batch and are processed in trolley quantity of 300 parts (which is exactly 30 boxes as 10 parts make a box) in stages 1, 2, 3 and 4

areas of the system. In stages 5, 6 and 7 they are processed in trolley quantity of 100 parts (which is exactly 10 boxes as 10 parts make a box). Finished goods are stored in the supermarket area as boxes of 10 parts.

- Unsatisfied demands are considered as backlog when at the end of a production week, the demands are not met.
- Set-up time is assumed to occur only in stage 1.
- Negligible set-up is assumed for other stages.
- The breakdown is operation dependent such that failures occur only during processing of a part. Each stage has a different breakdown profile modelled independently.

Raw materials for production are considered always available. It is the availability of the dedicated Kanban, dedicated CONWIP or the production capacity that delays the production authorisation.

The punching stage (stage 1) is considered to have a production unit of one trolley. Production of product starts in stage 1. In order to begin production on stage 1, raw materials are attached to an appropriate Kanban card or CONWIP card. However in Push model no authorisation card is required for production to commence. If the appropriate Kanban or CONWIP card is not available the part will not be processed, causing a delay. The production capacity of the system is largely controlled by the hours available for operators to work in a scheduled shift. In stage 2, the production unit is considered as one trolley. Each stage has a buffer stage set to infinity because the buffer capacity has negligible effect on the system. The process is similar in the remaining stages with the exception of bulk repartition output. Stage 7's output is in box quantity of 10 parts and stored in the supermarket area for shipment. Production hours available have the biggest impact on the system followed by the availability of trollies. Preventive maintenance is modelled for all stages to render the breakdown independent.

Finished goods are held in the supermarket area in box quantities. On a two-hour interval, the 'shopper' will seek to satisfy demand. When the shopper selects a box the Kanban or CONWIP is released. Pictorial representation of the model structure is shown in the Figure below.

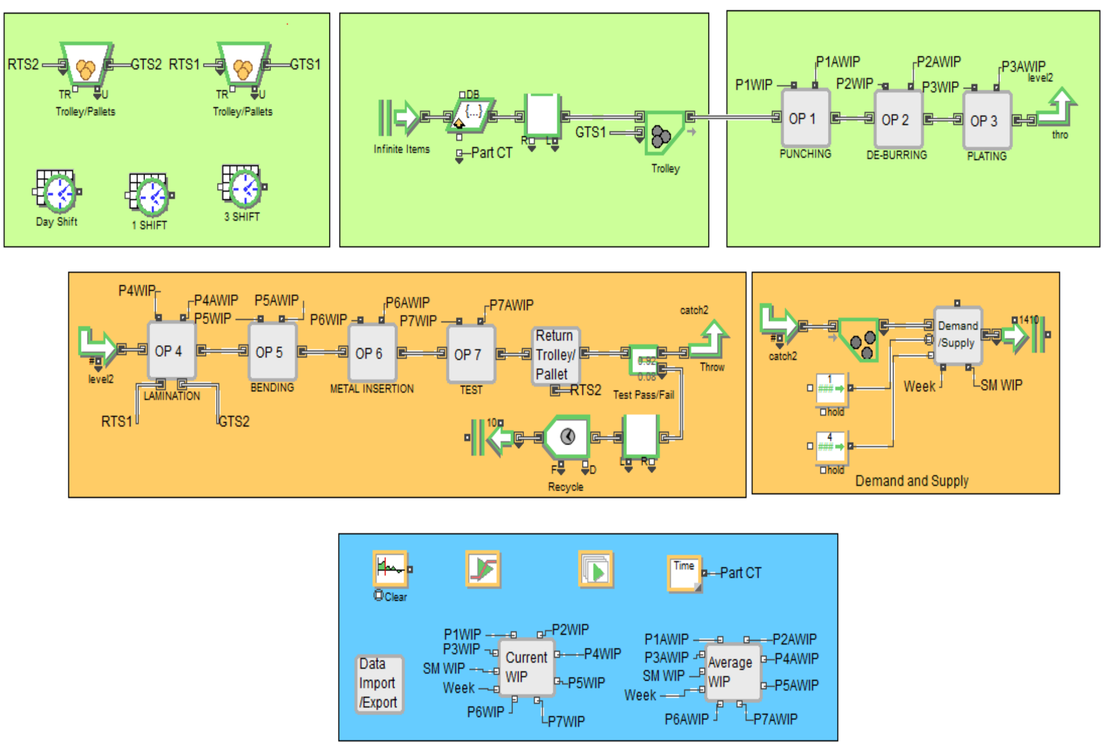


Figure 36. Model Structure.

Numerical simulation was carried out to find the optimal control parameters. Data used in parameters optimization and selection is shown in table 30. A warm-up period of four weeks was used. Average demand was computed over a 6-week period. The selection was to avoid biased data. Moreover, there was no-initialisation of the supermarket area with products from each product type. Also ten simulation replications were performed for each of the weekly demand profile for convergence.

Table 30

Kanban and CONWIP card Configuration

Stages	KANBAN (trolley quantity of 300 ~ "TrolleyA", trolley quantity of 100 ~ "TrolleyB", Box quantity of 10 ~ "BoxC")		CONWIP (trolley quantity of 300 ~ "TrolleyA", trolley quantity of 100 ~ "TrolleyB", Box quantity of 10 ~ "BoxC")	
	Search setting for Kanbans	Best Setting	Search setting for CONWIP	Best Setting
1	2 – 10 (TrolleyA)	5 (TrolleyA)	100 – 340 (BoxC)	320 (BoxC)
2	2 – 20 (TrolleyA)	6 (TrolleyA)		
3	2 – 10(TrolleyA)	5 (TrolleyA)		
4	60 – 210 (BoxC)	157 (BoxC)		
5	3 – 10 (TrolleyB)	8 (TrolleyB)		
6	3 – 10 (TrolleyB)	6 (TrolleyB)		
7	3 – 10 (TrolleyB)	5 (TrolleyB)		

EXPERIMENTAL CONDITIONS

The production capacity, loading, unloading, transporting time and the level of variability in the system were given a considerable attention to achieve high levels of precision. The demand profile, processing times, set-up times, downtime data were collected from the system and used for experimentation.

DEMAND PROFILE AND SYSTEM CONFIGURATION SETTINGS

The demand profile has high variations. A six week demand profile for the product is given in Table 31. On a two-hour interval, a shopper access the supermarket where the finished goods are stored based on the weekly demand.

Table 31

Demand Profile for Week 20

Demand in Box Quantity	Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Wk 20	240	240	84	228	168	228
Wk 21	252	216	96	216	168	264
Wk 22	264	168	132	204	168	252
Wk 23	264	192	120	216	144	252
Wk 24	144	300	120	132	264	132
Wk 25	252	276	120	156	240	156

In modelling the demand profiles, the weekly demands for each of the products are recorded in an internal database. On a two-hour interval, the 'shopper' reads this database and another containing the number of shipped (satisfied) demands for each product in the appropriate week. If demand has not been fully satisfied the shopper will try to acquire as many products as possible. The unsatisfied demand is treated as backlog and the following week demand becomes the week demand in addition to the previous week's backlog. The objective is to target zero backlogs while maintaining low WIP.

The processing times for the products at each stage is detailed in Table 32 as well as the MTBF, MTTR and setup times.

Table 32

The Configuration of the Manufacturing System for Modelling

Stage	Loading Times/Trolley (Hours)	Processing Times/Trolley (Hours)	Unloading Times/Trolley (Hours)	Transporting Times/Trolley (Hours)	Maintenance MTBF (Hours)	Maintenance MTTR (Hours)	Setup Times (Hours)
1	2.5	5.35	5	0.833333	480	Uni. Real (1, 2)	Uni. Real (0.5
2	0.833333	3	0.8333	0.833333	480	Uni. Real (1, 2)	0
3	Uni. Real (0.1282, 0.1603)	0.75	0.0641	1.666667	120	Uni. Real (1, 3)	0
4	2.5	15	2.5	0.138889	480	Uni. Real (0.75,	0
5	0.083333	0.566667	0.0833	0.277778	480	Uni. Real (1, 2)	0
6	0.138889	1.666667	0.1389	0.138889	480	Uni. Real (0.5,	0
7	0.138889	2.333333	0.1389	0.833333	480	Uni. Real (0, 0.5)	0

EXPERIMENTAL RESULTS

The weekly WIP level versus the Backlog was collected and examined. The total weekly WIP and Backlog of each PCS were recorded. Results of the WIP and Backlog for Push, KANBAN and CONWIP PCS are shown in Tables 33-38.

Table 33

Week 20 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	442.1	529.3	588.3	609.6	658.8	710.7
Kanban	Total Backlog	89	176	105	177	202	272
CONWIP	Total WIP	261.2	260	229.5	227.6	203.8	201.6
CONWIP	Total Backlog	79	170	103	174	199	270
Push	Total WIP	442.2	523.5	593.1	612	655	713
Push	Total Backlog	80	174	100	173	193	269

Table 34

Week 21 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	443.1	527.7	578.1	616.9	654	713
Kanban	Total Backlog	96	169	112	169	185	295
CONWIP	Total WIP	249.1	244.3	227.5	224.2	203.6	191.5
CONWIP	Total Backlog	92	157	98	156	173	278
Push	Total WIP	443.1	524.3	593.1	617	656	712.9
Push	Total Backlog	98	168	104	162	184	294

Table 35

Week 22 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	442	525.4	586.2	610.9	650.9	711.9
Kanban	Total Backlog	107	130	118	165	187	284
CONWIP	Total WIP	254.6	251.3	227.7	239.5	203.4	189.9
CONWIP	Total Backlog	109	129	100	149	173	268
Push	Total WIP	443.2	531.6	584.3	615	656.9	712.9
Push	Total Backlog	107	134	119	168	193	293

Table 36

Week 23 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	443.1	530.6	581.2	613	656	713
Kanban	Total Backlog	105	149	107	170	166	266
CONWIP	Total WIP	265.5	246.1	225.9	229.3	211	198.2
CONWIP	Total Backlog	108	154	118	177	177	275
Push	Total WIP	443.2	533.6	587.1	620.8	653	712.9
Push	Total Backlog	114	168	129	187	188	285

Table 37

Week 24 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	453.1	529.5	591	611.8	655	711.8
Kanban	Total Backlog	0.8	141.8	107.8	86.8	199.8	172.8
CONWIP	Total WIP	246.5	230.2	213.5	208.1	197.5	190.4
CONWIP	Total Backlog	0.4	149.4	114.4	87.4	202.4	174.4
Push	Total WIP	450.4	532.6	582.4	612	652	713
Push	Total Backlog	0.8	146.8	108.8	81.8	193.8	168.8

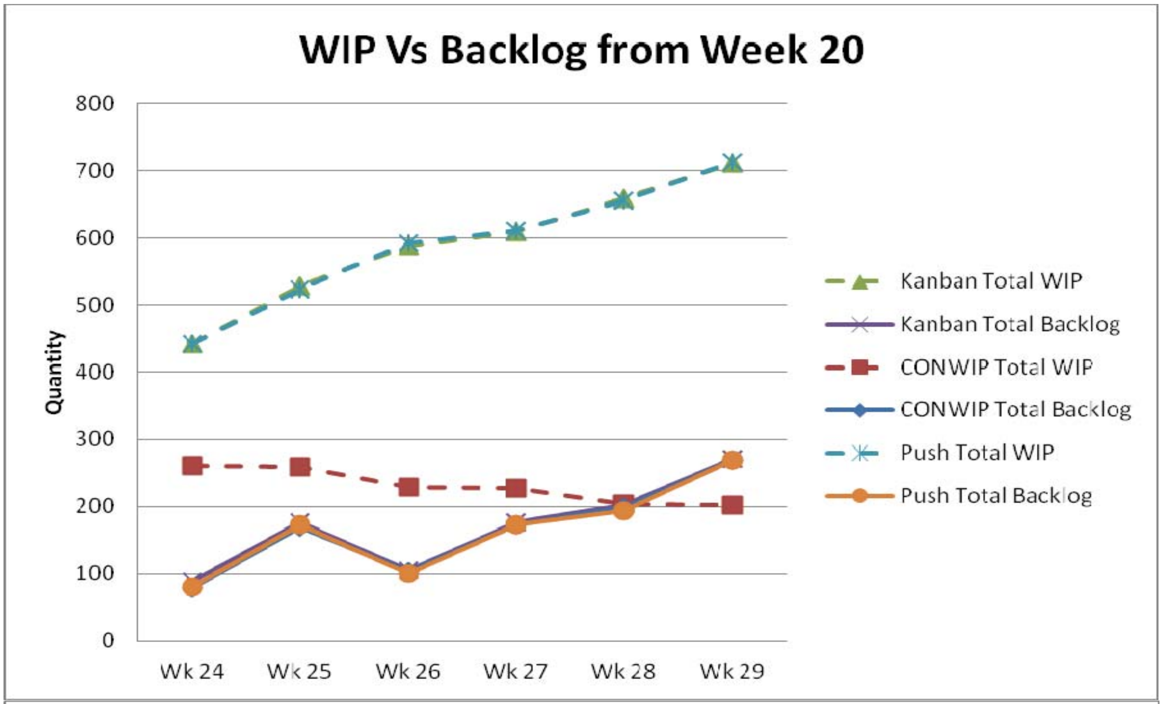
Table 38

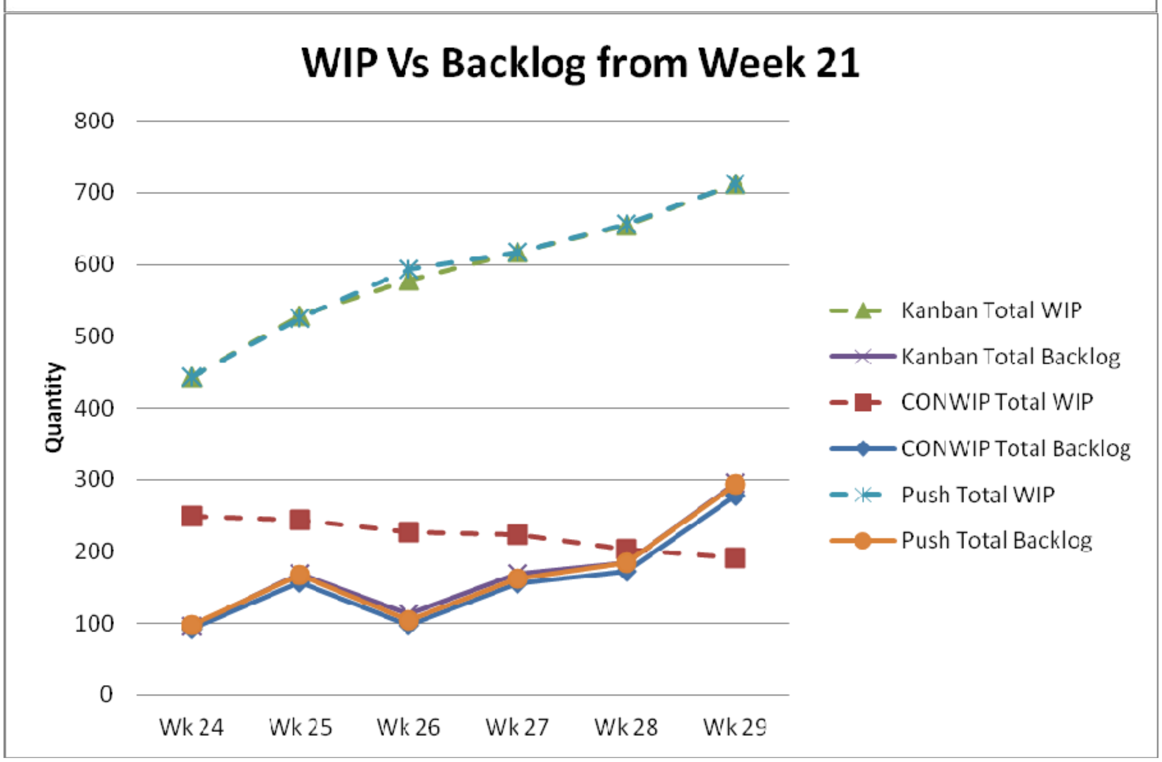
Week 25 WIP and Backlog Results

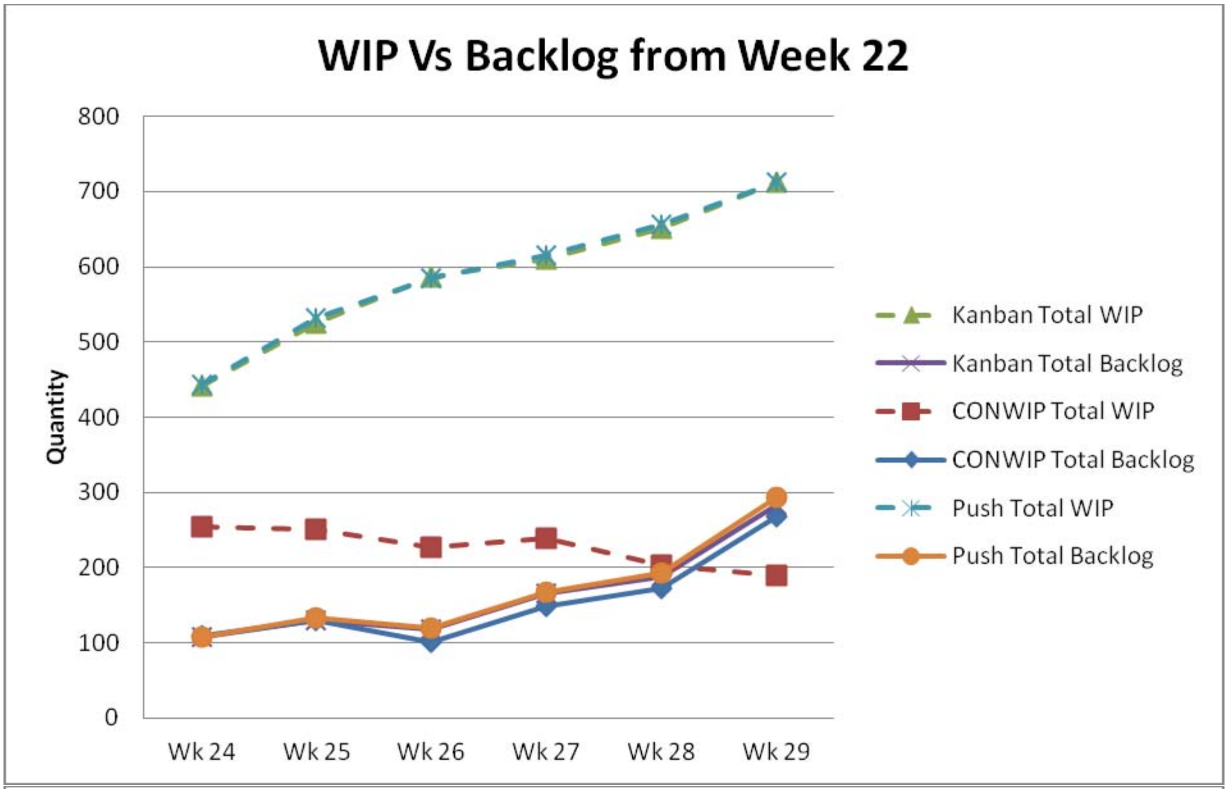
PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	443	525.4	595	617	659	711.9
Kanban	Total Backlog	101	234	202	200	296	297
CONWIP	Total WIP	274.4	271.3	239.4	257.8	214.8	218.5
CONWIP	Total Backlog	92	218	183	178	271	272
Push	Total WIP	442	519.3	601	620	666	711
Push	Total Backlog	94	224	192	192	279	281

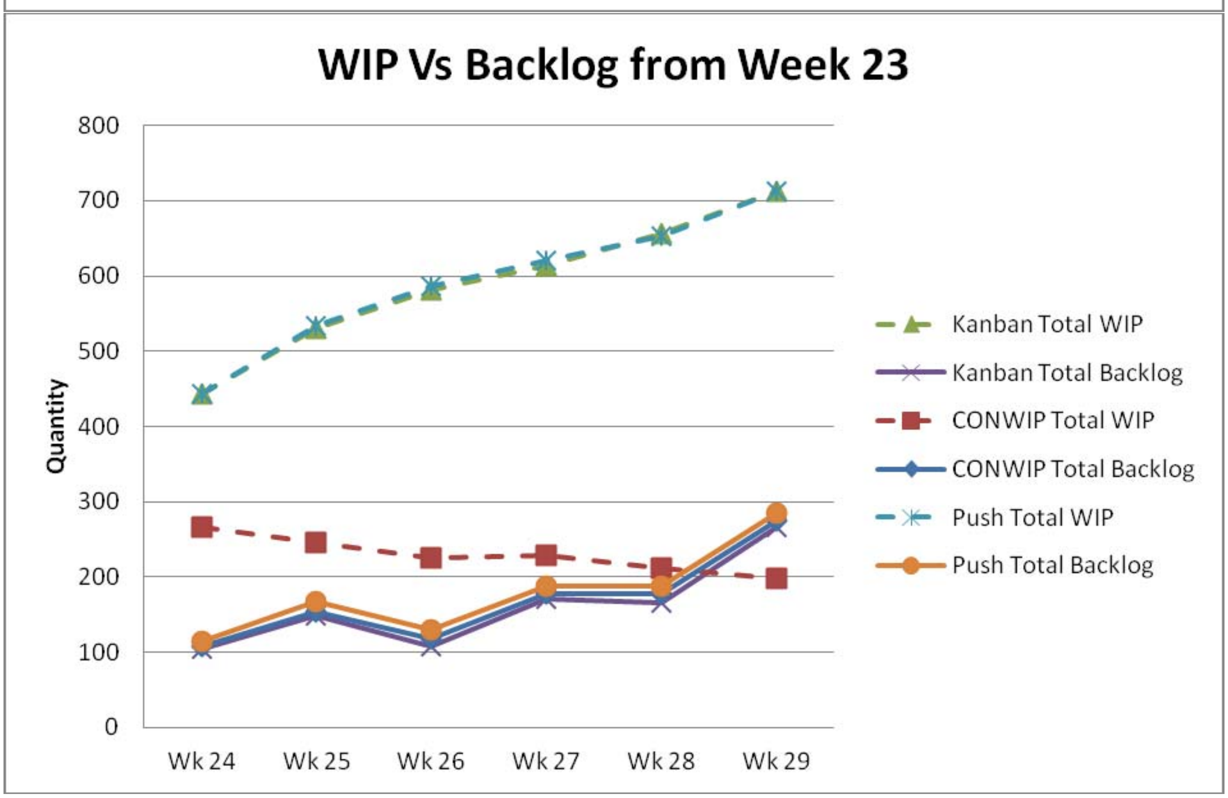
GRAPHICAL REPRESENTATION OF WIP VS. BACKLOG

Results show that CONWIP was consistently the best performer of the three examined PCS. It was observed that KANBAN behaved similarly to Push which was attributed to the capacity restriction. The latter limits the performance of KANBAN by restricting the authorised parts to stay until capacity is released. That was present however not significant in CONWIP. There was little or no significant difference in the performance of KANBAN and push PCS.






WIP Vs Backlog from Week 22
Quantity
800
700
600
500
400
300
200
100
0
Wk 24
Wk 25
Wk 26
Wk 27
Wk 28
Wk 29
Kanban Total WIP
Kanban Total Backlog
CONWIP Total WIP
CONWIP Total Backlog
Push Total WIP
Push Total Backlog


WIP Vs Backlog from Week 23
Quantity
800
700
600
500
400
300
200
100
0
Wk 24
Wk 25
Wk 26
Wk 27
Wk 28
Wk 29
Kanban Total WIP
Kanban Total Backlog
CONWIP Total WIP
CONWIP Total Backlog
Push Total WIP
Push Total Backlog

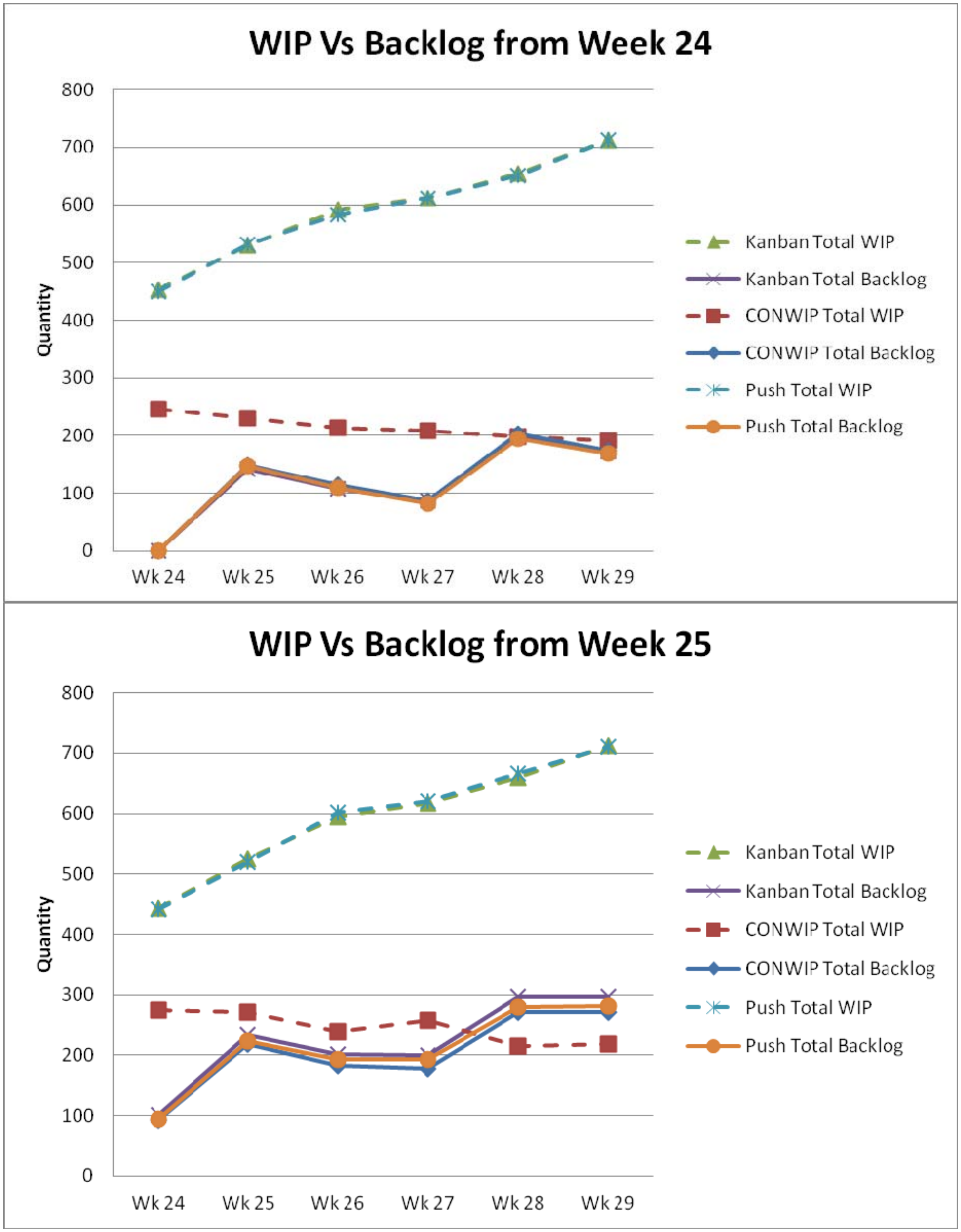


Figure 37. WIP vs. Backlog from Week 20 to Week 25.

DISCUSSION

There was a significant level of difference between CONWIP and the other investigated PCS. CONWIP performance was the optimal; however it had a high backlog. The backlog of three PCS followed the same trend. Since the objective function was set to have a targeted zero backlog while maintaining low WIP, the WIP level was not restricted to enable the attainment of zero backlogs. All PCS failed to attain zero backlogs. The good performance of CONWIP over KANBAN is largely attributed to the way in which demand information is used by the strategy.

Push PCS had high level of WIP in the system in anticipation to satisfy the demand in view. However, due to the production capacity constraint it could not respond to demand adequately. Push and KANBAN were observed to perform in the same way all through the six weeks view. In this case and type of assembly environment CONWIP is preferred to Kanban and Push with respect to their performance in terms of WIP and Backlog.

We then applied the ARK to highlight the effectiveness of the ARK-intervention module. It has been shown that ARK could be effective when having different line configuration/manufacturing environment. We chose to run the calculation using week 24 demands' at ZERO on hand. The demand pattern of this item is very erratic, ranging from 120 to 276 per week. There was also a shift in the weekly demands. This rendered the case typical for ARK. In fact, the system triggered an intervention of 32 pcs in the current week to satisfy the shift in demand which was not catered for in the previous week's simulation (Final Kanban Lot Size). We chose to use a different container type: The type of product and the manufacturing configuration lea us to use the ‘Multiple container’. The latter proved to be more suitable for this demand pattern as it resulted in a lower Final Kanban Lot Size of 276 pcs vs 300 pcs of the Single Full option (2 boxes of 12 pcs less). With this option the system could react immediately to the various shifts in demand without getting caught with excessive stocks.

So considered ‘Start On Hand’ as zero (0), the ‘On Order Due’ is 220. The first run used a TKLS of 276 failed the simulation in week 24 (current production week). As it can be noted: Demand was of 252 but the on order due were 220. This left a shortage of 32 which needed to be highlighted immediately. Such cases require intervention so that production reacts accordingly. Reaction could be by adding more capacity to inform the customer that delta sales will be sent next week.

KanBan simulation

Part Number	1.990014	On Hand *(oh)CMS*	-	Safty Weeks	-	Supplier Ship Time	1
Description:	CT BusBar	Replen Lead Time	1 weeks	Multiple *(Box size)*	12		-
Item Cont Option:	Multiple	Average Demand	200	Minimum	12	Percent Increase	5%
Current Qty Containers	19	Prelim Qty Containers	18				

	Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
	Simulation Try Number : 1				Test KanBan Lot Size		276	PKLS					
	start		-									-	
1	24	252	0	0	0		220	276	0	0	32	0	INTERVENTION REQ.
2	25	276	0	0	0			276	276	276	0	0	PASS
3	26	120	0	0	0			120	276	276	0	156	PASS
4	27	156	12	12	12			156	120	120	0	120	PASS
5	28	240	0	0	0			240	156	156	0	36	PASS
6	29	156	0	0	0			156	240	240	0	120	PASS

Figure 38. Week 24 simulation – Zero on hand.

CHAPTER 6

CONCLUSION AND FUTURE WORKS

Applying ARK to this high variable demand environment, our inventory and backlog could be driven to be ZERO. In terms of efficiency and economic viability, ARK for erratic demands may be considered easier to implement than Kanban or CONWIP. ARK, as presented, has been shown to be the most suitable replenishment system of the other three PCS in terms of minimizing WIP at a minimum backlog when the demand profile falls within the range of robustness of the optimal settings. ARK showed that there is a need to effectively address the level of volume flexibility of PCS in order to adjust and respond quickly to changes in the product mix and product volume in a system.

Our major contributions are separately shown below.

Operator Intervention

ARK offers an operator the ability to intervene to meet target demand. This offers a novelty in production control systems that are usually unidirectional without operator flexibility. Figure 39, below, presents the buyer intervention logic that takes place within the regular replenishment lead time

This module even enhanced supplier reaction time

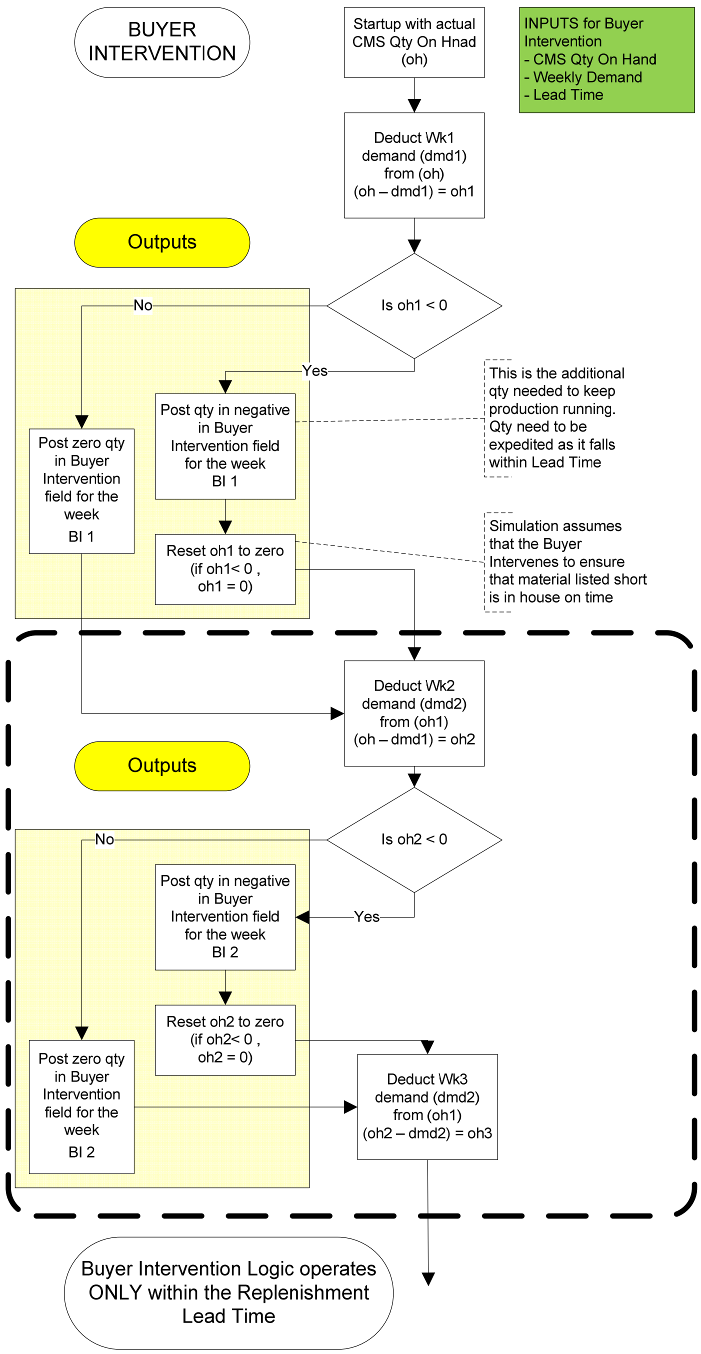


Figure 39. Buyer intervention.

Forecast Module

Our own generated forecast calculator is affected by regular as well as irregular metrics: It presents a novel helping hand for the ARK deployment.

Generating a better forecast that accounts for out-of-hand constraints from employees' unions and managerial decisions enables ARK to overcome overproduction easily and efficiently.

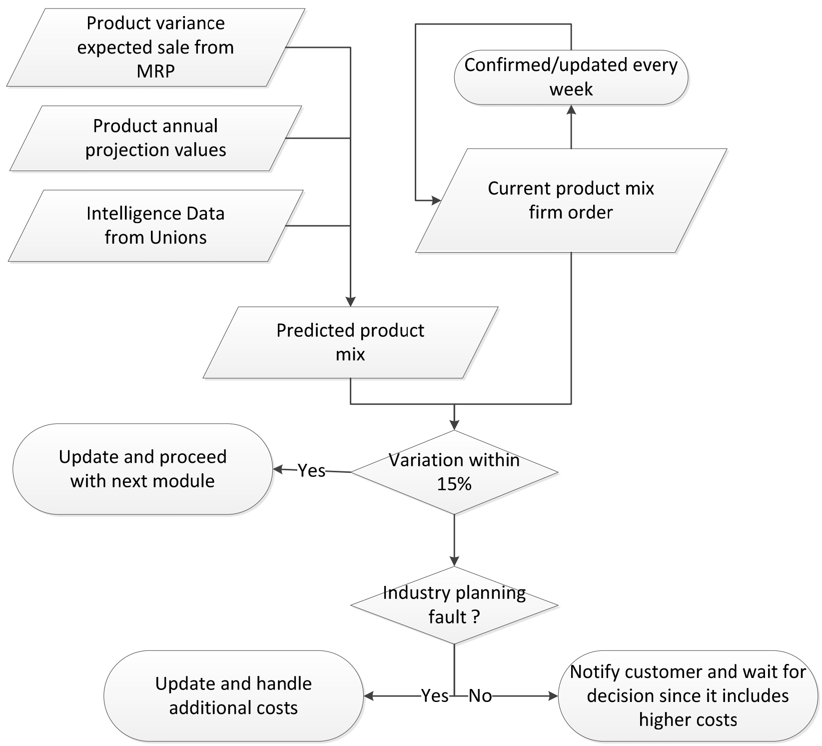


Figure 40. Forecast Calculator.

Cultural Impact

Another major added value brought by the deployment and implementation of ARK is the massive participation of company employees. Actually, the solution required operators to be ready for a major lean initiative that rendered the system dynamics in shape to deploy the new methodology. Operators were trained on major lean concepts and they were granted enough time and incentives to rapidly accept change and the upcoming production system functionality. It is well known that cultural resistance to change is a major setback for several managerial initiatives, and throughout our work we ensured to integrate the operator opinion and to include him in the change process. Currently efforts are persisting and persevering to further advance Methode in the lean direction and the organization culture is completely ready to adopt it.

Industrial Integration

The fact that the presented solution is already integrated at an industry validates it. Currently Methode engineering has deployed the solution in its Malta production facility and will be doing so shortly in its Egypt facility.

Other industrial facts, following the implementation of our solutions:

- Overhead is reduced due to rapid operator intervention
- Labor hours are reduced generating revenue (and paying back the technical hours spent on deploying the solution)
- Human error is controlled and decreased affecting cost per produced part

The figure below shows the post-deployment data:

- Inventory went from very high to low (17 turns)
- Delivery performance was around 95%
- Short shipments were drastically reduced.

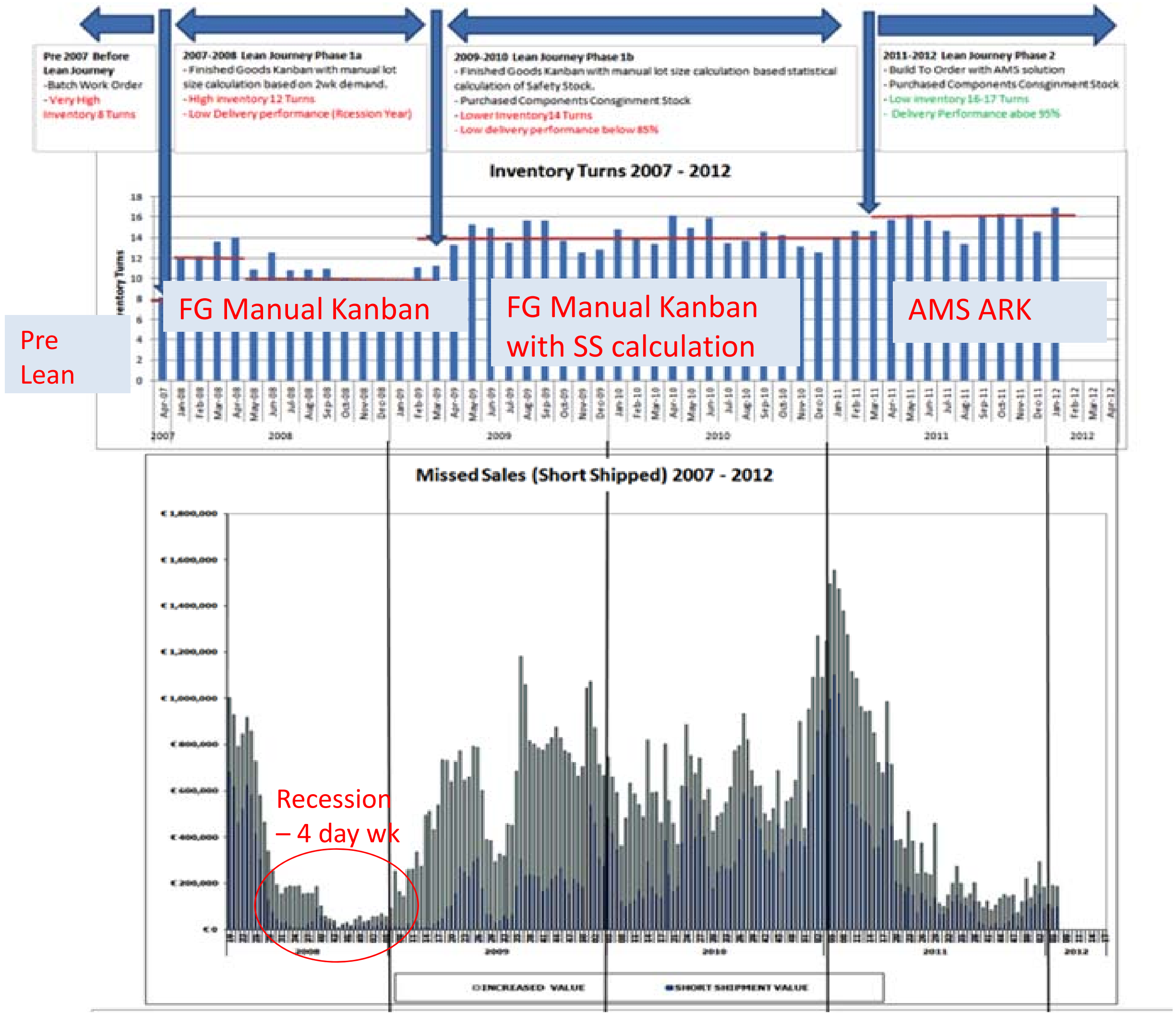


Figure 41. Inventory turns and Missed sales (2007-2012).

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APPENDIXES

APPENDIX A: DETAILED PRODUCTION SYSTEMS COMPARISON

Within this appendix we will propose multiple reviews and comparisons between productions systems based on the parameters identified in section 2.2.d. At first a straight forward comparison between push and pull systems will take place. Then, KANBAN and CONWIP will be studied followed by the comparison between TOC and CONWIP. Finally we will review multiple literature reviews taking into account multiple production systems.

PUSH VS. PULL SYSTEMS

Perhaps the most basic difference between push and pull systems is through parameters Work in Progress (3) and Throughput (8). In Push systems parameter 8 is controlled and parameter 3 is observed while in pull systems it is the opposite: parameter 8 is observed and parameter 3 is controlled.

Another constraint is the linkage between the release rate and the system capacity (14): If the release rate is too high the system will be choked with WIP and, if the release rate is too low, the revenue will be lost because of lacking throughput. However, the task of estimating the appropriate system capacity is not simple, and the factors participating in delineating a clear figure of the system capacity range from machine outages to operator’s unavailability and another set of detractors. These elements combined makes the task of estimating capacity a complex one, even further, this makes the push system harder to optimize than a pull system.

On another level, pull systems are constrained with a pre-specified limit on the WIP Level. This constraint overrides any circumstance taking place on the production floor. Hopp and Spearman (2008) mention that if product stops, input stops on the material flow strong emphasis placed in pull systems. This insures that any shutdown or line disruption will not allow the work in progress to jump a certain barrier. On the other hand no such limit exists for pure push systems, i.e.: In MRP, when the master production schedule is established it determines the complete set of order releases which in turn determines what is released into the system…The WIP is never controlled; it might float up and down over time. It is worthwhile to mention that in push environments, no correction measures are placed as prevention: when the error happens we try to correct it. However, at this advanced stage, the WIP would have been already out of control.

Comparing another element of push and pull systems would require to study the efficiency of such lines. Spearman and Zazanis (1992) state that the WIP level required to achieve a given throughput is lower in a pull system than in a push system. This makes the pull systems more efficient than push systems for serial lines manufacturing (performing operation for one item). Moreover, Hopp and Spearman (2008) state that for a given level of throughput push system will have longer average cycle times than pull systems. Spearman et al. (1990) analyze variable cycle times in comparison between push and pull systems: the latter will have less variability than push systems. The variability of cycle time will directly influence lead times, making them longer to be able to achieve a certain level of on-time delivery. Concluding this comparison, we would give a clear benefit to pull systems based on the production system robustness (and not WIP reduction). Hopp and Spearman (2008) indicate that an "A CONWIP system is more robust to errors in WIP level than a pure push system is to errors in release time". Table 34 is a comparison table between push and pull production systems based on selected parameters, deemed of interest.

Table 39

Push/Pull Systems

	Parameters	**Push**	**Pull**
1	Upstream information	Required	Irrelevant
2	Actual Demands	Irrelevant	Required
3	Work in Progress	Uncontrolled	Controlled (reduced)
4	Lead Time	Fixed Assumption (not realistic – over safe)	Shorter lead and cycle times
5	Machine Downtime	Accounted for with a safe margin	Accounted for with a safe margin
8	Throughput	Controlled	Uncontrolled
11	Control Parameters	Throughput	WIP
14	Capacity	Complex to calculate and optimize	Lesser complexity

KANBAN VS. CONWIP

The Kanban and CONWIP production systems exhibit similar behavior with respect to parameters 2, 3, 4, and 8: They both require parameter 2 (Actual demand) which acts as the production system trigger, they both have a limit on WIP, their cycle variability is low and they will achieve throughput with lesser WIP.

Hall (1983) highlighted a major difference: Kanban is applicable only in repetitive manufacturing environments. This implies a flow along a fixed path at steady rates. Also, this indicates that large variations will destroy this flow. Also the optimal count of cards is a function of a mix.

Table 40

Kanban vs. CONWIP

	Parameters	Kanban	CONWIP
2	Actual Demands	Required and acts as the trigger	Required and acts as the trigger
3	Work in Progress	WIP has a cap	WIP has a cap
4	Lead Time	Cycle time variability is low	Cycle time variability is low
7	Standardization	Required (which restraints the system)	Not Required
8	Throughput	Achieved with lesser WIP	Achieved with lesser WIP
9	Implementation	Not trivial to implement	
10	Production Line	Fixed path and repetitive manufacturing lines	Able to swing in product mix. Thus applicable to wider variety of production environment.
11	Control Parameters	Requires more control parameters	Is intrinsically easier to control

THEORY OF CONSTRAINTS VS. CONWIP

A short comparison between the theory of constraints and the constant work in progress (CONWIP) model would be based on the bottleneck control:

- (Stable bottleneck) In TOC the release strategies have an edge on CONWIP: they generate a better throughput (given a constant WIP level).

- (Unstable bottleneck) The bottleneck location affects the TOC while the CONWIP is insensitive to its location.

MULTIPLE SYSTEMS

In this section we will present different literature comparison reviews between the production systems.

Bonvik and Couch (1997) presented a detailed study comparing Kanban Control Systems, minimal blocking Kanban Control systems, BSCS, CONWIP and hybrid Kanban-CONWIP. The main points highlighting this study can be summarized as follows:

- The comparison was based on the same example: a four-stage tandem production
- The simulation was a discrete event
- Demand was studied as constant as well as demand increasing / decreasing in steps
- The hybrid Kanban-CONWIP decreased inventories up to 20% over Kanban control systems (having the same service level)
- The performance of BSCS and CONWIP was not good in comparison with the hybrid-CONWIP and KCS

Bonvik and Couch (1997) also studied the impact of a sudden demand rate decrease and concluded that the KCS line would better handle the situation with the semi-finished inventory distributed throughout the line (and not having the buffer to reach the WIP cap like in CONWIP).

(Gaury et al., 2000; Gaury et al., 2001) proposed a generic pull model encapsulating the three basic control strategies (KCS, CONWIP and BSCS). The model was studied by simulation and the studied factors were line imbalance as well as machine reliability.

Kleijnen and Gaury (2003) highlighted that the most important parameter in the selection of a production system would be robustness and not the ability of a system to optimize itself. 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.” The presented methodology was a combination of simulation, optimization, risk and bootstrapping. The authors concluded that the hybrid Kanban-CONWIP was properly functioning when risk was not ignored.

Taylor (1999) studied the different systems for the same targeted throughput and concluded that a hybrid push-pull system had the lowest WIP, a pure push system the highest and a pure pull system had the highest throughput.

Beamon and Bermudo (2000) also suggested a hybrid push/pull algorithm developed for multi-line/multi-state assembly type production systems. The aim was to reduce costs of inventory as well as maintaining a high level of customer service. Simulations gave results favoring this hybrid system.

Cochran and Kaylani (2008) proposed a horizontally integrated hybrid production system with multiple part types. The research was investigating whether to have multiple junction points between the push/pull elements by each part type, or to have one for the whole production system. The authors developed a genetic algorithm and tested the model on a Boeing study case. The authors concluded that cost savings were important, bottleneck process should have junction points located afterwards, lower safety stock.

CONCLUSION

This appendix provided an opportunity to study the different production systems: Push/pull systems, Basestock control, Synchro-MRP, CONWIP, Kanban and their ramifications, theory of constraints and a multitude of literature systems.

APPENDIX B: FORECASTING SHORTCOMINGS

Literature on erratic demand divides the forecasting approaches into two main ones: parametric and non-parametric. This appendix proves that both fall short in accurately estimating erratic demand.

NON-PARAMETRIC FORECASTING

This section summarizes the work of Croston (1972) previously referenced. He investigated the failure of exponential smoothing (most used non parametric forecasting technique) facing erratic demand.

The author considered a routine stock control system. The latter is updated at fixed intervals, and these intervals are much smaller than the time between successive demands. As a first step, Croston considered uniform demand while noting that usually this is not the case and that both inter arrival time and size of demand are random variables. However, this will be a starting point to be extended to the stochastic case. Having said this, and assuming the first demand occurs at time t = 1, the demand y_t is as follows.

Equation 2. Demand equation

$$y_t = \begin{cases} \mu, t = np + 1, n = 0,1,2 \ldots \\ 0, otherwise \end{cases}$$

Where demands are of magnitude μ and occur every p review intervals, n indexes the non-zero demands.

The typical approach for single-stage exponential smoothing is used through the equations below where y_t is the demand at time t, $\hat{y}_t$ the forecast of the average demand made at time t, and used as a one step ahead forecast of the demand at time $t+1$, e_t is the error of the forecast, m_t the estimated mean absolute deviation of the errors, R_t the replenishment level to which the stock is raised and k is a constant for all products in the system; in particular, k regulates the safety stock to protect against variability of demand.

Equation 3. Computing forecast error

$$e_t = y_t - \hat{y}_{t-1}$$

Equation 4. Demand

$$\hat{y}_t = \hat{y}_{t-1} + a e_t$$

Equation 5. Estimated mean absolute deviation of the errors

$$m_t = (1 - a) m_{t-1} + a |e_t|$$

Equation 6. Replenishment level

$$R_t = \hat{y}_t + k m_t$$

Note that from Equation 2 and Equation 3, the following can be deduced:

Equation 7. Replenishment level

$$\hat{y}_t = a y_t + (1 - a) \hat{y}_{t-1}$$

In other words, the forecast given is a weighted average between the new demand observed and the previous forecast (which represents all past demands). It is suggested to use small values of α, of the order of 0.1-0.2. A small value of α indicates that more weight is given to historical data rather than the new demand; i.e. giving the forecast more stability versus fluctuations with every new demand point.

Croston (1972) noted that such systems are usually robust against changes in demand patterns; however, serious errors arise when the demand is erratic. The author proceeded in his study by describing the pattern of forecast, error, and mean absolute deviation for regular intermittent demands over four cycles as shown in the Figure below, where the initial values of $\hat{y}_t$, m_t for $t = 0$ are based on the previous demands. The effect of these initial assumptions decreases with time. The author indicated that replenishment will only be made following each demand and solely dependent on $\hat{y}$ and m. The reason for this is that following a demand, the stock would be at its minimum. The values used are designated $\hat{y}*$ and $m*$.

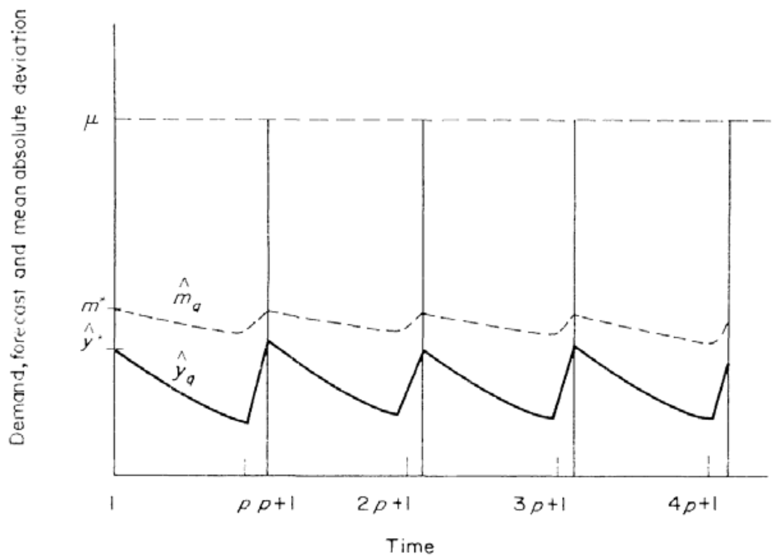


Figure 42. Response to demand occurring at time t = 1 and then at intervals p (Croston, 1972).

Next, Croston showed the effects incurred when demands occur at regular intervals, and then continued for the case of stochastic intervals and sizes.

Equation 8. The equations for the forecasts $\hat{y}^*$ and mean absolute deviation m^* when demand consists of regular orders for μ units received every p review intervals

$$\hat{y}^* = \frac{\mu\alpha}{1-\beta^p}, \quad m^* = \frac{\alpha\mu\left\{1-\beta^{p-1}\left[1-\alpha(p-1)\right]\right\}}{(1-\beta^p)^2},$$

Whereβ = 1-α.

$\hat{y}^*$ and m^* are then used to calculate the replenishment level R_t from (Equation 6). He tested for a range of inter arrival times of 1-15 review intervals, with smoothing constants α between 0.05 and 1. The results indicated that the forecasts of demand $\hat{y}^*$ underestimate the size of the demands which occur, as would be expected, leading to stock-outs. However, they also overestimate the long term average demand $\bar{y}$ where $\bar{y}$ = μ/p; the author observed that for the commonly used range of smoothing constants of

0.05-0.20 the level of replenishment is more than twice the ideal replenishment level, and therefore considerable excess stock would be carried.

Stochastic Arrival and Size of demand

Next, Croston extended his model to cover stochastic arrival and size of demand. In particular, he generated demand occurrences in each interval by a Bernoulli process, with a constant probability *1/p* that a demand will occur; i.e. the average inters arrival interval remains *p* review intervals. Furthermore, the demand size followed a normal distribution N (μ, σ2). Assuming the same replenishment system as the previous section, Croston regenerated the expected value and the variance of the estimate $\hat{y}^*$ used for forecasting and control and noted what follows. The average demand is again inflated by the fact that replenishment immediately follows a demand, and the results indicated an increase in estimating error produced by the Bernoulli arrival of demand as compared with constant inter arrival intervals.

In summary, we showed in this section that the most used statistical method in the literature (Exponential Smoothing) would lead to stock-outs and (or) excessive stock when demand is erratic. In fact, a study conducted by Smart (2002) confirmed two things:

- Both exponential smoothing and a variant of exponential smoothing, developed by (Croston, 1972), are effective in forecasting mean (average) demand per period when demand is intermittent.
- Neither Croston's method nor exponential smoothing accurately forecasts the entire distribution of demand values, especially customer service level inventory

requirements for satisfying total demand over a lead time (for example, the amount of inventory required to provide a 90, 95 or 99 percent likelihood of not stocking out of a product item).

PARAMETRIC FORECASTING

This section summarizes the work of Lau and Lau (2002) previously referenced. We attempt to answer if we can directly generate using the normal approximation the appropriate inventory settings or whether we have to check the D_L's distribution.

Most literature points out the appropriateness of using the normal distribution to approximate lead-time-demand (D_L) even if the latter is non-normal; in fact, D_L is often approximated by that fractile of a normal distribution. With this procedure, it is easy to set safety stocks for an (*s, Q*) inventory system. However, there are numerous studies that prove otherwise by identifying cases where the normal approximation yields excessive costs and/or lower service than desired. Note that typically D_Ls are asymmetrical and non-normal.

Lau and Lau (2002) summarized the studies done on the effects of distributions on inventory policies. They were consistent in the sense that the normal-D_L approximation is not robust when c_w is large (greater than 0.5), where c_w refers to the coefficient of variation of D_L's distribution.

The more difficult task was to prove the inappropriateness of the normal distribution when $c_w < 0.3$. Lau and Lau (2002) generated D_L from a Beta distribution and showed through experiments that the normality assumption led to stock-outs. The reason they chose a Beta distribution was to test for a wide range of situations.

In summary, most literature agrees that the normal approximation is not appropriate when cw is > 0.5, and new studies also showed that it is also not appropriate when cw< 0.3. Lau and Lau (2002) recommend that instead of searching for extremely complicated rules (non-parametric methods) to decide if the normal distribution is appropriate in a particular scenario or not, one can easily with the aid of today's hardware and software capabilities estimate the correct D_L distribution and use it to compute (Q*,R*).

CONCLUSION

In this section, we showed that in the case of erratic demand, both parametric and non-parametric forecasting cannot avoid errors and stock-outs. In other words, statistics would not work. In the case of parametric forecasting, the normality assumption lead to high stock-out costs; literature advises on attempting to estimate the correct D_L distribution and use it to compute (Q*,R*). On the other hand, the main approach that is used in non-parametric forecasting (exponential smoothing) also ends with stock-outs and excessive average stock in the case of erratic demand.

APPENDIX C: NORMALITY ASSUMPTION AT METHODE

Even though we listed previous works that proved the inappropriateness of the normal distribution, and as there is still an ample ration of literature that recommends the normal approximation in parametric forecasting, in this section real demand from Methode is used to reassess the normality assumption.

DEMAND DURING LEAD TIME AND SERVICE LEVEL

When dealing with uncertain demand and assuming a continuous review policy is used, stock-outs will only occur during lead time. This is because the continuous monitoring of inventory allows the manager to adjust the timing of the replenishment order, depending on the demand experienced. If demand is very high, inventory reaches the Reorder Point (ROP) quickly, leading to a quick replenishment order. If demand is very low, inventory drops slowly to the ROP, leading to a delayed replenishment order. The manager, however, has no recourse during the lead time once a replenishment order has been placed. The available safety inventory (ss) thus must cover for uncertainty of demand during this period.

Next, let's define the Cycle Service Level (CSL), where CSL = Prob (Demand during Lead ≤ ROP)

In other words, CSL gives us the probability of not stocking out during a cycle, or the fraction of replenishment cycles that ends with all demands met. Assuming that demand across periods is independent (not correlated), demand during lead time is normally distributed with the following:

Mean demand during Lead: $D_L = DxL$ $D_L = D \times L$

Safety Stock: ss = ROP – D_L. (1)

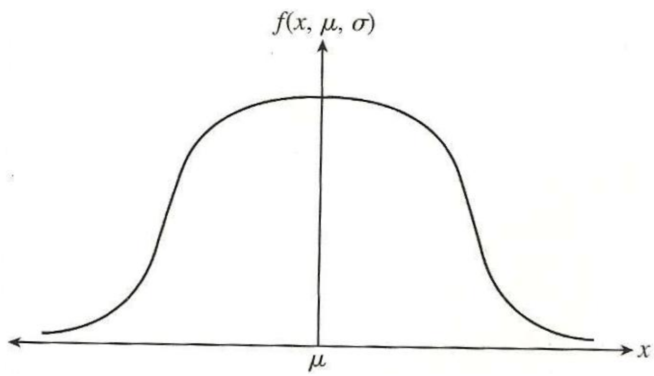
Standard Deviation of demand during Lead: $\sigma_L = \sqrt{L} \times \sigma_D$ $\sigma_L = \sqrt{L} \times \sigma_D$;

Where σ_D is the standard deviation of demand per period (forecast error); σ_D can also be calculated as $\sigma_D = 1.25 \times MAD$ $\sigma_D = 1.25 \times MAD.$

Normal Distribution has a probability density function

$$f(x,\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[\frac{(x-\mu)^2}{2\sigma^2}\right]$$ $$\frac{1}{\sigma\sqrt{2\pi}} \exp\left[\frac{(x-\mu)^2}{2\sigma^2}\right].$$

And the cumulative distribution function $F(x,\mu,\sigma)$



$$= \int_{x=-\infty}^{x} f(X,\mu,\sigma)\,dX$$ $$\int_{X=-\infty}^{x} f(X,\mu,\sigma)\,dX.$$

Following the above, CSL can be computed as follows:

$$CSL = F\ (ROP,\ DL,\ \sigma L). \qquad (2)$$

Following (1) and (2), we can calculate the ss needed from a starting CSL as follows:

$$\text{Prob (demand during lead time} \leq D_L + ss) = CSL$$

$$\rightarrow CSL = F\ (D_L + ss,\ D_L,\ \sigma_L)$$

$$\rightarrow D_L + ss = F^{-1}(CSL, DL, \sigma_L)$$

$$\rightarrow ss = F^{-1}(CSL, D_L, \sigma_L) - D_L$$

A normal distribution with a mean $\mu = 0$ and $\sigma = 1$ is referred to as standard normal distribution. The standard normal density function is denoted by $f_S(x)$ and the cumulative standard normal distribution function is denoted by $F_S(x)$. Thus:

$$f_S(x) = f(x, 0, 1) \text{ and } F_S(x) = F(x, 0, 1)$$

Given a probability p, the inverse normal $F^{-1}(p, \mu, \sigma)$ is the value x such that p is the probability that the normal variable takes on a value x or less. Thus if $F(x, \mu, \sigma) = p$ then $x = F^{-1}(p, \mu, \sigma)$. For the standard normal: $F^{-1}{}_S(p) = F^{-1}(p, 0, 1)$.

$$\rightarrow ss = F^{-1}{}_S(CSL) \times \sigma_L$$

TOP CONTRIBUTORS DEMAND AT METHODE

This section is composed as follows: first, the correct demands during lead time distributions are generated and their performance compared to the normal distribution assumption; next, the optimal CSL levels along with the rest of inventory parameters are determined for every part. Finally, these parameters are simulated to test their appropriateness under stochastic data.

Each part's demand was fitted into the appropriate distribution. The appropriateness of fit was determined using Chi-square and K-S tests, which gives a 95% confidence of the success of the fit. However, for some parts (e.g. Part 1.453060), the tests could not be validated. In this case, the distribution with the closest fit (i.e. smallest squared error) was used.

PART SWXX - 750129 – 31

This part's demand is depicted in the Figure below. The best fitted distribution is a triangular one with the following parameters: TRIA (a = min = 96; c = mode = 2710; b = max = 3900). The corresponding p-values of the Chi-Square and Kolmogorov-Smirnov tests are respectively 0.279 and 0.15 (greater than 0.05), indicating that the triangular distribution was successful in representing the real demand distribution.

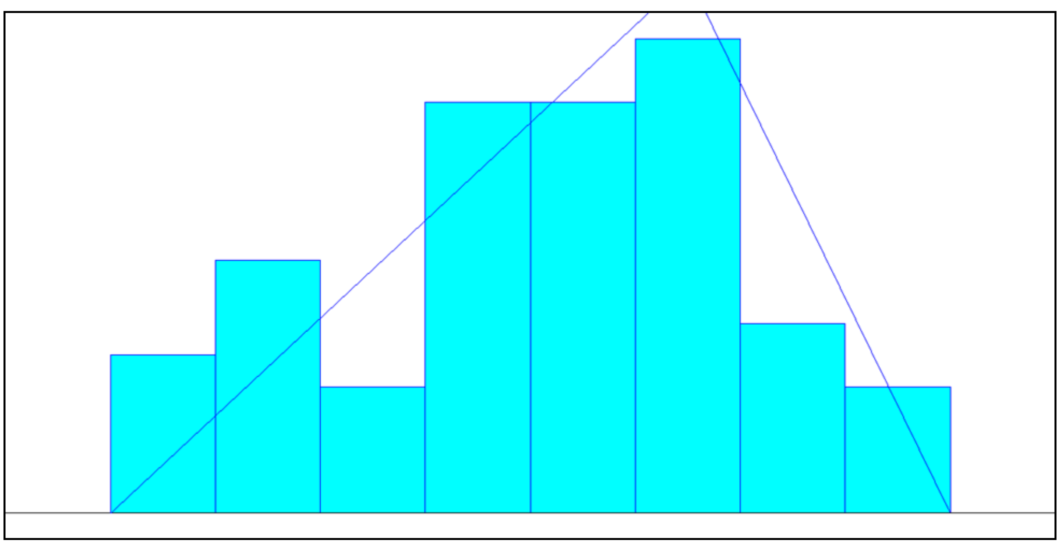


Figure 43. Demand for SWxx - 750129 – 31.

As previously explained, ROP is equal to the inverse of the demand distribution with a p = CSL. Having said this, in the case of the triangular distribution, Equation (3) is used for calculation of ROP.

$$ROP = D_L + ss = \begin{cases} a + \sqrt{CSL(b-a)(c-a)}, & a \leq ROP \leq c \\ b - \sqrt{(1-CSL)(b-a)(b-c)}, & a \leq ROP \leq c \end{cases} \quad (3)$$

Note that the average of the triangular distribution is as follows:

$$\mu = \frac{a+b+c}{3} \quad (4)$$

The inventory parameters associated with the fitted triangular distribution are shown in the Table below.

Normal Distribution Assumption

Using the traditional approach in inventory management, the assumption of normality would have been implemented. The average and standard deviation of this part demand are $\bar{x} = 2050$ $\bar{x} = 2050$ and $s = 934$ $s = 934$ respectively; i.e. the distribution NORM (2050, 934) is used for the generation of inventory parameters. We recall here that ROP= D_L + ss = F^{-1}(CSL, DL, σ_L).

Inventory Parameters & Comparison between Fitted and Normal Distribution

In this section, I will generate the corresponding inventory parameters of each distribution, using the same CSL and Lead time for both distributions. In particular, a CSL = 80% will be used (a lower CSL would reduce inventory but might increase stock-outs), and a lead time L = 8 weeks to allow for supplier planning. Table 2550 highlights the difference between the actual fitted distribution (TRIA) and the normality assumption. As can be seen, using the normal distribution led to stock-outs; however, using the actual fitted distribution with the same CSL caused no stock-outs. Table 41 explains in detail the difference between the distributions.

Table 41

Comparison between Triangular & Normal for SWxx - 750129 – 31

	Triangular Distribution *Using (8)&(9)*	**Normal Distribution**
Demand during Lead	$a = L * 96 = 8 * 26 = 7$ $c = 8 * 2710 = 21680$ $b = 8 * 3900 = 31200$ $\mu = 2235.33$ $D_L = 8 * \mu \approx 17883$	$D_L = 8 * \mu \approx 16400$ $\sigma_L = \sqrt{L} * \sigma_D = 2641.75$
Inventory Parameters	CSL = 80% ss = 5706 ROP = 23588	CSL = 80% ss = 2223 ROP = 18623
Stock-outs	0	2328

Table 42

Detailed difference for CSL = 0.8 between Triangular and normal distributions for SWxx - 750129 – 31

Weeks	Orders	Inventory		
		Triangular Distribution		
0		23588		
2/9/2010	800	22788	23588	Triggered
2/16/2010	1952	20836		
2/23/2010	1824	19012		
3/2/2010	2016	16996		
3/9/2010	1920	15076		
3/12/2010	2592	12484		
3/19/2010	640	11844		
3/25/2010	1600	10244		
3/29/2010	1216	32616	23588	Due
4/1/2010	1760	30856		
4/9/2010	1792	29064		
4/16/2010	2848	26216		
4/23/2010	2688	23528	23588	Triggered
4/30/2010	1664	21864		
5/7/2010	1824	20040		
5/14/2010	2432	17608		
5/21/2010	1600	16008		
5/27/2010	2080	13928		
6/4/2010	2720	11208		
6/11/2010	512	10696		
6/18/2010	992	33292	23588	Due
6/25/2010	800	32492		
7/2/2010	352	32140		
7/9/2010	752	31388		
7/16/2010	752	30636		
7/23/2010	384	30252		
7/30/2010	96	30156		
8/6/2010	2656	27500		
8/13/2010	928	26572		
8/20/2010	2016	24556		
8/27/2010	3712	20844	23588	Triggered
9/3/2010	2432	18412		
9/10/2010	1696	16716		
9/17/2010	3136	13580		
9/24/2010	3040	10540		
10/1/2010	1632	8908		
10/8/2010	2304	6604		
10/15/2010	2528	4076		
10/22/2010	2720	24944	23588	Due
10/29/2010	1248	23696		
11/5/2010	3328	20368	23588	Triggered
11/12/2010	3904	16464		
11/19/2010	3872	12592		
11/26/2010	896	11696		
12/3/2010	2048	9648		
12/10/2010	1280	8368		
12/17/2010	2880	5488		
12/24/2010	2016	3472		
12/31/2010	2944	24116	23588	Due
1/3/2011	2592	21524	23588	Triggered
1/7/2011	3648	17876		
1/14/2011	3136	14740		
1/21/2011	3392	11348		
1/28/2011	1696	9652		
2/4/2011	2048	7604		
2/11/2011	1408	6196		
2/18/2011	224	5972		
2/25/2011	1856	27704	23588	Due
3/4/2011	2848	24856		
3/11/2011	2592	22264	23588	Triggered
3/18/2011	2496	19768		
3/25/2011	2496	17272		
4/1/2011	2624	14648		
4/8/2011	2400	12248		
4/15/2011	2464	9784		
4/21/2011	2240	7544		
4/29/2011	2080	5464		
5/6/2011	3328	25724	23588	Due

Weeks	Orders	Inventory				
		Normal Distribution				
0		18623				
2/9/2010	800	17823	18623	Triggered		
2/16/2010	1952	15871				
2/23/2010	1824	14047				
3/2/2010	2016	12031				
3/9/2010	1920	10111				
3/12/2010	2592	7519				
3/19/2010	640	6879				
3/25/2010	1600	5279				
3/29/2010	1216	22686	18623	Due		
4/1/2010	1760	20926				
4/9/2010	1792	19134				
4/16/2010	2848	16286	18623	Triggered		
4/23/2010	2688	13598				
4/30/2010	1664	11934				
5/7/2010	1824	10110				
5/14/2010	2432	7678				
5/21/2010	1600	6078				
5/27/2010	2080	3998				
6/4/2010	2720	1278				
6/11/2010	512	19389	18623	Due		
6/18/2010	992	18397	18623	Triggered		
6/25/2010	800	17597				
7/2/2010	352	17245				
7/9/2010	752	16493				
7/16/2010	752	15741				
7/23/2010	384	15357				
7/30/2010	96	15261				
8/6/2010	2656	12605				
8/13/2010	928	30300	18623	Due		
8/20/2010	2016	28284				
8/27/2010	3712	24572				
9/3/2010	2432	22140				
9/10/2010	1696	20444				
9/17/2010	3136	17308	18623	Triggered		
9/24/2010	3040	14268				
10/1/2010	1632	12636				
10/8/2010	2304	10332				
10/15/2010	2528	7804				
10/22/2010	2720	5084				
10/29/2010	1248	3836				
11/5/2010	3328	508				
11/12/2010	3904	15227	18623	Due	18623	Triggered
11/19/2010	3872	11355				
11/26/2010	896	10459				
12/3/2010	2048	8411				
12/10/2010	1280	7131				
12/17/2010	2880	4251				
12/24/2010	2016	2235				
12/31/2010	2944	-709				
1/3/2011	2592	15322	18623	Due	18623	Triggered
1/7/2011	3648	11674				
1/14/2011	3136	8538				
1/21/2011	3392	5146				
1/28/2011	1696	3450				
2/4/2011	2048	1402				
2/11/2011	1408	-6				
2/18/2011	224	-230				
2/25/2011	1856	16537	18623	Due	18623	Triggered
3/4/2011	2848	13689				
3/11/2011	2592	11097				
3/18/2011	2496	8601				
3/25/2011	2496	6105				
4/1/2011	2624	3481				
4/8/2011	2400	1081				
4/15/2011	2464	-1383				
4/21/2011	2240	15000	18623	Due		
4/29/2011	2080	12920				
5/6/2011	3328	9592				

CSL O*PTIMAL* L*EVELS*

As mentioned earlier, the CSL level impacts the trade-off between inventory and stock-outs (assuming the appropriate distribution has been identified). The CSL of 80% used above is acceptable in the literature; however, a better approach would be to find the optimal CSL that will fulfill our target goal (*In this case: minimize inventories while maintaining zero stock-outs*). For this part, the assumption is that we are not allowed to have any stock-outs. Then the following Mathematical Model can be used:

$$\begin{aligned} &Min\ Inventory \\ &Stock - outs = 0; \\ &0.4 \leq CSL \leq 1; \end{aligned}$$

Following this, CSL was generated to be equal to 0.512 and leading to zero stock-outs (same as before) but a reduction in inventory by 34%. In this case ROP = 18821 &ss = 939 Details in Table 43.The optimal ROP is still higher than when using the normal approximation; i.e. the latter was misleading.

Table 43

Results with optimized CSL=0.512 (Using Fitted Triangular)

Weeks	Orders	Inventory				
0		18821				
2/9/2010	800	18021	18821	Triggered		
2/16/2010	1952	16069				
2/23/2010	1824	14245				
3/2/2010	2016	12229				
3/9/2010	1920	10309				
3/12/2010	2592	7717				
3/19/2010	640	7077				
3/25/2010	1600	5477				
3/29/2010	1216	23082	18821	Due		
4/1/2010	1760	21322				
4/9/2010	1792	19530				
4/16/2010	2848	16682	18821	Triggered		
4/23/2010	2688	13994				
4/30/2010	1664	12330				
5/7/2010	1824	10506				
5/14/2010	2432	8074				
5/21/2010	1600	6474				
5/27/2010	2080	4394				
6/4/2010	2720	1674				
6/11/2010	512	19983	18821	Due		
6/18/2010	992	18991				
6/25/2010	800	18191	18821	Triggered		
7/2/2010	352	17839				
7/9/2010	752	17087				
7/16/2010	752	16335				
7/23/2010	384	15951				
7/30/2010	96	15855				
8/6/2010	2656	13199				
8/13/2010	928	12271				
8/20/2010	2016	29076	18821	Due		
8/27/2010	3712	25364				
9/3/2010	2432	22932				
9/10/2010	1696	21236				
9/17/2010	3136	18100	18821	Triggered		
9/24/2010	3040	15060				
10/1/2010	1632	13428				
10/8/2010	2304	11124				
10/15/2010	2528	8596				
10/22/2010	2720	5876				
10/29/2010	1248	4628				
11/5/2010	3328	1300				
11/12/2010	3904	16217	18821	Due	18821	Triggered
11/19/2010	3872	12345				
11/26/2010	896	11449				
12/3/2010	2048	9401				
12/10/2010	1280	8121				
12/17/2010	2880	5241				
12/24/2010	2016	3225				
12/31/2010	2944	281				
1/3/2011	2592	16510	18821	Due	18821	Triggered
1/7/2011	3648	12862				
1/14/2011	3136	9726				
1/21/2011	3392	6334				
1/28/2011	1696	4638				
2/4/2011	2048	2590				
2/11/2011	1408	1182				
2/18/2011	224	958				
2/25/2011	1856	17923	18821	Due	18821	Triggered
3/4/2011	2848	15075				
3/11/2011	2592	12483				
3/18/2011	2496	9987				
3/25/2011	2496	7491				
4/1/2011	2624	4867				
4/8/2011	2400	2467				
4/15/2011	2464	3				
4/21/2011	2240	16584	18821	Due		
4/29/2011	2080	14504				
5/6/2011	3328	11176				

PART 1.327800

FITTING THE CORRECT DISTRIBUTION & INVENTORY PARAMETERS

The same as before applies here, with some extra notes as follows. This part's demand is portrayed below in Figure 44. As can be seen, there are two values that can be assumed to be outliers. Following this, the values of 32,920 and 35,880 were removed and the remaining data fitted.

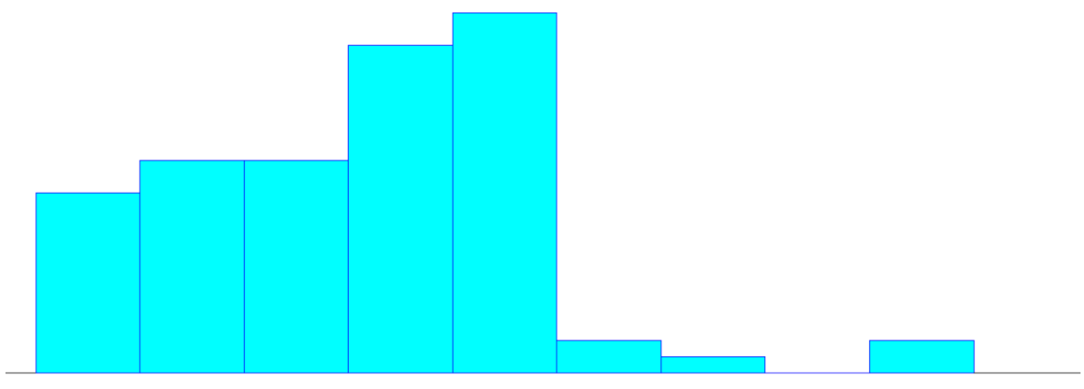


Figure 44. Original Demand of Part 1.327800.

FITTED STATISTICAL DISTRIBUTION VERSUS NORMAL DISTRIBUTION

This part's updated demand is depicted in Figure 45. The best fitted distribution is a triangular one with the following parameters: TRIA (a = min = 960; c = mode = 15700; b = max = 25000).

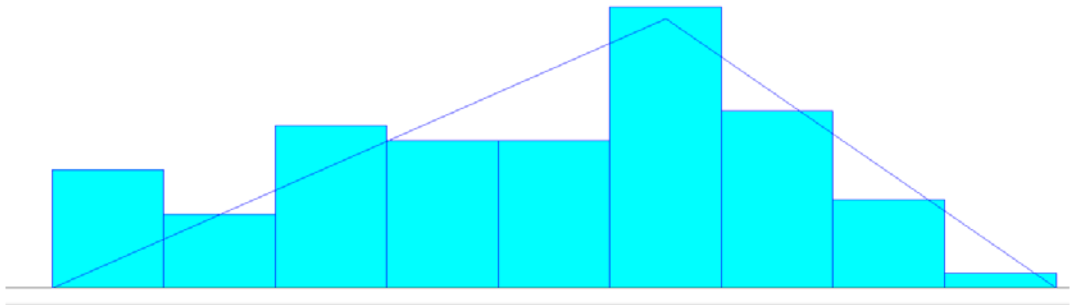


Figure 45. Updated Demand of Part 1.327800.

On the other hand, if we assume normality, we get the following distribution: NORM (12370, 5572).

Following this, Table 44 describes the difference between the fitted triangular and normal distributions, and Table 45 gives a detailed description of these differences.

Table 44

Comparison between Triangular & Normal for Part 1.327800

	Triangular Distribution *Using (8)&(9)*	**Normal Distribution**
Demand during Lead	$\mu = 13886.67$ $D_L = 8 * \mu \approx 111093$	$D_L = 8 * \mu \approx 98960$ $\sigma_L = \sqrt{L} * \sigma_D = 15760$
Inventory Parameters	CSL = 80% ss = 35412 ROP = 146505	CSL = 80% ss = 13264 ROP = 112224
Stock-outs	0	160744

Same observation as the previous part; normal distribution led to stock-outs, while the correct distribution (Triangular) had none.

CSL Optimal Levels

The optimal CSL when using the fitted triangular distribution was determined to be 0.787 with ROP = 144,894 and ss = 33,800, leading to the same output of zero stock-outs but with an extra advantage of 4.26% reduction in inventory. Details in Table 45.

Table 45

<u>Detailed difference for CSL = 0.8 between Triangular and normal distributions for Part 1.327800</u>

		Triangular Distribution				
Weeks	Orders	Inventory				
0		146505				
8/4/2009	2000	144505	146505	Triggered		
8/18/2009	2000	142505				
9/1/2009	8000	134505				
9/15/2009	2040	132465				
10/6/2009	20160	112305				
10/13/2009	10080	102225				
10/20/2009	15960	86265				
10/27/2009	10080	76185				
11/3/2009	18000	204690	146505	Due		
11/10/2009	13440	191250				
11/17/2009	7200	184050				
11/24/2009	2040	182010				
12/8/2009	20880	161130				
1/5/2010	25000	136130	146505	Triggered		
1/12/2010	16000	120130				
1/19/2010	20600	99530				
1/26/2010	16120	83410				
2/2/2010	20000	63410				
2/9/2010	20000	43410				
2/16/2010	20000	23410				
3/2/2010	18000	5410				
3/9/2010	18000	133915	146505	Due	146505	Triggered
3/16/2010	8040	125875				
3/23/2010	10080	115795				
3/30/2010	12000	103795				
4/6/2010	15960	87835				
4/13/2010	10080	77755				
4/20/2010	12000	65755				
4/27/2010	15960	49795				
5/4/2010	12960	183340	146505	Due		
5/11/2010	4400	178940				
5/18/2010	14000	164940				
5/25/2010	11200	153740				
6/1/2010	13240	140500	146505	Triggered		
6/8/2010	3340	137160				
6/15/2010	8140	129020				
6/22/2010	8260	120760				
6/29/2010	12000	108760				
7/6/2010	4060	104700				
7/13/2010	9000	95700				
7/20/2010	14000	81700				
7/27/2010	6840	221365	146505	Due		
8/3/2010	8040	213325				
8/10/2010	15240	198085				
8/17/2010	15240	182845				
8/24/2010	8040	174805				
8/31/2010	16040	158765				
9/7/2010	5080	153685				
9/14/2010	8320	145365	146505	Triggered		
9/21/2010	9880	135485				
9/28/2010	8040	127445				
10/5/2010	9280	118165				
10/12/2010	3880	114285				
10/19/2010	8040	106245				
10/26/2010	16520	89725				
11/2/2010	15000	74725				
11/9/2010	960	220270	146505	Due		
11/16/2010	17040	203230				
11/23/2010	17040	186190				
11/30/2010	17040	169150				
12/7/2010	17040	152110				
12/14/2010	17040	135070	146505	Triggered		
12/21/2010	16520	118550				
12/28/2010	14760	103790				
1/4/2011	10080	93710				
1/11/2011	11160	82550				
1/18/2011	5760	76790				
1/25/2011	16520	60270				
2/1/2011	16480	43790				
2/8/2011	16520	173775	146505	Due		
2/15/2011	1080	172695				
3/1/2011	16520	156175				
3/8/2011	17400	138775	146505	Triggered		
3/15/2011	17400	121375				
3/22/2011	3240	118135				
3/29/2011	17520	100615				
4/5/2011	14400	86215				
4/12/2011	14400	71815				
4/19/2011	13560	58255				
4/26/2011	16080	42175				
5/3/2011	13680	175000	146505	Due		
5/10/2011	17280	157720				

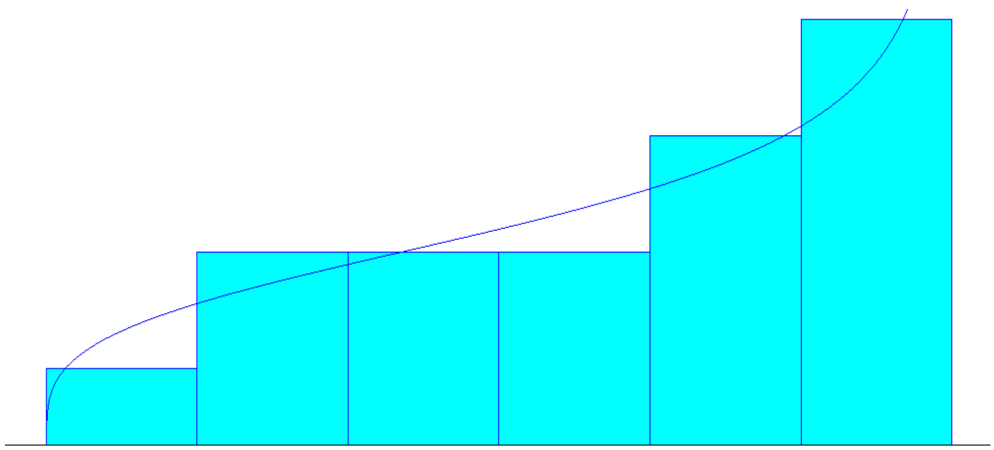
		Normal Distribution				
Weeks	Orders	Inventory				
0		112224				
8/4/2009	2000	110224	112224	Triggered		
8/18/2009	2000	108224				
9/1/2009	8000	100224				
9/15/2009	2040	98184				
10/6/2009	20160	78024				
10/13/2009	10080	67944				
10/20/2009	15960	51984				
10/27/2009	10080	41904				
11/3/2009	18000	136128	112224	Due		
11/10/2009	13440	122688				
11/17/2009	7200	115488				
11/24/2009	2040	113448				
12/8/2009	20880	92568	112224	Triggered		
1/5/2010	25000	67568				
1/12/2010	16000	51568				
1/19/2010	20600	30968				
1/26/2010	16120	14848				
2/2/2010	20000	-5152				
2/9/2010	20000	-25152				
2/16/2010	20000	-45152				
3/2/2010	18000	49072	112224	Due	112224	Triggered
3/9/2010	18000	31072				
3/16/2010	8040	23032				
3/23/2010	10080	12952				
3/30/2010	12000	952				
4/6/2010	15960	-15008				
4/13/2010	10080	-25088				
4/20/2010	12000	-37088				
4/27/2010	15960	59176	112224	Due	112224	Triggered
5/4/2010	12960	46216				
5/11/2010	4400	41816				
5/18/2010	14000	27816				
5/25/2010	11200	16616				
6/1/2010	13240	3376				
6/8/2010	3340	36				
6/15/2010	8140	-8104				
6/22/2010	8260	95860	112224	Due	112224	Triggered
6/29/2010	12000	83860				
7/6/2010	4060	79800				
7/13/2010	9000	70800				
7/20/2010	14000	56800				
7/27/2010	6840	49960				
8/3/2010	8040	41920				
8/10/2010	15240	26680				
8/17/2010	15240	123664	112224	Due		
8/24/2010	8040	115624				
8/31/2010	16040	99584	112224	Triggered		
9/7/2010	5080	94504				
9/14/2010	8320	86184				
9/21/2010	9880	76304				
9/28/2010	8040	68264				
10/5/2010	9280	58984				
10/12/2010	3880	55104				
10/19/2010	8040	47064				
10/26/2010	16520	142768	112224	Due		
11/2/2010	15000	127768				
11/9/2010	960	126808				
11/16/2010	17040	109768	112224	Triggered		
11/23/2010	17040	92728				
11/30/2010	17040	75688				
12/7/2010	17040	58648				
12/14/2010	17040	41608				
12/21/2010	16520	25088				
12/28/2010	14760	10328				
1/4/2011	10080	248				
1/11/2011	11160	101312	112224	Due	112224	Triggered
1/18/2011	5760	95552				
1/25/2011	16520	79032				
2/1/2011	16480	62552				
2/8/2011	16520	46032				
2/15/2011	1080	44952				
3/1/2011	16520	28432				
3/8/2011	17400	11032				
3/15/2011	17400	105856	112224	Due	112224	Triggered
3/22/2011	3240	102616				
3/29/2011	17520	85096				
4/5/2011	14400	70696				
4/12/2011	14400	56296				
4/19/2011	13560	42736				
4/26/2011	16080	26656				
5/3/2011	13680	12976				
5/10/2011	17280	107920	112224	Due		

PART EP2602500 - SW B-Class

Fitting the Correct Distribution & Inventory Parameters

For this part there was one outlier value of 96 which was removed. The updated demand was fitted into a Beta distribution (Fig. 46) with the following Expression: $\zeta + L' * BETA(\alpha = 1.28, \beta = 0.774)$.

$$576 \oplus 3170 \otimes BETA(\alpha = 1.28, \beta = 0.774)$$



<u>Figure 46.</u> Demand for EP2602500 - SW B-Class.

On the other hand, if we assume a normal distribution, the following applies: NORM (2549, 879).

In the case of the beta distribution, the following Excel equation can be used for calculation of

$$ROP = D_L + SS = 8 \otimes [576 \oplus 3170 \otimes B \mid ETA.INV(CSL, 1.28, 0.774)]$$

$$ROP = D_L + ss = 8 * [576 + 3170 * BETA.INV(CSL, 1.28, 0.774)] \quad (5)$$

Note that the mean of the expression (i.e. average demand) is calculated using (5): $\mu = 576 + 3170 \otimes \frac{\alpha}{\alpha + \beta}$ (6)

$\rightarrow \mu = 2552$

Table 46

Results for Part 1.327800with optimized CSL = 0.787

Weeks	Orders	Inventory				
0		144894				
8/4/2009	2000	142894	144894	Triggered		
8/18/2009	2000	140894				
9/1/2009	8000	132894				
9/15/2009	2040	130854				
10/6/2009	20160	110694				
10/13/2009	10080	100614				
10/20/2009	15960	84654				
10/27/2009	10080	74574				
11/3/2009	18000	201468	144894	Due		
11/10/2009	13440	188028				
11/17/2009	7200	180828				
11/24/2009	2040	178788				
12/8/2009	20880	157908				
1/5/2010	25000	132908	144894	Triggered		
1/12/2010	16000	116908				
1/19/2010	20600	96308				
1/26/2010	16120	80188				
2/2/2010	20000	60188				
2/9/2010	20000	40188				
2/16/2010	20000	20188				
3/2/2010	18000	2188				
3/9/2010	18000	129082	144894	Due	144894	Triggered
3/16/2010	8040	121042				
3/23/2010	10080	110962				
3/30/2010	12000	98962				
4/6/2010	15960	83002				
4/13/2010	10080	72922				
4/20/2010	12000	60922				
4/27/2010	15960	44962				
5/4/2010	12960	176896	144894	Due		
5/11/2010	4400	172496				
5/18/2010	14000	158496				
5/25/2010	11200	147296				
6/1/2010	13240	134056	144894	Triggered		
6/8/2010	3340	130716				
6/15/2010	8140	122576				
6/22/2010	8260	114316				
6/29/2010	12000	102316				
7/6/2010	4060	98256				
7/13/2010	9000	89256				
7/20/2010	14000	75256				
7/27/2010	6840	213310	144894	Due		
8/3/2010	8040	205270				
8/10/2010	15240	190030				
8/17/2010	15240	174790				
8/24/2010	8040	166750				
8/31/2010	16040	150710				
9/7/2010	5080	145630				
9/14/2010	8320	137310	144894	Triggered		
9/21/2010	9880	127430				
9/28/2010	8040	119390				
10/5/2010	9280	110110				
10/12/2010	3880	106230				
10/19/2010	8040	98190				
10/26/2010	16520	81670				
11/2/2010	15000	66670				
11/9/2010	960	210604	144894	Due		
11/16/2010	17040	193564				
11/23/2010	17040	176524				
11/30/2010	17040	159484				
12/7/2010	17040	142444	144894	Triggered		
12/14/2010	17040	125404				
12/21/2010	16520	108884				
12/28/2010	14760	94124				
1/4/2011	10080	84044				
1/11/2011	11160	72884				
1/18/2011	5760	67124				
1/25/2011	16520	50604				
2/1/2011	16480	179018	144894	Due		
2/8/2011	16520	162498				
2/15/2011	1080	161418				
3/1/2011	16520	144898				
3/8/2011	17400	127498	144894	Triggered		
3/15/2011	17400	110098				
3/22/2011	3240	106858				
3/29/2011	17520	89338				
4/5/2011	14400	74938				
4/12/2011	14400	60538				
4/19/2011	13560	46978				
4/26/2011	16080	30898				
5/3/2011	13680	162112	144894	Due		
5/10/2011	17280	144832				

Following this, Table 47 describes the difference between the fitted beta and traditional normal distributions, and Table 48 gives a detailed description of these differences. A CSL of 67% was used to highlight that the normal underestimates the inventory needed when compared to the correct distribution.

Table 47

Comparison between Triangular & Normal for EP2602500 - SW B-Class

	Beta Distribution *Using (10)&(11)*	**Normal Distribution**
Demand during Lead	$\mu = 2552$ $D_L = 8 * \mu \approx 20416$	$D_L = 8 * \mu \approx 20392$ $\sigma_L = \sqrt{L} * \sigma_D = 2486$
Inventory Parameters	CSL = 67% ss = 4767 ROP = 25183	CSL = 67% ss = 1094 ROP = 21486
Stock-outs	0	262

CSL Optimal Levels for EP2602500 - SW B-Class

The optimal CSL was determined to be 0.518 with ROP = 21987 and ss = 1575, leading to the same output of zero stock-outs but with an extra advantage of 43.5% reduction in inventory. Details in Table 48.

Table 48

Detailed difference for CSL = 67% between Beta and normal distributions for EP2602500 - SW B-Class

		Beta Distribution					*Normal Distribution*				
Weeks	Orders	Inventory			**Weeks**	**Orders**	**Inventory**				
0		25183			0		21486				
8/19/2010	1972	23211	25183	Triggered	**8/19/2010**	1972	19514	21486	Triggered		
9/2/2010	2644	20567			**9/2/2010**	2644	16870				
9/9/2010	1440	19127			**9/9/2010**	1440	15430				
9/16/2010	2592	16535			**9/16/2010**	2592	12838				
9/23/2010	2880	13655			**9/23/2010**	2880	9958				
9/30/2010	3552	10103			**9/30/2010**	3552	6406				
10/4/2010	3744	6359			**10/4/2010**	3744	2662				
10/11/2010	2688	3671			**10/11/2010**	2688	-26				
10/21/2010	3456	25398	25183	Due	**10/21/2010**	3456	18004	21486	Due	21486	Triggered
10/28/2010	1824	23574	25183	Triggered	**10/28/2010**	1824	16180				
11/4/2010	3360	20214			**11/4/2010**	3360	12820				
11/11/2010	3360	16854			**11/11/2010**	3360	9460				
11/18/2010	3648	13206			**11/18/2010**	3648	5812				
11/25/2010	1824	11382			**11/25/2010**	1824	3988				
12/2/2010	1920	9462			**12/2/2010**	1920	2068				
12/9/2010	2304	7158			**12/9/2010**	2304	-236				
12/21/2010	576	6582			**12/21/2010**	576	20674	21486	Due	21486	Triggered
12/30/2010	2880	28885	25183	Due	**12/30/2010**	2880	17794				
1/6/2011	2880	26005			**1/6/2011**	2880	14914				
1/13/2011	3264	22741	25183	Triggered	**1/13/2011**	3264	11650				
1/20/2011	3264	19477			**1/20/2011**	3264	8386				
1/27/2011	3264	16213			**1/27/2011**	3264	5122				
2/3/2011	3072	13141			**2/3/2011**	3072	2050				
2/10/2011	1248	11893			**2/10/2011**	1248	802				
2/17/2011	1248	10645			**2/17/2011**	1248	21040	21486	Due	21486	Triggered
2/24/2011	1056	9589			**2/24/2011**	1056	19984				
3/3/2011	3264	6325			**3/3/2011**	3264	16720				
3/10/2011	1145	30363	25183	Due	**3/10/2011**	1145	15575				
3/17/2011	3648	26715			**3/17/2011**	3648	11927				
3/24/2011	1913	24802	25183	Triggered	**3/24/2011**	1913	10014				
3/31/2011	1337	23465			**3/31/2011**	1337	8677				
4/7/2011	2400	21065			**4/7/2011**	2400	6277				
4/14/2011	3072	17993			**4/14/2011**	3072	24691	21486	Due		
4/20/2011	3072	14921			**4/20/2011**	3072	21619				
4/28/2011	2880	12041			**4/28/2011**	2880	18739	21486	Triggered		
5/5/2011	3072	8969			**5/5/2011**	3072	15667				

Table 49

Results using fitted BETA with optimized CSL=51.8%for EP2602500 - SW B-Class

Weeks	Orders	Inventory				
0		21987				
8/19/2010	1972	20015	21987	Triggered		
9/2/2010	2644	17371				
9/9/2010	1440	15931				
9/16/2010	2592	13339				
9/23/2010	2880	10459				
9/30/2010	3552	6907				
10/4/2010	3744	3163				
10/11/2010	2688	475				
10/21/2010	3456	19006	21987	Due	21987	Triggered
10/28/2010	1824	17182				
11/4/2010	3360	13822				
11/11/2010	3360	10462				
11/18/2010	3648	6814				
11/25/2010	1824	4990				
12/2/2010	1920	3070				
12/9/2010	2304	766				
12/21/2010	576	22177	21987	Due		
12/30/2010	2880	19297	21987	Triggered		
1/6/2011	2880	16417				
1/13/2011	3264	13153				
1/20/2011	3264	9889				
1/27/2011	3264	6625				
2/3/2011	3072	3553				
2/10/2011	1248	2305				
2/17/2011	1248	1057				
2/24/2011	1056	21988	21987	Due		
3/3/2011	3264	18724	21987	Triggered		
3/10/2011	1145	17579				
3/17/2011	3648	13931				
3/24/2011	1913	12018				
3/31/2011	1337	10681				
4/7/2011	2400	8281				
4/14/2011	3072	5209				
4/20/2011	3072	2137				
4/28/2011	2880	21244	21987	Due		
5/5/2011	3072	18172	21987	Triggered		

PART SW-IGN

FITTING THE CORRECT DISTRIBUTION & INVENTORY PARAMETERS

For this part the best demand fit was in fact a Normal Distribution: NORM (16400, 5580).

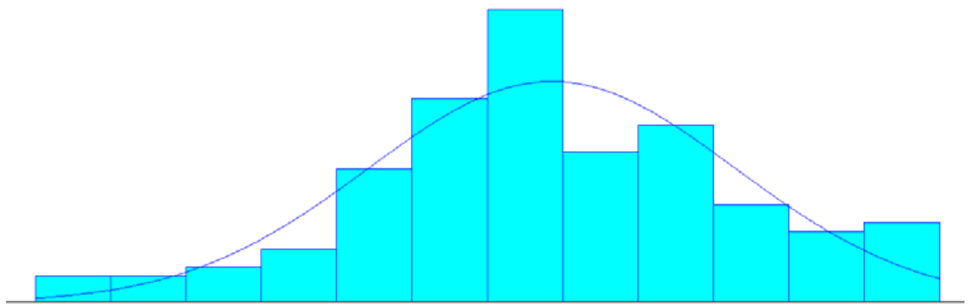


Figure 47. Demand for part SW-IGN.

Being that this is normal distribution, the CSL is more accurate so need to choose a high one. In all cases, the CSL was optimized while maintaining zero stock-outs and the value of CSL = 0.985549 was reached. This CSL was then applied to the fitted Normal and also to the normal assumption where we simply use the average and deviation of the data; i.e. in our case NORM (16352, 5603). The comparison is shown in Tables below. The results reflect that even when the data follows a normal distribution, the correct one should be fitted or else we could have stock-outs.

Table 50

Comparison between Fitted Normal & Normal (CSL=98.55%)

	Fitted Normal Distribution	Normal Distribution
Demand during Lead	$D_L = 8 * \mu \approx 131200$ $\sigma_L = \sqrt{L} * \sigma_D = 15783$	$D_L = 8 * \mu \approx 130816$ $\sigma_L = \sqrt{L} * \sigma_D = 15848$
Inventory Parameters	ss = 34482 ROP = 165682	ss = 34624 ROP = 165440
Stock-outs	0	4036

Table 51

Details for NORM (16352,5603) ~ normality assumption for part SW-IGN

		Normal Distribution NORM(16352,5603) with CSL = 0.985549				
Weeks	Orders	Inventory				
0		165440				
5/19/2008	18720	146720	165440	Triggered		
5/26/2008	20700	126020				
6/2/2008	26280	99740				
6/9/2008	19890	79850				
6/16/2008	20270	59580				
6/23/2008	17100	42480				
6/30/2008	13070	29410				
7/7/2008	11700	17710				
7/14/2008	16650	166500	165440	Due		
7/21/2008	13950	152550	165440	Triggered		
7/28/2008	2090	150460				
8/4/2008	10800	139660				
8/11/2008	12600	127060				
8/18/2008	18270	108790				
8/25/2008	18900	89890				
9/1/2008	21330	68560				
9/8/2008	19460	49100				
9/15/2008	11370	203170	165440	Due		
9/22/2008	15400	187770				
9/29/2008	21070	166700				
10/6/2008	20970	145730	165440	Triggered		
10/13/2008	22860	122870				
10/20/2008	16650	106220				
10/27/2008	16390	89830				
11/3/2008	15300	74530				
11/10/2008	16650	57880				
11/17/2008	15400	42480				
11/24/2008	15670	26810				
12/1/2008	17370	174880	165440	Due		
12/8/2008	17820	157060	165440	Triggered		
1/5/2009	15300	141760				
1/12/2009	23400	118360				
1/19/2009	18360	100000				
1/26/2009	4330	95670				
2/2/2009	13320	82350				
2/9/2009	9180	73170				
2/16/2009	13950	59220				
2/23/2009	15380	209280	165440	Due		
3/9/2009	13050	196230				
3/16/2009	13410	182820				
3/23/2009	15300	167520				
3/30/2009	6750	160770	165440	Triggered		
4/6/2009	1620	159150				
4/13/2009	5490	153660				
4/27/2009	7200	146460				
5/4/2009	9990	136470				
5/11/2009	11790	124680				
5/18/2009	7920	116760				
5/25/2009	18000	98760				
6/1/2009	13050	251150	165440	Due		
6/8/2009	20250	230900				
6/15/2009	24750	206150				
6/22/2009	16650	189500				
6/29/2009	11610	177890				
7/6/2009	11610	166280				
7/13/2009	4790	161490	165440	Triggered		
7/20/2009	28170	133320				
7/27/2009	24750	108570				
8/3/2009	17280	91290				
8/10/2009	14240	77050				
8/17/2009	7220	69830				
8/24/2009	13880	55950				
8/31/2009	13430	42520				
9/7/2009	14780	193180	165440	Due		
9/14/2009	26100	167080				
9/21/2009	26370	140710	165440	Triggered		
9/28/2009	24120	116590				
10/5/2009	20700	95890				
10/12/2009	13860	82030				
10/19/2009	26640	55390				
10/26/2009	19440	35950				
11/2/2009	18000	17950				
11/9/2009	19620	-1670				
11/16/2009	16110	147660	165440	Due	165440	Triggered
11/23/2009	18000	129660				
11/30/2009	19440	110220				
12/7/2009	15750	94470				
12/14/2009	14400	80070				
12/21/2009	630	79440				
12/28/2009	25360	54080				
1/4/2010	16040	38040				
1/11/2010	15480	188000	165440	Due		

1/18/2010	27810	160190	165440	Triggered	
1/25/2010	26640	133550			
2/1/2010	8298	125252			
2/8/2010	22500	102752			
2/15/2010	22230	80522			
2/22/2010	21600	58922			
3/1/2010	15480	43442			
3/8/2010	15480	27962			
3/15/2010	15048	178354	165440	Due	
3/22/2010	16110	162244	165440	Triggered	
3/29/2010	21150	141094			
4/5/2010	20250	120844			
4/12/2010	22950	97894			
4/19/2010	24570	73324			
4/26/2010	26010	47314			
5/3/2010	23310	24004			
5/10/2010	26370	-2366			
5/17/2010	24030	139044	165440	Due	165440
5/24/2010	19278	119766			
5/31/2010	22860	96906			
6/7/2010	22860	74046			
6/14/2010	20160	53886			
6/21/2010	21060	32826			
6/28/2010	15480	17346			
7/5/2010	15750	1596			
7/12/2010	13320	153716	165440	Due	165440
7/19/2010	13320	140396			
7/26/2010	14400	125996			
8/2/2010	16400	109596			
8/9/2010	23200	86396			
8/16/2010	19638	66758			
8/23/2010	15300	51458			
8/30/2010	15390	36068			
9/6/2010	20430	181078	165440	Due	
9/13/2010	20178	160900	165440	Triggered	
9/20/2010	24120	136780			
9/27/2010	24120	112660			
10/4/2010	17820	94840			
10/11/2010	11628	83212			
10/18/2010	19260	63952			
10/25/2010	16740	47212			
11/1/2010	16415	30797			
11/8/2010	16380	179857	165440	Due	
11/15/2010	10620	169237			
11/22/2010	10620	158617	165440	Triggered	
11/29/2010	8460	150157			
12/6/2010	10440	139717			
12/13/2010	10260	129457			
12/20/2010	10260	119197			
12/27/2010	10260	108937			
1/3/2011	14760	94177			
1/10/2011	18900	75277			
1/17/2011	12240	228477	165440	Due	
1/24/2011	15210	213267			
1/31/2011	4680	208587			
2/7/2011	9720	198867			
2/14/2011	18450	180417			
2/21/2011	18090	162327	165440	Triggered	
2/28/2011	15300	147027			
3/7/2011	14400	132627			
3/14/2011	11700	120927			
3/21/2011	13360	107567			
3/28/2011	14130	93437			
4/4/2011	14080	79357			
4/11/2011	14130	65227			
4/18/2011	9090	221577	165440	Due	
4/25/2011	14850	206727			
5/2/2011	14840	191887			
5/9/2011	13320	178567			
5/16/2011	17100	161467	165440	Triggered	

Table 52

Details for NORM (16400, 5580) ~ fitted normal for part SW-IGN

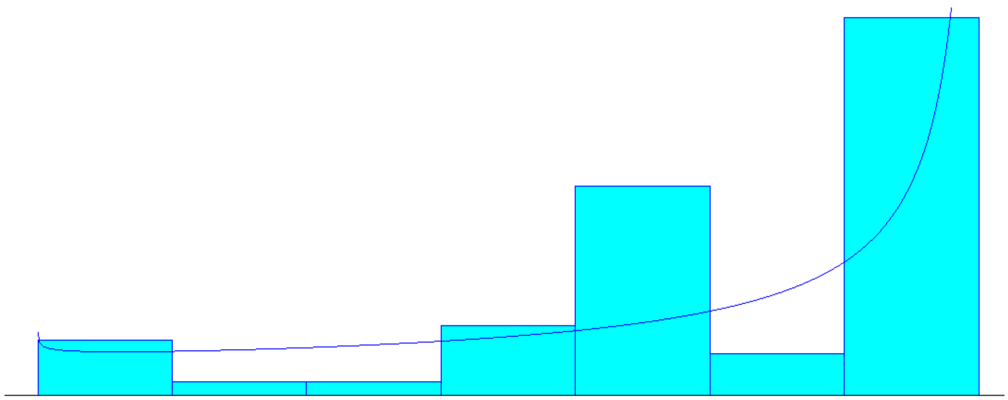
Fitted Normal Distribution NORM(16400,5580) with CSL = 0.985549

Weeks	Orders	Inventory				
0		165682				
5/19/2008	18720	146962	165682	Triggered		
5/26/2008	20700	126262				
6/2/2008	26280	99982				
6/9/2008	19890	80092				
6/16/2008	20270	59822				
6/23/2008	17100	42722				
6/30/2008	13070	29652				
7/7/2008	11700	17952				
7/14/2008	16650	166984	165682	Due		
7/21/2008	13950	153034	165682	Triggered		
7/28/2008	2090	150944				
8/4/2008	10800	140144				
8/11/2008	12600	127544				
8/18/2008	18270	109274				
8/25/2008	18900	90374				
9/1/2008	21330	69044				
9/8/2008	19460	49584				
9/15/2008	11370	203896	165682	Due		
9/22/2008	15400	188496				
9/29/2008	21070	167426				
10/6/2008	20970	146456	165682	Triggered		
10/13/2008	22860	123596				
10/20/2008	16650	106946				
10/27/2008	16390	90556				
11/3/2008	15300	75256				
11/10/2008	16650	58606				
11/17/2008	15400	43206				
11/24/2008	15670	27536				
12/1/2008	17370	175848	165682	Due		
12/8/2008	17820	158028	165682	Triggered		
1/5/2009	15300	142728				
1/12/2009	23400	119328				
1/19/2009	18360	100968				
1/26/2009	4330	96638				
2/2/2009	13320	83318				
2/9/2009	9180	74138				
2/16/2009	13950	60188				
2/23/2009	15380	210490	165682	Due		
3/9/2009	13050	197440				
3/16/2009	13410	184030				
3/23/2009	15300	168730				
3/30/2009	6750	161980	165682	Triggered		
4/6/2009	1620	160360				
4/13/2009	5490	154870				
4/27/2009	7200	147670				
5/4/2009	9990	137680				
5/11/2009	11790	125890				
5/18/2009	7920	117970				
5/25/2009	18000	99970				
6/1/2009	13050	252602	165682	Due		
6/8/2009	20250	232352				
6/15/2009	24750	207602				
6/22/2009	16650	190952				
6/29/2009	11610	179342				
7/6/2009	11610	167732				
7/13/2009	4790	162942	165682	Triggered		
7/20/2009	28170	134772				
7/27/2009	24750	110022				
8/3/2009	17280	92742				
8/10/2009	14240	78502				
8/17/2009	7220	71282				
8/24/2009	13880	57402				
8/31/2009	13430	43972				
9/7/2009	14780	194874	165682	Due		
9/14/2009	26100	168774				
9/21/2009	26370	142404	165682	Triggered		
9/28/2009	24120	118284				
10/5/2009	20700	97584				
10/12/2009	13860	83724				
10/19/2009	26640	57084				
10/26/2009	19440	37644				
11/2/2009	18000	19644				
11/9/2009	19620	24				
11/16/2009	16110	149596	165682	Due	165682	Triggered
11/23/2009	18000	131596				
11/30/2009	19440	112156				
12/7/2009	15750	96406				
12/14/2009	14400	82006				
12/21/2009	630	81376				
12/28/2009	25360	56016				
1/4/2010	16040	39976				
1/11/2010	15480	190178	165682	Due		

Weeks	Orders	Inventory				
1/18/2010	27810	162368	165682	Triggered		
1/25/2010	26640	135728				
2/1/2010	8298	127430				
2/8/2010	22500	104930				
2/15/2010	22230	82700				
2/22/2010	21600	61100				
3/1/2010	15480	45620				
3/8/2010	15480	30140				
3/15/2010	15048	180774	165682	Due		
3/22/2010	16110	164664	165682	Triggered		
3/29/2010	21150	143514				
4/5/2010	20250	123264				
4/12/2010	22950	100314				
4/19/2010	24570	75744				
4/26/2010	26010	49734				
5/3/2010	23310	26424				
5/10/2010	26370	54				
5/17/2010	24030	141706	165682	Due	165682	Triggered
5/24/2010	19278	122428				
5/31/2010	22860	99568				
6/7/2010	22860	76708				
6/14/2010	20160	56548				
6/21/2010	21060	35488				
6/28/2010	15480	20008				
7/5/2010	15750	4258				
7/12/2010	13320	156620	165682	Due	165682	Triggered
7/19/2010	13320	143300				
7/26/2010	14400	128900				
8/2/2010	16400	112500				
8/9/2010	23200	89300				
8/16/2010	19638	69662				
8/23/2010	15300	54362				
8/30/2010	15390	38972				
9/6/2010	20430	184224	165682	Due		
9/13/2010	20178	164046	165682	Triggered		
9/20/2010	24120	139926				
9/27/2010	24120	115806				
10/4/2010	17820	97986				
10/11/2010	11628	86358				
10/18/2010	19260	67098				
10/25/2010	16740	50358				
11/1/2010	16415	33943				
11/8/2010	16380	183245	165682	Due		
11/15/2010	10620	172625				
11/22/2010	10620	162005	165682	Triggered		
11/29/2010	8460	153545				
12/6/2010	10440	143105				
12/13/2010	10260	132845				
12/20/2010	10260	122585				
12/27/2010	10260	112325				
1/3/2011	14760	97565				
1/10/2011	18900	78665				
1/17/2011	12240	232107	165682	Due		
1/24/2011	15210	216897				
1/31/2011	4680	212217				
2/7/2011	9720	202497				
2/14/2011	18450	184047				
2/21/2011	18090	165957				
2/28/2011	15300	150657	165682	Triggered		
3/7/2011	14400	136257				
3/14/2011	11700	124557				
3/21/2011	13360	111197				
3/28/2011	14130	97067				
4/4/2011	14080	82987				
4/11/2011	14130	68857				
4/18/2011	9090	59767				
4/25/2011	14850	210599	165682	Due		
5/2/2011	14840	195759				
5/9/2011	13320	182439				
5/16/2011	17100	165339	165682	Triggered		

PART 1.453060

For this part the best demand fit was the following expression: $-1500 \oplus 6500 \otimes BETA(0.936, 0.321)$



<u>Figure 48.</u> Demand for part 1.453060.

Following this, Tables 53 & 54 highlights the difference between using the fitted distribution (BETA) and assuming the normal one. The optimized CSL of 46.05% was used.

Table 53

Comparison between Beta & Normal for part 1.453060

	Beta Distribution *Using (4)&(5)*	**Normal Distribution** *Using (3)*
Demand during Lead	$\mu = 6340$ $D_L = 8 * \mu \approx 50721$	$D_L = 8 * \mu \approx 50712$ $\sigma_L = \sqrt{L} * \sigma_D = 5337$
Inventory Parameters	ss = 5029 ROP = 55750	ss = 0 ROP = 50712
Stock-outs	0	74590

Table 54

Detailed difference for optimal CSL = 46.05% between fitted Beta and normal distributions for part 1.453060

	Fitted BETA Distribution with Optimal CSL = 0.460523					
Weeks	Orders	Inventory				
0		55750				
5/3/2010	7500	48250	55750	Triggered		
5/10/2010	6250	42000				
5/17/2010	7500	34500				
5/24/2010	7500	27000				
5/31/2010	7500	19500				
6/14/2010	2250	17250				
6/21/2010	5500	11750				
6/28/2010	5250	6500				
7/5/2010	1500	60750	55750	Due		
7/12/2010	1500	59250				
7/19/2010	1500	57750				
7/26/2010	5250	52500	55750	Triggered		
8/2/2010	5000	47500				
8/9/2010	5500	42000				
8/16/2010	5750	36250				
8/23/2010	8000	28250				
8/30/2010	5500	22750				
9/6/2010	8000	14750				
9/13/2010	3750	11000				
9/20/2010	6000	60750	55750	Due		
9/27/2010	8000	52750	55750	Triggered		
10/4/2010	4750	48000				
10/11/2010	8000	40000				
10/14/2010	8000	32000				
10/21/2010	8000	24000				
10/28/2010	8000	16000				
11/4/2010	8000	8000				
11/11/2010	8000	0				
11/15/2010	8000	47750	55750	Due	55750	Triggered
11/22/2010	8000	39750				
11/29/2010	8000	31750				
12/6/2010	8000	23750				
12/13/2010	4750	19000				
12/20/2010	4500	14500				
12/27/2010	5000	9500				
1/3/2011	8000	1500				
1/10/2011	8000	49250	55750	Due	55750	Triggered
1/17/2011	5750	43500				
1/24/2011	5750	37750				
1/31/2011	8000	29750				
2/7/2011	5750	24000				
2/14/2011	5500	18500				
2/21/2011	5750	12750				
2/28/2011	8000	4750				
3/7/2011	8000	52500	55750	Due	55750	Triggered
3/14/2011	8000	44500				
3/21/2011	6250	38250				
3/28/2011	2750	35500				
4/4/2011	8000	27500				
4/11/2011	8000	19500				
4/18/2011	5500	14000				
4/25/2011	6000	8000				
5/2/2011	5750	58000	55750	Due		
5/9/2011	8000	50000	55750	Triggered		
5/16/2011	8000	42000				
5/23/2011	6750	35250				

		Normal Distribution				
Weeks	Orders	Inventory				
0		50712				
5/3/2010	7500	43212	50712	Triggered		
5/10/2010	6250	36962				
5/17/2010	7500	29462				
5/24/2010	7500	21962				
5/31/2010	7500	14462				
6/14/2010	2250	12212				
6/21/2010	5500	6712				
6/28/2010	5250	1462				
7/5/2010	1500	50674	50712	Due	50712	Triggered
7/12/2010	1500	49174				
7/19/2010	1500	47674				
7/26/2010	5250	42424				
8/2/2010	5000	37424				
8/9/2010	5500	31924				
8/16/2010	5750	26174				
8/23/2010	8000	18174				
8/30/2010	5500	63386	50712	Due		
9/6/2010	8000	55386				
9/13/2010	3750	51636				
9/20/2010	6000	45636	50712	Triggered		
9/27/2010	8000	37636				
10/4/2010	4750	32886				
10/11/2010	8000	24886				
10/14/2010	8000	16886				
10/21/2010	8000	8886				
10/28/2010	8000	886				
11/4/2010	8000	-7114				
11/11/2010	8000	35598	50712	Due	50712	Triggered
11/15/2010	8000	27598				
11/22/2010	8000	19598				
11/29/2010	8000	11598				
12/6/2010	8000	3598				
12/13/2010	4750	-1152				
12/20/2010	4500	-5652				
12/27/2010	5000	-10652				
1/3/2011	8000	32060	50712	Due	50712	Triggered
1/10/2011	8000	24060				
1/17/2011	5750	18310				
1/24/2011	5750	12560				
1/31/2011	8000	4560				
2/7/2011	5750	-1190				
2/14/2011	5500	-6690				
2/21/2011	5750	-12440				
2/28/2011	8000	30272	50712	Due	50712	Triggered
3/7/2011	8000	22272				
3/14/2011	8000	14272				
3/21/2011	6250	8022				
3/28/2011	2750	5272				
4/4/2011	8000	-2728				
4/11/2011	8000	-10728				
4/18/2011	5500	-16228				
4/25/2011	6000	28484	50712	Due	50712	Triggered
5/2/2011	5750	22734				
5/9/2011	8000	14734				
5/16/2011	8000	6734				
5/23/2011	6750	-16				

In this section, we showed, using real demand from Methode that the normality assumption would lead to stock-outs when the demand is non-linear. Furthermore, and as mentioned in some literature earlier in the section "FORECASTING SHORTCOMINGS", better results were obtained when the correct D_L distribution was used instead of the normal approximation.

It is also worth pointing out again to the demand of *part SW-IGN*, where we showed that even though this part's demand follows a normal distribution, the latter's correct fitted one should be used as simply assuming a normal distribution with parameters of average and deviation of data led to stock-outs.

VALIDATING PARAMETERS USING AREA SIMULATION

In this section, we simulate the inventory parameters of every part to assess the validity of the parameters obtained in section "NORMALITY ASSUMPTION AT METHODE".

Simulation of inventory parameters for all parts

The logic of the simulation model is shown in Figure 53. The latter is needed to adjust the ROP (or CSL) in order to guarantee zero stock-outs. In particular, in every simulation, 1000 orders are generated from the fitted distribution of a part, and tested on the calculated ROP of this particular part. Arena 13 from Rockwell systems was used for the simulation. As expected, stock-outs will occur on the optimal ROP as they were very small.

Having said this, the ROP will be optimized to minimize inventory while maintaining zero stock-outs. Furthermore, replications are run from each simulation in order to get results with 95% CI; i.e. the ROPs generated from the simulation for each part will guarantee with 95% confidence that no stock-outs will occur if the orders follow the fitted distribution.

The simulation results are highlighted in Table 55. They show for all parts that even the parameters generated using the fitted distribution would still lead to stock-outs. On the other hand, the parameters obtained using simulation led to almost zero stock-outs. In summary, the simulated ROPs in Table 55 represent a better option to use at Methode production as they guarantee almost zero stock-outs.

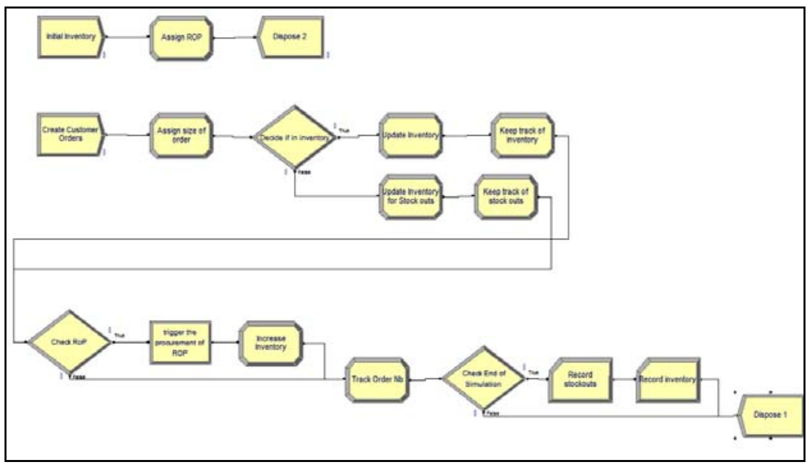


Figure 49. Simulation model for testing inventory parameters.

Table 55

Simulation Results

	Simulation of fitted distributions' paramters			Inventory Parameters obtained through Simulation		
Part Number	Excel Solver Optimal (ROP)	ss	INV	ARENA Simulated (ROP)	ss	INV
SWC-750129-31	18,821	4	41,365	21,850	~0	47,335
1.327800-ISS	144,894	-	316,290	160,650	~0	354,369
SWC-2602500	21,987	2	48,365	23,548	~0	51,036
ISS-327612-H	165,682	1	359,695	169,854	~0	370,166
ATL-1.453060	55,750	1	122,183	60,241	~0	130,272

In the section "Forecasting Shortcomings", we concluded by the recommendation in the literature that good inventory parameters are obtained when the correct D_L distribution is used. We showed in this section that while fitting the D_L into its distribution is definitely a better option than using the normal approximation, stock-outs would still occur due to the non-linearity of the demand.

CONCLUSION

We showed in this study that current traditional production systems have many shortcomings when dealing with non-linear demand. In particular, MRP uses forecasting, and the latter's failings and Pull Systems (JIT) use Kanban lot sizes that are not recalculated and it is not appropriate for erratic and intermittent demand.

In the "Forecasting Shortcomings" section, we showed that both parametric and non-parametric forecasting methods led to stock-outs when the demand was non-linear. The limitations of the non-parametric methods, and in particular, the exponential smoothing one, were described and proved by **Croston (1972)**. As for the parametric forecasting, previous works in the literature have showed the inappropriateness of the Normality assumption, and recommended that the correct D_L distribution be used when estimating the inventory parameters.

We showed in the section "Simulation at Methode" that even the parameters generated following the correct D_L led to stock-outs. In fact, they either overestimated or under estimated the demand.

Methode has thousands of part numbers which have highly erratic demand which more than likely are not good candidates for statistics as they need to fit a normal distribution curve. Furthermore, a part number may fit a normal distribution curve today and would not fit in the next planning period.

APPENDIX D: ARK CASE STUDY 2

DEMAND PROFILE

The demand profile has a high level of uncertainty and is classified as erratic. This initiates various complexities in production control strategy under study. Demand profiles for six weeks are detailed by product in Tables 56-62. On a two-hour interval, customers access the supermarket where finished goods are stored based on the weekly demand. In modeling the profiles, the weekly demand is recorded in an internal database. Following, the 'shopper' checks a table containing the number of shipped demands by product. If demand has not been satisfied the shopper will try to acquire as many products of that product-type as possible. The unsatisfied demand is treated as backlog and the following week demand becomes the week demand added to the previous week's backlog.

Table 56

Demand Profile for Week 20

Product	Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
1	542	452	404	503	247	483
2	130	224	142	118	129	114
3	130	184	131	159	125	147
4	110	138	147	71	61	39

Table 57

Demand Profile for Week 21

Product	Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
1	503	366	413	365	381	480
2	147	212	147	108	112	144
3	115	194	128	143	169	137
4	121	158	131	62	61	51

Table 58

Demand Profile for Week 22

Product	Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
1	502	405	352	403	369	612
2	149	153	212	109	122	108
3	145	169	132	103	129	111
4	111	141	149	72	81	41

Table 59

Demand Profile for Week 23

Product	Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
1	461	450	463	493	330	445
2	231	156	137	116	134	170
3	99	145	107	97	174	101
4	128	161	140	81	70	78

Table 60

Demand Profile for Week 24

Product	Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
1	481	451	400	412	492	1133
2	308	151	146	90	221	120
3	103	165	92	115	137	111
4	118	161	130	60	77	51

Table 61

Demand Profile for Week 25

Product	Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
1	481	544	461	412	461	429
2	296	225	141	107	130	200
3	103	25	111	122	119	97
4	101	20	128	68	57	48

Table 62

The Configuration of the Manufacturing System for Modeling

Stage	Product 1	Product 2	Product 3	Product 4	Maintenance: Exponential Distribution Mean		Setup Times (Hours)
	Lead Times/Box (Hours)	Lead Times/Box (Hours)	Lead Times/Box (Hours)	Lead Times/Box (Hours)	MTBF (Hours)	MTTR (Hours)	
P1	0.162	0.162	0	0	3.5	0.23	0
P2	0.126	0.126	0	0	3.5	0.23	0
P3	0.0975	0.0975	0.13	0.13	6.1	0.23	~N(0.327, 0.109)
P4	0.0975	0.0975	0.13	0.13	6.1	0.23	~N(0.327, 0.109)
P5	0.0975	0.0975	0.13	0.13	6.1	0.23	~N(0.327, 0.109)

SETTINGS OF CONTROL PARAMETERS

The performance of a pull controlled system depends greatly on the settings of the control parameters. It is therefore important to set the control parameters of KANBAN and CONWIP to their logical values. This will ensure a good understanding of their behaviors before carrying out a comparison of their performance. Ideal value for authorization cards are the minimum number of cards assigned to a system in order to achieve the maximum throughput. Addition of authorization cards above the settings will only raise the WIP level in a system without improving the throughput of the system (Olaitan, 2011). ExtendSim simulation software has inbuilt optimization block which uses Genetic Algorithm to search for solution of parameters with objective function inputted for a search. Objective functions are incorporated as an equation to maximize profit or to minimize inventory and backlog. Also objective function could be defined in the optimization block to a target service level. The optimization block was used to find the preferred setting for the set-up minimization parameters (the change overs and the authorization cards). The optimization carried out was only for week 20 demand profile. The search spaces for Push, KANBAN and CONWIP PCS are described in Tables 63 to 67.

Table 63

Change over Setting in Push Model

Product – Type	Search Range (Pallet Quantity)	Change over Value (Pallet Quantity)
Product BB-12	1 - 20	15
Product BB-13	1 - 12	4
Product II-20	1 - 10	4
Product II-21	1 - 10	2

Table 64

Kanban card Configuration

Product – Type	Search Range K1 Kanbans (Pallet Quantity)	Quantity of K1 Kanbans (PalletQuantity)	Search Range K2 Kanbans (Box Quantity)	Quantity of K2 Kanbans (Box Quantity)
Product BB-12	2 – 30	8	10 – 160	81
Product BB-13	2 – 20	3	5 – 100	62
Product II-20			5 – 100	74
Product II-21			5 – 100	47

Table 65

Change over Setting in Kanban Model

Product – Type	Search Range (Pallet Quantity)	Optimal Change over Value (Pallet Quantity)
Product BB-12	1 - 16	11
Product BB-13	1 - 8	3
Product II-20	1 - 4	3
Product II-21	1 - 4	4

Table 66

CONWIP card Configuration

Product – Type	Search Range CONWIP cards (Box Quantity)	Optimal Quantity of CONWIP cards (Box Quantity)
Product BB-12	16 – 160	121
Product BB-13	16 – 100	89
Product II-20	5 – 100	89
Product II-21	5 – 100	68

Table 67

Change over Setting in CONWIP Model

Product – Type	Search Range (Pallet Quantity)	Optimal Change over Value (Pallet Quantity)
Product BB-12	1 - 16	5
Product BB-13	1 - 8	4
Product II-20	1 - 4	4
Product II-21	1 - 4	2

EXPERIMENTAL RESULTS

This section reports the results of the experiment. The weekly WIP level versus the Backlog is examined. The Total weekly WIP and Backlog of each PCS are documented. The results of the WIP and Backlog for Push, KANBAN and CONWIP PCS are recorded in the tables below. They show the WIP level in order to achieve a minimum backlog in the system.

Table 68

Week 20 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	319	271	281	297	301	433
Kanban	Total Backlog	0	1	0	0	0	0
CONWIP	Total WIP	242	249	215	260	148	360
CONWIP	Total Backlog	0	12	3	0	0	0
Push	Total WIP	469	558	575	600	657	805
Push	Total Backlog	236	429	524	746	675	867

Table 69

Week 21 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	316	265	296	299	297	439
Kanban	Total Backlog	0	0	0	0	0	0
CONWIP	Total WIP	221	230	191	148	146	361
CONWIP	Total Backlog	0	0	0	0	0	0
Push	Total WIP	490	558	592	585	603	817
Push	Total Backlog	183	304	408	473	585	762

Table 70

Week 22 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	320	295	300	298	299	458
Kanban	Total Backlog	0	0	0	0	0	0
CONWIP	Total WIP	240	196	212	146	144	350
CONWIP	Total Backlog	0	0	1	0	0	0
Push	Total WIP	559	482	590	577	642	805
Push	Total Backlog	211	350	394	451	504	794

Table 71

Week 23 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	302	276	291	315	302	425
Kanban	Total Backlog	0	0	0	0	0	0
CONWIP	Total WIP	263	247	239	191	144	360
CONWIP	Total Backlog	1	0	0	0	0	0
Push	Total WIP	563	567	579	574	531	776
Push	Total Backlog	137	287	447	569	623	727

Table 72

Week 24 WIP and Backlog Results

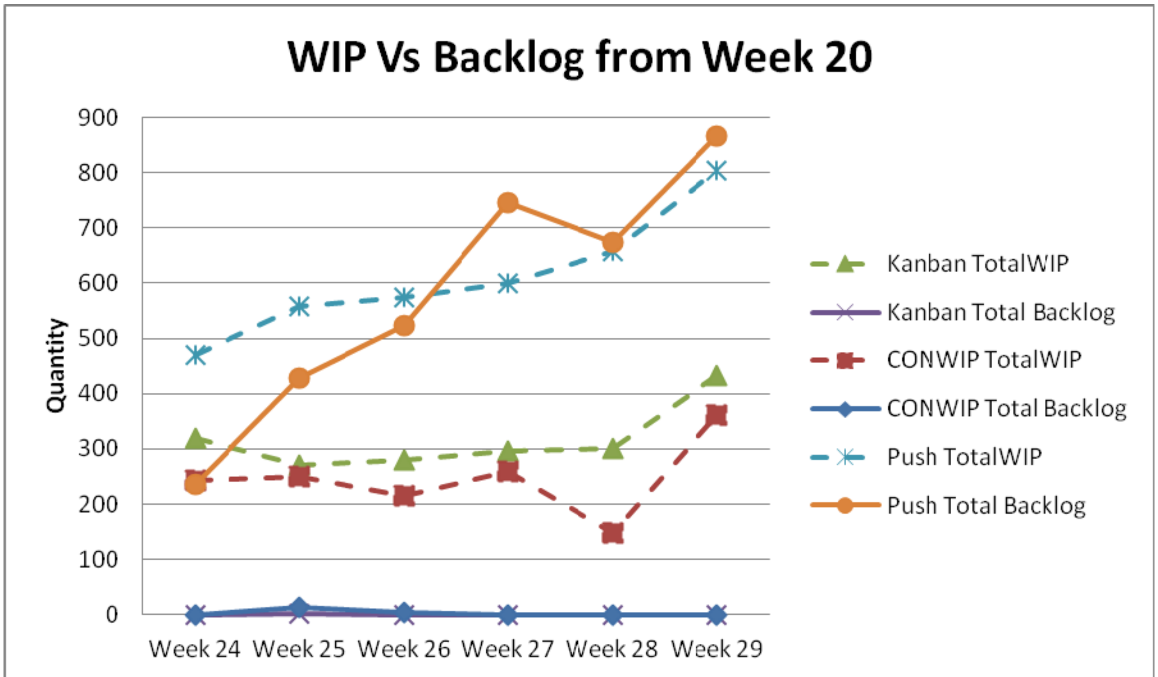
PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	274	251	252	311	312	337
Kanban	Total Backlog	139	165	52	0	2	506
CONWIP	Total WIP	264	239	241	230	291	358
CONWIP	Total Backlog	121	154	50	0	3	536
Push	Total WIP	563	554	608	480	607	813
Push	Total Backlog	153	316	376	456	647	1455

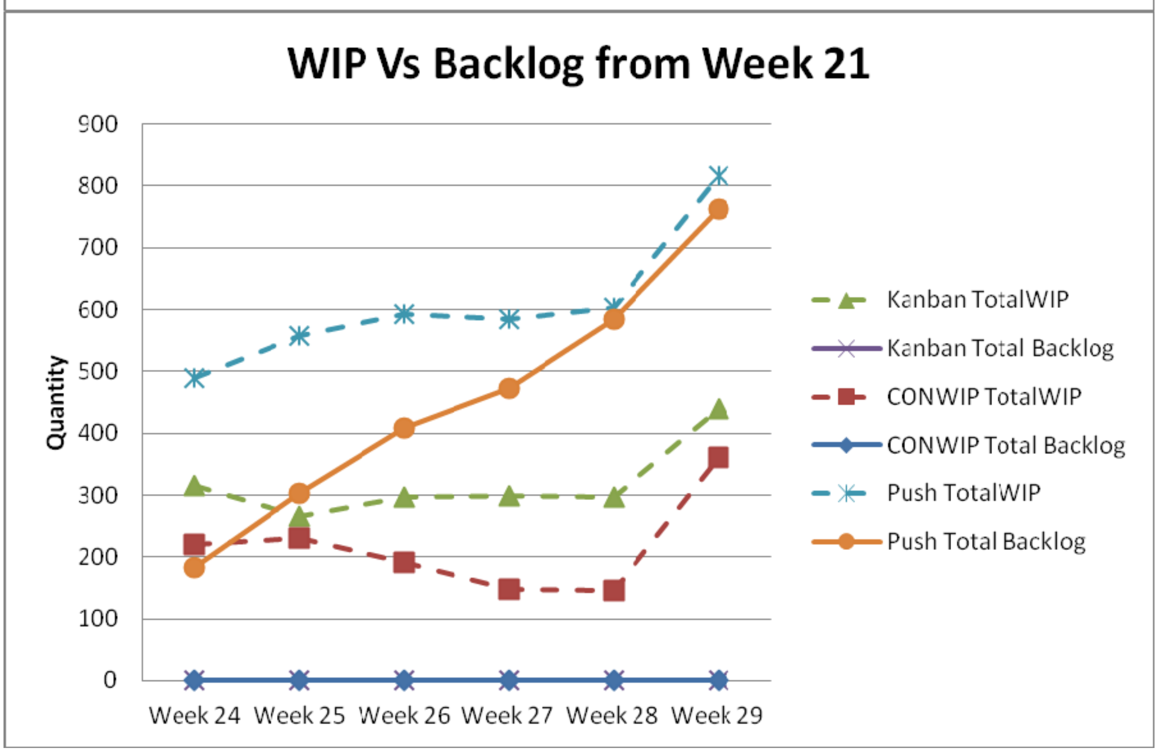
Table 73

Week 25 WIP and Backlog Results

PCS		Wk 24	Wk 25	Wk 26	Wk 27	Wk 28	Wk 29
Kanban	Total WIP	316	312	305	316	311	360
Kanban	Total Backlog	114	227	194	65	5	6
CONWIP	Total WIP	330	329	309	314	309	361
CONWIP	Total Backlog	111	223	190	65	14	2
Push	Total WIP	668	679	746	728	653	907
Push	Total Backlog	157	376	511	601	734	838

Figure 50 represents the total weekly backlog and inventory achieved by the PCS investigated. The results show that CONWIP was consistently the preferred performer of the three PCS examined, up to week 23 demand. In week 24 there is variation in the product mix unlike the previous three week demand profiles; CONWIP was seen to perform poorly in terms of WIP and backlog. There was little or no significant difference between CONWIP and KANBAN in weeks 24 and 25. Also there was a high level significant difference in performance measure between KANBAN and push PCS.


WIP Vs Backlog from Week 20
Quantity
900
800
700
600
500
400
300
200
100
0
Week 24
Week 25
Week 26
Week 27
Week 28
Week 29
Kanban TotalWIP
Kanban Total Backlog
CONWIP TotalWIP
CONWIP Total Backlog
Push TotalWIP
Push Total Backlog


WIP Vs Backlog from Week 21
Quantity
900
800
700
600
500
400
300
200
100
0
Week 24
Week 25
Week 26
Week 27
Week 28
Week 29
Kanban TotalWIP
Kanban Total Backlog
CONWIP TotalWIP
CONWIP Total Backlog
Push TotalWIP
Push Total Backlog

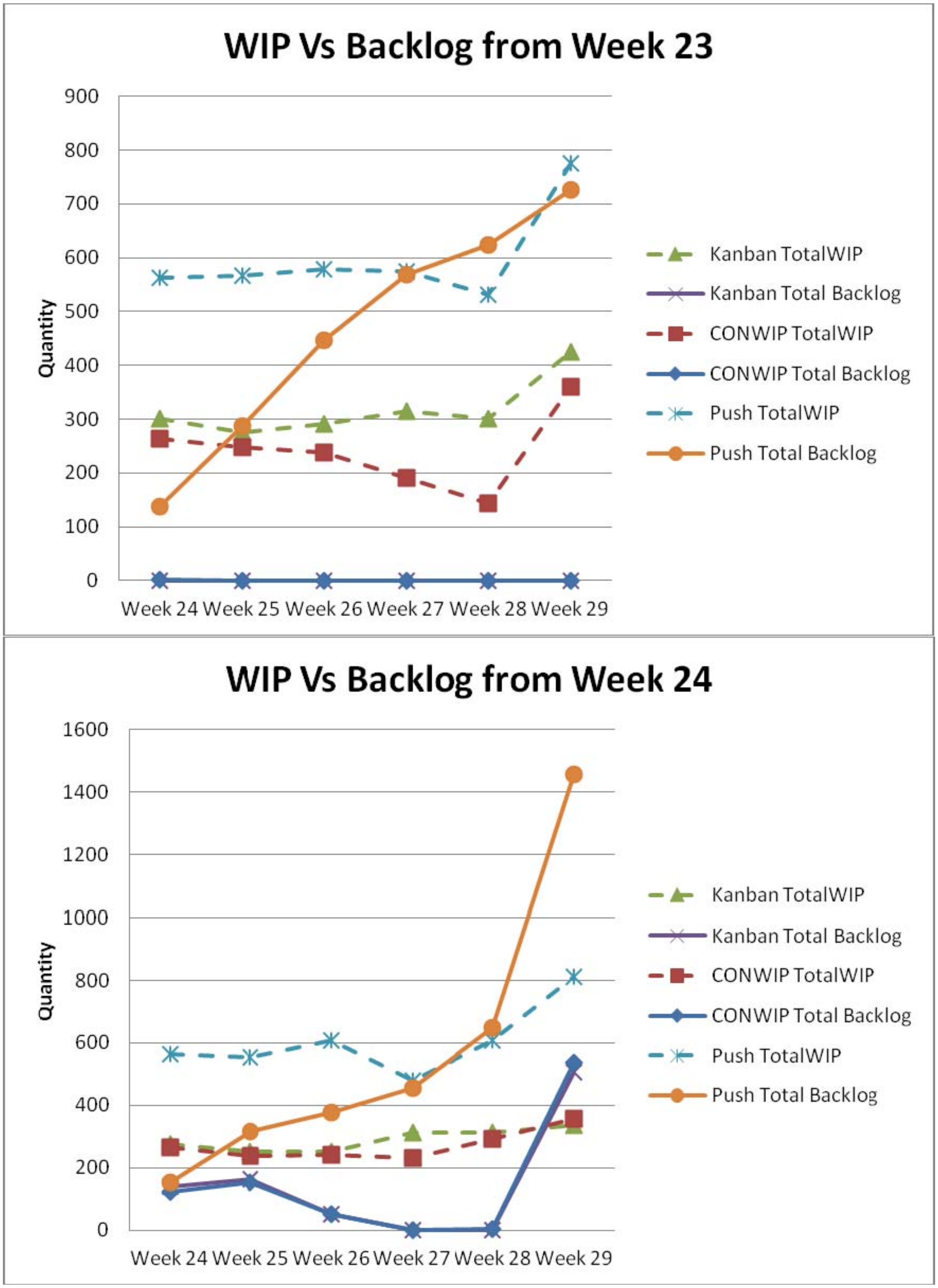


Figure 50. WIP vs. Backlog from Week 20 to Week 25.

ASSUMPTIONS AND SYSTEM STARTING POINT

A few assumptions are made so we can conduct the simulation using ARK: Different versions are added to one total demand. The demand pattern is erratic. Changes are occurring in the last minutes before the production of week 24 starts. All other replenishment system will fail by increasing WIP and increasing backlog as previously demonstrated. WIP and backlog will serve as a buffer to compensate for erratic demands. Sales orders for weeks 24 to 29 were tracked on weekly basis to identify their behaviour and how constant they remained. In order not to introduce further parameters, orders prior to week 24 and orders after week 29 were taken as a constant 82,111 (which is the average sales demand coming from the previous workings.) The simulation will Consider 'Start On Hand' as average demand of 82,111 in order to make up for Week 19 demand and start off the simulation. This is considered as a starting point for the system.

PRELIMINARY TESTS AT SELECTED STARTING WEEK

The Simulation starts with the first run/try 1; we test the Kanban Lot Size by applying the TKLS of 80,640. The simulation passed week 19 but failed in Week 20 since ending on hand resulted below zero. Since it did fail week 20, we apply the step logic and increase the TKLS by 5% from 80,640 to 84,690.

KanBan simulation							
Part Number	XXXX	On Hand (oh)CMS	82,111	Safty Weeks	-	Supplier Ship Time	1
Description:	Electro	Replen Lead Time	1 weeks	Multiple (Box size)	90		-
Item Cont Option:	Single Full	Average Demand (??)	80,615	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 1				Test KanBan Lot Size		80,640	PKLS					
Containers in the system		1										
start		82,111									82,111	
19	82,111	0				0	80,640		80,640	0	0	PASS
20	82,111	(1,471)					80,640	80,640	80,640	1,471	0	FAIL
21	82,111	(1,471)					80,640	80,640	80,640	1,471	0	FAIL
22	82,111	(1,471)					80,640	80,640	80,640	1,471	0	FAIL
23	82,111	(1,471)					80,640	80,640	80,640	1,471	0	FAIL
24	89,168	(8,528)					80,640	80,640	80,640	8,528	0	FAIL
25	99,450	(18,810)					80,640	80,640	80,640	18,810	0	FAIL
26	72,273	8,367					80,640	80,640	80,640	0	8,367	PASS
27	83,344	5,663					80,640	80,640	80,640	0	5,663	PASS
28	56,080	30,223					80,640	80,640	80,640	0	30,223	PASS
29	75,892	34,971					80,640	80,640	80,640	0	34,971	PASS
30		115,611					0	80,640	0		115,611	
31		115,611					0	0	0		115,611	
32		115,611					0	0	0		115,611	

Figure 51. Week 19 simulation.

After doing that we apply the second run (Simulation try 2) by using a test Kanban Lot Size (TKLS) of 84,690. Now we passed week 19 to week 24 but failed in week 25 since ending on hand inventory was negative. Again, the TKLS was increased by 5% from 84,690 to 89,010.

KanBan simulation							
Part Number	XXXX	On Hand (oh)CMS	82,111	Safty Weeks	-	Supplier Ship Time	1
Description:	Electro	Replen Lead Time	1 weeks	Multiple (Box size)	90		
Item Cont Option:	Single Full	Average Demand (??)	80,615	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 2				Test KanBan Lot Size		84,690	PKLS					
Containers in the system		1										
start		82,111									82,111	
19	82,111	0				0	84,690		84,690	0	0	PASS
20	82,111	2,579					84,690	84,690	84,690	0	2,579	PASS
21	82,111	5,158					84,690	84,690	84,690	0	5,158	PASS
22	82,111	7,737					84,690	84,690	84,690	0	7,737	PASS
23	82,111	10,316					84,690	84,690	84,690	0	10,316	PASS
24	89,168	5,838					84,690	84,690	84,690	0	5,838	PASS
25	99,450	(8,922)					84,690	84,690	84,690	8,922	0	FAIL
26	72,273	12,417					84,690	84,690	84,690	0	12,417	PASS
27	83,344	13,763					84,690	84,690	84,690	0	13,763	PASS
28	56,080	42,373					84,690	84,690	84,690	0	42,373	PASS
29	75,892	51,171					84,690	84,690	84,690	0	51,171	PASS
30		135,861					0	84,690	0		135,861	

Figure 52. Week 19 simulation – Run 2.

Following, a simulation run/try 3 started using Test Kanban Lot Size (TKLS) of 89,010. Week 19 to week 29 passed the simulation and none of the weeks ended with a negative inventory. The final kanban lot size for week 19 was set to 89,010.

Part Number	XXXX	On Hand *(oh)CMS*	82,111		Safty Weeks	-		Supplier Ship Time	1
Description:	Electro	Replen Lead Time	1	weeks	Multiple *(Box size)*	90			-
Item Cont Option:	Single Full	Average Demand *(??)*	80,615		Minimum			Percent Increase	5%
Current Qty Containers		Prelim Qty Containers							

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 3				Test KanBan Lot Size		89,010	PKLS					
Containers in the system		1										
start		*82,111*									82,111	
19	82,111	0				0	89,010		89,010	0	0	PASS
20	82,111	6,899					89,010	89,010	89,010	0	6,899	PASS
21	82,111	13,798					89,010	89,010	89,010	0	13,798	PASS
22	82,111	20,697					89,010	89,010	89,010	0	20,697	PASS
23	82,111	27,596					89,010	89,010	89,010	0	27,596	PASS
24	89,168	27,438					89,010	89,010	89,010	0	27,438	PASS
25	99,450	16,998					89,010	89,010	89,010	0	16,998	PASS
26	72,273	33,735					89,010	89,010	89,010	0	33,735	PASS
27	83,344	39,401					89,010	89,010	89,010	0	39,401	PASS
28	56,080	72,331					89,010	89,010	89,010	0	72,331	PASS
29	75,892	85,449					89,010	89,010	89,010	0	85,449	PASS
30		174,459					0	89,010	0		174,459	

Figure 53. Week 19 simulation – Run 3.

SIMULATING FURTHER WEEKS UNTIL CONDITIONS ARE MET

Now in week 20, and considering that 'Start On Hand' to be zero (0) since week19 demand consumed all on hand and triggered a production order for 89,010. Hence 'On Order Due' is 89,010. The process is similar to the previous; the first simulations starts with a TKLS of 81,000, simulation passed from week 20 to week 23 but failed in week 24, since ending on hand resulted below zero.

KanBan simulation

Part Number	XXXX	On Hand (oh)CMS	-	Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1 weeks	Multiple (Box size)	90		-
Item Cont Option:	Single Full	Average Demand (??)	80,917	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Simulation Try Number : 1 — Test KanBan Lot Size 81,000 PKLS

Containers in the system 1

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
start		-									-	
20	82,111	6,899				89,010	81,000		81,000	0	6,899	PASS
21	82,111	5,788					81,000	81,000	81,000	0	5,788	PASS
22	82,111	4,677					81,000	81,000	81,000	0	4,677	PASS
23	82,111	3,566					81,000	81,000	81,000	0	3,566	PASS
24	86,542	(1,976)					81,000	81,000	81,000	1,976	0	FAIL
25	94,245	(13,245)					81,000	81,000	81,000	13,245	0	FAIL
26	81,219	(219)					81,000	81,000	81,000	219	0	FAIL
27	66,868	14,132					81,000	81,000	81,000	0	14,132	PASS
28	71,970	23,162					81,000	81,000	81,000	0	23,162	PASS
29	78,686	25,476					81,000	81,000	81,000	0	25,476	PASS
30	82,111	24,365					81,000	81,000	81,000	0	24,365	PASS
31		105,365					0	81,000	0		105,365	

Figure 54. Week 20 simulation.

So TKLS was increased by 5% from 81,000 to 85,050 and the second run starts using TKLS of 85,050, passed week 20 to week 30 and none of the weeks ended with a negative balance. Hence a final kanban lot size for week 20 set to 85,050.

KanBan simulation

Part Number	XXXX	On Hand (oh)CMS	-	Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1 weeks	Multiple (Box size)	90		-
Item Cont Option:	Single Full	Average Demand (??)	80,917	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Simulation Try Number : 2 — Test KanBan Lot Size 85,050 PKLS

Containers in the system 1

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
start		-									-	
20	82,111	6,899				89,010	85,050		85,050	0	6,899	PASS
21	82,111	9,838					85,050	85,050	85,050	0	9,838	PASS
22	82,111	12,777					85,050	85,050	85,050	0	12,777	PASS
23	82,111	15,716					85,050	85,050	85,050	0	15,716	PASS
24	86,542	14,224					85,050	85,050	85,050	0	14,224	PASS
25	94,245	5,029					85,050	85,050	85,050	0	5,029	PASS
26	81,219	8,860					85,050	85,050	85,050	0	8,860	PASS
27	66,868	27,042					85,050	85,050	85,050	0	27,042	PASS
28	71,970	40,122					85,050	85,050	85,050	0	40,122	PASS
29	78,686	46,486					85,050	85,050	85,050	0	46,486	PASS
30	82,111	49,425					85,050	85,050	85,050	0	49,425	PASS
31		134,475					0	85,050	0		134,475	

Figure 55. Week 20 simulation – Run 2.

In week 21, we consider a ‘Start On Hand’ of 6,899 since week 20 demand left a surplus of 6,899. At the same time triggered a production order for 85,050. So the ‘On Order Due’ is 85,050. Start the first simulation using TKLS of 81,810, the simulation passed from week 21 to week 23 but failed in week 24, since ending on hand resulted below 0.

KanBan simulation

Part Number	XXXX	On Hand *(oh)CMS*	6,899	Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1 weeks	Multiple *(Box size)*	90		-
Item Cont Option:	Single Full	Average Demand *(??)*	81,761	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 1				Test KanBan Lot Size		81,810	PKLS					
Containers in the system 1												
start		*6,899*									6,899	
21	82,111	9,838				85,050	81,810		81,810	0	9,838	PASS
22	82,111	9,537					81,810	81,810	81,810	0	9,537	PASS
23	82,111	9,236					81,810	81,810	81,810	0	9,236	PASS
24	98,084	(7,038)					81,810	81,810	81,810	7,038	0	FAIL
25	87,238	(5,428)					81,810	81,810	81,810	5,428	0	FAIL
26	84,289	(2,479)					81,810	81,810	81,810	2,479	0	FAIL
27	66,921	14,889					81,810	81,810	81,810	0	14,889	PASS
28	69,330	27,369					81,810	81,810	81,810	0	27,369	PASS
29	82,956	26,223					81,810	81,810	81,810	0	26,223	PASS
30	82,111	25,922					81,810	81,810	81,810	0	25,922	PASS
31	82,111	25,621					81,810	81,810	81,810	0	25,621	PASS
32		107,431					0	81,810	0		107,431	

Figure 56. Week 21 simulation.

In this case the TKLS was increased by 5% from 81,810 to 85,950. We than run the second simulation using a TKLS of 85,950, passed week 21 to week 31. After second simulation, none of the weeks ended with a negative balance. Hence a Final Kanban Lot Size for week 21 set to 85,950.Table 19 and 20.

KanBan simulation

Part Number	XXXX	On Hand *(oh)CMS*	6,899	Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1 weeks	Multiple *(Box size)*	90		-
Item Cont Option:	Single Full	Average Demand *(??)*	81,761	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 2				Test KanBan Lot Size		85,950	PKLS					
Containers in the system		1										
start		*6,899*									6,899	
21	82,111	9,838				85,050	85,950		85,950	0	9,838	PASS
22	82,111	13,677					85,950	85,950	85,950	0	13,677	PASS
23	82,111	17,516					85,950	85,950	85,950	0	17,516	PASS
24	98,084	5,382					85,950	85,950	85,950	0	5,382	PASS
25	87,238	4,094					85,950	85,950	85,950	0	4,094	PASS
26	84,289	5,755					85,950	85,950	85,950	0	5,755	PASS
27	66,921	24,784					85,950	85,950	85,950	0	24,784	PASS
28	69,330	41,404					85,950	85,950	85,950	0	41,404	PASS
29	82,956	44,398					85,950	85,950	85,950	0	44,398	PASS
30	82,111	48,237					85,950	85,950	85,950	0	48,237	PASS
31	82,111	52,076					85,950	85,950	85,950	0	52,076	PASS
32		138,026					0	85,950	0		138,026	

Figure 57. Week 21 simulation – Run 2.

Now for week 22, we consider a 'Start On Hand' of 9,838 since week 21 demand consumed most of the on hand produced but left a surplus of 9,838 at same time triggered a production order for 85,950. So the 'On Order Due' is 85,950. Using this parameter, we start with the first run/simulation using a TKLS of 81,720. In the first run, the simulation passed from week 22 to week 24 but failed in week 25, since ending on hand resulted below zero.

KanBan simulation							
Part Number	XXXX	On Hand *(oh)CMS*	9,838	Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1 weeks	Multiple *(Box size)*	90		-
Item Cont Option:	Single Full	Average Demand *(??)*	81,655	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 1				Test KanBan Lot Size		81,720	PKLS					
Containers in the system		1										
start		*9,838*									9,838	
22	82,111	13,677				85,950	81,720		81,720	0	13,677	PASS
23	82,111	13,286					81,720	81,720	81,720	0	13,286	PASS
24	89,376	5,630					81,720	81,720	81,720	0	5,630	PASS
25	91,081	(3,731)					81,720	81,720	81,720	3,731	0	FAIL
26	83,461	(1,741)					81,720	81,720	81,720	1,741	0	FAIL
27	76,014	5,706					81,720	81,720	81,720	0	5,706	PASS
28	71,040	16,386					81,720	81,720	81,720	0	16,386	PASS
29	76,679	21,427					81,720	81,720	81,720	0	21,427	PASS
30	82,111	21,036					81,720	81,720	81,720	0	21,036	PASS
31	82,111	20,645					81,720	81,720	81,720	0	20,645	PASS
32	82,111	20,254					81,720	81,720	81,720	0	20,254	PASS
33		101,974					0	81,720	0		101,974	

Figure 58. Week 22 simulation.

Applying the step logic approach, the TKLS was increased by 5% from 81,720 to 85,860 and the second run starts using a TKLS of 85,860. Second simulation passed week 22 to week 32 and none of the weeks ended with a negative balance. The Final Kanban Lot Size for week 22 set to 85,860.

KanBan simulation							
Part Number	XXXX	On Hand *(oh)CMS*	9,838	Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1 weeks	Multiple *(Box size)*	90		-
Item Cont Option:	Single Full	Average Demand *(??)*	81,655	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 2				Test KanBan Lot Size		85,860	PKLS					
Containers in the system		1										
start		*9,838*									9,838	
22	82,111	13,677				85,950	85,860		85,860	0	13,677	PASS
23	82,111	17,426					85,860	85,860	85,860	0	17,426	PASS
24	89,376	13,910					85,860	85,860	85,860	0	13,910	PASS
25	91,081	8,689					85,860	85,860	85,860	0	8,689	PASS
26	83,461	11,088					85,860	85,860	85,860	0	11,088	PASS
27	76,014	20,934					85,860	85,860	85,860	0	20,934	PASS
28	71,040	35,754					85,860	85,860	85,860	0	35,754	PASS
29	76,679	44,935					85,860	85,860	85,860	0	44,935	PASS
30	82,111	48,684					85,860	85,860	85,860	0	48,684	PASS
31	82,111	52,433					85,860	85,860	85,860	0	52,433	PASS
32	82,111	56,182					85,860	85,860	85,860	0	56,182	PASS
33		142,042					0	85,860	0		142,042	

Figure 59. Week 22 simulation – Run 2.

The ‘Start On Hand’ for week 23 is 13,677 since week 22 demand consumed most of the on hand produced but left a surplus of 13,677 but triggered a production order for 85,860. So the ‘On Order Due’ is 85,860. Starting the first run using a TKLS of 87,750, the simulation passed from week23 to week28 but failed in week29, since ending on hand resulted below zero.

KanBan simulation

Part Number	XXXX	On Hand *(oh)CMS*	13,677	Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1 weeks	Multiple *(Box size)*	90		-
Item Cont Option:	Single Full	Average Demand *(??)*	87,685	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 1				Test KanBan Lot Size		87,750	PKLS					
Containers in the system		1										
start		***13,677***									13,677	
23	82,111	17,426				85,860	87,750		87,750	0	17,426	PASS
24	97,308	7,868					87,750	87,750	87,750	0	7,868	PASS
25	93,103	2,515					87,750	87,750	87,750	0	2,515	PASS
26	75,596	14,669					87,750	87,750	87,750	0	14,669	PASS
27	66,144	36,275					87,750	87,750	87,750	0	36,275	PASS
28	89,770	34,255					87,750	87,750	87,750	0	34,255	PASS
29	132,059	(10,054)					87,750	87,750	87,750	10,054	0	FAIL
30	82,111	5,639					87,750	87,750	87,750	0	5,639	PASS
31	82,111	11,278					87,750	87,750	87,750	0	11,278	PASS
32	82,111	16,917					87,750	87,750	87,750	0	16,917	PASS
33	82,111	22,556					87,750	87,750	87,750	0	22,556	PASS
34		110,306					0	87,750	0		110,306	

Figure 60. Week 23 simulation.

KanBan simulation

Part Number	XXXX	On Hand *(oh)CMS*	13,677		Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1	weeks	Multiple *(Box size)*	90		-
Item Cont Option:	Single Full	Average Demand *(??)*	87,685		Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers						

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 2				Test KanBan Lot Size		92,160	PKLS					
Containers in the system		1										
start		***13,677***									13,677	
23	82,111	17,426				85,860	92,160		92,160	0	17,426	PASS
24	97,308	12,278					92,160	92,160	92,160	0	12,278	PASS
25	93,103	11,335					92,160	92,160	92,160	0	11,335	PASS
26	75,596	27,899					92,160	92,160	92,160	0	27,899	PASS
27	66,144	53,915					92,160	92,160	92,160	0	53,915	PASS
28	89,770	56,305					92,160	92,160	92,160	0	56,305	PASS
29	132,059	16,406					92,160	92,160	92,160	0	16,406	PASS
30	82,111	26,455					92,160	92,160	92,160	0	26,455	PASS
31	82,111	36,504					92,160	92,160	92,160	0	36,504	PASS
32	82,111	46,553					92,160	92,160	92,160	0	46,553	PASS
33	82,111	56,602					92,160	92,160	92,160	0	56,602	PASS
34		148,762					0	92,160	0		148,762	

Figure 61. Week 23 simulation – Run 2.

In this case the *TKLS was increased by 5% from 87,750 to 92,160. The second simulation using a* TKLS of 92,160, passed week 23 to week 33 and none of the weeks ended with a negative balance. The final Kanban Lot Size for week23 set to 92,160.

Now, week 24 should be simulated similar to the one before. We considered 'Start On Hand' to be 17,426 since week 23 demand consumed most of the on hand produced but left a surplus of 17,426 but triggered a production order for 92,160. So the 'On Order Due' is 92,160. We then start the first run using TKLS of 80,010. The simulation passed from week 24 to week 34 and none of the weeks ended with a negative balance. Hence the Final Kanban Lot Size for week 24 set to 80,010.

KanBan simulation

Part Number	XXXX	On Hand *(oh)CMS*	17,426	Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1 weeks	Multiple *(Box size)*	90		-
Item Cont Option:	Single Full	Average Demand *(??)*	79,943	Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers					

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number : 1				Test KanBan Lot Size		80,010	PKLS					
Containers in the system		1										
start		*17,426*									17,426	
24	94,212	15,374				92,160	80,010		80,010	0	15,374	PASS
25	74,471	20,913					80,010	80,010	80,010	0	20,913	PASS
26	82,701	18,222					80,010	80,010	80,010	0	18,222	PASS
27	69,338	28,894					80,010	80,010	80,010	0	28,894	PASS
28	74,240	34,664					80,010	80,010	80,010	0	34,664	PASS
29	73,859	40,815					80,010	80,010	80,010	0	40,815	PASS
30	82,111	38,714					80,010	80,010	80,010	0	38,714	PASS
31	82,111	36,613					80,010	80,010	80,010	0	36,613	PASS
32	82,111	34,512					80,010	80,010	80,010	0	34,512	PASS
33	82,111	32,411					80,010	80,010	80,010	0	32,411	PASS
34	82,111	30,310					80,010	80,010	80,010	0	30,310	PASS
35		110,320					0	80,010	0		110,320	

Figure 62. Week 24 simulation.

The simulation we just showed is mainly without applying the intervention module. The IM allows us to have 0 inventories and zero backlogs.

We will start the production in week 24 with zero on hand. Knowing that our production system adjusts its weekly plan based on the actual orders for the week so that the on hand balance should be zero.

So considered 'Start On Hand' as zero (0) since week 23 demand consumed all the one hand and left no surplus but triggered a production order for 92,160. So the 'On Order Due 'is 92,160. The first run using a TKLS of 80,010, simulation failed in week24 (current production week). As can be noted the 'On order due' was of 94,212 but the on order due was of 92,160. This leaves a shortage of 2,052 which needs to be highlighted immediately – INTERVENTION REQUIRED so that production will react accordingly. Reaction could be in different forms and shapes, starting with adding more capacity to informing the customer that the delta sales will be sent next week. In this case, we added more capacity and the Final Kanban Lot Size for week 24 set to 80,010 but an INTERVENTION of 2,052 needs to be done to satisfy Week 24’s demand.

KanBan simulation

Part Number	XXXX	On Hand *(oh)CMS*	-		Safty Weeks	-	Supplier Ship Time	1
Description:	C170	Replen Lead Time	1	weeks	Multiple *(Box size)*	90		-
Item Cont Option:	Single Full	Average Demand *(??)*	79,943		Minimum		Percent Increase	5%
Current Qty Containers		Prelim Qty Containers						

Date n	Demand dmd1MRP	KB1 Ending	KB2 Ending	KB3 Ending	KB4 Ending	Download On Order Due	Simulated Trigger T1, T2...	Trigger Due	Supplier Ship Date	Intervention Required	Ending on Hand (bn)=A-dmd1	A=oh+T1
Simulation Try Number :	1			Test KanBan Lot Size		80,010	PKLS					
Containers in the system		1										
start		-									-	
24	94,212	(2,052)				92,160	80,010		80,010	2,052	0	INTERVENTION REQ.
25	74,471	5,539					80,010	80,010	80,010	0	5,539	PASS
26	82,701	2,848					80,010	80,010	80,010	0	2,848	PASS
27	69,338	13,520					80,010	80,010	80,010	0	13,520	PASS
28	74,240	19,290					80,010	80,010	80,010	0	19,290	PASS
29	73,859	25,441					80,010	80,010	80,010	0	25,441	PASS
30	82,111	23,340					80,010	80,010	80,010	0	23,340	PASS
31	82,111	21,239					80,010	80,010	80,010	0	21,239	PASS
32	82,111	19,138					80,010	80,010	80,010	0	19,138	PASS
33	82,111	17,037					80,010	80,010	80,010	0	17,037	PASS
34	82,111	14,936					80,010	80,010	80,010	0	14,936	PASS
35		94,946					0	80,010	0		94,946	

Figure 63. Week 24 simulation – Zero on hand.

CURRICULUM VITAE

NAME: Joseph Elias El Khoury

ADDRESS: Department of Industrial Engineering
Louisville
Louisville, Kentucky 40292

DOB: Lebanon – September 2, 1963

EDUCATION
& TRAINING:

University of Applied Sciences BINGEN/GERMANY
Diploma in Automotive Engineering
1986-1990

University of Applied Sciences MAINZ/GERMANY
Diploma in Economic Engineering
1991-1995

NTU School of Engineering and Applied Science
Walden University, Minneapolis, MN 55401
Master in Mechanical Engineering
1999 – 2005

University of Louisville USA
PhD Industrial Engineering
2009- Present

AWARDS: Award by the Republic of Malta
(Gieh Ir-Repubblika)
2010

PROFESSIONAL SOCIETIES: Member of IEEE
(Institute of Electrical and Electronics Engineers)

Member of ASME
(American Society of Mechanical Engineers)

Member of HFES
(Human Factors and Ergonomics Society)

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