Double Speed Single Production Line: A new hybrid manufacturing planning & control method based on the optimal allocation of resources

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Abstract

Today, more than ever manufacturing industries have to face severe competition due to the globalization of the markets. Having more suppliers to choose from, customers are becoming more and more demanding with respect to prices, quality requirements, product customization and delivery times. Consequently, in order to keep an advantage over competitors, manufacturing companies have to respond to the market demand in the most economical manner.

In this work this issue is addressed by the development of a new hybrid manufacturing planning & control (MPC) method whose key concepts are based on the combination of the classical Just-in-Time (JIT) and Material Requirement Planning (MRP) or Inventory control MPC methods for the management of two product groups. Due to its characteristics the new hybrid MPC method is termed Double Speed Single Production Line (DSSPL).

The development and validation of the new hybrid MPC concept is performed by applying a four-step research methodology that includes reviews of existing MPC methods, a study of a Markovian model, a simulation analysis and pilot projects in real industrial cases.

In the first step, the conceptual framework of the new MPC method is developed based on a problem statement that is derived from particular situations that a certain type of manufacturing companies are confronted with. In addition, a review of the state-of-the-art in manufacturing planning & control helps to identify the novel aspects and approximative application domain of the new MPC concept.

The analysis of the basic mechanics of the new MPC concept is performed in the second step. This is done with a study of a Markovian model that allows the comparison of performances of the new MPC concept with those of the MRP concept. This analysis helps also to identify settings of the manufacturing environment that are critical for its logistic performance.

A more detailed analysis is performed in the third step with the help of a simulation study that compares several configurations of the new MPC method with the MRP and Inventory control method. The most important issues of this study are the optimal configuration and the analysis of the behavior of the new MPC method when confronted with an uncertain manufacturing environment.

In the last step, the key concepts of the new MPC method are validated in pilot projects in real industrial environments. The outcome of these projects serves also as a guideline for the development of an implementation procedure.

Version abrégée

L'industrie manufacturière est confrontée aujourd'hui à une compétition de plus en plus sévère à cause de la globalisation des marchés. Ayant un plus grand choix de fournisseurs, les clients sont devenus plus exigents par rapport aux prix, la qualité, la spécification des produits et les délais de livraison. Par conséquent, pour garder un avantage, les industries manufacturières doivent répondre le plus près possible et d'une manière économique à la demande client.

Dans ce travail, cette problématique est abordée par le dévelopement d'une nouvelle méthode hybride de gestion de production qui est basée sur la combinaison de méthodes de gestion de production classiques Juste-à-Temps (Just-in-Time, JIT) et Material Requirement Planning (MRP) ou Gestion de Stocks pour la gestion de deux groupes de produits différents. Cette nouvelle méthode hybride de gestion de production est nommée Ligne de production à deux vitesses (Double Speed Single Production Line, DSSPL).

Le dévelopement et la validation de la nouvelle méthode de gestion se sont déroulés suivant une méthodologie de recherche à quatres étapes, qui contient la recherche de litterature de méthodes de gestion de production existantes, l'analyse d'un modèle markovien, des analyses de simulation et des projets pilotes dans des cas industriels.

Dans la première étape, les concepts de base de la nouvelle méthode de gestion de production sont dérivés à partir d'un ensemble de problèmes et situations auxquelles certaines entreprises manufacturières sont confrontées. Les aspects novateurs et le domaine d'application approximatif de la nouvelle méthode sont determinés à l'aide d'une revue de l'état de l'art dans le domaine de gestion de production.

Le fonctionnement de base de la nouvelle méthode de gestion de production est analysé à l'aide d'un modèle markovien qui permet la comparaison de la performance de la nouvelle méthode de gestion de production avec celle de MRP. Cette analyse permet l'identification de paramètres qui ont un impact significatif sur la performance de DSSPL.

Dans la troisième étape, une analyse détaillée de simulation est effectuée. Cette simulation a pour but de comparer la performance de differentes configurations de DSSPL avec celles de MRP et Gestion de Stocks opérant dans un environnement de production incertain.

Dans la dernière étape, le concept de DSSPL est validé dans des projets pilotes dans des cas industriels. Les résultats de ces projets permetttent également de guider le développment d'une procédure d'implantation de DSSPL.

Zusammenfassung

Produktionsfirmen sind heute immer stärker mit den Auswirkungen des globalen Marktes konfrontiert. Dies manifestiert sich durch eine Erhöhung der kundenseitigen Anforderungen im Bereich der Kosten, der Qualität, der Lieferzeiten sowie von kundenspezifischen Anpassungen. Um in diesem Umfeld weiterhin konkurrenzfähig zu bleiben, müssen Produktionsfirmen diesen veränderten Kundenanforderungen so schnell und wirtschaftlich wie möglich gerecht werden.

In dieser Arbeit wird ein Lösungsbeitrag zu diesem Problembereich durch die Entwicklung einer neuen hybriden Produktionsplanung und -steuerung-Methode (PPS) geliefert, welche die klassischen PPS-Methoden JIT (Just-in-Time) und MRP (Material Requirement Planning) oder Lagerhaltung zur Planung und Steuerung von zwei verschiedenen Produktegruppen kombiniert. Diese neue PPS-Methode wird wegen ihrer Eigenschaften Double Speed Single Production Line (DSSPL) genannt.

Die Entwicklung und Validierung von DSSPL wird in vier Schritten mit Hilfe einer Übersicht existierender PPS-Methoden, eines Markov-Modells, einer Simulationsanalyse sowie Pilotstudien in Produktionsfirmen durchgeführt.

Das Konzept von DSSPL wird im ersten Schritt von einer Problembeschreibung abgeleitet welche für gewisse Produktionsfirmen typisch ist. Zusätzlich wird mit Hilfe einer Übersicht über den Stand der Forschung im Bereich der Produktionsplanung und -steuerung die neuen Aspekte sowie das ungefähre Anwendungsgebiet von DSSPL ermittelt.

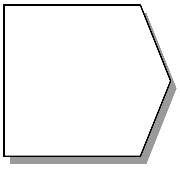
Mit Hilfe eines Markov-Modells wird im zweiten Schritt die grundsätzliche Funktionsweise von DSSPL analysiert. Diese Analyse hilft im weiteren im Ermitteln von Faktoren und Randbedingungen, welche besonders kritisch für die Leistungsfähigkeit und Effizienz von DSSPL sind.

Eine detailliertere Analyse von DSSPL wird mit Hilfe einer Simulationsanalyse durchgeführt, bei welcher die Effizienz verschiedener PPS-Methoden unter stochastischen Randbedingungen verglichen wird. Die Ermittlung einer optimalen Konfiguration von DSSPL ist ein weiteres Ziel dieser Simulationsanalyse.

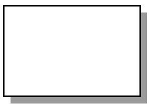
Im letzten und vierten Schritt wird das Konzept von DSSPL in Pilotprojekten in Produktionsfirmen validiert. Diese Pilotprojekte dienen ebenfalls als Grundlage für die Entwicklung einer Implementations-Methodik, welche die spezifischen Eigenschaften und Anforderungen von DSSPL berücksichtigt.

Description of graphical elements

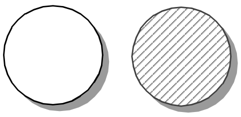
If not otherwise defined, the following list of symbols defines the graphical elements used in this thesis together with the corresponding abbreviations.



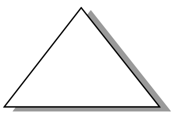
Business unit (BU)



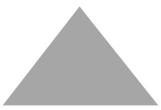
Central planning unit (CPU)



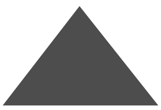
Manufacturing center (MC), external supplier (SUP)



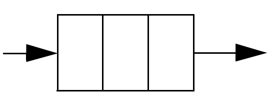
Central inventory (CI)



Intermediate inventory or work in process (WIP)



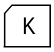
Final goods inventory (FGI)



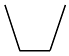
Queue for production orders or kanbans

Dispatching of production orders and/or kanbans

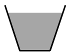
Production order (PO)



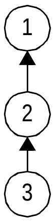
Kanban (K)



Empty container

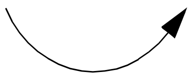


Filled container

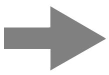


Product structure

Flow of information



Flow of material



Actual customer demand or demand derived from scheduled production plan

List of mathematical symbols

The following list summarizes the mathematical symbols used in the work.

Symbol	Unit	Description
a	[-]	Form factor
α	[-]	Shortage risk
asup[i], *bsup[i]*	[-]	Parameters defining the relative delay (asymmetrical triangular law) of suppliers
breadth[i]	[-]	Breadth of product structure (number of immediate components per parent) of final product *i*
c	[-]	Form factor
C	[currency]	Average combined cost
C_I	[currency]	Unit inventory holing cost
ck[i]	[item]	Capacity of kanban for item *i* (JIT/kanban)
C_O	[currency]	Ordering costs
commonnality	[-]	Component commonality of aggregate product structure
CostRatio	[-]	Ratio between the inventory holding cost for the raw material and the finished product (Markovian analysis)
C_S	[currency]	Unit shortage costs
ct	[time unit]	Cycle time
CT	[time unit]	Mean cycle time
cvds[i]	[-]	Variability (*CV)* of demand size of item *i*
cvid[i]	[-]	Variability (*CV*) of interval size between two orders for item *i*
cvpt[i,k]	[-]	Variability (*CV*) of processing time of item i on machine *k*

Symbol	Unit	Description
cvsc[i]	[-]	Variability (*CV*) of normally distributed stochastic component of demand for item *i*
cvstp[i,j,k]	[-]	Variability (*CV*) of setup time
d	[item]	Demand (over a certain period)
D	[item]	Mean demand
depth[i]	[-]	Depth of product structure (number of levels in the bill of material structure) of final product i
DR	[item/time unit]	Mean demand rate
freq	[time unit]	MRP replanning frequency (MRP)
γ	[-]	DSSPL dispatching rule parameter
g	[-]	Gini's index
g	[-]	Index describing the heterogeneity of the demand
Γ	[-]	Complexity of MPC method
il	[item]	Inventory level
IL	[item]	Mean inventory level
K	[-]	Constant
λ	[time unit^{-1}]	Mean arrival rate (Markovian analysis)
llow[i]	[-]	Lower limit for kanban queue (Dispatching rule of DSSPL)
ls[i]	[item]	Lot size of item *i* (MRP)
lt	[time unit]	Lead time
lt[i]	[time unit]	Planned lead time of item *i* (MRP)
lup[i]	[-]	Upper limit for kanban queue (Dispatching rule of DSSPL)
μ	[time unit^{-1}]	Mean service rate
mds[i]	[item]	Mean demand size of item *i*
mdt[i]	[time unit]	Maximum delivery time demanded by market for item *i*
mid[i]	[time unit]	Mean interval size between two orders for item *i*
mpt[i,k]	[time unit]	Mean process time of item *i* on machine *k*
mttf[k]	[time unit]	Mean time to failure of machine *k*
mttr[k]	[time unit]	Mean time to repair of machine *k*
$\mathbf{n}$	[-]	State vector (Markovian analysis)
N_A	[-]	Number of waiting A-jobs
nk[i]	[-]	Number of kanbans in kanban-loop for item *i* (JIT/kanban)
nreq	[item]	Net requirement
NV	[-]	Number of logistic variables or parameters

Symbol	Unit	Description
p_n	[-]	Steady-state probability of a birth-death process of being in state *n*
peo[i]	[-]	Proportion of emergency orders of item *i*
phor	[time unit]	Planning horizon (MRP)
q	[item]	Order quantity
q[i]	[item]	Order quantity for item *i* (Inventory Control)
ρ	[-]	Ratio between ordering costs C_O and unit inventory holding cost C_I
r[i]	[item]	Reorder point for item *i* (Inventory Control)
R	[shop calender days]	Mean range
RatioAB	[-]	Ratio between load generated by A- and B-jobs
RatioS	[-]	Ratio between the size of A- and B-jobs
relc[i]	[-]	Relative cost of item *i* (with respect to raw material cost)
relint[i]	[-]	Relative intensity of item *i* (Sum of *relint*[1... *n*] = 1, *n* final products)
reo[i]	[-]	The parameter *a* of the asymmetrical triangular law defining the due date error expressed by the product of *reo* and *mpd*.
req	[item]	Cumulated requirement for a certain period
σ	[-]	Safety factor
s	[time unit]	Service time per job
sdt[i]	[time unit]	Standard delivery time demanded by market for item *i*
SL	[-]	Ratio of fulfilled jobs or orders
slt[i]	[time unit]	Safety lead time of item *i* (MRP)
ss[i]	[item]	Safety stock level of item *i* (MRP)
stp[i,j,k]	[time unit]	Mean setup for item *i* after item *j* has been processed on machine *k*
sysint	[-]	System intensity (load) or utilization
tb	[time unit]	Maximum waiting time of B-jobs
tcrit[i]	[time unit]	Critical waiting time of item *i* (Dispatching rule of DSSPL)
tp	[time unit]	Process time of one job
TP	[time unit]	Mean process time
T_{PH}	[-]	Number of time buckets within planning horizon
TQ	[time unit]	Mean queue time
Perf	[hours/shop calender days]	Mean performance
WIP	[time unit]	Work in process
X	[-]	Number of items
X_C	[-]	Number of components

Symbol	Unit	Description
X_{FP}	[-]	Number of final products
$z[i]$	[-]	Standard normal distribution multiplier for adjustment of risk for being out-of-stock of item i (Inventory Control)

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Chapter 1

Introduction

Today, more than ever manufacturing industries have to face severe competition due to the globalization of markets. Having more suppliers to choose from, customers are becoming more and more demanding with respect to prices, quality requirements, product customization and delivery performances. Consequently, in order to keep an advantage over its competitors, manufacturing companies have to respond to market demand in the most economical manner. From the manufacturing planning & control point of view, this goal can only be achieved by an optimal usage of the production resources at low inventory levels. However, by responding more accurately to the customer demand, that is, by its very nature highly variable and thus difficult to forecast, this goal is more and more difficult to achieve. This divergence between the needs to respond accurately to market demand and to optimize economically the production system leads to the so called manufacturing planning & control dilemma, whose solution is the main topic of most research activities in the field of production research.

The majority of manufacturing planning & control (MPC) concepts analyzed and developed in research and applied in practice are based on one of the three classical MPC concepts: Inventory Control, Material Requirement Planning (MRP) or Just-In-Time (JIT/kanban). The first MPC method used in modern manufacturing was the Inventory Control concept that is based on the idea of controlling production based on inventory levels and the expected replenishment times. The main advantage of this method is its conceptual simplicity, but its focus on stock keeping leads in practice to high inventory levels. The development of the other two classical MPC methods MRP and JIT/kanban were both inspired by the shortcomings of the Inventory Control concept. In the case of MRP, production is planned and controlled based on a time-phased production schedule that is computed based on the current and forecasted demand of the final products (Master production schedule, independent demand), the product structure (Bill of material), the estimated production lead times and the inventory records of every item. Due to the amount and complexity of the required computations, MRP's development was closely linked to the increasing availability of computer systems during the 1960s. By contrast, the JIT concept developed in Japan at Toyota, modified only slightly the principles of the Inventory Control concept by introducing the concept of kanbans that trigger production only when a consumption has occurred. Thus, the JIT or JIT/kanban concept is often termed as “pull concept” since production is governed (pulled) only by the effective demand. On the other hand, MRP is often termed as “push concept” since production is governed (pushed) by future demand. Mainly due to their different origins, but also to their contrasting characteristics and application domains, JIT/kanban and MRP were considered for a long time as incompatible MPC methods. However, impressed by the obvious success of Japanese firms using the JIT/kanban concept, researchers started in the 1980s to develop hybrid methods that combine the advantages of both methods JIT/kanban and MRP. The driving idea behind these developments was, therefore, to combine the ability of the JIT/kanban concept to manage production efficiently with the planning capability of MRP.

In this thesis, a new hybrid MPC concept is developed that allows the improvement of the logistic performance of manufacturing enterprises offering a wide variety of products by respecting the constraint of limited resources. It is based on the following key concepts:

- By applying a multiple-criteria ABC analysis (demand topology, product characteristics, marketing objectives), products are divided into the two groups A- and B-products. A-products are characterized by a high and stable demand and their unavailability would have a significant impact on customer service and satisfaction. By contrast, B-products are characterized mainly by a lower and unstable demand;
- According to the characteristics of the demand topology of the product groups, the JIT/kanban concept is applied for the management of A-products and the MRP or Inventory Control method is applied for management of B-products;
- Local scheduling at production stages producing both product groups is governed by specific dispatching rules that handle the different priorities. In the simplest case, priority is always given to A- over B-products.

The division of the products into different product groups allows companies to concentrate their limited resources on the most important products without the need for additional production resources. Furthermore, by applying the JIT/kanban technique only to the limited number of A-products, the Just-in-Time/kanban implementation efforts can be better focused. In addition, local scheduling at every production stage is simplified due to a transparent allocation of priorities to the different product groups which is particularly important when a wide variety of products is produced.

Due to its characteristics the new hybrid manufacturing planning & control concept is termed **D**ouble **S**peed **S**ingle **P**roduction **L**ine (DSSPL).

Research goals

The different research goals of this thesis are derived from the main issue of this study that consists of developing, analyzing and validating the new hybrid MPC method DSSPL. They can be summarized as follows:

- *Concept design*: The following DSSPL key concepts have to be developed: (1) Criteria for the choice of A-products, (2) the choice of the optimal manufacturing planning & control concept for the different product groups and (3) the development of the local dispatching rules handling the different priorities of the different product groups;
- *Logistic performance*: The expected logistic performance of DSSPL has to be determined for representative manufacturing environments in comparison to the classical MPC methods MRP and Inventory Control. It is assumed that these two MPC methods have a application domain comparable to those of DSSPL. For this reason a performance comparison with the JIT/kanban MPC method is not required since its application domain is significantly different from DSSPL's one;

- *Application domain*: The application domain of DSSPL has to be determined with respect to the manufacturing strategy, the demand topology, the manufacturing process design and DSSPL's relative performance compared to the classical MPC methods MRP and Inventory Control;
- *Configuration, management and implementation guidelines*: Guidelines for the optimal configuration, implementation and management of DSSPL have to be developed for the most representative manufacturing environments.

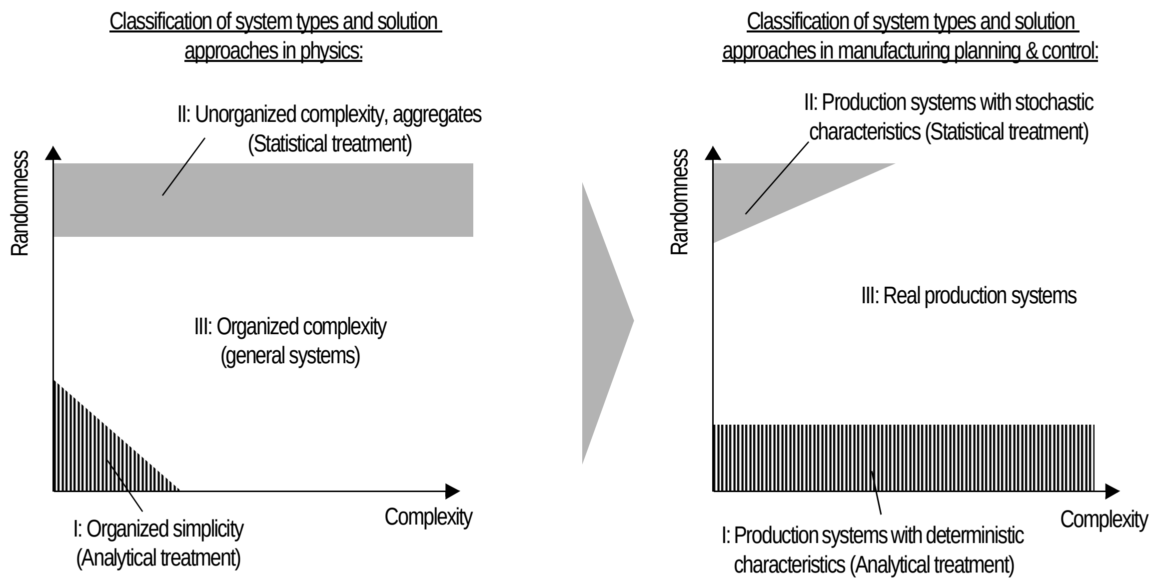
Research tools and methodology

In order to achieve the research goals of this thesis, tools and methods have to be chosen that best take into account the specific characteristics of manufacturing systems. In fact, when analyzing manufacturing systems, one is confronted with the challenge of modelling or handling their complexity, variability and diversity.

The complexity of manufacturing systems is mainly due to the fact that their performance is influenced by a large number of parameters such as the topology of the demand, the capacity and capability of the human and technical production resources and the characteristics of the MPC concept. Another important feature of manufacturing systems is their variability. Most of the processes in a manufacturing system are stochastic by nature. Typical examples are the processing, setup and transportation times and customer demand. Furthermore, configurations of many real manufacturing systems change constantly due to changes in market demand, the introduction of new products or variations in the capacity of the production resources. Finally, there exists an uncountable number of possible configurations of manufacturing systems and direct comparisons among them are often only possible for variables such as the manufacturing strategy, the master production schedule approach or the manufacturing process type.

The issue of choosing tools and methodologies for the analysis of manufacturing systems is best illustrated by taking as reference the classification of system types and solution methods according to general system theory (Weinberg 2001). As shown in Figure 1.1 physical systems can be divided into three domains with respect to the two system characteristics *Randomness* and *Complexity.* The first domain is

Figure 1.1 Classification of system types and solution approaches (Weinberg 2001)



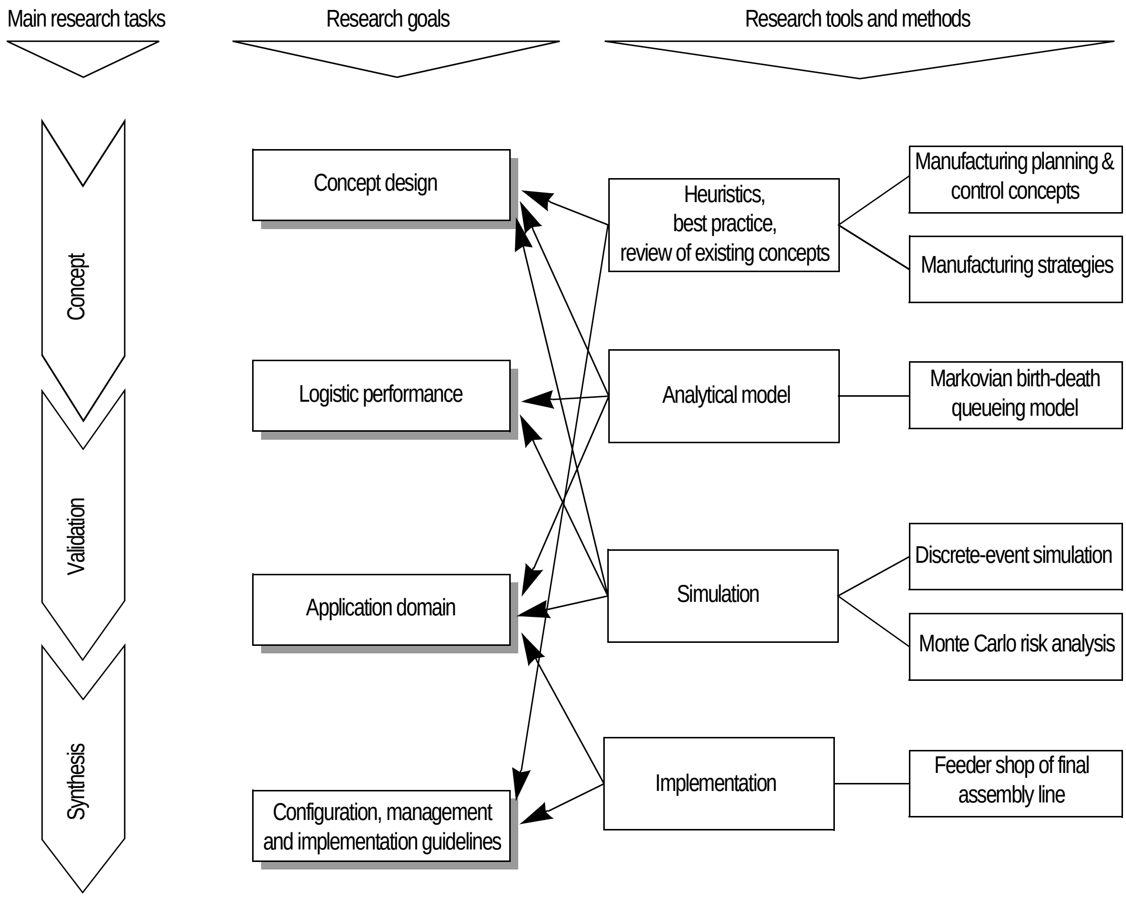
characterized by a low randomness and complexity (I: Organized simplicity). Consequently, problems related to this domain are generally tractable with analytic tools and methods (Newton's mechanics). The second domain is characterized by a high randomness and complexity (II: Unorganized complexity, aggregates) and problems of this domain can generally be described and solved with the help of statistical tools (gas theory). Finally, the third domain (III: Organized complexity, general systems) is characterized by properties that are generally too complex to be treated analytically and too organized to be treated statistically. With the advent of computer resources, simulation has become the dominant tool for the analysis of such systems.

In the case of manufacturing systems, an analogous classification can be applied. The first domain is characterized by low randomness (I: Production systems with deterministic characteristics). Production systems having such properties are generally tractable with analytical methods. Representative examples have been provided by Bitran and Chang (1987) and Moeeni and Chang (1990) who both developed models of deterministic kanban controlled production systems. Other well known or widely used results derived from such models are the economic order quantity (EOQ) used in inventory control, the Material Requirement Planning (MRP) framework or scheduling algorithms for two-machine production lines (Johnson 1954). The validity of all these results is less limited by the complexity of the problem than by the inability of representing accurately the stochastic behavior of manufacturing systems. A typical example supporting this fact is provided by Cochran and Kim (1998) who developed a model of a serial hybrid push/pull production system based on mathematical programming. In fact, solutions obtained from a model with an approximation of the stochastic components of variables differed significantly from those obtained with a model without stochastic approximation. The second domain is characterized by a high randomness (II: Production systems with stochastic characteristics) whereas stochastic queueing models (Gross and Harris 1998) are the most appropriate analytical method for the analysis of such systems having those properties. Numerous examples such as single work stations subject to failures or single-stage, single-product pull-type manufacturing systems have been developed and presented by Buzacott and Shanthikumar (1993) and Altiok (1996). Thus, the results obtained from stochastic queueing models can give valuable insights into the basic mechanics of manufacturing systems. However, as pointed out by Nyhuis and Wiendahl (1999) and Jordan (1988) this approach suffers mainly from the limited choice of stochastic distributions and the "state space" explosion problem that limits its application domain to problems with a low number of variables (low complexity). Furthermore, other dispatching rules than FIFO (first in, first out) or LIFO (last in, first out) are difficult or impossible to model. Finally, the third domain is characterized by characteristics that are typically found in real manufacturing systems and defined at the beginning of this subsection (III: Real production systems). The most adopted tool for the analysis of such systems is thus discrete-event simulation (Law and Kelton 1991) that is able to analyze problems of virtually unlimited complexity. A typical example of a model of a complex manufacturing system has been developed by Krajewski et al. (1987) who included parameters such as forecast errors, varying supply lead times, lot-sizing rules and worker flexibility. However, as described by Nyhuis and Wiendahl (1999) and shown in a review of simulation models in §4, results obtained from simulation models are difficult to generalize and compare with other results from different simulation studies. In addition, it is often not clear, whether the simulation results are mainly due to the particular configuration of the simulation model or due to the characteristics of the analyzed concepts.

By considering the characteristics of the available methods and tools for the analysis of manufacturing systems, it can be stated that an attempt to solve the particular problems of this thesis (high number of products, modelling of MRP, presence of forecast errors and dispatching rules for DSSPL) using a direct analytical solution is impractical (Mahoney 1997). Consequently, in order to reach the goals, trade-off decisions have to be made between the different analysis methods and their underlying assumptions, the accuracy and the generality of their results.

The research methodology adopted is, therefore, characterized by a four-step approach that is illustrated in Figure 1.2. In the first step, the DSSPL key concepts are developed based on a problem statement that is derived from the particular situation with which a certain type of manufacturing companies are confronted.

Figure 1.2 Research road map



The novel aspects of DSSPL are identified based on a review of existing manufacturing planning & control concepts, manufacturing strategies and heuristics. In the second step, through the use of an analytical Markovian birth-death queueing model of a single-stage, two-product production system, the performance and the behavior of the basic DSSPL concept are analyzed and compared to the classical MRP or push concept. It is assumed that the use of a Markovian model allows the capture of the basic mechanics of DSSPL when applied to a stochastic environment. In the third step, discrete-event simulation is used to explore the DSSPL concept in more detail. Emphasis is put on the determination of the optimal configuration of DSSPL when confronted with an uncertain manufacturing environment. The simulation models are developed and analyzed based on a simulation analysis framework that has been developed in order to minimize the lack of generality that is usually associated with simulation model results. This framework is mainly based on the outcome of a review of existing simulation studies and the combined use of Monte Carlo and risk analysis. Finally, in the fourth step, the DSSPL concept is implemented and validated in industrial case studies. In this last step, emphasis is put on the development of configuration, management and implementation guidelines for DSSPL.

A similar approach of combining several research methods and tools for the development of a new MPC method has been applied by Wiendahl (1987). He used simple stochastic models, simulation studies and industrial case studies for the development of the Load-oriented manufacturing control method. A further similar example is provided by Hopp and Spearman (1996) who developed the CONWIP concept based on a review of existing MPC methods, stochastic models and simulation studies.

Organization of the thesis

This thesis is organized into seven chapters, the first of which is this introduction. In chapter §2, existing manufacturing planning & control concepts are reviewed. This review serves mainly to determine the state-of-the-art of the research activities in the field of the development of new manufacturing planning & control concepts. This review serves also to define the specifications and novel aspects of the DSSPL key concepts that are explored by the use of a Markovian model in the following chapter §3. The simulation framework used for the simulation studies is developed and presented in chapter §4. Chapter §5 presents the performance of DSSPL that has been evaluated based on simulation studies. Implementation and configuration guidelines together with an industrial case study are presented in the chapter §6. Finally, concluding remarks with directions for future research are given in chapter §7.

Summary and conclusions of chapter 1

- The main research issues of this thesis are to develop, analyze and validate the new hybrid manufacturing planning & control method DSSPL (**D**ouble **S**peed **S**ingle **P**roduction **L**ine);
- The new hybrid manufacturing planning & control (MPC) method DSSPL combines the classical MPC methods JIT/kanban and MRP (or Inventory control) for the production of different classes of products (A- and B-products based on a market or customer oriented analysis) on one single production line by respecting the constraint of limited resources;
- The review of existing MPC methods and theories, discrete-event simulation, implementation case studies and a Markovian model are the main research tools used in this work;

Chapter 2

Review of existing manufacturing planning & control methods

Two main approaches for manufacturing planning & control (MPC) methods can be identified. The first approach has led to the development of the MRP (Material Requirement Planning) method, which relies heavily on the use of mathematical methods and thus the use of computer resources. Typically, an MRP system determines, based on the actual demand, forecasts, the product structure and the inventory levels, all production activities at all levels of the production process. Due to the manner in which the demand triggers the production activities, the term “push system” is often used for this concept of controlling production. Historically, the development of this concept was initiated around 1960 in the US (Orlicky 1975). The second approach has led to the development of the JIT (Just-In-Time) concept, which is based on a philosophy of continuous reduction of perturbations and waste occurring in a production system. Production itself is often controlled by a system based on cards (kanbans) circulating between production stages. Due to the manner in which the demand triggers production activities, the term “pull system” is often used for this concept of controlling production. The JIT concept has been continuously developed since its origins in 1958 at Toyota Inc. in Japan (Ohno 1988). Thus, due to the origins and characteristics of both approaches, push systems have mainly been implemented in industries in western countries offering a wide variety of rather customized products, whereas pull systems were found mainly in industries in Japan, operating in the standard product markets.

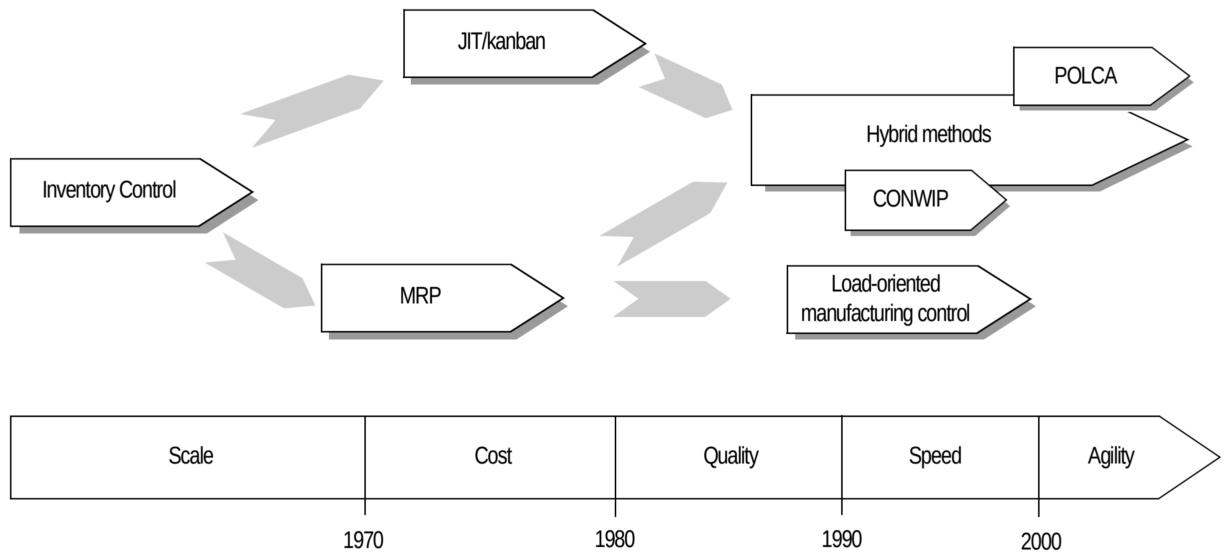
More recently, motivated by the apparent success of the JIT concept, researchers began to compare and analyze the characteristics and performances of implementations of both push and pull concepts and to finally develop new hybrid MPC systems combining the advantages of both approaches. In fact, in order to further improve the performance of production systems, most hybrid MPC concepts combine the ability of the push concept to plan and manage the production of a wide variety of products with the efficiency of the pull concept for production control. Typical examples of modern hybrid concepts are the CONWIP and POLCA methods that have been developed by Spearman et al. (1990) and Suri (1998) respectively.

Another important MPC concept has been introduced by Wiendahl (1987, 1995). Its load-oriented manufacturing control concept forms, together with the POLCA and CONWIP methods, a class of MPC methods whose development has been primarily initiated by the shortcomings of MRP that are essentially linked to the assumption of unlimited capacity. In contrast to MRP, all these three concepts focus on limiting the work-in-process (WIP) in order to achieve better control of capacity constrained production systems. POLCA and CONWIP limit the WIP by the use of generic kanban cards. In the case of the load-oriented manufacturing control concept, the same is achieved by continually monitoring and limiting the load of the production system.

Finally, a still widely used MPC method is Inventory control that is conceptually the simplest of all MPC methods. It is focused on optimizing the inventory control variables with the objective to minimize inventory holding costs. From an operational and historical point of view JIT/Kanban and MRP have both been developed based on this concept.

As shown in Figure 2.1 the development of new MPC methods is linked closely to the evolution of manufacturing strategies (Suri 1998).

Figure 2.1 Evolution of MPC methods and manufacturing strategies



Until around 1970, Inventory control was the dominant MPC method used in manufacturing companies. In this scale-based phase of competition, most of the companies were focused towards growth rather than towards efficiency. When Japanese firms entered the world markets in the 1970's cost issues became the primary concern. In western countries, Inventory control was replaced more and more by MRP systems that were able to improve the performance of the production system. Japanese firms were also the driving force behind the subsequent manufacturing strategy shifts. They were not only able to reduce the costs, but also to increase significantly the quality of their products (Mahoney 1997). More recently, to the cost and quality advantage they added also the competitive weapon of short lead times (Stalk 1988). Most of these achievements have been reached by a consequent application of JIT principles in Japanese companies together with an optimization of the whole supply chain. In western countries, the increased competitive pressure on cost, quality and time has led to the development and implementation of hybrid MPC methods. These generally fit better the manufacturing environments found in western countries than the pure JIT concept. The last shift in manufacturing strategy has been initiated by the agile manufacturing initiative. Rather than offering the customer a wide variety of options and models from which to choose, the customer works with the producer to arrive at solutions to the customer's specific problem. But as a survey of Gunasekaran and Yusuf (2002) shows, most related research activities are focused rather on issues like virtual enterprise formation, new information technologies and rapid prototyping technologies than on new MPC concepts. Nevertheless, customer driven manufacturing can generally be considered as the driving force behind the development of new MPC concepts. Similar conclusions have already been found earlier by Bullinger et al. (1986) and Landis (1997) who present requirements for manufacturing concepts, which have been derived from assumed future developments of the market conditions. They can be summarized as follows:

- *Higher flexibility*: Market conditions are changing faster and faster (shorter product life cycles, shorter intervals of product and process innovation).
- *Higher speed*: Due to increasing market pressure, higher delivery speed and reliability is required;
- *Higher customization*: Due to increasing market pressure, the variety of types will be increased (customer focus).

The goal of this chapter is threefold. First, a review of the classical MPC methods JIT/kanban, MRP and Inventory Control gives an overview of their underlying concepts that are either used to model these approaches in the simulation models or to understand better the design decisions taken for the hybrid MPC methods that are based on these classical MPC concepts. Second, by presenting an overview of existing hybrid MPC concepts, a state-of-the-art review is given for the development of modern MPC concepts. Third, the review of the characteristics of existing MPC methods serves as a basis for the definition of the novel aspects and the approximative application domain of DSSPL.

All reviewed MPC methods are analyzed and compared with respect to their concept, application domain and industrial experience, if available. Their concepts are further compared to basic principles or best practices in manufacturing planning & control that are presented in the following section.

2.1 Fundamental laws of Manufacturing Planning & Control

The development of principles and fundamental laws of manufacturing systems has surprisingly not a very long tradition. In the field of the development of new MPC methods, only recent research studies (Wiendahl 1987, Spearman et al. 1990, Suri 1997) have taken into account such fundamental principles as the limited capacity of production systems. In contrast, classical MPC methods like MRP typically assume unlimited capacity and fixed lead times. This section presents, therefore, principles of manufacturing system that are relevant to the development and configuration of production systems. These principles will serve as a basis for criticism of existing (classical and hybrid) MPC methods that are reviewed in the following sections.

2.1.1 Guidelines for the configuration and control of production systems

Wiendahl (1987) developed a new MPC method called Load-oriented manufacturing control that takes into account the dynamics of real manufacturing systems. In fact, the performance or throughput *TH* (average output of a production process per time unit) can only be increased to a certain level and further loading of a production system results only in increasing cycle times *CT* (time from when a job is released into a station or production stage to when it exits) and work in process *WIP*. Figure 2.2 shows the typical relationship between these variables that is valid for any capacity-constrained production system. It shows also the optimal working domain which represents a compromise between the achieved throughput *TH* and the work in process *WIP*.

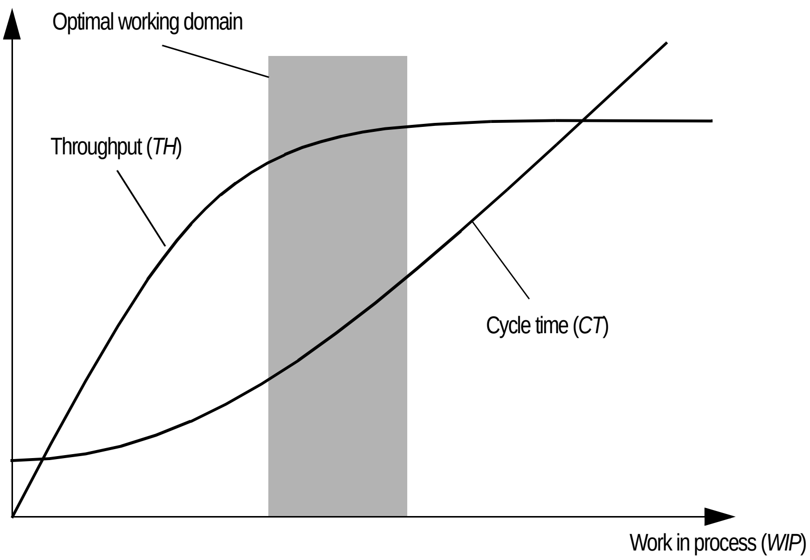
By extending the work of Wiendahl, Nyhuis and Wiendahl (1999) developed a set of fundamental laws describing the behavior of a general production system. The most important laws with respect to the configuration and design of MPC methods are as follows.

- Dispatching methods have a significant impact on the performance of a production system only if the job size is variable and if the *WIP* level is high;
- The variability of the job cycle times depends on the dispatching rule, the *WIP* level and the variability of the job sizes. Dispatching rules such as SPT (shortest process time) or LPT (longest process time) always generate a higher variability of job cycle times than the simplest dispatching rule FIFO (first in, first out);
- The service level of a production system depends on the average and variability of the job size. Short and stable job length therefore reduce the probability of lateness;
- The necessary *WIP* level for a certain throughput level depends mainly on the ability of the production system to adjust its capacity to load variations.

A very interesting characteristic of production systems is revealed by the first and second law that states that dispatching rules and local scheduling have only a significant impact on the performance if the *WIP* levels are high and that the simplest dispatching rule FIFO induces the lowest variability in the system. These laws are particularly intriguing with respect to the huge effort that is done in research and practice to find optimal solutions for scheduling and dispatching problems.

In another study, manufacturing systems are considered from the system dynamics theory point of view (Towill 1997). The approach presented in this paper is to avoid complexity in a supply chain or in a manufacturing system wherever possible. In fact, the theory of system dynamics shows that the probability of stable operation decreases dramatically if the number of system variables increases. The dynamic effects of batch and queue are identified as a typical source of self-induced fluctuations in a supply chain or in a manufacturing system. These are induced when two or more parts use the same segment of material flow, and when their flow is regulated by either ROP (Inventory Control) or MRP systems. The longer the lead time, the greater the problem arising from system instabilities. In order to reduce or avoid these problems, Towill presents six *Laws of Manufacturing* which can be applied as guidelines for the design of supply chains or manufacturing systems:

Figure 2.2 Relation between throughput (*TH*), cycle time (*CT*) and work in process (*WIP*) in a typical production system



- *Law of Gestalt*: The whole is not the sum of its parts and by extension a set of sub-optimum solutions can never produce a true optimum solution;
- *The law of material flow*: The efficiency of a manufacturing system is inversely proportional to the complexity of its material flow system;
- *The law of prescience*: It is not given to human beings to foretell the future;
- *The law of industrial dynamics*: If demand for goods is transmitted along a series of inventories using stock control (i.e. level triggered) ordering, then the amplitude of the demand variation will increase with each transfer;
- *The ordering cycle law*: If the various components made in a factory are ordered and made to different time cycles, they will generate high amplitude and unpredictable variations in both stocks and load;
- *The law of connectance*: A given direction of change in the value of any manufacturing system variable will induce, or be induced by a given direction of change in at least one other variable.

A similar approach is presented by Segerstedt (1999). He states that decreasing the product structure, both in width and depth, shortening the throughput times, standardizing and reducing complexity, and identifying bottlenecks are the keys to improve significantly efficiency and profitability of production systems.

Concepts and laws comparable to those of Wiendahl (1987) and Nyhuis and Wiendahl (1999) have been presented by Hopp and Spearman (1996) who developed a set of principles governing the behavior of production systems. Some of the most important laws that guided the development of the CONWIP method (Spearman et al. 1990) are listed below:

- *Variability*: Increasing variability always degrades the performance of a production system;
- *Variability buffering*: Variability in a production system will be buffered by some combination of inventory, capacity and time;
- *Utilization*: If a station increases utilization without making any other changes, average *WIP* and cycle time will increase in highly nonlinear fashion;
- *Assembly operations*: The performance of an assembly station is degraded by increasing any of the following: (1) Number of components being assembled, (2) Variability of component arrivals, (3) Lack of coordination between component arrivals;

Another important result presented by these authors is the relation that illustrate the impact of variability on the performance of production systems. One typical example is the following expression

$$TQ = \frac{cvid^2 + cvds^2}{2} \frac{sysint}{1 + sysint} TP \qquad \text{(Eq. 2.1)}$$

that shows how the mean queue time of a job *TQ* depends on the two coefficients of variability of the intervals between two consecutive orders $cvid$ and the processing time $cvds$, the utilization or system load *sysint* and the mean effective processing time *TP*.

2.1.2 Best practice

One of the most extensive lists of best practices in manufacturing has been published by Sheridan (1997). Based on the results of a competition held annually called "*America's Best Plants - 10 leading-edge facilities that have demonstrated excellence in manufacturing, as well as a flair for making signif-*

icant improvements in performance" published by the magazine *Industry Week*, he presented manufacturing concepts and practices that lead to high performance. The metrics applied were: Annual number of work-in-process turns, first-pass quality yields, parts-per-million defect rates, reduction in manufacturing cycle time, inventory ratios and on-time delivery. The following activities are stressed by all winners: Total quality management, continuous improvement, employee empowerment, use of work teams, employee cross-training and cross-functional teams. Most of the finalists also put emphasis on the following activities: Cycle time reduction, JIT/continuous flow, competitive benchmarking, inventory reduction, agile manufacturing, supplier partnership, preventive maintenance, reduction of order lead-time and cellular manufacturing (team environment). Thus, most of the best companies adopt a JIT/continuous-flow concept, typically using kanban signals to pull production along. The vast majority also operate primarily in a build-to-order mode. In markets that demand customized products, one strategy today is to build generic subassemblies that can be quickly customized to meet the end user‘s needs. Beside technological aspects, all finalists show a high commitment to employee involvement and empowerment, teamwork and innovation.

2.1.3 Complexity of MPC methods

As pointed out by Towill (1997) and Segerstedt (1999) the complexity and effort needed for generating feasible production plans often determines the effective performance of an MPC method that can be achieved in practice. Unfortunately, as shown by a review of Edmond (1996), there exists no single definition of complexity. Most of these definitions have, however, in common that complexity is characterized by the two aspects of variety and constraints[1]. Variety is related to the number of different parts or possible states of a system whereas constraints define the interdependencies between them. Complexity with respect to manufacturing systems can, therefore, be defined for the production process itself and for the MPC method that is used to control it. The link between the complexities of these two subsystems is defined by Ashby's law (Ashby, 1956) of requisite variety. This law states that a control system (MPC method) must have at least as many degrees of freedom as the controlled system (production system) in order to achieve complete control. The required degree of control over the production process is, however, imposed by the applied manufacturing strategy. As illustrated at the beginning of this chapter (Figure 2.1) manufacturing strategies which only focus on volume lead to simpler MPC methods like Inventory Control than more demanding manufacturing strategies (costs, quality, speed, agility,...) that lead to MPC methods allowing a finer control of the production process.

In this work this issue is addressed by defining the complexity Γ of an MPC method that is assumed to be proportional to the number of logistic variables and parameters that have to be determined and/or reviewed in order to "run" a given production system. By generalizing the process of "running" a production system, two distinct activities can be defined. The first activity corresponds to the configuration of the MPC method by defining its parameters e.g. the order quantities or lead times, whereas the second activity corresponds to the monitoring of current logistic variables that are necessary to make decisions e.g. order releases. The complexity Γ of an MPC method is therefore defined by the two terms $\Gamma 1$ and $\Gamma 2$ that represent the two above defined activities. Finally, a relative complexity Γ_{rel} is defined for the analyzed MPC methods with respect to the complexity of the Inventory Control method that is considered as the simplest MPC method. Consequently, a high positive relative complexity of MPC methods signifies an increased complexity that can, with respect to the statement of Towill (1997) and Segerstedt (1999), lead to difficulties in achieving feasible production plans.

1. Principia Cybernetica Web: http://pespmc1.vub.ac.be (Editors: F. Heylighen, C. Joslin and V. Turchin)

2.2 Inventory control

Inventory control is focused on optimizing the inventory control variables with the objective of assuring a required level of logistic performance at minimum cost. Typical inventory control variables are the order quantity, the reorder point and the safety stock level whereas the demand, replenishment lead time and inventory carrying and ordering or setup costs are normally the given logistic and cost parameters. All the inventory control models presented have in common that no interaction is assumed between different inventory items (single-product, single-location models) and that all cost parameters are constant. More sophisticated concepts such multi-item or multi-level inventory control methods (see Klose and Tüshaus 1994 for a review) are not included in this review basically due to their increased complexity. In fact, as pointed out by Federgruen (1993), solutions can particularly in the case of multi-level problems only be found with the help of heuristics. The main advantage of the Inventory Control Method over other existing MPC methods, the simplicity of the concept, is thus lost. Probably due to this reason, no industrial implementation case studies of these methods are known that have been performed in the assumed application domain of DSSPL.

The simplest and oldest class of inventory models termed Economic Order Quantity (EOQ) model is based on the assumption of a deterministic and stationary demand. A second important class of inventory models termed Dynamic Lot Sizing inventory models is derived from the EOQ models by relaxing the assumption of a stationary demand. Finally, the last important class of inventory models, termed Statistical Inventory models, is characterized by the assumption of a stochastic demand.

2.2.1 Economic Order Quantity models

One of the first Inventory control models has been developed by Harris (1913), which solved the problem of the optimal or economic order quantity for given ordering and inventory carrying costs. Thus, the expression of the optimal order quantity or lot size EOQ

$$EOQ = \sqrt{2DR\rho} \qquad \text{(Eq. 2.2)}$$

has been found by assuming no capacity constraints (instantaneous delivery) and a constant deterministic demand rate DR and by introducing the ratio $\rho = C_O / C_I$ of the ordering costs C_O and unit inventory carrying costs C_I.

An inventory control model directly derived from the EOQ model is the periodic order quantity (POQ) model, which determines the economic time between two orders TBO by dividing the EOQ by the demand rate. The time between two orders becomes therefore

$$TBO = \frac{EOQ}{DR} = \sqrt{\frac{2\rho}{DR}} . \qquad \text{(Eq. 2.3)}$$

More recently, the EOQ model has been extended by including assumptions such as quantity discounts (Hadley et al. 1963), inflation (Buzacott 1975) or demand with trends (Resh et al. 1976). However, surveys in industry have shown that the basic EOQ model is still the most widely used inventory model in practice (Osteryoung et al. 1986).

2.2.2 Dynamic Lot Sizing models

Dynamic Lot Sizing inventory models are based in contrast to the EOQ model on the assumption of a variable, but still deterministic demand. Wagner & Whiting (WW) formulated first a solution for this problem (Wagner and Whitin 1958) which is equivalent to finding optimal order sizes for the next n periods $(q_1, q_2, \ldots, q_n)$ for given requirements over the next n periods $(req_1, req_2, \ldots, req_n)$. For the end inventory il_t in period t

$$il_t = \sum_{j=1}^{t} (q_j - req_j) \qquad \text{(Eq. 2.4)}$$

and inventory carrying costs $C_I(t, il_t)$ and order costs $C_O(t, q_t)$ incurred in period t, the objective is to find order quantities that

$$\text{minimize} \sum_{t=1}^{n} [C_O(t, q_t) + C_I(t, il_t)] \qquad \text{(Eq. 2.5)}$$

$$\text{subject to} \quad \begin{array}{c} il_t = \sum_{j=1}^{t} (q_j - req_j), \\ il_t \geq 0,\ t = 1, \ldots, n, \\ il_0 = 0. \end{array} \qquad \text{(Eq. 2.6)}$$

Wagner and Whitin developed an algorithm using dynamic programming techniques which is based on the observation that an optimal ordering policy has the so-called Wagner-Whitin property

$$q_t il_{t-1} = 0, \quad t = 1, 2, \ldots, n. \qquad \text{(Eq. 2.7)}$$

The solution algorithm, whose detailed description is out of the scope of this thesis, allows the determination of an optimal solution for the problem. However, due to the computational burden, heuristics have been developed that approximate the exact WW solution such as the Silver & Meal (SM) method.

In the case of the SM method (Silver and Meal 1973), the average cost $C(N)$ of inventory carrying and ordering costs is evaluated as a function of the number of periods N. If $(req_1, req_2, \ldots, req_n)$ are the requirements over the next n periods, it follows that

$$C(N) = \frac{1}{N}\left(C_O + C_I \sum_{j=1}^{N} \frac{2j-1}{2} req_j\right). \qquad \text{(Eq. 2.8)}$$

The method is to compute $C(N)$ for $N = 1, 2, \ldots,$ stop the first time that

$$\frac{1}{N}\left(\rho + \sum_{j=1}^{N} \frac{2j-1}{2} req_j\right) > \frac{1}{N-1}\left(\rho + \sum_{j=1}^{N-1} \frac{2j-1}{2} req_j\right), \qquad \text{(Eq. 2.9)}$$

and set

$$q_1 = \sum_{j=1}^{N-1} req_j . \qquad \text{(Eq. 2.10)}$$

The process is started again at period N and continues until the end of the planning horizon is reached.

The principal interest of the dynamic lot sizing methods lies in the fact that they are used frequently in Material Requirement Planning (MRP) systems for the determination of the optimal lot sizes.

2.2.3 Statistical Inventory models

The wide variety of Statistical Inventory models can be grouped according to the two criteria cost model and review frequency. The first criterion divides the Statistical Inventory models into the full cost and reduced cost models. The difference between the two approaches is whether or not shortage costs (unsatisfied demand) are included in the cost model. In the full cost model, total costs also include shortage costs in addition to the inventory carrying and ordering costs. Due to the difficulty of estimating shortage costs with any level of confidence, the reduced cost model replaces the shortage costs by a service level constraint.

The second criterion divides the reorder point models into continuous and periodic review systems. In continuous review systems, inventory levels are monitored continuously and inventory ordering decisions are made as soon as the inventory level drops below the reorder point. In a periodic review system, inventory levels are monitored only at specific review times.

This review focuses on so-called (q, r) models (Wilson 1934), which assume continuously monitored inventory levels, replenishment quantities greater than one and a stochastic demand occurring possibly in batches. (q, r) models are based on the determination of a fixed order quantity q that is ordered every time the reorder point r is reached. Therefore, in the full cost version of the (q, r) model, values of q and r have to be found that minimize the total costs including inventory carrying, ordering and shortage costs. Figure 2.3 illustrates the mechanics of the (q, r) model with *ss* as the safety stock level and $D = E(\zeta)$ as the mean of the random demand ζ during the replenishment lead time *lt*.

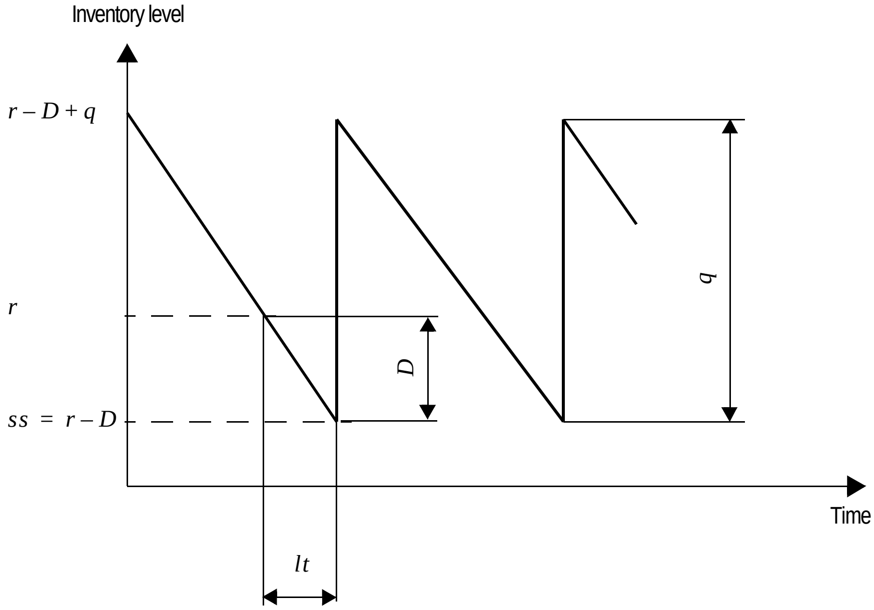
With C_S as shortage costs per unit, *d* as the average annual demand and $f(x) = d/dxF(x)$ as the density function of demand during replenishment lead time *lt* (with $F(x) = P(\zeta \le x)$), the expression for the total cost becomes

$$C(q, r) = C_O\frac{d}{q} + C_I\left(\frac{q}{2} + r - E(\zeta)\right) + C_S\frac{d}{q}E[(\zeta - r)]^+ \qquad \text{(Eq. 2.11)}$$

with

$$E[(\zeta - r)]^+ = \int_r^{\infty} (x - r)f(x)dx \qquad \text{(Eq. 2.12)}$$

Figure 2.3 (*q*, *r*) model



as the expected number of shortages. By setting the first derivates of $C(q, r)$ with respect to q and r, respectively, to 0, one gets

$$q = \sqrt{\frac{2d(C_O + C_S(E[(\zeta - r)]^+))}{C_I}} \qquad \text{(Eq. 2.13)}$$

and

$$F(r) = 1 - \frac{C_I q}{C_S d} \qquad \text{(Eq. 2.14)}$$

that must be solved simultaneously.

As already mentioned, shortage costs are very difficult to estimate. In fact, the true shortage costs include not only expenses due to keeping track of unfilled orders and lost profit, but also loss of customer goodwill (Leonard and Roy 1994). For that reason, shortage costs are, in the reduced cost model, replaced by a service level constraint which is easier to estimate with respect to the chosen corporate manufacturing strategy. Thus, with a required service level *SL*, the total costs

$$C(q, r) = C_O \frac{d}{q} + C_I\left(\frac{q}{2} + r - E(\zeta)\right) \qquad \text{(Eq. 2.15)}$$

must be minimized with respect to the service level constraint (fill rate criterion)

$$\frac{E[(\zeta - r)]^+}{q} \le SL \, . \qquad \text{(Eq. 2.16)}$$

From the practitioner point of view, the disadvantage of the classical (q, r) models (full and reduced cost models) is the need for iterative solution algorithms. Even though heuristics have been developed to solve the problem more conventionally (Tijms and Groenevelt 1982 and Yano 1985 for reduced cost models), q is often determined directly based on the EOQ model (Lee and Nahmias 1993). Then, by assuming that the demand during the replenishment time ζ and the replenishment time lt are normally distributed independent variables, the reorder point r can be determined by solving

$$r = E(lt)E(\zeta) + z\sqrt{Var(lt\zeta)} \qquad \text{(Eq. 2.17)}$$

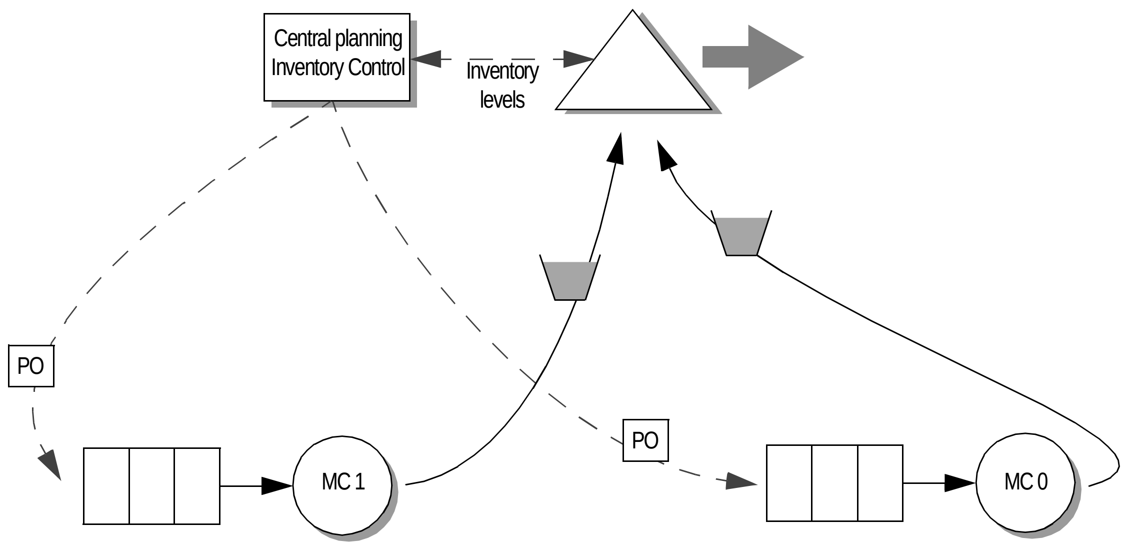
with

$$Var(L\zeta) = E(lt)^2 Var(\zeta) + E(\zeta)^2 Var(lt) + Var(lt)Var(\zeta) \qquad \text{(Eq. 2.18)}$$

and z as the appropriate value from the standard normal distribution corresponding to the shortage risk 1-α.

As shown in Figure 2.4, production systems managed by an Inventory Control system are generally characterized by a centralized planning with central inventory.

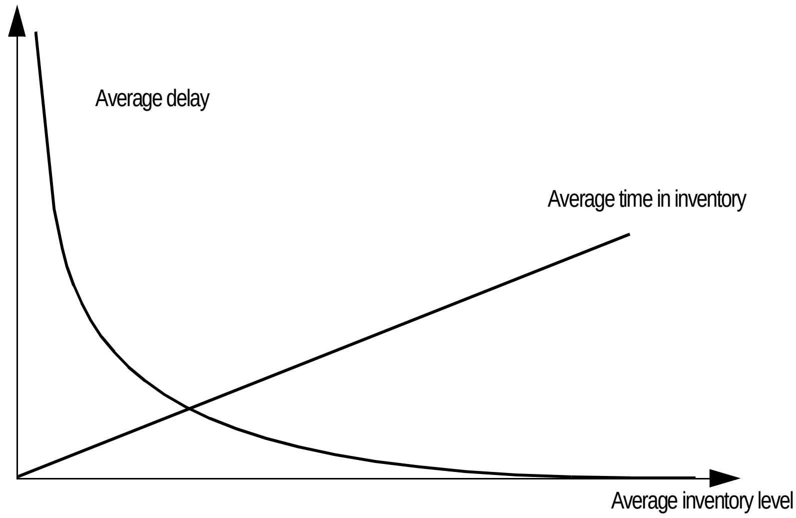
Figure 2.4 Inventory Control concept applied to a two-stage production system



2.2.4 *Critique of the Inventory Control method*

The application domain of the Inventory Control MPC method is virtually unlimited. It was the dominant MPC method until the advent of the MRP and JIT/kanban method. Even though its simplicity is attractive, its performance is poor compared to modern methods. The relationship between the inventory level, the average delay and the inventory cycle time is illustrated according to Nyhuis and Wiendahl (1999) in Figure 2.5. With the Inventory control MPC method, high service levels can, therefore, only be achieved with increased inventory levels. Furthermore, as shown by Towill (1997), it has the tendency to amplify the effective demand. However, since production is triggered only when a demand has occurred, it is generally insensitive to forecast errors as long as the estimated average demand does not increase significantly.

Figure 2.5 Relationship between inventory level, average delay and time in inventory (Nyhuis and Wiendahl 1999)



The complexity Γ_{IC} of the Inventory Control method is defined for the (q, r) method. With NV as the number of parameters or logistic variables, $\Gamma1_{IC}$ and $\Gamma2_{IC}$ become therefore

$$\Gamma1_{IC} = XNV1_{IC} \qquad \text{(Eq. 2.19)}$$
$$\Gamma2_{IC} = XNV2_{IC}$$

with
X = number of items (final products and components);
$NV1_{IC}$ = 2 (order quantity q and reorder point r);
$NV2_{IC}$ = 1 (inventory level il).

The choice for the Inventory Control method is a trade-off decision between its simplicity (simple concept, low planification effort, relative insensitivity to forecast errors) and increased inventory holding costs.

2.3 MRP

The development of the MRP method (Orlicky 1975) illustrated in Figure 2.6 was initiated primarily by the limitations of statistical inventory systems and the beginning of availability of computer resources in the 1960s. In fact, by ignoring the specific timing of actual and future demands and the link between dependant and independent demand, statistical inventory systems, particularly in lumpy demand environments lead to high inventory levels. The MRP concept addresses this problem by introducing a procedure that determines a time-phased production schedule for all items based on the master production schedule (independent demand) for final products, the product structure (bill of material, BoM), the estimated production lead times and inventory records of every item. It is further assumed in most MRP systems that time is divided into constant periods (time buckets). The MRP procedure is normally divided into four steps that are executed for every item, starting from the lowest (final products) to the highest level of the bill of material (Vollmann et al. 1997). In the first step called *Netting*, the net requirement of every item is determined based on the demand (gross requirement) and the projected on-hand inventories including the scheduled receipts. It is assumed that the demand d is covered by the on-hand inventory il until a certain period t' when demand exceeds the remaining on-hand inventory level. The period t' is found by evaluating the recursive expression for the on-hand inventory

$$il = il_{t-1} - d_t \qquad \text{(Eq. 2.20)}$$

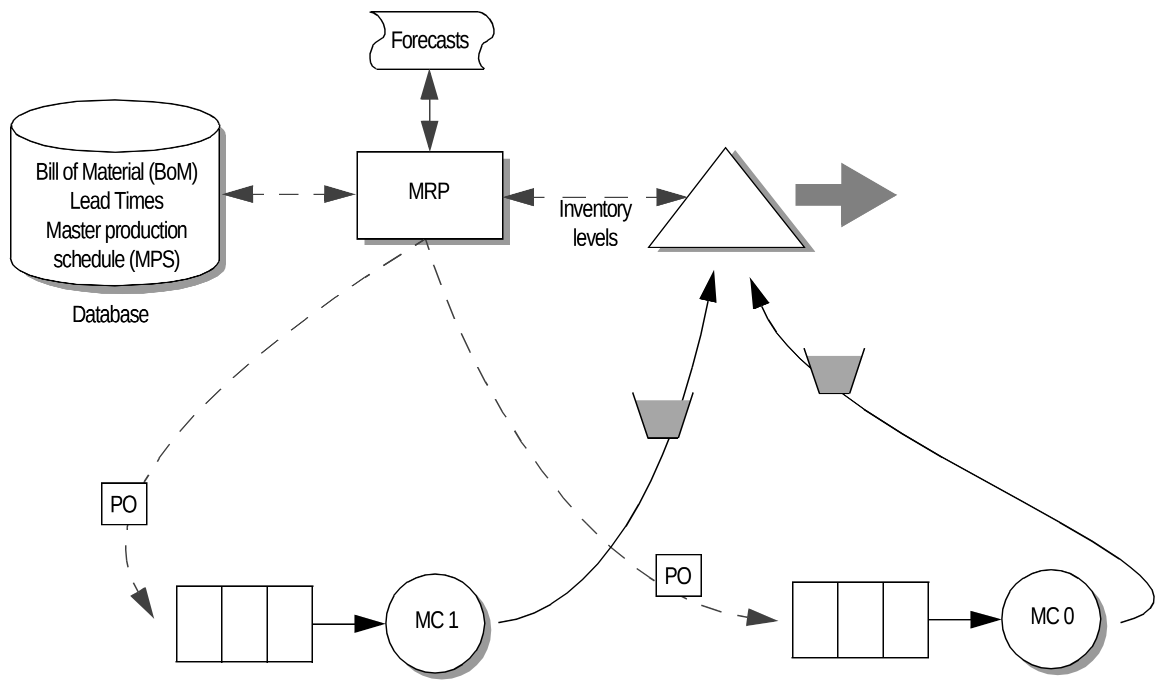
for every period starting with the current period $t = 1$ with il_0 equal to the current on-hand inventory level. Consequently, the period t' is defined as the period for which il_t becomes less than zero. For that period t', the net requirement $nreq_t$ is consequently defined by the difference between the gross requirement and the on-hand inventory level. For periods beyond t', the net requirement is equal the demand.

$$nreq_t = \begin{cases} 0 & \text{for } t < t' \\ -il_t & \text{for } t = t' \\ d_t & \text{for } t > t' \end{cases} \qquad \text{(Eq. 2.21)}$$

The second step called *Lot Sizing* consists in scheduling production quantities to satisfy the net requirements by applying a lot-sizing technique. Typical lot-sizing rules are the lot-for-lot technique and rules based on the WW or *EOQ* model described in the previous section §2.2. In the case of the lot-for-lot (LFL) lot sizing technique, the production quantities (planned order receipts) are equal to the net requirement.

In the third step called *Time Phasing*, the planned order release are determined by subtracting the estimated lead time from the period where the production quantities defined in step 2 are required. The

Figure 2.6 MRP applied to a two-stage production system



estimated lead time for a particular item corresponds in most MRP systems to a constant, independent of the lot size and the actual capacity of the production resources.

Finally, in the last step called *BoM Explosion*, the planned order releases is translated according to the bill of material to gross requirements for all subitems of the considered item. The *BoM Explosion* procedure thus translates the independent demand for final products into the dependant demands for the components.

2.3.1 Critique of the MRP method

Over the last three decades, MRP has become the principal MPC method used in western countries. One of the most representative surveys on the impact and benefits of MRP has been performed by Anderson et al. (1982). Based on the responses of 679 companies they evaluated mainly the impact of MRP on logistic performance measures as well as on marketing or strategical issues. The following Tables 2.1 and 2.2 summarize these results.

Table 2.1: Impact of MRP on logistic performance (Anderson et al. 1982)

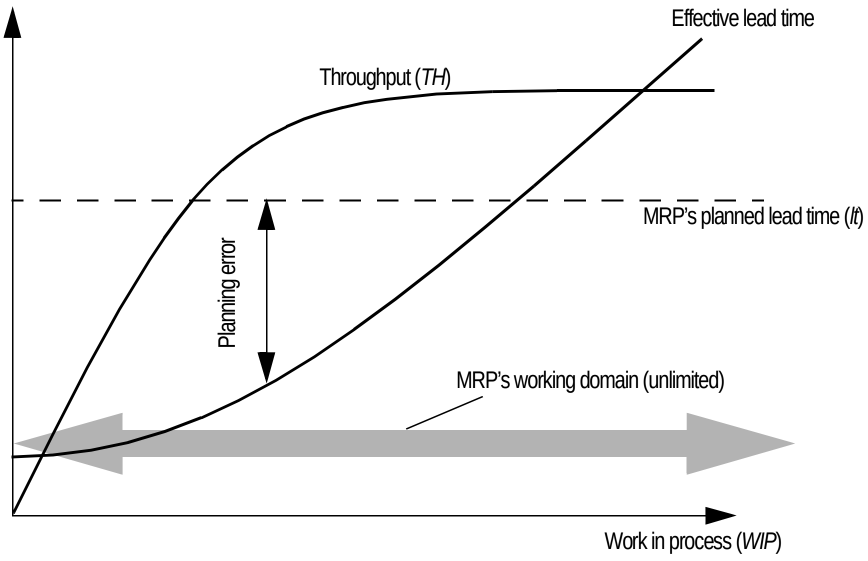
	"Pre-MRP" Estimate	**Current Estimate**
Inventory turnover	3.2	4.3 (+34%)
Delivery lead time (days)	71	59 (-17%)
Percent of time meeting delivery promises (%)	61	76 (+25%)
Percent of orders requiring "splits" because of unavailable material (%)	32	19 (-40%)

Table 2.2: Impact of MRP on the improvement (1 = little/none, 2 = some, 3 = much, 4 = very much) of marketing or strategical issues of companies (Anderson et al. 1982)

	Average score
Improved competitive position	2.1
Improved customer satisfaction	2.5
Improved plant efficiency	2.4
Better production scheduling	2.7
Better control of inventory	3

The results in Table 2.1 show that an implementation of MRP can result in an increase of approximately 30% of the logistic performance of a company. It is assumed that this improvement is due to the advanced concept of MRP compared to the Inventory Control method. However, the rather disappointing results shown in Table 2.2 are typical for similar findings from other reviews. Higher scores have only been achieved for the ability of MRP to improve production scheduling and inventory control. On the other hand, the overall competitive position of companies has not been improved significantly due to the implementation of MRP. Despite an improved performance compared to inventory control systems, several problems of the basic MRP procedure described above were recognized therefore early on. In fact, particularly the underlying concept of MRP assuming infinite production capacity and its dependency on accurate forecasts often results in unrealistic production plans. Figure 2.7 illustrates how MRP's concept of

Figure 2.7 MRP's working domain



unlimited capacity and constant lead times contrasts with the effective behavior of a capacity-constrained production system. Furthermore, due to the characteristics of certain lot-sizing rules, minor changes in the master production schedule often result in a large change in planned order releases (MRP nervousness). These problems have been addressed by the development of the MRPII or Material Resource Planning concept, which combines the basic MRP procedure with an integrated planning and control framework. Instead of assuming infinite capacity, production plans are checked against the available capacity and modified when necessary. Other important concepts of MRPII are demand management, improved forecasting, freezing techniques of the master production schedule to reduce MRP nervousness and the production activity control function which monitors the feasibility of the production plan (Vollmann et al. 1997). However, as pointed out by Hopp and Spearman (2000), even the integration of capacity planning in the MRPII concept does not solve the infinite capacity problem since capacity planning itself is also based on the obviously wrong assumption of constant cycle times. Furthermore, the complexity, particularly of the MPRII concept, leads to a system that is difficult to control (see Yeung et al. 1998 for a review of parameters affecting the effectiveness of MRP systems).

The complexity Γ_{MRP} of MRP is significantly higher than that of the Inventory Control method mainly due to MRP's production planning. In fact, a future demand has to be forecast for every final product (independent demand) for a planning period (planning horizon) that is at least as long as the total accumulated cycle time of the final products. Thus, $\Gamma 1_{MRP}$ and $\Gamma 2_{MRP}$ become:

$$\begin{aligned} \Gamma 1_{MRP} &= XNV1_{MRP} + K_{MRP} \\ \Gamma 2_{MRP} &= X_{FP} T_{PH} NV21_{MRP} + XNV22_{MRP} \end{aligned} \quad \text{(Eq. 2.22)}$$

with

X = number of items (final products and components);
$NV1_{MRP}$ = 3 (lead time *lt*, safety stock *ss*, lot-sizing rule);
K_{MRP} = 1 (aggregate product structure, bill of material);
X_{FP} = number of final products (independent demand);
T_{PH} = number of time buckets within the planning horizon;
$NV21_{MRP}$ = 1 (forecasts);
$NV22_{MRP}$ = 2 (inventory level *il* and work-in-process *WIP*).

The application domain of MRP is similar to that of the Inventory Control method and thus virtually unlimited. MRP is able to control and plan the production of a wide variety of complex products. The decision for the choice of MRP is therefore a trade-off between its planning and control capacity (wide application domain) and its problems with accurate production control.

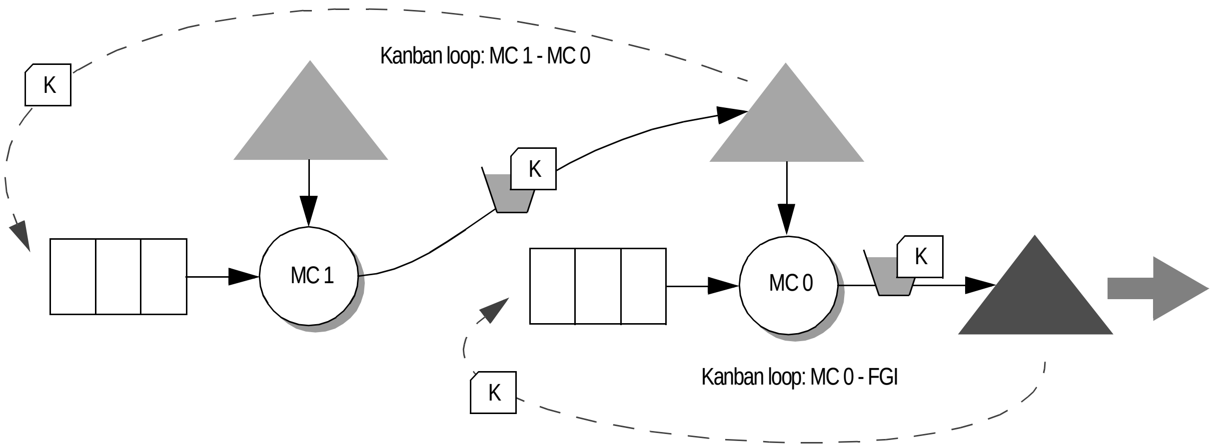
2.4 JIT/Kanban

The Just-in-Time (JIT) concept originated in Japan at Toyota in the 1950s where it was developed in order to improve the performance of the classical Inventory control systems. However, instead of just extending the existing production concepts, a system-oriented approach has been adopted which takes into account the whole production system. The JIT concept includes, therefore, not only a production control concept but also techniques and guidelines for the product and process design and for human and organizational aspects. The ten most important JIT practices are: quality circles, total quality control, focused factory, total productive maintenance, reduced setup times, group technology, uniform workload, multi-function employees, Kanban and just-in-time purchasing (White et al. 1999). According to Golhar and Stamm (1991) the overall goal of these actions are the reduction of waste in time, space and material.

One of the most important tools for realizing the JIT concept from an operational point of view is the kanban production control concept that is illustrated in Figure 2.8. In a kanban controlled production system, production is only triggered when consumption has occurred. This is realized by a certain number of cards, called kanbans, circulating between two consecutive work centers where the first work center produces items that are consumed by the second work center. Kanbans act as production orders and are sent from the consuming work center back to the supplying work center as soon as a certain quantity of items has been consumed. In the first work center, the reception of the kanbans triggers production as soon as their number is equal to or higher than a predefined trigger level. After completion, the fulfilled production order (kanban) is sent forward to the consuming work center.

The kanban system described above is based on the one-card or single-card kanban concept where only production authorizing kanbans (production kanbans) are used. In the two-card or dual-card kanban concept, the same procedure is divided into two activities production authorization and transport. The first activity is, as in the one-card concept, controlled by production kanbans, whereas the transport between the

Figure 2.8 One-card kanban concept applied to a two-stage production system with material flow from machining center MC1 to machining center MC0



work centers is triggered by the so called transport kanbans. In this thesis, only the single-card concept is considered since the dual-card kanban system is mainly used at Toyota (Schonberger 1983).

Due to the success and popularity of JIT/kanban its optimal configuration has attracted much attention in research. The most simple approach is the so-called Toyota formula

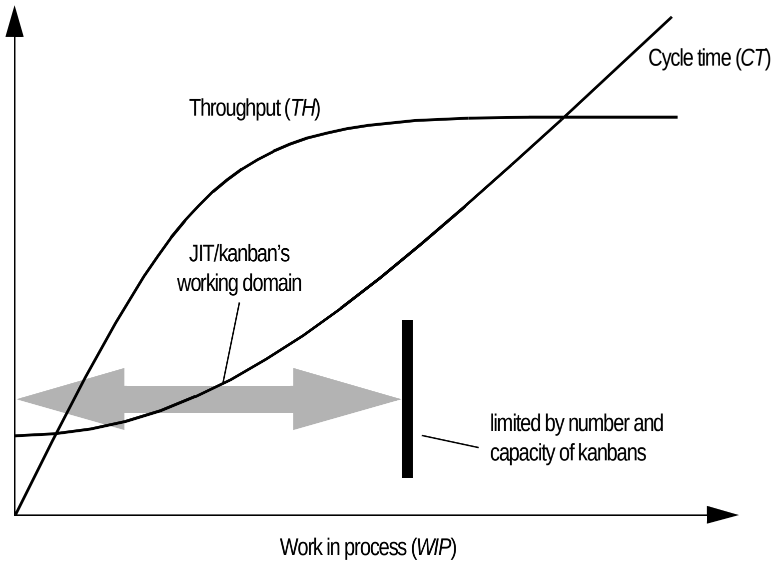
$$nk = \frac{DRlt(1+\sigma)}{ck} \qquad \text{(Eq. 2.23)}$$

that computes the number of kanbans nk circulating in one kanban loop as a function of the average demand rate DR, the replenishment lead time of one kanban lt, the capacity of one kanban ck and a safety factor σ (Monden 1983). A review of more sophisticated approaches based on either mathematical programming, stochastic theory or simulation is given by Price et al. (1994). However, as pointed out by them, models based on mathematical programming and stochastic theory suffer from high mathematical complexity that exclude their application in real-world environments. In contrast, optimization models based on simulation are not limited with respect to the complexity of the problem but rather by the effort to generate and calibrate the simulation model (Hachen et al. 2000).

2.4.1 Critique of the JIT/kanban method

During the last two decades, many companies decided to implement some or all aspects of the JIT/ Kanban method concept due to its apparent success in Japanese firms. Two of the most representative reviews of existing JIT implementations have been presented by Crawford et al. (1988) and Gilbert (1990).

Figure 2.9 JIT/kanban’s working domain



Based on the analysis of 36 and 141 companies respectively, they studied the impact of the JIT/kanban concept on logistic performance. Table 2.3 summarizes the results obtained by Crawford et al. (1988).

Table 2.3: Impact of JIT/Kanban on logistic performance (Crawford et al. 1988)

	Mean improvement [%]	**Range [%]**
Inventory reduction	41	10-90
Manufacturing costs	17	5-33
Lead Time	40	10-90
Improved product quality	26	1-50
Improved competitive position	15	3-30
Increased profit margin	54	5-400

The results show that the logistic performance is significantly improved with the JIT/Kanban method. However, as indicated by the large range of possible improvements, both reviews stress the difficulties in implementing JIT/Kanban correctly. They define as principle obstacles for a successful implementation of JIT cultural resistance to change, lack of resources and lack of top management understanding or commitment. However, there exist not only organizational obstacles for a successful implementation of JIT/kanban. In fact, as shown by many simulation studies (see in §4) only products with a relative stable demand and manufacturing processes (low setups, low failure rates, only occasional quality problems) can be managed efficiently by the JIT/kanban method. These prerequisites are obviously easier to fulfill in a mass production environment with mature products and low product variety than in manufacturing environments with customized products and consequently a significantly higher product variety. A review of these organizational and operational problems related to an implementation of JIT/kanban is given by Prasad (1995). He presents a structured methodology to implementing the right JIT techniques, such as quick setup, reduced lot sizes or product simplification, that are adapted to the manufacturing environment in which JIT/kanban is expected to operate.

The choice for JIT/kanban is, therefore, a trade-off decision between the improvement potential of JIT/kanban and the difficulties and obstacles to implementing it in manufacturing environments that are not considered as optimal. There exists, however, a consensus in research and practice that JIT/kanban is the most efficient MPC method if the above mentioned JIT conditions are fulfilled. From an operational point of view, JIT/kanban's advantage over other MPC methods is, as illustrated in Figure 2.9, mainly due to the efficient and simple limitation of the *WIP* by the use of kanbans.

The number of variables needed to "run" the JIT/Kanban method is similar to those required for Inventory Control. In contrast to the Inventory Control and MRP method though, no logistic variables have to be reviewed in the case of JIT/kanban, since the production orders are created only once in the form of kanbans. However, as described by Courtois (1995), JIT/kanban can handle only a limited number of products at one production stage due to limited space (containers) and dispatching problems. For these practical reasons, eight is generally considered as a maximum of products that can be managed by JIT/Kanban at one stage. The complexities $\Gamma1_{JIT}$ and $\Gamma2_{JIT}$ become therefore

$$\begin{aligned} \Gamma1_{JIT} &= XNV1_{JIT} \\ \Gamma2_{JIT} &= XNV2_{JIT} \end{aligned} \qquad \text{(Eq. 2.24)}$$

with

X = number of items (final products and components);

$NV1_{JIT}$ = 4 (number *nk* and capacity *ck* of kanbans, lower and upper trigger level *llow* and *lup*).

$NV2_{JIT}$ = 1 (kanban level).

Finally, a very illustrative example of the impact of the classical MPC methods Inventory Control, MRP and JIT/kanban on the inventory levels at Xerox is given by Flapper et al. (1991) and illustrated in Figure 2.10. They do not indicate, however, if the improvement of the inventory levels are only due to the introduction of a new MPC method or are also the consequence of a possible improvement of the manufacturing environment (new manufacturing equipment, lower setup times, better suppliers, different design,...).

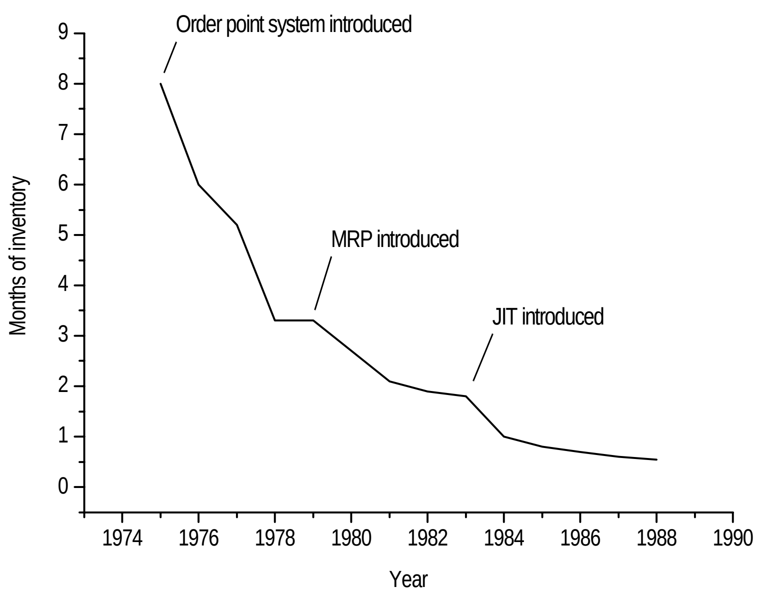
2.5 Load-oriented manufacturing control

The Load-oriented manufacturing control method takes into account the dynamic relationship between the variables that describe the performance and state of a production system. This relationship can be described with the help of the expression

$$L = \lambda W \qquad \text{(Eq. 2.25)}$$

called *Little's law* that has been developed in queuing theory (Gross and Harris 1998). It states that the mean number of customers in a stationary queuing system L is equal to the product of the customer arrival rate λ and the mean waiting time in the system W. The equivalent relationship for production systems is therefore found by assuming that the arrival rate of incoming orders (λ) is equal to the throughput TH if the system is in a stationary state. By further assuming that L and W are equivalent to WIP and CT respectively, *Little's law* becomes for production systems

Figure 2.10 The history of inventories at a Xerox plant (Flapper et al. 1991)



$$CT = \frac{WIP}{TH}. \qquad \text{(Eq. 2.26)}$$

In the Load-oriented manufacturing control method, a formula similar to (Eq. 2.26) is used that has been developed based on the funnel model. In contrast to (Eq. 2.26) the funnel formula is based on a work-content description of the variables. Thus, the work-in-process *WIP* is described by the work-content of the waiting jobs in hours. With *Perf* as the mean performance measured in work in hours per shop calender days and *R* as the mean range (mean runout time of production system measured in shop calender days), the funnel formula becomes

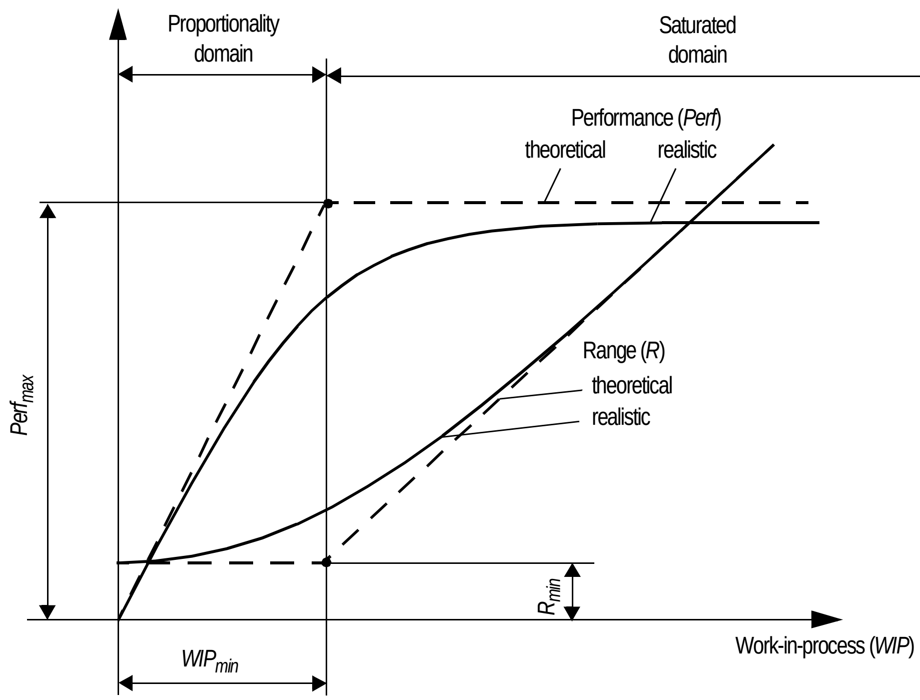
$$R = \frac{WIP}{Perf}. \qquad \text{(Eq. 2.27)}$$

In the Load-oriented manufacturing method (Eq. 2.27) is used together with the theory of logistic operating curves (Nyhuis and Wiendahl 1999) to generate diagrams similar to those shown in Figure 2.2 that represent the current state of a production system. Figure 2.11 shows such a diagram that can be generated for every capacity-constrained production system by a two-step approach. In the first step, the theoretical curves are determined based on (Eq. 2.27) and the minimal (idealized) mean work-in-process WIP_{min}, the maximally available performance $Perf_{max}$ and the minimal range R_{min} have to be determined. WIP_{min} is determined by

$$WIP_{min} = TP_m(1 + TP_{sd}^2) \qquad \text{(Eq. 2.28)}$$

with TP_m and TP_{sd} as the mean and standard deviation of the planned processing and setup times. $Perf_{max}$ is equal to the performance of the production system when the human and technical resources are fully available. R_{min} is obtained by dividing WIP_{min} by $Perf_{max}$.

Figure 2.11 Relation between performance (*Perf*), Range (*R*) and work-in-process (*WIP*) in a typical production system



Then, in the second step the effective (realistic) curves are constructed based on the transformation of the c-Norm-function $1 = x^c + y^c$ to a coordinate system that corresponds to the theoretical performance. The transformed c-Norm-function becomes therefore

$$x = x_1\left(at + 1 - \sqrt[c]{1 - t^c}\right) \qquad \text{(Eq. 2.29)}$$

and

$$y = y_1\left(1 - \sqrt[c]{1 - t^c}\right)$$

with
x, y = coordinates of a point of the theoretical throughput;
x_1 = WIP_{min};
y_1 = $Perf_{max}$;
t = 0...1;
a, c = form factors.

Then, by replacing *x* and *y* by *WIP* and *Perf* and by replacing the form factors *a* and *c* by estimates based on empirical and simulation studies, one gets

$$WIP = WIP_{min}(10t + 1 - (1 - \sqrt[4]{t})^4) \qquad \text{(Eq. 2.30)}$$

and

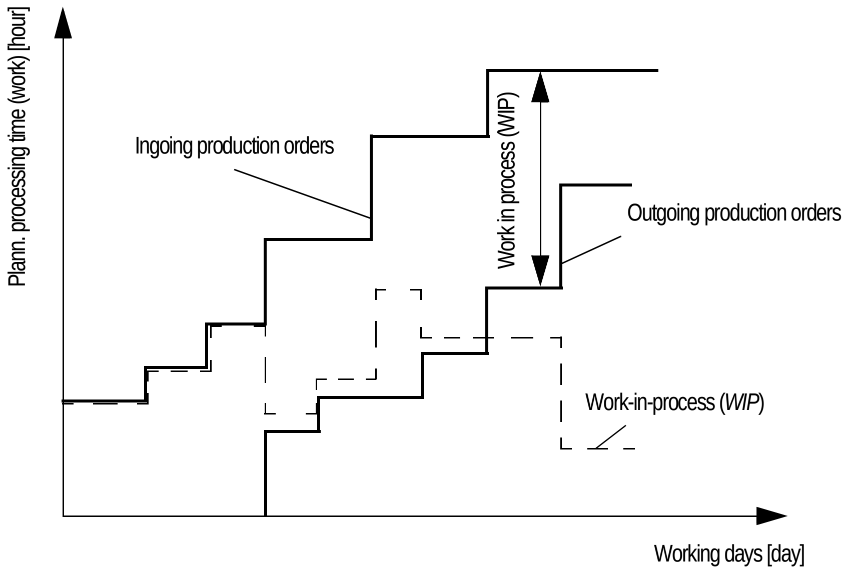
$$Perf = Perf_{max}(1 - (1 - \sqrt[4]{t})^4)\,. \qquad \text{(Eq. 2.31)}$$

Further important measures and tools frequently used in the Load-oriented manufacturing control method is the so-called flow rate *FR* and the load diagram. The flow rate *FR* expresses the ratio between the mean values of the cycle time and the effective production time

$$FR = \frac{CT}{TP} \qquad \text{(Eq. 2.32)}$$

and is an effective measure to detect congestions in a production system. Empirical and simulation studies show that average values of *FR* of 3...4 are a good compromise between the achieved throughput *TH* and average cycle times *CT*. The load diagram of a production system is based on the sampling and representation of all incoming and outgoing production orders with their planned production time over a certain

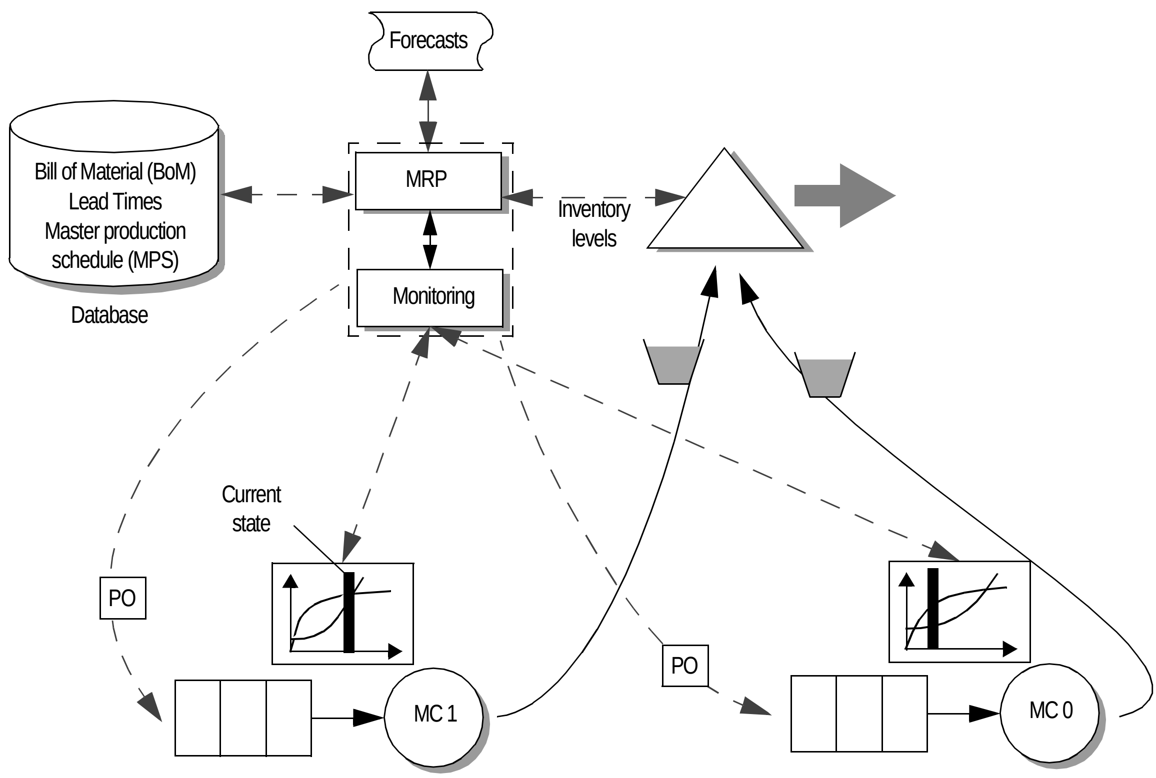
Figure 2.12 Illustration of load diagram of (fictive) production system



time period. As illustrated in Figure 2.12 this diagram allows the visual identification of current problems (over- or underload, production interruptions,...) of the analyzed production system.

The measures and diagrams described above allow the quick determination of the current state of a production system. They can also be used to estimate more accurately expected average cycle times and to monitor the current load level of the production system. As illustrated in Figure 2.13 the concepts of the Load-oriented manufacturing control method can therefore be used as a monitoring tool in an existing

Figure 2.13 Load-oriented manufacturing control integrated into a MRP system



MRP system. The description of the Load-oriented manufacturing control method as an MPC system (order release, capacity control, scheduling, lot sizing techniques) is outside the scope of this thesis.

2.5.1 *Critique of the Load-oriented manufacturing control method*

The application domain of the Load-oriented manufacturing control method corresponds mainly to job shop environments. A survey in 100 German companies has revealed that this method is after cellular manufacturing and JIT the third technique or philosophy used in manufacturing firms (Wiendahl 1991). A case study presented by Wiendahl et al. (1983) shows that the application of the principles of the Load-oriented manufacturing control method in a job shop led to a reduction of 30% of the *WIP* level without causing a reduction of the average throughput *TH*.

In the case of job shops, the Load-oriented manufacturing control method constitutes an invaluable tool for monitoring and analyzing. In the case of the complete MPC method, there are currently not yet enough results available due to the recent development of the lot sizing and scheduling model. This method is therefore considered in this thesis only as an analysis and monitoring tool.

2.6 *Hybrid MPC methods*

An appropriate choice of the manufacturing planning & control (MPC) system is an important success factor for any manufacturing firm. The characteristics of the chosen MPC system must not only meet the requirements of the focused market place, but also those of the manufacturing process design (Vollmann et al. 1997, Olhager and Rudberg 2002). In the field of business strategy research, the issue of optimal configurations of typical MPC design options for market and manufacturing design requirements is addressed by the development of manufacturing strategy frameworks (Bozarth and McDermott, 1998). Two of the most representative frameworks have been developed by Hayes and Wheelwright (1979, 1984) and Berry and Hill (1992). Hayes and Wheelwright describe in their framework the relationship between the product characteristics and the manufacturing process type. As shown in Table 2.4, Berry and Hill refined this framework by adding links from product and process characteristics to strategic MPC design options ranging from time-phased MRP (push) to rate-based JIT/Kanban (pull). It is further assumed that MRP is typically applied in make-to-order (MTO) environment whereas JIT is applied in a make-to-stock (MTS) environment. The assemble-to-order (ATO) environment is considered as a intermediate (hybrid) environment integrating aspects of both MTO and MTS environments.

Table 2.4: Linking manufacturing strategy with the MPC concept (Berry and Hill 1992)

Strategic variables (market requirements)	**MTO Time-phased MRP (push)**	**ATO**	**MTS Rate-based JIT (pull)**
Product type	Special	←→	Standard
Product range	Wide	←→	Narrow
Volume	Low	←→	High
Accommodating demand versatility: total volume	Easy	←→	Difficult

Table 2.4: Linking manufacturing strategy with the MPC concept (Berry and Hill 1992)

Strategic variables (market requirements)	**MTO Time-phased MRP (push)**	**ATO**	**MTS Rate-based JIT (pull)**
Accommodating demand versatility: product mix	High	◄──►	Low
Delivery speed	Difficult	◄──►	Easy
Delivery reliability	Difficult	◄──►	Easy

These frameworks not only give a valuable insight into the characteristics of optimal configurations of manufacturing systems, they also illustrate the fact that the two classical MPC design options MRP and JIT fit unambiguously only manufacturing environments with opposite characteristics (MRP to low-volume, high-mix, job shop environments, JIT to high-volume, low-mix, line flow environments). For intermediate manufacturing environments not having such extreme characteristics however, the optimal MPC design choice is less obvious. Empirical studies show that such environments are frequent in practice at least in western countries. In fact, Safizadeh et al. (1996) show in their analysis of 144 U.S. manufacturing plants that 57% of them are organized according to a batch shop or production line structure that can generally be attributed to an intermediate configuration. Another interesting finding of Safizadeh et al. (1996) concerning the process choices and the corresponding degree of customization is shown in Table 2.5.

Table 2.5: Process choices and corresponding degree of customization (Safizadeh et al. 1996)

Process choice	**Customized product**	**Standard product with modified options**	**Standard Product modified to customer order**	**Standard product with standard options**	**Standard product with no options**
Job shop	13	14	3	1	0
Batch shop	13	11	6	12	4
Production line	1	13	6	13	3
Continuous shop	4	2	6	10	7

These empirical results further support the view (with respect to the degree of customization, variable “product type” in Table 2.4) that extreme configurations of manufacturing plants are rather the exception than the rule. In addition, as pointed out by Higgins et al. (1996), MTO and MTS environments have today, due to the increased market pressure, the tendency to be transformed into ATO environments that combine the advantage of being able to handle a wide variety of products with reduced delivery times. This is normally achieved by final product configurations that are made from combinations of basic components and subassemblies. The issue of providing the optimal MPC method for intermediate configurations has therefore generated much research, focused on either extending the application domain of classical MPC concepts (MRP and JIT) or on developing new (hybrid) MPC concepts.

In contrast to the first research direction, the second abandons the view of mutually exclusive MPC concepts and considers particularly the advantages and flaws of the MRP and the JIT concept as complementary. This consensus about the benefits of hybrid MPC designs, combining the advantages of MRP and JIT, is based on the outcome of a debate between proponents of pure JIT or MRP solutions that emerged after the introduction of the JIT concept in western countries.

Impressed by the obvious success of JIT in Japan (Monden 1983) some authors have seen JIT as the only MPC system design able to meet world class manufacturing standards. As one of the most influential advocates of JIT, Schonberger (1986) claimed in opposition to the concepts of the focused factory (Skinner 1974) and the theory of performance trade-offs (Porter 1980, 1985) that the adoption of JIT enables firms to excel simultaneously in all important types of manufacturing performance. Other concepts such as the Zero Inventory management introduced by Hall (1983) supported this optimistic view.

In opposition, advocates of MRP tried to prove that JIT techniques are less beneficial in manufacturing environments found in western countries. Most of these studies are based on the following two-step research structure (Krajewski et al. 1987, Rees et al. 1989, Sarker and Fitzsimmons 1989). In the first step, MRP and JIT systems are analyzed separately in manufacturing environments judged as typical of the corresponding MPC concept (low setups, small lot sizes and reduced variability for the JIT, big lot sizes, high setups and strong variability for the MRP manufacturing environment). In the second step, the MRP system is analyzed in the manufacturing environment defined for the analysis of the JIT concept. The principal findings of these studies are similar. JIT systems outperform MRP systems when analyzed in their corresponding manufacturing environment. However, the MRP system exhibits comparable or even better results when analyzed in manufacturing environments used for the JIT system.

Both opposing views have in common that they do not take into account constraints found in practice. The success of typical JIT implementations is uncontested but surveys of implementation cases show that successful JIT implementations depend basically on two conditions (Crawford et al. 1998, Gilbert 1990). First, the company product characteristics and manufacturing process design should be as close as possible to typical JIT configurations. Second, successful JIT implementations are generally accompanied by a reorganization of the whole manufacturing and planning process. However, both conditions cannot be met by a wide range of companies.

Similarly, studies in favour of the MRP technique underestimate the difficulties found in practice related to the underlying flaws of the MRP concept. In fact, in a manufacturing environment with accurate lead times and forecasts and infinite capacity, MRP is effectively the optimal MPC concept. However, if these conditions are not met, MRP leads to inefficient and unrealistic production plans (Hopp and Spearman 2000).

As a conclusion and as shown in the following survey of existing hybrid MPC concepts, the general strategy for the integration of JIT and MRP is based on the strengths of both concepts. MRP is superior to JIT in its capacity for long term planning and to handle lumpy demand. JIT on the other hand, offers the simplest solution for the execution of the production process.

Hybrid MPC methods are broadly classified into three classes that are characterized according to the way the different classical MPC methods are combined and integrated. In vertically integrated hybrid production systems (VIHPS) the JIT method is exclusively applied at the shop floor level whereas MRP is used to generate the production plans. Horizontally integrated hybrid production systems (HIHPS) are characterized by the use of either the MRP or JIT method for the management of the different production stages. Finally, in parallel integrated hybrid production systems (PIHPS), production can be triggered by more than one MPC method applied in parallel. Table 2.6 summarizes the studies that have been reviewed in the following three subsections.

Table 2.6: Summary of reviewed studies in hybrid MPC methods

Author(s)	**Type**	**Main research method**	**Comments**
Cochran & Kim (1988)	HIHPS	Simulation	Optimal junction point in serial production line
Hodgson & Wang (1991a, b)	HIHPS	Analytical	General series/parallel multistage production system
Huang & Kusiak (1998)	HIHPS	Simulation	Optimal configuration of general production system

Table 2.6: Summary of reviewed studies in hybrid MPC methods

Author(s)	Type	Main research method	Comments
Lackes (1994)	HIHPS	Simulation	Extended MRP and information concept
Olhager & Östlund (1990)	HIHPS	Industrial case study	Packaging industry
Pandey & Khokhajaikiat (1996)	HIHPS	Analytical	Four stage series/parallel production system
Takahashi et al. (1994)	HIHPS	Analytical	6-stage linear production system
Deleersnyder et al. (1992)	PIHPS	Analytical	N-stage linear production system
Hall (1983)	PIHPS	Industrial case study	SynchroMRP
Lackes (1994)	PIHPS	Simulation	JIT/kanban concept with authorization
Suri (1998)	PIHPS	Industrial case study	POLCA
Behera (1991)	VIHPS	Industrial case study	Aerospace industry
Bonvik et al. (1997)	VIHPS	Simulation	Modified CONWIP concept
Chang & Yih (1994)	VIHPS	Simulation	Generic kanban system
Chang & Yih (1994)	VIHPS	Simulation	Optimal configuration of generic kanban system
Flapper et al. (1991)	VIHPS	Empirical	Implementation guidelines
Gupta & Brennan (1993)	VIHPS	Simulation	Decision support tool
Hopp & Roof (1998)	VIHPS	Simulation	Optimal configuration of CONWIP
Huq & Huq (1994)	VIHPS	Simulation	Implementation of hybrid production system in Job shop environment
Kindinger (1998)	VIHPS	Industrial case study	Chemical industry
Nagendra & Das (1999)	VIHPS	Analytical	Extended MRP concept
Spearman & Zazanis (1992)	VIHPS	Analytical	Analysis of pull control of CONWIP
Spearman et al. (1990)	VIHPS	Simulation	CONWIP

2.6.1 *Vertically integrated hybrid production systems*

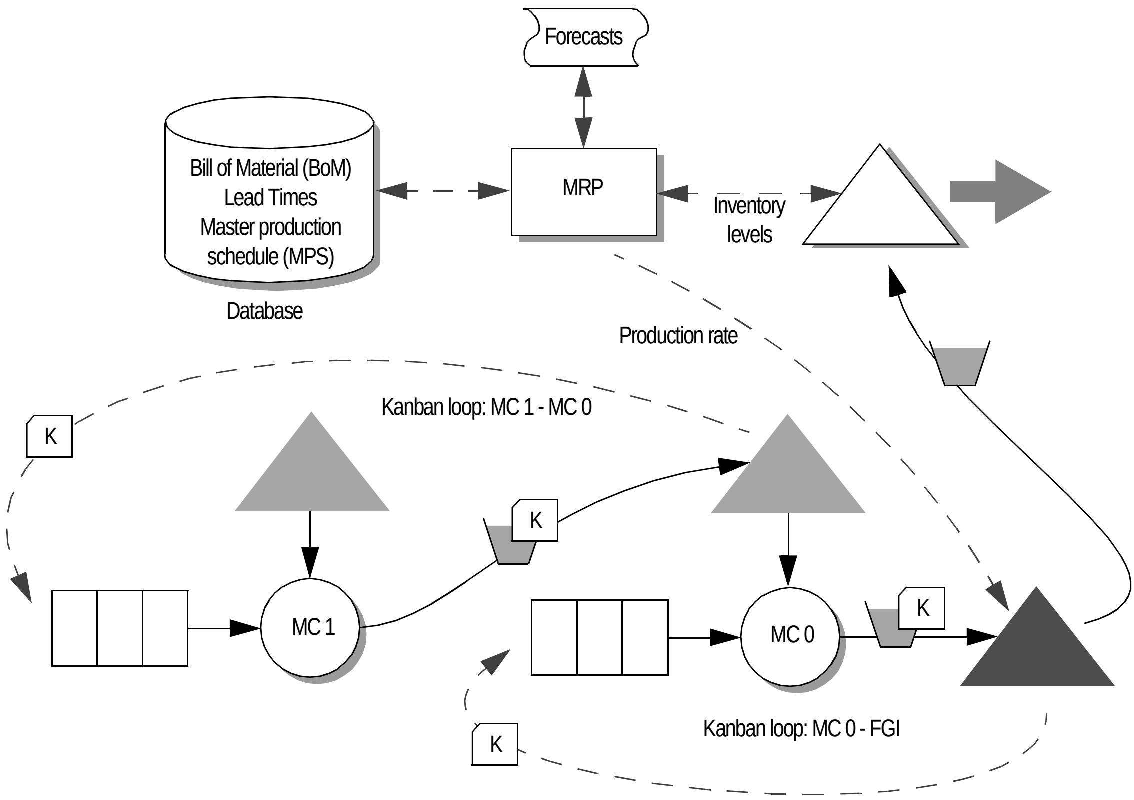
The determination of conditions and strategies and the development of tools for the successful embedding of JIT in an MRP environment has been one of the major concerns of research related to VIHPS (illustrated in Figure 2.14).

Flapper et al. (1991) present an implementation methodology that helps embedding JIT into MRP. With respect to MRP, mainly the two techniques backflushing and phantoms (Vollmann et al. 1997) are applied. Backflushing is the automatic registration of standard quantities of resources (material, labour, machine time and tooling) allowed for performing some or all of the operations for a particular manufacturing order, after the order has been completed. Phantoms are items on the bill of material for which no manufacturing orders or purchase orders will be generated. That is, MRP does not generate requirements for phantom items and phantom items cannot have inventories. Both techniques help to flatten and simplify the bill of material and are applied in a three-step framework for embedding JIT gradually into an MRP environment. In the first step, a logical line flow is created by rapid material handling. In the second step, kanbans are introduced as a production control system in the logical line. Finally, in the third step, all stages of the logical line are physically displaced to form a line flow.

Based on a simulation study, Huq and Huq (1994) addressed the problem of implementing JIT into an MRP controlled job shop environment. They were mainly interested in the impact of setups, varying processing times, machine breakdowns and load imbalance on the performance of a VIHPS that are generally considered as critical factors for a successful implementation of JIT. The results from their simulation study show that load levelling has a significantly higher impact on a VIHPS than variations in setup and processing times.

The problem of the choice of the typical JIT design parameters (number and size of kanbans) implemented in an MRP environment is addressed by Gupta and Brennan (1993) and Nagendra and Das (1999). Gupta and Brennan propose a knowledge based simulation system, which allows the simulation and

Figure 2.14 VIHPS MPC method



dimensioning of such systems. Nagendra and Das on the other hand, propose a concept for additional four modules for the MRP system, which better interface the two MPC methods MRP and JIT. These modules mainly perform the task of translating the planning outputs of MRP into the executable input for JIT/ kanban.

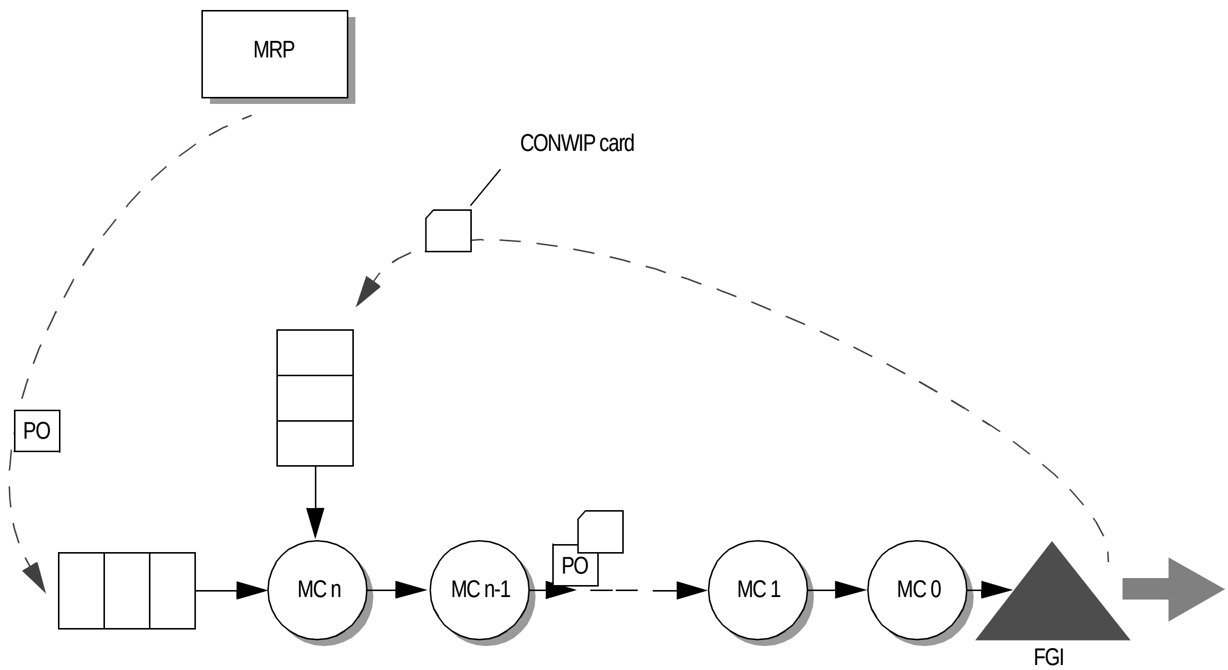
Two special cases of VIHPS are the CONWIP and Generic kanban concept developed by Spearman et al. (1990) and Chang and Yih (1994) respectively. These are both characterized by the use of generic kanbans not specific to a certain item. Both concepts relax, therefore, the constraint of product specific kanbans with respect to their limited ability to handle a wide variety of products at one production stage.

As illustrated in Figure 2.15, CONWIP (CONstant Work In Process) uses MRP to generate the production schedule and generic kanban cards attached to production orders that traverse a circuit including the entire production line. Since the cards are not assigned to a particular item and limited in number, they represent an efficient way to limit the work in process.

Consequently, production can only start at the first stage of the production line if CONWIP cards are available (sent back from the final goods inventory FGI after a consumption has occurred) and if production orders generated by MRP are present. The advantages of the pull concept applied in CONWIP are discussed in detail by Spearman and Zazanis (1992). They show that this concept results in less congestion of the production line and that it is inherently easier to control than a push system like MRP. The problem of setting the correct WIP level to meet target production rates in a CONWIP controlled production system is addressed by Hopp and Roof (1998). The configuration methodology based on statistical estimates of the throughput is validated by a simulation study.

The generic kanban concept developed by Chang and Yih (1994a) is comparable to the CONWIP concept with the exception that generic kanbans loops exist between all stages. They justify this choice by the fact that their concept has a higher adaptability to dynamic changes occurring in an manufacturing environment. The superior performance of the generic kanban concept over the classical kanban and CONWIP concept is shown with the help of a simulation model of a three-stage, two-product production line. The problem of the correct configuration of a generic kanban system is addressed by the same authors (Chang and Yih 1994b). In fact, this optimization problem becomes computationally NP-hard, particularly in the case where the number and capacity of generic kanbans at each stage can be different. They solve

Figure 2.15 CONWIP concept



this problem by obtaining (suboptimal) solutions from a optimization model based on the simulated annealing approach.

Finally, a modified CONWIP concept has been developed by Bonvik et al. (1997). They present a concept that combines CONWIP and JIT/kanbans at some stations. Thus, by using kanban control parallel to the CONWIP control concept, the accumulation of WIP in front of bottleneck stations is prevented. The validation of their solution has been performed with the help of a simulation model of a linear four-stage, one-product production line.

Industrial case studies of VIHPS are presented by Behara (1991) and Kindinger (1998). Based on the case of a leading manufacturer of products for the aerospace industry, Behara presents how JIT has been implemented into an MRP environment. The phased-implementation approach is comparable to those presented by Flapper at al. (1991). The implementation of the VIHPS resulted mainly in reduced manufacturing lead times (-40%), increase of the production output (+100%) and reduced material planning efforts. In a similar study, Kindinger presents three pilot implementation studies of a manufacturer producing semi-finished products for the chemical industry. The main benefits of the implementation of the VIHPS method are reported to be an increased flexibility at the shop floor level and minimized WIP levels.

2.6.2 Horizontally integrated hybrid production systems

The problem of the optimal integration of different production control methods and master production schedule approaches in a production line is addressed by researchers who develop and analyze HIHPS. Cochran and Kim (1998) developed a methodology to determine the optimal configuration of a HIHPS applied to serial production lines. As illustrated in Figure 2.16, they assume that the first production stages are managed by the push (MRP) approach up to a production stage called a “junction point”. The intermediate stock for the intermediate items at the junction point serves as the input buffer for the succeeding production stages managed by the JIT/Kanban method. The optimal solution for the location and safety stock level of the junction point, and the number of kanbans with respect to minimized inventory carrying and shortage costs were found by applying the simulated annealing optimization technique to a simulation model.

In the HIHPS described by Lackes (1994), no restriction is made on the location of the production stages controlled by the pull concept. For the case where production stages controlled by the JIT/Kanban method are followed by push controlled production stages he developed an algorithm that smooths the demand for the pull controlled production stages by minimizing inventory and instability costs. Instability costs are defined as costs caused by an unstable demand in a Kanban controlled production system.

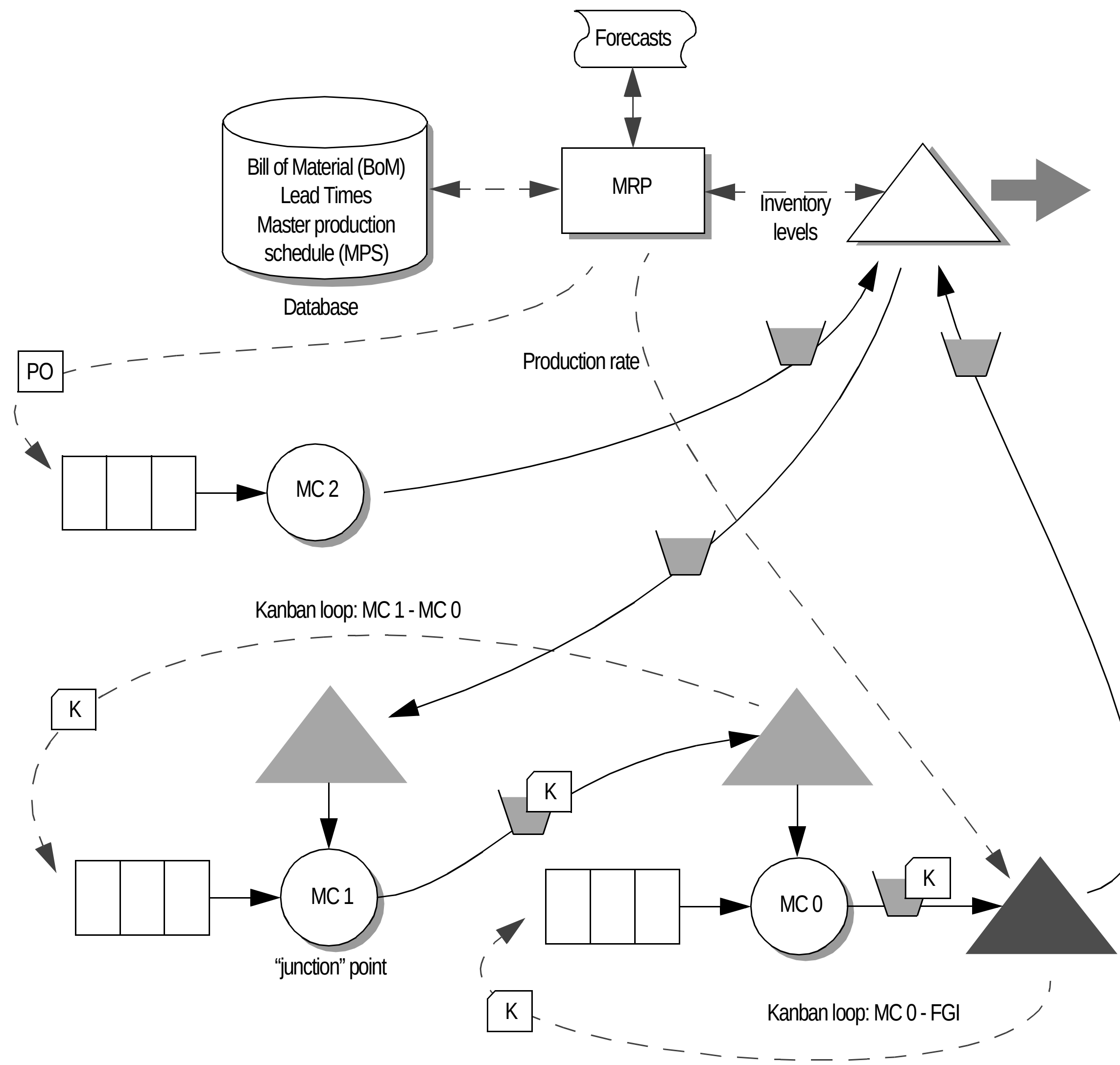
Other research work performed by Hodgson and Wang (1991a, b), Huang and Kusiak (1998) and Pandey and Khokhajaikiat (1996) were mainly concerned with the development of general guidelines for the optimal choice of the push or pull concept for individual production stages in an HIHPS. Hodgson and Wang (1991a, b) found by using a Markov decision process model of a production system with converging network structure that the HIHPS concept is superior in terms of total costs to a pure push or pull solution. They conclude from their results that the best control strategy for a general parallel and/or serial multistage production/inventory system is to use the push policy for all top upstream stages of each branch of the production line, and pull policy at other stages.

In a similar study, Pandey and Khokhajaikiat (1996) extended the work of Hodgson and Wang (1991a, b) with respect to uncertainty in demand, production and raw material supply. They generally confirmed the results obtained by Hodgson and Wang (1991a, b) with the exception of situations with a large variability in demand. In such cases, no policy has been found that performs significantly better than the others.

Huang and Kusiak (1998) developed a set of six (contradicting) rules to determine the production control method (push or pull) for every individual production stage:

1. Push at the critical stages (stages along the critical path with the total flow time equal to the flow time of the entire product);
2. Pull at the value-adding stages (stages increasing the value of parts of products);
3. Pull parts up to the bottleneck stages (stages utilized most);
4. Pull parts up to the assembly stages (stages where assembly operations are performed after all parts needed have been arrived);
5. Push at upstream stages up to the batch-production stages (stages in which parts are processed in batches to decrease the setup costs);
6. Push at the initial stages and pull at the final stages which do not belong to any of the special stages above.

Figure 2.16 HIHPS MPC method (push at first stage, pull at final two stages)



By using a simulation model with a converging 7-stage network structure, they found that their HIHPS configuration performed better in terms of total costs than a pure push solution.

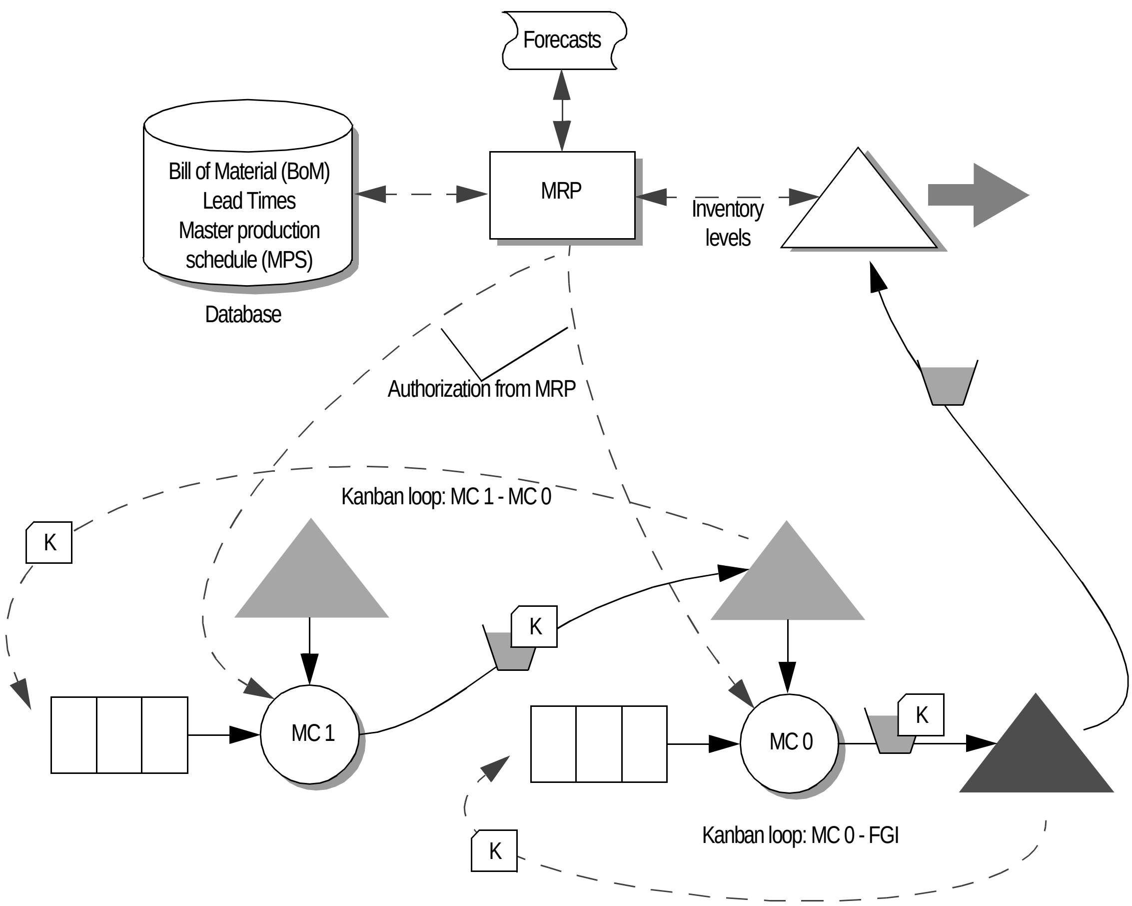
An industrial case study of an HIHPS has been presented by Olhager and Östlund (1990). They implemented successfully an HIHPS in a semi-repetitive, make-to-order production system of the packaging industry according to a methodology that relates possible integration points between push and pull systems to the order penetration point (the point where a product is assigned to a specific customer), to bottleneck resources and to the product structure.

2.6.3 Parallel integrated hybrid production systems

Existing PIHPS, for which the general concept is illustrated in Figure 2.17, can be grouped according to the use of product specific or generic kanbans. In the case of PIHPS with product specific kanbans, MRP is primarily used to widen the application domain of the kanban concept to production environments with an unstable demand. In the concept proposed by Deleersnyder et al. (1992), production for one item is triggered either by a kanban or a production order. Based on the results of a Markovian model of a 3-stage and 4-stage serial production line, the authors conclude that their hybrid approach is superior to the pure pull approach particularly in the presence of fluctuating demand. Under such conditions, the PIHPS performs at lower inventory levels and with less fluctuations in the total inventory.

In the SynchroMRP concept presented by Hall (1983), production at a stage is only allowed in the presence of a kanban or a corresponding production order. Still another approach has been presented by Lackes (1995) where information provided by the MRP system about changes in demand is transmitted to

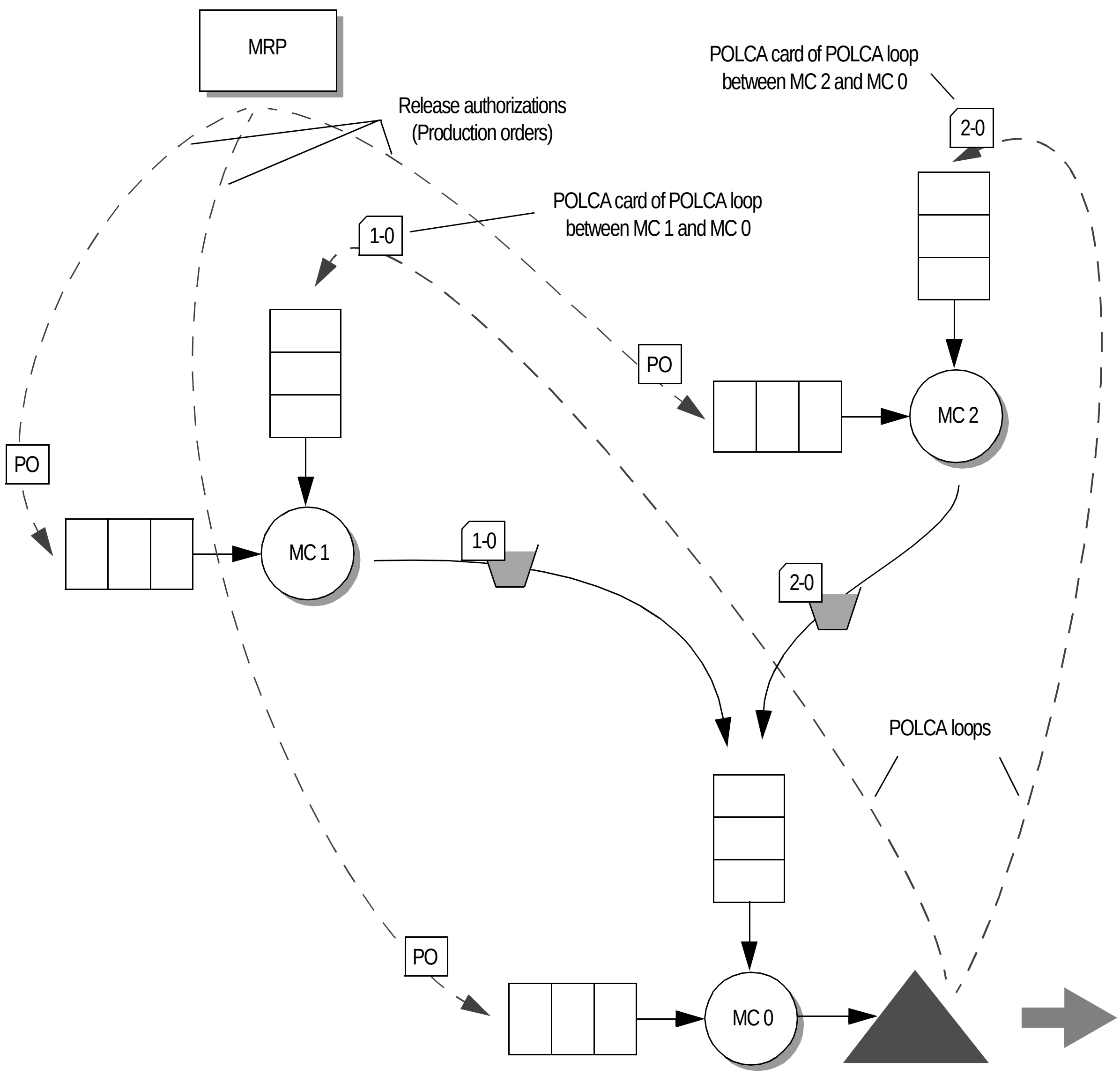
Figure 2.17 PIHPS MPC method



all stages. This allows the production stages to anticipate future fluctuations in demand and to begin production even before the presence of a Kanban.

A PIHPS inspired by the CONWIP concept called POLCA (Paired-cell Overlapping Loops of Cards with Authorization) has been developed by Suri (1998). As shown in Figure 2.18, POLCA can be compared to the SynchroMRP concept with the exception that generic kanbans (POLCA cards) instead of product specific cards are used. POLCA cards are specific to certain pairs of manufacturing cells and are attached to a job during its journey through both manufacturing cells in the pair before they loop back to the first cell in the pair (POLCA loops 1-0 and 2-0 in Figure 2.18). Production is triggered in POLCA therefore only if the required components (with attached POLCA cards from the first manufacturing cell of the POLCA loop pair) and a free POLCA card is available, and if a release authorization generated by the MRP system is present. Ideally, POLCA cards should correspond to one customer order. If however these orders are too large, a quantum (limit on the job size of jobs associated with a single card) has to be determined. The number of POLCA cards *nc* for a given loop between manufacturing cells A and B is given by (Eq. 2.31) that is a simple application of Little's Law (Eq. 2.25 and 2.26):

Figure 2.18 POLCA concept



$$nc = (CT_A + CT_B)\frac{num(A, B)}{nwd} \qquad \text{(Eq. 2.33)}$$

with

CT_A, CT_B = average job cycle times in manufacturing cells A and B;

$num(A, B)$ = expected number of jobs that go from manufacturing cell A to B during the planning horizon;

nwd = number of working days during the planning horizon.

2.6.4 *Critique of existing hybrid MPC methods*

The application domain of a typical VIHPS is restricted by the same constraints as those of JIT/kanban. The conditions for HIHPS are less restrictive than those of VIHPS and JIT/kanban since JIT/kanban is used only on some stages. However, a critical issue of HIHPS is the choice of the stages where JIT/kanban can be applied. The different approaches of the reviewed research works show that this problem is not yet solved. The six (contradicting) decision rules presented by Huang and Kusiak (1998) illustrate this fact. In practice, JIT/kanban is generally used in the last (assembly) stages. Thus, ATO manufacturing environments can be considered as HIHPS's typical application domain.

PIHPS are confronted with the difficulty of integrating the concepts of MRP and JIT/kanban for the management of a particular product. The application domain of PIHPS is less restricted with respect to fluctuation in demand than JIT/kanban. It is, however, still limited in its capacity to handle the production of a wide variety of products. VIHPS, HIHPS and PIHPS can therefore only be implemented in manufacturing with a wide variety of products if resources are available to add additional production lines since JIT/kanban is used exclusively on some or all production stages.

An exception to this rule are the CONWIP and POLCA concepts. Due to its use of generic kanban cards, CONWIP can handle the production of a wide variety of products. CONWIP is also less sensitive to fluctuations in demand than the pure kanban concept. In addition, due to the limited work-in-process, cycle times are more stable than in the case of MRP which simplifies the planning of production. Its major drawbacks are, however, its limitation to linear production lines and its dependency on accurate forecasts of the effective demand since production is triggered at the beginning of the production line by MRP.

POLCA is, in contrast to CONWIP, not restricted to linear production lines. On the other hand, since POLCA cards are attached to jobs (customer orders), its application domain is restricted with respect to the variability of the job sizes and the presence of forecast errors. In fact, POLCA's logic imposes that jobs have to be finished until the final production stage once they have entered the production system at the first stage. The application domain of POLCA and CONWIP corresponds, therefore, mainly to MTO manufacturing environments and final assembly lines.

The complexity of VIHPS, HIHPS and PIHPS is determined by combining the results obtained for the MRP and JIT/Kanban method.

$$\begin{aligned}\Gamma1_{VIHPS} &= XNV1_{JIT} + X_{FP}NV1_{MRP} \\ \Gamma2_{VIHPS} &= X_{FP}(T_{PH}NV21_{MRP} + NV22_{MRP}),\end{aligned} \qquad \text{(Eq. 2.34)}$$

$$\begin{aligned}\Gamma1_{HIHPS} &= (X - X_{MTS})NV1_{JIT} + X_{MTS}NV1_{MRP} + K_{MRP} \\ \Gamma2_{HIHPS} &= X_{FPS}T_{PH}NV21_{MRP} + X_{MTS}NV22_{MRP}\end{aligned} \qquad \text{(Eq. 2.35)}$$

with

X_{MTS} = number of items managed with MRP (make to stock);

X_{FPS} = number of items at final stage managed by MRP;
and

$$\Gamma1_{PIHPS} = X(NV1_{JIT} + NV1_{MRP}) + K_{MRP}$$ (Eq. 2.36)
$$\Gamma2_{PIHPS} = X_{FP}T_{PH}NV21_{MRP} + X(NV22_{MRP} + NV2_{JIT}).$$

Particular cases are CONWIP and POLCA that are characterized by the use of generic kanban cards.

$$\Gamma1_{CONWIP} = K1_{CONWIP} + X_{FP}NV1_{MRP}$$ (Eq. 2.37)
$$\Gamma2_{CONWIP} = K2_{CONWIP} + X_{FP}(T_{PH}NV21_{MRP} + NV22_{MRP})$$

with
$K1_{CONWIP}$ = 2 (number and capacity of CONWIP cards);
$K2_{CONWIP}$ = 1 (first stage, CONWIP card queue)

and

$$\Gamma1_{POLCA} = X_{POLCA}NV1_{POLCA} + XNV1_{MRP} + K_{MRP}$$ (Eq. 2.38)
$$\Gamma2_{POLCA} = X_{FP}T_{PH}NV21_{MRP} + XNV22_{MRP} + X_{POLCA}NV2_{POLCA}$$

with
X_{POLCA} = number of POLCA-loops;
$NV1_{POLCA}$ = 1 (number of POLCA cards per loop);
$NV2_{POLCA}$ = 1 (number of POLCA cards).

Summary and conclusions of chapter 2

- Customer driven manufacturing is the driving factor for the development of new MPC methods. Consequently, modern MPC methods must respond to the need to deliver quickly and economically highly customized products;
- The Inventory control method is focused on optimizing the inventory control variables with the objective of minimizing inventory holding costs. Even though its conceptual simplicity and its relative insensitivity to forecast errors are attractive its application leads normally to high inventory levels compared to those of more modern MPC methods;
- The MPR method determines, based on the actual demand, forecasts, the product structure and the current inventory levels, all production activities at all levels of the production process. MRP systems are therefore characterised by their wide application domain and planning capacity, but also by their often unrealistic production plans due to flaws of MPR's logic (assumption of unlimited capacity, dependency on forecasts, constant cycle times,...);
- The JIT philosophy is a system-oriented approach that includes not only a production control method but also guidelines for the product and process design, for human and organisational aspects. From an operational point of view JIT is realized by the kanban control concept (JIT/kanban). Empirical data show that JIT/kanban's logistic performance is normally superior to those of the MPR and Inventory control concept. Its application domain is, however, restricted to manufacturing environments with low variability and customization;
- The Load-oriented manufacturing control method is an analysis and monitoring tool that takes into account the dynamics of real production systems. In contrast to classical methods such as Inventory control or MRP, manufacturing cycle times are not assumed to be constant or normally distributed but to be a variable dependent on the load (throughput) and the work-in-process level;
- The general strategy for the design of hybrid MPC methods is the integration of the strengths of the classical MPC methods MPR and JIT/kanban. The different hybrid MPC methods are broadly classified into three classes that are characterized according to the way the different classical MPC methods are combined and integrated;
- In vertically integrated hybrid production systems (VIHPS) the JIT method is exclusively applied at the shop floor level whereas MRP is used to generate the production plans. Horizontally integrated hybrid production systems (HIHPS) are characterized by the use of either the MRP or JIT method for the management of the different production stages. Finally, in parallel integrated hybrid production systems (PIHPS), production can be triggered by more than one MPC method applied in parallel;
- Hybrid MPC methods have expanded the application domain of the original JIT/kanban method. In the case of complex production systems with a high product variety and process complexity, MRP and Load-oriented manufacturing control are, however, the only feasible options.

Chapter 3

Double Speed Single Production Line

The goal of this chapter is the development of the concept of the new hybrid MPC method **D**ouble **S**peed **S**ingle **P**roduction **L**ine (DSSPL). The development process is based on the following four-step approach: In the first step, a problem statement is derived from the review of fundamental laws of manufacturing planning & control and MPC methods given in chapter §2. This problem statement, consisting of four hypotheses, serves as a guideline for the development of the DSSPL key concept and elements that are presented and justified in the second step. The application domain and the novel aspects of DSSPL, compared to existing MPC methods, are presented in the third step. In the fourth step finally, a Markovian model is developed in order to analyze and validate the basic mechanisms of the DSSPL concept.

3.1 Concept of DSSPL

3.1.1 Problem statement

Many production systems found in practice are rarely in a state where the production capacity is in balance with the external demand. As illustrated in the previous chapter, such overloading of a production system leads to inefficiencies due to increased work-in-process levels and cycle times. The reasons for such overloaded production systems are not only a presumably increased and/or fluctuating external demand but also evolving market requirements, common management practices and the widely used MRP concept.

Today, the market requirements tend towards highly customized products, combined with minimal delivery times. However, for a given production system, an increased product variety does not only increase variety-related costs (Stalk 1988) but also the overall production lead times (Hopp and Spearman 2000). As pointed out by Suri (1998), the most common management practices resulting in overloaded production systems are scale- and cost-based strategies. Typically, production resources are scheduled to run close to 100% utilization in order to minimize the amortization period. Finally, as already mentioned, flaws of the MRP concept lead to production plans that do not respect the limited capacity of production systems. Even capacity requirement planning (CRP) modules available for MRPII systems cannot adequately solve this problem, since their logic is based on fixed lead times (Hopp and Spearman, 2000). The situation described above leads to the first hypothesis of the conceptual DSSPL framework that is stated as follows:

> *H1*: Production systems tend to be in overloaded states.

The problems related to the situation stated in the first hypothesis *H1* can be solved principally by increasing the production capacity if the demand topology cannot be modified. Significant modifications of the capacity can be achieved by either improving the efficiency of the existing production system (new MPC methods, reduced setup times, improved maintenance concept,...) or by adding additional production resources. However, most of these approaches have in common that considerable financial, organizational and technical resources are required to implement them. As already mentioned in the previous chapter, such redesigns are, in the case of JIT, particularly difficult to perform when the product structure and manufacturing processes do not fit the typical JIT requirements (linear production flow, low variety,...). Further problems associated with the implementation of JIT techniques have been presented by authors who studied the transferability of JIT to small and middle-sized enterprises (SMEs). White et al. (1999) revealed in their survey of 454 U.S. manufacturers that large companies (more than 1000 employees) have implemented significantly more JIT techniques than small companies. For Prajogo and Johnston (1997) and Inman and Mehra (1990), this difference is mainly due to two facts. First, most successful JIT implementations are accompanied by extensive training and education programs that require additional financial and human resources. Second, SMEs lacking leverage with respect to their suppliers and clients often exclude the possibility of improving significantly the purchasing (smaller and more frequent batches) and levelling of the production load (production levelling). The problem of the limited JIT application domain has been addressed by the development of hybrid MPC methods that are described in the previous chapter. Even though these hybrid MPC methods extend the typical application domain of the JIT MPC method their application in complex manufacturing environments is still difficult. In fact, POLCA and CONWIP are adapted only to simple manufacturing environments (make-to-order, linear production lines,...) whereas the exclusive use of the JIT MPC method on some or all production stages in the case of VIHPS, HIHPS, PIHPS inhibits their application in manufacturing environments with a wide variety of products. The second hypothesis deals, therefore, with the problem of limited resources and the need to improve logistic performance due to evolving market requirements:

> *H2*: For companies with a complex production system, significant improvements of the logistic performance are difficult to achieve when financial, technical and organizational resources are limited.

An important theory for the appropriate choice of the manufacturing strategy is the performance trade-off theory that was introduced by Skinner (1974) and Porter (1980, 1985). This theory states that manufacturing organizations cannot simultaneously pursue different and conflicting types of performance, such as producing a wide range of products, of high quality, with low stock levels, with short, reliable delivery times, and with low costs. The validation of this theory has been addressed by Filippini et al. (1998) who made a survey of 43 Italian manufacturing companies. Even though some trade-offs can be overcome by the implementation of advanced manufacturing concepts such as JIT (delivery time versus punctuality or quality consistency versus price), their results indicate the presence of the two discriminating factors *market share* and *product complexity/variety* that reduce the possibility of a company to achieve high ratings in many types of performances. Furthermore, the trade-off most frequently found was punctuality (service level) versus economic performance. This result indicates that high punctuality can often only be achieved by increased inventory levels that buffer against the uncertainty of demand. The third hypothesis of the conceptual DSSPL framework states therefore that certain types of companies have only a limited choice of manufacturing strategies:

> *H3*: Companies with a high product variety/complexity can achieve high service levels for all products only by accepting high inventory levels and thus reduced economic performance.

A still unexplained statistical relationship called Pareto's law is often found in large systems. This law, also known as the 80-20 rule, describes a relation between two parameters that can be often described by the fact that a few account for the most. In manufacturing Pareto's law is regularly found with the help of multiple-criteria ABC analysis (Flores and Whybark 1986) that is used to classify products. Typical criteria used are the demand topology (annual cost volume usage, regularity of the demand), product characteristics (substitutability, severity of the impact of running out) and marketing objectives (product life cycle, product market share, number of clients). The fourth and final hypothesis of the conceptual DSSPL framework states, therefore, that the validity of Pareto's law increases with increasing product variety:

> *H4*: The results of a multiple-criteria ABC analysis follow Pareto's law (80-20 rule) if the company produces a wide variety of products.

Empirical evidence supporting *H4* is shown in chapter §6 where results from several ABC-analyses performed in different industries are presented.

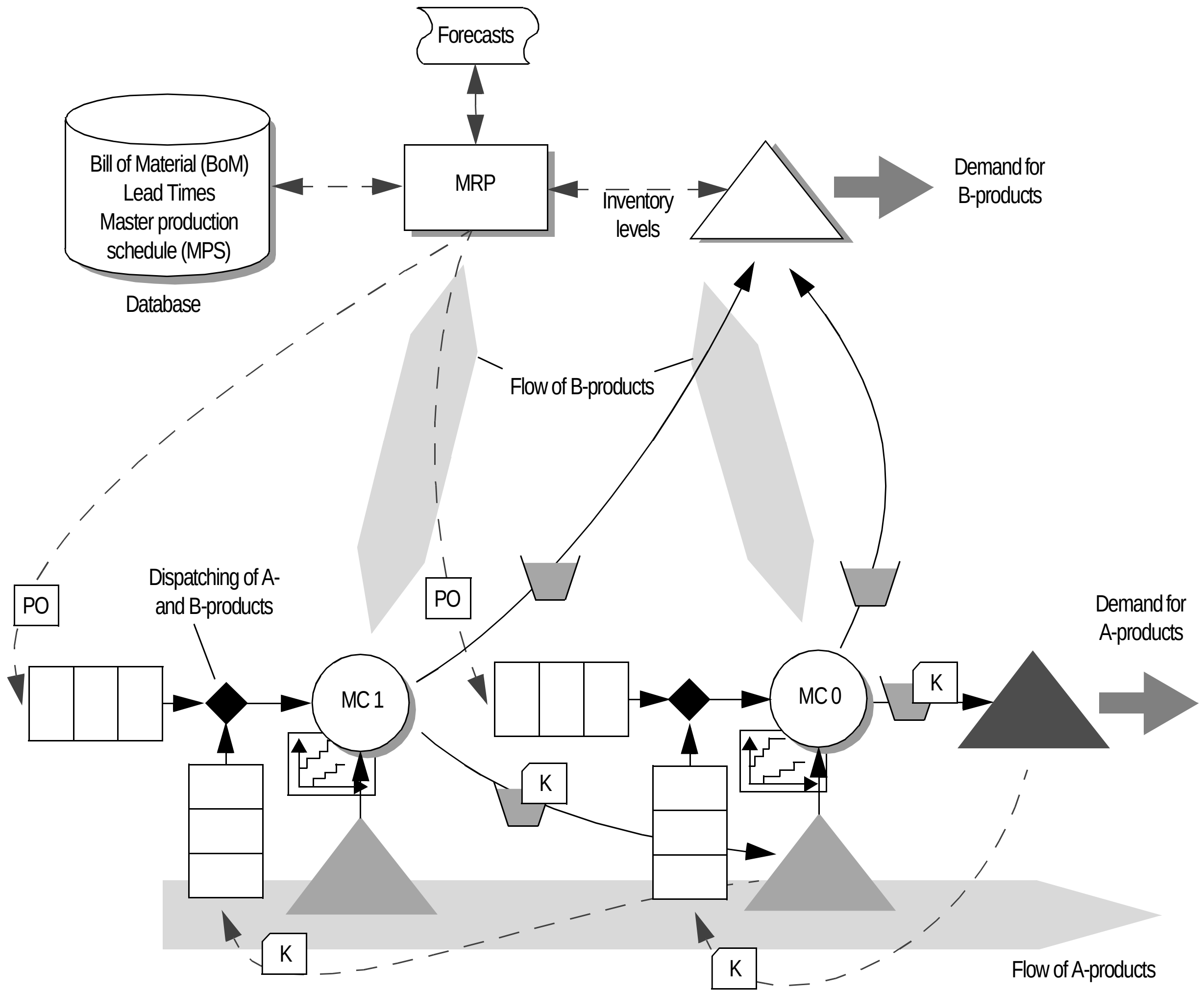
3.1.2 DSSPL

The set of hypotheses described above depicts a situation with which a certain type of manufacturing companies is confronted. To summarize, these companies are characterized by a wide variety of products which makes it difficult to implement modern MPC methods in order to achieve improved logistic performance. This problem is reenforced if the company's human, technical or financial resources are limited.

To solve these specific problems a new hybrid MPC method called DSSPL is proposed that is based on the following key concepts (illustrated in Figure 3.1):

- By applying a multiple-criteria ABC analysis (demand topology, product characteristics, marketing objectives), products are divided into two A- and B-product groups. A-products are characterized by a relatively high and stable demand and that running out of these products would have an important impact on customer service and satisfaction. B-products are characterized mainly by a lower and unstable demand;
- According to the characteristics of the demand topology of the product groups, the JIT/kanban concept is applied for the management of the A-products and MRP (or possibly Inventory Control) for B-products;
- Local scheduling at production stages processing A- and B-products is governed by specific dispatching rules that handle the different priorities. In the simplest case, priority is always given to A- over B-products.
- The performance of every stage is monitored by using the tools of the Load-oriented manufacturing control method (measurement of flow rate, throughput diagram). They help to limit the work-in-

Figure 3.1 Concept of DSSPL



process of the B-products and to control the validity of the JIT/kanban (kanban loops for the management of A-products) and dispatching rule configurations.

The division of the products into different product groups allows companies to concentrate their limited resources on the most important products without the need for additional production resources. Furthermore, by applying JIT techniques to the limited number of A-products, the JIT implementation efforts can be better focused. In addition, local scheduling at every production stage is simplified due to the transparent allocation of priorities to the different product groups which is particularly important in cases where a wide variety of products is produced.

A first critical factor influencing the performance of DSSPL is the appropriate choice of the A-products since JIT/kanban is efficient only in a restricted application domain. Furthermore, the choice of A-products should be valid for a certain period which requires a relative stability of the product mix. An important criterion is, therefore, the product life cycle of each potential A-product. Generally, the life cycle of a product or item can be divided into the four consecutive periods *Introduction*, *Growth*, *Maturity* and

Decline whereas particularly the first and last period are critical with respect to the choice of A-products (Mahoney 1997). Table 3.1 summarizes the most important criteria for the choice of A-products.

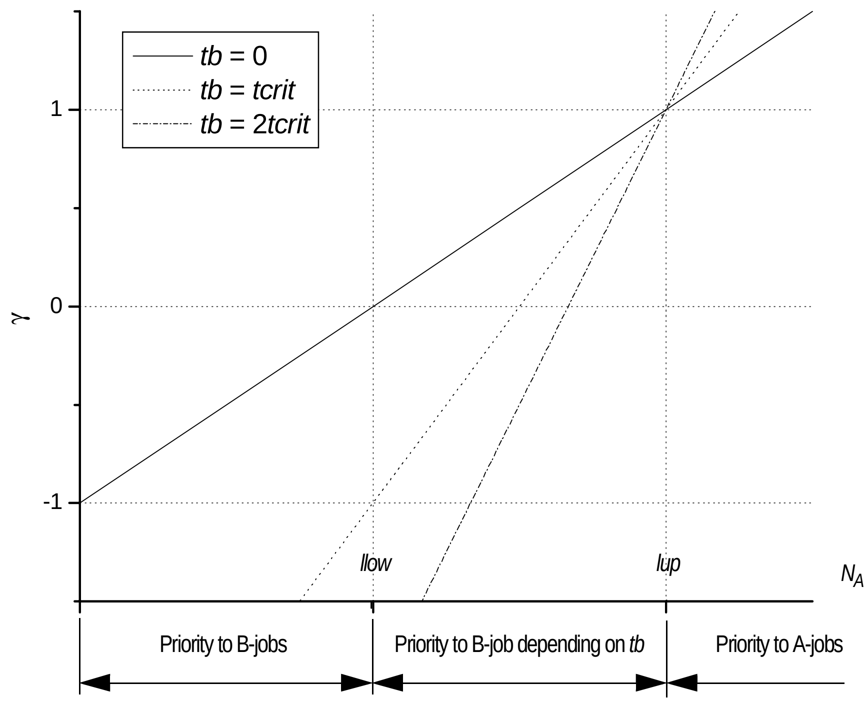
Table 3.1: Criteria for A-products

Criteria	**Conditions for A-products**
Demand variability	Low demand variability (Coefficient of variation lower than one)
Volume of demand	A- or possibly B-classification according the ABC-analysis (volume and cost volume)
Product life cycle	Mature or possibly growth life cycle (stability of product mix)
Product characteristic	Standard product without any options
Production process characteristic	Production process under control (high product quality, low equipment failure rate) and low setup times

A second critical factor influencing the performance of DSSPL is the dispatching rule that manages the different priorities of A- and B-products. In the simplest case, priority is always given to the A-products if both A- and B-jobs are present in the queues. This is in accordance with the SI dispatching rule (shortest imminent operation) that in a survey of dispatching rules for manufacturing job shops realized by Blackstone et al. (1982) showed the best overall performance. One condition is consequently that the job sizes of A-products (kanbans) are generally smaller than those of B-products (production orders). It can however be imagined that job sizes of A-products are bigger than those of B-products particularly in the case of a customized low-volume B-product. The general application of a higher priority to A-products can therefore lead to long waiting times of production orders for B-products that decreases the overall logistic performance (increased WIP, decreased service level).

This problem has been addressed by Stagno et al. (2000) who developed a dispatching rule that allocates priority to A- and B-products depending on the waiting time of B-jobs (production orders) and on

Figure 3.2 Behavior of the DSSPL dispatching rule



the number of waiting A-jobs (kanbans). Two priority levels are therefore defined for the kanban queue. The lower and upper levels *llow* and *lup* define the domain in which priority can potentially be allocated to A-jobs. Thus, no priority is allocated to A-products if the number of waiting A-jobs N_A is smaller than *llow*. If N_A lies between *llow* and *lup* priority is allocated to A-jobs only if the maximum waiting time of B-jobs *tb* is lower than the limit *tcrit*. If N_A is, however, equal to or higher than *lup*, priority is always allocated to the A-products. The dispatching rule described above is translated into the following expression where priority is allocated to A- or B-jobs according to the value of γ defined by

$$\gamma = \frac{N_A - llow}{lup - llow} - \left(1 - \frac{N_A - llow}{lup - llow}\right)\frac{tb}{tcrit} \qquad \text{(Eq. 3.1)}$$

where

$$0 \le llow < lup, \quad tcrit > 0.$$

If *llow* = *lup*, equation 3.33 must be replaced by

$$\gamma = N_A - llow. \qquad \text{(Eq. 3.2)}$$

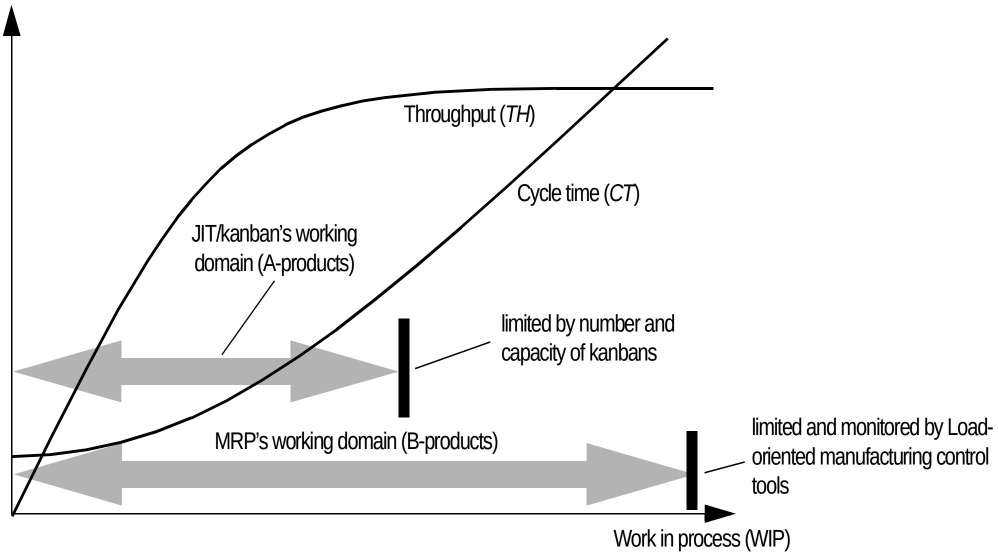
Consequently, if γ is greater than or equal to zero, priority is allocated to the A-jobs. The behavior of the dispatching rule is illustrated in Figure 3.2 where the value of γ is plotted as a function of N_A for different values of *tcrit*. Long waiting times for B-jobs are therefore prevented by setting high values for *llow* and *lup* and low values for *tcrit*. If *llow* and *lup* are set to zero, priority is always allocated to A-jobs.

Dispatching rules like those presented above are useful for handling items with different priorities but they are not adopted to prevent the production system from (too) high work loads. In the case of DSSPL this issue is particularly important for the management of B-jobs. In fact, by allocating priority to A-jobs, waiting times for B-jobs would increase significantly in the case of high work loads and consequently high *WIP* levels. As already discussed in the previous chapter the issue of limiting the work load by limiting the work-in-process is addressed in the case of the MPC methods POLCA and CONWIP by the use of generic kanban cards and in the case of the Load-oriented manufacturing control method by the use of monitoring tools. Since generic kanban cards are difficult to use in complex manufacturing environments, the monitoring tools of the Load-oriented manufacturing control method are more adopted for use in DSSPL to control the *WIP* level of B-items. Furthermore, they also allow the validation of the configuration of the dispatching rule and the JIT/kanban method (kanban loops) that is used for the management of the A-items. Table 3.2 lists a certain number of possible scenarios for *FR* levels of A- and B-jobs and corresponding comments concerning the configuration of DSSPL and the work load of the production system. The possible causes listed in Table 3.2 are validated by the simulation study presented in chapter §5.

Table 3.2: Configuration of DSSPL with optimal *FR* level FR_{opt} equal to 3...5

***FR* (A-jobs)**	***FR* (B-jobs)**	**Possible (not exclusive) causes**
$> FR_{opt}$	$<= FR_{opt}$	- Kanban loops overdimensioned; - Too low demand for A-items; - Too high kanban trigger levels *llow* and *lup*.
$<= FR_{opt}$	$> FR_{opt}$	- Kanban loops underdimensioned; - (Too) high demand for A-items.
$> FR_{opt}$	$> FR_{opt}$	- Too high work load.

Figure 3.3 DSSPL's working domain



The monitoring of DSSPL can further be improved by using load diagrams and throughput diagrams that allow the visual control of the "state" of a production system. Figure 3.3 illustrates the working domain of DSSPL that is monitored and controlled according to the concept described above.

3.1.3 Critique of DSSPL

Compared to existing MPC concepts, DSSPL can be distinguished by three characteristics. First, DSSPL relies on a strategic thinking about which goal is the optimal allocation of limited resources in order to obtain the maximum impact in terms of customer service and satisfaction. Second, in contrast to existing hybrid MPC approaches, DSSPL chooses the different MPC methods (JIT/kanban, MRP or Inventory control) according to a multiple-criteria analysis taking into account strategic aspects (marketing objectives) as well as operational ones (demand topology and product characteristics). The different MPC methods are therefore not allocated to certain or all production stages but to the flow of a certain class of

Figure 3.4 Comparison of MPC allocation concepts

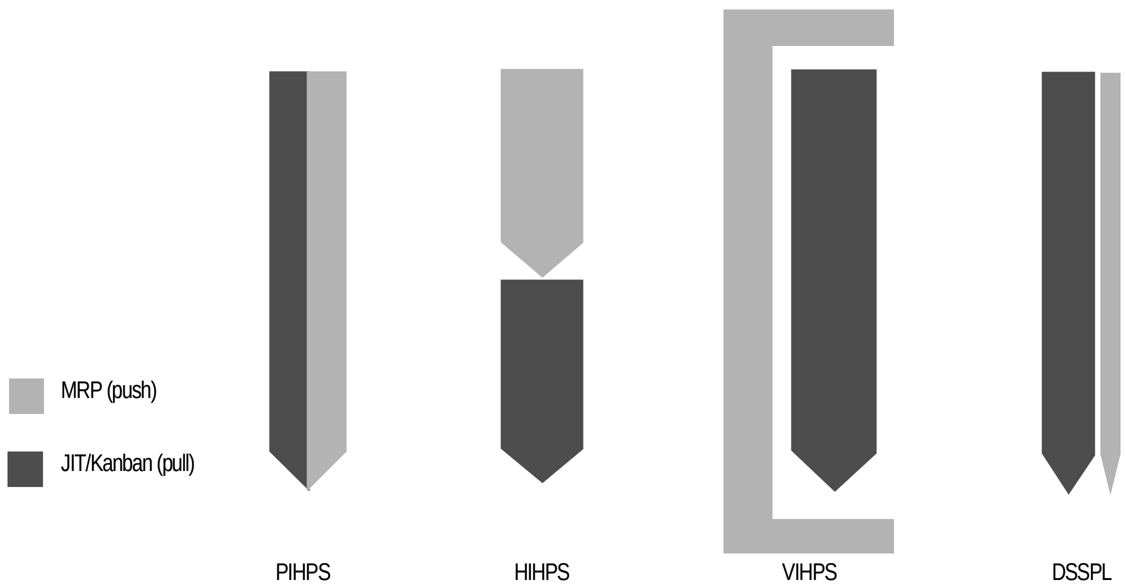
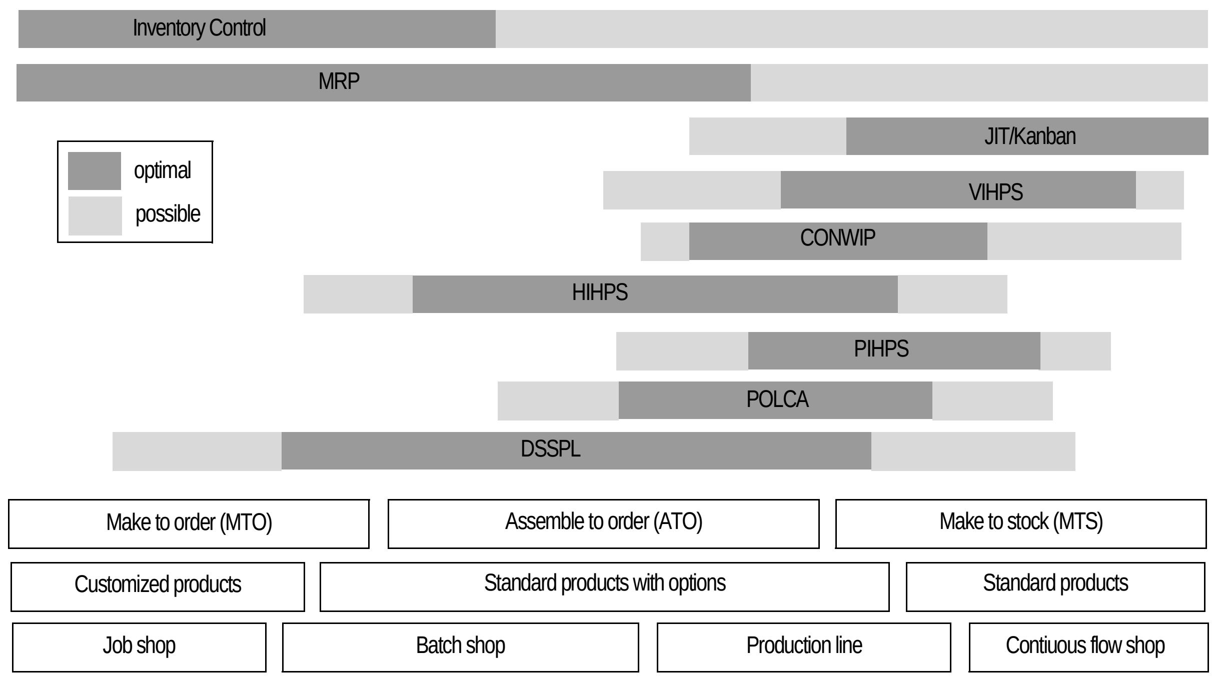


Figure 3.5 Application domain of reviewed MPC methods



products (A- and B-products). The impact of this concept of allocating MPC methods to the flow of products is illustrated in Figure 3.4 where DSSPL is compared to the other types of hybrid MPC methods. Finally, the third important DSSPL characteristic is its capacity to handle a wide variety of products. This is achieved by applying the JIT/kanban method to a limited number of dedicated products (A-products) and by the use of the monitoring tools developed for the Load-oriented manufacturing control method to control the work-in-process levels. As already discussed in the previous chapter, the application domains of existing hybrid MPC methods are either limited by the exclusive allocation of JIT/kanban to some or all production stages or by the use of generic kanban cards. Figure 3.5 illustrates the application domains of the reviewed MPC methods with respect to the manufacturing process design, product range and type and master production schedule approach. The most contrasting characteristics are observed for the three classical MPC methods Inventory Control, MRP and JIT/kanban. Inventory Control has, among existing MPC methods, the best capacity to handle a wide variety of products that have variable demand. MRP has similar capacities but performs with an improved inventory efficiency. JIT/kanban achieves the highest efficiency among existing MPC methods if the conditions (stable demand, standard products) are met. Consequently, with respect to the comparison of the application domain of MPC methods illustrated in Figure 3.5, DSSPL is the only hybrid MPC method that can be applied in an application domain comparable to those of MRP. But in contrast to MPR, DSSPL allows the management of production with reduced complexity. In fact, the number of variables to determine to run DSSPL is given for the case where B-items are managed by MRP by:

$$\begin{aligned} \Gamma 1_{DSSPL\_MRP} &= X_B NV1_{MRP} + K_{MRP} + X_B NV11_{DSSPL} + X_A NV12_{DSSPL} \\ \Gamma 2_{DSSPL\_MRP} &= X_{FPB} T_{PH} NV21_{MRP} + X_B NV22_{MRP} + X_A NV2_{JIT} \end{aligned} \quad \text{(Eq. 3.3)}$$

with

X_A = number of A-items;

X_B = number of B-items ($X_A + X_B = X$);

$NV11_{DSSPL}$ = 1 (critical waiting time *tcrit*);

$NV12_{DSSPL}$ = 4 (number *nk* and capacity *ck* of kanban, lower and upper trigger levels *llow* and *lup*);
X_{FPB} = number of B-final products.

In the case where B-items are managed by the Inventory control method the complexity becomes

$$\begin{aligned} \Gamma1_{DSSPL\_IC} &= X_B NV1_{IC} + X_B NV11_{DSSPL} + X_A NV12_{DSSPL} \\ \Gamma2_{DSSPL\_IC} &= X_B NV2_{IC} + X_A NV2_{JIT} \end{aligned} \qquad \text{(Eq. 3.4)}$$

Table 3.3 summarizes the results concerning the relative complexity $\Gamma_{rel} = \Gamma / \Gamma_{IC}$ of the reviewed MPC methods for two fictive scenarios if Inventory Control is chosen as reference. Consequently, values smaller than one correspond to a lower complexity, higher values than one to a higher complexity than those of Inventory Control. The first scenario corresponds to a production system that is characterized by simple linear product structures with low commonality and the following parameter settings: X = 50, X_{FP} = 10, T_{PH} = 10, X_{POLCA} = 5, X_{MTS} = 30, X_A = 12, X_{FPB} = 8 and X_{FPS} = 10. The second scenario corresponds to a production system that is characterized by complex product structures and the following parameter settings: X = 200, X_{FP} = 50, T_{PH} = 20, X_{POLCA} = 10, X_{MTS} = 100, X_A = 30, X_{FPB} = 42 and X_{FPS} = 40.

Table 3.3: Relative complexity of reviewed MPC methods compared to Inventory Control

	Relative complexity: Simple scenario		**Relative complexity: Complex scenario**	
MPC method	$\Gamma1_{rel}$	$\Gamma2_{rel}$	$\Gamma1_{rel}$	$\Gamma2_{rel}$
MRP	1.51	4	1.5	7
JIT/kanban	2	2	2	2
VIHPS	2.3	2.4	2.38	5.5
CONWIP	0.32	2.4	0.38	5.5
HIHPS	1.71	3.2	1.75	5
PIHPS	3.51	5	3.5	8
POLCA	1.56	4.1	1.53	7.05
DSSPL_IC	1.62	1.24	1.58	1.15
DSSPL_MRP	2	3.12	2	5.9

Concerning the complexity represented by the first term Γ1 (configuration of MPC system), the two MPC methods CONWIP and PIHPS are of particular interest. CONWIP is characterized by a particularly low complexity that is achieved by managing the production by generic kanban loops. Parameters have thus to be defined only for the items produced at the last stages of the loops. In contrast, PIHPS is characterized by a high complexity that is due to the fact that parameters for both MPC methods, JIT/kanban and MRP, have to be defined in parallel for each item. Concerning the complexity represented by the second term Γ2 (monitoring of logistic variables), the two MPC methods JIT/kanban and DSSPL_IC are of particular interest. These two MPC methods are characterized by low complexity compared to those of MRP, since they do not plan the production over a certain period (planning horizon). Concerning complexity of DSSPL two different conclusions can be drawn depending on the MPC method that is chosen for the management of B-items. DSSPL has a significantly lower complexity than MRP if B-items are managed by the Inventory Control method (DSSPL_IC). If B-items are managed with the MRP method, DSSPL's complexity is only lower than those of MRP in the case of the second term Γ2. The relative high complexity of DSSPL with respect to the configuration of the MPC method (Γ1) is mainly due to the additional parameter for the dispatching rule (*tcrit*). In chapter §5 of this work (simulation analysis) this issue is addressed by defining general rules for the setting of these parameters that help reduce the complexity of configuring DSSPL. It can be concluded that some of the reviewed MPC methods differ significantly with respect to their complexity. The highest overall complexity of all reviewed MPC methods exhibit PIHPS methods. This critical issue of this class of hybrid methods has been taken into account by Suri (1998) who proposes to use the POLCA concept only together with manufacturing cells that have the potential to simplify significantly the production process. The MPC methods requiring the lowest effort for configuration (Γ1) is CONWIP. The two DSSPL methods have a complexity that is depending on the configuration between those of MRP and Inventory Control or JIT/kanban.

Due to its characteristics, DSSPL has not only an impact on production planning but also on other sectors of a company’s supply chain. All these modifications are dictated by the characteristics of the MPC methods that are applied for A- and B-products respectively. In the case of purchasing and supplier relationships, the two product groups impose different solutions. Components and raw material for B-products are managed according to classical concepts whereas those for A-products must be modified. For these components JIT-purchasing techniques such as smaller lot sizes and more regular and reliable deliveries have to be adopted (Gunasekaran 1999). Both product groups also have an impact on the material planning approach. In fact, for A-products, a rate-based planning approach has to be adopted whereas B-products are planned with a time-phased approach (Vollmann et al. 1997). The rate-based planning approach is characterized by establishing rates of production rather than single time-phased orders that are generated in the time-phased approach. Finally, the application of JIT/Kanban also has a significant impact on the availability and delivery times of A-products. These articles can be delivered directly to the customers without adding a production delay to the delivery time. In contrast, since B-products are managed by the MRP concept, higher delivery times can be expected for these products. An exception to this rule is the case when B-products are managed by the Inventory Control. In this case, the availability of B-products is comparable to those of A-products, however with a lower economic efficiency due to higher inventory levels.

It can be concluded that DSSPL can be distinguished to other MPC methods particularly due to its capacity to manage a wide variety of products. As already mentioned before, DSSPL’s application domain is not limited by the exclusive allocation of JIT/kanban to some or all production stages or by the use of generic kanban cards. Critical issues of DSSPL are, however, the configuration of the dispatching rule and the choice of the A-products. The configuration of the dispatching rule has a significant impact on the performance of the two product groups that are managed with DSSPL. Its configuration must correspond to a compromise between the need to allocate priority to A-products and to minimize the lead times of B-products. The appropriate choice of the A-products as well as the stability of the A-/B-product-mix are a second important issue for the performance and applicability of DSSPL. Typically, manufacturing environments with highly variating product mixes (in quantity and time) exclude, therefore, the application of DSSPL.

3.2 Markovian analysis of DSSPL

The performances of DSSPL are analyzed and compared to those of the classical MRP concept through the use of a Markovian birth-death queueing model of a single-stage, two-product production system. The use of a Markovian model allows the capture of the basic mechanics of DSSPL when applied to a stochastic manufacturing environment. The service level and inventory holding costs are chosen as principal performance metrics.

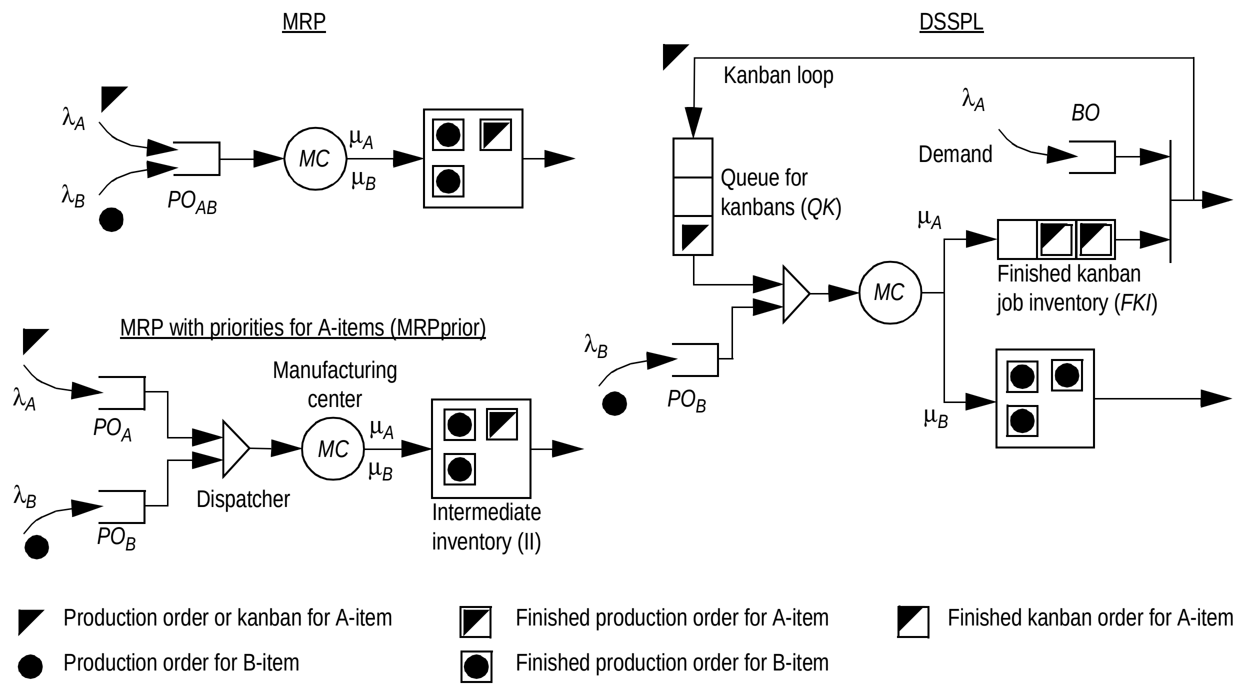
The choice of a Markovian birth-death process for the analysis of DSSPL is justified mainly by the fact that the elements of the Markov transition matrix can easily be determined by the use of rate transition diagrams and that the computations involve well-known and easily implemented matrix operations (Gross and Harris 1998, Davis and Kennedy Jr. 1987). Rate transition diagrams can be constructed for every possible state *n* and its neighboring states *n+1* and *n-1* of a system by assuming that state *n* goes to state *n-1* if a service is completed or to *n+1* if an arrival occurs. The restrictions of Markovian birth-death processes are that only single step transitions (no bulk arrivals) are allowed and that the interarrival times and processing times are exponentially distributed (poisson process). It is assumed however that these restrictions do not interfere with the goals of this analysis.

3.2.1 Model description

As shown in Figure 3.6, the manufacturing environment which is modelled consists of a single-stage, two-item production system (one manufacturing center *MC*, A- and B-products), that is managed either by the MRP (MRP with and without priority for A-products) or DSSPL concept.

In the MRP model, the production of both A- and B-products is initiated by production orders waiting in the production order queue PO_{AB}. At this stage no priority rule is applied to the two types of product. Consequently, all incoming production orders (mean arrival rates: $\lambda_A = 1/E[t_A]$ and $\lambda_B = 1/E[t_B]$ with *t* as the exponentially distributed time between two arrivals) are processed according to the FIFO (first in, first out) dispatching rule. The mean service rates are defined by $\mu_A = 1/E[s_A]$ and $\mu_B = 1/E[s_B]$ where *s* corresponds to the exponentially distributed service time per job. After completion, the finished A- and B-jobs are sent to the intermediate inventory *II*, from where they are removed after a predefined lead time *lt* (counted from arrival time into the production order queue) for further use or delivery to the client.

Figure 3.6 Concept of the MRP-, MRPprior and DSSPL-model



In the MRP model with priorities (MRPprior), production orders of A-products (in PO_A) are served ahead of production orders for B-products (in PO_B) without preemption. The MRPprior model is a first transition from the classical MRP to the DSSPL concept where, in addition to the priority rule, the kanban technique is also used instead of the MRP concept for management of the A-products. In the case of DSSPL, the kanban technique is used to initiate production only when an effective demand has occurred. As shown in Figure 3.6, the demand for A-products arrives at queue *BO* and waits there if it cannot be satisfied immediately by finished A-jobs waiting in the queue *FKI*. That is, accumulations in queue *BO* are considered as back orders. If finished A-jobs are available, the attached kanban is removed and sent back to the queue for kanbans *QK* in order to initiate production for A-products. Non-preemptive priority is allocated to the kanban production orders over the production orders for B-products depending on a predefined priority threshold level *thl* ($1 \le thl \le nk$, where *nk* = number of kanbans). In fact, priority is allocated to the kanbans only if the number of waiting kanbans in *QK* is equal to or higher than *thl*. This represents a simplified concept of the DSSPL dispatching rule presented in section §3.1.2. Consequently, kanbans always have higher priority than production orders for B-products if *thl* is set to one.

Besides the different MPC concepts, the manufacturing environment that has been modelled is further characterized by the following parameters:

stp = set-up time in case of a change from A- to B-jobs or vice-versa;
RatioAB = ratio between load generated by A- and B-jobs defined by $RatioAB = sysint_A / sysint_B$ where $sysint_A = \lambda_A / \mu_A$ and $sysint_B = \lambda_B / \mu_B$;
RatioS = ratio between the size of A- and B-jobs defined by $RatioS = s_A / s_B$;
CostRatio = ratio between the inventory holding cost for the raw material (C_1) and the finished product (C_0) defined by $CostRatio = C_0 / C_1$.

In the case that set-ups are required, the mean service rates are, therefore, modified to be $\mu_{As} = 1/E[s_A + stp]$ and $\mu_{Bs} = 1/E[s_B + stp]$.

The system states of the different models are represented by vectors that describe the state of the corresponding queues. In the case of the MRP model, a state is defined by the sequence of production orders of A- and B-products waiting in PO_{AB}. If *M* and *N* are the capacity of A- and B-production orders waiting in PO_{AB} respectively, then the total number of states is given by:

$$\Omega_{MRP} = \sum_{m=0}^{M} \sum_{n=0}^{N} \binom{m+n}{m}. \qquad \text{(Eq. 3.1)}$$

For the particular case of *M* = 2 and *N* = 2, one out of six possible state vectors with dimension $(M + N)$ becomes therefore $\mathbf{n}_{MRP} = (A, B, B, A)$ where the first element of the vector is defined as the production order in service.

With p_n as the steady-state probability of a birth-death process being in state *n* (*n* corresponding to state vector $\mathbf{n}_{MRP}$ described above and p_0 equal to zero state) the steady-state balance equations for the MRP model with both M and N set to two become:

$$0 = -(\lambda_A + \lambda_B)p_0 + \mu_A p_A + \mu_B p_B,$$

$$0 = -(\lambda_A + \lambda_B)p_A + \mu_{Bs} p_{AB} + \mu_A p_{AA} + \lambda_A p_0,$$

$$0 = -(\lambda_A + \lambda_B)p_B + \mu_B p_{BB} + \mu_{As} p_{BA} + \lambda_B p_0,$$

$$0 = -(\lambda_A + \lambda_B + \mu_{Bs})p_{AB} + \mu_B p_{ABB} + \mu_{As} p_{ABA},$$

$$0 = -(\lambda_A + \lambda_B + \mu_{As})p_{BA} + \mu_A p_{BAA} + \mu_{Bs} p_{BAB},$$
$$0 = -(\lambda_B + \mu_A)p_{AA} + \mu_{Bs} p_{AAB},$$
$$0 = -(\lambda_A + \mu_B)p_{BB} + \mu_{As} p_{BBA},$$
$$0 = -(\lambda_A + \mu_B)p_{ABB} + \mu_{As} p_{ABBA},$$
$$0 = -(\lambda_A + \mu_{Bs})p_{BAB} + \mu_{As} p_{BABA}, \qquad \text{(Eq. 3.2)}$$
$$0 = -(\lambda_A + \mu_{Bs})p_{BBA} + \mu_A p_{BBAA},$$
$$0 = -(\lambda_B + \mu_{Bs})p_{AAB} + \mu_B p_{AABB},$$
$$0 = -(\lambda_B + \mu_{As})p_{ABA} + \mu_{Bs} p_{ABAB},$$
$$0 = -(\lambda_B + \mu_A)p_{BAA} + \mu_{Bs} p_{BABA},$$
$$0 = -\mu_B p_{AABB} + \lambda_A p_{ABB},$$
$$0 = -\mu_{Bs} p_{ABAB} + \lambda_A p_{BAB},$$
$$0 = -\mu_{Bs} p_{BAAB} + \lambda_B p_{AAB},$$
$$0 = -\mu_{As} p_{ABBA} + \lambda_A p_{BBA},$$
$$0 = -\mu_{As} p_{BABA} + \lambda_B p_{ABA},$$
$$0 = -\mu_A p_{BBAA} + \lambda_B p_{BAA}.$$

In the case of the MRPprior model, a state is defined by the number of production orders waiting in PO_A (m) and PO_B (n) as well as by the type r of the product being serviced (r = A or B). If M and N are the capacities of PO_A and PO_B for A- and B-production orders respectively, the number of different state vectors $\mathbf{n}_{MRPprior} = (m, n, r)$ becomes

$$\Omega_{MRPprior} = (N+1)M + (M+1)N \qquad \text{(Eq. 3.3)}$$

With p_n as the steady-state probability of a birth-death probability of a birth-death process being in state n (n corresponding to state vector $\mathbf{n}_{MRPprior}$ described above and p_0 equal to zero state) the steady-state balance equations for the MRPprior model become:

$$0 = -(\lambda_A + \lambda_B)p_0 + \mu_A p_{101} + \mu_B p_{012},$$
$$0 = -(\lambda_A + \lambda_B + \mu_{As})p_{101} + \mu_A p_{201} + \mu_{Bs} p_{112} + \lambda_A p_0,$$
$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{m01} + \mu_{Bs} p_{m12} + \mu_{Bs} p_{m12} + \lambda_A p_{m-1,1,2}$$

with $(2 \le m \le M)$,

$$0 = -(\lambda_B + \mu_A)p_{m01} + \lambda_A p_{M-1,0,1} + \mu_{Bs} p_{M12},$$
$$0 = -(\lambda_A + \lambda_B + \mu_B)p_{012} + \mu_{As} p_{111} + \mu_B p_{022} + \lambda_A p_0,$$

$$0 = -(\lambda_A + \lambda_B + \mu_{As})p_{1n1} + \mu_A p_{2n1} + \mu_{Bs} p_{1,\,n+1,\,2} + \lambda_B p_{1,\,n-1,\,1}$$

with $(1 \le n < N)$,

$$0 = -(\lambda_B + \mu_{As})p_{Mn1} + \lambda_A p_{M-1,\,n,\,1} + \mu_{Bs} p_{M,\,n+1,\,2} + \lambda_B p_{M,\,n-1,\,1}$$

with $(1 \le n < N)$,

$$0 = -(\lambda_A + \lambda_B + \mu_B)p_{0n2} + \mu_{As} p_{1n1} + \mu_B p_{0,\,n+1,\,2} + \lambda_B p_{0,\,n-1,\,2}$$

with $(2 \le n < N)$,

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{mn1} + \mu_A p_{m+1,\,n,\,1} + \mu_{Bs} p_{m,\,n+1,\,1} + \lambda_A p_{m-1,\,n,\,1} + \lambda_A p_{m,\,n-1,\,1}$$

with $(2 \le m < M)$ and $(1 \le n < N)$,

$$0 = -(\lambda_A + \mu_B)p_{0N2} + \lambda_B p_{0,\,N-1,\,2} + \mu_{As} p_{1N1}, \qquad \text{(Eq. 3.4)}$$

$$0 = -(\lambda_A + \mu_A)p_{mN1} + \lambda_B p_{m,\,N-1,\,1} + \mu_A p_{m+1,\,N,\,1} + \lambda_A p_{m-1,\,N,\,1}$$

with $(2 \le n < N)$,

$$0 = -(\lambda_A + \mu_{As})p_{1N1} + \mu_A p_{2N1} + \lambda_B p_{1,\,N-1,\,1},$$

$$0 = -\mu_A p_{MN1} + \lambda_A p_{M-1,\,N,\,1} + \lambda_B p_{M,\,N-1,\,1},$$

$$0 = -(\lambda_A + \lambda_B + \mu_{Bs})p_{mn2} + \lambda_A p_{m-1,\,n,\,2} + \lambda_B p_{m,\,n-1,\,2}$$

with $(1 \le m < M)$ and $(2 \le n < N)$,

$$0 = -(\lambda_B + \mu_{Bs})p_{Mn2} + \lambda_A p_{M-1,\,n,\,2} + \lambda_B p_{M,\,n-1,\,1}$$

with $(2 \le n < N)$,

$$0 = -(\lambda_A + \lambda_B + \mu_{Bs})p_{m12} + \lambda_A p_{m-1,\,1,\,2}$$

with $(1 \le m < M)$,

$$0 = -(\lambda_A + \mu_{Bs})p_{M12} + \lambda_A p_{M-1,\,1,\,2},$$

$$0 = -(\lambda_A + \mu_{Bs})p_{mN2} + \lambda_A p_{m-1,\,N,\,2} + \lambda_B p_{m,\,N-1,\,2}$$

with $(1 \le m < M)$,

$$0 = -\mu_{Bs} p_{MN2} + \lambda_A p_{M-1,\,N,\,2} + \lambda_B p_{M,\,N-1,\,2}.$$

A state of the DSSPL model is described by the state vector $\mathbf{n}_{DSSPL} = (b, m, n, r)$ (b demands back ordered in *BO*, *m* waiting kanbans in *QK*, *n* production orders in PO_B and the type *r* of product in service). If *B*, *M* and *N* are the capacities of *BO* for back ordered demands and of PO_A and PO_B for A- and B-production orders respectively, the number of different states becomes

$$\Omega_{DSSPL} = thl + (N+1)(M+B) + (M+B+1)N. \qquad \text{(Eq. 3.5)}$$

With p_n as the steady-state probability of a birth-death process being in state n (n corresponding to state vector $\mathbf{n}_{DSSPL}$ described above and p_0 equal to zero state) the steady-state balance equations for the DSSPL model become:

$$0 = -(\lambda_A + \lambda_B)p_0 + \mu_A p_{0101} + \{\mu_B p_{0012} \text{ if } thl = 1\},$$

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{0101} + \lambda_A p_0 + \mu_{Bs} p_{0112},$$

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{0m01} + \mu_A p_{0,\, m+1,\, 0,\, 1} + \mu_{Bs} p_{0m12} + \lambda_A p_{0,\, m-1,\, 0,\, 1}$$

with $(2 \le m < M)$,

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{0M01} + \mu_A p_{1M01} + \mu_{Bs} p_{0M12} + \lambda_A p_{0,\, M-1,\, 0,\, 1},$$

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{bM01} + \mu_A p_{b+1,\, M,\, 0,\, 1} + \mu_{Bs} p_{b+1,\, M,\, 0,\, 1} + \lambda_A p_{b-1,\, M,\, 0,\, 1}$$

with $(1 \le b < B)$,

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{01n1} + \mu_A p_{0221} + \lambda_B p_{0,\, 1,\, n-1,\, 1} + \{\mu_{Bs} p_{0,\, 1,\, n+1,\, 2} \text{ if } thl = 1\}$$

with $(1 \le n < N)$,

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{0mn1} + \mu_A p_{0,\, m+1,\, n,\, 1} + \lambda_A p_{0,\, m-1,\, n,\, 1} + \lambda_B p_{0,\, m,\, n-1,\, 1} + \{\mu_{Bs} p_{0,\, m,\, n+1,\, 2} \text{ if } thl \le m\}$$

with $(1 \le n < N)$ and $(2 \le m < M)$,

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{0Mn1} + \mu_A p_{0Mn1} + \mu_{Bs} p_{0,\, M,\, n+1,\, 2} + \lambda_A p_{0,\, M-1,\, n,\, 1} + \lambda_B p_{0,\, M,\, n-1,\, 1}$$

with $(1 \le n < N)$,

$$0 = -(\lambda_A + \lambda_B + \mu_A)p_{bMn1} + \mu_A p_{b+1,\, M,\, n,\, 1} + \mu_{Bs} p_{0,\, M,\, n+1,\, 2} + \lambda_A p_{b-1,\, M,\, n,\, 1} + \lambda_B p_{b,\, M,\, n-1,\, 1}$$

with $(1 \le b < B)$ and $(1 \le n < N)$,

$$0 = -(\lambda_B + \mu_A)p_{BMn1} + \mu_{Bs} p_{B,\, M,\, n+1,\, 2} + \lambda_A p_{B-1,\, M,\, n,\, 1} + \lambda_B p_{B,\, M,\, n-1,\, 1}$$

with $(1 \le n < N)$,

$$0 = -(\lambda_A + \mu_A)p_{0MN1} + \mu_A p_{1MN1} + \lambda_A p_{0,\, M-1,\, N,\, 1} + \lambda_B p_{0,\, M,\, N-1,\, 1},$$

$$0 = -(\lambda_A + \mu_{As})p_{01N1} + \mu_A p_{02N1} + \lambda_B p_{0,\, 1,\, N-1,\, 1}, \qquad \text{(Eq. 3.6)}$$

$$0 = -(\lambda_A + \mu_A)p_{0mN1} + \mu_A p_{0,\, m+1,\, N,\, 1} + \lambda_A p_{0,\, m-1,\, N,\, 1} + \lambda_B p_{0,\, m,\, N-1,\, 2}$$

with $(2 \le m < M)$,

$$0 = -(\lambda_A + \mu_A)p_{bMN1} + \mu_A p_{b+1,\, M,\, N,\, 1} + \lambda_A p_{b-1,\, M,\, N,\, 1} + \lambda_B p_{b,\, M,\, N-1,\, 1}$$

with $(1 \le b < B)$,

$$0 = -\mu_A p_{BMN1} + \lambda_A p_{B-1,\, M,\, N,\, 1} + \lambda_B p_{B,\, M,\, N-1,\, 1},$$

$$0 = -(\lambda_A + \lambda_B)p_{0mn2} - \{\mu_B p_{0mn2} \text{ if } thl > 1\} + \lambda_A p_{0,\, m-1,\, n,\, 2} + \lambda_B p_{0,\, m,\, n-1,\, 2} + \{\mu_{Bs} p_{0mn2} \text{ if } thl = 1\} + \{\mu_B p_{0,\, m,\, n+1,\, 2} \text{ if } thl \ge 1\},$$

with $(1 \le m < M)$ and $(2 \le n < N)$,

$$0 = -(\lambda_A + \lambda_B + \mu_{Bs})p_{0m12} + \lambda_A p_{0,\, m-1,\, 1,\, 2} + \{\mu_B p_{0m22} \text{ if } thl > 1\}$$

with $(1 \le m < M)$,

$$0 = -(\lambda_A + \mu_{Bs})p_{0MN2} + \lambda_A p_{0,\, M-1,\, N,\, 2} + \lambda_A p_{0,\, M,\, N-1,\, 2},$$

$$0 = -(\lambda_A + \mu_{Bs})p_{bMN2} + \lambda_A p_{b,\, M-1,\, N,\, 2} + \lambda_B p_{b,\, M,\, N-1,\, 2}$$

with $(1 \le b < B)$,

$$0 = -\mu_{Bs}p_{BMN2} + \lambda_A p_{B,\, M-1,\, N,\, 2} + \lambda_B p_{B,\, M,\, N-1,\, 2}.$$

3.2.2 Performance metrics

The performance metrics chosen are the inventory holding costs *IC* and the service level *SL*. In the case of MRP the inventory holding costs are defined as the sum of costs generated by the raw material allocated to production orders waiting or being processed in the production system and the final products waiting in the intermediate inventory *II* where the production orders are sent after completion. The first term of the expression for the inventory costs is thus defined by assuming that the quantity of raw material is proportional to the work content of the production orders in the system. Consequently, the first term becomes

$$\frac{C_1}{\mu}\sum_{i}^{\Omega} p_i m_i$$

with

Ω = number of system states;
p_i = steady-state probability of state i;
m_i = number of production orders (m for A-products, n for B-products) in the system (queue and service);

The second term of the expression for the inventory holding costs is computed based on the assumption that the waiting time of the finished products in the intermediate inventory *II* is equal to the difference between the lead time *lt* and the average time in the system of a production order. It is assumed that the final products are removed from the intermediate inventory *II* after time *lt* counted from the moment when the production order is sent to the production system. If, however, the average time in the system of the production orders is longer than lt, it is assumed that the fulfilled production orders leave the production system without passing by the intermediate inventory. The second term becomes, therefore, by applying Little's law and assuming that the mean arrival rate of finished products into the intermediate inventory is equal to the mean arrival rate λ of production orders into the production system:

$$\frac{C_0\lambda}{\mu}\sum_{i}^{\Omega} p_i max\left(lt - \frac{m_i}{\lambda};0\right)$$

with

lt = predefined lead time for A- or B-product;

The expression for the inventory holding costs of the MRP model becomes, finally, by introducing the parameter *CostRatio* and setting the inventory holding cost C_0 for raw material to one:

$$IC_{MRP} = \frac{1}{\mu}\sum_{i}^{\Omega} p_i\left(m_i + CostRatio\lambda max\left(lt - \frac{m_i}{\lambda};0\right)\right) \quad \text{(Eq. 3.7)}$$

By applying the same assumptions the expression for the inventory holding costs for the A- product managed by the kanban technique becomes

$$IC^A_{Kanban} = \frac{1}{\mu_A}\sum_{i}^{\Omega} p_i(m_i + CostRatio(M - m_i)) \quad \text{(Eq. 3.8)}$$

with
m_i = number of waiting kanbans for state i in queue for kanbans;
M = total number of kanbans.

Consequently, the total inventory costs for the MRP, MRPprior and DSSPL model become

$$IC_{MRP(prior)} = IC^A_{MRP} + IC^B_{MRP} \quad \text{(Eq. 3.9)}$$

and

$$IC_{DSSPL} = IC^A_{Kanban} + IC^B_{MRP} . \quad \text{(Eq. 3.10)}$$

Since the production schedule of all products in MRP based systems is generated based on predefined lead times, a job is considered as fulfilled if its time in the system (queue and service) is shorter than or equal to the predefined lead time *lt*. Consequently, the service level for the MRP and MRPprior concept becomes

$$SL_{MRP(prior)} = \frac{\frac{\rho_A L'_A}{\mu_A} + \frac{\rho_B L'_B}{\mu_B}}{\frac{\rho_A L_A}{\mu_A} + \frac{\rho_B L_B}{\mu_B}} \quad \text{(Eq. 3.11)}$$

where

$$L' = \sum_{i}^{\Omega'} p_i m_i \text{ and } L = \sum_{i}^{\Omega} p_i m_i$$

with
Ω' = system states where the time in system (m_i/λ_A or n_i/λ_B) is smaller than or equal to the predefined lead time (lt_A or lt_B);

The determination of the service level for products managed by the kanban technique is not based on the effective and predefined lead time but on the capacity to satisfy a demand immediately from finished kanban jobs. The service level for the DSSPL concept becomes therefore:

$$SL_{DSSPL} = \frac{\dfrac{\rho_A L'_K}{\mu_A} + \dfrac{\rho_B L'_B}{\mu_B}}{\dfrac{\rho_A L_K}{\mu_A} + \dfrac{\rho_B L_B}{\mu_B}} \qquad \text{(Eq. 3.12)}$$

where

$$L'_K = \sum_i^{\Omega^K} p_i m_i \text{ and } L_K = \sum_i^{\Omega} p_i (m_i + b_i)$$

with
Ω^K = system states where no back orders occur ($b_i = 0$);
b_i = number of back ordered jobs for state i in BO.

3.2.3 Experimental design

The experimental design is based on a two-step approach. In the first step, a configuration with a service level $SL = 0.95$ for every MPC concept is determined for standard parameter values and for a system intensity (load) $sysint = sysint_A + sysint_B$ equal to 0.4. The lead times *lt* and the number of kanbans *nmbk* are therefore adjusted in order to reach the targeted service level. In the second step, the models are evaluated with the parameter values indicated in Table 3.4.

Table 3.4: Experimental design (standard values in bold face)

Parameter	**Values**
stp	**0**, 0.5
RatioAB	**1**, 4
RatioS	**1**, 0.4 (only for A-products in DSSPL)
CostRatio	**1**, 5
sysint	0.4
thl	**1**, 2
s_A, s_B	1
lt_A, lt_B	10, **15**, 20

A reduction of the lot size expressed by *RatioS* is only applied to A-products in the DSSPL concept, since it is assumed that significant lot size reductions are only applicable with the kanban technique. The variation of *lt* represents the forecast error due to the fact that MRP has to determine production orders before the effective demand has occurred. The low and high values of *lt* represent, therefore, an under- or overestimation of the real demand.

The capacities of the queues defining the standard configuration of the analyzed MPC models are summarized in Table 3.5.

Table 3.5: Standard configuration for a service level of 0.95

Capacity of queues	MRP	MRPprior	DSSPL
M	8	8	4 (*nmbk*)
N	8	8	8
B	-	-	4

3.2.4 Computational results

The computational results of the three models (the three configurations of the DSSPL model, DSSPL.1.1, DSSPL.1.04, and DSSPL.2.04, are termed according to the syntax DSSPL.*thl*.*RatioS*.) shown in Figure 3.1 were obtained by solving the stationary equations:

$$\begin{aligned} \mathbf{0} &= \mathbf{pQ}, \\ \mathbf{1} &= \mathbf{pe}, \end{aligned} \qquad \text{(Eq. 3.13)}$$

where **p** is the steady-state probability vector, **Q** the infinitesimal generator of the continuous-time Markov chain, and **e** a vector of ones (Gross and Harris 1998). In the case of the MRP model, an iterative Gauss-Seidel procedure has been chosen to solve (Eq. 3.13) due to the high number of states. For the two other models, DSSPL and MRPprior, a standard Gauss-Jordan technique has been chosen to solve (eq. 3.13) due to the moderate model size. All models have been programmed in C and implemented on an HP-9000 workstation. CPU-time ranged from 10 sec. for the MRPprior and DSSPL models to approximately one hour in the case of the MRP model. The following Tables 3.6, 3.7 and 3.8 show the results obtained together with results that have been computed with the help of discrete-event versions (simulation package ARENA) of the analyzed models. A further (partial) validation of the computational results has been performed with the help of expressions for priority queues (see Appendix A) developed by Gross and Harris (1998) that are valid for all cases with setup equal to zero (*stp* = 0).

Table 3.6: Computational Results for *lt* = 15 (results from discrete-event simulator in italics)

Ratio AB	Cost Ratio	Setup	MRP		MRPprior		DSSPL.1.1		DSSPL.1.04		DSSPL.2.04	
			SL	IC	SL	IC	SL	IC	SL	IC	SL	IC
1	1	0	0.95	1.51	0.94	1.5	0.95	4.79	0.96	2.32	0.97	2.34
			0.95	*1.51*	*0.95*	*1.51*	*0.97*	*4.75*	*0.97*	*2.28*	*0.98*	*2.31*
1	1	0.5	0.89	1.85	0.89	1.77	0.91	4.95	0.89	2.57	0.93	2.51
			0.91	*1.63*	*0.91*	*1.63*	*0.92*	*5.03*	*0.86*	*2.66*	*0.92*	*2.59*
1	5	0	0.95	4.88	0.94	4.82	0.95	21.31	0.96	9.75	0.97	9.06
			0.95	*4.88*	*0.95*	*4.89*	*0.97*	*21.1*	*0.97*	*9.57*	*0.98*	*8.83*
1	5	0.5	0.89	5.65	0.89	5.47	0.91	21.39	0.89	10.12	0.93	9.32
			0.91	*5.13*	*0.91*	*5.13*	*0.92*	*21.02*	*0.86*	*9.78*	*0.92*	*9.1*

Table 3.6: Computational Results for *lt* = 15 (results from discrete-event simulator in italics)

Ratio AB	Cost Ratio	Setup	MRP		MRPprior		DSSPL.1.1		DSSPL.1.04		DSSPL.2.04	
			SL	IC	SL	IC	SL	IC	SL	IC	SL	IC
4	1	0	0.94	1.83	0.94	1.81	0.97	4.18	0.96	1.74	0.97	1.75
			0.94	*1.83*	*0.94*	*1.84*	*0.97*	*4.15*	*0.95*	*1.72*	*0.96*	*1.73*
4	1	0.5	0.9	2.03	0.92	1.97	0.95	4.23	0.92	1.81	0.94	1.8
			0.91	*1.9*	*0.92*	*1.9*	*0.94*	*4.22*	*0.86*	*1.79*	*0.9*	*1.79*
4	5	0	0.94	6.47	0.94	6.4	0.97	18.26	0.96	7.33	0.97	6.59
			0.94	*6.47*	*0.94*	*6.51*	*0.97*	*18.12*	*0.95*	*7.26*	*0.96*	*6.43*
4	5	0.5	0.9	6.92	0.92	6.83	0.95	18.16	0.92	7.29	0.94	6.58
			0.91	*6.61*	*0.92*	*6.63*	*0.94*	*17.61*	*0.86*	*6.97*	*0.9*	*6.19*

Table 3.7: Computational Results for *lt* = 10 (results from discrete-event simulator in italics)

Ratio AB	Cost Ratio	Setup	MRP		MRPprior		DSSPL.1.1		DSSPL.1.04		DSSPL.2.04	
			SL	IC	SL	IC	SL	IC	SL	IC	SL	IC
1	1	0	0.84	1.04	0.83	1.04	0.89	4.55	0.89	2.10	0.92	2.11
			0.84	*1.04*	*0.85*	*1.04*	*0.92*	*4.52*	*0.92*	*2.07*	*0.94*	*2.08*
1	1	0.5	0.75	1.31	0.76	1.25	0.82	4.68	0.78	2.30	0.85	2.25
			0.79	*1.14*	*0.79*	*1.14*	*0.85*	*4.74*	*0.78*	*2.35*	*0.86*	*2.30*
1	5	0	0.84	2.54	0.83	2.51	0.89	20.11	0.89	8.63	0.92	7.90
			0.84	*2.54*	*0.85*	*2.55*	*0.92*	*19.93*	*0.92*	*8.49*	*0.94*	*7.71*
1	5	0.5	0.75	2.95	0.76	2.86	0.82	20.06	0.78	8.74	0.85	7.99
			0.79	*2.68*	*0.79*	*2.68*	*0.85*	*19.54*	*0.78*	*8.25*	*0.86*	*7.62*
4	1	0	0.82	1.27	0.83	1.26	0.91	4.16	0.86	1.72	0.91	1.73
			0.82	*1.27*	*0.83*	*1.27*	*0.93*	*4.13*	*0.87*	*1.71*	*0.92*	*1.71*
4	1	0.5	0.76	1.42	0.80	1.38	0.90	4.21	0.81	1.78	0.88	1.78
			0.79	*1.32*	*0.80*	*1.33*	*0.90*	*4.19*	*0.79*	*1.76*	*0.85*	*1.77*
4	5	0	0.82	3.66	0.83	3.63	0.91	18.15	0.86	7.24	0.91	6.49
			0.82	*3.66*	*0.83*	*3.68*	*0.93*	*18.02*	*0.87*	*7.17*	*0.92*	*6.34*
4	5	0.5	0.76	3.9	0.8	3.88	0.90	18.03	0.81	7.17	0.88	6.46
			0.79	*3.74*	*0.8*	*3.75*	*0.90*	*17.48*	*0.79*	*6.84*	*0.85*	*6.09*

Table 3.8: Computational Results for *lt* = 20 (results from discrete-event simulator in italics)

Ratio AB	Cost Ratio	Setup	MRP		MRPprior		DSSPL.1.1		DSSPL.1.04		DSSPL.2.04	
			SL	IC	SL	IC	SL	IC	SL	IC	SL	IC
1	1	0	0.98	2.00	0.98	1.98	0.98	5.05	0.99	2.56	0.99	2.58
			0.98	*2.00*	*0.99*	*2.00*	*0.99*	*5.00*	*0.99*	*2.51*	*0.99*	*2.54*
1	1	0.5	0.95	2.43	0.95	2.32	0.95	5.24	0.95	2.88	0.97	2.80
			0.96	*2.15*	*0.96*	*2.15*	*0.96*	*5.36*	*0.90*	*2.99*	*0.95*	*2.91*
1	5	0	0.98	7.35	0.98	7.25	0.98	22.58	0.99	10.93	0.99	10.26
			0.98	*7.34*	*0.99*	*7.36*	*0.99*	*22.33*	*0.99*	*10.70*	*0.99*	*9.98*

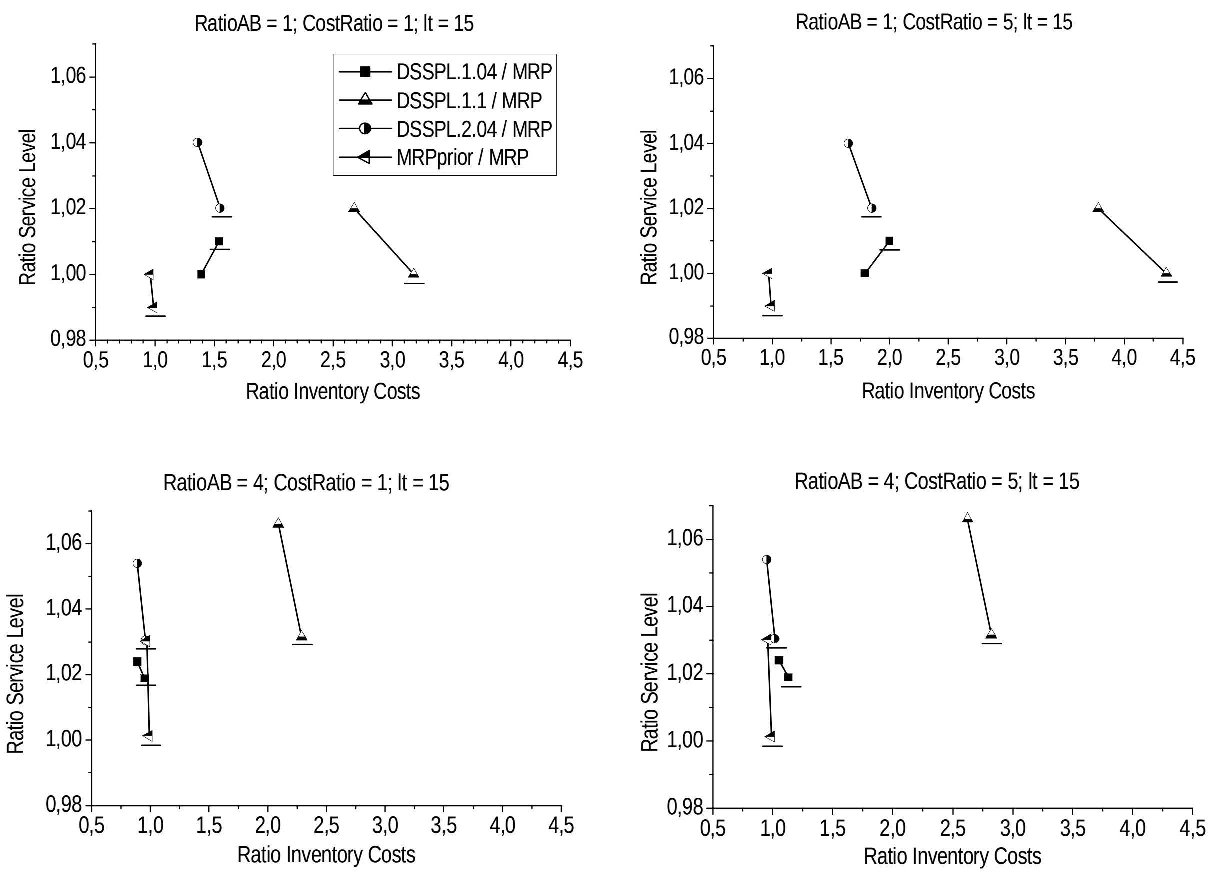
Table 3.8: Computational Results for *lt* = 20 (results from discrete-event simulator in italics)

Ratio AB	Cost Ratio	Setup	MRP		MRPprior		DSSPL.1.1		DSSPL.1.04		DSSPL.2.04	
			SL	**IC**	**SL**	**IC**	**SL**	**IC**	**SL**	**IC**	**SL**	**IC**
1	5	0.5	0.95	8.57	0.95	8.26	0.95	22.85	0.95	11.63	0.97	10.76
			0.96	*7.74*	*0.96*	*7.73*	*0.96*	*22.62*	*0.90*	*11.44*	*0.95*	*10.68*
4	1	0	0.98	2.42	0.97	2.40	0.97	4.23	0.96	1.78	0.97	1.79
			0.98	*2.42*	*0.98*	*2.44*	*0.97*	*4.19*	*0.95*	*1.76*	*0.96*	*1.77*
4	1	0.5	0.96	2.68	0.96	2.60	0.95	4.28	0.92	1.86	0.94	1.85
			0.97	*2.51*	*0.97*	*2.52*	*0.94*	*4.27*	*0.86*	*1.84*	*0.9*	*1.84*
4	5	0	0.98	9.44	0.97	9.32	0.97	18.48	0.96	7.52	0.97	6.79
			0.98	*9.45*	*0.98*	*9.50*	*0.97*	*18.33*	*0.95*	*7.44*	*0.96*	*6.61*
4	5	0.5	0.96	10.16	0.96	9.96	0.95	18.42	0.92	7.55	0.94	6.83
			0.97	*9.67*	*0.97*	*9.71*	*0.94*	*17.86*	*0.86*	*7.21*	*0.9*	*6.44*

The differences between the results are mainly due to the fact that the analytical versions have, in contrast to their discrete-event counterparts, only limited input buffer capacities (*N*, *M* and *B*).

The graphs depicted in Figure 3.7 were obtained by dividing the results from the MRPprior and DSSPL model by those from the MRP model. By taking the MRP model as reference, service level ratios higher than one and inventory cost ratios smaller than one indicate, therefore, an improvement of the logistic

Figure 3.7 Comparison of logistic performance of MRP vs. MRPprior, DSSPL.1.1, DSSPL.1.05, DSSPL.2.1 and DSSPL.2.05 for setup = 0 and 0.5 (_ Symbol for setup = 0)



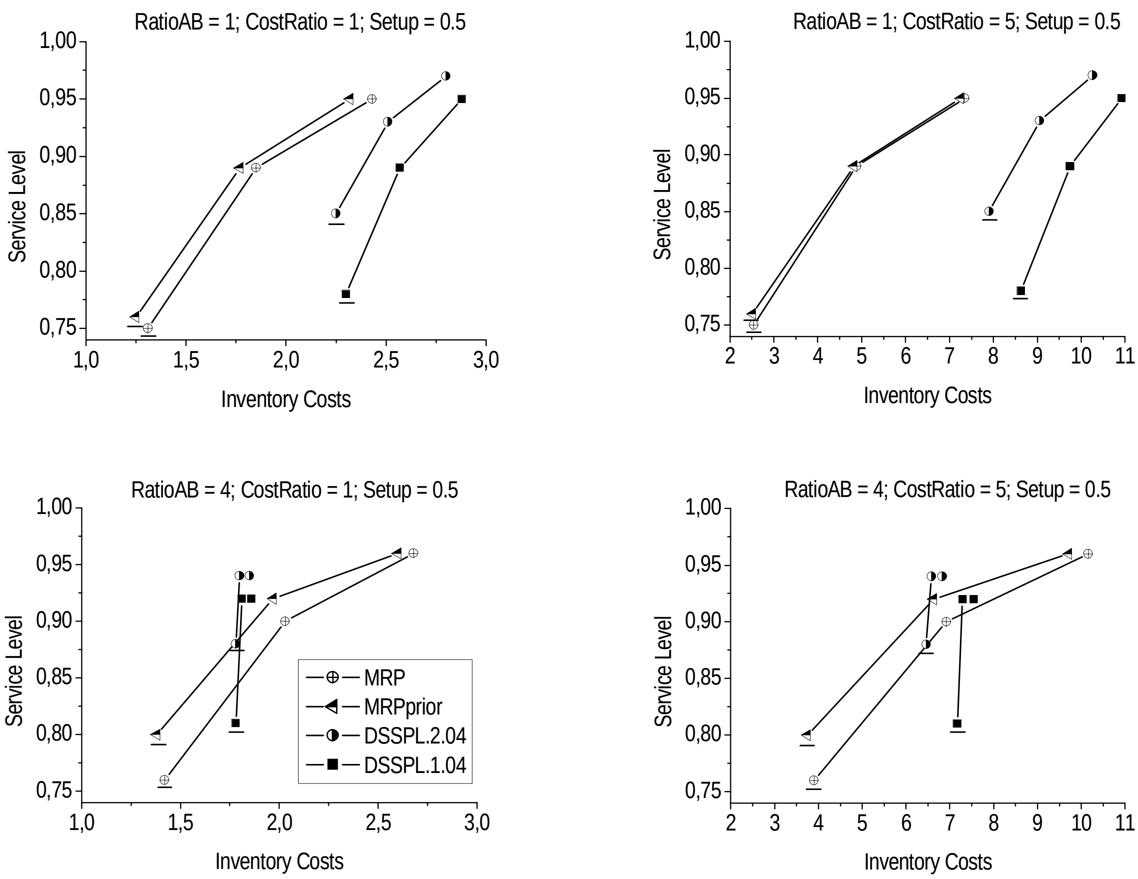
performance of MRPprior and DSSPL compared to those of MRP. The following observations can be made concerning the obtained results:

- MRPprior's service level performance is significantly better than those of MRP only for high values of *RatioAB* and *stp*;
- The service level performance of DSSPL.1.1 is better than those of MRP particularly for high values of *RatioAB* and *stp*, however, at significantly higher inventory levels;
- The inventory cost performance of DSSPL.1.04 and DSSPL.2.04 is similar to those of MRP for high values of *RatioAB* for a similar or improved service level performance;
- A relationship between the parameters *thl*, *stp* and *RatioAB* can be observed particularly for DSSPL.1.04. In fact, for low values of *RatioAB* and *thl*, an increase of *stp* results in a reduced service level compared to those of MRP due to an increased number of changes from A- to B-jobs or vice-versa. The results of DSSPL.2.04 show that this number of changes can be reduced by increasing the value of the threshold level *thl* which leads to a grouping of A-jobs.

The impact of a variation of the lead time *lt* on the performance of MRP, MRPprior, DSSPL.1.04 and DSSPL.2.04 is shown in Figure 3.8 where the following observations can be made:

- The variation of *lt* (and thus forecast errors) has a significant impact on the logistic performance of MRP and MRPprior. High service levels are achieved for high values of *lt* (*lt* = 20), with however

Figure 3.8 Performance of MRP, MRPprior and DSSPL for increasing values of *lt* (*lt* = 10, 15 and 20, _ symbol for *lt* = 10)



increased inventory levels. Low inventory levels can only be reached with low values of *lt* (*lt* = 10) that result, however, in a poor service level performance;

- The variation of *lt* has a significantly smaller impact on the inventory cost performance of DSSPL than on MRP and MRPprior particularly for high values of *RatioAB*, since only the performance of the production of B-products is affected by variations of *lt*. In the case of DSSPL.2.04, it has also a significant smaller impact on the service level performance.

Generally, DSSPL exhibits satisfactory inventory level performance only when the lot size for the A-products (capacity of kanbans) can be decreased compared to those used in an MRP system. This is due to the fact that the replenishment of the finished kanban jobs is triggered only when a demand has occurred. Finished kanban jobs produced due to a past demand thus have to wait until a new demand occurs. If the capacity and number of kanbans and the added value (*CostRatio*) are high, JIT/kanban systems lead generally to increased inventory values compared to those of the MRP system (DSSPL.1.1), that triggers production only before a future demand occurs. However, as shown in Figure 3.8, the performance of the MRP (push) concept depends significantly on the accuracy of the forecast of future demand. The resulting uncertainties in an MRP system must be buffered by time and/or inventory that leads to increased lead times and inventory levels. In addition, by allocating a higher priority to A-products having smaller lot sizes than B-products, DSSPL behaves like the SI dispatching rule (shortest imminent operation) which showed, in a survey on dispatching rules, the best overall results (Blackstone et al. 1982).

Besides the size of the kanbans for A-products, the priority threshold level *thl* is another important parameter. The results in Figures 3.7 and 3.8 show how the logistic performance of DSSPL.2.04 is improved compared to those of DSSPL.1.04. The improved service level is mainly due to a reduced number of setups that is achieved by a grouping of kanban jobs. The reduced inventory costs is mainly due to the lower level of waiting finished kanban jobs, since replenishment is triggered only when more than one job has been consumed by the demand.

Summary and conclusions of chapter 3

- DSSPL's application domain corresponds to companies that are characterized by a wide variety of products which makes it difficult to implement modern MPC methods in order to achieve improved logistic performance. This problem is reenforced if the company's human, technical or financial resources are limited;
- DSSPL's key concepts allow companies to concentrate their limited resources on the most important products without the need for additional production resources. Furthermore, by applying JIT techniques to the limited number of A-products, the JIT implementation efforts can be better focused. In addition, local scheduling at every production stage is simplified due to the transparent allocation of priorities to the different product groups which is particularly important in cases where a wide variety of products is produced;
- The most critical factors influencing the performance of DSSPL are the configuration of the dispatching rule and the appropriate choice of A-products;
- Compared to existing (hybrid) MPC concepts, DSSPL can be distinguished by three characteristics. First, DSSPL relies on strategic thinking about which goal is the optimal allocation of limited resources in order to obtain the maximum impact in terms of customer service and satisfaction. Second, in contrast to existing hybrid MPC approaches, DSSPL chooses the different MPC methods according to a multiple-criteria analysis taking into account strategic aspects as well as operational ones. Third, DSSPL is able to handle complex production environments (complex production processes, wide variety of products);
- The performances of DSSPL have been analyzed and compared to those of the classical MRP concept through the use of a Markovian birth-death queueing model of a single-stage, two-product production system. Service level and inventory holding costs have been chosen as principal performance metrics;
- The service level performance of DSSPL is generally higher than that of MRP if the load generated by the A-items is higher than those generated by the B-items (high values of *RatioAB*);
- Generally, DSSPL exhibits satisfactory inventory level performance only when the lot size for the A-product (capacity of kanbans) can be decreased compared to those used in an MRP system and if the volume of A-products is higher than those of B-products;
- The Markov analysis has given a valuable insight into the mechanisms of the DSSPL concept and its performance. More complex issues like forecast errors, multi-item, multi-stage production environments, different versions and configurations of DSSPL or various demand uncertainties have, however, to be studied with the help of a simulation study (see following two chapters).

Chapter 4

Simulation analysis framework

Simulation is chosen in this work to determine the characteristic behavior and application domain of DSSPL due to the complexity of the analyzed manufacturing system. However, in contrast to analytic methods such as Markov chains, there exists virtually no limitation to the complexity of simulation models. Consequently, the critical issues of the development of a simulation analysis framework for the analysis of DSSPL are as follows:

- Manufacturing systems are generally characterized by a virtually unlimited number of possible parameters and design options. In order to make the simulation analysis more tractable, the set of variables has to be limited to parameters and design options with the highest impact on the performance metrics;
- Since one of the goals of the simulation analysis is the comparison of different MPC concepts, experimental factors have to be chosen that are relevant for at least one MPC concept;
- Performance metrics should be representative for all analyzed MPC concepts. Furthermore, the performance metrics should also be suited for use in a real manufacturing environment;
- When comparing different MPC concepts with the help of simulation studies it is generally difficult to distinguish between effects due to particular (optimized) parameter settings and effective characteristics of the compared concepts. An experimental design should therefore be chosen that minimizes the probability of attributing to MPC methods characteristics that are only due to particular parameter settings difficult to reproduce in practice.

4.1 Review of related literature

This review of literature is focused on research work studying or comparing the performance of push (MRP), pull (JIT/Kanban) and hybrid systems with the help of simulation models. Thus, the main purpose of this literature review is threefold. First, identification of the parameters and design options with the highest impact on the performance of the manufacturing systems. Second, identification of the most common parameter settings to represent authentic manufacturing environments. Third, identification of performance metrics representative for most MPC concepts.

4.1.1 Analysis of push or MRP systems

There exists a huge amount of research studies analyzing push or MRP systems. This is basically due to the numerous design options of the MRP concept and due to difficulties found in practice of handling such a complex system. In their review on parameters affecting the effectiveness of MRP systems, Yeung, Wong and Ma (1998) reviewed a total number of 45 research studies, even though they considered only the most important ones. Consequently, emphasis is put in this review only on studies dealing with an uncertain demand, since this characteristic is considered as indispensable to represent an authentic manufacturing environment.

Most of the following studies on push systems (MRP) are focused on the optimal settings of the numerous MRP design options in order to reduce system nervousness or the total costs including inventory carrying, ordering and setup costs.

Whybark and Williams (1976) performed one of the first research works on MRP systems dealing with the uncertainty of the manufacturing environment. Based on a single-product, single-stage simulation model, they analyzed the impact of demand and supply uncertainties on the performance of the MRP system. The range of coefficients of variation used corresponded to values observed in actual MRP records of several manufacturing companies. The authors conclude that under conditions of uncertainty in timing, safety lead time is the preferred buffering technique whereas in the case of quantity uncertainty, safety stock is the preferred buffering technique. Furthermore, the simulation results indicate that supply time and demand quantity uncertainty have the most significant impact on the service level performance indicator.

Forecast errors as an important source of uncertainty in an MRP system have been analyzed by De Bodt and Van Wassenhove (1983). Based on a single-product, single-stage simulation model, they analyzed the impact of different lot-sizing rules, demand variability, forecast errors and cost structure (different levels of *TBO*) on the total cost including inventory carrying and ordering cost. As in many other similar studies, the economic time between two orders *TBO* has been used to represent the cost structure of a product (ratio between ordering and inventory carrying costs). The cost performance was measured relative to the performance of the Wagner-Whitin (WW) lot-sizing technique (Wagner and Whitin 1958). Forecast errors have been introduced by using, for all periods except for the actual period, a forecast demand based on Brown's exponential smoothing technique. Hence, the error introduced corresponds approximately to the level of uncertainty introduced by the demand. The simulation results show that the demand variability and the cost structure have the most significant impact on the cost performance measure. Furthermore, all lot-sizing techniques except lot-for-lot (LFL) exhibited similar results, particularly in the presence of high levels of demand uncertainty. The LFL lot-sizing technique performance was significantly lower than those of the other lot-sizing techniques, particularly in case of cost structures corresponding to a high ratio between ordering and inventory carrying costs (high values of *TBO*).

Wemmerlöw and Whybark (1984) evaluated the performance of fourteen different lot-sizing rules under uncertainty in a rolling schedule environment. The experimental factors of their simulation model were, besides the fourteen lot-sizing rules, the variability of the demand and the forecast error, two cost structures (two levels of *TBO*) and two levels of lead time. Thus stochastic variability was limited in their model only to the demand rate and the forecast error. The performance indicators used were the total cost including inventory carrying and ordering costs for a service level of 100%. This level was achieved by increasing the safety stock for every lot-sizing procedure until the targeted service level was reached. Their results show that the ranking of the best lot-sizing rules changes significantly with the introduction of demand uncertainty. The WW and the part-period-balancing (PPB) lot-sizing techniques exhibit the best overall results even though the difference between the six best rules is insignificant for the case with demand uncertainty. The LFL lot-sizing technique performed worst in all experimental settings.

The effect of product structure complexity on the performance of lot-sizing techniques has been evaluated in a simulation study by Benton and Srivastava (1985). The experimental factors of their simulation model were the demand variability, lot-sizing rules, cost structure and the product structure, which has been expressed by the breadth and depth complexity of the aggregate product structure. Total cost including inventory carrying and ordering cost was chosen as the performance indicator. The results show that the cost and product structures have the highest impact on the performance measures. It has also been shown that the product structure only has a small effect on the performance of the different lot-sizing rules.

In the research work developed by Lee and Adam (1986), the effect of inaccurate forecasts on the performance of MRP is investigated in a single-product, multi-level environment. Their simulation model included as experimental factors lot-sizing rules, product structure complexity and forecast error. Operation costs including inventory carrying costs, setup costs and final product shortage costs was chosen as principal performance indicator. The results show that product structure complexity is the dominant factor influencing the total costs. Besides product structure complexity, lot-sizing rules and the bias of the forecast error have the most significant impact on the results. One unexpected result is the fact that a significant over forecast (positive bias of 10%...30%) results in lower total costs. Concerning the lot-sizing rules, the periodic-order-quantity (POQ) rule exhibits the best overall results. The authors also indicate the fact that lot-sizing rules and forecast errors have generally a higher impact on total costs with complicated rather than with simple product structures.

One of the main studies analyzing the consequences of freezing a portion of the master production schedule (MPS) has been carried out by Sridharan and Berry (1990). They investigated the impact of order- or period-based MPS freezing methods on the number of rescheduling events and on the total costs including inventory carrying and rescheduling costs under stochastic demand conditions in a rolling planning horizon environment. Further experimental factors were the cost structure (*TBO*), the MPS replanning frequency, lot-sizing methods and forecast errors. For all simulation runs, the safety stock values were adjusted in order to meet the service level target of 98%. The results show that the forecast error and the cost structure have the highest impact on the cost performance measure. Concerning the number of rescheduling events, the authors concluded that the cost structure, the MPS freezing method and the lot-sizing method have the most significant impact.

In an extensive simulation study, Zhao, Goodale and Lee (1995) analyzed the performance of lot-sizing rules and freezing methods in a single-item, multi-stage MRP production system. Product structure, demand variability, forecasting method, cost parameters, lot-sizing rules and MPS freezing parameters have been defined as experimental factors. In contrast to other studies, the demand variability also included, in addition to a normally distributed error, a trend component. Furthermore, besides classical lot-sizing rules, the experimental design also included compound lot-sizing rules using the LFL rule for the dependent components and cost dependent lot-sizing techniques for the final products. Service level, schedule instability and total cost including inventory carrying and setup cost have been used as performance indicators. The results show that lot-sizing rules have a significant impact on all performance measures whereas the compound lot-sizing techniques generally performed better than lot-sizing rules using only one technique. The authors state that this result is due to the fact that by using the LFL rule for dependent items, changes in the MPS are not amplified in the MRP plans for lower level items. Concerning the MPS freezing methods, the results show that the order-based method is generally superior to the period-based method for most experimental factor settings. Another noteworthy result is the fact that significant interaction effects have been found for most of the experimental factors.

Ho and Ireland (1998) examined the impact of forecast errors on the scheduling instability of a multi-product, multi-stage MRP system. The experimental factors of their simulation model were the variability of the forecasting error, demand and lead time uncertainty, four lot-sizing rules and the cost structure.

Schedule instability was used as performance indicator. Their results indicate that the lead time uncertainty has a much higher impact on the number of rescheduling messages than the other experimental factors. If the lead time uncertainty factor is omitted, then the Silver-Meal (Silver and Meal 1973) and the PPB lot-sizing rules can significantly reduce the MRP system nervousness introduced by forecast errors.

Enns (2002) investigated, based on a simulation study, the use of inflated planned lead time and safety stock to compensate for forecast errors. The simulation model consisted mainly of a capacity-constrained two-product, three-stage production system that executed the production plans generated by an MRP system. Forecast errors were introduced by means of demand uncertainty and forecast bias. The impact of the forecast error was measured by the mean tardiness and service level. In contrast to many other studies, both performance measures were not only applied on the master production schedule (MPS) level of the MRP system but also on the job shop level. This made it possible to distinguish between the impact of forecast errors on the validity of the production plans and the customer requirements. The results indicate that forecast bias and demand uncertainty have a different impact on master scheduling performance and customer service level. For example, forecast bias has a significantly higher impact on the delivery tardiness than on the MPS tardiness. Concerning compensation for forecast errors, the results indicate a better effectiveness of increased planned lead times and safety stock than “inflated” forecasts (positive forecast bias).

Table 4.1 summarizes the reviewed research works with additional information concerning the structure of the simulation models.

Table 4.1: Summary of reviewed simulation studies of MRP/push systems

Autor(s)	**Production system (Constants)**	**Experimental factors (Independent variables)**	**Performance measures (Dependent variables)**
Whybark et al. (1976)	1 product 1 stage	Demand timing uncertainty: Interchanging gross requirements between periods; Supply time uncertainty: ± 2 periods6 CV of demand quantity: 0.58 to 1.85,uniform distribution CV of supply quantity: 0.58 to 1.85, uniform distribution Safety lead time Safety stock	Service level Inventory level
De Bodt et al. (1983)	1 product Single-stage Forecast horizon: 12 periods, first period = actual demand, periods 2 to 12 = forecast Forecast method: Brown's exponential smoothing Lead time = 0	CV of demand rate: 0.0 to 0.25, normal distribution Lot-sizing rules: EOQ, POQ, LFL, LUC, SM, LTC, WW Cost structure (TBO = 2 to 12 periods)	Inventory carrying costs Ordering costs
Wemmerlöv et al. (1984)	1 product 1 stage	CV of demand rate: 0.0 to 1.75, uniform distribution Cost structure: TBO = 2 or 6 periods Lead time uncertainty: 2 or 7 periods Lot-sizing rules: EOQ, POQ, SM, PPB, LFL, WW	Inventory carrying costs Ordering costs At service level of 99.99% Relative to perfor-mance of WW algorithm
Benton et al. (1985)	1 product Multi-stage	CV of demand rate: 0.0 to 1.27, uniform distribution Product structure: 3 to 6 stages, linear or converging structure Lot-sizing rule: POQ, SM, MOM, WW Cost structure: TBO = 2 to 6 periods	Inventory carrying costs Ordering costs
Lee et al. (1986)	1 product	Product structure: 3 or 6 stages, linear or converging structure Lot-sizing rules: LFL, EOQ, POQ, PPB Forecast error: CV = 0.1 to 0.4, normal distribution, bias = 0 to 50% of nominal demand	Inventory carrying costs Setup costs Shortage costs Number of shortages Number of shortage units

Table 4.1: Summary of reviewed simulation studies of MRP/push systems

Autor(s)	**Production system (Constants)**	**Experimental factors (Independent variables)**	**Performance measures (Dependent variables)**
Sridharan et al. (1990)	1 product 1 stage	MPS freezing method: Period- or order-based Forecast error: CV = 0.15 to 0.3, normal distribution, bias = 0 Lot-sizing rules: SM, WW Cost structure: TBO = 2 to 10 periods Planning Horizon: 4 to 80 periods Replanning frequency: 1/4 to 4/4th of frozen interval Freeze interval: 1/8 to 8/8th of planning horizon	Service level Cost error relative to performance of WW algorithm Schedule instability
Zhao et al. (1995)	1 product	Product structure: 2 or 5 stages, linear or converging structure Demand rate: Combination of constant, trend and variability components Forecasting method: Double exp. smoothing or Winters' three parameter trend and seasonality model Cost structure: TBO = 4 or 8 periods Lot-sizing rule: SM, PPB, EOQ, POQ, LFL Planning horizon: 16 to 64 periods Freezing proportion: 1/4 to 4/4th of planning horizon Replanning periodicity: 1/4 to 4/4th of frozen interval MPS freezing method: Period- or order-based	Setup cost Inventory carrying costs Schedule instability Service level
Ho et al. (1998)	4 products Multi-stage	CV of demand rate: 0.3 to 0.8, normal distribution CV of forecast error: 0.3 to 0.6, normal distribution CV of lead time: 0.2 to 0.4, normal distribution Lot-sizing rule: LFL, EOQ, PPB, SM Ordering/Carrying cost ratio: 100:1 to 500:1	Scheduling instability
Enns (2002)	2 products 3 stages FOQ lot-sizing rule	Demand uncertainty: CV = 0.0 to 0.2 Forecast bias: 0.95 to 1.05 Final assembly planned lead time: 0.8 to 1.2 weeks Safety stock levels: 0 to 600	Mean absolute deviation (MAD) and mean squared error (MSE) between forecast and demand Mean tardiness Service level Inventory costs

Concerning the general structure of the simulation models and the experimental design, the following comments can be made:

- As already stated in the literature review presented by Yeung, Wong and Ma (1998), most research on MPR/push systems has been performed in order to study the impact of the following seven parameters: MPS frozen interval, MPS replanning frequency, MPS planning horizon, product structure, forecast error, safety stock and lot-sizing rules;
- In most of the studies, setup, inventory carrying and ordering costs have been used as experimental factors. However, none of these studies gave a reasonable justification for the values chosen, even though the cost structure had in most of the cases a significant impact on the (cost) performance indicators;
- Uncertainty has been modelled in most studies using an unbiased normal distribution. However, studies of real industrial data show that these assumptions are too optimistic particularly in the case of the demand, lead time and forecast errors (Meunier Martins 2001);
- The coefficient of variability (*CV*) of the demand varies in most studies between values of 0.0 and 1.5. In the case of forecast errors, the values of *CV* vary generally between values of 0.0 and 1.0;
- Most of the studies were based on simulation models without capacity constraints. The (obviously wrong) MRP concept of deterministic lead times was therefore included in most of the studies. However, some studies added a normally distributed error to the planned lead times, but without taking into account the actual load;
- Some outcomes of MRP studies are contradictory particularly in the case of the choice of lot-sizing rules and the determination of planned lead time and safety stock levels. This is mainly due to the fact that many studies did not include forecast errors or capacity constraints that obviously have a significant impact on the performance of an MRP system. However, the average results confirm that MRP system parameters like the choice of the lot-sizing rules have a bigger impact on performance than MPS freezing methods;
- A critical issue for MRP systems is the choice of the optimal lot-sizing rule. In fact, all lot-sizing rules except the LFL, rely on economical values such as ordering and inventory carrying costs. Since these cost values are difficult to estimate, most of the results obtained are biased by arbitrarily chosen cost structures. Furthermore, some results indicate that the difference between the lot sizing techniques is not significant in the presence of increased uncertainty.

4.1.2 Analysis of pull or JIT/Kanban systems

Research studies on the analysis of pull systems (JIT/kanban) are mainly concerned with the question whether this technique, originating from Japan with its particular manufacturing boundary conditions (stable demand, low setups, high quality,...), can also be applied with success to less optimal manufacturing environments. The criteria for the research works chosen were the use of the classical model of a kanban system with production kanbans (single-card kanban system) or a combination of transport and production kanbans (dual-card kanban system).

One of the first research work on JIT/Kanban systems was performed by Kimura and Tereda (1981). Their mathematical formulation of a pull system served as a starting point for many research activities in the field of the design and optimization of kanban systems. By using simulation, they also analyzed the impact of the kanban size on the amplification of inventory and production fluctuations in a pull production system. Hence, the simulation model of a linear one-product, multi-stage production system included principally as experimental factors the kanban size and a normally distributed demand. The amplification of inventory and production fluctuations at the last production stage were chosen as performance indicators. The results show that production and inventory fluctuations depend on the ratio of the kanban size to the daily demand. In fact, an exponential increase of fluctuations has been observed for values above 5% of the ratio between of the kanban size and the daily demand. However, the generality of these results is limited due to the fact that the number of kanbans and consequently the WIP is not limited in the analyzed model.

The adaptability of the JIT/kanban system to variable processing times, schedules that are not frozen, variable input rates and imbalanced work loads among stations has been analyzed in a study of Huang, Rees and Taylor (1983). The simulation model of a multi-line, multi-stage production system included as experimental factors the variability of the processing time, the number of kanbans, the capacity of the production stages and a normally distributed demand rate. Overtime has been chosen as performance indicator. In the first of four simulation experiments, the impact of variable processing times on system performance has been analyzed. The second experiment consisted of determining the impact of bottlenecks at different stages. The impact of variability in the demand rate has been analyzed in the third experiment. The combined effect of variable processing times and demand rates has been analyzed in the fourth experiment. The authors concluded from the results that variable processing times and demand rates have the most significant impact on the performance of the production system. Furthermore, it has been shown that demand-rate fluctuations resulted in even larger swings in overtime requirements. A noteworthy finding concerning the configuration of the kanban system was the fact that kanban loops consisting of only one container required in all experimental configurations significantly higher levels of overtime than systems with two or more containers.

Philipoom, Rees, Taylor and Huang (1987) investigated factors that influence the required number of kanbans in their research study. Their simulation model of a multi-stage, multi-product production system included as experimental factors the variability and auto correlation of the processing times and the utilization of the work centres. Lead time and the required number of kanbans were chosen as performance indicators whereas the number of kanbans was computed by a heuristic developed by the authors. The results indicate that all the experimental factors have a significant impact on the performance indicators in the analyzed range. Consequently, the authors conclude that an increased variability and utilization of the production system requires a higher number of kanbans.

Lee (1987) investigated, using a simulation model, the impact of scheduling rules, demand level, kanban size, minimum kanban level and job mix on the performance of the analyzed production systems. The most interesting aspect of this research work is the analysis of the performance of different scheduling rules in a pull production environment. Five scheduling rules (FIFO, SPT, HPF, SPT/Late, HPF/Late) were applied to schedule the production of multi-stage, multi-product production system whereas SPT/Late exhibited the best overall results. Generally, among all analyzed experimental factors, scheduling rules had the highest and the job mix the lowest impact on the performance of the production system.

Sarker and Harris (1988) analyzed the effect of imbalance on a single-product, multi-stage production system. The imbalance of the production line was modelled by a variation of the normally distributed processing times in the different work stations. The just-in-time production concept was implemented as a single-card Kanban system. The experimental factors were five different cases of processing time imbalances for a given deterministic load. The results show that the production rate depends significantly on the imbalance of the production system. An imbalance ratio of 1 ± 0.10 was indicated by the authors as a tolerance limit, which affects the system's performance beyond 10%. However, the generality of these results is limited since the pull concept was modelled using a concept similar to a base stock inventory control system. In fact, a pull demand at the final product level triggers the whole production line simultaneously to produce the WIP products.

One of the main studies concerning the analysis of JIT production systems was carried out by Gupta and Gupta (1989). They analyzed the impact of various management policies such as changing the number of kanbans and changing the size of the containers, and of operational characteristics such as production stoppages and processing time uncertainties on a multi-line, multi-stage dual-card kanban production system. Six experiments were performed with different configurations of the experimental factors. The inventory levels (WIP), production efficiency expressed as capacity utilization and the accumulated time during which a subsequent stage has been starved of components were used as performance indicators. The principal results of their study show that the JIT production system is, as expected, very sensitive to the variability of the manufacturing environment. Other noteworthy findings are the fact that the performance of a kanban system depends significantly on an appropriate choice of the number of kanbans and the size of the containers.

The difficulty of designing and implementing JIT/Kanban systems in uncertain manufacturing environments is addressed by the research work of Moeeni, Sanchez and Vakharia (1997). They developed, based on Tagushi's robust design concept, a methodology which allows the identification of the best JIT/kanban system parameter settings for a given uncertain manufacturing environment. The experimental factors were categorized into parameters of the JIT/Kanban system and noise factors representing the uncertain manufacturing environment. Loss functions including the mean and the variance of inventory and service level were chosen as performance indicators. The results of the sensitivity analysis using a simulation model of a single-item three stage manufacturing system show that the container size had the highest impact on the performance indicator. However, the other experimental factors, number of kanbans and kanban review period, also had a significant impact on the performance indicators.

Takahashi and Nakamura (1998) investigated in their simulation study the impact of auto correlated demand on the performance of a pull system. Consequently, their simulation model included as experimental factors the auto correlation of the inter-arrival time of the demand, the variability of the production time and the number of kanbans. The mean waiting time of demands and the inventory levels were defined as performance indicators. The results indicate that all experimental factors have a significant impact on the performance of the production system.

Table 4.2 summarizes the reviewed research works with additional information concerning the structure of the simulation models.

Table 4.2: Summary of reviewed simulation studies of pull systems

Autor(s)	**Production system (Constants)**	**Experimental factors (Independent variables)**	**Performance measures (Dependent variables)**
Kimura et al. (1983)	1 product 5 stages Linear structure Demand (CV = 0.1)	Capacity of kanbans (ratio to average demand: 0.1 to 1.0)	Amplification of production and inventory fluctuations at last stage.
Huang et al. (1983)	1 product 3 stages Converging structure Kanban size = 100	CV of processing times (0.0 to 1.0) Number of kanbans (1 to 6) CV of demand rate (0.0 to 1.0) Capacity imbalance (1.0 to 2.0)	Required overtime
Philipoom et al. (1987)	2 products (X and Y) 3 stages Network structure Kanban size = 10 (product X), 20 (product Y)	CV of processing times: 0 to 0.3 Demand level: 0.6 to 0.95 Autocorr. of processing times: 0.0 to 1.0	Lead time Number of kanbans (computed with heuristics)

Table 4.2: Summary of reviewed simulation studies of pull systems

Autor(s)	Production system (Constants)	Experimental factors (Independent variables)	Performance measures (Dependent variables)
Lee (1987)	29 products 8 stages Linear structure Kanban size = 1	Scheduling rules: FCFS, SPT/Late, HPF/Late Demand level: 0.1 to 1.875 Kanban size: 1 to 7 Product mix Minimum Kanban level: 0 to 3	Jobs drawn Job tardiness Job queue time Process utilization Set/run times ratio Output kanban inventory level
Sarker et al. (1988)	1 product 5 stages Converging structure Kanban size = 2 Number of kanbans = 1	Capacity imbalance: 0.333 to 3.0	Production rate Length of queues Job queue time Process utilization
Gupta et al. (1989)	1 product 3 stages Converging structure	Number of kanbans: 8 to 12 Kanban size: 8 to 12 Production stoppages CV of processing times: 0.25 Capacity imbalance: 1.0 to 1.33	Production and conveyance rate Inventory level Level of shortage Idle time
Moeeni et al. (1997)	1 product 3 stages Linear structure 6 noise factors	Number of kanbans: 15 to 19 Kanban review period: 0 to 480 min. Kanban size: 10 to 20	Inventory level Service level
Takahashi et al. (1998)	1 product N stages Linear structure Kanban size = 1	CV of demand: 0.25 to 1.0 Autocorrelation of demand CV of processing times: 0.56 to 1.12 Number of kanbans: 1 to 10	Waiting time of product demand Inventory level

The findings of the reviewed articles verify the fact (already confirmed by empirical studies of Crawford et al. 1988 and Gilbert 1990) that kanban systems are very sensitive to variability of the manufacturing environment and to the chosen design options (number of kanbans, capacity of containers).

The following comments can be made concerning the general structure of the simulation models:

- The stochastic character of the demand and processing times is generally modelled by a (truncated) normal, exponential or gamma law, whereas the coefficients of variation vary between 0.0 and 1.0;
- In all reviewed research works, the parameters describing the production system (number of stages, structure) were chosen arbitrarily. It is therefore difficult to determine the impact of the structure of the production system on the performance of a pull production system. However, the most common configuration consisted of a linear or converging production system with 3 to 5 stages;
- Generally, the JIT/kanban system design parameters (number and size of kanbans) were chosen arbitrarily or based on simple heuristics like the Toyota formula. In contrast to numerous studies concerning lot-sizing rules used in MRP systems, no comparative studies about kanban loop design concepts (determination of number and size of kanban containers) were found;

- The following experimental factors were found to have a significant impact on the performance of a pull production system in at least the majority of reviewed research works: Number and size of kanbans, variability of demand and capacity imbalance.

4.1.3 Comparative studies of push and pull systems

The last group of articles reviewed is concerned with the direct comparison of push (MRP) and pull (JIT/kanban) systems for given manufacturing environments.

The main study about the comparison of push and pull systems has been carried out by Krajewski, King, Ritzman and Wong (1987). They analyzed, based on a large-scale simulation study, the impact of different factors of the manufacturing system on the performance of MRP-, JIT/kanban and reorder point systems (ROP). A total number of 36 experimental factors were grouped into the following experimental factor clusters: Customer influence, vendor influence, buffer mechanisms, product structure, facility design, process, inventory and other factors. Thus the most important experimental factors used to describe the manufacturing environment were: demand forecast errors, lead time errors for purchased items, capacity limitations of the production system, product structure complexity, facility design, setup times, equipment failures and worker flexibility. Lot-sizing rules, inventory accuracy, safety stock and safety lead time, number of kanbans and size of containers were added as factors describing the MRP and JIT/Kanban production concept. The performance measures used were the average weekly labour hours, the average inventory investment expressed in weeks of supply and service level. The results concerning the MRP system show that the factors equipment failures, lot-sizing rules, capacity limitations and forecast errors have the highest impact on the performance measures. Lead time errors for purchased items, equipment failures and product structure complexity exhibited the highest impact on the performance measures for a JIT/kanban system. Both analyses were performed with typical MRP (high variability settings) and JIT/kanban (low variability settings) environment settings respectively, where the JIT/kanban system performed significantly better than the MRP system. In order to analyze the question of whether the improved performance of the JIT/system was due to the characteristics of the JIT system or due to the improved manufacturing environment, a third analysis was performed. In a manufacturing environment corresponding to the JIT/kanban system, an ROP system has been analyzed in order to compare its performances to those of the JIT/kanban system. The results show that ROP systems exhibits similar performances to those of the JIT/kanban system. Consequently, the authors conclude that the characteristics of the manufacturing environment have a much higher impact on the performance of a manufacturing system than the choice of a particular manufacturing concept.

In another study, Rees, Huang and Taylor (1989) performed a comparative simulation analysis of an MRP and JIT system in a multi-product, multi-stage production environment. The chosen experimental factors were the number and capacity of kanbans, the variability of the demand and processing times, the lead time and lot sizes. Total costs including setup, inventory carrying and backorder costs were chosen as performance indicators. Similar to the study of Krajewsi et al. (1987), two studies of a JIT and MRP system with their corresponding manufacturing environment settings for the experimental factors were performed. The results show that JIT performs better than MRP, but a third study showed that MRP performs even better than JIT when studied using the JIT manufacturing settings.

Sarker and Fitzsimmons (1989) investigated the effect of variance of operation times and the size of inter-stage buffers on the performance of push and pull system. They found that the production rate of a pull system decreases much faster than those of a push system as the coefficient of variation of the processing times increases. However, in the same case, the work in process (WIP) increased in the push system, whereas the WIP was limited in the pull system by the number of kanbans and the size of the containers. Further studies like those of Bonney, Zhang, Head, Tien and Barson (1999) found similar results when comparing push and pull systems in simple multi-stage production systems.

More recently, Huang, Wang and Ip (1998) compared the performance of the push (MRP), JIT/kanban and CONWIP system in a multi-stage multi-product manufacturing environment. The variable settings (product structure, routings, processing times, demand, lead times) of the simulation model were derived from real data from a cold rolling plant. Costs, WIP and utilization were chosen as principal performance indicators. Their results show that the pull systems JIT/kanban and CONWIP perform better than the push system MRP.

Finally, Kim, Chhajed and Palekar (2002) compared the performance of push and pull systems in the presence of emergency orders. MRP and an (s, S) system were chosen as representatives of a push and pull system respectively. Their simulation results indicate that the push system can reach the same service level as the pull system with lower costs when the demand variability is low. However if the demand variability increases, the opposite is true and the pull system performs with lower costs. This is mainly due to the fact that the pull system does not differentiate between the types of orders. In contrast, emergency orders increase significantly the nervousness of the MRP system and consequently its performance deteriorate.

Table 4.3 summarizes the research works reviewed with additional information concerning the structure of the simulation models.

Table 4.3: Summary of reviewed simulation studies comparing push and pull systems

Autor(s)	**Production system (Constants)**	**Experimental factors (Independent variables)**	**Performance measures (Dependent variables)**
Krajewski et al. (1987)	Total number of items (end, intermediate and purchased items) = 50 Number of workstations (fabrication and assembly) = 50	Customer influence: CV of forecast errors: 0.0 to 0.3 Vendor influence: CV of supply lead time (0.07 to 0.14, Normal distribution), CV of requested shipment size: 0.07 to 0.14 Buffer mechanisms: Load: 88 to 94%, safety stock and safety lead time Product structure: 2 to 7 stages, 10 to 25 products, diverging or converging structure Facility design: Flow or job shop Process: Scrap losses: 0 to 50%, equipment failures, worker flexibility Inventory: Inventory accuracy, Lot-sizing rules, number and size of kanbans Other factors: Randomly assigned processing times: 1 to 87 minutes	Average weekly labor hours Average inventory investment Average past-due demand (Service level)
Rees et al. (1989)	2 products 3 stages Network structure	Demand rate: Sine function CV of processing times: 0.0 to 0.4, truncated normal distribution MRP lead times Setup times Size and number of kanbans	Inventory carrying cost Setup cost Backorder cost
Sarker et al. (1989)	1 product 9 stages Linear structure	CV of processing times: 0.0 to 1.0 Breakdowns	Line efficiency Queue length Inventory level Machine utilization

Table 4.3: Summary of reviewed simulation studies comparing push and pull systems

Autor(s)	**Production system (Constants)**	**Experimental factors (Independent variables)**	**Performance measures (Dependent variables)**
Huang et al. (1998)	2 products Multi-stage Network structure	Optimized configurations for each production concept	Inventory levels Throughput rate Inventory carrying cost Machine utilization
Bonney et al. (1999)	2 products Multi-stage Linear structure	Order size Batch and kanban size	Mean waiting time Inventory level
Kim et al. (2002)	10 products 2 stage EOQ lot-sizing rule CV of daily customer demand: 0.2	Proportion of emergency demand: 0 to 30% Mean time between emergency orders: 0 to 4 weeks	Total cost Fill rate Delay time of regular orders Delay time of emergency orders Throughput time

Some of the reviewed research studies applied the following research structure in their comparative studies. In the first step, push and pull systems were analyzed separately in manufacturing environments judged as typical for the production systems analyzed. In the second step, the push system was analyzed and compared to the pull system in a manufacturing environment defined for the analysis of the pull system. The principal findings were similar. Pull systems outperformed push systems, when analyzed in their corresponding manufacturing environments. However, the push system exhibited comparable or even better results when analyzed in manufacturing environments used for the pull system. One of the critical points in this approach is the fact that design parameter settings were applied to push systems, that are difficult or impossible to realize in practical cases. Thus, the following remarks can be made related to the structure of the reviewed comparative simulation studies of push and pull production systems.

- Most of the comparative studies have been made in manufacturing environments without forecast errors. Consequently, one of the experimental factors with the highest impact on push systems has been left out;
- Most of the push systems used for direct comparison with pull systems correspond to MRP systems with backflushing applied to the whole analyzed production line with reduced time bucket (< 1 day) and lot sizes. Such manufacturing environments for push systems can only be imagined in a make-to-order environment (final assembly line) with small and stable cycle times. Hence, findings of such studies are of limited generality;
- Most of the studies were performed at given (low) system load levels. Congestion effects occurring in push systems especially with high system loads and leading to increased cycle times have therefore not been analyzed;
- Most of the studies performed the analysis of MRP (push) or JIT/kanban (pull) systems with arbitrarily chosen design options settings. It is not clear if different or optimized design option settings would have led to different results (particularly important for JIT/kanban systems where no design strategy for the kanban loops has been defined).

4.1.4 *Conclusions of literature review*

The following conclusions concerning the structure of the simulation studies can be given:

- No standard simulation analysis framework has been used in the reviewed research studies. Consequently, a direct comparison of the results is difficult due to different design option settings of the manufacturing systems and various performance indicator choices. The need for a general analysis framework for comparative studies of production control concepts has already been established by Grünwald, Striekwold and Weeda (1989). In fact, they developed a framework characterizing product, market and manufacturing processes that describes production situations before a production control concept is chosen. It allows, therefore, a comparison of different production control concepts for a given, well-defined manufacturing environment. However, a framework for the different production control concepts itself is still lacking;
- Most research studies use costs as one of the principal performance indicators. Normally, these costs include inventory carrying, setup and backorder costs with arbitrarily chosen values that are in most of the cases not justified. In practice, however, it is difficult to attribute justified values to such costs. Leonard and Roy (1995) confirmed this fact in a research study of inventory control policies, that are generally based on the same cost parameters. Similarly, Schmitt, Klastorin and Shtub (1985) admit the same problems concerning a cost formula that they developed for a production classification scheme. In fact, they suggest using surrogates for the cost performance indicators. The choice of the surrogates depends on the overall objectives of the production system, such as low inventory levels or high service levels. They claim that such strategic decisions are easier to verify using a set of performance indicators than cost objectives relying heavily on a particular choice of the cost variables;
- Normally, comparative studies of production systems are performed in specific manufacturing environments. Such an approach is in contrast to the situation found in practice, where boundary condition change constantly due to changing market environments. This observation is confirmed by the results of a research study of Gaury and Kleijnen (1998) where they compare different pull production systems in an uncertain manufacturing environment. They show that the ranking of the analyzed production systems changes when manufacturing environment uncertainty factors are taken into account. This result illustrates the importance of considering robustness issues in comparative studies in order to minimize the impact of arbitrarily chosen manufacturing system options. A similar view has been presented by Asbjornslett and Rausand (1999) who developed a framework to assess the vulnerability of production systems to internal and external disturbances;
- Forecast errors are generally modelled using normally distributed unbiased error added to the effective demand. However, an analysis of forecast error data from real industrial cases shows that this is too optimistic a view in most of the cases (Meunier Martins 2001). In fact, forecast errors are generally characterized by large biases;
- In contrast to studies of pull systems, most of the studies of MRP systems do not consider capacity constraints. By omitting this parameter, some of the most critical aspects of MRP systems (variability of effective lead time, congestion of production line) are not taken into account in the analyses;
- Most studies assume that raw material is always available at the beginning of the production process. This assumption is particularly critical with respect to today’s tendency of production processes that are more and more decentralized and distributed;
- A critical issue in every comparative study of manufacturing systems is the significant conceptual difference between MPR and JIT/kanban systems. The biggest problem is the fact that the values of MRP parameters such as lead times or lot sizes are based on the time bucket length which cannot be reduced below certain practical limits (except in continuous time MRP systems). Thus, the practice of analyzing MRP systems with JIT/kanban design option settings (small lot and time bucket sizes) is

based on too optimistic a view of the flexibility of MRP systems. Furthermore, it can be argued that small lot sizes would significantly increase the rescheduling costs in the presence of inaccurate planned lead times and forecasts.

Based on the above observations and on the research goals of this thesis stated in chapter §1, specifications for a simulation analysis framework for the analysis of DSSPL can be defined as follows:

1. *Choice of experimental factors describing manufacturing environment*: The following experimental factors describing the manufacturing environment exhibit the most significant impact on the performance of a production system and must be included in simulation studies analyzing the performance of MPC methods: Variability of demand, variability of processing times, load (capacity constrained production system), capacity imbalance, setup times, product and process structure;
2. *Choice of parameters and experimental factors for representing accurately MRP systems*: The following parameters and experimental factors exhibit the most significant impact on the performance of MRP systems and must be included in simulation studies analyzing this MPC method: Forecast errors, safety stock, planned lead time and lot sizing technique;
3. *Choice of parameters and experimental factors for representing accurately JIT/kanban systems:* The following parameters of the JIT/Kanban system exhibit the most significant impact on the performance of a JIT/kanban system and must be included in simulation studies analyzing this MPC method: Number and size of kanbans;
4. *Definition of classification schemes*: Virtually every parameter or subsystem of manufacturing systems can be characterized by its variability. In order to allow a more structured analysis of the factors of a production system a variability classification scheme has to be developed. In addition, a heterogeneity classification scheme has to be determined in order to better analyze the impact of the relative demand volume of different product groups on the performance of DSSPL;
5. *Choice of performance metrics*: The principal performance metrics of a production system are the customer service level and the inventory level or (relative) inventory holding costs;
6. *Costs*: Instead of using cost parameters, the relative cost parameter *TBO* is used to determine the parameters of the lot sizing techniques used in MRP and stock replenishment systems. The chosen values for the relative cost parameters (*TBO*) correspond to scenarios defined by the overall objective of the production system. To determine the relative inventory holding costs, ratios are determined that express the added value over the production process from raw material to final product;
7. *Configuration of MPC methods*: The main objective of comparative studies of different production systems is to determine in which manufacturing environment a particular MPC concept with typical parameter settings performs better or worse than other MPC concepts. Parameter settings that do not correspond to natural settings of the particular MPC concept (e.g. too small lot sizes in an MRP system) must be avoided since such settings are difficult or impossible to achieve in practice;
8. *Availability of raw material*: The assumption of full availability of raw material has to be replaced by the modelling of suppliers who deliver the required subcomponents and raw material with a realistic reliability with respect to the predefined due dates;
9. *Comparative study concept*: The different MPC concepts must be compared based on their robustness in uncertain manufacturing environments.

The above list of specifications for the simulation analysis framework used in this work addresses most of the critical issues of simulation studies that are relevant to the research goals of this thesis. The problem of comparing results from different research studies is, however, still unresolved. The application of unified classification schemes and modelling concepts for the design of simulation models helps create more realistic and representative simulation models, but their characteristics can still be significantly different. A comparison of different concepts would thus be simplified if different research studies would use simulation models based on unified boundary conditions. Such simulation testbeds should be defined by the research community in order to assure that their characteristics cover the majority of the needs and requirements of research issues in manufacturing planning & control. A further development of these ideas is, however, outside the scope of this thesis.

4.2 Description of simulation analysis framework

The following issues can be derived from the previous list of specifications for the definition of the simulation analysis framework:

- Variability classification scheme;
- Heterogeneity classification scheme;
- Modelling concept of manufacturing environment;
- Modelling concept of MPC methods;
- Choice of performance metrics;
- Experimental design concept.

4.2.1 Variability classification scheme

Variability is one of the principal factors for the choice and dimensioning of manufacturing systems (Nyhuis and Wiendahl 1999, Hopp and Spearman 1997), since it has a major impact on the accuracy of the underlying assumptions of the different MPC concepts (production capacity, cycle times, demand, forecasts,...). The sources of this variability are the external load (demand) and the variability of the production process itself. In general, three scenarios are defined for each variability occurring in a manufacturing system. These scenarios correspond to high variability (HV), moderate variability (MV) and low variability (LV). The typical relative measure of variability is the coefficient of variation (CV), which is defined as the ratio of the standard deviation σ and the mean μ of a random variable.

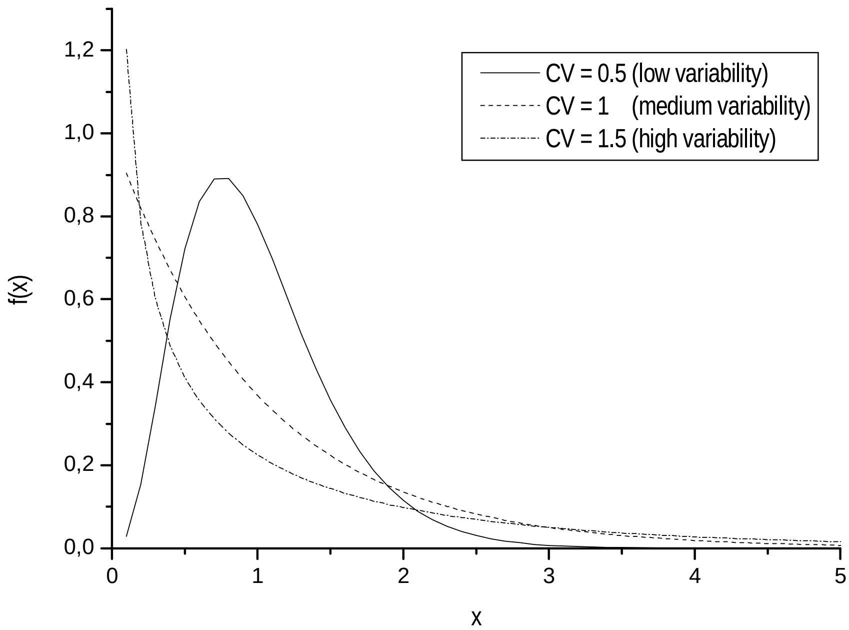
$$CV = \frac{\sigma}{\mu} \qquad \text{(Eq. 4.1)}$$

In this research work, variability classification schemes are defined for the external and internal variability. For the external variability (external demand), the following classification scheme, from Hopp and Spearman (2000), is applied:

Table 4.4: Variability classification scheme for external demand

Range of variability	**Classification**
$CV > 1.33$	High variability (HV)
$1.33 \geq CV > 0.75$	Moderate variability (MV)
$CV < 0.75$	Low variability (LV)

Figure 4.1 Illustration of variability classification scheme (Gamma density plots with mean values equal to one)



This classification scheme is derived from the fact that processes having a natural variability (arrival of customers) can be modelled in general by the exponential distribution having unit *CV*. Consequently, taking the unit *CV* as reference, high and low variability are defined by values of *CV* above and below one. Based on the analysis of industrial data performed by Willemain et al. (1994) it is assumed that this classification scheme is applicable to the intervals between two consecutive demands as well as to the size of the demands.

The three variability classes are illustrated in Figure 4.1 by gamma density plots having three different coefficients of variation *CV*.

The classification scheme defining the variability of the production process (processing times) is defined as follows.

Table 4.5: Variability classification scheme for internal variability

Range of variability	**Classification**
$CV > 0.3$	High variability (HV)
$0.3 \geq CV > 0.1$	Moderate variability (MV)
$CV < 0.1$	Low variability (LV)

This classification scheme for processing times is derived from the values applied in the simulation research studies reviewed in the previous chapters. Its relative low values are due to the fact that equipment failures are taken into account separately (Philipoom et al. 1987, Gupta et al. 1989).

4.2.2 Heterogeneity classification scheme

In contrast to variability, which is adequate for the characterization of stochastic processes, heterogeneity is adopted for the characterization of structures. The heterogeneity of structures of manufacturing system is an important issue since it expresses the difference between conceptual homogenous structures and heterogeneous structures found in practice. A typical measure for quantifiable heterogeneity is Gini's index g which is used basically in socioeconomics (Alker, 1965). Applied to the cumulated demand of several items over a certain period, this index measures the inequality of the proportion of the total demand that each item has generated.

With y_i as the cumulated proportion of the demand of item i and x_i as the cumulated proportion of the total number of items n, g becomes

$$g = 1 - \sum_{i=0}^{n-1} (y_{i+1} + y_i)(x_{i+1} - x_i), \qquad \text{(Eq. 4.2)}$$

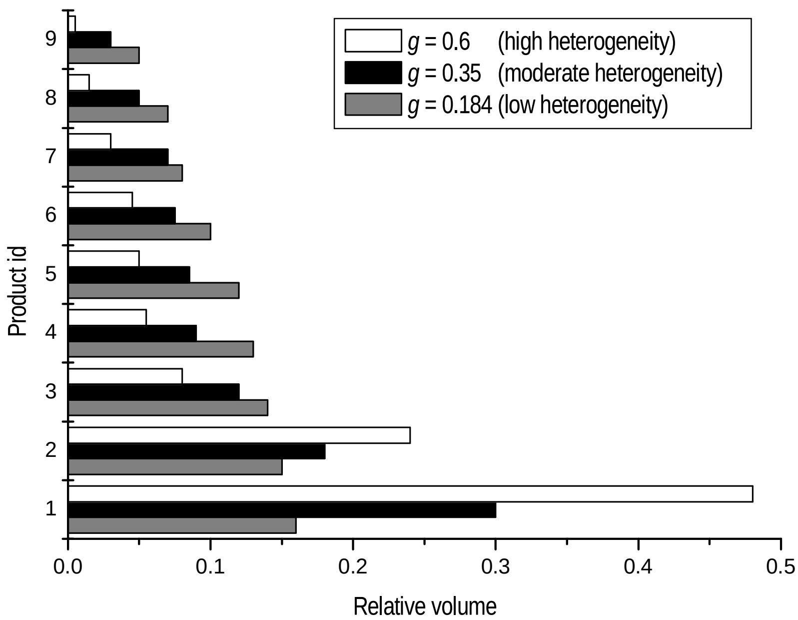
where $y_i / x_i > y_{i-1} / x_{i-1}$. Typical values of g ($g \in [0, 1[$) are 0 for a homogenous distribution and 0.6 for a distribution following Pareto's law. Consequently, a heterogeneity classification scheme can be defined as follows:

Table 4.6: Heterogeneity classification scheme

Range of heterogeneity	Classification
$0.6 \le g < 1$	High heterogeneity
$0.2 \le g < 0.6$	Moderate heterogeneity
$0 \le g < 0.2$	Low heterogeneity

The heterogeneity classification scheme defined in Table 4.6 is illustrated in Figure 4.2 for an example of nine products.

Figure 4.2 Heterogeneity classification scheme applied to relative volume of nine products



4.2.3 *Modelling of the manufacturing environment*

The manufacturing environment is defined by the characteristics of the two subsystems *Load* and *Technical production resources*. In reality, human production resources are a further important subsystem of a manufacturing environment. However, in order to simplify the analysis, it is assumed that the influence of human production resources can be approximated by particular settings of the variables of the *Technical production resources* subsystem.

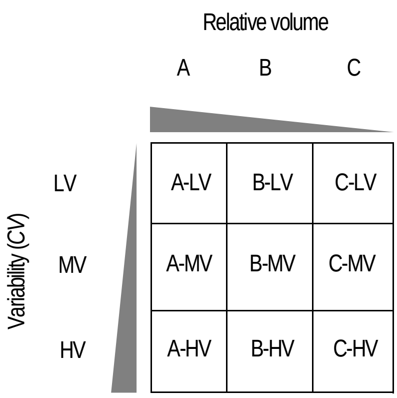
Load

The load of a manufacturing system is defined by the topology of the demand and the aggregate product structure. The topology of the demand describes the load level and the regularity of the demand as well as the mix of forecasts and confirmed orders. The aggregate product structure is characterized by its depth, width and the commonality.

Topology of demand:

Generally, the problem of load generation for manufacturing systems is twofold. First, the load should be representative for loads occurring in real industrial cases or at least cover a wide range of possible load configurations. Second, the load should be parametrized by variables which have a significant impact on the choice of MPC techniques for particular items or an entire production system. These problems are addressed by parametrizing the load by its regularity and relative volume. In fact, the division of items into product groups according to their relative volume corresponds to one of the key concepts of the new hybrid MPC system, whereas the criteria of demand variability plays an important role for the choice of the appropriate MPC technique. Consequently, the total demand can be classified into nine groups (Wildemann, 1988), as defined in Figure 4.3.

Figure 4.3 Classification of load



The distribution of the accumulated volume follows a distribution according to a particular level of heterogeneity (see Figure 4.2), whereas the distribution of the variability is less obvious. However, an analysis of the demand of real industrial cases (Hachen et al. 2000) has shown, that there is a correlation between the relative volume and the stability of the demand (high volume $\rightarrow$ low variability, low volume $\rightarrow$ high variability). Consequently, it is assumed that the largest proportion of the load with a high relative volume (A) has a stable demand (LV), whereas the largest proportion of the demand with a low relative volume (C) has an unstable demand (HV). In Table 4.7, the nine product groups are defined for g = 0.6 (high heterogeneity).

Table 4.7: Load distribution with respect to relative volume and variability for a high heterogeneity case (g = 0.6)

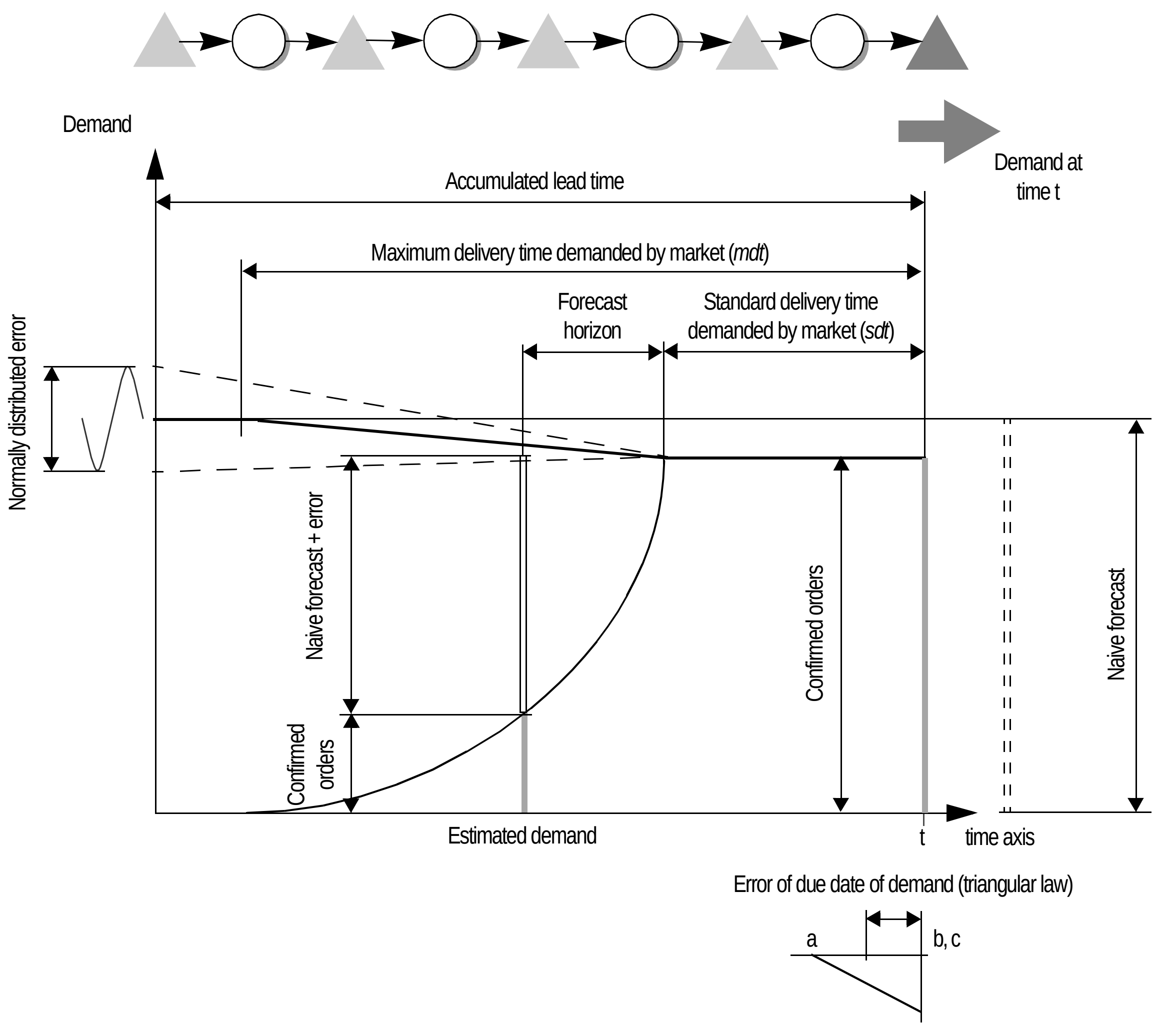
		Relative proportion of variability groups [%]		
Relative volume classification	**Accumulated volume [%]**	**LV**	**MV**	**HV**
A	80	60 (A-LV = 48%)	30 (A-MV = 24%)	10 (A-HV = 8%)
B	15	33.3 (B-LV = 5.5%)	33.3 (B-MV = 5%)	33.3 (B-HV = 4.5%)
C	5	10 (C-LV = 0.5%)	30 (C-MV = 1.5%)	60 (C-HV = 3%)

Determination of estimated demand:

The demand for items having a longer lead time than the delivery time demanded by the market has to be estimated. In practice, the demand for such items is derived generally from a mixture of forecasts and confirmed orders whereas the proportion of forecasts increases with the length of the forecast horizon. Thus, the accuracy of the estimated demand is dependent on the length of the forecast horizon, since both the proportion of forecasts and the forecast errors increase with its length. Consequently, the following assumptions, illustrated in Figure 4.4, are made in order to determine the estimated demand affected by forecast errors and taking into account the time dependency of the mixture of forecasts and confirmed orders:

1. The estimated demand for items having a longer cumulative lead time than the standard delivery time demanded by the market (*sdt*) is affected by forecast errors proportional to the length of the forecast horizon and the variability of the demand. The length of the forecast horizon is equal to the difference of the cumulative lead time and the standard delivery time demanded by the market (*sdt*);
2. The forecasts are determined using the naive forecasting technique which has two important characteristics. First, it is very often taken as basis for the relative measure of forecast errors and second, its forecast performance is equal or superior to more sophisticated forecast techniques particularly in the case of non deterministic demands (Makridakis et al. 1998);
3. The proportion of forecasts in the mixture of forecasts and confirmed orders is determined by the ratio of the actual length of the forecast horizon and the difference between the maximum and the standard delivery time demanded by the market for the product considered. If the forecast period is longer than the difference between maximum and the standard delivery time demanded by the market, the estimated demand is established based on the naive forecast;
4. In order to add a stochastic component to the estimated forecast, the proportion of forecasts is multiplied by a normally distributed variable with zero mean and variable *CV*;

Figure 4.4 Determination of estimated demand



5. In addition to the error in quantity, an error is added to the time when the effective demand occurs. It is assumed in this study that this error is always negative (effective demand occurs before it was planned) since such errors are a much bigger challenge for a production system than delayed orders. In fact, the capacity of a production system to handle such emergency orders gives a company the opportunity to react faster to sales opportunities (Kim et al. 2002). It is further assumed that only a certain percentage of orders become emergency orders (*peo*) and that the time error follows a asymmetrical triangular law.

The corresponding algorithm becomes in pseudocode:

```
Declarations:
tnow           = current time
sdt[i]         = standard delivery time demanded by market (item i)
mdt[i]         = maximum delivery time demanded by market (item i)
demand[i,j]    = jth effective demand of item i
estimate[i,j] = estimate of demand[i,j]
dd[i,j]        = due date of demand[i,j]
ed[i,j]        = effective demand date of demand[i,j]
cv[i]          = CV of normally distributed stoch. component (item i)
peo            = percentage of emergency orders
reo            = parameter defining max. amplitude of due date error

Estimated demand estimate[i,j] of demand[i,j] at tnow:
if (dd[i,j] - tnow <= sdt[i])
     estimate[i,j] = demand[i,j]                ! no forecast error
else if (dd[i,j] - tnow >= mdt[i])
     estimate[i,j] = demand[i, j-1]             ! naive forecast
else
     x = 1 - (dd[i,j] - tnow - sdt[i])/(mdt[i] - sdt[i])
     ratio = sqrt(1 - x^2)
     estimate[i,j] = (1 - ratio) * demand[i,j] +
                        ratio * N(0, cv[i]) * demand[i,j-1]

Forecast error of due date:
ed[i,j] = dd[i,j] - triang(a,b,c)          ! b = c = mdt
                                           ! a = mdt * reo
                                           ! Error probability = peo
```

The law defining the proportion of forecasts and confirmed orders is assumed to be a good approximation of the current market characteristics (tendency towards short delivery times).

Product structure:

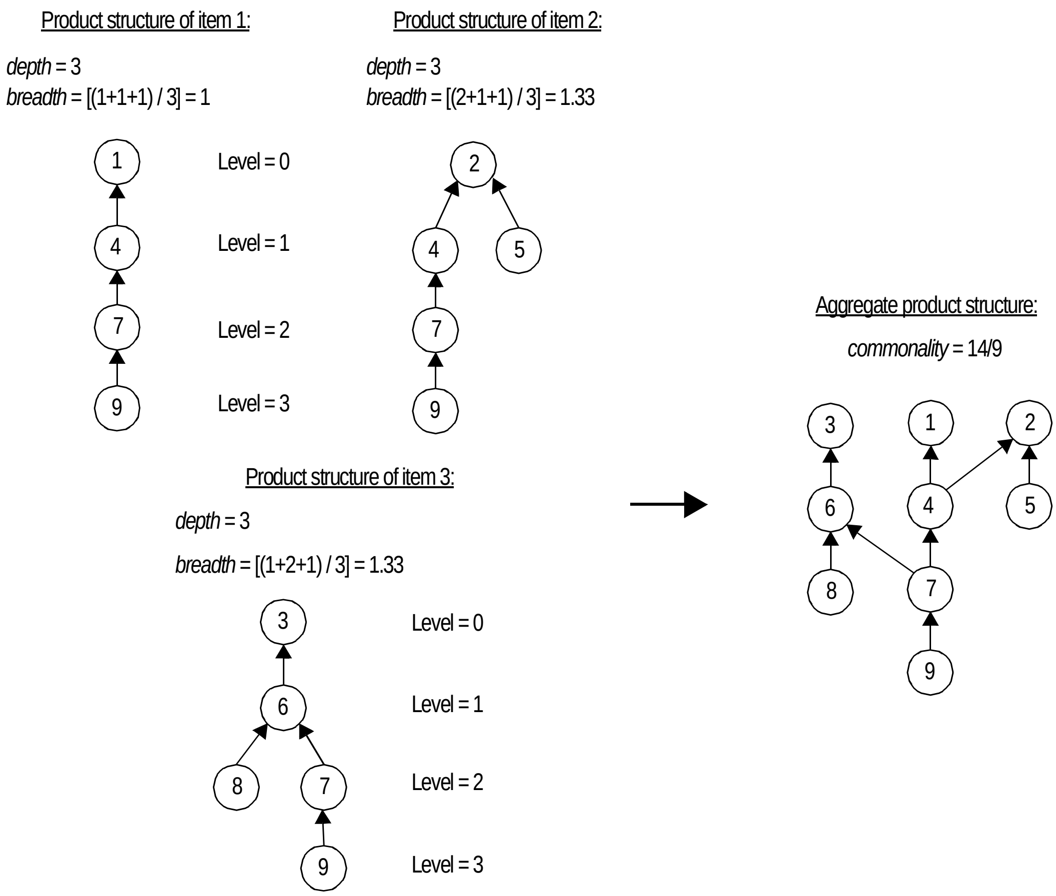
Product structures are generally defined by bill of materials that can be represented by a directed network (product structures of items 1, 2 and 3 in Figure 4.5). The nodes of this network represent products. With respect to the process structure, these nodes also imply a process that is required to produce the product represented by the node. Arcs indicate relations between products. Incoming arcs show the predecessor of a product. Outgoing arcs show the successor of a product. Final products have only incoming arcs and supplied products have only outgoing arcs. As shown in Figure 4.5, the structures of all final products can be combined to the aggregate product structure. In this network, each particular product is represented by one and only one node. All relations between nodes in the structures making up the final product are maintained.

The most important characteristics of the product structure from a production planning and control point of view are the number of levels, the number of assembly operations and the degree of component commonality of the aggregate product structure. According to Grünwald et al. (1989) and Benton et al.

(1985), the first two characteristics can be expressed by the factors *breadth* (number of immediate components per parent) and *depth* (number of levels in the bill of material structure). The factor *breadth* of a product structure is determined by dividing the sum of immediate components per parent by the number of levels (*depth*) of the product structure. The component commonality *commonality* is determined by dividing the total number of items in the product structures of the final products by the number of items in the aggregate product structure.

In Figure 4.5, the use of these factors is illustrated for the case of a simple aggregate product structure with three final products (Item 1, 2 and 3).

Figure 4.5 Example of aggregate product structure



System load:

Finally, the most important parameter of the load is the system load *sysint*. It is determined by dividing the capacity of the bottleneck stage of the production system by the workload. Table 4.8 summarizes the parameters defined for the subsystem *Load*.

Table 4.8: Parameters of subsystem *Load*

Parameter	**Unit**	**Description**
breadth[i]	[-]	Breadth of product structure (number of assembly operations) of final product i
commonnality	[-]	Component commonality of aggregate product structure
cvds[i]	[-]	Variability (CV) of demand size of item i

Table 4.8: Parameters of subsystem *Load*

Parameter	Unit	Description
cvid[i]	[-]	Variability (CV) of interval size between two orders for item i
cvsc[i]	[-]	Variability (CV) of normally distributed stochastic component of demand for item i
depth[i]	[-]	Depth of product structure (number of levels) of final product i
g	[-]	Index describing the heterogeneity of the demand
mdt[i]	[time unit]	Maximum delivery time demanded by market for item i
mds[i]	[item]	Mean demand size of item i
mid[i]	[time unit]	Mean interval size between two orders for item i
peo[i]	[-]	Proportion of emergency orders of item i
relc[i]	[-]	Relative cost of item i (with respect to raw material cost)
relint[i]	[-]	Relative intensity of item i (Sum of relint[1... n] = 1, n final products)
reo[i]	[-]	The parameter a of the asymmetrical triangular law defining the due date error expressed by the product of reo and mpd.
sdt[i]	[time unit]	Standard delivery time demanded by market for item i
sysint	[-]	System load (intensity)

Technical production resources

The characteristics of the technical production resources of a manufacturing system are defined by the characteristics of every single workstation as well as by the structure of the whole set of workstations. Every workstation is defined by its capacity, processing time, setup time and availability. According to the reliability theory, the availability of a workstation depends on the two parameters mean time between failure (MTBF) and mean time to repair (MTTR). It is assumed in this research work that the failure behavior of the workstations follows the exponential distribution since complex equipment composed of many subcomponents is best described by a constant failure rate. The other stochastic production resource processes (process and setup) are modelled by a symmetric triangular law.

An important factor influencing the performance of a production system is the availability of raw material or subcomponents that are delivered by external suppliers. Instead of assuming a full availability, it is assumed that the delivery time of supplied components follows an asymmetrical triangular law (illustrated in Figure 4.6). Thus, similar to the forecast error of the due date of the final products, delivery of supplied components is affected by a delay. The parameters defining the asymmetrical triangular law are defined as ratios of the planned delivery time. From the modelling point of view, suppliers are therefore defined as work centers with infinite capacity that deliver a job according to a statistical law with the planned lead time as mean value.

Figure 4.6 Supply of raw material and subcomponents

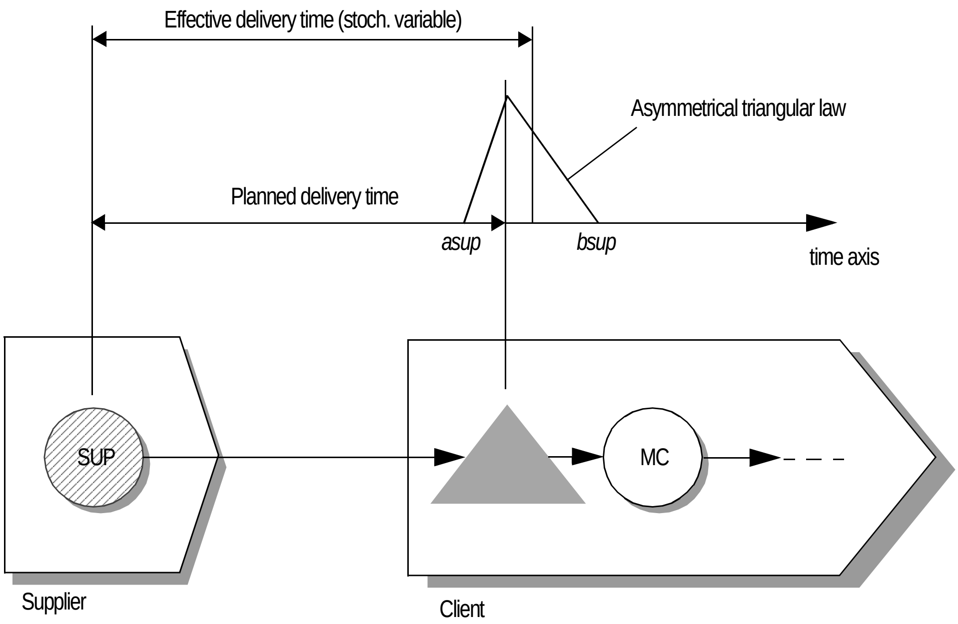


Table 4.9 summarizes the parameters describing the technical production resources.

Table 4.9: Parameters of subsystem *Technical production resources*

Parameter	**Unit**	**Description**
mpt[i,k]	[time unit]	Mean process time of item i on machine k
cvpt[i,k]	[-]	Variability (CV) of processing time of item i on machine k
stp[i,j,k]	[time unit]	Mean setup for item i after item j has been processed on machine k
cvstp[i,j,k]	[-]	Variability (CV) of setup time
mttf[k]	[time unit]	Mean time to failure of machine k
mttr[k]	[time unit]	Mean time to repair of machine k
asup[i], bsup[i]	[-]	Parameters defining the relative delay (asymmetrical triangular law) of suppliers

4.2.4 Modelling concept of MPC methods

The logic of the MPC methods Inventory control, MRP, JIT/kanban and DSSPL has already been described in detail in previous sections. Therefore, Table 4.10 summarizes thus only those parameters that are used to define the different MPC methods.

Table 4.10: Parameters of MPC methods

Parameter	Unit	Description
ck[i]	[item]	Capacity of kanban for item i (JIT/kanban)
freq	[time unit]	MRP replanning frequency (MRP)
llow[i]	[-]	Lower limit for kanban queue (Dispatching rule of DSSPL)
ls[i]	[item]	Lot size of item i (MRP)
lt[i]	[time unit]	Planned lead time of item i (MRP)
lup[i]	[-]	Upper limit for kanban queue (Dispatching rule of DSSPL)
nk[i]	[-]	Number of kanbans in kanban-loop for item i (JIT/kanban)
phor	[time unit]	Planning horizon (MRP)
q[i]	[item]	Order quantity for item i (Inventory Control)
r[i]	[item]	Reorder point for item i (Inventory Control)
slt[i]	[time unit]	Safety lead time of item i (MRP)
ss[i]	[item]	Safety stock level of item i (MRP)
tcrit[i]	[time unit]	Critical waiting time of item i (Dispatching rule of DSSPL)
z[i]	[-]	Standard normal distribution multiplier for adjustment of risk for being out-of-stock of item i (Inventory Control)

4.2.5 Performance metrics

The three measures customer service level *SL*, inventory level *IL* and inventory holding costs *IC* are chosen as principal logistic performance metrics. The customer service level *SL* is defined as the proportion of customer requests that have been served without any delay. The inventory level *IL* is defined as the sum of the central inventory, work in process (WIP) and final goods inventory (FGI). The inventory holding costs *IC* are obtained by multiplying the average inventory levels by the corresponding relative inventory cost value. *IC* is therefore a relative inventory holding cost measure which allows the emphasis of inventory levels at certain production stages. Table 4.11 summarizes the performance metrics that are used in this study.

Table 4.11: Performance metrics

Parameter	**Unit**	**Description**
SL	[-]	Service level
IL	[item]	Average inventory level
IC	[item]	Average inventory holding cost (based on relc)

4.2.6 Experimental design concept

A review of the related literature shows that basically three experimental concepts can be used to analyze production systems (Jain 1991). The simplest approach is to use explorative experimental designs where one or two factors are varied over a certain range in order to analyze their impact on a particular performance metric. This approach normally requires no statistical treatment of the results and is primarily designed to explore the behavior of systems. The second approach is based on statistical methods and is designed to determine the impact of factors on the performance of a system with a minimal effort. Typical tools used for this approach called sensitivity analysis, are $2^k r$ factorial designs and analysis of variance (ANOVA). The last approach is the Monte Carlo simulation technique that analyzes the impact of one or several uncertain variables (factors) on the performance of a system. Closely related to this approach is risk analysis which allows to determine, based on the results of a Monte Carlo simulation, the risk of obtaining a certain result.

In order to reach the research goals of this study, the first and third approach are chosen. Both approaches are best adopted to analyze and explore the behavior and performance of DSSPL and to compare with other MPC methods. Whereas explorative experimental design concepts are the most widely used approach, Monte Carlo simulation techniques have emerged in MPC research only recently with the availability of improved computer resources. The experimental design concept adopted for this study is based on a simulation study performed by Gaury and Kleijnen (1998) who first introduced an approach that combines a Monte Carlo simulation with a risk analysis approach. They proposed a framework that seeks to determine the MPC design that minimizes the probability of getting poor performance in the presence of an uncertain environment. The following list summarizes the procedure of the experimental design adopted:

1. A base scenario is defined with environmental factor settings that correspond to the medium values of the variability and heterogeneity classification schemes. Environmental factors include the parameters defined for the *Load* and *Technical production resources* subsystem;
2. The MPC methods are configured in order to reach a target service level of *SL* = 0.95 for every base scenario;
3. A range of possible values is defined for all environmental factors that is limited by the low and high values of the variability and heterogeneity classification schemes. It is assumed that all values within the defined range have the same probability (uniform distribution);
4. Based on the Monte Carlo sampling technique environmental scenarios are generated for which the logistic performance (inventory and service levels) of the different MPC methods is evaluated. It is assumed that all environmental scenarios have the same probability;

5. Based on the results cumulative probability distributions are generated for the performance metrics. This allows the determination of the probability or risk of achieving certain performance levels.

This approach has two main advantages: First, by evaluating the performance of the different MPC methods for defined ranges of environmental factors, the probability that conclusions are derived for MPC methods that are only due to a specific configuration of the simulation model is minimized. Second, the evaluation of the probability of getting a certain value of a performance metric allows the determination of the robustness of an MPC method in the presence of an uncertain environment. By taking into account the DSSPL assumptions of limited capacity and performance trade-offs the issue of robustness is of particular interest. The review of MPC methods in chapter §2 shows that JIT/kanban can be characterized by its high efficiency and its narrow application domain. On the other hand, Inventory control has the widest application domain of all reviewed MPC methods, but its application often leads to high and inefficient inventory levels. As the characteristics of other modern MPC methods also show, there seems to exist a trade-off between the size of the application domain of an MPC method and its efficiency. This is in accordance with Fisher's law about natural selection of organisms that can be generalized to systems and organizations in general (Weinberg 1985). It states that the better adapted a system is to a certain environment, the less adaptable it tends to be to unknown future conditions. This is in accordance with the results of Gaury and Klejinen (1998) that they obtained by comparing the robustness of optimized and non-optimized MPC concepts. In uncertain manufacturing environments with limited resources, a robust system is, therefore, more efficient than an optimized one that achieves high performances only for particular boundary conditions.

The results of the Monte Carlo simulation are presented, as mentioned before, by cumulative probability functions of the measured performance metrics. The relative ranking of these cumulative probability function can be performed by applying the theory of stochastic dominance (Hader and Russel 1969) that defines the two criteria first- and second-order stochastic dominance. If *F(x)* and *G(x)* are two cumulative density function then *F(x)* first-order stochastically dominates *G(x)* if

$$F(x) \geq G(x), \quad \text{for all } x. \qquad \text{(Eq. 4.3)}$$

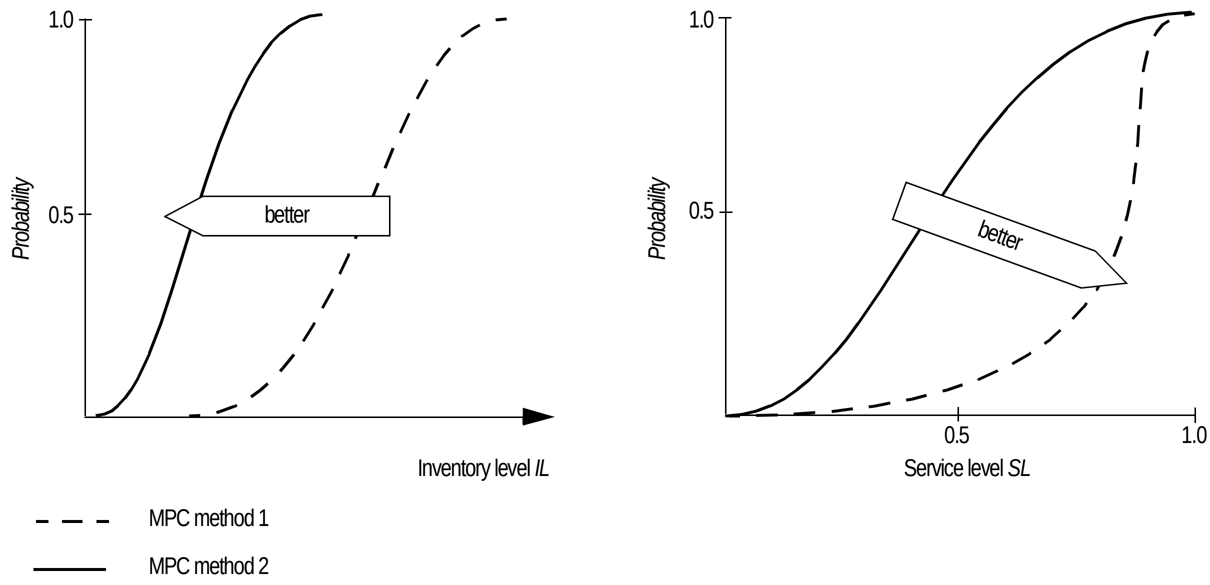
Consequently, according to the first-order stochastic dominance criteria, *F(x)* is preferred to *G(x)* if its cumulative probability function has always at least the level of *G(x)*. According to the second-order stochastic dominance criteria, *F(x)* dominates *G(x)* if

$$\int_a^z [F(x) - G(x)]\,dx \geq 0, \quad \text{for all } z > a. \qquad \text{(Eq. 4.4)}$$

Thus, *F(x)* second-order stochastically dominates *G(x)* if the area (limited by *a* and *z*) under *F(x)* is always at least the area under *G(x)*. Figure 4.7 illustrates how the results of Monte Carlo Simulations are interpreted when different MPC methods are compared. In the case of the inventory level *IL* the best results are those that show the highest probabilities for low inventory levels. Consequently, in the example shown in Figure 4.7, MPC method 2 is preferred to MPC method 1. In the case of the service level *SL,* the best results are those that show a low probability of getting a low service level. In the language of risk analysis, low service levels are considered as a disaster. MPC method 1 minimizes the probability of disaster and is, therefore, preferred to MPC method 2. For ordering MPC methods with respect to their service level *SL*, (Eq. 4.3) and (Eq. 4.4) are, therefore, applied with reversed sign.

Experimental design based on sensitivity analysis techniques are used in many simulation studies. In this study, this technique is not used for several reasons. The most critical issue with sensitivity analysis is the fact that the outcome of this analysis is valid for only one particular configuration of the analyzed system. Therefore, in systems with nonlinear behavior, the choice of the analysis point influences signifi-

Figure 4.7 Illustration of results of a (fictive) Monte Carlo simulation



cantly the results. There is a high probability that the outcome of a sensitivity analysis is strongly biased by a particular setting of the manufacturing environment variable like the system intensity *sysint*. This technique is, therefore, more adapted to performing an optimization of a particular production system with given manufacturing environment settings than to explore and analyze various MPC methods.

Summary and conclusions of chapter 4

- A review of simulation studies analysing and comparing push (MRP), pull (JIT/kanban) and hybrid systems reveals that the results are difficult to compare directly due to different design option settings and various performance indicator choices. It is therefore often difficult to determine if the outcomes of a simulation study are due to the characteristics of the MPC method or due to the particular settings of the manufacturing environment;
- The following experimental factors describing the manufacturing environment exhibit the most significant impact on the performance of a production system: Variability of the demand and the processing times, system load, capacity imbalance, product and process structure;
- The following parameters of the MRP system exhibit the most significant impact on the performance of a production system: Forecast errors, safety stock, planned lead time and lot sizing rule;
- The following parameters of the JIT/kanban system exhibit the most significant impact on the performance of a production system: Number and capacity of kanbans;
- A simulation analysis framework has been developed that is based on a variability and heterogeneity classification scheme, a modelling concept for manufacturing environments and MPC methods and an experimental design concept.

Chapter 5

Simulation analysis

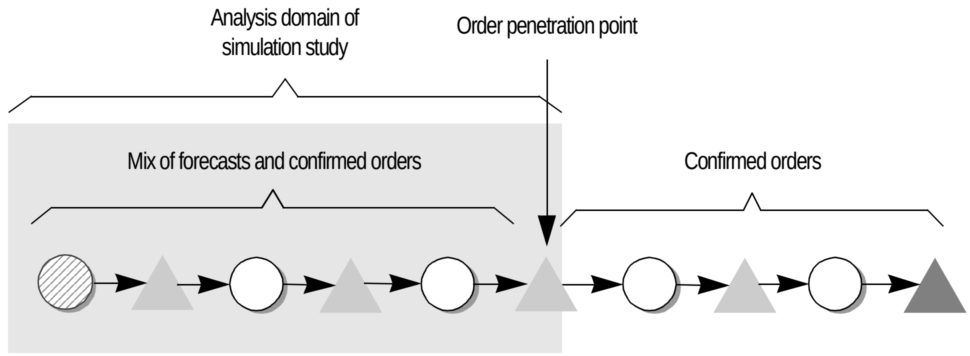
The goal of this chapter is the presentation of the results that have been obtained based on a simulation study. Based on the overall research goals defined in chapter §1, the following list summarizes in more detail the research issues that are treated:

- Which dispatching rule for DSSPL defined in section §3.2.2 exhibits the best performance?
- What is the impact of forecast errors on the performance of MRP and DSSPL (B-products)?
- In which manufacturing environment can MRP be replaced by the Inventory control method for the management of the B-products?
- What is the impact of variations of the load (heterogeneity of the demand, load level, variability) and the choice of A-products on the performance of DSSPL?
- What is the impact of component commonality and process structure on the performance of DSSPL?
- What MPC concept has the best robustness in the presence of an uncertain manufacturing environment?
- What MPC concept minimizes the risk of getting poor performance in the presence of an uncertain manufacturing environment?

The simulation analysis is performed for the two versions of DSSPL, DSSPL_MRP and DSSPL_IC, for MRP and Inventory control. DSSPL_MRP corresponds to the version of DSSPL where B-products are managed with the MRP method. In the case of DSSPL_IC, B-products are managed by the Inventory Control method. All MPC methods are analyzed and compared in a manufacturing environment that is assumed to be representative for the application domain of DSSPL defined in chapter §3. It is further assumed that other hybrid concepts such as POLCA or CONWIP are not an option for such manufacturing systems with a wide variety of products and non-linear process structure.

One of the most critical issues in manufacturing planning & control is the presence of forecast errors. As illustrated in Figure 5.1, the production system modelled corresponds, therefore, to the segment of production that is limited by the initial stage (supplier) and the order penetration point. The order penetration point is defined as the point from where production is only triggered by confirmed customer orders. The production system modelled can correspond to several manufacturing environments. It is equivalent to an MTS environment where the customers are served directly by the FGI or where the FGI corresponds to the inventory buffer between the MTS and MTO environment if the whole production system corresponds to an ATO environment (standard delivery time demanded by the market *sdt* = 0). It can further be imagined that the FGI also corresponds to the junction point between the push (MTS) and pull (MTO) production system of an HIHPS.

Figure 5.1 Analysis domain of the simulation study



It is further assumed that the load is derived from a Master Production Schedule (MPS) that has been established by taking into account approximately the capacity constraints of the production system. This means that all MPC methods are compared and analyzed in manufacturing environments with a demand having a constant mean (constant *sysint*, no seasonality effects). The DSSPL models therefore include no logic to limit the system load or work-in-process for the B-items.

In the following chapter, the simulation model is described as follows: The load and the product structure are defined in section §5.1.1. This includes the definition of the relative load and variabilities of the different product groups as well as the definition of their product structure with respect to the product commonality and the breadth and depth of the aggregate product structure. The technical production resources and the production process are defined in section §5.1.2. This includes the description the characteristics of the suppliers and manufacturing centers and the definition of the routings. Finally, in section §5.1.3, the analyzed MPC methods Inventory Control, MRP, DSSPL_MRP and DSSPL_IC are described. This includes the definition of reorder points, order quantities, lot sizing rules, safety stocks, lead times, number and capacity of kanbans and dispatching rules.

5.1 Description of the simulation model

In the following sections, all subsystems of the simulation model are defined according to the simulation analysis framework defined in chapter §4.

5.1.1 Load

Table 5.1 summarizes the chosen values of the *Load* subsystem that are specific to each final product (level = 0). Each final product corresponds to one of the nine product groups defined in section §4.2.3 (Figure 4.3).

Table 5.1: Definition of *Load* parameters specific to final products

	Relative intensity *relint*			Mean demand size *mds*	Variability of demand size and interval *cvds, cvid*		
Product #	**high** $g = 0.6$	**medium (default)** g=0.35	**low** g=0.18	**default**	**high**	**medium (default)**	**low**
1 (A-LV)	0.48	0.3	0.16	100	0.625	0.5	0.375
2 (A-MV)	0.24	0.18	0.15	60	1.25	1.0	0.75
3 (A-HV)	0.08	0.12	0.14	40	1.875	1.5	1.125
4 (B-LV)	0.055	0.09	0.13	30	0.625	0.5	0.375
5 (B-MV)	0.05	0.085	0.12	28	1.25	1.0	0.75
6 (B-HV)	0.045	0.075	0.1	25	1.875	1.5	1.125
7 (C-LV)	0.03	0.07	0.08	23	1.875	1.5	1.125
8 (C-MV)	0.015	0.05	0.07	16	1.25	1.0	0.75
9 (C-HV)	0.005	0.03	0.05	10	0.625	0.5	0.375

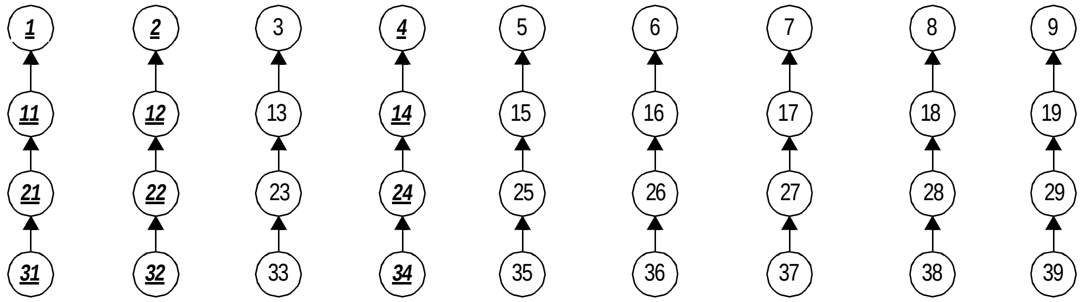
Both interval size and demand size follow the Gamma law with the above defined mean values and variabilities whereas the mean interval size *mid* is derived from the given values of relative intensity *relint*, system load *sysint*, mean process time per item *mpt* and mean demand size *mds* with

$$mid = \frac{mds \cdot mpt}{sysint \cdot relint}. \qquad \text{(Eq. 5.5)}$$

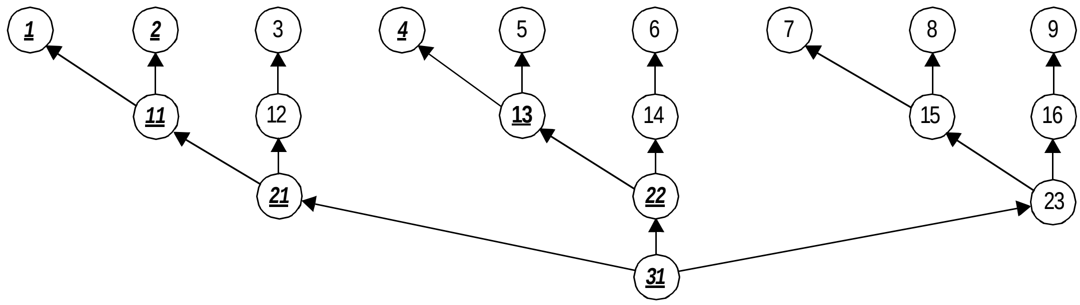
Concerning the product structure, two configurations low and high are assumed for the product complexity (*breadth* = 1 and 2.33) and component commonality of the aggregate product structure (*commonality* = 1 and 1.9). Figure 5.2 illustrates the resulting four scenarios defined for the product structure. The *depth* of all analyzed product structures is therefore constant. The chosen value of *depth* = 3 is assumed to be a good compromise between the generality of the model and the need to limit the complexity of the simulation analysis. The A-items (final products 1, 2 and 4) have been chosen according

Figure 5.2 Product structures (*depth* = 3, *breadth* = 1, *commonality* = 1 and 1.9), A-items in underlined bold and face

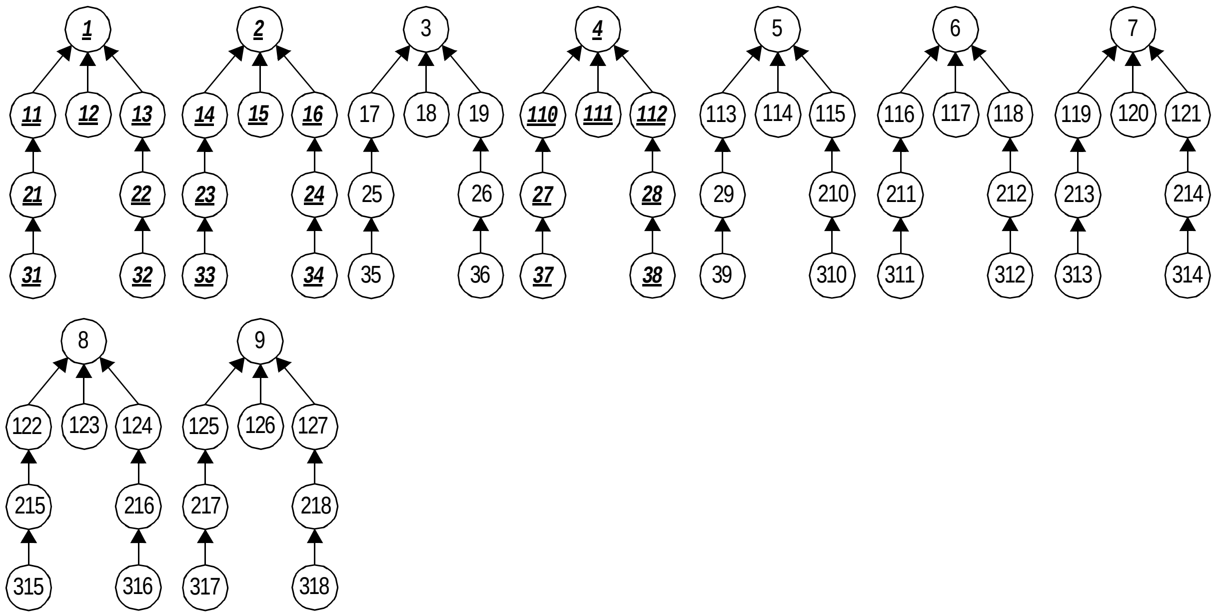
Aggregate product structure 1 (depth = 3, breadth = 1, commonality = 1):



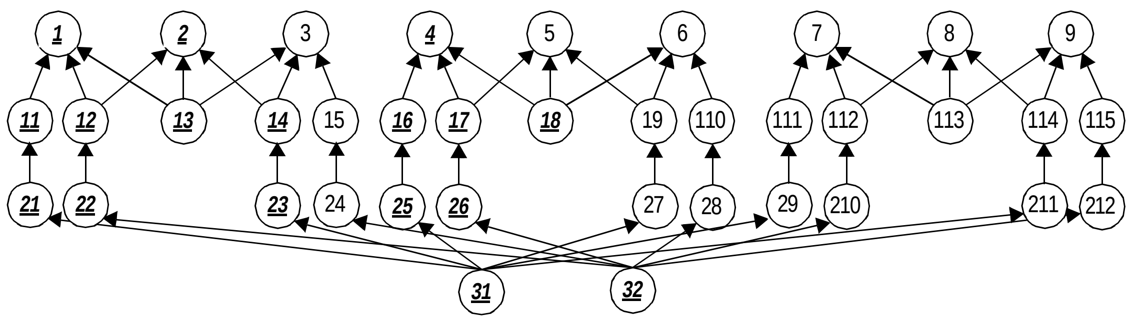
Aggregate product structure 2 (depth = 3, breadth = 1, commonality = 1.9):



Aggregate product structure 3 (depth = 3, breadth = 2.33, commonality = 1):



Aggregate product structure 4 (depth = 3, breadth = 2.33, commonality = 1.9):



to the criteria defined in chapter §4. This choice is also in accordance with the criteria for items managed with the JIT method defined by Wildemann (1988).

Table 5.2 summarizes the variables of the subsystem *Load* that define the forecast error generation procedure and the cost structure.

Table 5.2: Definition of variables of subsystem *Load*

Variable	**low**	**medium (default)**	**high**
Variability (*CV*) of normally distributed stochastic component of demand *cvsc*	0.4	0.6	0.8
Proportion of emergency orders *peo*	0.05	0.2	0.65
Relative costs *relc* (Stage 0 to 3)	1.0 / 1.1 / 1.2 / 1.3	1.0 / 1.5 / 2.0 / 2.5	1.0 / 2.0 / 3.0 / 4.0
Due date error *reo*	0.05	0.3	0.5
Standard delivery time *sdt*	-	0	-
Maximum delivery time *mdt*	-	3000	-
System load *sysint*	0.7	0.8	0.9

5.1.2 *Technical production resources*

The production process structure illustrated in Figure 5.3 is derived from the product structures defined in the previous section. The first linear process structure is used for product structures 1 and 2 with *breadth* = 1 whereas the second converging process structure is defined for product structures 3 and 4 with *breadth* = 2.33.

The corresponding routing is defined in Tables 5.3 and 5.4.

Table 5.3: Definition of routing for linear process structure

Manufacturing center, Supplier	**Product structure 1**	**Product structure 2**
MC 0	11 → 1; 12 → 2; 13 → 3; 14 → 4; 15 → 5; 16 → 6; 17 → 7; 18 → 8; 19 → 9	11 → 1; 11 → 2; 12 → 3; 13 → 4; 13 → 5; 14 → 6; 15 → 7; 15 → 8; 16 → 9
MC 1	21 → 11; 22 → 12; 23 → 13; 24 → 14; 25 → 15; 26 → 16; 27 → 17; 28 → 18; 29 → 19	21 → 11; 21 → 12; 22 → 13; 22 → 14; 23 → 15; 23 → 16
MC 2	31 → 21; 32 → 22; 33 → 23; 34 → 24; 35 → 25; 36 → 26; 37 → 27; 38 → 28; 39 → 29	31 → 21; 31 → 22; 31 → 23
SUP 3	→ 31; → 32; → 33; → 34; → 35; → 36; → 37; → 38; → 39	→ 31

Figure 5.3 Definition of linear and converging production process structure

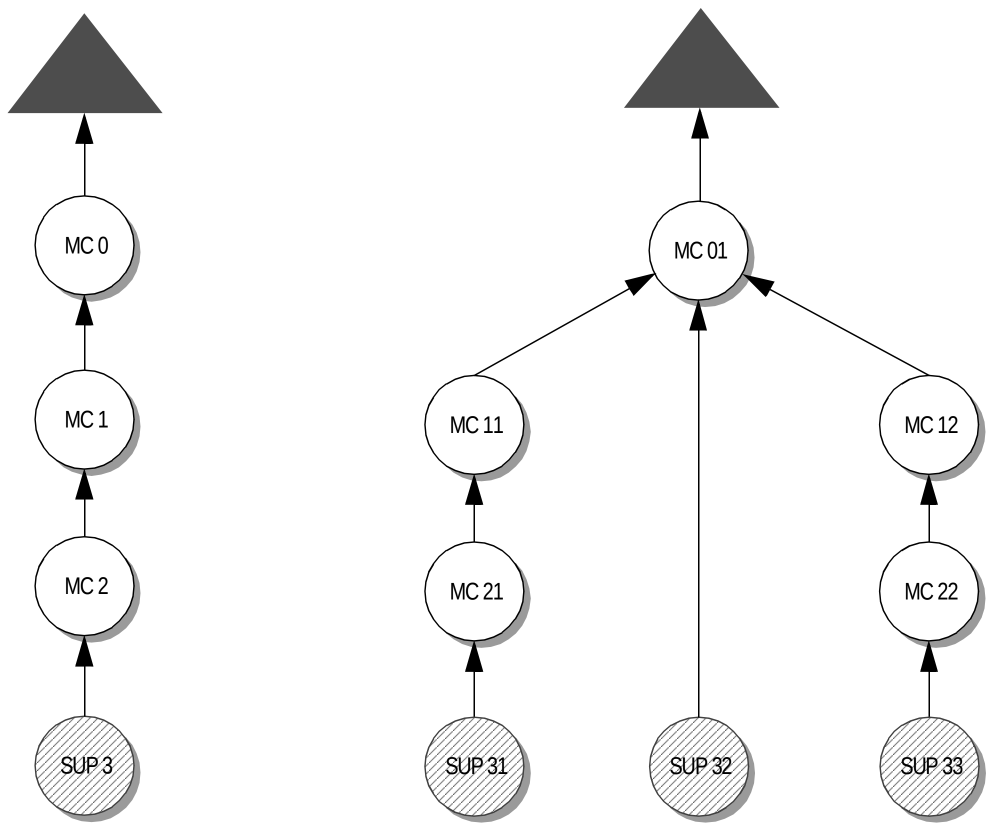


Table 5.4: Definition of routing for converging process structure

Manufacturing center, Supplier	**Product structure 3**	**Product structure 4**
MC 01	11,12,13 → 1; 14,15,16 → 2; 17,18,19 → 3; 110,111,112 → 4; 113,114,115 → 5; 116,117,118 → 6; 119,120,121 → 7; 122,123,124 → 8; 125,126,127 → 9	11,12,13 → 1; 12,13,14 → 2; 13,14,15 → 3; 16,17,18 → 4; 17,18,19 → 5; 18,19,110 → 6; 111,112,113 → 7; 112,113,114 → 8; 113,114,115 → 9
MC 11	21 → 11; 23 → 14; 25 → 17; 27 → 110; 29 → 113; 211 → 116; 213 → 119; 215 → 122; 217 → 125	21 → 11; 23 → 14; 25 → 16; 27 → 19; 29 → 111; 211 → 114
MC 12	22 → 13; 24 → 16; 26 → 19; 28 → 112; 210 → 115; 212 → 118; 214 → 121; 216 → 124; 218 → 127	22 → 12; 24 → 15; 26 → 17; 28 → 110; 210 → 112; 212 → 115
MC 21	31 → 21; 33 → 23; 35 → 25; 37 → 27; 39 → 29; 311 → 211; 313 → 213; 315 → 215; 317 → 217	31 → 21; 31 → 23; 31 → 25; 31 → 27; 31 → 29; 31→ 211
MC 22	32 → 22; 34 → 24; 36 → 26; 38 → 28; 310 → 210; 312 → 212; 314 → 214; 316 → 216; 318 → 218	32 → 22; 32 → 24; 32 → 26; 32 → 28; 32 → 210; 32 → 212
SUP 31	→ 31; → 33; → 35; → 37; → 39; → 311; → 313; → 315; → 317	→ 31
SUP 32	→ 12; → 15; → 18; → 111; → 114; → 117; → 120; → 123; → 126	→ 13; → 18; → 113
SUP 33	→ 32; → 34; → 36; → 38; → 310; → 312; → 314; → 316; → 318	→ 32

Characteristics of the machining centers (MC) and the suppliers (SUP) are summarized in Table 5.5:

Table 5.5: Definition of machining centers and suppliers

Variable	**low**	**medium (default)**	**high**
Mean process time *mpt*	-	1	-
Variability of processing time *cvpt*	0.05	0.15	0.35
Mean setup *stp*	1	5	10
Variability of setup time *cvstp*	-	0.5	-
Mean time to failure *mttf*	100000	500	500
Mean time to repair *mttr*	1	25	50
Parameters defining the relative delay *asup*, *bsup*	0.9/1.1	0.95/1.5	0.99/2.0

The processing and setup time follow a symmetrical triangular law whereas the failure and repair rates follow an exponential law.

5.1.3 MPC methods

As defined in chapter §4 all parameters of the different MPC methods have been adjusted in order to reach a target service level of approximately 0.95. This procedure is divided into two steps. In a first step, initial values are chosen for the parameters of the MPC methods based on available heuristics and analytical methods. In the second step, the chosen values are corrected in an iterative procedure in order to assure that the target service level is reached for all nine end items at minimum inventory levels.

In the case of the Inventory Control method initial values of the reorder point *r* and order quantity *q* have been determined based the methodology presented in §2.1 (eq. 2.19 and eq. 2.20) and the *EOQ* model (eq. 2.4 and eq. 2.5) with an assumed value of *TBO* equal to 6. The chosen value for *TBO* corresponds approximately to the average of those values used in the reviewed simulation studies in §4.

The same initial values as for the order quantity *q* have been chosen for the lot sizes *ls* of the MRP method that adopts, therefore, a fixed-order-quantity (FOQ) lot-sizing rule. The FOQ lot-sizing rule has been chosen for several reasons. By using the FOQ lot-sizing rule, a direct comparison of the performance of the MRP and the Inventory Control methods is simplified. Furthermore, as shown by the study of De Bodt and Van Wessenhove (1983), complex (dynamic) lot-sizing rules such as McLaren's order moment (MOM) or Silver-Meal (SM) exhibit significantly higher performance than simple lot-sizing rules only in deterministic manufacturing environments. Finally, FOQ is a lot-sizing rule frequently used in real manufacturing environments that are similar to those analyzed in this study. The safety stock levels *ss* have only been increased (higher than zero) if the target service level could not been reached by an appropriate setting of the lot sizes *ls* and lead times *lt*.

In the case of the items managed by the JIT/kanban concept (DSSPL_IC and DSSPL_MRP) initial values for the kanban capacity *ck* were determined based on the assumption that the product of *ck* and *nk* is equal to the order size *q* determined for the Inventory Control method. The number of kanbans *nk* is assumed to be constant for all items (*nk* = 4). This value is, according to a study of Mertins and Lewand-rowski (1999), a good compromise between the reactivity and flexibility of the JIT/kanban system and the kanban capacity whose lower limit is normally determined by technological constraints (capacity and setup of manufacturing center).

In the case of the base scenarios 2 and 4, some B-items are composed of A-items. This signifies for DSSPL that items managed by the MRP or the Inventory Control method are composed of items that are managed by kanbans (typical example: aggregate product structure 2, item 12 composed of item 21). In this case, these items are directly taken from the kanbans and not sent with the production order.

The four analyzed MPC methods have therefore been determined for four base scenarios that are defined as follows:

Table 5.6: Definition of base scenarios

Base scenario	Aggregate product structure	Production process structure
1	1	linear
2	2	linear
3	3	converging
4	4	converging

Inventory Control

The following four Tables 5.7, 5.8, 5.9 and 5.10 summarize the parameters chosen for the Inventory Control method. For the case of the base scenarios 1 and 2, the additional values (low and high setting) have been determined for different heterogeneity levels *g* of the demand.

Table 5.7: Parameters of Inventory Control method for base scenario 1

	Reorder point *r*			**Order quantity *q***			**Lead time *lt* (if item produced by supplier)**		
Item	**low (*g*=0.18)**	**medium (default)**	**high (*g*=0.6)**	**low (*g*=0.18)**	**medium (default)**	**high (*g*=0.6)**	**low (*g*=0.18)**	**medium (default)**	**high (*g*=0.6)**
1, 11, 21, 31	130	720	1200	370	770	1100	2	2	3
2, 12, 22, 32	140	350	300	360	460	550	2	2	2
3, 13, 23, 33	160	135	100	330	310	190	2	2	2
4, 14, 24, 34	100	110	40	300	220	130	2	2	2
5, 15, 25, 35	110	110	80	280	220	120	2	2	2
6, 16, 26, 36	130	100	70	240	190	110	2	2	2
7, 17, 27, 37	80	90	40	180	140	80	2	2	2
8, 18, 28, 38	60	75	40	160	80	50	2	2	2
9, 19, 29, 39	50	50	10	115	75	40	2	2	2

Table 5.8: Parameters of Inventory Control method for base scenario 2

	Reorder point *r*			**Order quantity *q***			**Lead time *lt* (if item produced by supplier)**		
Item	**low (*g*=0.18)**	**medium (default)**	**high (*g*=0.6)**	**low (*g*=0.18)**	**medium (default)**	**high (*g*=0.6)**	**low (*g*=0.18)**	**medium (default)**	**high (*g*=0.6)**
1	130	850	1200	370	770	1100	-	-	-
2	140	400	300	360	460	550	-	-	-
3, 12	180	170	100	330	310	190	-	-	-
4	100	140	40	300	220	130	-	-	-
5	140	140	40	280	220	120	-	-	-
6, 14	150	130	70	240	190	110	-	-	-
7	100	120	40	180	140	80	-	-	-
8	80	100	40	160	80	50	-	-	-
9, 16	70	70	10	115	75	40	-	-	-
11	2500	2000	2000	1200	1100	1100	-	-	-
13	420	250	250	450	400	400	-	-	-
15	180	120	120	320	280	280	-	-	-

Table 5.8: Parameters of Inventory Control method for base scenario 2

Item	Reorder point *r*			Order quantity *q*			Lead time *lt* (if item produced by supplier)		
	low (g=0.18)	medium (default)	high (g=0.6)	low (g=0.18)	medium (default)	high (g=0.6)	low (g=0.18)	medium (default)	high (g=0.6)
21	3500	3200	3200	1600	1400	1400	-	-	-
22	500	350	350	650	580	580	-	-	-
23	380	230	230	500	460	460	-	-	-
31	4000	4000	4000	2300	2300	2300	4	4	4

Table 5.9: Parameters of Inventory Control method for base scenario 3

Item	Reorder point *r*	Order quantity *q*	Lead time *lt* (if item produced by supplier)
1, 11, 12, 13, 21, 22, 31, 32	720	770	2
2, 14, 15, 16, 23, 24, 33, 34	350	460	2
3, 17, 18, 19, 25, 26, 35, 36	135	310	2
4, 110, 111, 112, 27, 28, 37, 38	110	220	2
5, 113, 114, 115, 29, 210, 39, 310	110	220	2
6, 116, 117, 118, 211, 212, 311, 312	100	190	2
7, 119, 120, 121, 213, 214, 313, 314	90	140	2
8, 122, 123, 124, 215, 216, 315, 316	75	80	2
9, 125, 126, 127, 217, 218, 317, 318	50	75	2

Table 5.10: Parameters of Inventory Control method for base scenario 4

Item	Reorder point *r*	Order quantity *q*	Lead time *lt* (if item produced by supplier)
1, 11, 21	720	780	-
2	350	470	-
3, 15, 24	135	320	-
4, 16, 25	110	230	-
5	100	200	-
6, 110, 28	90	150	-
7, 111, 29	90	150	-
8	75	90	-
9, 115, 212	50	85	-
12, 22	2100	1110	-
13	3300	1410	-

Table 5.10: Parameters of Inventory Control method for base scenario 4

Item	Reorder point *r*	Order quantity *q*	Lead time *lt* (if item produced by supplier)
14, 23	460	790	-
17, 26	260	410	-
18	360	590	-
19, 27	145	320	-
112, 210	120	230	-
113	240	470	-
114, 211	100	180	-
31	2100	1500	4
32	2100	1500	4

MRP

The following four Tables 5.11, 5.12, 5.13 and 5.14 summarize the parameters chosen for the MRP method that are specific to each item. For the case of the base scenarios 1 and 2, the additional values (low and high setting) have been determined for different heterogeneity levels *g* of the demand. The MRP replanning frequency is set to 5 which corresponds to a replanning frequency of one week, often found in practice.

Table 5.11: Parameters of MRP method for base scenario 1

	Lot size *ls* (FOQ)			Safety stock *ss*			Lead time *lt*		
Item	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**
1, 11, 21, 31	250	650	850	0	0	0	2	3	3
2, 12, 22, 32	300	400	500	0	0	0	2	3	3
3, 13, 23, 33	150	250	200	0	0	0	2	2	2
4, 14, 24, 34	170	180	150	0	0	0	2	2	2
5, 15, 25, 35	120	170	120	0	0	0	2	2	2
6, 16, 26, 36	150	150	100	0	0	0	2	2	2
7, 17, 27, 37	110	140	80	0	0	0	2	2	2
8, 18, 28, 38	100	100	50	0	0	0	2	2	2
9, 19, 29, 39	60	50	50	0	0	0	2	2	2

Table 5.12: Parameters of MRP method for base scenario 2

	Lot size *ls* (FOQ)			**Safety stock *ss***			**Lot size *lt***		
Item	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**
1	240	650	850	150	150	550	2	3	4
2	290	400	500	150	150	600	2	3	3
3, 12	150	250	250	80	80	450	2	2	2
4	150	180	150	60	60	160	2	2	2
5	110	170	120	60	60	200	2	2	2
6, 14	140	150	100	60	60	180	2	2	2
7	110	140	80	40	40	40	2	2	2
8	90	100	50	40	40	40	2	2	2
9, 16	50	50	50	40	40	40	2	2	2
11	740	1250	1350	300	300	800	4	5	7
13	300	350	280	200	200	300	3	3	3
15	190	240	140	200	200	200	3	3	3
21	1300	1600	1600	300	300	800	7	7	7
22	490	550	450	300	300	500	3	3	3
23	280	300	200	300	300	300	4	4	4
31	4500	4500	4500	0	0	0	4	4	4

Table 5.13: Parameters of MRP method for base scenario 3

Item	**Lot size *ls* (FOQ)**	**Safety stock *ss***	**Lead time *lt***
1, 11, 12, 13, 21, 22, 31, 32	650	0	3
2, 14, 15, 16, 23, 24, 33, 34	400	0	3
3, 17, 18, 19, 25, 26, 35, 36	250	0	2
4, 110, 111, 112, 27, 28, 37, 38	180	0	2
5, 113, 114, 115, 29, 210, 39, 310	170	0	2
6, 116, 117, 118, 211, 212, 311, 312	150	0	2
7, 119, 120, 121, 213, 214, 313, 314	140	0	2
8, 122, 123, 124, 215, 216, 315, 316	100	0	2
9, 125, 126, 127, 217, 218, 317, 318	50	0	2

Table 5.14: Parameters of MRP method for base scenario 4

Item	**Lead time *ls* (FOQ)**	**Safety stock *ss***	**Lead time *lt***
1, 11, 21	400	300	3
2	350	350	3
3, 15, 24	150	250	2
4, 16, 25	180	250	2
5	150	250	2
6, 110, 28	100	200	2
7, 111, 29	100	200	2
8	100	200	2
9, 115, 212	60	100	2
12, 22	350	350	3
13	400	550	4
14, 23	300	250	4
17, 26	230	390	3
18	450	0	3
19, 27	200	250	2
112, 210	150	350	3
113	350	0	4
114, 211	170	100	2
31, 32	1500	0	4

DSSPL_IC

The following four Tables 5.15, 5.16, 5.17 and 5.18 summarize the JIT/kanban parameters of the A-items chosen for the DSSPL_IC method. For the case of the base scenarios 1 and 2, the additional values (low and high setting) have been determined for different heterogeneity levels *g* of the demand. The parameters of the B-items are equal to those parameters chosen for the Inventory Control method.

Table 5.15: JIT/kanban parameters of DSSPL_IC method (A-items) for base scenario 1

			Size of kanbans *sk*			**Number of kanbans *nk***
Item	**Source**	**Target**	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**	**default**
1	MC 0	FGI	120	160	160	4
11	MC 1	MC 0	120	160	160	4
21	MC 2	MC 1	120	160	160	4

Table 5.15: JIT/kanban parameters of DSSPL_IC method (A-items) for base scenario 1

			Size of kanbans *sk*			Number of kanbans *nk*
Item	**Source**	**Target**	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**	**default**
31	SUP 3	MC 2	120	160	160	4
2	MC 0	FGI	80	120	100	4
12	MC 1	MC 0	80	120	100	4
22	MC 2	MC 1	80	120	100	4
32	SUP 3	MC 2	80	120	100	4
4	MC 0	FGI	60	90	60	4
14	MC 1	MC 0	60	90	60	4
24	MC 2	MC 1	60	90	60	4
34	SUP 3	MC 2	60	90	60	4

Table 5.16: JIT/kanban parameters of DSSPL_IC method (A-items) for base scenario 2

			Size of kanbans *sk*			Number of kanbans *nk*
Item	**Source**	**Target**	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**	**default**
1	MC 0	FGI	180	240	260	4
11	MC 1	MC 0	260	290	240	4
21	MC 2	MC 1	200	240	260	4
31	SUP 3	MC 2	700	850	900	4
2	MC 0	FGI	200	210	200	4
4	MC 0	FGI	150	160	100	4
13	MC 1	MC 0	200	210	180	4
22	MC 2	MC 1	230	240	210	4

Table 5.17: JIT/kanban parameters of DSSPL_IC method (A-items) for base scenario 3

Item	**Source**	**Target**	**Size of kanbans *sk***	**Number of kanbans *nk***
1	MC 01	FGI	160	4
11	MC 11	MC 01	160	4
21	MC 21	MC 11	160	4
13	MC 12	MC 01	160	4
22	MC 22	MC 12	160	4
31	SUP 31	MC 21	160	4

Table 5.17: JIT/kanban parameters of DSSPL_IC method (A-items) for base scenario 3

Item	Source	Target	Size of kanbans *sk*	Number of kanbans *nk*
32	SUP 33	MC 22	160	4
12	SUP 32	MC 01	160	4
2	MC 01	FGI	120	4
14	MC 11	MC 01	120	4
23	MC 21	MC 11	120	4
16	MC 12	MC 01	120	4
24	MC 22	MC 12	120	4
33	SUP 31	MC 21	120	4
34	SUP 33	MC 22	120	4
15	SUP 32	MC 01	120	4
4	MC 01	FGI	90	4
110	MC 11	MC 01	90	4
27	MC 21	MC 11	90	4
112	MC 12	MC 01	90	4
28	MC 22	MC 12	90	4
37	SUP 31	MC 21	90 (lt = 2)	4
38	SUP 33	MC 22	90 (lt = 2)	4
111	SUP 32	MC 01	90 (lt = 2)	4

Table 5.18: JIT/kanban parameters of DSSPL_IC method (A-items) for base scenario 4

Item	Source	Target	Size of kanbans *sk*	Number of kanbans *nk*
1	MC 01	FGI	150	4
11	MC 11	MC 01	150	4
21	MC 21	MC 11	150	4
31	SUP 31	MC 21	450 (lt = 2)	4
2	MC 01	FGI	110	4
12	MC 12	MC 01	260	4
22	MC 22	MC 12	260	4
32	SUP 33	MC 22	450 (lt = 2)	4
13	SUP 32	MC 01	500 (lt = 2)	4
14	MC 11	MC 01	140	4
23	MC 21	MC 11	140	4
4	MC 01	FGI	90	4

Table 5.18: JIT/kanban parameters of DSSPL_IC method (A-items) for base scenario 4

Item	Source	Target	Size of kanbans *sk*	Number of kanbans *nk*
16	MC 11	MC 01	90	4
25	MC 21	MC 11	90	4
17	MC 12	MC 01	110	4
26	MC 22	MC 12	110	4
18	SUP 32	MC 01	320 (*lt* = 2)	4

DSSPL_MRP

The following four Tables 5.19, 5.20, 5.21 and 5.22 summarize the JIT/kanban parameters of the A-items chosen for the DSSPL_MRP method. For the case of the base scenarios 1 and 2, the additional values (low and high setting) have been determined for different heterogeneity levels *g* of the demand. The parameters of the B-items are equal to those parameters chosen for the MRP method.

Table 5.19: JIT/kanban parameters of DSSPL_MRP method (A-items) for base scenario 1

			Size of kanbans *sk*			Number of kanbans *nk*
Item	**Source**	**Target**	**low (g=0.18)**	**medium (default)**	**high (g=0.6)**	**default**
1	MC 0	FGI	120	140	160	4
11	MC 1	MC 0	120	140	160	4
21	MC 2	MC 1	120	140	160	4
31	SUP 3	MC 2	120 (*lt* = 2)	140 (*lt* = 2)	160 (*lt* = 2)	4
2	MC 0	FGI	80	100	110	4
12	MC 1	MC 0	80	100	110	4
22	MC 2	MC 1	80	100	110	4
32	SUP 3	MC 2	80 (*lt* = 2)	100 (*lt* = 2)	110 (*lt* = 2)	4
4	MC 0	FGI	60	80	70	4
14	MC 1	MC 0	60	80	70	4
24	MC 2	MC 1	60	80	70	4
34	SUP 3	MC 2	60 (*lt* = 2)	80 (*lt* = 2)	70 (*lt* = 2)	4

Table 5.20: JIT/kanban parameters of DSSPL_MRP method (A-items) for base scenario 2

Item	**Source**	**Target**	**Size of kanbans *sk*** low (g=0.18)	medium (default)	high (g=0.6)	**Number of kanbans *nk*** default
1	MC 0	FGI	140	140	260	4
11	MC 1	MC 0	220	150	240	4
21	MC 2	MC 1	160	180	260	4
31	SUP 3	MC 2	600 (lt = 2)	660 (lt = 2)	900 (lt = 2)	4
2	MC 0	FGI	160	110	200	4
4	MC 0	FGI	120	90	100	4
13	MC 1	MC 0	160	120	180	4
22	MC 2	MC 1	180	130	210	4

Table 5.21: JIT/kanban parameters of DSSPL_MRP method (A-items) for base scenario 3

Item	**Source**	**Target**	**Size of kanbans *sk***	**Number of kanbans *nk***
1	MC 01	FGI	160	4
11	MC 11	MC 01	160	4
21	MC 21	MC 11	160	4
13	MC 12	MC 01	160	4
22	MC 22	MC 12	160	4
31	SUP 31	MC 21	160 (lt = 2)	4
32	SUP 33	MC 22	160 (lt = 2)	4
12	SUP 32	MC 01	160 (lt = 2)	4
2	MC 01	FGI	120	4
14	MC 11	MC 01	120	4
23	MC 21	MC 11	120	4
16	MC 12	MC 01	120	4
24	MC 22	MC 12	120	4
33	SUP 31	MC 21	120 (lt = 2)	4
34	SUP 33	MC 22	120 (lt = 2)	4
15	SUP 32	MC 01	120 (lt = 2)	4
4	MC 01	FGI	90	4
110	MC 11	MC 01	90	4
27	MC 21	MC 11	90	4
112	MC 12	MC 01	90	4

Table 5.21: JIT/kanban parameters of DSSPL_MRP method (A-items) for base scenario 3

Item	**Source**	**Target**	**Size of kanbans *sk***	**Number of kanbans *nk***
28	MC 22	MC 12	90	4
37	SUP 31	MC 21	90 (lt = 2)	4
38	SUP 33	MC 22	90 (lt = 2)	4
111	SUP 32	MC 01	90 (lt = 2)	4

Table 5.22: JIT/kanban parameters of DSSPL_MRP method (A-items) for base scenario 4

Item	**Source**	**Target**	**Size of kanbans *sk***	**Number of kanbans *nk***
1	MC 01	FGI	150	4
11	MC 11	MC 01	150	4
21	MC 21	MC 11	150	4
31	SUP 31	MC 21	450 (lt = 2)	4
2	MC 01	FGI	110	4
12	MC 12	MC 01	260	4
22	MC 22	MC 12	260	4
32	SUP 33	MC 22	450 (lt = 2)	4
13	SUP 32	MC 01	500 (lt = 2)	4
14	MC 11	MC 01	140	4
23	MC 21	MC 11	140	4
4	MC 01	FGI	90	4
16	MC 11	MC 01	90	4
25	MC 21	MC 11	90	4
17	MC 12	MC 01	110	4
26	MC 22	MC 12	110	4
18	SUP 32	MC 01	320 (lt = 2)	4

5.2 Description of the simulator

The simulator used in this study has been written in JAVA (Sun Microsystems, Inc.). The motivation to develop a new discrete-event simulator tool emerged basically from the drawbacks of existing simulation packages and the research goals of this thesis.

A review of existing discrete-event simulator packages shows that support for modern programming languages and visual modelling methodology are the most critical issues. In most programming packages, the models are designed with the help of a graphical user interface (ProModel, Arena,...). This approach is optimal for small and simple models but not appropriate for more complex systems often found in manufacturing environments. Therefore, most of the model logic has therefore to be implemented in the programming language that comes with the simulation package. Unfortunately, most of these programming languages are characterized by proprietary language features and poor support of modern object-oriented programming practices. Simulators without graphical user interfaces are based either on general purpose programming languages like C++ (Sim++) or JAVA (PSim/Java) or on proprietary programming languages (QNAP). These simulators are more suitable for complex models but their major drawback is that their logic is often based on a queueing-network concept. These characteristics of existing simulator packages increase considerably the coupling between the different subsystems (MPC method and production system) of the manufacturing system modelled and a flexible configuration of an arbitrarily chosen manufacturing system and MPC method (Inventory Control, MRP or DSSPL) is difficult to achieve. In the case of the simulator used in this thesis this problem has been solved by implementing a communication protocol between the different subsystems that is based on the current states of the objects rather than on concrete messages sent between them. The following list summarizes the most important characteristics of the simulator:

- The simulation model is generated based on a configuration file written in XML. As shown in Appendix C this configuration file defines all aspects of the model including the definition of the model (load, technical production resources, MPC method), the experimental design and the performance metrics;
- The simulation is piloted (reconfiguration of model before each replication) according to one of two available experimental design types (factorial or Monte Carlo design);
- The MersenneTwister (MT19937) random number generator has been used from the Colt library developed at CERN (http://tilde-hoschek.home.cern.ch/~hoschek/colt/index.htm; Open Source Libraries for High Performance Scientific and Technical Computing in Java). This generator has a very large period (10^{6001}) and is one of the strongest uniform pseudo-random generators known so far.

The simulator has been validated according to the classical approach presented by Robinson (1997) that includes the four consecutive steps *Conceptual Model Validation*, *Data Validation*, *White-box Validation* and *Black-box Validation*. In the first step called *Conceptual Model Validation*, the level of detail of the simulation model is determined in order to meet the objectives of the simulation study. In the second step called *Data Validation*, all data are verified that are necessary for building the simulation model. In the third step called *White-box Validation*, the code is checked and tested with respect to the concept of the simulation model. In the last step called *Black-box Validation*, the overall behavior of the simulation model is checked against real systems and other similar simulation models. In the case of this simulation study, the first two steps have basically been performed by applying the simulation analysis framework presented in chapter §4. The simulation analysis framework defines the required variables for representing accurately the analyzed MPC methods and manufacturing environments and with the help of the classification schemes, configurations are chosen that are representative for real manufacturing environments. The third step has been performed by creating “traces” of simulation runs and inspecting these output reports against the expected results. Finally, the last step has been performed by comparing the output with the results of the simulation studies reviewed in chapter §4. Furthermore, the interdependency between the two metrics inventory and service level, and the manufacturing environment parameters system load and demand uncertainty (demand variability and forecast errors) have been verified for each MPC method and manufacturing environment.

A more detailed description of the simulator is given in Appendix B and C where the different program modules and the configuration file are explained in more detail.

5.3 *Results*

All the following results have been evaluated based on the average of five replications of each design point of the experimental design. In order to assure convergence of the results, the simulation length for each replication was set to 1’000’000 time units (2083 time buckets) with a warm-up period equal to 300’000 time units (625 time buckets). The CPU-time on a Pentium III-1GHz-PC was approximately 20 seconds for one replication.

An overview of the performed experiments is given in Table 5.23:

Table 5.23: Overview of performed experiments

Experiment	**Base scenarios**	**Factors**	**Goal**
A	1	Kanban loop parameters and system load	Analysis of impact of kanban loop configuration on the performance of DSSPL_IC and DSSPL_MRP
B	1	DSSPL dispatching rule parameters and system load	Determination of DSSPL dispatching rule configuration
C	1, 2, 3, 4	Forecast error parameters and system load	Evaluation of the impact of forecast errors on the performance of DSSPL_IC, DSSPL_MRP, MRP and IC
D	1, 2	Demand variability and forecast error parameters and system load	Evaluation of the impact of demand variability (uncertainty) on the performance of DSSPL_IC, DSSPL_MRP, MRP and IC
E	1, 2	Demand heterogeneity parameters, setup and system load	Evaluation of the impact of demand heterogeneity and setup on the performance of DSSPL_IC, DSSPL_MRP, MRP and IC
F	1, 2, 3, 4	Demand and process parameters	Evaluation of robustness of DSSPL_IC, DSSPL_MRP, MRP and IC when confronted with an uncertain manufacturing environment

Experiments A and B are basically designed for the determination of the impact of various configurations of DSSPL (kanban loops and dispatching rule) on the performance of the production system. They have only been performed for the base scenario 1 since these experiments are focused on the exploration of the basic behavior of DSSPL that is independent of the product and production process configuration of the production system. It is thus assumed that the resulting guidelines for the configuration of DSSPL are valid in any configuration of the manufacturing environment. Experiments C to F are designed for the comparison of the MPC methods DSSPL_IC, DSSPL_MRP, MRP and IC when confronted with an uncertain manufacturing environment (forecast error, demand variability,...). Experiments D and E are only performed for the base scenarios 1 and 2, since only the base scenarios 1 and 2 or 3 and 4 were significant for the outcome of the experiments (high impact of parameter *commonality*, low impact of parameter *breadth*).

5.3.1 *Configuration of kanbans (Experiment A)*

The first set of experiments has been performed in order to analyze the impact of the configuration of the kanban loops on the performance of the two methods DSSPL_IC and DSSPL_MRP. Based on the initial (default) configuration of the kanban loops (Tables 5.15, 5.16, 5.19 and 5.20) the performance is evaluated for a range of kanban sizes, applied to all kanban loops simultaneously, that correspond to an under- and overdimensioning of the JIT/kanban method used for the management of the A-items. The dispatching rule has been configured with *llow* = 1, *lup* = 4 and *tcrit* = 0. Table 5.24 summarizes the configuration of the performed experiments:

Table 5.24: Configuration of experimental design A

Main factor:
(1) Variation of default kanban size $sk_{default}$: level 1 ($sk = 0.55\ sk_{default}$), level 2 ($sk = 0.7\ sk_{default}$), level 3 ($sk = 0.85\ sk_{default}$), level 4 ($sk = sk_{default}$), level 5 ($sk = 1.15\ sk_{default}$), level 6 ($sk = 1.3\ sk_{default}$), level 7 ($sk = 1.45\ sk_{default}$)

Experiment (Design point)	**Base scenario**	**MPC method**	***sysint***
A1	1	DSSPL_IC	low
A2	1	DSSPL_IC	medium
A3	1	DSSPL_IC	high
A4	1	DSSPL_MRP	low
A5	1	DSSPL_MRP	medium
A6	1	DSSPL_MRP	high

Figure 5.4 Exp. A1, A2 and A3: Impact of kanban size variation on the performance of DSSPL_IC (_ symbol for level 1)

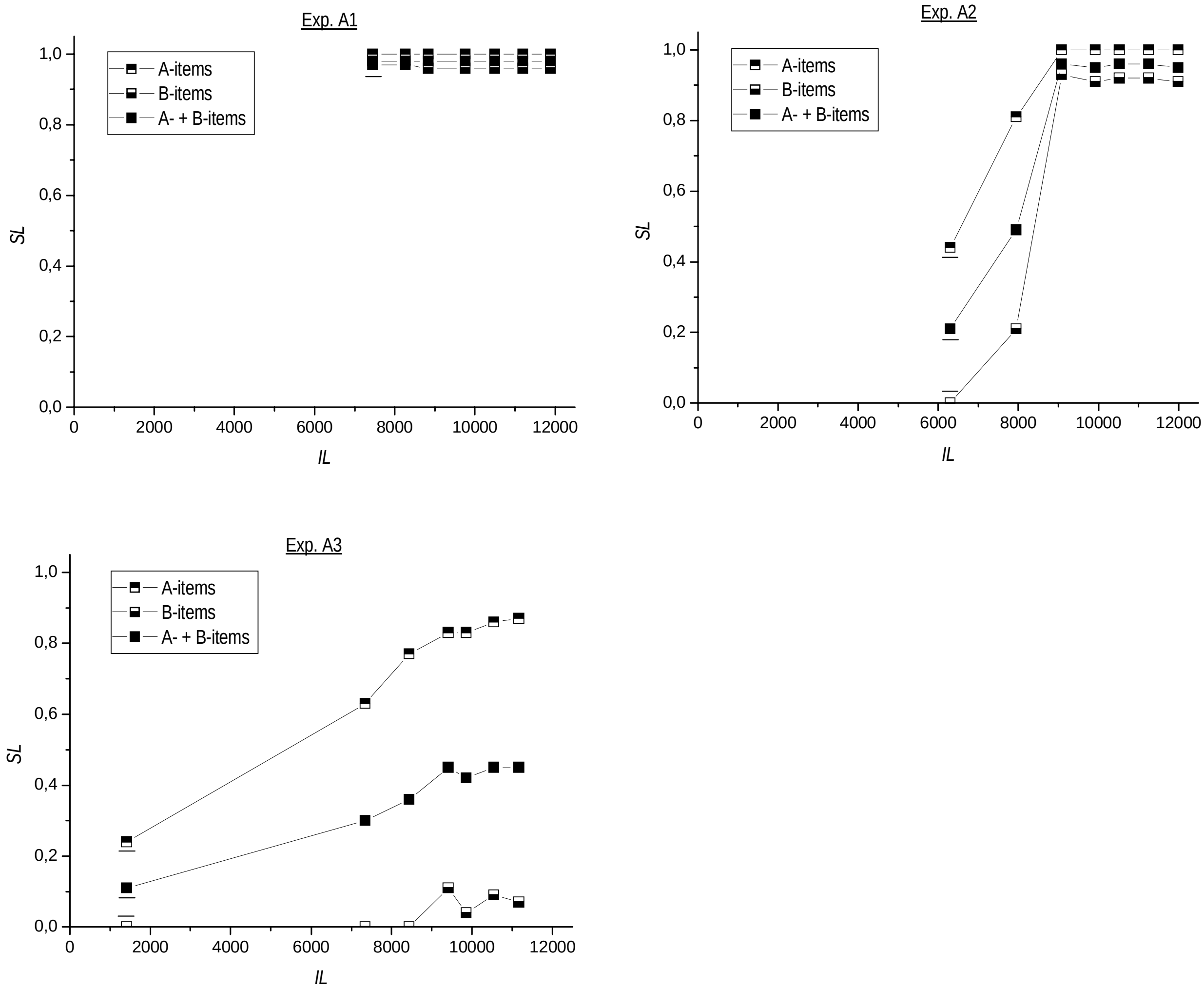
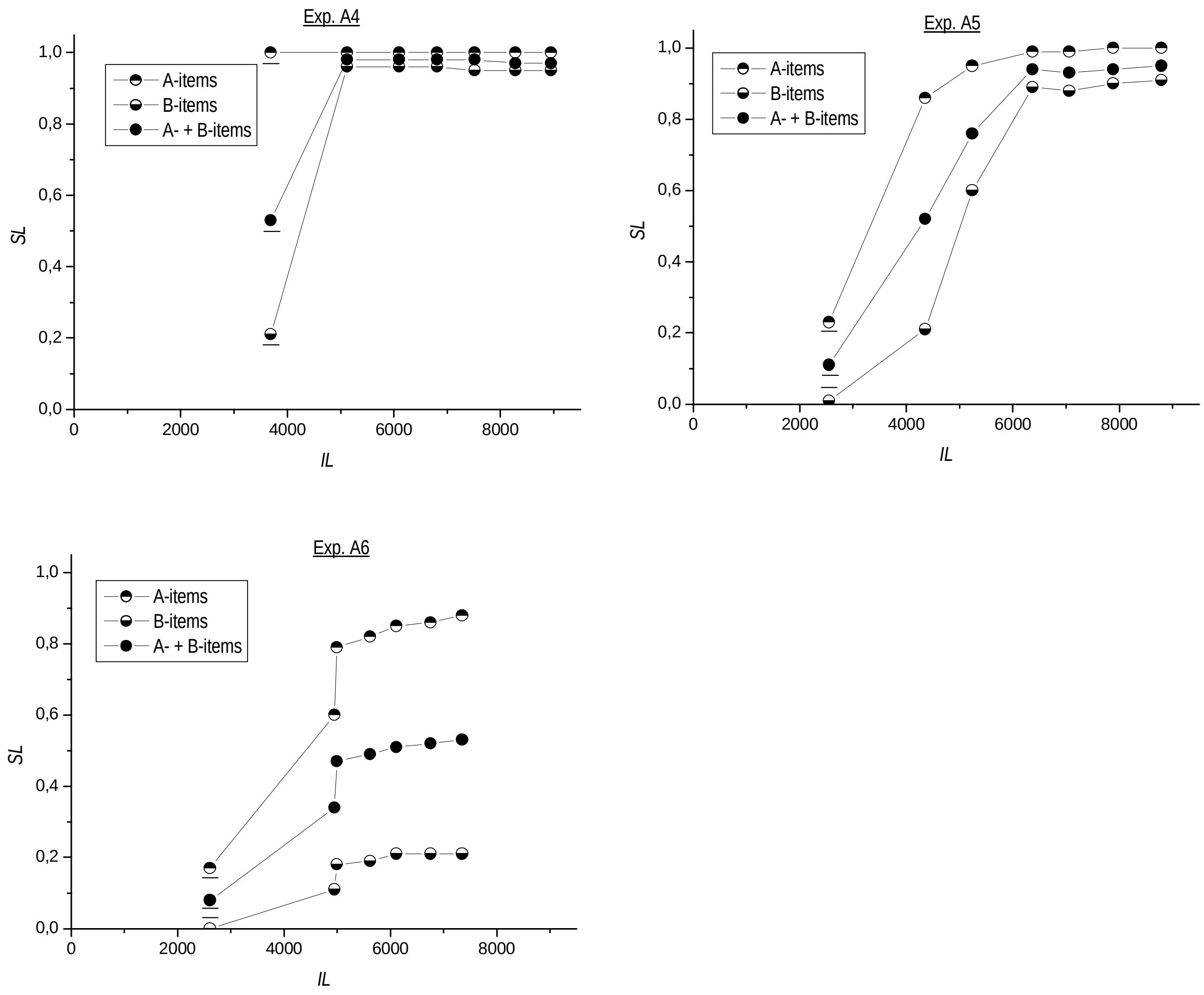


Figure 5.5 Exp. A4, A5 and A6: Impact of kanban size variation on the performance of DSSPL_MRP (_ symbol for level 1)



The results show clearly that underdimensioning of the kanban capacity has a much more significant impact on the service level performance than overdimensioning. The service level performance for both A- and B-item drops sharply if the kanban capacity is smaller than a certain capacity limit. The value of this capacity limit depends on the system load *sysint*, where higher load levels obviously also result in higher values for this capacity limit. If the kanban capacity is overdimensionned the service level performance is not increased significantly. A further observation is the fact that the difference between the service level performance for A- and B-items increases with higher system load levels. Due to the priority rule applied in DSSPL, the service level for A-items is always higher than those for B-items.

The obtained results are mainly due to the characteristics of the dispatching rule and the kanban production system. If the JIT/kanban system is dimensioned accurately in a multi-item manufacturing environment, there is always a certain time between two replenishments of a particular item. During this time, other items are manufactured. If the system load increases or if the kanban capacity is underdimensioned this time between two replenishments diminishes and the kanban system starts to monopolize the production resources since A-items have a higher priority in DSSPL than B-items. This effect is observed for both analyzed MPC methods DSSPL_MRP and DSSPL_IC without significant difference.

5.3.2 Configuration of dispatching rule (Experiment B)

The configuration of the dispatching rule has, beside, the optimal dimensioning of the JIT/kanban method, the most significative impact on the performance of the DSSPL method. As described in section §3.2.2 DSSPL's dispatching rule is basically governed by the two parameters *tcrit* and *llow* that handle the priorities of the A- and B-items. In order to simplify the configuration of the dispatching rule it is assumed that the third parameter *lup* is always equal to the number of kanbans *nk*. Table 5.25 summarizes the experiments performed.

Table 5.25: Configuration of experimental design B

Main factors:
(1) Modification of dispatching rule *tcrit*: level 1 (*tcrit* = 0), level 2 (*tcrit* = 960)
(2) Modification of dispatching rule *llow*: level 1 (*llow* = 1), level 2 (*llow* = 2), level 3 (*llow* = 3)

Experiment (design point)	***Base scenario***	**MPC method**	***tcrit***	***llow***	***sysint***
B1	1	DSSPL_IC	level 1, 2	level 1, 2, 3	low
B2	1	DSSPL_IC	level 1, 2	level 1, 2, 3	medium
B3	1	DSSPL_IC	level 1, 2	level 1, 2, 3	high
B4	1	DSSPL_MRP	level 1, 2	level 1, 2, 3	low
B5	1	DSSPL_MRP	level 1, 2	level 1, 2, 3	medium
B6	1	DSSPL_MRP	level 1, 2	level 1, 2, 3	high

Figure 5.6 Exp B1, B2 and B3: Impact of dispatching rule configuration on the performance of DSSPL_IC (_ symbol for *llow* at level 1)

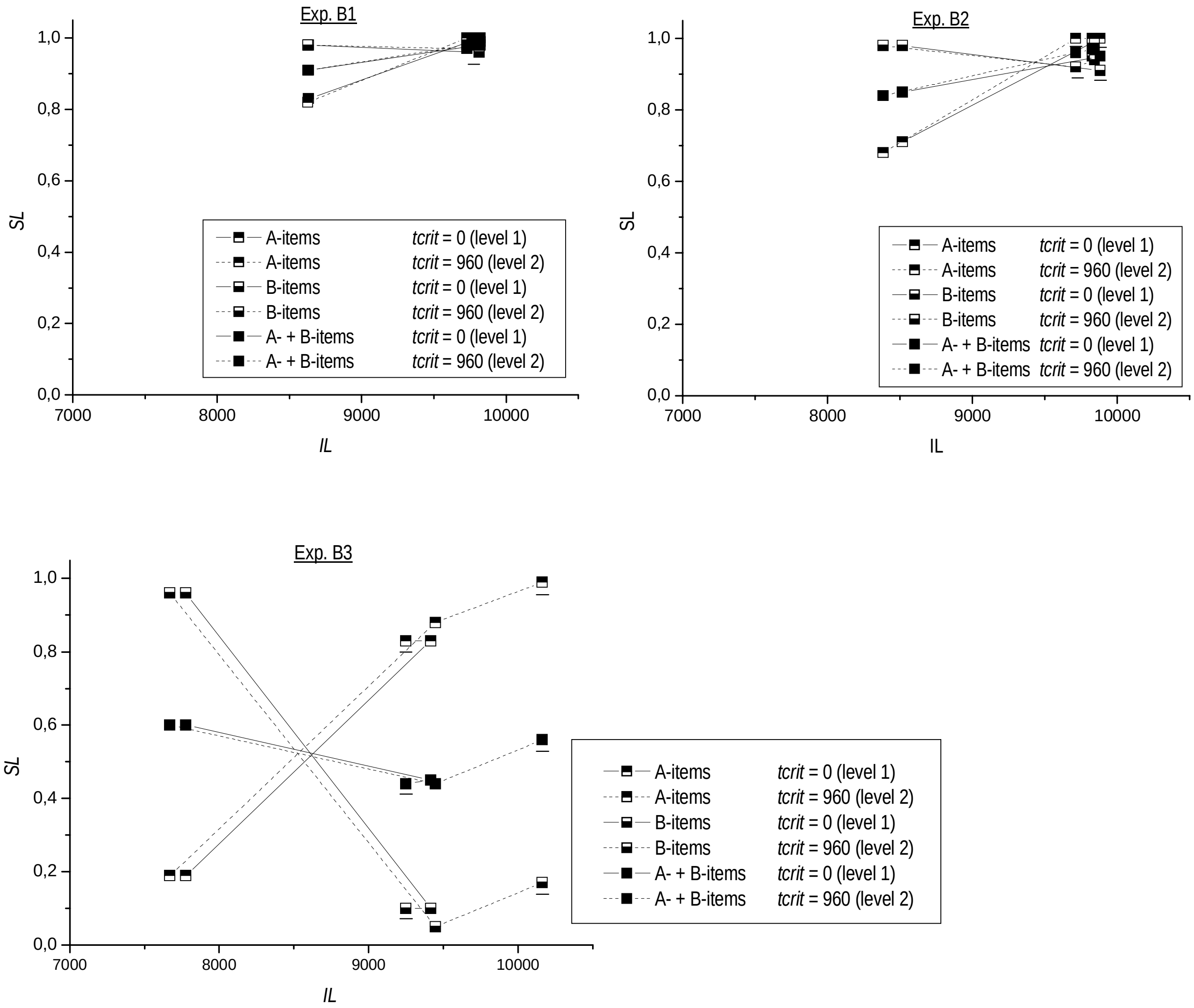
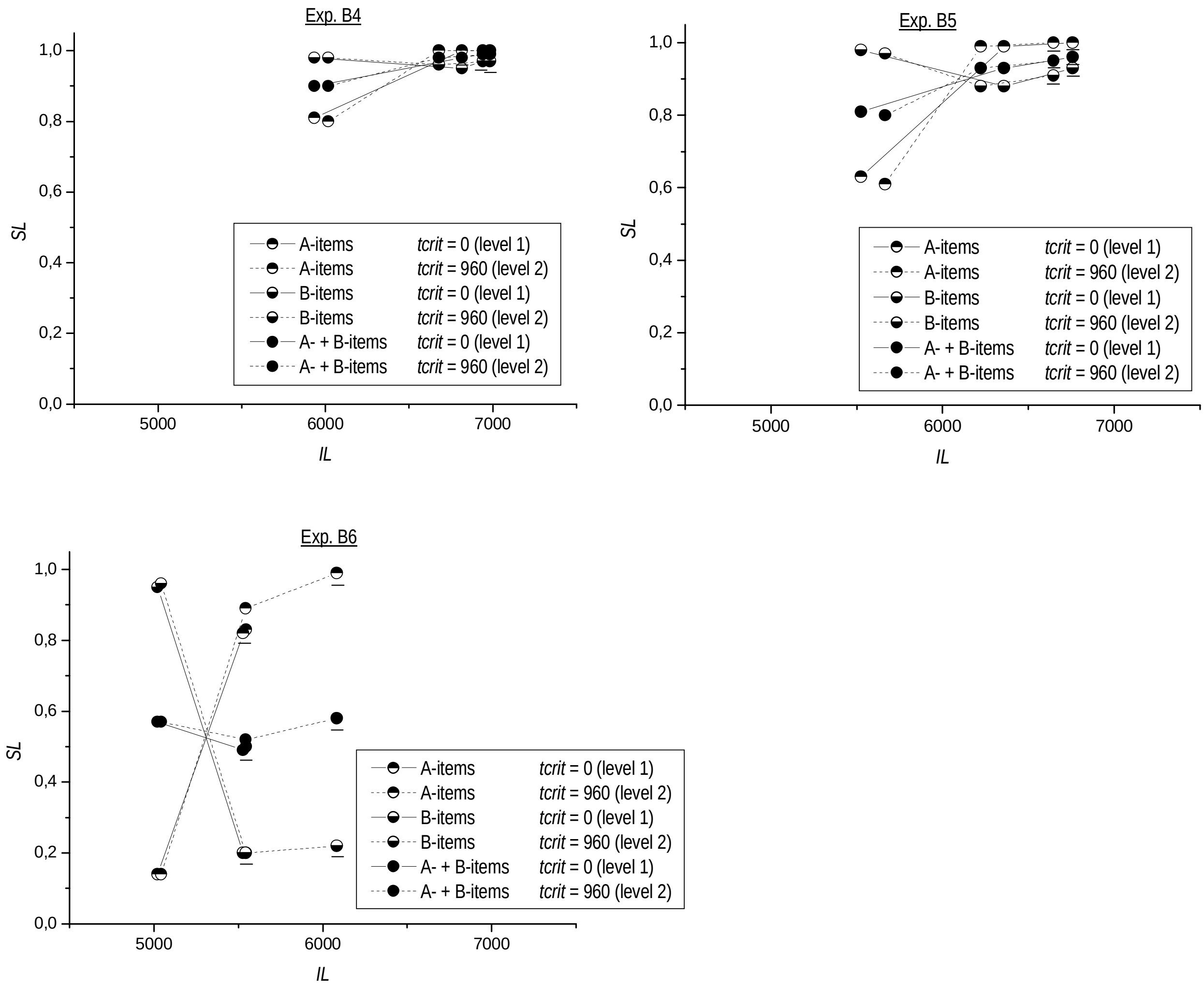


Figure 5.7 B4, B5 and B6: Impact of dispatching rule configuration on the performance of DSSPL_MRP (_ symbol for *llow* at level 1)



The results indicate that the variable *llow* has a much higher impact on the performance of DSSPL than *tcrit*. For lower system load levels, *llow* has mainly an impact on the inventory performance whereas the service level performance for A- and B-items is mainly influenced at high system load levels. Except for high system load levels, low values for llow minimize the difference between the service level performance of A- and B-items and maximize the combined service level performance (A- and B-items). For high values of *llow* however, the A-item service level performance drops below those of the B-items. Thus, priority switches to the B-items if *llow* is set to a high value close to the number of kanbans *nk*. As in the case of the previous experiments no significant difference is observed between the two analyzed MPC methods DSSPL_MRP and DSSPL_IC.

The dispatching method used in DSSPL therefore allows allocation of priority to either A- or B-items depending on the level of *llow*. However, in accordance with the results obtained from the Markovian model in chapter §3, optimal settings for *llow* are rather low values close to one. The parameter *tcrit* has a much lower impact on the performance of DSSPL, but the majority of the obtained results indicate that a better overall performance is reached with increased values of *tcrit*. For the following experiments, the DSSPL dispatching rule is therefore configured with *llow* = 1, *lup* = *nk* and *tcrit* = 960.

5.3.3 Impact of forecast error (Experiment C)

The third set of experiments was performed in order to analyze the impact of forecast errors on the performance of the four analyzed MPC methods. Their performance is therefore evaluated for increasing levels of forecast errors (*peo* and *cvsc*). Both forecast errors in time and quantity have been applied simultaneously whereas the values of *peo* and *cvsc* have been chosen in order to generate approximately the same impact on the performance measures when applied alone. Table 5.26 summarizes the configuration of the experiments performed:

Table 5.26: Configuration of experimental design C

Main factor:
(1) Variation of forecast error (*peo* and *cvsc*): level 1 (*peo* = 0, *cvsc* = 0), level 2 (*peo* = 0.05, *cvsc* = 0.05), level 3 (*peo* = 0.25, *cvsc* = 0.3), level 4 (*peo* = 0.45, *cvsc* = 0.55), level 5 (*peo* = 0.65, *cvsc* = 0.8)

Experiment (Design point)	**Base scenario**	**MPC method**	**Forecast error**	***sysint***
C1	1	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	low
C2	1	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	medium
C3	1	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	high
C4	2	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	low
C5	2	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	medium
C6	2	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	high
C7	3	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	low
C8	3	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	medium
C9	3	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	high
C10	4	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	low
C11	4	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	medium
C12	4	DSSPL_IC, DSSPL_MRP, MRP, IC	level 1...5	high

Figure 5.8 Exp. C1, C2 and C3: Impact of forecast error on analyzed MPC methods for base scenario 1 (_ symbol for forecast error at level 1)

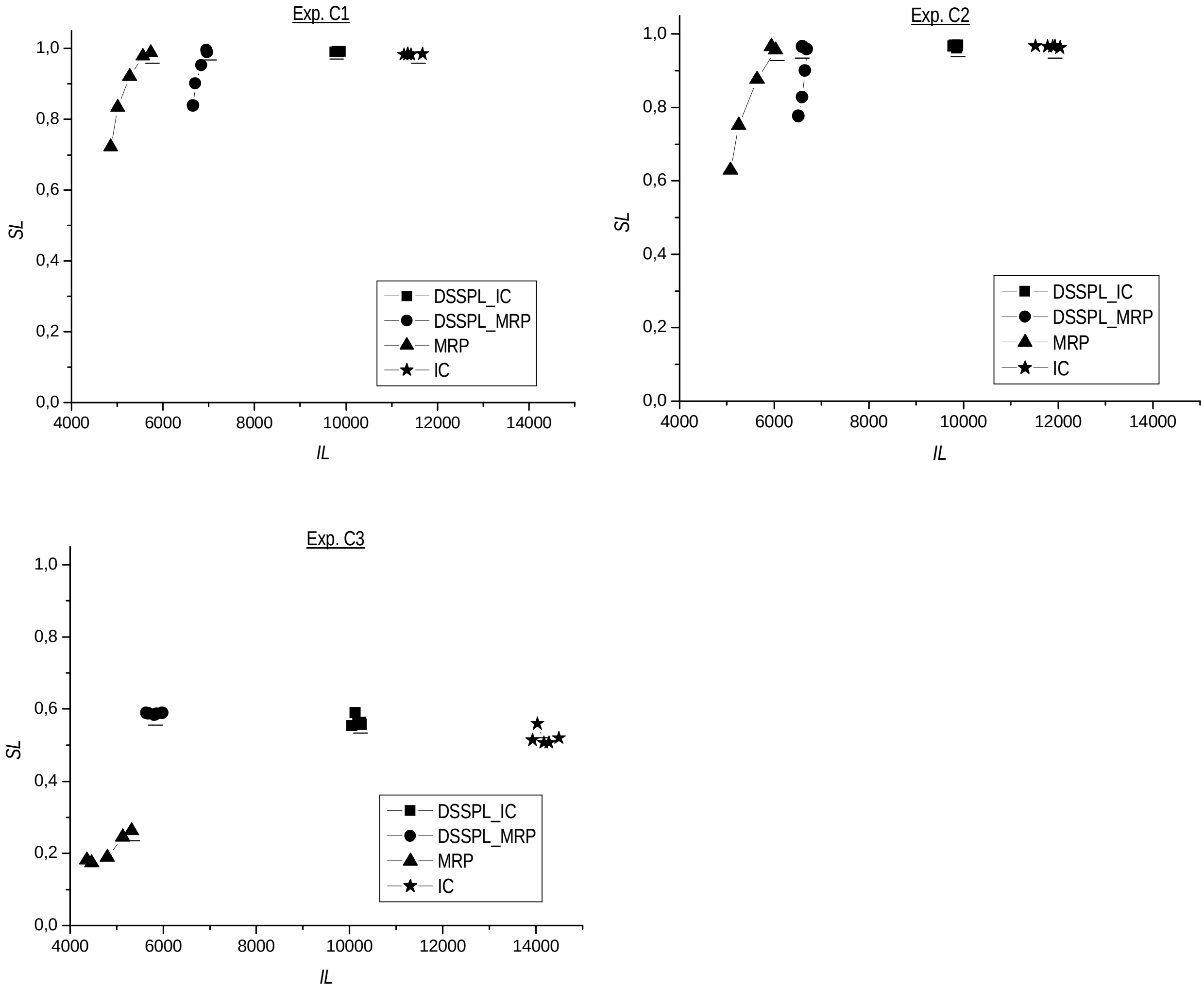


Figure 5.9 Exp. C4, C5 and C6: Impact of forecast error on analyzed MPC methods for base scenario 2 (_ symbol for forecast error at level 1)

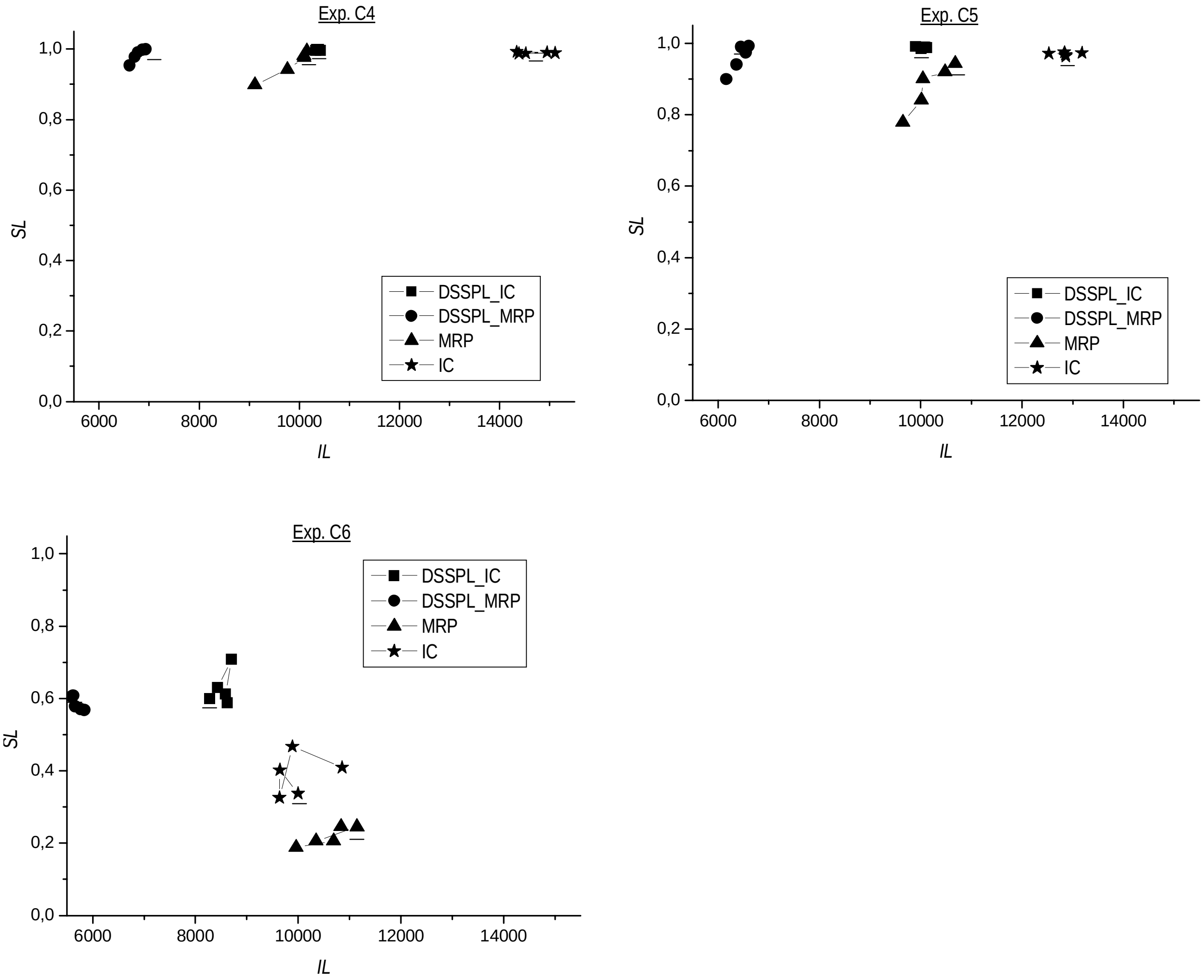


Figure 5.10 Exp. C7, C8 and C9: Impact of forecast error on analyzed MPC methods for base scenario 3 (_ symbol for forecast error at level 1)

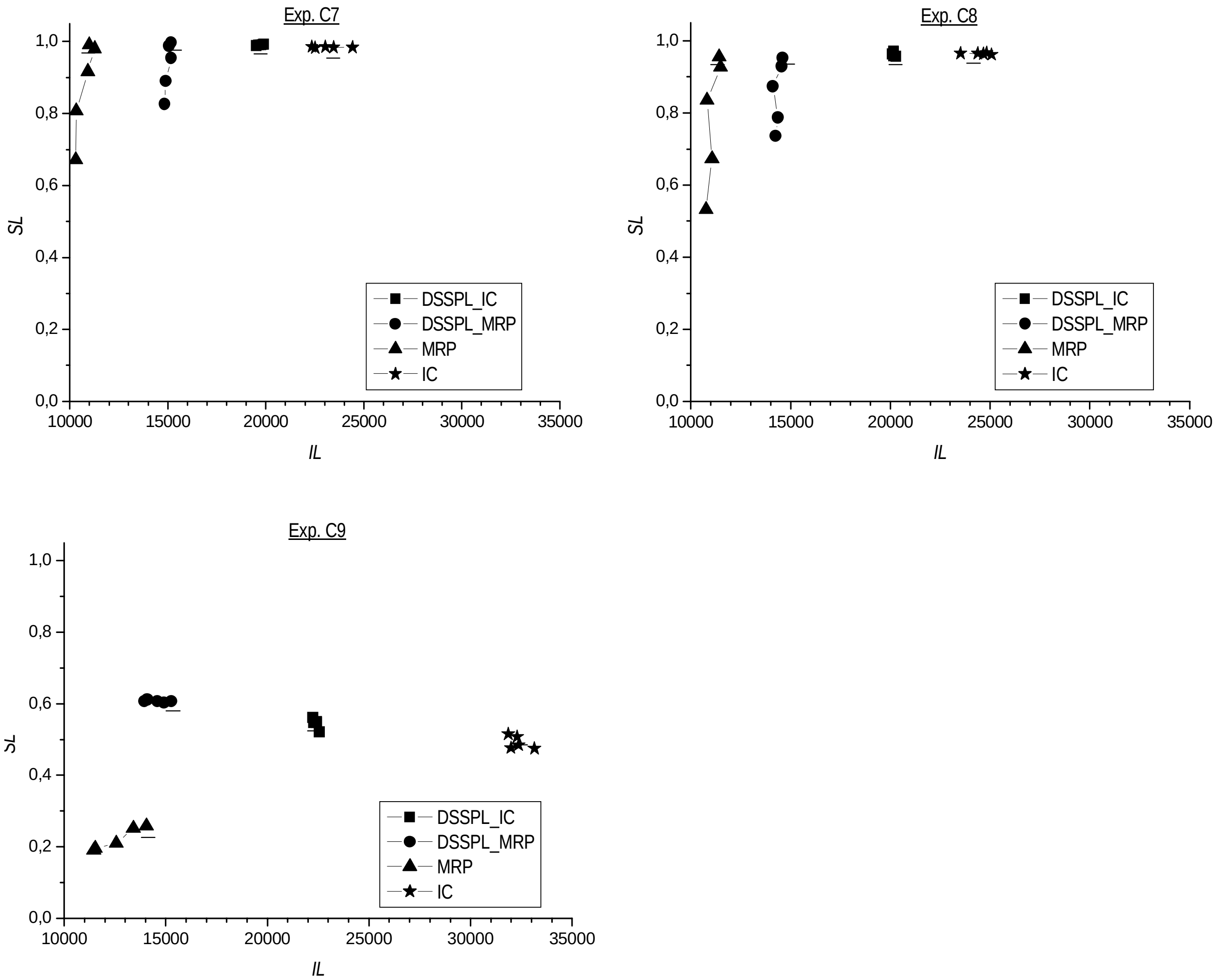
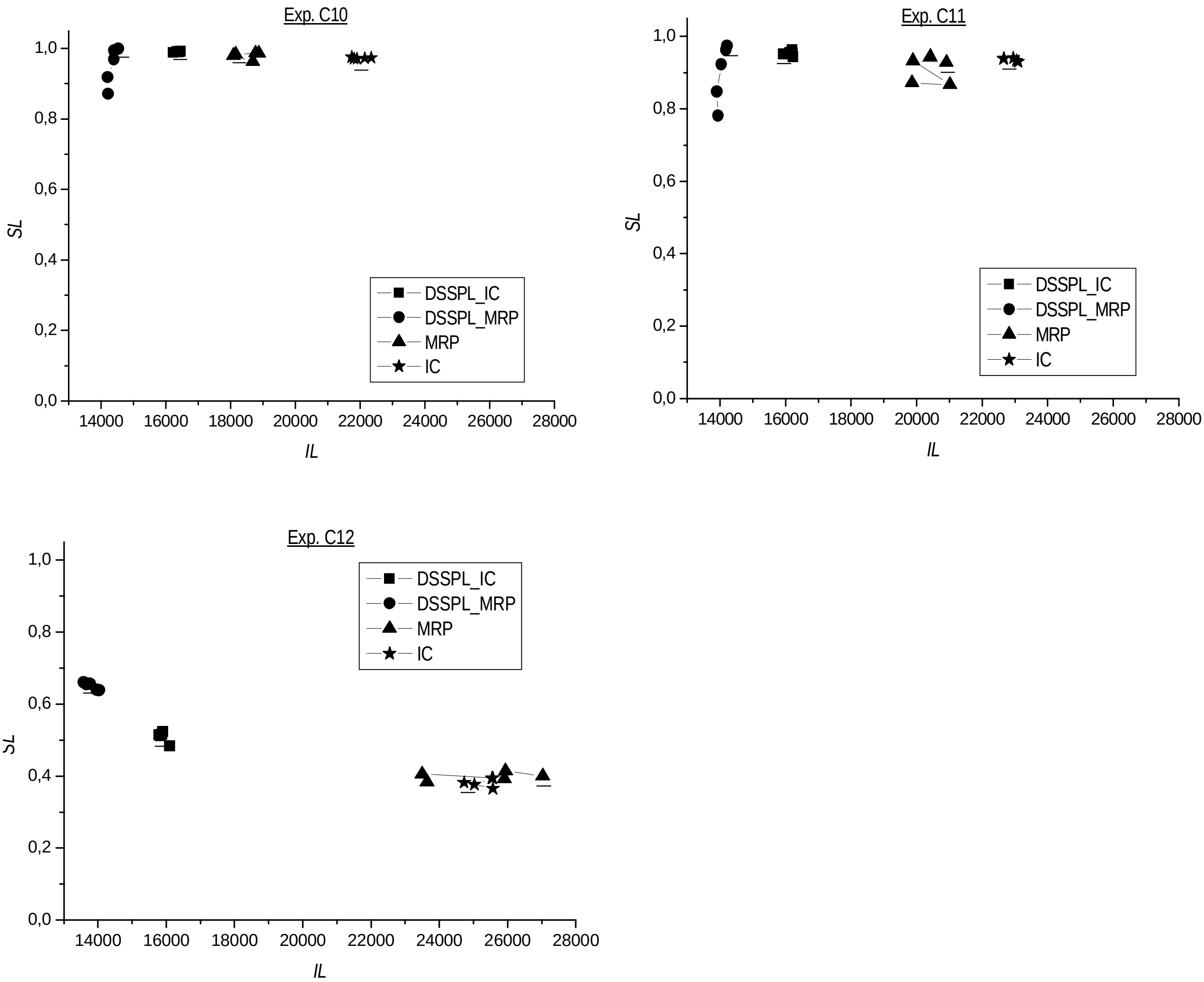


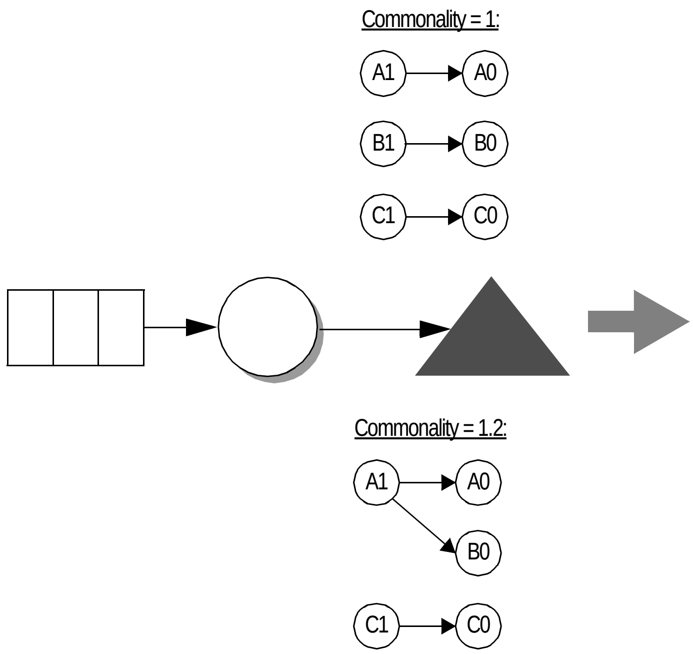
Figure 5.11 Exp. C10, C11 and C12: Impact of forecast error on analyzed MPC methods for base scenario 4 (_ symbol for forecast error at level 1)



In the case of the base scenarios 1 and 3 (*commonality* = 1) MPR has the best inventory performance of all compared MPC methods. On the other hand, MRP also exhibits the highest sensitivity to forecast errors. In fact, at high forecast error levels, MRP has the lowest service level performance. DSSPL_MRP has a lower sensitivity to forecast errors than MRP, but at an increased inventory level. As expected a insensitivity for forecast errors is also shown by the two MPC methods Inventory Control and DSSPL_IC. Their inventory levels are, however, particularly in the case of the Inventory Control MPC method, up to 100% higher than those of MRP and DSSPL_MRP. A further interesting finding is the fact that DSSPL_MRP performs best at high system loads.

In the case of the base scenarios 2 and 4 (commonality = 1.9) MRP performs at significantly higher inventory levels than DSSPL_MRP. The increase of the commonality resulted, for both MPC methods MRP and Inventory Control, in a significant increase of the average inventory levels. These high inventory levels are due to the significant increase of the lot sizes *ls* and order quantities *q* of the Inventory Control and MRP MPC method made necessary in order to achieve the target service level of 0.95 for the base scenarios with increased commonality. In order to analyze the reasons for this fact in more detail, a small model has been created in ARENA. It serves to analyze the impact of an increased product commonality on the variability and mean values of the effective production lead times in a capacity constrained production system. As illustrated in Figure 5.13 the simulation model corresponds, therefore, to a single-stage, three-item production system.

Figure 5.12 Simulation model for the analysis of the impact of product commonality on the production lead times



The simulation model is based on the same concept that was used in the Markovian model in chapter §3 to represent MRP. Production orders are sent, therefore, to the manufacturing center and after fulfillment to the intermediate stock. The difference between the generation of a production order and the corresponding demand or consumption is equal to the predefined lead time. Thus, a production order is considered as fulfilled if the effective cycle time is smaller than or equal to the predefined lead time. Furthermore, production orders are only generated if the projected inventory level is smaller than the current demand quantity. The interarrival times of the demand follow the exponential law whereas the processing times correspond to a symmetrical triangular law with a *CV* equal to 0.2. Further details of the simulation model are summarized in Table 5.27.

Table 5.27: Configuration of the simulation model for the analysis of the impact of product commonality on the production lead times (*commonality* = 1)

Item	**Predef. lead time**	**Demand and production lot size** ***mds***	**Mean interval betw. two orders** ***mid***	**Intensity per item** ***sysint***
A	1300	100	200	0.5
B	1300	50	200	0.25
C	1300	30	150	0.2

The values for the predefined lead time were chosen in order to reach a target service level of 0.95 for each item. This simulation model served as reference for a second model that differed from the reference model only in a modified product structure with increased commonality. The results obtained from these two models are summarized in Table 5.28.

Table 5.28: Summary of results of the simulation for the analysis of the impact of product commonality on the production lead times

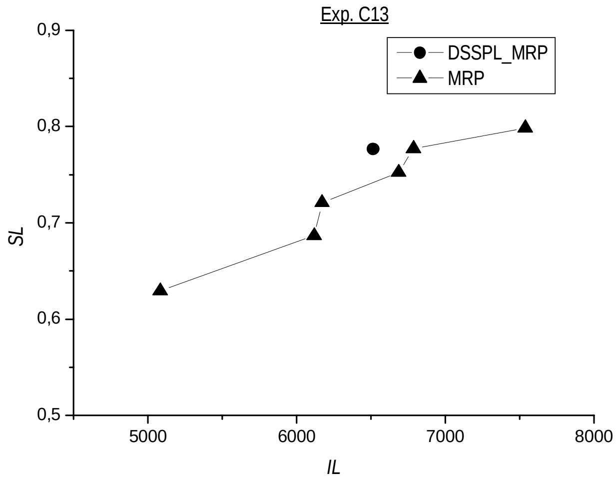
	Commonality = 1 lead time = 1300		Commonality = 1.2 lead time = 1300		Commonality = 1.2 lead time = 2000	
Item	**Service level**	**Inventory level**	**Service level**	**Inventory level**	**Service level**	**Inventory level**
A	0.94	370	0.68	515	0.9	969
B	0.95	190	-	-	-	-
C	0.95	158	0.7	140	0.92	261

The results show how an increase of the commonality reduces the service level performance significantly. As the last results show, improved service levels can be achieved by increasing the lead times which also results in increased inventory levels. This is mainly due to the difference between the demand lot size and the production lot size that is inevitable in cases of increased commonality. In the case of the present model a demand for a B-item results in a production order for the A-component if the inventory level is equal to zero. If the following demand is for an A-item, a new production order has to be generated. This overloading of the production system has an impact on the production for C-items since the probability of longer waiting times for C-item production orders is increased. In a capacity constraint production system, a modification of the product structure therefore has an impact on all items and not only on those items whose structure has been modified. This small study shows how questionable the modelling of lead times is that is based on constant (mean) values. As already discussed in chapter §4, this approach is found in many research works focusing on the performance of MRP systems. A typical example is the simulation study performed by Portoli (1997) who investigated the impact of component commonality on MRP system nervousness. In his study, increased component commonality resulted in significantly lower MRP nervousness.

Another critical issue revealed by this study is the choice of the lot-sizing rule for the common component. The results show that the use of the FOQ lot-sizing rule is not optimal since it leads to the observed demand amplification. A better choice would be the LFL lot-sizing rule where the chosen lot size corresponds to the requirement. A deeper investigation of the optimal choice of the MRP lot-sizing rule for the analyzed manufacturing environment is outside the scope of this work. However, as shown by the example of DSSPL_MRP and DSSPL_IC this problem can be solved by reduced lot sizes (kanbans) that increase the flexibility and reactivity of the production system.

In MRP, uncertainties are normally buffered by safety stock or by safety lead time. In experiment C13 shown in Figure 5.14, experiment C1 has been repeated for the case of the highest forecast error but with increasing safety stock levels. The results show that safety stock effectively increases the service level but the increase of the average inventory level is considerable.

Figure 5.13 Exp. C13: Impact of safety stock on the performance of MRP at high forecast error level



5.3.4 *Impact of demand variability (Experiment D)*

The impact of demand variability on the performance of the compared MPC methods is analyzed in the fourth set of experiments by varying the demand variability parameters according to the values defined in Table 5.1. Table 5.29 summarizes the configuration of the performed experiments:

Table 5.29: Configuration of experimental design D

Main factors:
(1) Variation of forecast error (*peo* and *cvsc*): level low (*peo* = 0.05, *cvsc* = 0.05), level high (*peo* = 0.45, *cvsc* = 0.55)
(2) Variation of demand uncertainty (*cvds* and *cvid*): level low (*cvds* and *cvid* at low level), level medium (*cvds* and *cvid* at medium level), level high (*cvds* and *cvid* at high level)

Experiment (Design point)	Base scenario	MPC method	Forecast error	Demand uncertainty	*sysint*
D1	1	DSSPL_IC, DSSPL_MRP, MRP, IC	low, high	low, medium, high	medium
D2	2	DSSPL_IC, DSSPL_MRP, MRP, IC	low, high	low, medium, high	medium

Figure 5.14 Exp D1: Impact of demand variability on analyzed MPC methods for base scenario 1

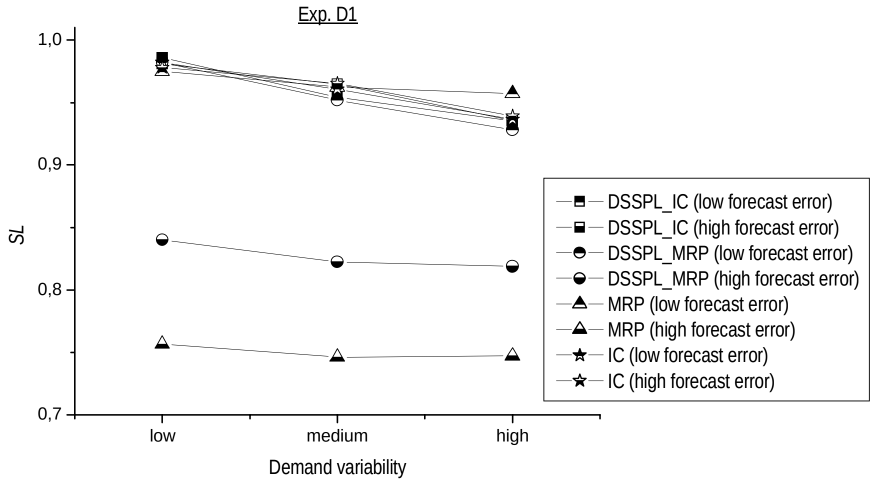
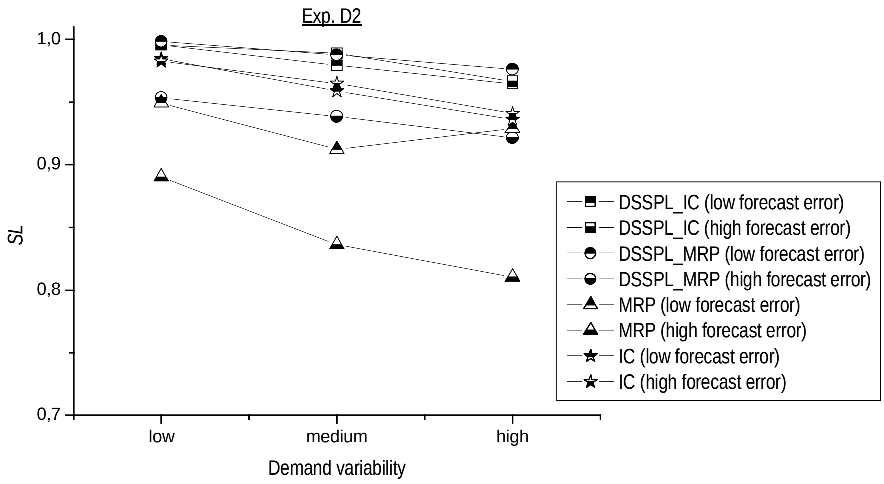


Figure 5.15 Exp. D2: Impact of demand variability on analyzed MPC methods for base scenario 2



As expected, only in the case of the two MPC methods DSSPL_MRP and MRP have forecast errors more significant impact on performance than the demand variability. On the other hand, the effect of increased demand variability is not significantly amplified by high forecast error levels.

5.3.5 *Impact of demand heterogeneity and setup (Experiment E)*

The impact of the demand heterogeneity and the setup length on the performance of the compared MPC methods is analyzed in the fifth set of experiments. The following Table 5.30 summarizes the configuration of the experiments performed:

Table 5.30: Configuration of experimental design E

Main factors:
(1) Variation of demand heterogeneity *g*: level low (*g* = 0.05), level medium (*g* = 0.45), level high (*g* = 0.6),
(2) Variation of setup *stp*: level 1 (*stp* = 1), level 2 (*stp* = 2.5), level 3 (*stp* = 5), level 4 (*stp* = 7.5), level 5 (*stp* = 10), level 6 (*stp* = 12.5)

Experiment (Design point)	**Base scenario**	**MPC method**	***g***	***stp***	***sysint***
E1	1	DSSPL_IC	low, medium, high	level 1...6	medium
E2	1	DSSPL_MRP	low, medium, high	level 1...6	medium
E3	1	MRP	low, medium, high	level 1...6	medium
E4	1	IC	low, medium, high	level 1...6	medium
E5	2	DSSPL_IC	low, medium, high	level 1...6	medium
E6	2	DSSPL_MRP	low, medium, high	level 1...6	medium
E7	2	MRP	low, medium, high	level 1...6	medium
E8	2	IC	low, medium, high	level 1...6	medium

Figure 5.16 Exp E1, E5: Impact of demand heterogeneity and setup on DSSPL_IC for base scenario 1 and 2

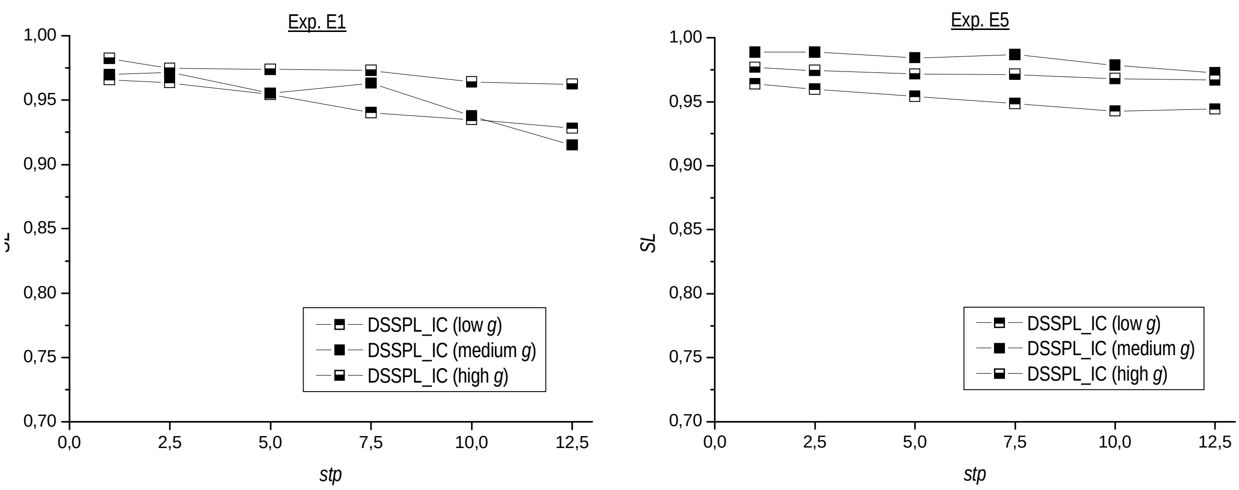


Figure 5.17 Exp E2, E6: Impact of demand heterogeneity and setup on DSSPL_MRP for base scenario 1 and 2

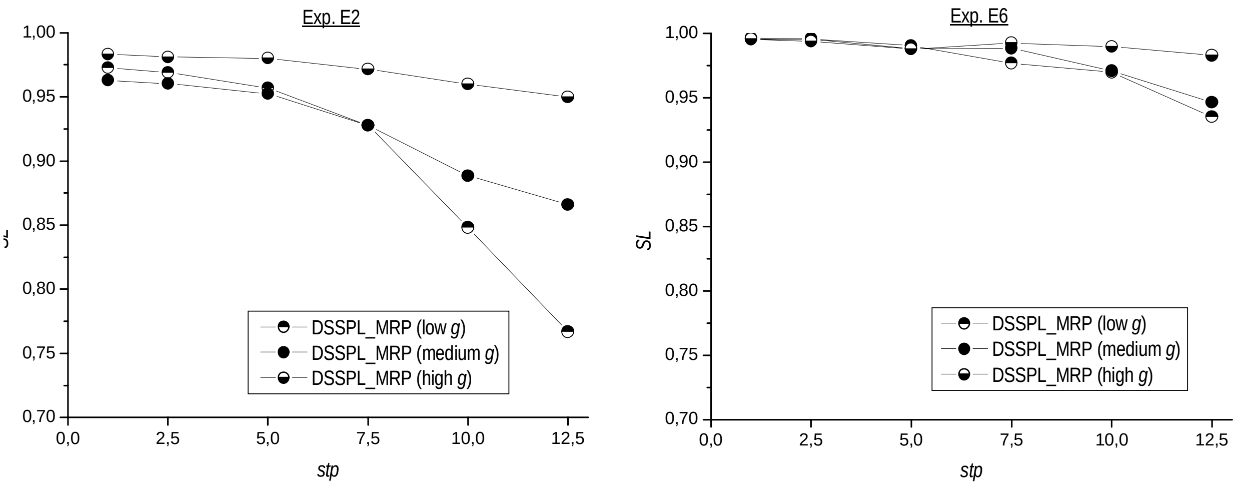


Figure 5.18 Exp E3, E7: Impact of demand heterogeneity and setup on MRP for base scenario 1 and 2

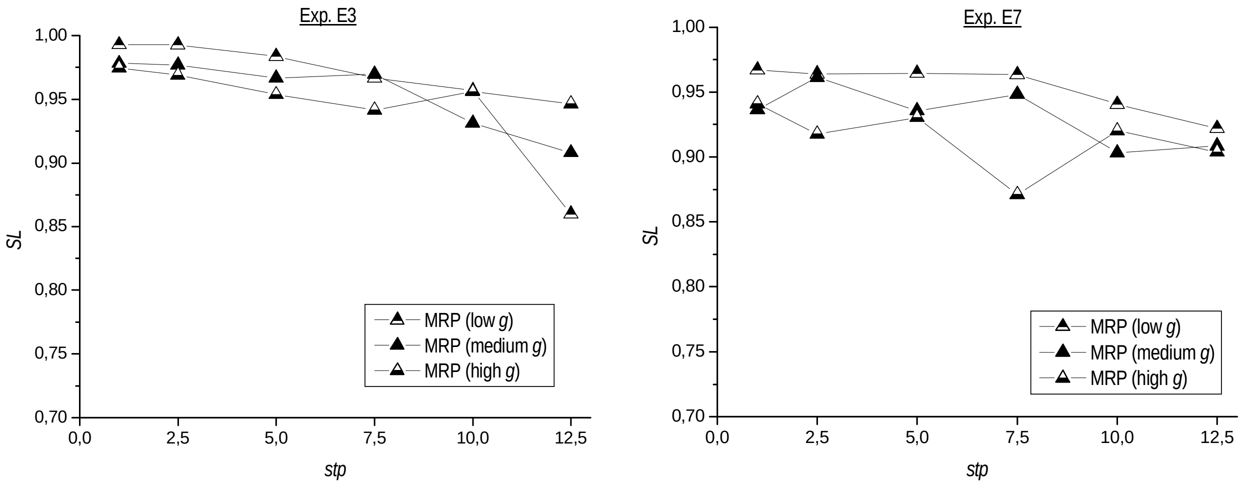
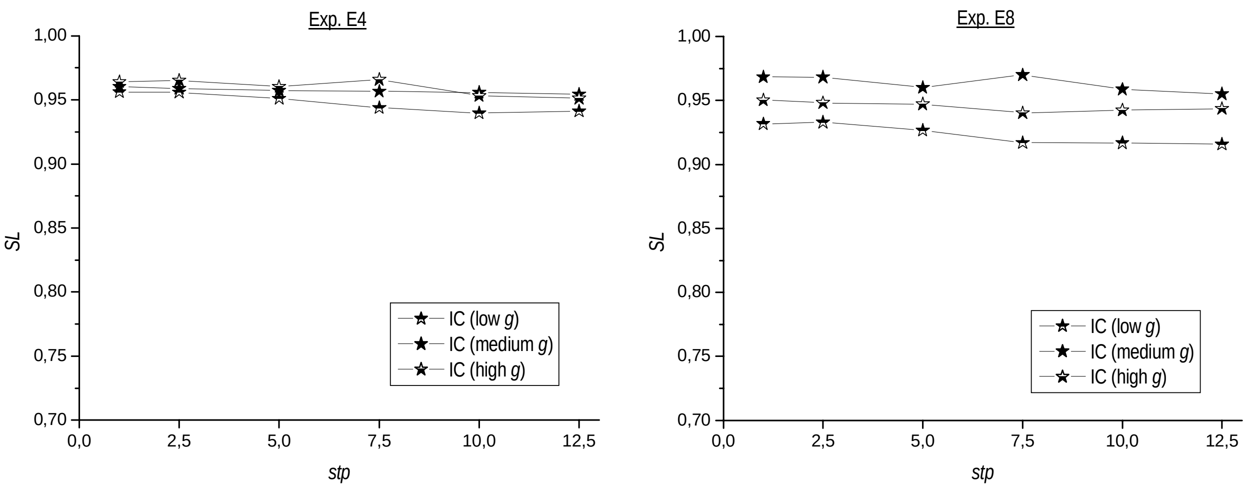


Figure 5.19 Exp E4, E8: Impact of demand heterogeneity and setup on IC for base scenario 1 and 2



The effects of high setup levels are in all cases amplified by a low heterogeneity of the demand. This expected result is due to the fact that more setups have to be performed in manufacturing environments with low product heterogeneity. The most important factor is, however, the average lot size that also explains the higher sensitivity of DSSPL_MRP for high setup values. In the case of DSSPL_MRP the effect of reduced lot sizes for the JIT/kanban concept are amplified by MRP that has a significantly higher sensitivity for setups than the Inventory Control method. This is due to the reduced average inventory level of MRP compared to Inventory Control, which has a lower capacity to buffer against uncertainties in the production process.

5.3.6 Robustness (Experiment F)

The impact of uncertainties of the demand and of the production process on the performance of the compared MPC methods are analyzed in the last set of experiments. Table 5.31 summarizes the configuration of the performed experiments:

Table 5.31: Configuration of experimental design F

Main factors:
(1) Variation of *load*: level low (*load* = 0.7) to level high (*load* = 0.9)
(2) Variation of demand heterogeneity *g*: level low (*g* = 0.05) to level high (*g* = 0.45)
(3) Variation of demand uncertainty (*cvds* and *cvid*): level low (*cvds* and *cvid* at low level) to level high (*cvds* and *cvid* at high level)
(4) Variation of setup *stp*: level low (*stp* = 1) to level high (*stp* = 12.5)
(5) Variation of processing time variability *cvpt*: level low (*cvpt* = 0.05) to level high (*cvpt* = 0.35)
(6) Variation of mean time to repair *mttr*: level low (*mttr* = 1) to level high (*mttr* = 50)
(7) Variation of forecast error (*peo* and *cvsc*): level low (*peo* = 0.05, *cvsc* = 0.05) to level high (*peo* = 0.45, *cvsc* = 0.55)

Experiment (Design point)	**Base scenario**	**MPC method**	***sysint*, *g*, demand uncertainty, *stp*, *cvpt*, *mttr*, forecast error**
F1	1	DSSPL_IC, DSSPL_MRP, MRP, IC	low...high
F2	2	DSSPL_IC, DSSPL_MRP, MRP, IC	low...high
F3	3	DSSPL_IC, DSSPL_MRP, MRP, IC	low...high
F4	4	DSSPL_IC, DSSPL_MRP, MRP, IC	low...high

Figure 5.20 Exp. F1a and b: Robustness of compared MPC methods for base scenario 1

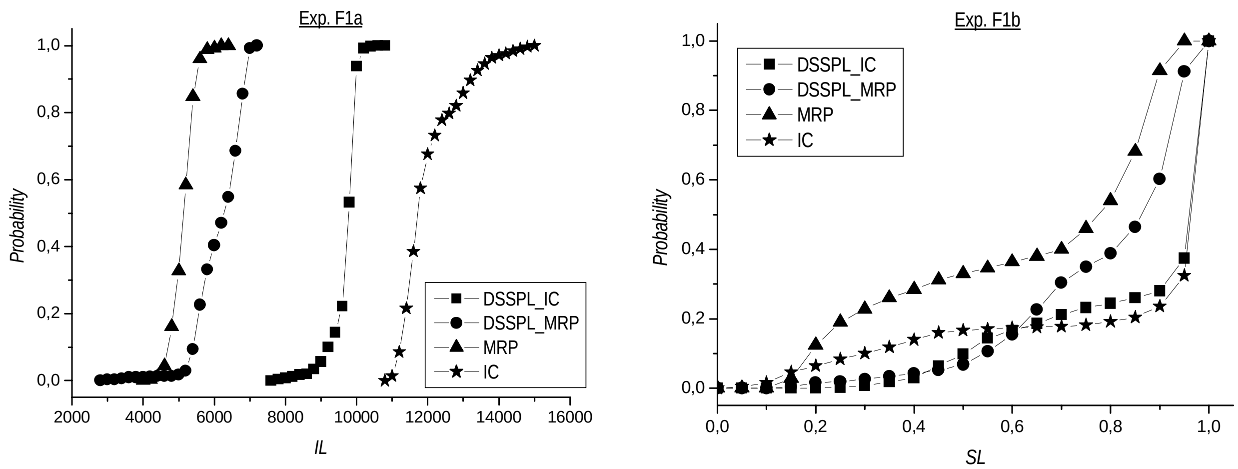


Figure 5.21 Exp. F2a and b: Robustness of compared MPC methods for base scenario 2

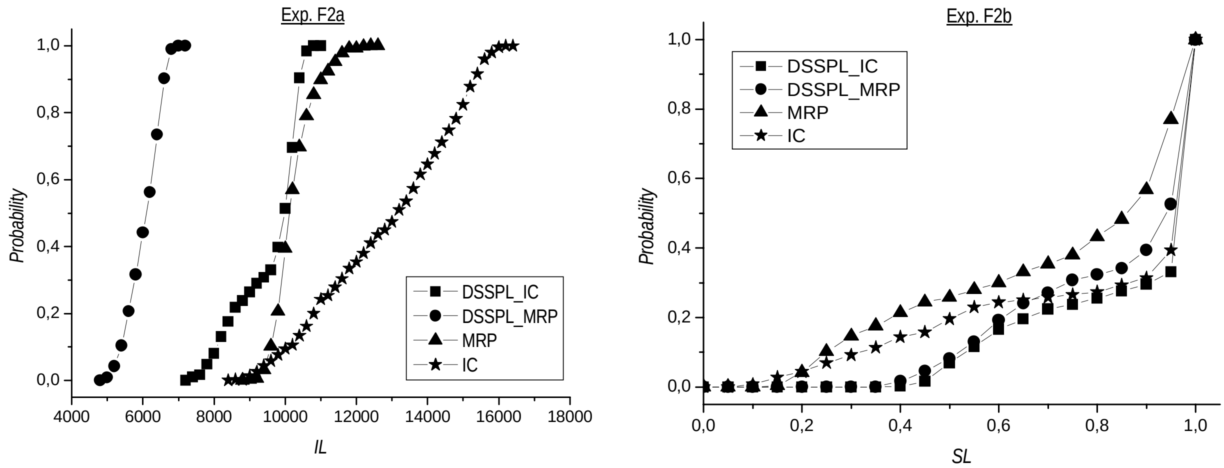


Figure 5.22 Exp. F3a and b: Robustness of compared MPC methods for base scenario 3

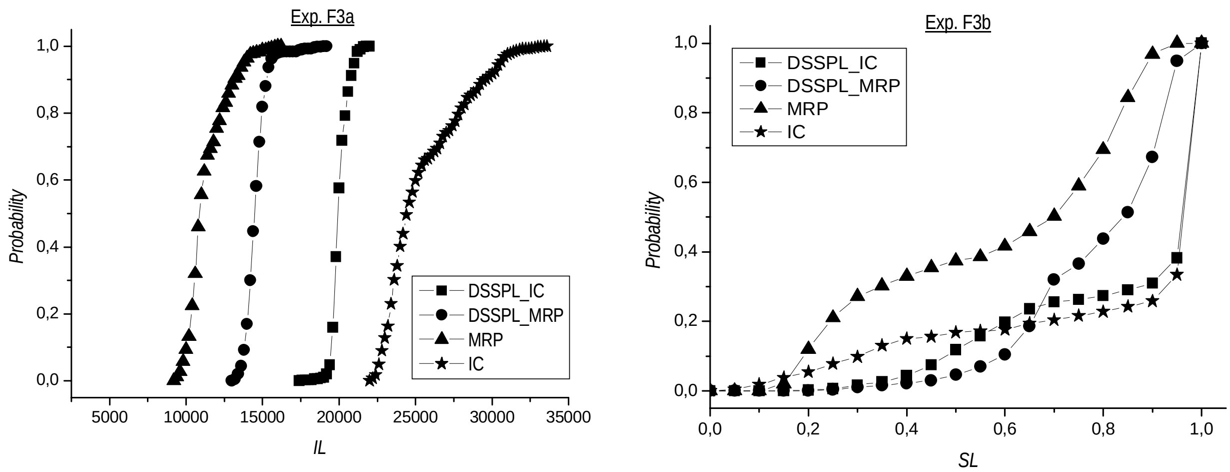
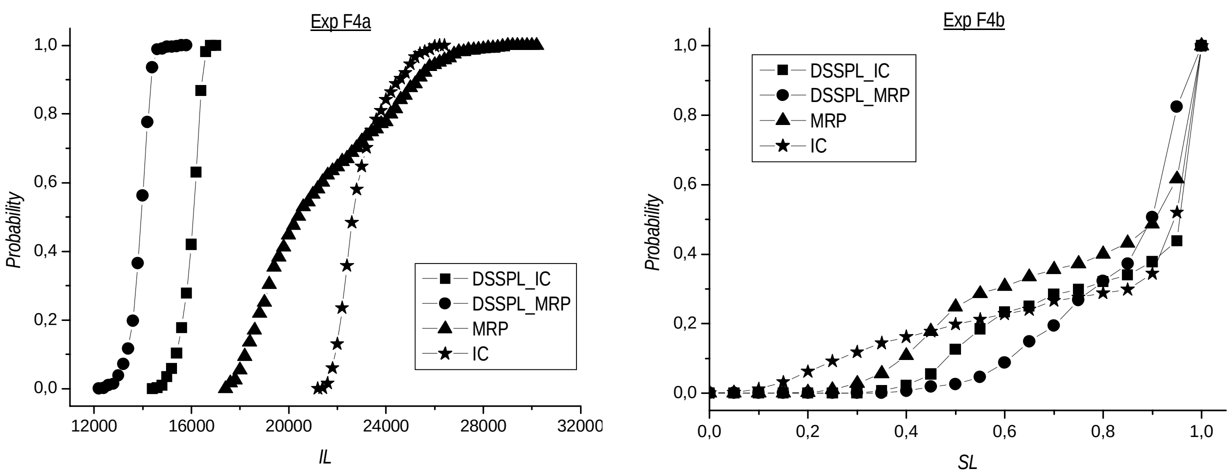


Figure 5.23 Exp. F4a and b: Robustness of compared MPC methods for base scenario 4



The comparison of the robustness of the different MPC methods confirms most of the results obtained so far. MRP has generally the lowest service level robustness of all compared MPC methods when confronted with uncertainties in the manufacturing environment. On the other hand, both DSSPL methods, DSSPL_MRP and DSSPL_IC, generally exhibit the smallest risk of achieving service levels lower than 0.5 (*Probability*(SL < 0.5)). In the case of base scenario 2 and 4 (commonality = 1.9) DSSPL_MRP achieves this good result even at the lowest average inventory level of all MPC method compared (low probability of getting high inventory levels). This result is particularly interesting since DSSPL achieves a high robustness without increased inventory levels that buffer against uncertainty. It is assumed that DSSPL obtains this good result due to the use of JIT/kanban for the management of the A-items. The low risk of achieving service levels lower than 0.5 (*Probability*(SL < 0.5)) shows that JIT/kanban can maintain a certain service level even if the conditions of the manufacturing environment deteriorate significantly.

The highest overall robustness exhibit as expected the Inventory Control and DSSPL_IC method. They have in general the lowest risk of failure of achieving service levels below 0.9 (*Probability*(SL < 0.9)).

These results also confirm the high impact of an increased product commonality on the performance of MRP. For base scenarios 2 and 4, MRP exhibits not only the highest risk of achieving low service levels but also inventory levels comparable to those of the inventory control method.

Table 5.32 shows the results of the analysis of the results with the help of the first- and second order stochastic dominance criteria. They confirm the above mentioned conclusions. It can be seen, however, that the application of these criteria does not always lead to unambiguous results.

Table 5.32: Ranking of MPS methods according to the stochastic dominance theory, best ranking = 1, same ranking for cases where no unambiguous choice possible (first-order stochastic dominance: fsd; second-order stochastic dominance: ssd)

Experimental design	**F1a, b**				**F2a, b**				**F3a, b**				**F4a, b**			
Dominance	**fsd**		**ssd**		**fsd**		**ssd**		**fsd**		**ssd**		**fsd**		**ssd**	
Performance metric	***IL***	***SL***	***IL***	***SL***	***IL***	***SL***	***IL***	***SL***	***IL***	***SL***	***IL***	***SL***	***IL***	***SL***	***IL***	***SL***
DSSPL_IC	3	1	3	1	2	1	2	1	3	1	3	1	2	1	2	1
DSSPL_MRP	2	1	2	2	1	2	1	2	2	1	2	1	1	1	1	1
MRP	1	4	1	4	2	4	2	4	1	4	1	4	3	1	3	1
IC	4	1	4	2	4	2	4	3	4	1	4	1	3	1	4	1

A final remark has to be made concerning the relative inventory cost levels. This measure has been introduced in order to emphasize increased inventory levels at particular production stages due to the characteristics of an MPC method. The results show, however, that there exists no significant difference between the relative cost levels of the analyzed MPC methods.

Summary and conclusions of chapter 5

- The simulation study has been performed with models based on one of four base scenarios representing the manufacturing environment. These base scenarios are distinguished by their product commonality and production process structure;
- Six experimental designs (A to F) were developed to analyse and compare the performance and the robustness of the four MPC methods MRP, Inventory Control, DSSPL_IC(B-items managed with inventory Control method) and DSSPL_MRP (B-items managed with the MRP method);
- An underdimensioning of the kanban capacities generally has a much higher impact on the performance of DSSPL_MRP and DSSPL_IC than an overdimensioning. It is therefore safer to overdimension the kanbans and accept the increased average inventory levels than to risk a low service level if the kanbans are dimensioned too small;
- The dispatching rules exhibit generally the best performance if the parameter *llow* is set close to one. The second parameter *tcrit* has a much smaller impact on the performance than llow but most of the results indicate that increased values help improve further the performance of DSSPL. In order to reduce the complexity of DSSPL, *lup* is always set to *nk* (number of kanbans);
- Forecast errors have the highest impact on the performance of MRP and DSSPL_MRP. The Inventory Control method and DSSPL_IC are, as expected, insensitive to this type of manufacturing environment uncertainty. If the product commonality is low MRP performs with the lowest inventory level. For high levels of commonality, MRP and Inventory control perform at significantly higher inventory levels than DSSPL_MRP and DSSPL_IC. If the system load is high, DSSPL_MRP generally exhibits the best performance;
- Due to the reduced lot sizes (kanbans) DSSPL_MRP’s performance is more sensitive to high setup values than the other MPC methods;
- The different relative cost levels have no significant impact on the inventory performance of the analysed MPC methods;
- Of all compared MPC methods MRP exhibits the lowest robustness when confronted with uncertainties in the manufacturing environment. DSSPL_IC and DSSPL_MRP have generally the lowest risk to achieve reach service levels lower than 0.6. In the case of increased commonality, DSSPL_MRP performs, in addition, at the lowest inventory level of all compared MPC methods;
- The choice between the DSSPL_IC and the DSSPL_MRP method is a trade-off decision between the excellent robustness of DSSPL_IC and the improved inventory performance of DSSPL_MRP.

Chapter 6

Industrial implementation of DSSPL

The goal of this chapter is the presentation of the practical aspects of DSSPL. Emphasis is therefore put on issues related to the implementation and configuration of DSSPL in real industrial cases. In the first section, a methodology is proposed that can be used as a guideline for any potential DSSPL implementation project. This methodology is based partly on the experience of a DSSPL implementation pilot project that is presented in the second section.

6.1 Implementation methodology

Several risks are related to the implementation of a new MPC method into an existing manufacturing process. Most of these problems are related to the fact that the diversity and complexity of manufacturing systems prevent the use of cook-book like implementation strategies (Prasad 1995, Hallihan et al. 1997). Furthermore, this problem is reinforced by difficulties such as cultural resistance to change or lack of available resources (Crawford et al. 1988, Prajogo and Johnston 1997).

In order to reduce the above mentioned risks of an implementation project, the optimal solution are the creation of a multidisciplinary project teams that include logistic, simulation, implementation and work psychology specialists as well as operators, engineers and managers from the industrial partner. Such an interdisciplinary approach ensures that the variety of potential problems can be treated by people who have a detailed understanding of the specific case. Since organizational aspects are outside the scope of this thesis, only logistical and technical aspects are treated in detail.

The implementation methodology is divided into four steps called *Analysis*, *Configuration*, *Implementation* and *Validation*. Some points of the presented methodology (illustrated in Figure 6.1) are specific to DSSPL (particularly *Configuration*) but most of the decisions and actions described are relevant for any implementation project of a new MPC method.

The goal of the first step is the analysis of the basic characteristics and the current state of the focused production system. The results from this analysis serve mainly as a decision support for the evaluation of the risks and benefits of an implementation of DSSPL. In this state of the analysis two types of manufacturing environment parameter have to be distinguished. The first type of parameter corresponds to characteristics of the manufacturing environment that can be influenced by the implementation of a new MPC method such as DSSPL. These parameters are generally related to the logistic aspects of the production system. Typical examples are, therefore, inventory levels, service levels, lead times, etc. The sampling and analysis of these parameters is also important with respect to the eventual validation of the implemented MPC method. The second type of parameters describes primarily the manufacturing environment and is characterized by the fact that a new MPC method has no significant impact on this type of parameter. Typical examples of manufacturing environment parameters are, therefore, the frequency and amount of quality problems and equipment failures, the topology (regularity and volume) of the customer demand and the supplier quality and reliability. These parameters can be further divided into two classes, depending on where they occur, inside or outside the analyzed production system. Problems related to the manufacturing environment can reduce significantly the benefits of an implementation of a new MPC method. There are MPC methods (JIT/kanban, Load-oriented manufacturing control) that make such problems more visible. Nevertheless, these problems must be addressed if possible by additional actions that have to be performed prior to or during the implementation project. If, however, external characteristics of the manufacturing environment (typically low supplier quality and reliability, instability of the demand) are the dominating problem other solutions than the implementation of a new MPC method have to be found to improve the efficiency of the production system.

Based on results of this first step, DSSPL is dimensioned and possibly tested and validated with the aid of simulation. The choice of a simulation analysis is a trade-off decision between the reduction of the risk to choose an inappropriate configuration and the effort of performing such analysis. Besides the choice of the A-items and the determination of the parameters of the kanban loops, the definition of the interface between the new system and the existing MPC method is another important task of this step.

The implementation itself is performed in the third step. Finally, validation and possible modifications of DSSPL are performed in the last step. This validation is based primarily on data that have been sampled before and after the implementation. Typical performance measures are inventory levels, service levels and lead times.

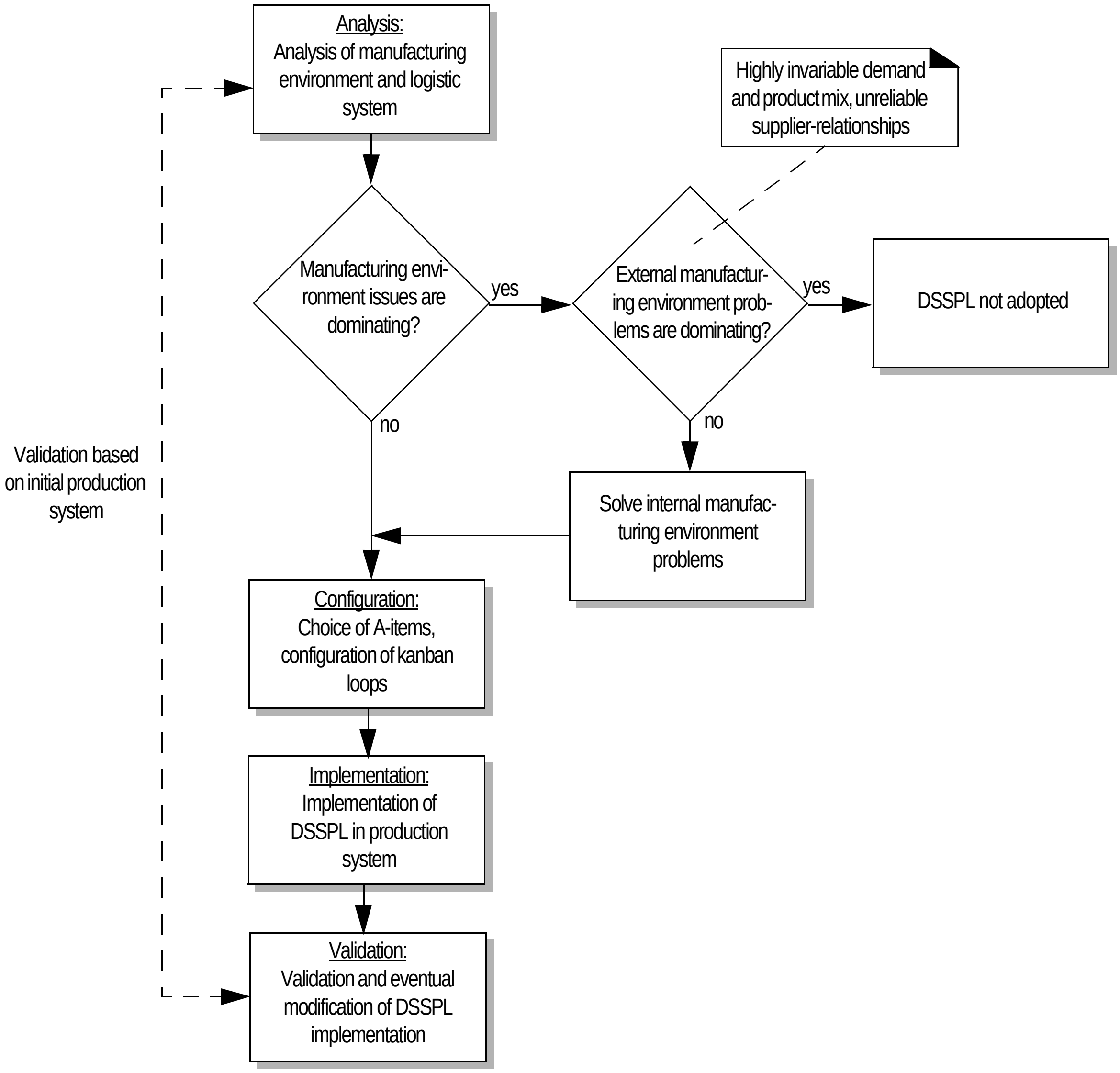
In the following two sections, the implementation steps *Analysis* and *Configuration* are described in more detail with examples from pilot projects.

6.1.1 Analysis

The goal of the first step *Analysis* in a DSSPL implementation project is the analysis of the current state of the focused production system. In order to better structure the analysis, the production system is divided into three subsystems *Load, Technical Production Resources* and *MPC method* (as defined in §4).

The analysis of the first subsystem *Load* is of particular importance for the future implementation of DSSPL since it determines the choice of the A-items. The most important criteria for their choice have already been presented in Table 3.1. The primary tool used for identifying A-items is the multiple-criteria ABC analysis (Flores and Whybark 1986, Vollmann et al. 1997). The analyzed criteria are, therefore, the cumulated values of each item over a certain time horizon of the volume and cost volume (volume times unit prize) and the regularity of the demand. The regularity of the demand is measured by the coefficient of variation of the series of demand sizes (or lot sizes) and the intervals between two consecutive demands that have occurred during the analyzed time horizon. Whereas standard values according to Pareto's law are used for the classification of the items with respect to their relative volumes (class A: 80%, class B: 15% and class C: 5%) the variability classification scheme defined in section §4.2.1 is used for the classifi-

Figure 6.1 Implementation procedure

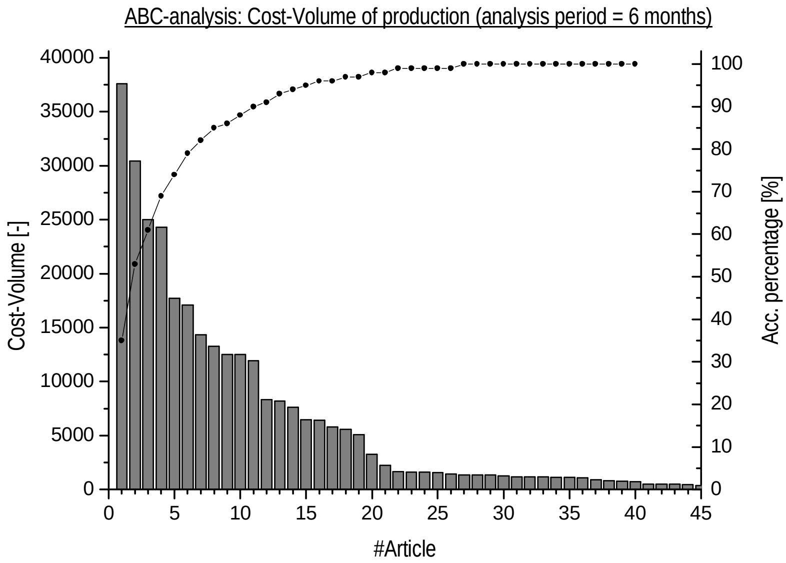


cation of the items with respect to the variability of the demand. Based on the principles and characteristics of DSSPL, the conditions for A-items are consequently a low variability of the demand (*cvds* and *cvid* < 0.75) and high relative volumes (class A). These criteria assure that items fulfilling these conditions can be managed by the JIT/kanban method at least from the demand topology point of view.

A first example of an ABC-analysis is shown in Figure 6.2. This analysis was performed in a manufacturing company with a typical job shop environment. The results indicate that 10 of the 45 fabricated products generate approximately 80% of the accumulated cost-volume.

A more detailed analysis has been performed by Hélie (2001) who performed a multiple-criteria ABC-analysis of the demand of a micromotor-producer from its external supplier. The demand for the 45 mechanical components has been analyzed with respect to the volume, the cost-volume, the criticality (number of products in which the component is used) and the regularity of the demand. Figure 6.3 shows the results of the ABC-analysis with respect to the volume whereas the overall results are presented in Table 6.1. The classification according to the regularity criterion has been performed according to the classification scheme defined in section §4.2.1 (low variability = class X, medium variability = Y and high

Figure 6.2 ABC-analysis in a job shop



variability = class Z). The criticality criteria has been done according to the rule that class A items are included in 80%, class B in 15% and class C in 5% of the articles concerned.

Figure 6.3 ABC-analysis of the demand of a micromotor producer for its external supplier

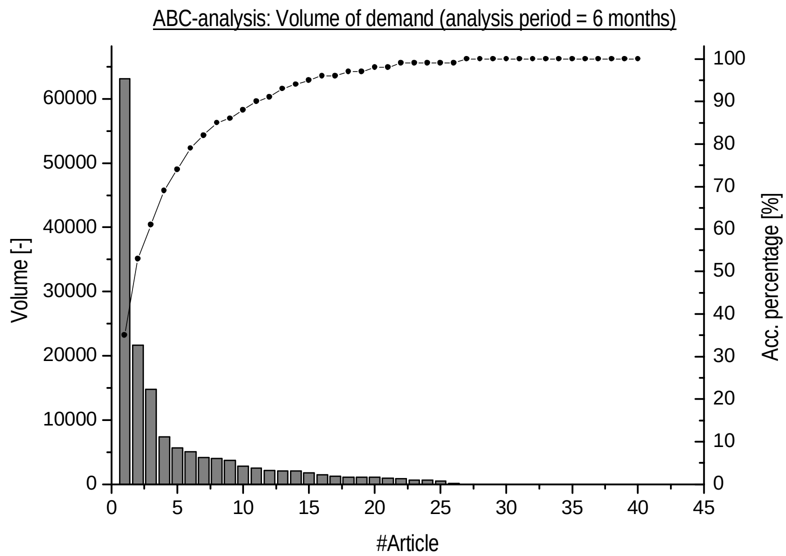


Table 6.1: Results of a multiple-criteria ABC-analysis for the demand of a micromotor-producer (only first 15 of 45 analyzed articles)

#Article	Volume	Cost-Volume	Criticality	Regularity of demand size	Regularity of interval betw. two demands
1	A	A	A	X	X
2	A	A	A	X	X
3	A	A	A	X	X

Table 6.1: Results of a multiple-criteria ABC-analysis for the demand of a micromotor-producer (only first 15 of 45 analyzed articles)

#Article	Volume	Cost-Volume	Criticality	Regularity of demand size	Regularity of interval betw. two demands
4	A	A	A	X	X
5	A	A	A	X	X
6	A	B	A	Y	X
7	A	B	B	X	X
8	A	B	A	X	Y
9	A	A	A	X	Y
10	B	A	C	X	Y
11	A	A	B	Y	X
12	B	B	C	X	X
13	C	B	C	X	X
14	B	B	A	X	Y
15	C	B	B	X	Y
:	:	:	:	:	:

According to the results indicated in Table 6.1 the first 5 articles (in bold face) have been chosen as A-items.

A similar study has been performed by Golay (2002) who analyzed the production of plastic parts for a color pencil producer. Figure 6.4 shows the ABC-analysis (volume) of the analyzed 43 items analyzed. The global results are summarized in Table 6.2.

Table 6.2: Results of a multiple-criteria ABC-analysis of a color pencil producer (only first 15 of 45 analyzed articles)

#Article	Volume	Cost-Volume	Criticality	Regularity of demand size
1	A	A	A	A
2	A	A	A	A
3	A	A	A	A
4	A	A	A	A
5	A	A	A	A
6	B	A	A	A
7	A	A	A	A
8	B	B	A	A
9	B	B	A	A
10	B	B	B	A
11	B	B	B	A

Table 6.2: Results of a multiple-criteria ABC-analysis of a color pencil producer (only first 15 of 45 analyzed articles)

#Article	Volume	Cost-Volume	Criticality	Regularity of demand size
12	B	A	C	A
13	B	B	B	A
14	B	B	B	A
15	B	B	C	A
:	:	:	:	:

According to the results indicated in Table 6.2 the first 7 articles (in bold face) have been chosen as A-items. The examples presented above from various manufacturing environments validate the fourth hypothesis of the DSSPL framework presented in section §3.1.1. They also validate the load model presented in section §4.2.3 that assumes that the demand of products with higher volume is generally more stable than those of products with low demand.

The analysis of the *Technical Production Resources* subsystem is focused on aspects that are critical for the implementation of the JIT/kanban method used for management of A-items. These critical aspects are generally best identified by analyzing the flexibility and availability of the production resources. As defined by Prasad (1995) low setup times (high flexibility) and a high availability of the production resources (low failure rates) are significant for a successful implementation of the JIT/kanban method. Another important factor is the quality level of the products that should be in accordance with the customer requirements.

Finally, the analysis of the *MPC method* subsystem is important with respect to the estimation of the benefits of an implementation of DSSPL. This analysis is best performed by applying the tools developed by Wiendahl (1987) that have been presented in section §2.5.

Figure 6.4 ABC-analysis of the production of a color pencil producer

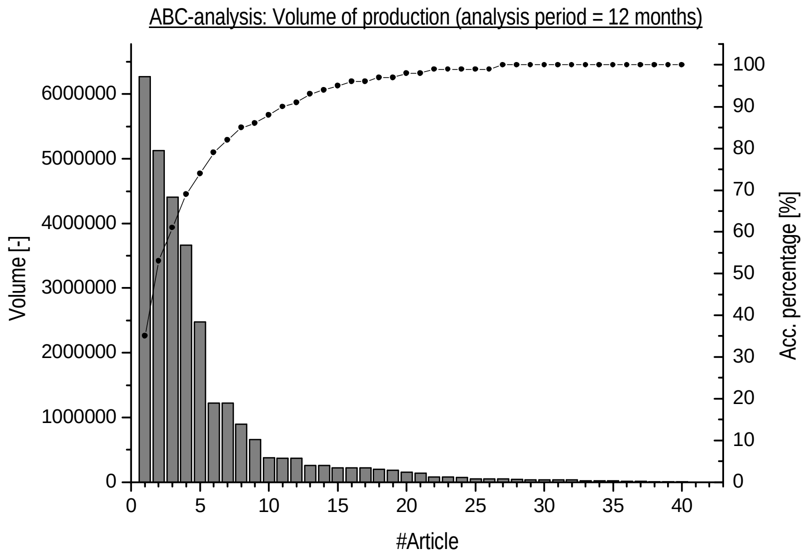


Table 6.3 summarizes the most important parameters of the production system that have to be analyzed and sampled in a DSSPL implementation project.

Table 6.3: Summary of analysis parameters (* indicates external manufacturing environment characteristics)

Parameter	**Analysis tool**
Volume*	ABC analysis
Cost-volume*	ABC analysis
Stability of demand*	ABC analysis
Criticality	ABC analysis
Reliability and quality of suppliers*	ABC analysis, statistics
Equipment failure rate	Statistics
Quality problems	Statistics
Flexibility of production resources (setups, flexibility of operators,...)	Data analysis
lot sizes	Data analysis
Work-in-process, lead times, delays, system load	Throughput and load diagram, measurement of flow rates
Central inventory level	Data analysis

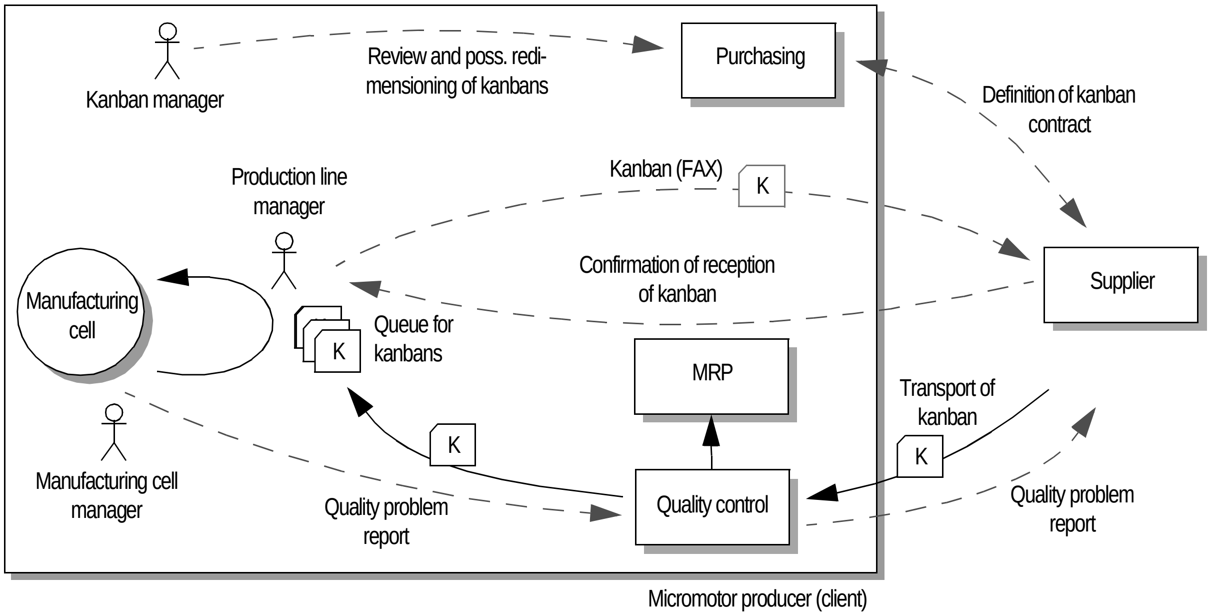
6.1.2 Configuration and implementation

The configuration of DSSPL consists mainly of the choice of the A-products based on the outcome of the previous step, the configuration of the JIT/kanban method used for the management of the A-items and the definition of the interface to the existing MPC method.

The choice of the A-items is based on the multiple-criteria ABC analysis and the practical limit of the number of items that can be managed by the JIT/kanban method in one production system (manufacturing center or manufacturing cell). In fact, due to difficulties in handling the different priorities, the upper limit of the number of items managed by the JIT/kanban method is set to approximately eight (Courtois 1995). The different kanban loops are first configured by assuming that the product $nk \cdot ck$ is equal to the current lot size. Normally, the capacity of the kanbans *ck* is imposed by technical constraints and the number of kanbans *nk* is therefore derived from the above expression.

The definition of the interface to the existing MPC method is particularly important in cases where the current production system is managed by the MRP method. In fact, MRP has to keep track of the logistical transactions performed by the JIT/kanban system in order to maintain the integrity of its database. Figure 6.5 shows a typical example of a definition of an interface between DSSPL and the existing production system for the case of a pilot project that has been performed for the supply chain between a micromotor producer and its external supplier.

Figure 6.5 Example of definition of interface



A particularity of the solution depicted in Figure 6.5 is the fact that kanbans coming from the supplier are not sent directly to the manufacturing cell. Instead, kanbans are first sent to the quality control departement in order to prevent perturbations of the manufacturing cells due to external supplier quality problems.

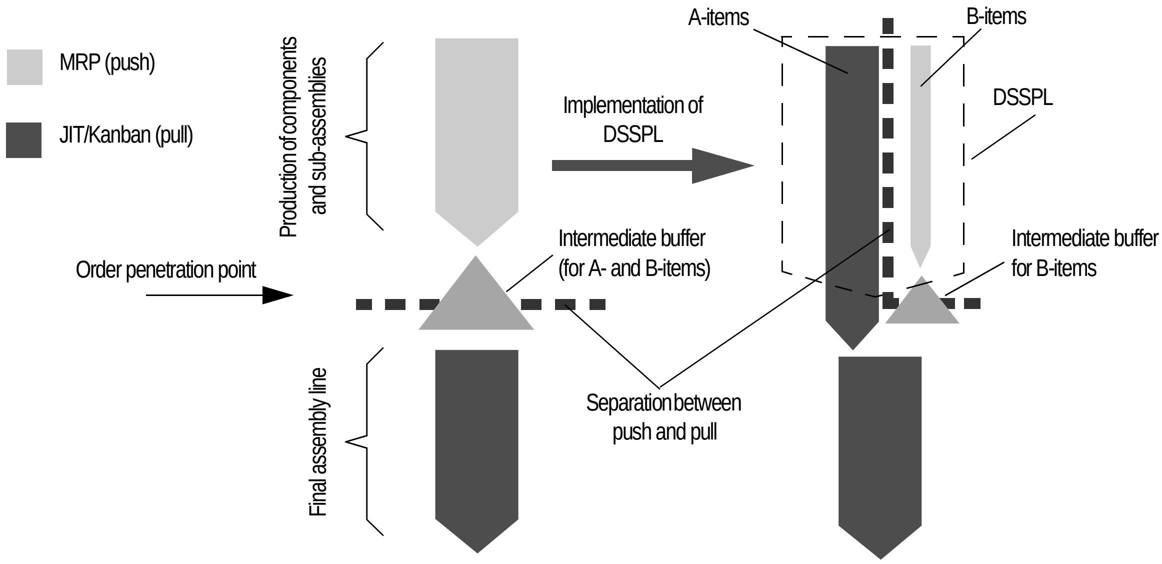
6.2 Industrial case study

In order to improve the logistic performance of a micromotor producer, DSSPL has been implemented between a supply unit and the final assembly line. The case presented with its particular manufacturing environment characteristics serves well to justify and validate the design decisions taken for DSSPL. It illustrates how DSSPL copes with problems of limited resources and interface coordination problems occurring in firms operating in assemble-to-order (ATO) manufacturing environments.

6.2.1 Problem description

Firms that offer a wide variety of products such as the micromotor producer considered typically choose an ATO master production schedule approach when delivery speed requirements and the changing product mix prevent the exclusive choice of the make-to-order (MTO) or make-to-stock (MTS) option, respectively (Vollmann et al. 1996). One condition for a successful implementation of the ATO concept is a certain modularization of the product structure where components and intermediate subassemblies are

Figure 6.6 Problem description



assembled in the last production steps to generate a wide variety of products. These final production or assembly steps are, as the name of the ATO master production schedule approach already suggests, performed in an MTO environment. Thus, in order to reduce further lead times and to fulfill the requirement of fast reacting to changing customer demand, firms can choose modern MPC methods (JIT/ Kanban, CONWIP, POLCA, flow manufacturing,...) for the management of these final assembly lines. However, an imperative condition for the performance of such final assembly lines is the availability of components and intermediate subassemblies supplied by internal or external supply units. In fact, the master production schedule of the supply units is partly or entirely derived from unreliable forecasts since the order penetration point (point in the production process where the product is assigned to a customer order) is typically defined at the beginning of the final assembly process. Due to these characteristics of the master production schedule, MRP is generally used for the management of the production units up to the assembly lines. These manufacturing environments are therefore characterized by final assembly lines and internal and external supply units that are separated by an intermediate buffer and are often characterized by increased inventory levels that buffer against the uncertainty of the demand.

As illustrated in Figure 6.6, this division into two production systems is based on a concept that chooses the appropriate MPC method with respect to the order penetration point. Due to the characteristics of the modularized product structure, however there is a tendency that certain components and subassemblies have a significantly higher and more stable demand than others since they are used in many final products. This is analogous to the fact that product-line forecasts are generally more accurate than detailed forecasts (Vollmann et al. 1997). The aggregate demand of a certain set of products that is characterized by using the same subassembly or components is, therefore, more stable than the demand of each particular product. Evidently, this tendency increases with an increased level of product commonality. Consequently, in such manufacturing environments, DSSPL is a more appropriate choice than MRP, since it takes advantage of the particular topology of the demand.

The following section describes an industrial case study that corresponds to the problem description described above.

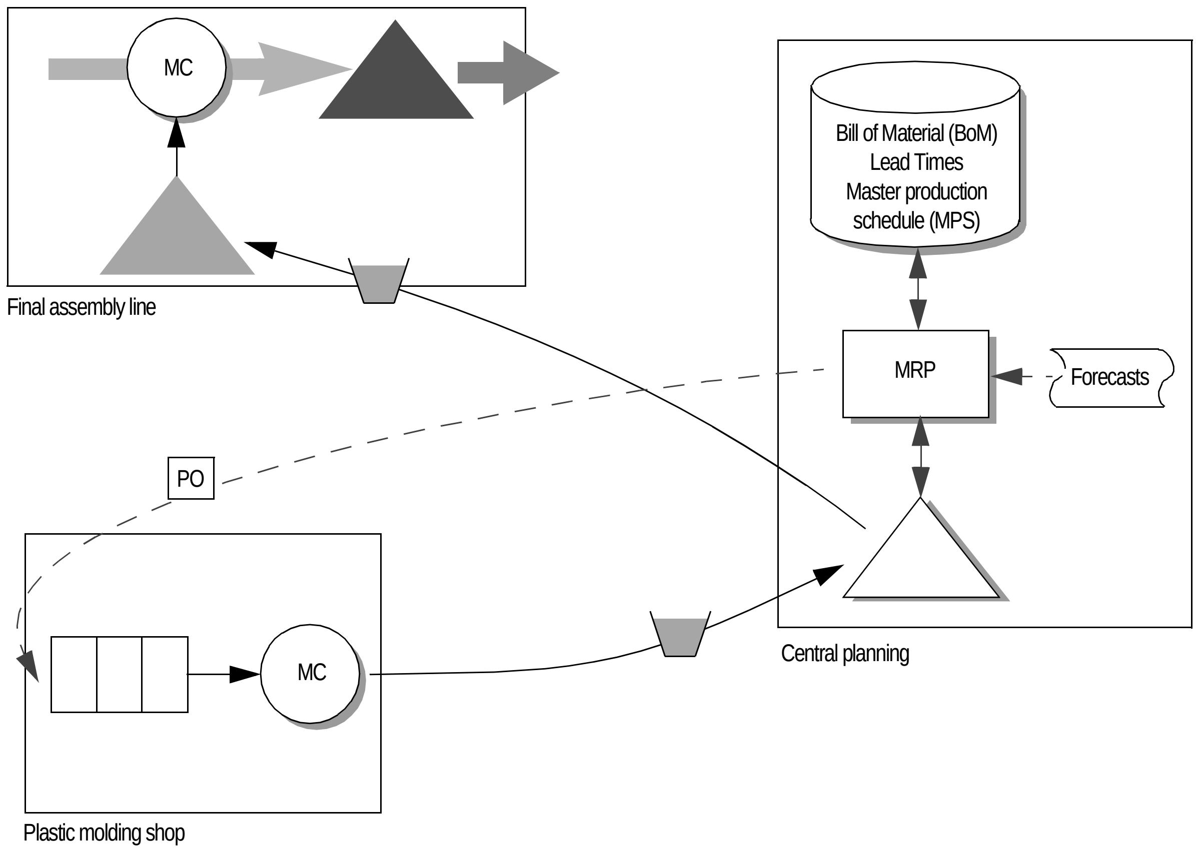
6.2.2 *Description of industrial case study*

In summary, the manufacturing environment of the selected DSSPL pilot line has the following characteristics (illustrated in Figure 6.7):

- The production system of the micromotor manufacturer is structured according to the ATO concept. The final assembly line is organized according to a flow manufacturing technique, whereas the feeder shops including the plastic molding shop are managed by an MRP-system;
- Coordination problems occur frequently between the final assembly line and the different feeder shops. In fact, most production interruptions where provoked by a lack of subassemblies supplied by the plastic molding shop. The coordination problems were mainly caused by production schedules for the feeder shop inconsistent with the final assembly schedule;
- An increase of the production capacity of the feeder shops (particularly of the plastic molding shop) is difficult due to limited financial and human resources;
- An outsourcing of the plastic molding unit is difficult due to the particular quality and technical requirements of the subassemblies.

The subassemblies manufactured by the plastic molding shop are mainly plastic molded parts with metallic inserts. Since the two subassemblies collector and flange show the biggest turnover within the plastic molding shop, it was decided to concentrate the analysis on these two types of parts. The approximately 100 variants of these two parts are manufactured on two work centers. The first work center producing the flange parts includes only one plastic molding machine whereas the work center producing

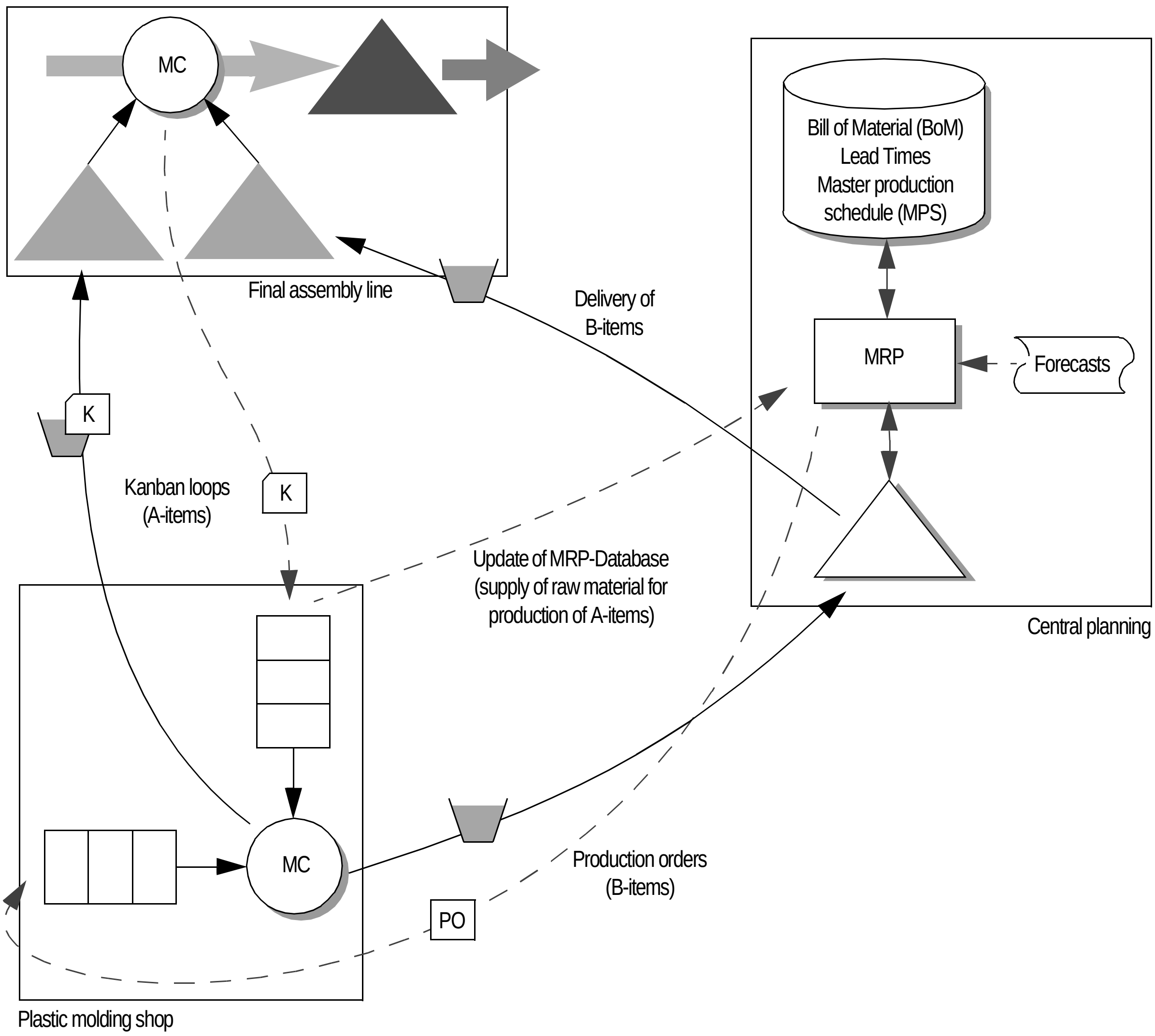
Figure 6.7 Manufacturing environment prior to implementation of DSSPL



the collector parts includes three plastic molding machines. All collector parts can be produced on one of the three plastic molding machines of the corresponding work center.

Every molding cycle is executed by an operator. Additionally, a mechanic is required to prepare the molding tools and adjust the molding process parameters in case of a setup. The setup times can vary from 20 minutes to one day. The working period for the operators and mechanics is normally one shift. However, in the case of high work load and the availability of additional operators, a second work shift can be added. Consequently, the main characteristics of this manufacturing process are the need for specialists for the handling of the expensive and sensitive molding tools and machines and the high setup times. An additional problem is the fact that the human resources (mainly the mechanics) are rarely available immediately when needed. This is due to the limited availability of qualified mechanics and operators and the fact that both mechanics and operators are involved in the production and maintenance of other machines and products of the plastic molding shop.

Figure 6.8 Plastic molding shop after implementation of DSSPL



6.2.3 Solution

The most important characteristics of the DSSPL pilot line are (illustrated in Figure 6.8):

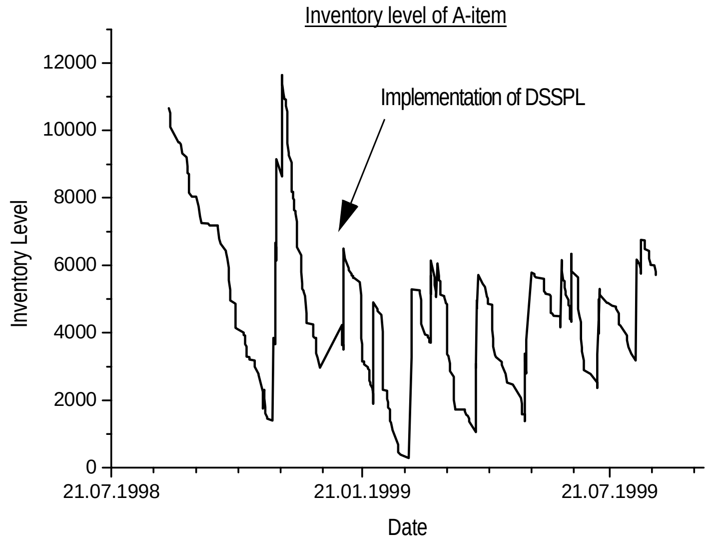
- Six out of the approximately 100 variants of the collector and flange parts have been designated as A-items. The criteria were a high relative volume and stable demand;
- The A-items are managed by a one-card Kanban system, connecting the plastic molding shop directly with the final assembly line. In order to keep the MRP database consistent also for the A-items, a notice is sent from the plastic molding shop to central planning after the completion of each kanban;
- The simplest dispatching rule, always giving priority to the A-items (nonpreemptive), is used in the two work centers;
- The choice of packaging of the delivered A-items and the quality control requirements has been unified and coordinated between the plastic molding shop and the final assembly line;
- The responsibility for releasing production quantities of the A-items has been shifted from central planning to the foremen of the plastic molding shop;

Weekly reunions of all involved responsibles of the final assembly line, central planning and plastic molding shop for coordination issues are held. The most important discussion topics are quality problems and anticipated changes in demand and capacity planning.

6.2.4 Results and validation

The impact of DSSPL on the average inventory level of the A-items has been analyzed based on the inventory level data for a period of three months before and after the implementation. For five of the selected A-items, the average inventory level has been decreased (-19... -39%) without causing shortages of items. The average inventory level of one A-item (due to reduced demand shortly after implementation of DSSPL) and all B-items did not change significantly. The plot in Figure 6.9 illustrates the impact of the kanban production system on the average inventory level of an A-item after the implementation of DSSPL.

Figure 6.9 Impact of implementation of DSSPL on inventory level of A-item



In addition to the validation of the new MPC method based on data analysis, a qualitative evaluation of the perceived success of the implemented DSSPL method was done by interviewing the people concerned, six months after implementation. The main outcomes of this survey are as follows:

- The lead time and the availability of the A-items on the final assembly line has been improved considerably. In fact no more out-of-stock situations were observed for the A-items;
- Even though priority was given to the production of A-items, the performance of the production for B-items was not decreased significantly. This is due to the fact that the production of the A-items is simplified and only triggered when really needed;
- Improved communication and coordination between the plastic molding shop, the final assembly line and the central planning;
- Further improvements of the performance of the plastic molding shop can only be achieved by either reducing the setup times or by increasing the availability of the operators and mechanics.

Summary and conclusions of chapter 6

- The most critical aspect for the feasibility and benefit of a DSSPL implementation are external manufacturing environment characteristics that do not correspond to the requirements of the DSSPL concept. Typical examples are a highly variable demand or unreliable supplier relationships;
- Studies in different manufacturing environments confirm the DSSPL concept that the demand generally follows Pareto's law. Furthermore, they also confirmed that items with a high volume (A-items) generally also have a more stable demand;
- An industrial case study in the plastic moulding shop of a micromotor producer has revealed the potential of the DSSPL concept to improve the logistic performance of a manufacturing system.

Chapter 7

Conclusions

The goal of this work to develop the new hybrid MPC method DSSPL has been achieved by applying a research methodology that is based on a Markovian model, a discrete-event simulation study and pilot projects where DSSPL has been implemented and tested in real industrial conditions. Many characteristics of DSSPL have, however, been derived from a comparison with existing (hybrid) MPC methods and the fact that DSSPL is based on the combination of classical MPC methods whose features are well known. DSSPL can be distinguished from other MPC methods by the strategic thinking that seeks to allocate optimally limited resources in order to obtain a maximum impact in terms of customer service and satisfaction. A further important characteristic of DSSPL is the fact that it can also be applied, in contrast to other hybrid MPC methods, in complex manufacturing environments.

The basic mechanics of the DSSPL concept have been analyzed with the help of a Markovian model. This study shows that the mix of A- and B-items and the lot size of the A-items are of primary importance for the performance of DSSPL. Compared to MRP, satisfactory inventory level performance can therefore only be achieved if the volume of A-products is higher than those of the B-products and if the lot size of the A-products is smaller than those of the B-items. This study also showed that DSSPL is less sensitive to forecast errors than MRP due to the use of the JIT/Kanban method for the management of A-items.

In a more complex simulation study, two versions of DSSPL, DSSPL_MRP and DSSPL_IC (DSSPL with MRP or Inventory Control for the management of the B-products), have been compared to the MRP and Inventory control MPC methods, in four manufacturing environments that are characterized by different production process complexities and product commonality. The results show that the configuration of the JIT/Kanban method used for the management of the A-items has the most significant impact on the performance of DSSPL. Particularly an underestimation of the kanban capacities can lead to a significant loss of the service level performance of the A-items, but particularly of the B-items. The most interesting feature of DSSPL is, however, its robustness when confronted with uncertainties in the manufacturing environment. DSSPL_IC and DSSPL_MRP exhibit, particularly in cases of increased product commonality, a significantly better result than MRP. Similar results were also obtained with the Inventory Control method but mainly due to the increased average inventory levels. This study has shown together with the previous study based on the Markovian model, that DSSPL can improve the logistic performance of a manufacturing environment by allocating a higher priority to the A-products that have the highest volume. However, this is not done at the expense of the logistic performance of the other B-products since A-products are produced in a way that causes less congestion in the production resources.

The DSSPL pilot studies in real industrial environments have confirmed the concepts of the DSSPL framework and shown its potential to improve significantly logistic performance. These studies also showed also that the design of the interface to the existing MPC method is the most critical issue of a DSSPL implementation project, particularly in presence of an enterprise resource planning (ERP) system.

The following list summarizes the outcome of this thesis with respect to the research goals defined in chapter §1:

- *Concept design (Choice of A-products)*: The criteria for the choice of A-products are a high demand volume (A-classification according to ABC-analysis) and a stable demand ($CV < 0.75$). Furthermore, A-products should be mature or possibly growing with respect to their product live cycle;
- *Concept design (Choice of MPC methods for DSSPL)*: Two MPC methods can be chosen for the management of the B-products (DSSPL_MRP and DSSPL_IC). The simulation analysis has shown that MRP performs better than the Inventory Control method particularly with respect to the inventory performance. The advantage of the Inventory Control method is, however, its robustness and its conceptual simplicity;
- *Concept design (Development of local dispatching rule)*: The dispatching rule developed for DSSPL allocates priorities to A- or B-items according to kanban priority levels for A-items and a critical waiting time for B-items. The simulation analysis has shown that good results are achieved by setting the lower and upper kanban priority levels to one and to the number of kanbans respectively, whereas the critical waiting time is set to the planned lead time;
- *Logistic performance*: DSSPL_MRP and DSSPL_IC exhibit a significantly better logistic performance than the MRP and Inventory Control methods, if the commonality is high and in the presence of forecast errors. In addition, DSSPL_MRP is significantly more robust than MRP when confronted with an uncertain manufacturing environment. The highest robustness of all analysed MPC methods is exhibited by the Inventory Control method and DSSPL_IC. However, DSSPL_IC performs at lower inventory levels than the Inventory Control method;
- *Application domain*: DSSPL extends the typical application domain of existing hybrid MPC methods towards manufacturing environments that are not limited by the production process or product structure complexity. The most critical issue is, however, the existence of products which fulfil the criteria for A-products. DSSPL is not adapted for manufacturing environments with highly varying demand and product mix;
- *Configuration and management guidelines*: The determination of the size and capacity of the kanbans is, together with the configuration of the dispatching rule, the most critical issue with respect to the configuration of DSSPL. The simulation studies have shown that an underestimation of the capacity of kanbans can lead to a significant loss of performance. The best performances have been achieved if the number of items in the kanbans is equivalent to the lot size that would have been applied if the items were managed with the MRP or the Inventory Control method. The management and control of the performance of DSSPL is best performed by applying the tools developed for the Load-oriented manufacturing control method.

Future efforts concerning the development of DSSPL should focus on two issues: The most important issue is related to the practical validation of DSSPL. Further pilot studies in various manufacturing environments are required to better validate the concept of DSSPL. A second important issue to be addressed in future works is the development of concepts and tools to integrate DSSPL into the forecasting, sales, purchasing and aggregate planning processes of a manufacturing firm. In a first step, it is necessary to determine if existing tools provided by the MRP framework just have to be reconfigured or if new tools have to be developed.

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Keywords

ABC classification	Classification of the items in decreasing order of annual cost volume or other criteria. This array is split normally into three classes, called A, B, and C. Standard values according to Pareto's law for the classification with respect to the relative annual cost volume are: Class A: 80%, class B: 15% and class C: 5%.
Aggregate product structure	Combination of the structure of all final products where each particular product is represented by only one node (Grünwald et al. 1989).
Assemble-to-order (ATO) manufacturing environment	In an ATO manufacturing environment, all components (subassemblies, fabricated, purchased,...) for a product used in the final assembly or finishing process, are planned and stocked in anticipation of a customer order.
Backlog	All of the customer orders received but not yet shipped.
BoM - Bill of material	A listing of all items that go into a parent assembly showing the quantity of each required to make the assembly (Vollmann et al. 1997).
CONWIP - CONstant Work In Process	Hybrid MPC method that is based on the concept of controlling the production by limiting the work in process (Hopp and Spearman 2000).
CT - Cycle time	The (average) time from when a job enters a production system or stage until it exits. It is therefore defined as the sum of the mean queue time (*TQ*) and the mean process time (*TP*).
CV - Coefficient of variation	Measure of relative variability of a stochastic variable expressed by the ratio between its standard deviation σ and its mean value μ (Hopp and Spearmann 2000).

Dispatching rule	The logic used to choose the single job to proceeded first in a work center.
DSSPL - Double Speed Single Production Line	Hybrid MPC method that combines the MRP and JIT/kanban MPC methods for the production of different classes of products on one single production line.
EOQ - Economic order quantity	Fixed order quantity, which has been determined in order to minimize the combined costs of acquiring and carrying inventory (Vollmann et al. 1997).
FGI - Final goods inventory	Final goods inventory
FIFO - First in, first out dispatching rule	Dispatching rule that allocates priorities to jobs according to their arrival time. Also known as the first come, first served (FCFS) dispatching rule
Fill rate	Ratio of orders served from inventory (used in Inventory Control theory, comparable to definition of service level).
FOQ - Fixed order quantity lot-sizing rule	Lot-sizing rule based on constant (fixed) order quantities.
Forecast bias	Difference between effective demand and forecast
FR - Flow rate	Ratio between cycle time (*CT*) and effective production time including setups (*PTE*) (Wiendahl 1995).
Funnel model	The funnel model describes a work system as the flow of a liquid through the funnel. The incoming orders, measured in hours of work content, form a stock of waiting jobs, which have to flow through the funnel outlet. The diameter of the outlet can be described as the capacity of the work system that is also measured in hours of work content (Wiendahl 1987).
HIHPS - Horizontally integrated hybrid production systems	In horizontally integrated hybrid production systems (HIHPS) MRP or JIT/kanban are used exclusively on certain stages of the production line. In most cases, MRP is used to manage the first stages whereas JIT/kanban is used for the final stages.
HPF - Highest priority first dispatching rule	Dispatching rule that chooses jobs depending on their priority. In JIT/kanban systems, greater priority is assigned to jobs with the higher pull frequency.
HPF/Late - Highest priority first/ Late dispatching rule	In the HPF/Late dispatching rule, the HPF rule is applied as long as all jobs in the queue are not late (negative lateness). Otherwise, priority is allocated according to the amount of lateness of the jobs (Lee 1987).
Inventory control method - (q, r)	Inventory control method that orders the order quantity q every time the current level drops below the reorder point r. The inventory levels are reviewed continually (Klose and Tüshaus 1994, Hopp and Spearman 2000).

Inventory control method - (s, S)	Inventory control method that increases the inventory level to S every time the current level drops below the safety stock level s. The inventory levels are reviewed only periodically (Klose and Tüshaus 1994).
Inventory control method - Basestock	Inventory control method that increases the inventory level in every review period to the level S (Klose and Tüshaus 1994).
Inventory Control MPC method	Inventory control MPC methods are focused on optimizing the inventory control variables such as the order quantity *q* or the safety stock *ss* with the objective to minimize holding, order and backorder costs.
Inventory turnover	Ratio between the (annual) sales or demand of an item and its average inventory level.
JIT - Just-in-time	The Just-in-time (JIT) MPC method is based on a philosophy of continuos reduction of perturbations and waste. JIT MPC systems are thus often characterized by small production lot sizes and setups, a continuos quality control concept, flexible workforce and simplified and/or modularized products (Ohno 1988, Golhar and Stamm 1991, Vollmann et al. 1997, Hopp and Spearman 2000).
JIT/kanban	The production in a JIT MPC system is generally controlled and triggered by cards called kanbans, that circulate between production stages (Schonberger 1983, Vollmann et al. 1997).
Lateness	The amount of time by which the completion time of a job exceeds its due date. Lateness may be negative, indicating an early completion.
LFL - Lot-for-Lot lot-sizing rule	Lot-sizing rule where the order quantity is equal to the requirement.
Load-oriented manufacturing control	MPC method that is based on the concept of controlling the production by limiting the work in process (Wiehndahl 1995, Nyhuis and Wiendahl 1999).
LPT - Longest process time dispatching rule	Dispatching rule that allocates priority to jobs with the longest operation time.
lt - Lead time	A span of time required to perform an activity. Lead times are typically performed in MRP systems to estimate the time an order needs to be fulfilled.
LTC - Least total cost lot-sizing rule	Lot-sizing rule that chooses order quantities for which the inventory holding and ordering costs are most nearly equal.
LUC - Least unit cost lot-sizing rule	Lot-sizing rule that chooses order quantity for which the sum of the inventory holding and ordering costs divided by the number of units in the lot size is lowest.

MOM - McLaren's order moment lot-sizing rule	Lot-sizing rule that determines the lot size by matching the number of accumulated part periods to the number that would be incurred if an order for an EOQ were placed under conditions of constant demand.
MPC - Hybrid manufacturing planning & control methods	Hybrid manufacturing planning & control (MPC) methods are based on concepts that combine classical MPC methods like MRP or JIT/kanban
MPC - Manufacturing planning & control system or method	A manufacturing planning & control (MPC) system addresses the issue of planning and controlling the manufacturing process including materials, machines, people and suppliers (Vollmann et al. 1997).
MPS - Master production schedule	The anticipated build schedule for final products or major components. A master production schedule takes into account the forecast, the production plan, the backlog and the availability of human and technical resources.
MPS tardiness - Master production schedule tardiness	MPS tardiness is equal the effective completion time minus the due date (defined in the MPS) if this value is positive, and zero otherwise
MRP - Material Requirement Planning	Material Requirement Planning (MRP) is a widely used MPC method that performs that task of production planning & control based on the actual and forecasted demand, the inventory levels and the product structure (Orlicky 1975, Vollmann et al. 1997, Hopp and Spearman 2000).
MRP backflushing	Backflushing is the automatic registration of standard quantities of resources (material, labour, machine time and tooling) allowed for performing some or all of the operations for a particular manufacturing order, after the order has been completed (Vollmann et al. 1997).
MRP phantom items	Phantoms are items on the bill of material for which no manufacturing orders or purchase orders will be generated. That is, MRP does not generate requirements for phantom items and phantom items cannot have inventories (Vollmann et al. 1997).
MTO - Make-to-order manufacturing environment	In a MTO manufacturing environment, products are fabricated after receipt of a customer order.
MTS - Make-to-stock manufacturing environment	In a MTS manufacturing environment, products are shipped from stock. Products are, therefore, fabricated prior to customer orders arriving.
Order penetration point	Point in the production line where a product is assigned to a specific customer.
Pareto's Law (80-20 rule)	A concept developed by the Italian economist Vilfredo Pareto, which states that a small percentage of a group accounts for the largest fraction of the impact, value, etc.

PIHPS - Parallel integrated hybrid production systems	In parallel integrates hybrid production systems, production is managed by MRP and JIT/kanban in parallel.
Planning horizon	The span of time from the current to some future point for which plans are generated.
POLCA - Paired-cell Overlapping Loops of Cards with Authorization	Hybrid MPC method that combines MRP and generic kanban loops (Suri 1998). Its approach is comparable to those of the CONWIP MPC method.
POQ - Periodic order quantity lot-sizing rule	Lot-sizing rule that generates orders only at intervals defined by an economic time between orders (TBO). TBO that is computed by dividing the economic order quantity (EOQ) by the mean demand rate.
PPB - Part period balancing lot-sizing rule	Lot-sizing rule that generates an approximative solution of the Wagner-Whitin model.
Product criticality	Product criticality is proportional to the number of final products in which the component is used
QT - Queue time	The (average) time queue time of a job at one production stage.
ROP - Reorder point system	General term for inventory control systems that generate replenishment orders as soon as the inventory level is below a certain limit.
Service level	Ratio of fulfilled orders
Setup	The process of preparing a machine in order to produce a new part or product.
SM - Silver-Meal lot-sizing rule	Lot-sizing rule that generates an approximative solution of the Wagner-Whitin model (Silver and Meal 1973, Vollmann et al. 1997).
SPT - Shortest process time dispatching rule	Dispatching rule that allocates priority to jobs with the shortest operation time. This rule is also known as Shortest imminent operation (SI) dispatching rule (Blackstone et al. 1982).
SPT/Late - Shortest process time/ late dispatching rule	In the SPT/Late dispatching rule, the SPT rule is applied as long as all jobs in the queue are not late (negative lateness). Otherwise, priority is allocated according to the amount of lateness of the jobs (Lee 1987).
Tardiness	Tardiness is equal the completion time minus the due date if this value is positive, and zero otherwise.
TBO - Economic time between two orders	An economic time between orders (*TBO*) that is computed by dividing the economic order quantity (*EOQ*) by the mean demand rate. *TBO* is often used to express the cost structure of a product (Vollmann et al. 1997).
TH - Throughput	Output of a production process per time unit.

Time bucket	In MRP systems, all time-phased data are accumulated into time periods or “buckets”.
TP - Process time	Average process time of one job including setups.
Utilization	Utilization is the ratio of the direct time charged for production activities (setup and processing time) to the clock time scheduled to be available for a given period of time (System load *sysint*).
VIHPS - Vertically integrated hybrid production systems	In vertically integrated hybrid production systems (VIHPS) MRP is used for the production planning and JIT/kanban for the production control.
WIP - Work-in-process	Inventory between the start and end points of a routing. There exists two definitions for WIP: (1) WIP = number of orders [-], (2) WIP = work-content [time unit].
WW - Wagner-Within lot-sizing rule	Lot-sizing rule that represents the exact solution for the dynamic lot-sizing problem (Wagner and Whitin 1958, Vollmann et al. 1997).

Appendix A

The following expressions were used to validate the results of the Markovian model presented in §3. They have been developed by Gross and Harris (1998) and are valid for single-stage, two-item production systems with 2 service rates and non-preemptive priority rules.

The first expression for the expected number of items in the queue L_q has been obtained for the model where A-items (arrival rate λ_A, service rate μ_A) have a higher priority than B-items (arrival rate λ_B, service rate μ_B).

$$L_{qA} = \frac{\lambda_A \hat{\rho}}{\mu_A} \frac{\lambda_A/\lambda + (\lambda_B/\lambda)(\mu_A^2/\mu_B^2)}{1 - \lambda_A/\mu_A},$$

$$L_{qB} = \frac{(\lambda_B/\mu_A)\hat{\rho}}{1 - \lambda_A/\mu_A} \frac{\lambda_A/\lambda + (\lambda_B/\lambda)(\mu_A^2/\mu_B^2)}{1 - \lambda_A/\mu_A - \lambda_B/\mu_B}$$

with

$$\hat{\rho} = \frac{\lambda}{\mu_A} \quad \text{and} \quad \lambda = \lambda_A + \lambda_B$$

The second expression for the expected number of items in the queue Lq has been obtained for the model without priority rules. Thus, A-items are not served in this model ahead of the B-items.

$$L_{qA} = \frac{\lambda_A \hat{\rho}}{\mu_A} \frac{1 - (1 - \mu_A/\mu_B)(\lambda_B/\mu_B)}{1 - \lambda_A/\mu_A - \lambda_B/\mu_B},$$

$$L_{qB} = \frac{\lambda_B \hat{\rho}}{\mu_A} \frac{\mu_A^2/\mu_B^2 + (1 - \mu_A/\mu_B)(\lambda_A/\mu_B)}{1 - \lambda_A/\mu_A - \lambda_B/\mu_B}.$$

Appendix B

The flow chart and the simplified UML-class diagram of the simulator are shown in Figures B.1 and B.2. They show that the main tasks of the simulator are *Loading Configuration File*, *Building Simulation Model*, *Configuration of Simulation Model according to Experimental Design Point* and *Simulation and Printing of Results*. These tasks are performed by the following objects:

- *Loading Configuration File*: This task is performed by the *ModelBuilder* object that reads in the XML configuration file (Appendix C) of the simulator;
- *Building Simulation Model*: The same *ModelBuilder* object generates based on the configuration data the different simulation objects. These are the objects *SystemLoad*, *SimPilot* and *Manufacturing-Center*. Depending on the MPC method configuration, the following objects are added: *MRP*, *Final-GoodsInventory* and/or *InventoryControl*;
- *Configuration of Simulation Model according to Experimental Design*: The different simulation objects are configured according to the design point of the experimental design in the *ModelBuilder* object;
- *Simulation and Printing of Results*: The most important objects beside the above mentioned objects during the simulation are the *DispatchQueue*, *Task* and *SimPilot* objects. The *DispatchQueue* object keeps track of all future discrete events and sorts and dispatches them with respect to the event dispatch time. The *Task* objects perform the processing of the production orders according to the configuration of the MPC methods. The tasks related to the configuration, running and printing of results are performed by the *SimPilot* object. This object also manages the reconfiguration logic with respect to the replications (print results, reset performance metrics and setting new seeds for random number generators) and configurations according to the experimental design points (print results, reset

performance metrics, setting new seed for random number generators and reconfiguration of simulation objects according to experimental design point definition).

Figure B.1 Flow chart of simulation model

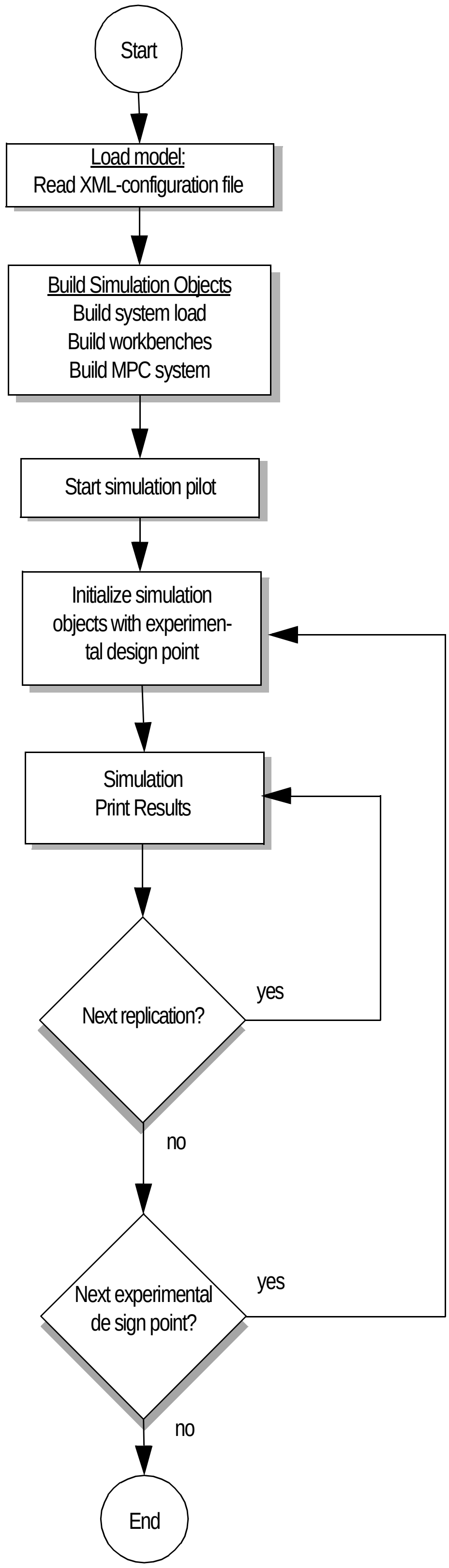
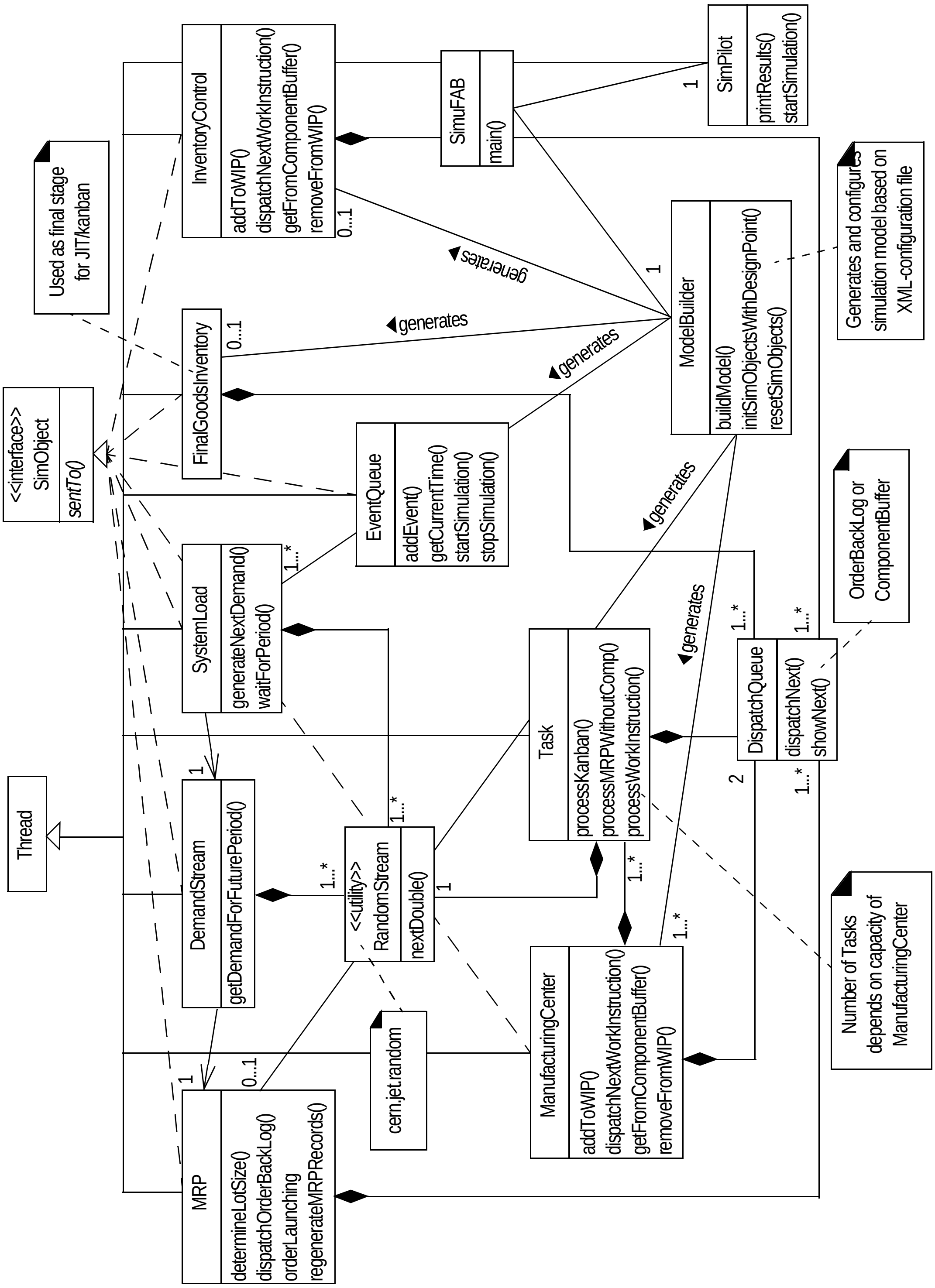


Figure B.2 Simplified UML-class-diagramm of simulator



Appendix C

This appendix shows the content of the XML-configuration file used for the experiment F1 (robustness of DSSPL_MRP).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<!--=========================================================================-->
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     <modelversion version="V1"/>
     <date day="03.9.2002"/>
     <username name="Christoph Hachen"/>
     <info text="Base scenario 01 (breadth = 1, commonality = 1, DSSPL_MRP"/>
   </siminfo>

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<!--                       Model definition                                 -->
<!--========================================================================-->
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    <meanval itemref="enditem0.08" val="10"/>
    <meanval itemref="enditem0.09" val="10"/>
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    <meanval itemref="enditem0.02" val="25"/>
    <meanval itemref="enditem0.03" val="25"/>
    <meanval itemref="enditem0.04" val="20"/>
    <meanval itemref="enditem0.05" val="20"/>
    <meanval itemref="enditem0.06" val="20"/>
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    <statlaw itemref="enditem0.09" law="Gamma"/>
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  <routing machineref="Workcenter1" itemgroupref="level1comp"/>
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level="default"/>
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level="level02"/>
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level="level03"/>
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<!--======================================================================-->
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  <lotsizingdef>
    <lotsizingdefED level="default" type="fixedorderquantity" p1="170" p2="0"/>
  </lotsizingdef>
  <stockdef>
    <stockdefED level="default" safetystock="0"  initstock="100"/>
  </stockdef>
</mrpdef>
<mrpdef itemgroupref="BZgroup">
  <leadtimedef>
    <leadtimedefED level="default" leadtime="2" safetyleadtime="0"/>
  </leadtimedef>
  <lotsizingdef>
    <lotsizingdefED level="default" type="fixedorderquantity" p1="150" p2="0"/>
  </lotsizingdef>
  <stockdef>
    <stockdefED level="default" safetystock="0"  initstock="100"/>
  </stockdef>
</mrpdef>
<mrpdef itemgroupref="BZgroupraw">
  <leadtimedef>
    <leadtimedefED level="default" leadtime="2" safetyleadtime="0"/>
  </leadtimedef>
  <lotsizingdef>
    <lotsizingdefED level="default" type="fixedorderquantity" p1="150" p2="0"/>
  </lotsizingdef>
  <stockdef>
    <stockdefED level="default" safetystock="0"  initstock="100"/>
  </stockdef>
</mrpdef>
<mrpdef itemgroupref="CXgroup">
  <leadtimedef>
    <leadtimedefED level="default" leadtime="2" safetyleadtime="0"/>
  </leadtimedef>
  <lotsizingdef>
    <lotsizingdefED level="default" type="fixedorderquantity" p1="140" p2="0"/>
  </lotsizingdef>
  <stockdef>
    <stockdefED level="default" safetystock="0"   initstock="100"/>
  </stockdef>
</mrpdef>
<mrpdef itemgroupref="CXgroupraw">
  <leadtimedef>
    <leadtimedefED level="default" leadtime="2" safetyleadtime="0"/>
  </leadtimedef>
  <lotsizingdef>
```

```
    <lotsizingdefED level="default" type="fixedorderquantity" p1="140" p2="0"/>
   </lotsizingdef>
   <stockdef>
    <stockdefED level="default" safetystock="0"   initstock="100"/>
   </stockdef>
  </mrpdef>
  <mrpdef itemgroupref="CYgroup">
   <leadtimedef>
    <leadtimedefED level="default" leadtime="2" safetyleadtime="0"/>
   </leadtimedef>
   <lotsizingdef>
    <lotsizingdefED level="default" type="fixedorderquantity" p1="100" p2="0"/>
   </lotsizingdef>
   <stockdef>
    <stockdefED level="default" safetystock="0"  initstock="100"/>
   </stockdef>
  </mrpdef>
  <mrpdef itemgroupref="CYgroupraw">
   <leadtimedef>
    <leadtimedefED level="default" leadtime="2" safetyleadtime="0"/>
   </leadtimedef>
   <lotsizingdef>
    <lotsizingdefED level="default" type="fixedorderquantity" p1="100" p2="0"/>
   </lotsizingdef>
   <stockdef>
    <stockdefED level="default" safetystock="0"  initstock="100"/>
   </stockdef>
  </mrpdef>
  <mrpdef itemgroupref="CZgroup">
   <leadtimedef>
    <leadtimedefED level="default" leadtime="2" safetyleadtime="0"/>
   </leadtimedef>
   <lotsizingdef>
    <lotsizingdefED level="default" type="fixedorderquantity" p1="50" p2="0"/>
   </lotsizingdef>
   <stockdef>
    <stockdefED level="default" safetystock="0"   initstock="100"/>
   </stockdef>
  </mrpdef>
  <mrpdef itemgroupref="CZgroupraw">
   <leadtimedef>
    <leadtimedefED level="default" leadtime="2" safetyleadtime="0"/>
   </leadtimedef>
   <lotsizingdef>
    <lotsizingdefED level="default" type="fixedorderquantity" p1="50" p2="0"/>
   </lotsizingdef>
   <stockdef>
    <stockdefED level="default" safetystock="0"   initstock="100"/>
   </stockdef>
  </mrpdef>
  </mrp>
  <!--                        JIT/Kanban                                           -->
  <jitkanban>
  <loopdef itemref="enditem0.01" source="Workcenter0" target="FGI">
   <loopdefED level="default" nmbkanbans="4"  capacity="140" leadtime="960"/>
  </loopdef>
  <loopdef itemref="comp1.01" source="Workcenter1" target="Workcenter0">
   <loopdefED level="default" nmbkanbans="4"  capacity="140" leadtime="960"/>
  </loopdef>
  <loopdef itemref="comp2.01" source="Workcenter2" target="Workcenter1">
   <loopdefED level="default" nmbkanbans="4"  capacity="140"  leadtime="960"/>
  </loopdef>
  <loopdef itemref="comp3.01" source="Supplier3" target="Workcenter2">
```

```
        <loopdefED level="default" nmbkanbans="4"  capacity="140"  leadtime="960"/>
      </loopdef>
      <loopdef itemref="enditem0.02" source="Workcenter0" target="FGI">
        <loopdefED level="default" nmbkanbans="4"  capacity="100" leadtime="960"/>
      </loopdef>
      <loopdef itemref="comp1.02" source="Workcenter1" target="Workcenter0">
        <loopdefED level="default" nmbkanbans="4"  capacity="100" leadtime="960"/>
      </loopdef>
      <loopdef itemref="comp2.02" source="Workcenter2" target="Workcenter1">
        <loopdefED level="default" nmbkanbans="4"  capacity="100" leadtime="960"/>
      </loopdef>
      <loopdef itemref="comp3.02" source="Supplier3" target="Workcenter2">
        <loopdefED level="default" nmbkanbans="4"  capacity="100" leadtime="960"/>
      </loopdef>
      <loopdef itemref="enditem0.04" source="Workcenter0" target="FGI">
        <loopdefED level="default" nmbkanbans="4"  capacity="80" leadtime="960"/>
      </loopdef>
      <loopdef itemref="comp1.04" source="Workcenter1" target="Workcenter0">
        <loopdefED level="default" nmbkanbans="4"  capacity="80" leadtime="960"/>
      </loopdef>
      <loopdef itemref="comp2.04" source="Workcenter2" target="Workcenter1">
        <loopdefED level="default" nmbkanbans="4"  capacity="80"  leadtime="960"/>
      </loopdef>
      <loopdef itemref="comp3.04" source="Supplier3" target="Workcenter2">
        <loopdefED level="default" nmbkanbans="4"  capacity="80"  leadtime="960"/>
      </loopdef>
      </jitkanban>
<!--                      DSSPL                                               -->
      <dsspl>
        <aitems itemgroupref="aitems"/>
        <bitems itemgroupref="bitems"/>
      </dsspl>
<!--                      DispatchRule                                         -->
      <pccmachinedispatch>
      <machinedispatchdef machinegroupref="allmachines">
            <machinedispatchdefED level="default" dispatchrule="QOMP" p1="0.1" p2="960"/>
            </machinedispatchdef>
      </pccmachinedispatch>
     </ppcrules>
   </modeldefinition>
<!--========================================================================-->
<!--                       Simulation control                            -->
<!--========================================================================-->
   <simcontrol>
     <simlength val="1000000"/>
     <warmup val="300000"/>
     <stoponconv val="false"/>
     <timebucket val="480"/>
   </simcontrol>
<!--========================================================================-->
<!--                       Experimental design                           -->
<!--========================================================================-->
   <experimentaldesign type="MonteCarlo" pcctype="DSSPL_MRP"  defaultlevel="default" replica-
tions="500" startat="5">
     <factordef type="DemandStream.quanterr"       parameter="allitems">level01;level04</
factordef>
     <factordef type="DemandStream.delayerr"       parameter="allitems">level01;level04</
factordef>
     <factordef type="SystemLoad.demandsizevar"    parameter="allitems">low;high</factordef>
     <factordef type="SystemLoad.interarrivalvar"  parameter="allitems">low;high</factordef>
     <factordef type="SystemLoad.intensity"        parameter="allitems">low;high</factordef>
     <factordef type="Machine.meansetup"           parameter="allmachines">low;high</factordef>
     <factordef type="Machine.proctimevar"         parameter="allmachines">low;high</factordef>
```

```
   </experimentaldesign>
<!--=============================================================================-->
<!--                       Metrics                              -->
<!--=============================================================================-->
   <metrics>
    <metricsdef type="Inventory.meanlevel"   itemgroupref="allitems" output="cumul"/>
    <metricsdef type="Inventory.meancost"    itemgroupref="allitems" output="cumul"/>
    <metricsdef type="ServiceLevel.absolute" itemgroupref="enditems" output="cumul"/>
    <metricsdef type="ServiceLevel.relative" itemgroupref="enditems" output="cumul"/>
   </metrics>
</simfabmodel>
```

Curriculum Vitae

Personal data

Name:	Christoph Hachen
Origin:	Switzerland, Rüeggisberg (BE)
Date of birth:	September 21, 1966

Education

1982 - 1986	Apprenticeship as technical designer at Gfeller AG, Bern
1986 - 1990	Mechanical engineering studies at the Biel School of Engineering and Architecture (HTA Biel)
1990 - 1994	Mechanical engineering studies at the Swiss Federal Institute of Technology in Lausanne (EPFL)

Professional experience

1986 - 1990	Part-time jobs as mechanical designer at Gfeller Automatisation AG, Bern, Autelca AG, Bern, and Vidmar AG, Bern
1992 - 1995	Teacher at the IBZ School of Engineering in *Mathematics*, *Physics* and *Structure mechanics*
1995 - 1997	Teacher at the ABB School of Engineering in *Structure mechanics* and *Mechanical design*
1994 - 1997	Development Engineer in the turbine development department at ABB Power Generation, Baden, Switzerland
1997 -	Research assistant to Prof. R. Glardon, EPFL