COMPARISON OF PUSH AND PULL CONTROL STRATEGIES FOR SUPPLY NETWORK MANAGEMENT IN MAKE-TO-STOCK ENVIRONMENT

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by

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To the Graduate School:

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ABSTRACT

Because operational planning and control (OPC) decisions by one company in a supply network impact decisions at other companies, decisions should not be made independently but should be coordinated. However, there exists little guidance on how to cooperatively plan and control inter-firm operations. More research is needed to examine OPC strategies for integrated planning and control of manufacturing and distribution operations in a supply network.

The primary objective of this study is to explore the performance differences of "push" and "pull" OPC strategies. The pull strategy is more common in current supply networks. The push strategy requires more integrative approach in generating the plans. This project developed a realistic OPC software system and used it to investigate the impact of the push and pull strategies on total inventory, throughput, and customer service level under different environmental conditions (forecast error and levels of inventory buffer) in a make-to-stock environment.

The results suggest that control strategy, forecast error, and levels of inventory buffer all significantly affect each of the performance measures. Under all combinations of different conditions of inventory buffer level and forecast error, push outperforms pull in terms of throughput and customer service level while pull outperforms push in term of total inventory. In terms of throughput and customer service level, push is more sensitive to forecast error but less sensitive to levels of inventory buffer than pull.

DEDICATION

I affectionately dedicate this dissertation to my wife, my parents, and my brother, whose love and support have been indispensable components of my successes.

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CHAPTER 1

INTRODUCTION

Problem Statement

Supply chain management has recently become an essential management concept (Davis 1993; Johnson and Davis 1995; Walton and Marucheck 1997; Mabert and Venkataramanan 1998; Lambert and Cooper 2000; Lancioni 2000). Hundreds of researchers have conducted various studies addressing a range of issues in supply chain management (Mabert and Venkataramanan 1998). These studies have demonstrated that companies can benefit from supply chain management. However, most prior studies only considered linear supply chains. Often, business entities are linked together as a network rather than a linear chain. A supply network is a network of autonomous or semi-autonomous business entities that cooperatively (according to global formal agreements) perform different processes and activities providing products or service to customers (Lee and Billington 1993; Lin and Shaw 1998; Mabert and Venkataramanan 1998). There still exists little guidance to companies on how to manage inter-firm operations in a supply network. Mabert and Venkataramanan (1998) reviewed the literature and found that only the surface of the supply network management (SNM) domain has been addressed. More research is needed to investigate numerous issues of SNM.

This research addresses one of the central issues of SNM, planning and control of the operations of a supply network. Since production planning and control decisions at one entity in a supply network impact decisions at other entities, decisions at each entity should not be made independently (Lee and Billington 1992). To maximize global performance of a supply network, firms should coordinate their planning and control activities (Lee and Billington 1992; Mabert and Venkataramanan 1998; Simchi-Levi, Kaminsky, and Simchi-Levi 2000, p. 10; Lambert and Copper 2000). The success of a supply network depends greatly on the extent of the coordination (Lambert and Copper 2000). The traditional manufacturing planning and control (MPC) systems considering the operations of a single organization have to be extended to support coordination of the planning and control activities in a supply network. When so extended, such systems are called "operational planning and control" (OPC) systems.

Several studies have visualized the architecture and management concepts of the OPC systems. The well-accepted approach consists of a central planning module coordinating with the local planning modules (Rupp and Ristic 2000; Klen et al. 2001; Sadeh et al. 2001). Nevertheless, the systems using this approach have different detailed architecture and management concepts. In addition to the diverse supporting infrastructures, the main differences between these systems are the planning and control algorithms used in the planning modules as well as the extents of the coordination between the central module and the local ones.

None of these studies paid much attention to strategies for planning and control of the operations of a supply network. These studies emphasized the algorithms and coordination mechanisms used to plan the network capacity. However, a proper planning and control strategy is as crucial as effective capacity management. According to the literature, push and pull strategies are typically employed to drive the operations in a supply network and determine when the components or products are required at each facility. These requirements in turn establish the constraints for the capacity planning.

Despite the significance of the planning and control strategies, little is known about how well these strategies perform. No prior research compares the performance differences of these strategies in a supply network, but such research is needed.

Prior studies also have not focused on the OPC systems for make-to-stock (MTS) environment. Most studies were interested in developing the OPC systems for make-to-order (MTO) environment and de-emphasized the issues of inventory and demand forecast. However, in a MTS environment, considering inventory and demand forecast is essential. It is well known that, in a MTS environment, the issues of inventory and demand forecast such as inventory buffer level and forecast error have significant impact on plant performance and affect the relationship between control strategy and plant performance (Krajewski et al. 1987; Rees, Huang, and Taylor 1989; Sarker 1989; Bonney et al. 1999; Grosfeld-Nir, Magazine, and Venberkel 2000; Taylor 2000). But their impacts in the supply network level have not been investigated.

Inventory buffer level is the target level of safety stocks at each firm in a supply network. For each safety stock, if the inventory level goes below the target level, the stock will be replenished to keep the target level. Forecast error is the difference between the actual demand and demand forecast (Finch and Luebbe 1995). A control strategy may work better than another strategy in one setting of inventory buffer level and forecast error but may work worse than the same strategy in another setting. More research is needed to investigate the impact of the control strategy on the performance of a MTS supply network under different settings of inventory buffer level and forecast error.

Research Objectives

The primary objective of this study is to determine the impact of OPC strategies (push and pull) on supply network performance under different settings of inventory buffer level and forecast error in MTS environment. Since the development of OPC systems is in its early stage, this study doesn't try to compare the performances of different designs of OPC systems. Instead, this study tries to address the significant issues ignored by other studies about OPC systems. Also, this study does not compare performance of an OPC system with other management schemes, such as those currently popular. Many research projects have already confirmed that coordinating planning and control of supply network operations can enhance the supply network performance (Lee and Billington 1992; Mabert and Venkataramanan 1998; Lambert and Copper 2000; Simchi-Levi, Kaminsky, and Simchi-Levi 2000, p. 10), but the question remains, which strategy works best?

The second objective is to design an OPC system for integrated planning and control of manufacturing and distribution operations in a supply network. The study develops an OPC system for MTS environment that considers inventory and demand forecast in planning processes. The system is designed using modern technologies (object-oriented design, distributing computing, and Internet). The design focuses on the modularity and reusability of the system. To support the main objective the design is implemented in software. This software provides a foundation for simulations to investigate the research questions.

Research Questions

According to the problem statement and research objectives described earlier, the following research questions are investigated in this study.

1. How is supply network performance affected by push and pull control strategies?
2. How is the relationship between the types of planning and control strategies and supply network performance moderated by inventory buffer level?
3. How is the relationship between the types of planning and control strategies and supply network performance moderated by forecast error?

Scope of the Study

This study focuses on the planning and control of the ordering, production and distribution operations of a supply network in MTS environment. Planning and control of these operations involve various decisions at different phases. This study primarily concentrates on material flow planning. In this phase, supply network configurations such as plant locations, warehouse locations, and transportation modes, are already determined. Generally, the time horizon of the plans in this phase is weekly or daily. Primary planning activity of this phase is generating a range of time-phased schedules such as production requirements, material from suppliers through in-bound logistics, and distribution-shipping schedules (Chopra and Meindl 2001).

A simulation model of an apparel supply network is used to examine the research questions of this study. In a MTS environment, a supply network has to produce the products according to the forecasts of the future product demands. Normally, customers' orders are satisfied using the products in inventory stocks at retailers. An apparel supply network is a good representation for supply networks in this environment. The results of this study should be germane to other MTS supply networks that have similar network structures to those of apparel supply networks.

In this study, only retailers, the entities at the first tier of a supply network, have independent demands while other entities have dependent demands. Independent demands are determined by the market whereas dependent demands can be calculated from independent demands of retailers (Finch and Luebbe 1995, p. 408-410).

The level of cooperation distinguishes the types of supply networks. This research addresses supply networks comprising of a set of highly cooperating and coordinating business entities of mixed ownership, that act like a single company to achieve common goals (Rupp and Ristic 2000; Klen et al. 2001; Sadeh et al. 2001). Generally this type of supply network has a single coordinator that generates global plans to accomplish best performance of the whole supply network. It is assumed that during the supply network creation phase each entity has formally agreed to operate according to the global plans. In general, the role of this global coordinator is taken by a core company in a supply network or by an external agent specializing in performing this role. It is possible that the entity performing the role of global coordinator may supervise more than one supply network at a time. In this case, this study assumes that each supply network is supervised and operated separately (without coordination between supply networks).

Architecture for OPC System

In this study, the OPC system consists of a central planning module coordinating with the local planning modules. This approach is commonly found in the literature (Rupp and Ristic 2000; Klen et al. 2001; Sadeh et al. 2001). The main differences between this system and the ones described in the literature are the planning and control algorithms used in the planning modules as well as the extent of the coordination between the central module and the local ones. Also this research involves a MTS environment, whereas most prior research addresses a MTO environment.

Figure 1 presents the architecture of the OPC system addressed by this study. Using information collected from business entities and stored in a centralized database, a central planning module coordinates with the local modules to establish plans in the supply network layer. These plans include Master Operations Schedules (MOS) and Detailed Operations Plans (DOP) that determines how much and when to produce or ship the products. The MOS and DOP are generated based on material and demand status of the entire network and are sent to each business entity. In the business entity layer, local planning and control systems in each business entity create the detailed schedules according to the MOS and DOP generated by the OPC system. A business entity can be a manufacturer, a distributor, or a retailer. Each business entity may use different planning tools and philosophies. For example, some business entities may utilize just-in-time (JIT) approach while others may use manufacturing resource planning (MRPII) approach.

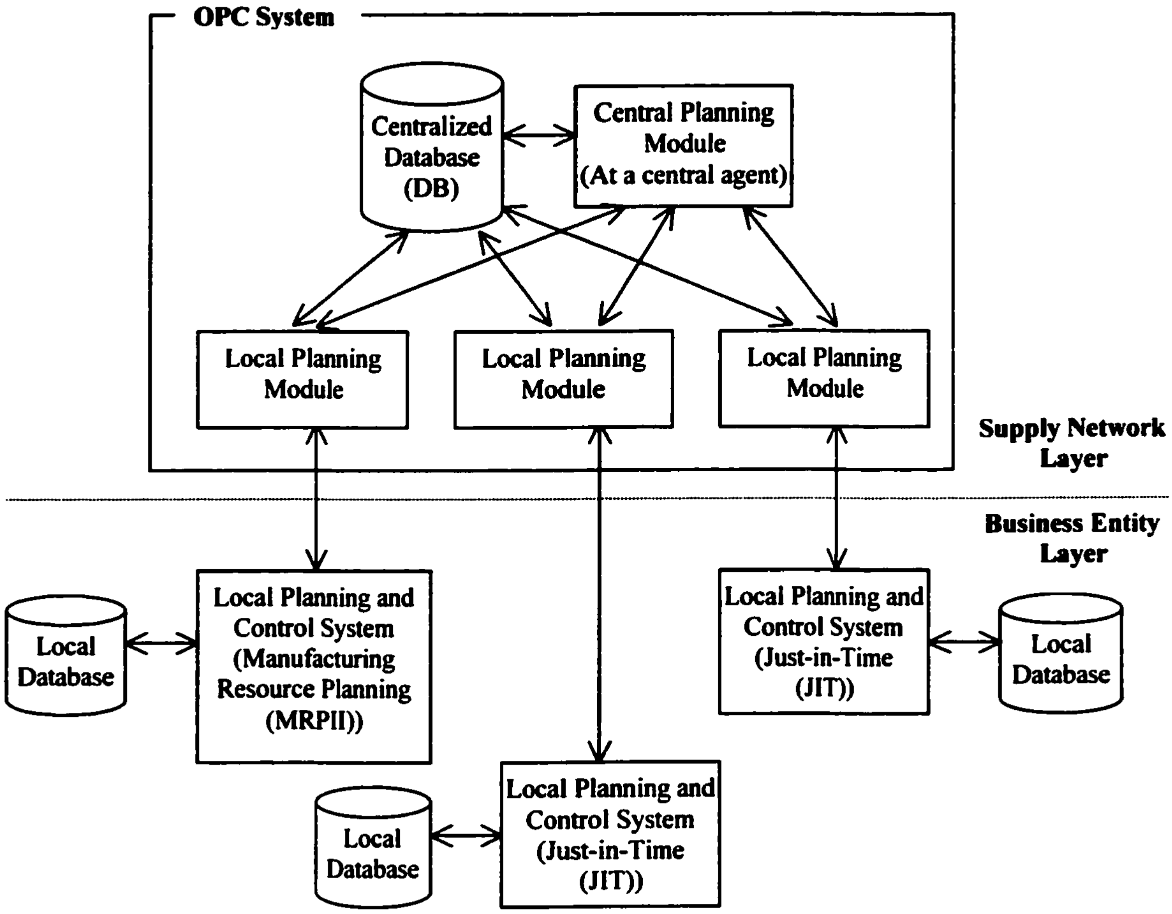


FIGURE 1

The Architecture of OPC System for a Supply Network

This study focuses on the issues in design and development of OPC system. It is assumed that legacy planning systems would continue to be used by each business entity for scheduling and planning in the business entity layer.

Summary of Research Approach

The research approach involves 3 main steps described below.

Step1: The model of OPC system was developed.

Step2: Based on the model developed in step1, the OPC software and simulation modules were implemented.

Step3: Using the software and simulation modules created in step2, the research questions were investigated.

The remainder of this paper is organized as follows. The next chapter reviews the relevant literature. Based upon the literature, a theory of OPC strategy is proposed and expanded. Based on the expanded theory, research hypotheses are developed. Chapter 3 presents the design of an OPC system developed in this research. Chapter 4 describes the research methodology and design of the research experiment. Chapter 5 presents and discusses the results of the research experiment. In Chapter 6, the proposed theory is refined based on the results of the research experiment. Finally this paper provides implications and limitations of this research along with suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the operations management literature relevant to the OPC system and strategy. Two different OPC strategies are identified and a theory of OPC strategy is developed. The theory specifies the relationship between OPC strategies and supply network performance. Then the theory is expanded by including other factors that may alter the impact of OPC strategies on supply network performance. Finally, the appropriate measures of supply network performance are discussed.

Operational Planning and Control System

Planning and control of supply network operations involve various decisions at different phases. Mabert and Venkataramanan (1998) classified the decisions in a supply network into five phases or levels: supply network design, aggregate supply planning, material flow planning, order fulfillment and scheduling/dispatching. Figure 2 demonstrates theses decision phases along with the general time horizon for implementation and the frequency of occurrence. This study primarily concentrates on material flow planning.

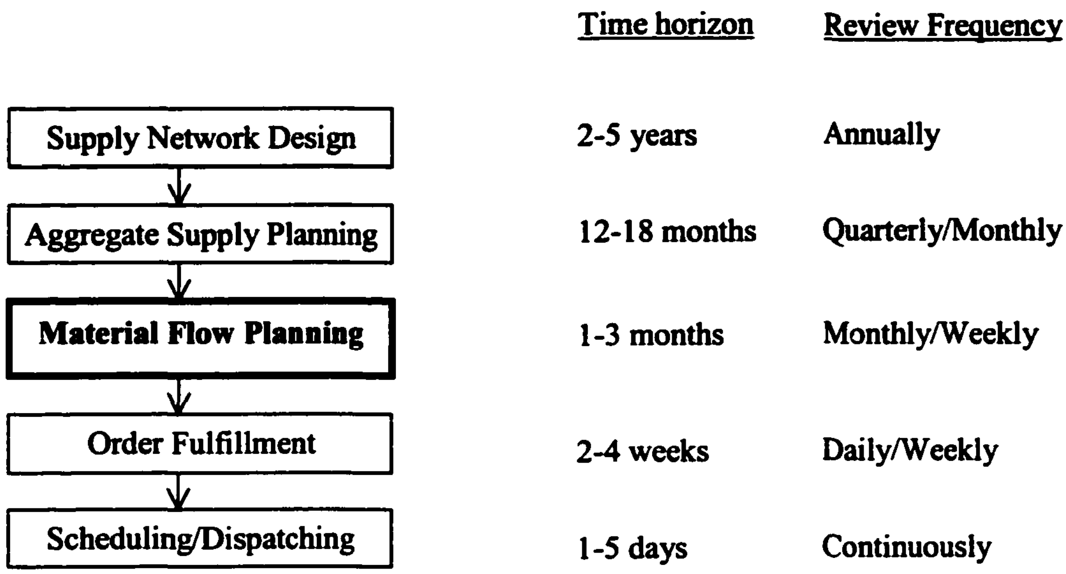


FIGURE 2

Decision Phases in a Supply Network

(Adapted from Mabert and Venkataramanan 1998)

In the Supply Network Design phase, supply network configurations such as plant locations, warehouse locations, and transportation modes are determined. Aggregate Supply Planning establishes annual business plans for resource allocation at each stage (Mabert and Venkataramanan 1998). In the Material Flow Planning phase, the primary planning activity is generating a range of time-phased schedules for production requirements, material from suppliers through in-bound logistics, and distribution-shipping schedules (Chopra and Meindl 2001). Generally, the time horizon of the plans in this phase is weekly or daily. An OPC system generates operational plans in the Material Flow Planning phase.

An OPC system extends the traditional MPC system. It integrates planning and control activities in a supply network. Several studies have designed and developed the OPC systems. Rupp and Ristic (2000) presented X-CITTIC system, which was a part of the ESPRIT project. X-CITTIC is an OPC system for semiconductor manufacturing supply networks in which the products are customized and made to order. It consists of five modules, Order Promise, Rough Planner, Fine Planner, Reactive Controller, and Information Manager. The Rough Planner and the Fine Planner generate operational plans for a supply network. Using distributed planning methodology, the Fine Planner optimizes order flow through a supply network by considering the rough due dates taken from the Rough Planner. The Rough Planner establishes the rough due dates based on capacity models of the local manufacturing units.

Sadeh et al. (2001) developed MASCOT (Multi-Agent Supply Chain cOordination Tool). This tool is based on a reconfigurable, multilevel, agent-based architecture for coordinated supply network planning. The architecture employs a customizable mixed-initiative agent wrapper. The lower-level agents are wrappers for planning and scheduling modules supporting single facilities while the higher-level agents are coordination wrappers for tactical and strategic planning and scheduling modules supporting multiple facilities. There exist three types of coordination protocols, high-level lateral coordination protocols supporting the interactions between higher-level agents, low-level lateral coordination protocols supporting the interactions between lower-level agents, and vertical coordination protocols supporting the interactions between high-level agents and lower-level agents. The study indicated that the proposed finite capacity coordination protocols could significantly improve supply network performance.

Klen et al. described the overview of DBPMS (Distributed Business Process Management System) developed under the PRODNET-II project. DBPMS provides reliable and timely production-related information about a supply network and supports the coordination between business entities in a supply network. In a supply network or a virtual enterprise (VE), a DBPMS is installed at the supply network or VE coordinator. Also, a minimal set of DBPMS services is placed at each member of the supply network or VE. These DBPMSs support rapid decision-making facilitating the coordination in the supply network or VE. A DBPMS comprises four main modules, VE supervisor, Decision Support System (DSS), Supervision Clause Configuration, and Interoperation. VE supervisor monitors the distributed business processes execution of a VE or a supply network. DSS assists the users in making a decision about a conflict in the supply network based on the information received by the VE supervisor. Supervision Clause Configuration specifies the rights and duties of the coordinator and members of a given supply network. Interoperation coordinates the DBPMS and the other modules.

These studies about the OPC system used a similar approach consisting of a central planning module coordinating with the local planning modules (Rupp and Ristic 2000; Klen et al. 2001; Sadeh et al. 2001). Nevertheless, these systems had different detailed architectures and management concepts. In addition to the diverse supporting infrastructures, the main differences between these systems were the planning and control algorithms used in the planning modules as well as the extents of the coordination between the central module and the local ones.

None of above studies had paid much attention to strategies for planning and control of the operations of a supply network. All of them emphasized the algorithms and coordination mechanisms used to plan the network capacity. Additionally, none of them concentrated on developing OPC systems for a make-to-stock (MTS) environment. Rupp and Ristic (2000) and Sadeh et al. (2001) focused on developing OPC systems for make-to-order (MTO) environment.

Operational Planning and Control Strategies

Two strategies commonly appear in the management literature, "push" and "pull" but authors use different definitions (Sarker and Fitzsimmons 1989; Hopp and Spearman 1996; Venkatesh et al. 1996; Bonney et al. 1999; Grosfeld-Nir, Magazine and Vanberkel 2000).

Two textbooks provided similar definitions for push and pull supply networks (Simchi-Levi, Kaminsky and Simchi-Levi 2000; Chopra and Meindl 2001). In a push-based supply network, production decisions are based on long-term forecasts of customer orders. On the other hand, in a pull-based supply network, production decisions are based on actual customer orders rather than forecasts. Furthermore, both books described that in some cases, it is possible to use push strategy to run part of a supply network and use pull strategy to run the rest of it. This is called a hybrid supply network. The push/pull boundary separates push-based stages from pull-based stages in a supply network. However, these definitions are not used in this research because, in both push and pull systems, production decisions can be made based on forecasts.

Although these two textbooks discussed performance differences between push and pull based supply networks, the authors of these books did not conduct any systematic research to verify their explanations about the performance differences between the different strategies. Thus, more research is needed to investigate OPC strategies in a supply network.

Various studies addressed the strategies used to plan and control a multistage production system in a factory. These strategies in the factory level can be adapted to use at the supply network level. Each business entity in a supply network can be considered a work center in a factory. A business entity in a supply network produces the components of a final product of a supply network while a work center produces the components of a final product of a factory.

Studies in the factory level used different definitions of OPC strategies. Some of these definitions distinguished push and pull by the information used to initiate the production. Push means to take action based on forecast or anticipation of a need, pull means to take action based on request or actual customer order (Goddard and Brooks 1984; Siha and David 1994). Other definitions were based on system status (Hopp and Spearman 1996), inventory replenishment (Lee 1989; BS 5192 1993), lead-time (BS 5192 1993), or lean production (Villa and Watanabe 1993). This study uses the definitions found in American Production and Inventory Control Society Dictionary (APICS 1998, p. 77-78).

The APICS dictionary defines a push system as: "1) In production, the production of items at times required by a given schedule planned in advance. 2) In material control, the issuing of material according to a given schedule or issuing material to a job order at its start time."

The APICS dictionary defines a pull system as: "1) In production, the production of items only as demanded for use or to replace those taken for use. 2) In material control, the withdrawal of inventory as demanded by the using operations. Material is not issued until a signal comes from the user."

APICS definitions use mechanism that triggers the flow of materials to describe the differences between push and pull strategies. They are more thorough and less disputable than are other definitions. These definitions were also used in Taylor (2000). Although APICS definitions describe the general differences between the two strategies, it is necessary to define in detail the push and pull systems investigated in this study. Operational definitions of these two systems appear in chapter 4.

Figure 3 illustrates two simple supply networks representing push and pull systems respectively. This study examines the effect of push and pull control strategies on supply network performance.

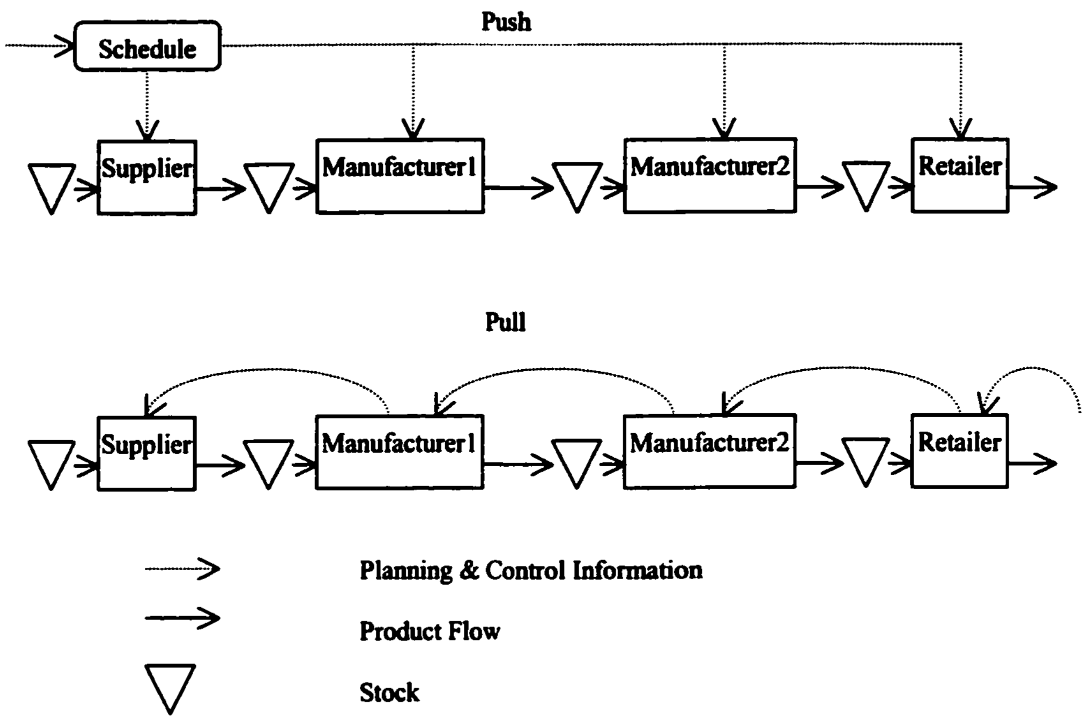


FIGURE 3

Push and Pull Systems

Although the definitions of push and pull strategies in the literature are inconsistent, many definitions use the same concepts to distinguish these strategies. That is, many studies used the mechanism that triggers the flow of materials to describe the differences between push and pull strategies (Lee 1989; Rees, Huang, and Taylor 1989; Sarkar and Fitzsmmons 1989; Spearman, Woodruff, and Hopp 1990; Spearman and Zazanis 1992; Wainwright, Harrison, and Leonard 1993; Hopp and Spearman 1996; Venkatesh, Zhou, and Kaighobadi 1996; Vollmann, Berry, and Whybark 1997; APICS 1998, p. 77-78; Bonney et al. 1999; Grosfeld-Nir, Magazine and Vanberkel 2000;

Persentili and Alptekin 2000; Taylor 2000). Most of these studies classified material requirement planning (MRP) as push and kanban as pull.

Theoretical Basis for the Study

A just-in-time (JIT) manufacturing system is widely described as a pull system. Its recent success has caused many people believe that pull systems are inherently better than push systems. However, JIT means more than a pull control strategy. It is a philosophy for continuously improving the manufacturing performance including kanban (a pull mechanism or strategy to schedule production) as well as other core components. From reviewing JIT literature and discussion with practitioners during 12 plant visits, Sakakibara, Flynn, and Schroeder (1993) found 16 core JIT components such as pull system support, kanban, setup time reduction, supplier quality level, small lot sizes, equipment layout, and small group problem solving. This study demonstrated that JIT's pull mechanism (kanban) is not the sole factor that contributes to the superior performance of the JIT system. Krejewski et al. (1987) also found that the type of the planning and control strategy used may have less effect on manufacturing performance than the factors in a production environment such as lot sizes and setup times. Hence, more research is needed to investigate the real impact of the control strategy on system performance by controlling other crucial factors in the production environment.

My review of the supply network literature found no investigations of how supply network performance is affected by OPC strategies. However, Bhaskaran (1998) evaluated the impact of the control strategy (kanban or MRP) used by each business entity (not a central agent) in a supply chain on supply chain performance in terms of schedule stability and inventory level. A simulation model based on a stamping pipeline in an automobile supply chain was used to compare kanban and MRP under the assumptions that there were no material shortages on any link in the supply chain. The strategies considered were the cases in which all the business entities in the supply chain used either kanban or MRP. The cases in which some business entities used MRP and some business entities used kanban were not included in the study. The results demonstrated that because MRP makes better use of forecasts, MRP is somewhat better than kanban for inventory control when lead-times are fixed and known. She also pointed out that when choosing between kanban and MRP, the ability of MRP to more effectively use forecasts must be weighted against the kanban system's visual appeal, incentive to reduce lead-time and local operator control.

In literature related to planning and controlling multistage production systems in the factory level, various studies examined the effects of planning and control strategies on system performance. These studies often made different assumptions regarding the production environments in which the studied systems operate. For example, Grosfeld-Nir, Magazine, and Venberkel (2000) observed that in the literature, the comparative analysis of push and pull was further complicated by the different assumptions regarding how raw material arrives at the system. Although comparing results among studies is difficult due to the differences in assumptions, it can lead to a better understanding of the theoretical basis for push and pull strategies.

Hopp and Spearman (1996, p. 316-323) suggested that a pull system outperforms a push system. The main benefit of a pull system is that the maximum amount of inventory in the system is limited. The Work in Process (WIP) level cannot exceed a pre-specified limit. Then they pointed out that in many cases, having limited WIP can reduce manufacturing cost, reduce variability, improve quality, maintain flexibility, and facilitate work ahead. Since a pull system reacts to system status, it may work ahead of schedule when things go well. For example, if WIP falls below the desired level and there exist no machine failures, staffing problems, materials shortages, and so on, it may be able to produce more than it had expected.

Spearman, Woodruff and Hopp (1990), Spearman and Zazanis (1992), and Hopp and Spearman (1996) described a fundamental distinction between push and pull systems:

Push systems control throughput and observe WIP.

Pull systems control WIP and observe throughput.

Spearman and Zazanis (1988) (cited in Spearman, Woodruff, and Hopp 1990) compared two equivalent systems, one a closed queuing network (representing a pull system) and the other an open queuing network (representing a push system) composed of machines with exponential processing times. The throughput of the closed system was set equal to the Poisson input stream in the open system. The results showed that the closed system had less average WIP at every station than the open system. Since both systems had the same average throughput, the one with less average WIP would have less average flow time. This can be explained by using Little's law:

$$\text{Average Flow Time} = \frac{\text{Average WIP}}{\text{Average Throughput}}.$$

Thus, pull systems (closed systems) have the total system WIP and the average flow time less than push systems (open systems). The study also found that the variance of flow time would be less in pull system than in an equivalent push system. Due to lower WIP, flow time means and variances, there is less congestion in pull systems than in push systems. This proposition was supported by a further study using analytical methodology (Spearman and Zazanis 1992). Moreover, a simulation study by Spearman, Woodruff and Hopp (1990) suggested that pull systems outperform push systems in terms of overall profit.

Using computer simulation, Lee (1989) compared the behavior of JIT pull systems and MRP push systems under various load (demand) conditions. The study found that a JIT system provides better throughput than a MRP system. Nevertheless, MRP results in a higher level of process utilization than JIT due to its high WIP.

Sarker and Fitzsimmons (1989) examined the effects of the variability in the production process on the performance of push and pull systems. The results from the simulation suggested that regardless of the variability in the production process, JIT systems always have less WIP than MRP systems. However, they are less efficient than the push ones, especially when there exists high variability in the production process.

From reviewing above studies, a theory of planning and control strategy is proposed:

> Under high system utilization, a pull system has less average WIP, less average flow time, and more throughput than a push system.

Figure 4 shows the relationship between the constructs in the theory. This theory guides this research project that is intended to clarify the relationship between control strategies and system performance. Previous studies have not provided a consistent explanation of this relationship. Some studies found that in general push systems outperform pull systems (Bonney et al. 1999; Grosfeld-Nir, Magazine, and Vanberkel 2000). Using computer simulation, Bonney et al. (1999) investigated the performance differences of push and pull systems under a range of different conditions. The results suggested that if the batch sizes are the same and orders are released order by order, push systems outperform pull systems whether when demand is backlogged or when no backlogging occurs. The study also found that push systems sometimes need lower stocks than pull systems in order to obtain same performance level.

Grosfeld-Nir, Magazine, and Vanberkel (2000) conducted a comparative analysis of push and pull strategies under random processing times. The results from a computer simulation indicated that push systems often outperform pull systems in terms of work-in-process inventory and throughput. Compared to pull systems, push systems maintain higher throughput with less work-in-process inventory. Furthermore, the study pointed out that push systems perform well if the time intervals of the release of material into the system are deterministic. In pull systems, work-in-process inventory linearly increases in the number of stages and is not affected by the variation of processing times.

The mixed results found in these comparative studies of push and pull strategies may be attributed to the different assumptions and parameters used in the simulations. Furthermore, previous studies have not addressed the performance differences of these strategies when they are used to plan and control the operations in supply network level. The results from this project provide more insight into the comparison of push and pull strategies. Additionally, this project helps to determine whether the existing knowledge about the performance differences of control strategies in the factory level applies to the supply network level.

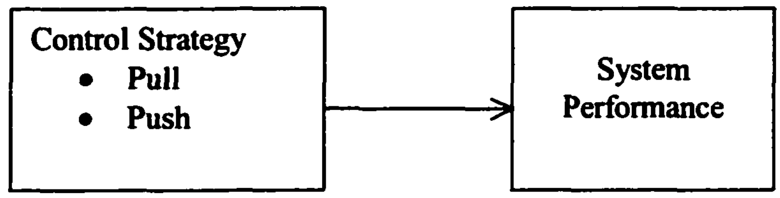


FIGURE 4

A Theory of Planning and Control Strategy

In addition to the inconsistent results among the studies, many studies found that the performance of the control strategy varies depending on other environmental factors such as the variability in the production process, inventory buffer levels, and product flexibility (Krajewski et al. 1987; Rees, Huang, and Taylor 1989; Sarker and Fitzsimmons 1989; Persentili and Alptekin 2000). The control strategy interacts with these factors to impact the system performance. Consequently, the theory has to be expanded by adding other factors in order to explain this more complex relationship between control strategies and system performance.

Theory Expansion

Table I summarizes the environmental factors commonly used in comparative studies of the performances of different control strategies. All factors appear to be theoretically significant. Conceptually, each of them can interact with the control strategy to affect system performance. However, to make the study manageable, only two factors are selected. As cited in Stone (1988, p. 306), Cohen and Cohen (1983) suggested that "Interactions greater than three-way are most difficult to conceptualize, not likely to exist and are costly (in terms of) statistical inference". Since inventory and demand forecast are key issues for the planning and control of the operations in MTS environment, two factors most appropriate for this study are inventory buffer level and forecast error.

TABLE I

Environmental Factors in Prior Research

Factors	Reference
Demand (load) conditions	Lee (1989)
Demand variability	Rees, Huang, and Taylor (1989); Bonney et al. (1999)
Scheduling rules	Krajewski et al. (1987); Lee (1989); Rees, Huang and Taylor (1989); Bonney et al. (1999)
Product flexibility	Krajewski et al. (1987); Persentili and Alptekin (2000)
Processing time	Krajewski et al. (1987); Rees, Huang, and Taylor (1989)
Lot size/batch size	Krajewski et al. (1987); Venkatesh et al. (1996); Bonney et al. (1999)
Setup time	Venkatesh et al. (1996); Bonney et al. (1999)
Variability of processing time	Krajewski et al. (1987); Rees, Huang, and Taylor (1989); Saker and Fitzsimmons (1989); Grosfeld-Nir, Magazine, and Venberkel (2000)
Plant layout	Wainwright, Harrison, and Leonard (1993)
WIP costs	Rees, Huang, and Taylor (1989); Wainwright, Harrison, and Leonard (1993)
Forecast error	Krajewski et al. (1987); Bhaskaran (1998)
Inventory buffer level	Krajewski et al. (1987); Rees, Huang, and Taylor (1989); Sarker (1989); Bonney et al. (1999); Grosfeld-Nir Magazine, and Venberkel (2000); Taylor (2000)
Number of Stages	Grosfeld-Nir, Magazine, and Venberkel (2000)

Inventory Buffer Level

Inventory buffer level is proven to be a crucial factor impacting the effect of the control strategy on system performance (Krajewski et al. 1987; Rees, Huang, and Taylor 1989; Sarker 1989; Bonney et al. 1999; Grosfeld-Nir, Magazine, and Venberkel 2000; Taylor 2000). Hopp and Spearman (1996, p. 385) concluded that to achieve the equivalent throughput, a pull system uses less average WIP than does a push system. However, recent studies disagreed with the above statement and found that a push system needs lower buffer level to attain the same throughput (Bonney et al. 1999; Grosfeld-Nir, Magazine, and Venberkel 2000). They also suggested that under a low level of inventory buffer, a push system outperforms a pull system. Therefore, more research is needed to further verify the impact of inventory buffer level on the relationship between control strategy and system performance especially in the supply network level where inventory buffer levels are very different from those in the factory level. The inventory buffer level needed for each business entity in a supply network could be a lot higher than the inventory buffer level needed for each workstation in a factory.

Forecast Error

Many studies have shown that forecast error has a significant effect on system performance (Wemmerlov and Whybark 1984; Krajewski et al. 1987; Sridharan and LaForge 1989; Zhao and Lee 1993; Kadipasaoglu and Sridharan 1995; Bhaskaran 1998). However, among the comparative studies of the performances of different control strategies, only a few studies considered this factor (see Krajewski et al. 1987; Sarker 1989). More research is needed to provide better insight into the effect of forecast error on the performance differences among the control strategies.

Furthermore, in a highly integrated supply network where only the forecasts at the retailers are used in generating the operational plans, this factor becomes even more vital. The impact of forecast error will increase as the orders are passed to upstream entities. Thus, forecast error is a significant factor in selecting the control strategy. Bhaskaran (1998) demonstrated that a push system has the ability to better use forecasts than a pull system. This implies a push system should outperform a pull system when accurate forecasts are available.

Inventory buffer level and forecast error are added to the planning and control strategy theory. Figure 5 displays the expanded theory. The "schedule rules" factor is excluded because the schedule rules in prior studies refer to the schedule rules used by each work center in a factory (such as First-Come-First-Serve (FCFC) and Shortest Process Time (SPT)). They are not the focus of this study addressing the planning in the supply network level. The “Process Variability” factor is excluded. It is well known that one of the major weaknesses of a push system is its use of constant standard production times to generate production schedules. If there exists high variability in the production process, a push system needs to set long standard production times to maintain schedule stability. Long standard production times, in turn, cause high level of inventory and a lack of responsiveness (Hopp and Spearman 1996, p. 130-134). Thus, a pull system should outperform a push system when the variability in the production process is high (Rees, Huang, and Taylor 1989; Saker and Fitzsimmons 1989). Other less relevant factors in Table I are excluded from the study.

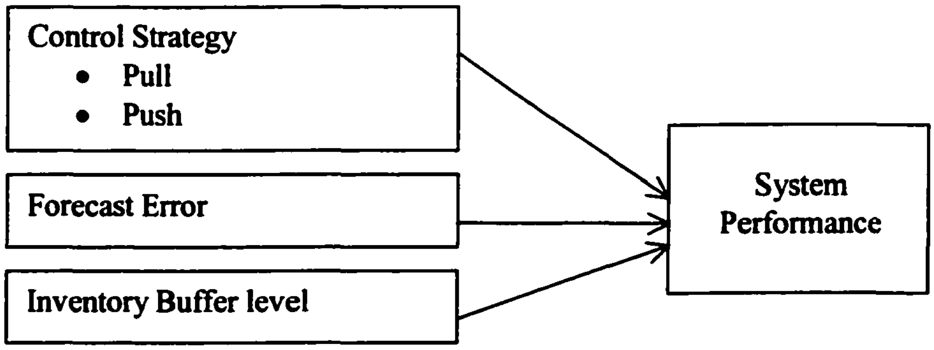


FIGURE 5

Expanded Theory

System Performance Measures

Table II summarizes the performance measures commonly found in comparative studies of the performances of different control strategies. Throughput, total inventory, flow time, and system utilization are commonly used. Since it is well understood that the pull system generally results in lower system utilization than the push system (Monden 1981 cited in Venkatesh et al. 1996; Lee 1989; Sarker and Fitzsimmons 1989), the system utilization is not included in this study. Also, high utilization does not always imply high profit. High utilization may just built up the system inventory.

Throughput, total inventory, and flow time are appropriate for this research. A supply network, which is a multistage production system, can be considered a queuing network (Spearman, Woodruff, and Hopp 1990; Spearman and Zazanis 1992, 1998; Wainwright, Harrison, and Leonard 1993; Hopp and Spearman 1996). Considering supply networks this way allows this study to apply queuing theory to validate and explain the study results. Throughput, total inventory, and flow time are commonly used to assess the performance of queuing networks. Since one of these three measures can be derived from Little's Law if another two are known, one measure, flow time, is excluded from this research. Throughput and total inventory are more closely related to the profit than flow time-so they are used in the study reported here.

In addition to throughput and total inventory, another performance measure used in this study is customer service level. Today, satisfying customers' needs is the top priority in maintaining companies' competitiveness. One of the objectives of operational planning and control is to deliver products to meet customers' requirements. Accordingly, customer service level is a significant measure of supply network success.

Figure 6 illustrates the modified study model including the performance measures. Based on this model, research hypotheses are developed in the next section.

TABLE II

Performance Measures in Prior Research

Measures	Reference
Throughput	Lee (1989); Sarker and Fitzsimmons (1989); Bonney et al. (1999); Grosfeld-Nir, Magazine, and Venberkel (2000); Persentili and Alptekin (2000); Taylor (2000)
WIP/total inventory	Krajewski et al. (1987); Lee (1989); Sarker and Fitzsimmons (1989); Spearman, Woodruff, and Hopp (1990); Spearman and Zazanis (1992, 1998); Wainwright, Harrison, and Leonard (1993); Hopp and Spearman (1996); Bhaskaran (1998); Bonney et al. (1999); Grosfeld-Nir, Magazine, and Venberkel (2000); Persentili and Alptekin (2000); Taylor (2000)
Flowtime/lead-time/ Job queue time	Lee (1989); Spearman, Woodruff, and Hopp (1990); Spearman and Zazanis (1992, 1998); Hopp and Spearman (1996); Bhaskaran (1998); Bonney et al. (1999)
System utilization	Monden (1981) (cited in Venkatesh et al. (1996)); Lee (1989); Sarker and Fitzsimmons (1989); Wainwright, Harrison, and Leonard (1993)
Profit	Spearman, Woodruff, and Hopp (1990)
Customer service level	Krajewski et al. (1987)
Schedule stability	Bhaskaran (1998)
Operations expense	Taylor (2000)

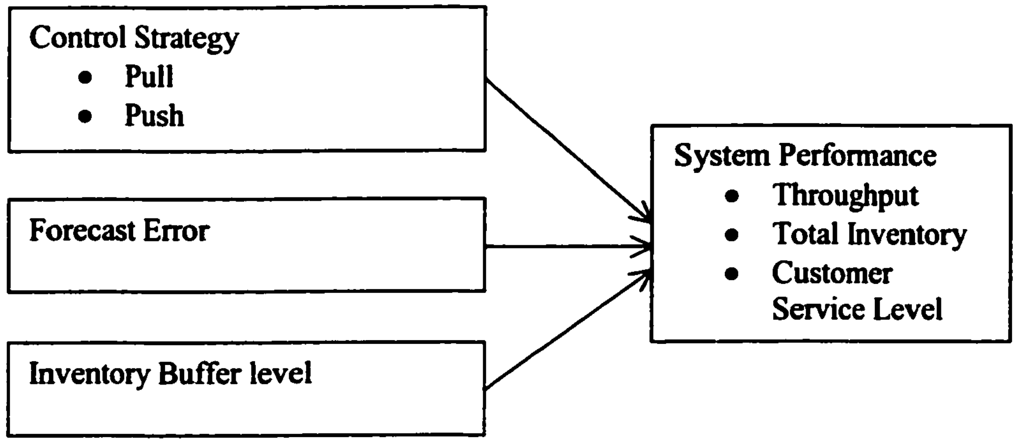


FIGURE 6

Expanded Theory with Performance Measures

Research Hypotheses

To make the study manageable, the expanded theory is only tested in a MTS environment. Research hypotheses are described below in null form. A push system refers to a system operated by using push strategy. A pull system refers to a system operated by using pull strategy.

RH1: In a MTS environment, there is no difference between push and pull systems when they are compared simultaneously on total inventory, throughput, and customer service level.

RH2: In a MTS environment, at different levels of forecast error, there exists the same effect of control strategies when compared simultaneously on total inventory, throughput, and customer service level.

RH3: In a MTS environment, at different levels of inventory buffer, there exists the same effect of control strategies when compared simultaneously on total inventory, throughput, and customer service level.

RH4: In a MTS environment, at different levels of forecast error, there exists the same effect of inventory buffer levels when compared simultaneously on total inventory, throughput, and customer service level.

RH5: In a MTS environment, at different levels of forecast error, there exists the same effect of the interaction between control strategy and inventory buffer level when compared simultaneously on total inventory, throughput, and customer service level.

CHAPTER 3

WEB-BASED MODULAR OPERATIONAL PLANNING AND CONTROL SYSTEM (WMOPCS) FOR MAKE-TO-STOCK SUPPLY NETWORK

This study required design and implementation of an OPC system for MTS environment that considers inventory and demand forecast in the planning processes. This software system, called Web-based Modular Operational Planning and Control System (WMOPCS), provided a foundation for the simulations used to investigate the research questions. This chapter describes the design of WMOPCS.

Comparison to Existing Operational Planning and Control Systems (OPCSs)

Literature review revealed that current OPCSs consist of a central planning module coordinating with the local planning modules (Rupp and Ristic 2000; Klen et al. 2001; Sadeh et al. 2001). Details of this architecture were given in the "Architecture for OPC System" section of Chapter 1. WMOPCS is also based on this architecture.

Most of the existing OPC systems were developed for supply networks in make-to-order (MTO) environment. These systems concentrated on effective capacity management and de-emphasized the issues of inventory and demand forecast. On the other hand, in a make-to-stock (MTS) environment, inventory and demand forecast greatly complicates the planning processes. WMOPCS is designed for MTS environment. It considers inventory and demand forecast in planning processes.

Overview of WMOPCS

The design of WMOPCS emphasizes modularity and reusability. The complexity of the OPCS involving numerous planning and control activities makes modularity and reusability necessary. Designing the software for each activity as a plug-and-play module decreases the coupling between the activities. This allows a supply network to redesign its business processes and structures according to the changes of customer requirements without having to reprogram the overall system. In addition, modularity enables the managers to explore different management policies by replacing the existing decision support modules of the systems with the alternative ones. Object technology was utilized to meet the modularity and reusability requirements.

During the development process, Unified Modeling Language (UML) was utilized to model the system. UML is a visual modeling language with a semi-formal specification for depicting object-oriented design constructs (Page-Jones 2000, p. 76-84). It is also very useful for documenting changes in design during the development process. UML provides several diagrams that can be used for expressing various aspects of object-oriented design graphically. These diagrams include class diagram, object diagram, use case diagram, sequence diagram, collaboration diagram, state diagram, activity diagram, component diagram and deployment diagram. Stevens and Pooley (1999) as well as Page-Jones (2000) explained each of these diagrams in detail.

WMOPCS was implemented in Microsoft Corporation's Visual Basic.Net programming language. Visual Basic.Net facilitates the development of web-based applications and includes new features for object-oriented programming. The following sections describe the requirement and design of WMOPCS. Since UML diagrams are helpful in expressing object-oriented system, they are used throughout these sections to describe different aspects of the WMOPCS.

The Requirements of WMOPCS

Object-oriented and component technologies were necessary to facilitate simulating different OPC strategies. A separate module was created for each strategy. Also, the system needed to be web-based.

Figure 7 displays a use case diagram summarizing the key requirements of WMOPCS. The associations between the actors in the WMOPCS are illustrated in Figure 8. An actor is a technical term used in UML to represent a user of the system in a particular role (Stevens and Pooley 1999). As shown in Figure 8, an actor Planner is a general form of the other types of planners. The other types of planners all inherit the properties of the Planner. A Local Planner is also a general form of Retail Planner, Distribution Planner, Supply Planner, and Manufacture Planner. A Central Planner represents a user employed by the supply network coordinator while a Retail Planner is a user employed by a retailer. As shown in Figure 7, all types of planners are able to browse MOS and DOP records and check the available-to-promise quantity of a product. A Retail Planner can also edit customer orders and MOS records. A Central Planner has permission to perform every function. Some functions of the WMOPCS that can be performed only by the Central Planner include generating MOS and DOP as well as rolling forward MOS.

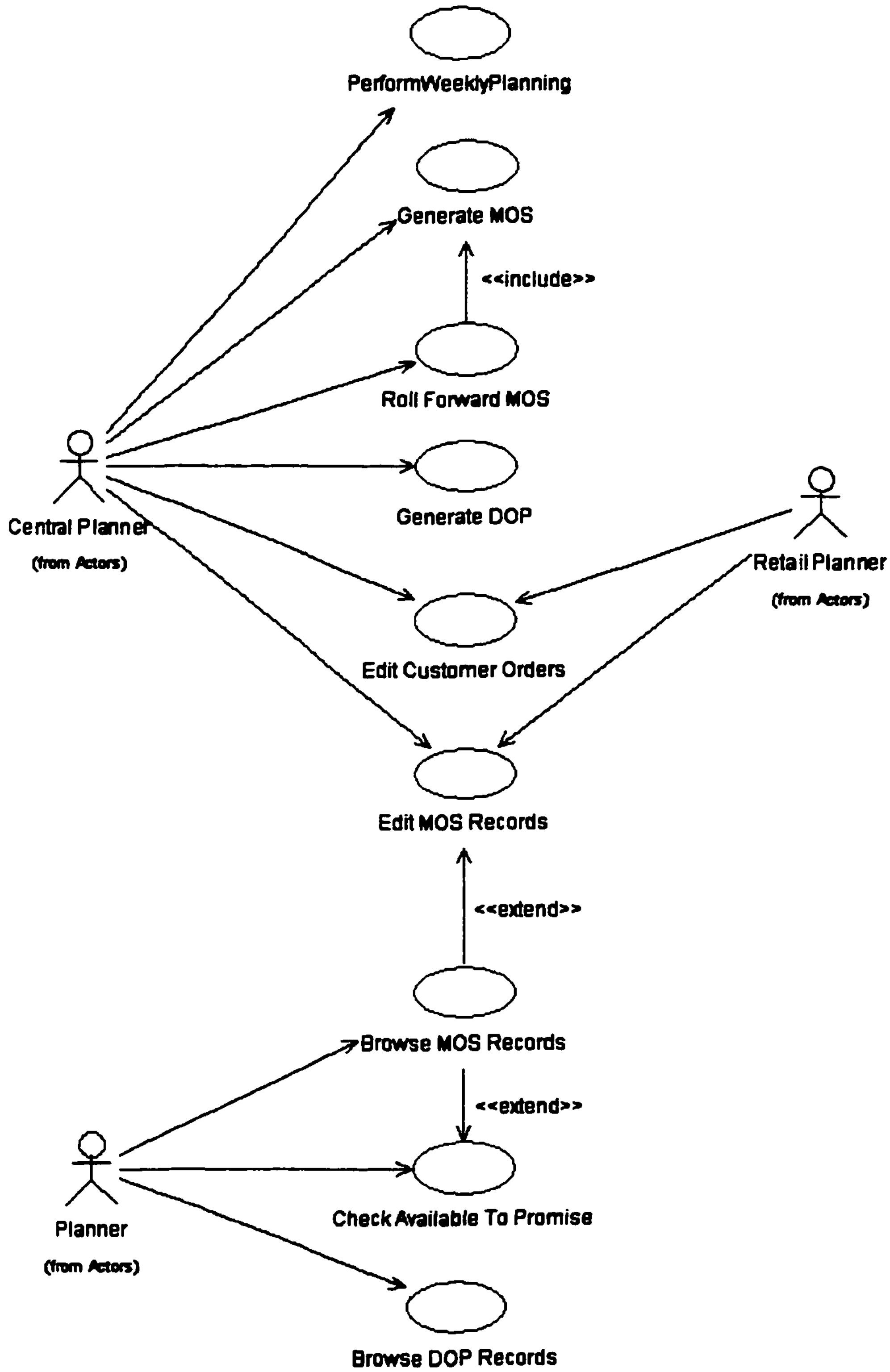


FIGURE 7

Use Case Diagram for WMOPCS

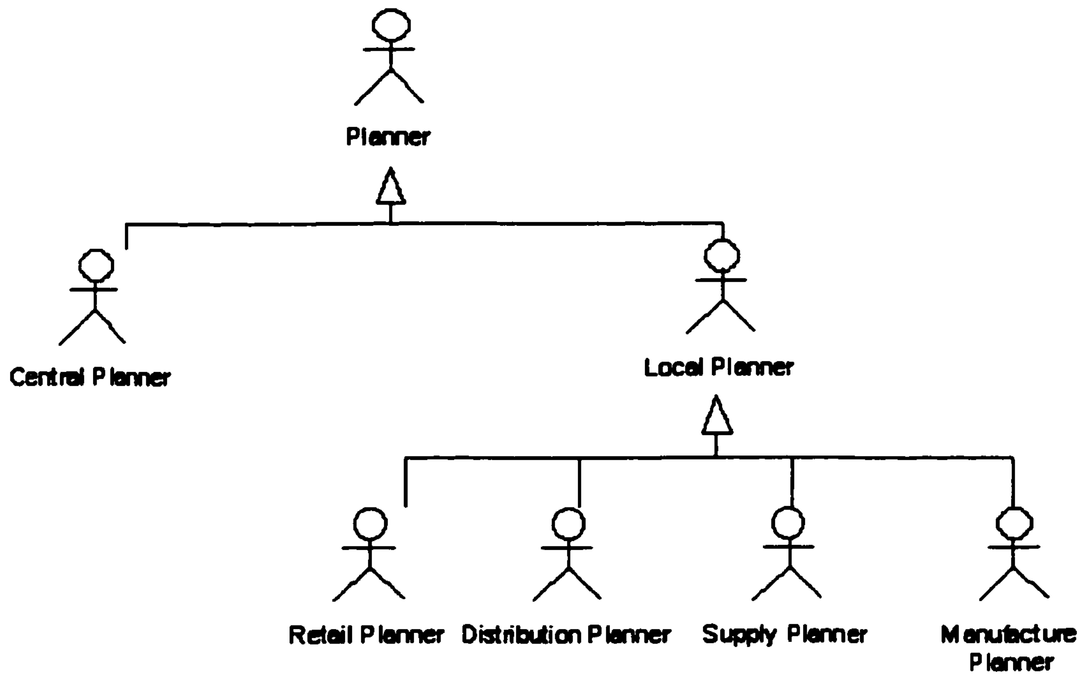


FIGURE 8

Actors in WMOPCS

The Architectural Design of WMOPCS

Following the Microsoft's Windows DNA (Distributed iNternet Architecture) programming model, the system is organized into three logical tiers, User Services Tier, Business Services Tier, and Data Storage/Services Tier

User Services (or Presentation) Tier

This tier comprises user interface modules. These modules provide web browser-based user interfaces. People would use these interfaces if this system supported actual firms, but in this research some of these interfaces were instead driven by simulation module. The main features of these modules are provided below.

- Provide the interfaces between users and the decision support modules
  - Able to get the input information from the users and send it to decision support modules
  - Display the results generated by the decision support modules
- Provide the interfaces between users and database through Data Access modules
  - Allow users to edit the database
  - Allow users to view the essential information (by querying the database) such as the inventory status of the network (supply network visibility) and the history of order lead-time.

Business Services (or Middle) tier

This tier handles business processing, including business rules, data validation rules, and database accessing. It consists of decision support modules generating production and distribution plans based upon current inventory levels, forecast demand, capacity availability and status of issued production and shipment orders. The decision support modules of WMOPCS generate two categories of plans, Master Operations Schedules (MOS) and Detailed Operations Plans (DOP). These two categories are in different levels of the supply network planning hierarchy as shown in Figure 9.

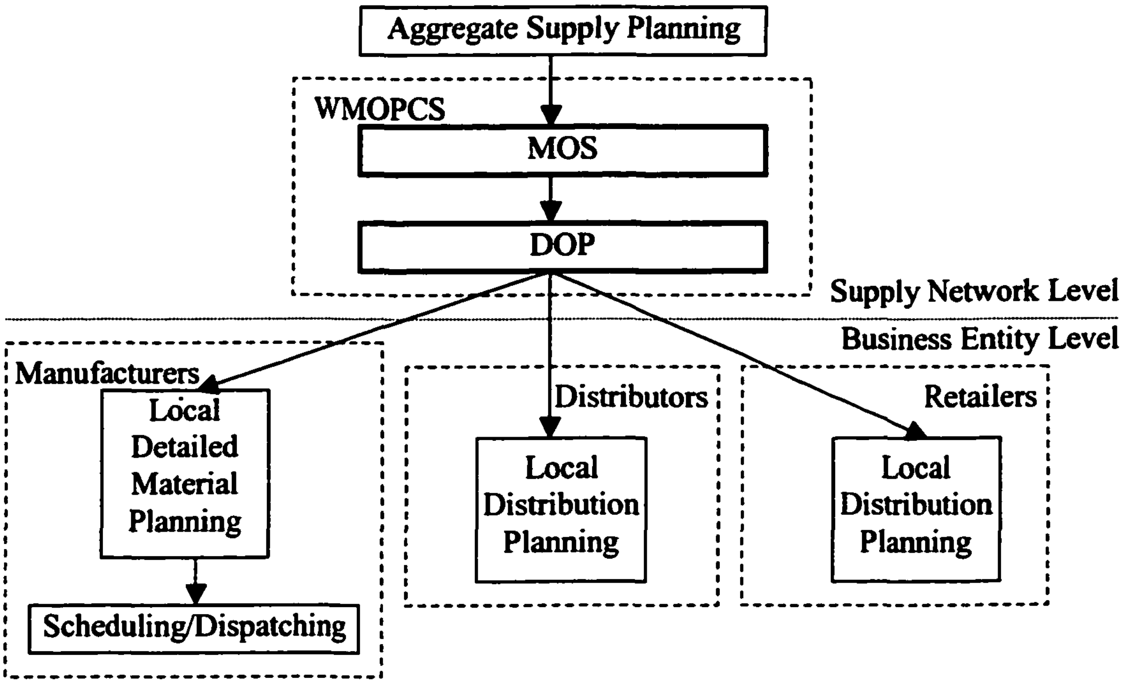


FIGURE 9

Supply Network Planning Hierarchy

- Master Operations Schedule: MOS is a master schedule of a supply network. The algorithm for generating MOS is based on the algorithm for generating the traditional Master Production Schedule. A MOS is established for each final product at the retailers. For example, if a supply network has 4 retailers and every retailer keeps final product A, there will be 4 MOSs for final product A in this supply network. At the beginning of each planning period, MOS determines the quantity of a final product required to be available at a retailer. MOS requirement of a final product is generated based on demand forecast, current customer orders and inventory status of that product as well as the resource allocation stated in Aggregate Supply Planning. It is the requirement used to generate DOP.

- Detailed Operations Plans: DOP is also a period-by period plan in supply network level. In this level, excluding the retailers, a finished good of a supply network member is actually a component part of a final product of a supply network. A DOP is established for each final product and component part in the supply network level. It determines how much and when to produce and/or ship a final product or a component part in order to fulfill the MOS requirements of the final products. As shown in Figure 9, the output from DOP is the input for the local planning system at each supply network member. For each supply network member, its local planning system could be its traditional planning system. The local planning system performs local detailed material planning or local distribution planning at the business entity level.

Two alternative modules for generating DOP were developed. The push and pull modules were developed based on push (MRP) and pull (kanban) strategies. To change the OPC strategy of WMOPCS, a different module can be plugged into the system. Hopp and Spearman (1996) as well as Vollmann, Berry, and Whybark (1997) thoroughly illustrated the concepts of MRP and kanban.

The algorithms of the push and pull modules are summarized in Figures 10 and 11 respectively. Both push and pull do not react directly to demand forecast or customer orders. Instead, they react to MOS requirements derived from demand forecast, current customer orders, and the status of the inventory. Based on the MOS requirement, push strategy generates a schedule specifying how much and when to produce or ship the products. The requirements in this schedule are the internal orders for the business entities in a supply network. Each business entity does not produce or ship its orders before the planned start dates of the orders. An order is processed only when 1) its planned start date is arrived or passed and 2) there are enough raw materials for processing it.

On the other hand, pull strategy does not generate a schedule. Based on a MOS requirement, it creates and sends an internal order (signal) to a retailer. The retailer can fulfill the order if it has enough inventories in stock. When the order is fulfilled and the inventory level of the stock decreases, the retailer issues a conveyance kanban to a manufacturer. The conveyance kanban asks the manufacturer to ship products to the retailer in order to replenish the retailer's stock. The manufacturer ships products to the retailer if there are enough inventories available in its finished goods stock. When the conveyance kanban is fulfilled, thus decreasing the manufacturer's inventory level of finished goods, the manufacturer issues a production kanban in order to replenish its finished goods stock. The processing of the production kanban uses inventories in raw material stock. When the level of inventory in raw material stock decreases, the manufacturer in turn issues a conveyance kanban to a supplier in order to replenish its raw material stock.

To further describe the logics of push and pull strategies, the following section illustrates an example comparing push and pull supply chains.

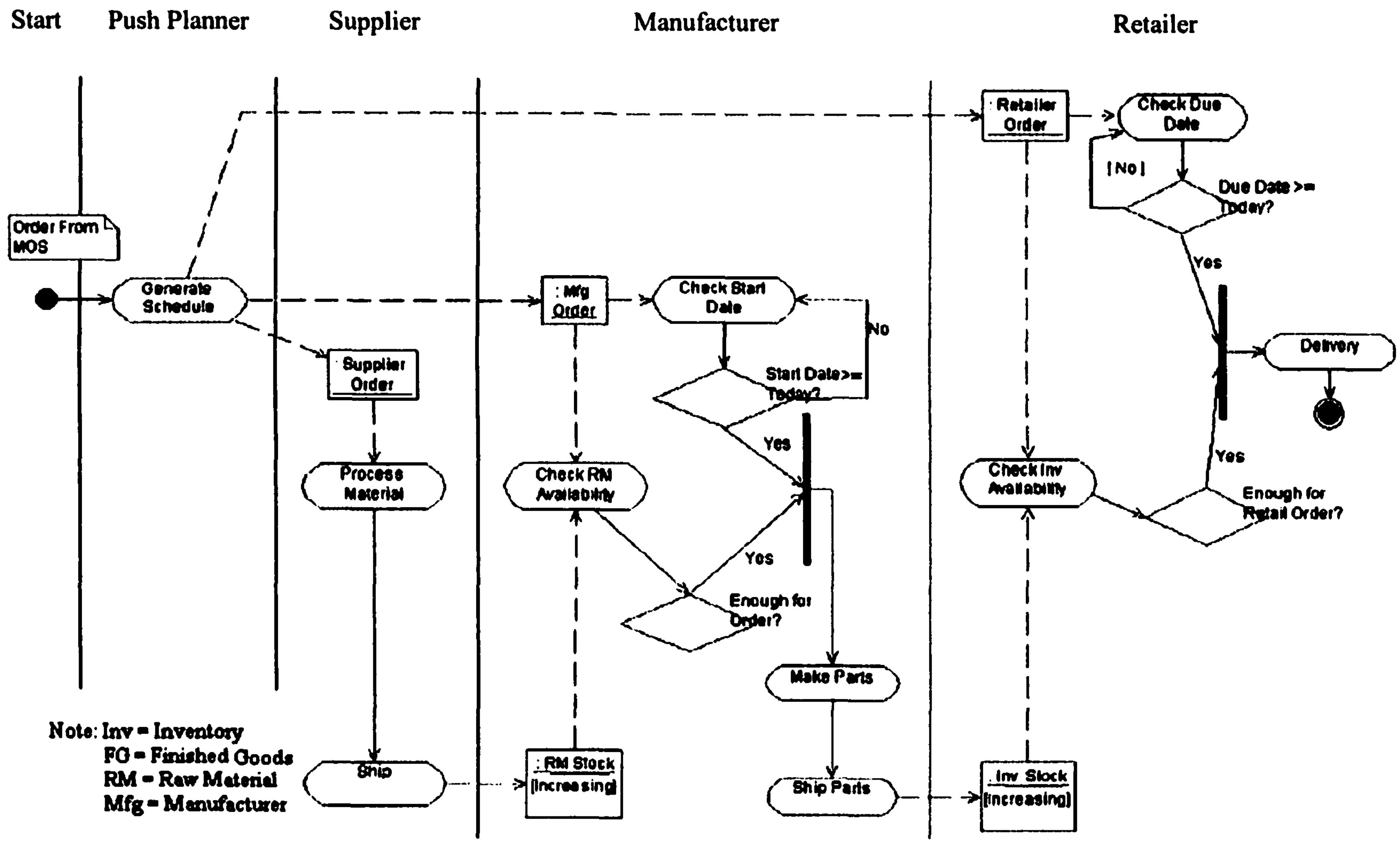


FIGURE 10

Push Strategy

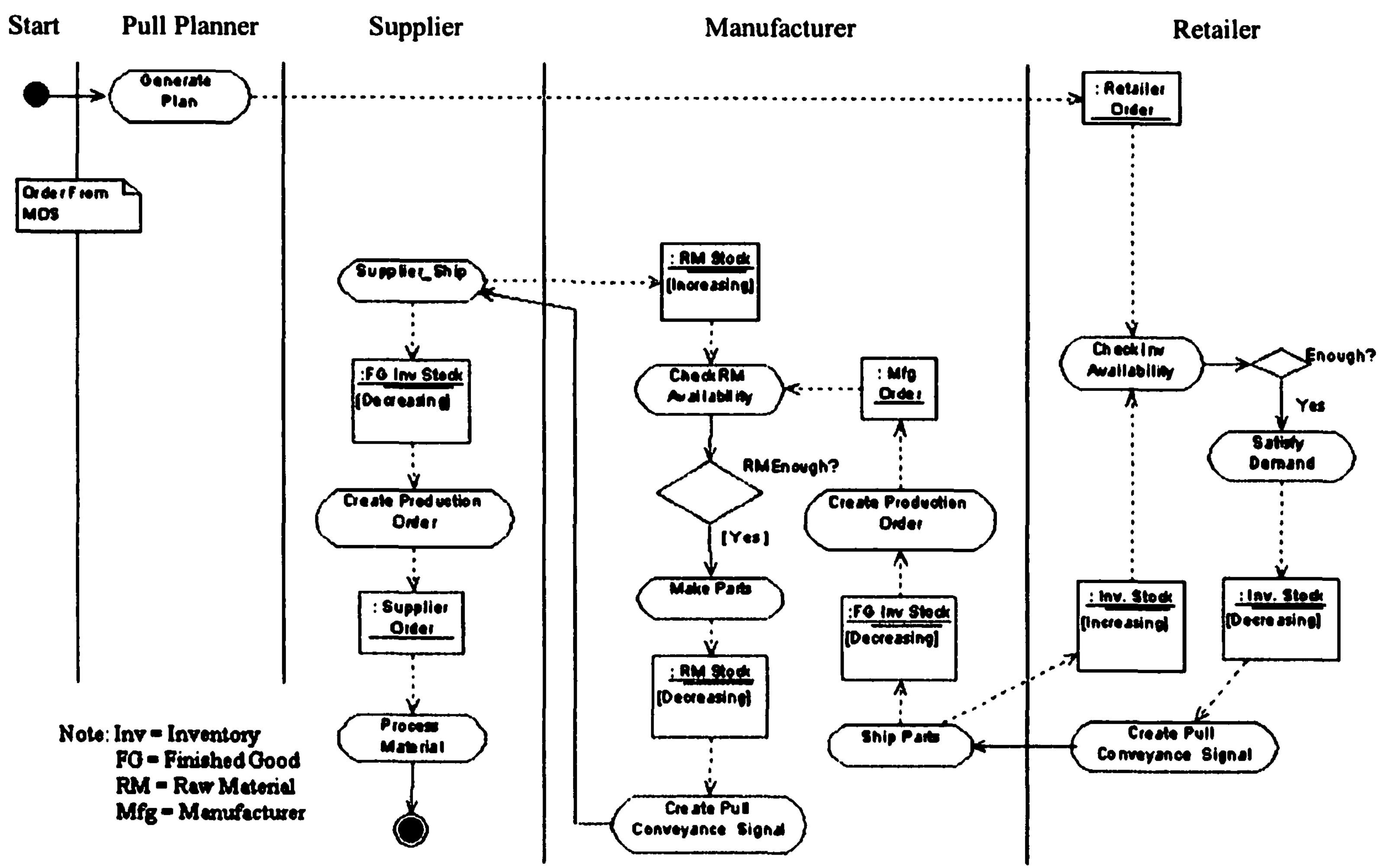


FIGURE 11

Pull Strategy

Example of Push and Pull Systems

A three-stage supply chain has one-week production lead-time at each stage. To simplify the example, it is assumed that there is zero transferring lead-time between the stages. Figure 12 displays the bill of materials for an end item of this supply chain. To produce this end item, one unit of part A from the second stage is needed. Initially, there exist 20 units of inventory at every stage. Every stock tries to keep its inventory level at a target of 20 units. If some parts (or end items) are taken from a stock, the system attempts to produce more to replenish the stock and keep the target. The MOS of this end item generated at the beginning of week 1 are shown in Table III. The MOS requirement of each week needs to be fulfilled at the beginning of the week. In week 1, the MOS requirement of 10 units is derived from the forecast of 10 units plus the inventory target of 20 units minus the on hand inventory of 20 units. The "available" row in the MOS shows the available quantity at the end of each week. The available quantity of 20 units at the end of week 2 (shown in column "week 2") is derived from the MOS requirement of 15 units in week 2 plus the available quantity of 20 units at the end of week1 minus the forecast of 15 units in week 2.

As shown in Figure 13, for this particular setting, using different strategies makes the system behave differently in achieving the same MOS requirements specified in Table III. Figure 13 shows weekly snap shots of system behavior for 5 weeks. For each stage, its inventory level at the end of each week is derived from the following equation:

For stage j,

the inventory level at the end of week i

= the inventory level at the end of week i-1

+ the quantity of parts (or end items) completed at the beginning of week i

- the quantity of parts (or end items) taken away from stage j in week i

For example, in the push system, the15 units inventory of stage3 at the end of week 2 is derived from 10 units of inventory at the end of week 1 plus 20 units of the end item completed at the beginning of week 2 minus 15 units taken away to fulfill the requirement of week 2.

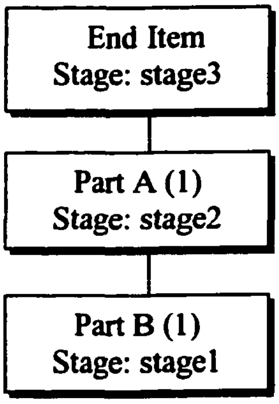


FIGURE 12

Bill of Materials for the End Item

On the left hand side of Figure 13, the supply chain uses push strategy. Using backward scheduling, stages 1, 2, and 3 produce according to future MOS requirements.

Stages 1, 2, and 3 process their parts (or end items) by looking ahead 3, 2, and 1 weeks respectively. For example, in week 3, stage 3 produces 15 units of the end item to satisfy the MOS requirement of 10 units in week 4 and the back order of 5 units in week 2. In week 1, stage 1 produces 55 units of part B for the MOS requirement of 10 units in week 4 and the back order of 45 units due to the MOS requirements of week 1-3. In push system, a schedule of DOP is generated for each item. Table IV displays the DOP schedule for the end item generated at the beginning of week 1. For the end item, the requirements in DOP are the MOS requirements in MOS. These are the requirements at the beginning of each week. Because of one-week production lead-time, the production orders for satisfying these requirements must be released one week earlier. The planned releases of the production orders at the beginning of each period are indicated in "PlannedOrderRelease" row. The planned order release of 10 units in "week 3" column is for the requirement of 10 units in week 4.

The system enters steady state in week 4. In week 4, stage 1 produces 10 units of part B for the end item requirement of week 7. At the beginning of week 4, 20 units of part B are completed at stage 1 and shipped to stage 2. The production of these 20 units started at the beginning of week 3. These 20 units of part B are used by stage 2 to produce 20 units of part A for the end item requirement of week 6. At stage 1, the inventory level at the end of week 4 is still 20 units, the same as the level at the end of week 3. This is because the quantity of part B completed at the beginning of week 4 is equal to the quantity of part B shipped to stage 2. Similarly, at the beginning of week 4, 15 units of part A are completed at stage 2 and shipped to stage 3. The production of these 15 units started at the beginning of week 3. These 15 units of part A are used by stage 3 to produce 15 units of the end item for the requirement of week 5. At stage 2, the inventory level at the end of week 4 is still 20 units, the same as the level at the end of week 3. This is because the quantity of part A completed at the beginning of week 4 is equal to the quantity of part A shipped to stage 3. At the end of week 4, stage 3 has 20 units of inventory that comes from 15 units of inventory at the end of week 3 plus 15 units of the end item completed at the beginning of week 4 minus 10 units taken away to fulfill the end item requirement in week 4.

Using pull strategy, the system does not operate according to the future MOS requirements. This scenario is shown on the left hand side of Figure 13. The system responds to the MOS requirement of the current week. The weekly MOS requirement is satisfied by using the items from the inventory stock, and then the production is triggered to replenish the stock. For example, at the beginning of week 4, 10 units of the end item at stage 3 are taken from the stock to satisfy the MOS requirement of week 4. To replenish its stock, stage 3 triggers a production of 10 units using 10 units of part A taken from the stock at stage 2. At the end of week 4, stage 3 has 10 units of inventory that comes from 0 unit of inventory at the end of week 3 plus 20 units of the end item completed at the beginning of week 4 minus 10 units taken away to fulfill the end item requirement in week 4. Likewise, to replenish its stock, stage 2 triggers a production of 10 units using 10 units of part B taken from the stock at stage 1. At the end of week 4, stage 2 has 10 units of inventory that comes from 0 unit of inventory at the end of week 3 plus 20 units of part A completed at the beginning of week 4 minus 10 units taken by stage 3. Also, stage 1 triggers a production of 10 units to replenish its stock. At the end of week 4, stage 1 has 10 units of inventory that comes from 0 unit of inventory at the end of week 3 plus 20 units of part B completed at the beginning of week 4 minus 10 units taken by stage 2.

TABLE III

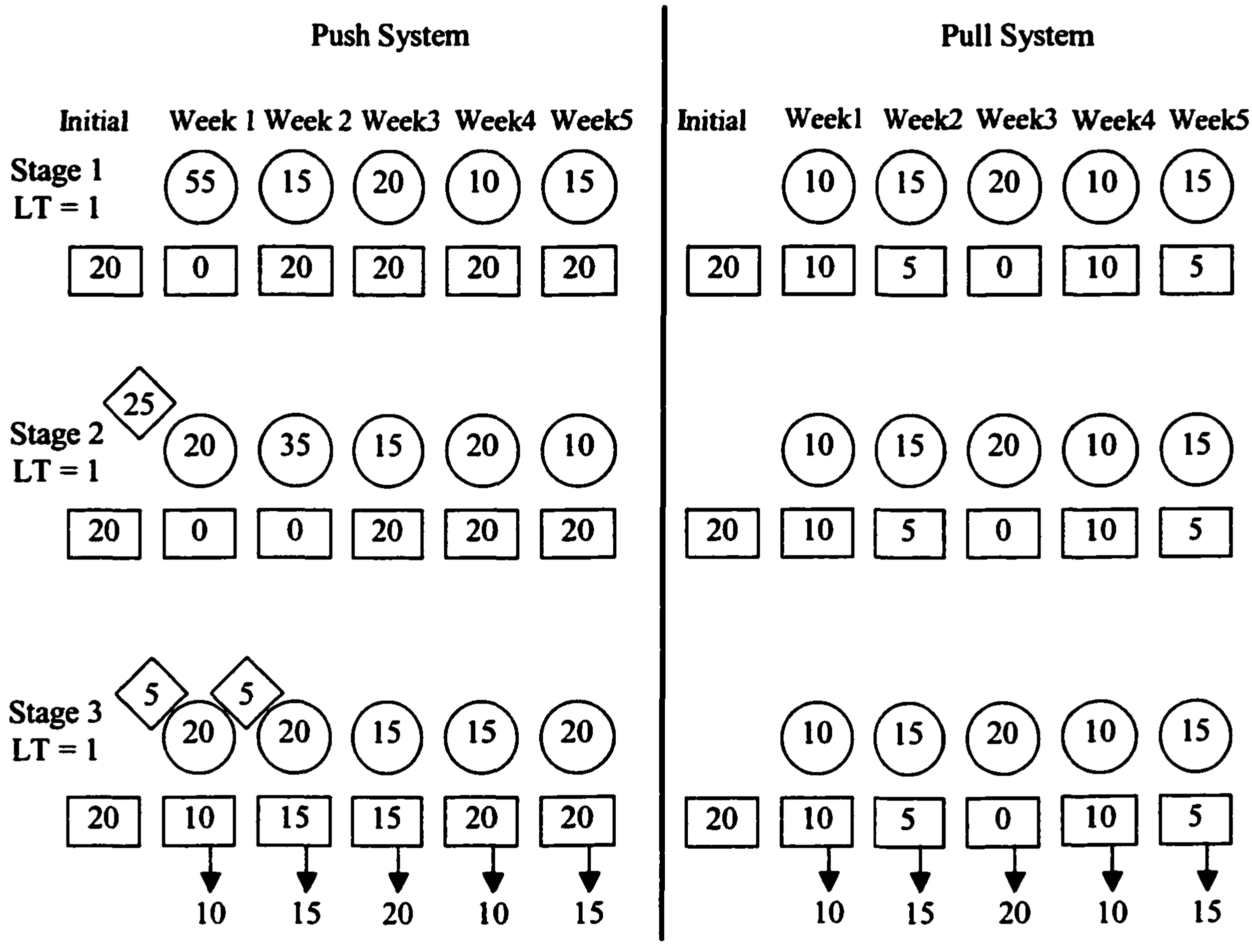
Master Operations Schedule for the End Item

Product	WeekNumber	1	2	3	4	5	6	7	8	9
End Item	Forecast	10	15	20	10	15	20	10	15	20
	Available	20	20	20	20	20	20	20	20	20
	MOS Requirement	10	15	20	10	15	20	10	15	20
	OnHand	20								

TABLE IV

Detailed Operations Plan for the End Item

Product	WeekNumber	1	2	3	4	5	6	7	8	9
End Item	Requirement	10	15	20	10	15	20	10	15	20
	Available	10	20	20	20	20	20	20	20	20
	PlannedOrderRelease	25	20	10	15	20	10	15	20	0
	OnHand	20								



12 : Inventory stock; the number inside is the level of the inventory at the end of each week.

5 : Back Order; the number inside is the total quantity of unsatisfied orders.

20 : Process; the number inside is the quantity of parts (or end items) being processed.

15 : The number represents the weekly requirement of the end item.

LT : Production lead-time (weeks).

FIGURE 13

Push and Pull Comparison

Data Storage/Services Tier

This tier comprises a central database keeping all the required data for supply network planning. The central database is a relational database stored in Microsoft SQL Server, a relational database system. Microsoft SQL Server provides data storage and services. Although a decentralized database could also be used, this study selected a centralized one because 1) a central database lessens the information technology burden on supply network members, thus facilitating participation by small firms, 2) a central database makes data synchronization easier, and 3) the study would like to concentrate on the issues of supply network planning rather than the technical issues related to distributed database (Davis and Peck 2000).

The Detailed Design of WMOPCS

WMOPCS consists of three key subsystems as shown in Figure 14. The DataServices and Central subsystems provide system-wide support, but each Local subsystem typically supports just one company. The DataServices subsystem is responsible for accessing the central database. The Central subsystem comprises main software components for generating MOS and DOP. To generate MOS and DOP, the Central subsystem needs to coordinate with Local subsystems installed at supply network members. Local subsystems are also responsible for communicating with traditional planning systems of supply network members.

Figure 15 illustrates the architecture of WMOPCS. Typically Local subsystems are run at application servers of individual firms while the Central subsystem is run at a web server operated by the supply network coordinator. All types of planners can access

WMOPCS through the web browsers. The Central subsystem communicates with Local subsystem via the Internet using web services technology, part of Microsoft's ASP.Net.

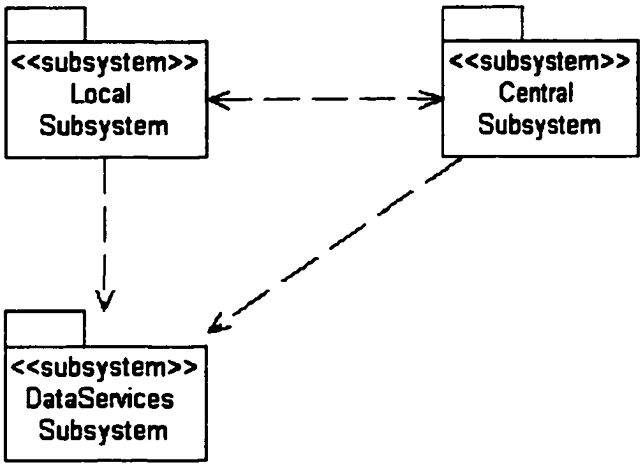


FIGURE 14

Key Subsystems in WMOPCS

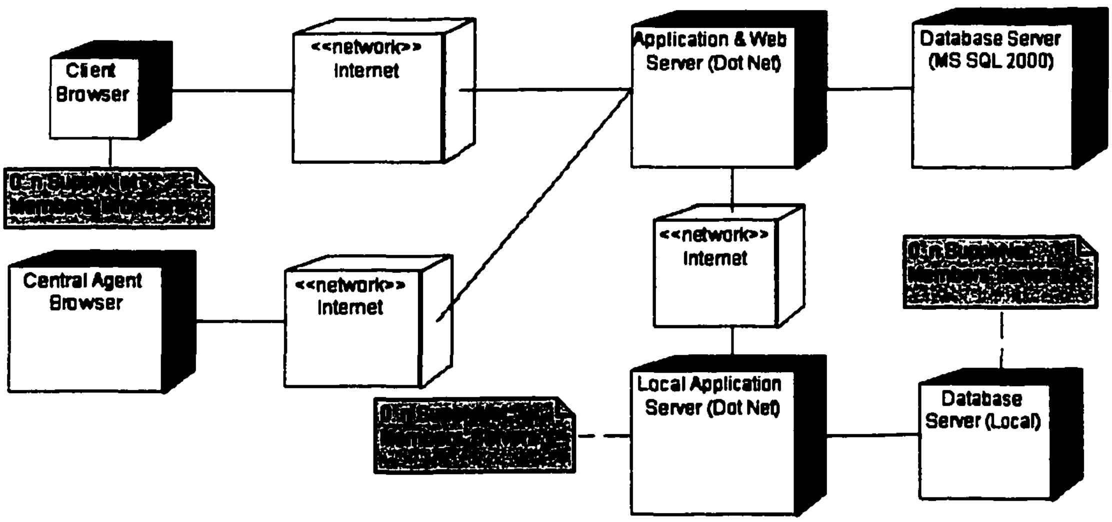


FIGURE 15

Architecture of WMOPCS

The component diagram in Figure 16 exhibits the software components that form the WMOPCS. Figure 16 illustrates the WMOPCS that uses push strategy. To change OPC strategy to pull, we can simply replace the PushLogic with PullLogic. This plug-and-play capability becomes possible because both PushLogic and PullLogic implement the same interface, IMaterialPlanner. The components of the Local subsystem include NodeClasses, Factory, Buffer Node, Distributor, Retail, and Supplier. These components communicate with the components in the Central subsystem via System Manager. The components of the Central subsystem include CommonClasses, System Manager, MOSUI, MOS Planner, and PushLogic. CommonClasses is a class library storing all the core classes used by the components in the Central subsystem while NodeClasses is a class library keeping the main classes used by the Local subsystem's components.

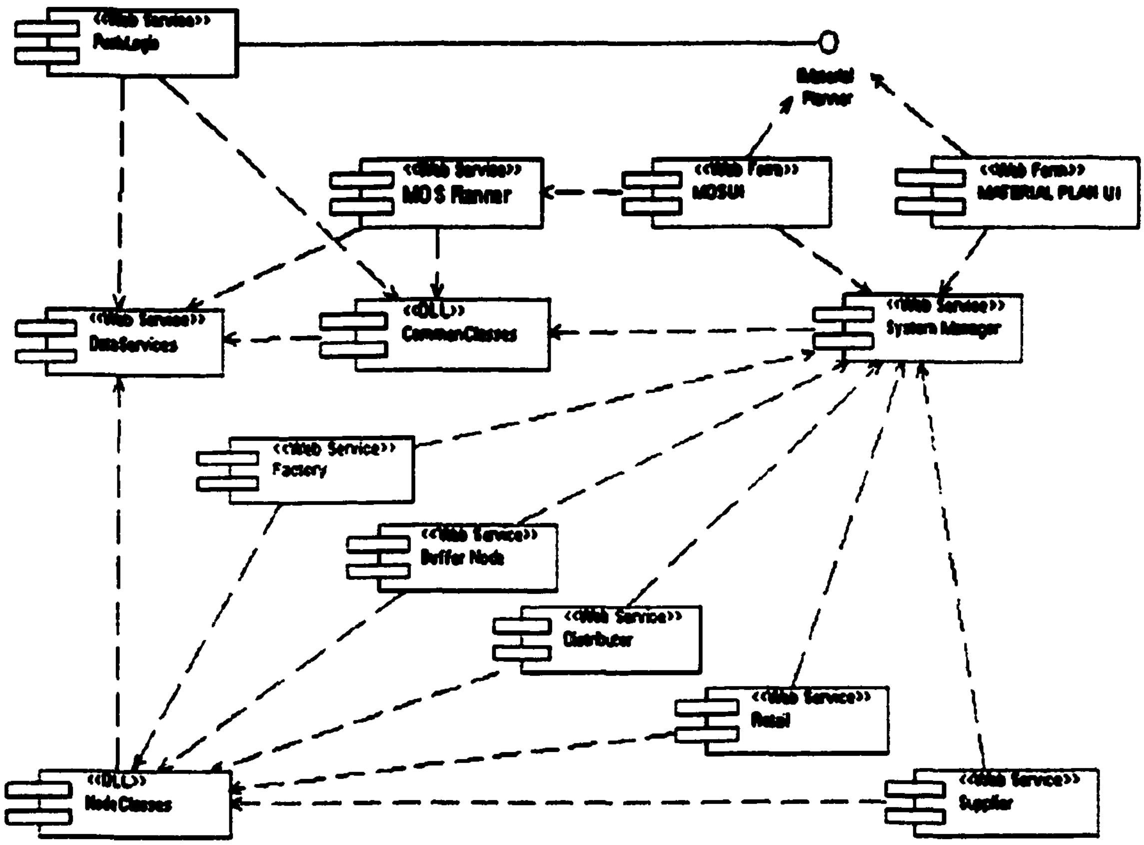


FIGURE 16

Component Diagram for WMOPCS

The class diagram in Figure 17 displays the classes in the CommonClasses library that provide services used by the components in the central subsystem. Figure 18 depicts the classes in the NodeClasses library that provide services used by the components in the local subsystem.

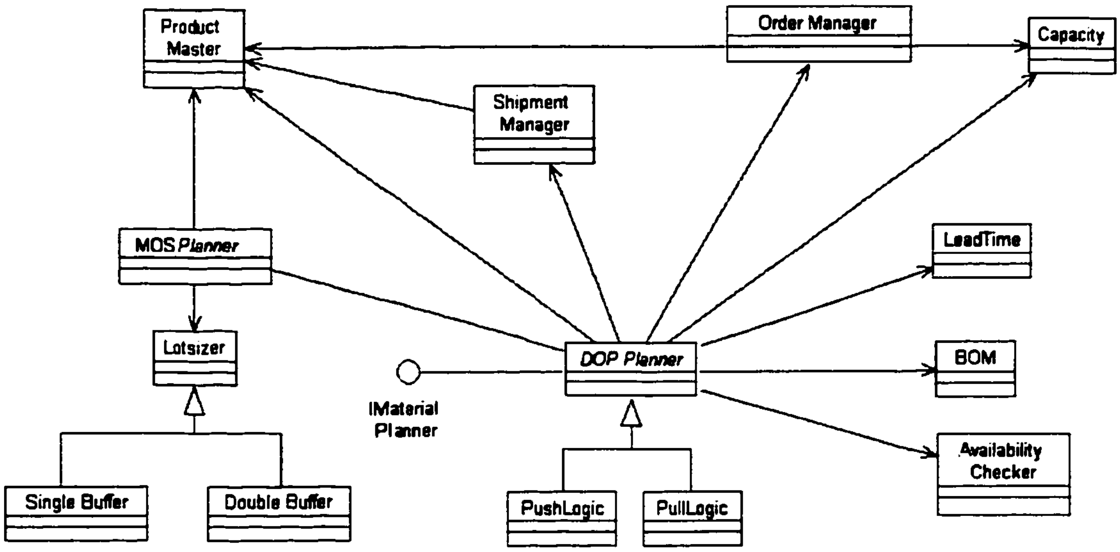


FIGURE 17

Class Diagram for Classes in CommonClasses Library

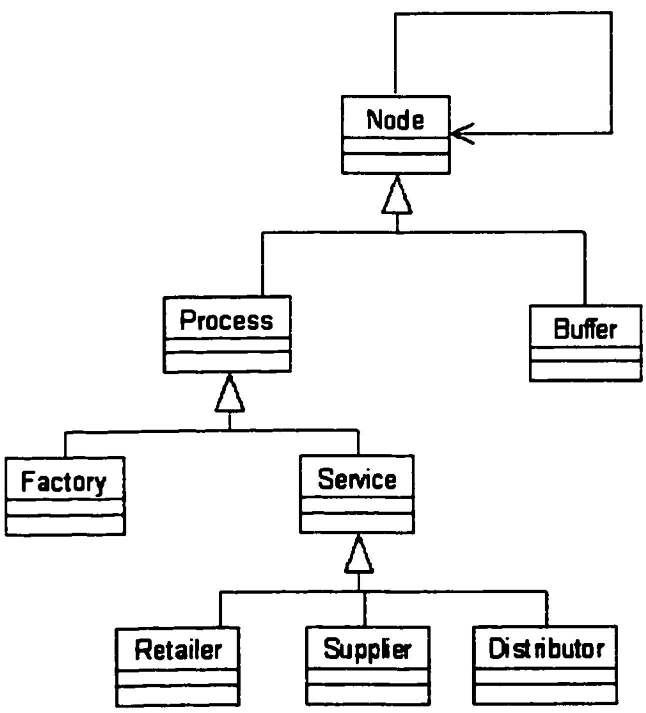


FIGURE 18

Class Diagram for Classes in NodeClasses Library

At the beginning of each period, a Central Planner generates MOS. Through the user interface, the Central Planner calls the MOS Planner to generate the MOS in order to update the changes during last week. After the MOS planner recalculates the MOS, the central planner calls the MOS planner to roll forward the MOS one period. After rolling forward, the MOS planner regenerates the MOS to accommodate the information of the new period coming into planning window. The sequence diagram of this process is shown in Figure 19.

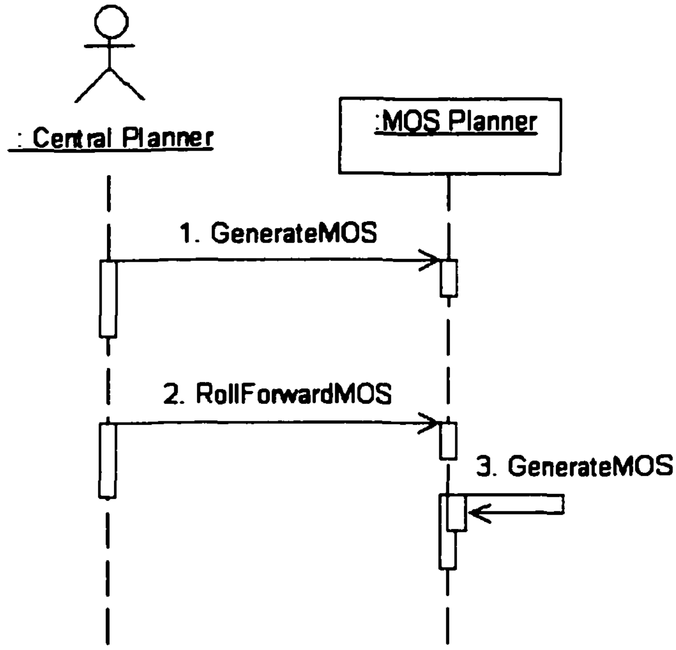


FIGURE 19

Sequence Diagram for "Generate MOS"

After generating MOS, a Central Planner calls PushLogic or PullLogic to generate DOP. Figure 20 displays a collaboration diagram depicting the process for generating the DOP using push strategy. First the Central Planner calls the PushLogic to roll forward the DOP. After rolling forward, the Central Planner calls "ExecuteMaterial Plan" function of the PushLogic. "ExecuteMaterial Plan" is a function for generating the DOP including sub-functions called ReceiveShipment, CalculateDOP, ProcessOrder, and IssueShipment. ReceiveShipment and IssueShipment are performed by the Shipment Manager.

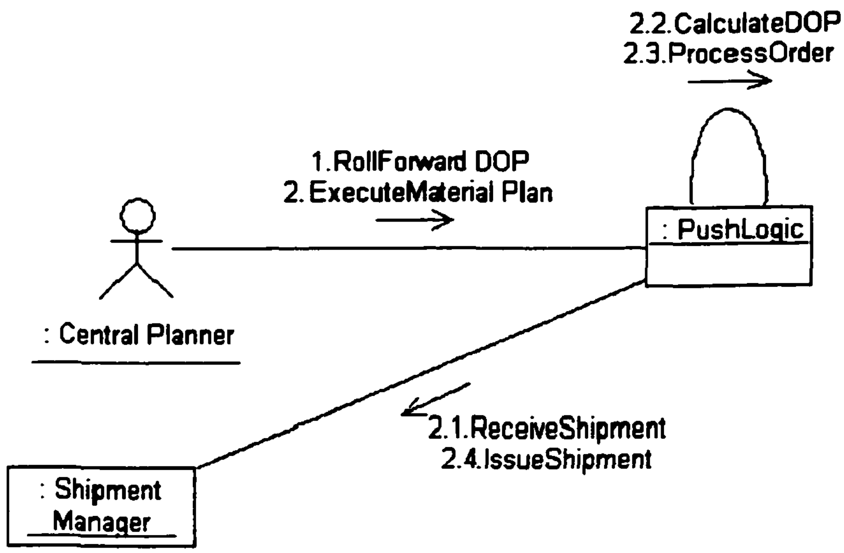


FIGURE 20

Collaboration Diagram for "Generate DOP" using Push Strategy

Figure 21 illustrates the process for generating DOP using pull strategy. Pull strategy uses kanbans instead of a schedule to trigger productions and shipments. A Central Planner calls "ExecuteMaterial Plan" function of the PullLogic. This function is for generating the DOP. Within this function, the PullLogic calls the Shipment Manager to receive shipments and calls the Order Manager to receive finished productions. Before generating plans for this period, the PullLogic calls the Order Manager to process unfilled production orders from previous periods. Then to establish plans for this period, the PullLogic calls "TransferMOSToConveyanceKanban" function of the Order Manager to generate conveyance kanbans based on inputs from the MOS. The creations of conveyance kanbans in turn generate production kanbans. The production kanbans are processed by "ProcessKanban" function of the PullLogic.

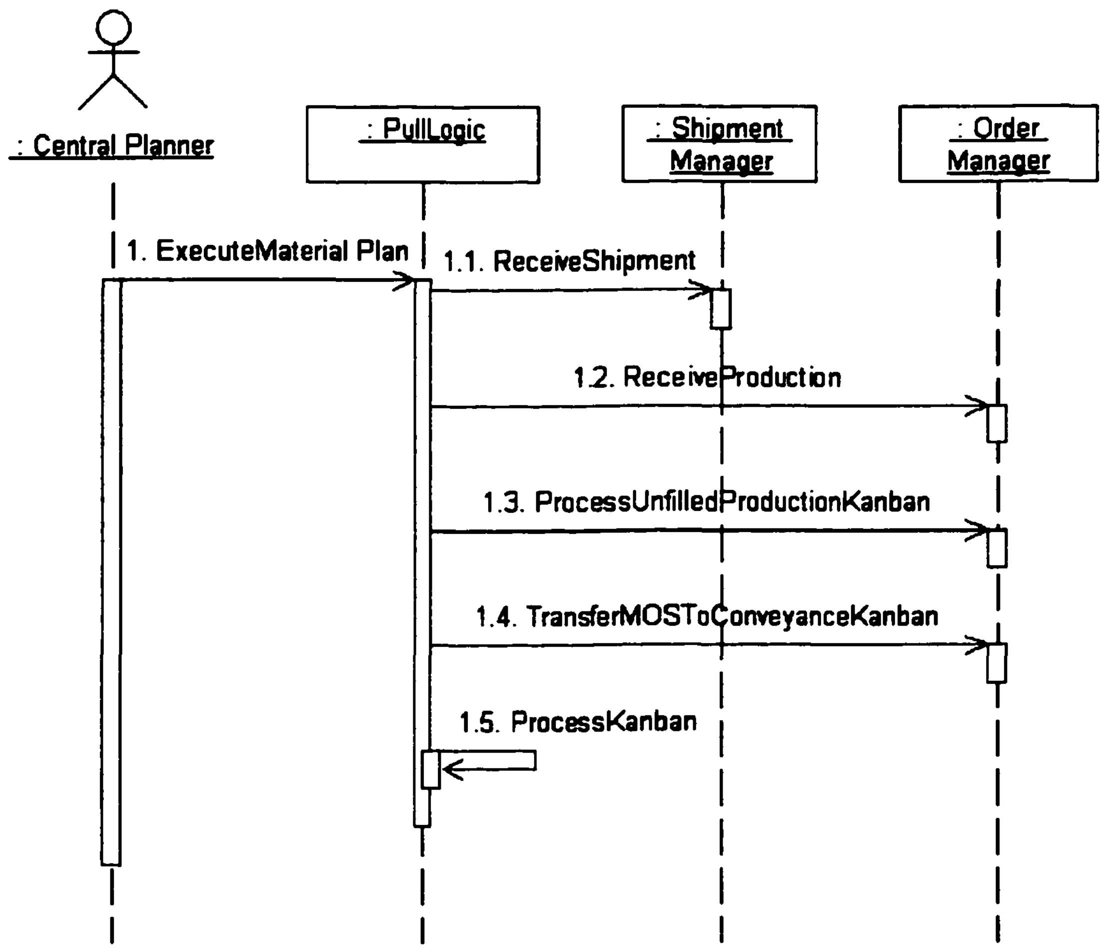


FIGURE 21

Collaboration Diagram for "Generate DOP" using Pull Strategy

CHAPTER 4

RESEARCH METHODOLOGY

In order to test the research hypotheses, a randomized experiment was conducted using computer simulation. Since the randomized experiment is ideally suited for the task of causal analysis (Judd, Smith, and Kidder 1991), it is appropriate for this study investigating the effect of OPC strategies on supply network performance. Computer simulation is commonly used in comparative studies of control strategies. It is an appropriate tool for analyzing production systems and supply networks, because their inherent complexities make other approaches impractical (Krajewski et al. 1987; Spearman and Zazanis 1992; Simchi-Levi, Kaminsk, and Simchi-Levi 1999, p 33; Persentili and Alptekin 2000).

Simulation models of a typical apparel supply network were developed. An apparel supply network is a good representation for MTS supply networks. It has to produce the products according to the forecasts of demand. Normally, customers' orders are satisfied using the products in inventory stocks. The results of this study should be germane to other MTS supply networks that have network structures and environments similar to those of apparel supply networks.

Experimental Design, Statistical Hypotheses and Data Analysis

Experimental Design

A 2x3x3 factorial design was used for the experiment in this study. The experiment included 3 factors: two types of control strategies, three levels of forecast error, and three levels of inventory buffer.

For each factor combination, the statistical model is given below:

$$Y_{ijk} = \mu + CS_i + FE_j + BL_k + CS_i * FE_j + CS_i * BL_k + FE_j * BL_k + CS_i * FE_j * BL_k + e_{ijk}$$

where

Y_{ijk} = Performance measurements

μ = Overall mean effect

CS_i = Control strategy effect (i = 0 and 1)

FE_j = Forecast error effect (j = 0, 1, and 2)

BL_k = Inventory buffer level effect (k = 0, 1, and 2)

e_{ijk} = Random effect

Statistical Hypotheses in Null Form

H1: In a MTS environment, there is no difference between push and pull supply networks when they are compared simultaneously on total inventory, throughput, and customer service level.

$CS_i = 0$ where $i = 0,1$

H2: In a MTS environment, at different levels of forecast error, there exists the same effect of control strategies when compared simultaneously on total inventory, throughput, and customer service level.

$CS_i * FE_j = 0$ where $i = 0,1$ and $j = 0,1,2$

H3: In a MTS environment, at different levels of inventory buffer, there exists the same effect of control strategies when compared simultaneously on total inventory, throughput, and customer service level.

$CS_i * BL_k = 0$ where $i = 0,1$ and $k = 0,1,2$

H4: In a MTS environment, at different levels of forecast error, there exists the same effect of inventory buffer levels when compared simultaneously on total inventory, throughput, and customer service level.

$FE_j * BL_k = 0$ where $j = 0,1,2$ and $k = 0,1,2$

H5: In a MTS environment, at different levels of forecast error, there exists the same effect of the interaction between control strategy and inventory buffer level when compared simultaneously on total inventory, throughput, and customer service level.

$CS_i * FE_j * BL_k = 0$ where $i = 0,1$, $j = 0,1,2$ and $k = 0,1,2$

Data Analysis

Multivariate Analysis of Variance (MANOVA) was used in data analysis. The reasons are 1) there is more than one dependent variable 2) dependent variables are expected to be correlated with each other 3) independent variables are categorical. Multivariate F's were used to test the effects of the experimental factors (independent variables) as well as the interactions among them. Then, to interpret the (statistically) significant factors and interactions, Univariate Analysis of Variance (ANOVA) and Student-Newman-Keuls (SNK) tests were conducted.

WMOPCS Software

I developed a prototype of WMOPCS in web-based software having potential to be applied in practice. WMOPCS allows seamless integration of a supply network. Business entities can easily exchange their information through the Internet. A central database keeps all the required data for supply network planning. To represent push and pull strategies, two different Detailed Operational Planner modules were developed. A different module was plugged into the WMOPCS to implement each strategy. The push and pull modules were developed based on push (MRP) and pull (kanban) strategies.

Microsoft Corporation's Visual Studio.Net was employed to develop the WMOPCS as well as the simulation module. Visual Studio.Net facilitates the development of web-based applications.

Simulation Model

By adding a simulation module to the WMOPCS, the author was able to investigate the research questions for this research. The WMOPCS and the simulation module were calibrated to represent a typical apparel supply network. The simulation module was responsible for generating input parameters for different simulation scenarios, administrating simulation runs as well as tracking supply network performances. Each simulation scenario represented each combination of the experimental factors. For example, one scenario represented a supply network having high forecast error as well as using pull strategy and high buffer level in its operations.

Number of Replications

In this research, there were 18 experimental combinations (2*3*3). 10 replications were collected for each combination. Ten is a conservative replication number widely used (Pegden, Shannon and Sadowski 1995). The Batch Means Method was used for getting the required replications. For each combination, a simulation ran for 36 weeks to attain the steady state. The statistics collection began after the steady state was achieved and the simulation continued for another 120 weeks representing 10 replications. Resulting data was partitioned to obtain mean values for each 12-week period (each replication).

Verification and Validation of Simulation Model

The simulation model was verified to determine that it worked as expected and validated to ensure that it was an accurate representation of the system under study (Law and Kelton, 1991). Because the simulation model was constructed using the component-based technology, each component could be individually verified. To verify each component, first its coding was checked for correctness. Then each component was tested against some simple data sets to compare its outputs with the manual calculations. The entire system was subsequently tested against a data set from an example 4-stage linear chain to accomplish the global correctness.

The validation was performed based on the entire system. Some parameters were substituted and the new results were compared against the original ones to see if they indicated a correct representation of the system under the given parameters. For example, two simulation runs were performed to observe the impact of system utilization on the congestion of the system. The same settings were applied for both simulation runs except 80% utilization used for one run and 100% utilization used for another run. The results indicated that the average work in process inventory when the utilization was 80% was lower than when the utilization was 100%. Higher utilization resulted in more congestion, as it should be.

Settings of Experimental Variables

In this study, there are three independent variables: control strategy, forecast error, and inventory buffer level, and three dependent variables: total inventory, throughput, and customer service level.

Control Strategy

Conceptual Definition

Control strategy is used to plan and control the information and material flows of the production system. It determines how much and when the items should be produced and transferred. This research addresses two types of control strategies, push and pull. The following definitions of push and pull strategies are used in this study. These definitions are found in American Production and Inventory Control Society Dictionary (APICS 1998, p. 77-78).

The APICS dictionary defines a system using push strategy as: "1) In production, the production of items at times required by a given schedule planned in advance. 2) In material control, the issuing of material according to a given schedule or issuing material to a job order at its start time."

The APICS dictionary defines a system using pull strategy as: "1) In production, the production of items only as demanded for use or to replace those taken for use. 2) In material control, the withdrawal of inventory as demanded by the using operations. Material is not issued until a signal comes from the user."

Taylor (2000) also used these definitions. Although these simple definitions describe the general differences between the two strategies, it is necessary to define in detail the push and pull systems investigated in this study. Operational definitions of these two types of systems appear in the next section.

Operational Definition

In this study, control strategy is a strategy utilized in a supply network to generate detailed operations plans (DOP). Based on Master Operations Schedule (MOS), a DOP specifies how much and when to produce or ship the products. Control Strategy is a categorical variable and has two values representing push and pull strategies.

The description of this variable is summarized below:

Variable name: Control Strategy (CS)

Categorical variable CS

= 0: Push strategy

= 1: Pull strategy

Push system

In this study, a push system refers to a supply network using push strategy to generate the DOP. The push strategy investigated in this study is adapted from the MRP concept. For the push system, a DOP is a schedule specifying how much and when to produce and/or ship a final product or a component part in order to fulfill the MOS requirements of the final products. At a particular time, a MOS requirement of a final product specifies the amount of that final product required to be available at the final stage of the system. It is the requirement specifying in the MOS and can be derived from demand forecast, committed customer orders and available inventory.

The production of a final product is launched at the beginning stages of the system and then the processed parts will reach a particular stage at the right time specified by the DOPs. The DOPs are derived by backward scheduling from desired completion times based on estimated lead times. The desired completion times are calculated from the MOS requirements of the final products. Through backward scheduling, the push system takes actions based on the future MOS requirements before the actual requirements of the final products take place at the retailers. Since the push system utilizes demand forecast (in calculating the future MOS requirements) and estimated lead-times in backward scheduling, its performance depends greatly on the accuracy of these data.

Pull System

In this study, a pull system refers to a supply network using pull strategy to generate the DOP. The pull strategy investigated in this study is adapted from the kanban concept. In pull system, every inventory stock has a fixed target level. Each stage produces only for the immediate replenishment of the items that are taken from the stock (BS 5192). For example, in a three-stage production system with one-day production lead-time at each stage and zero transferring lead-time between stages, suppose 20 units of an end item are needed at the beginning of day 6. Then at the beginning of day 6, this 20-unit requirement is satisfied by taking 20 units from the end item stock at the last stage. When the end items are removed from the stock, the last stage immediately issues a production order of 20 units to replenish its stock. The last stage starts the production by using the items from the fixed stock at the second stage as the raw materials. When the items are taken from its stock, the second stage immediately issues a production order to replenish the exact quantity taken away. In the same way, when the items are taken from the stock at the first stage in order to be used as the raw materials for the production of the second stage, the first stage immediately releases a production order to replenish the exact quantity taken away. All of these happen at the beginning of day 6.

A weakness for the push system is poor performance when the predictions of future requirements are inaccurate. To eliminate the effects of prediction errors, the pull system avoids reacting to the future requirements and instead reacts to the actual status or current requirements of the system. It can react this way because it has a fixed inventory stock for each item. The requirements are satisfied by using the items from the fixed stocks, and then the productions are triggered to replenish the stocks.

Push and Pull Differences

The main distinction between push and pull strategies is they utilize forecast information differently. A pull system reacts to the MOS requirements of the current period derived from the demand forecast of the current period. On the other hand, the push system reacts not only to the MOS requirements of the current period but also to future MOS requirements calculated from the forecasts of several periods in the future. Besides using the demand forecast of the current period to calculate the current MOS requirements, a pull system may use forecast information in determining the appropriate inventory targets for the fixed stocks. Then these targets may remain constant for a long period of time until there exist significant changes of demand pattern or there exist significant improvements of the operations processes allowing the reduction of overall inventory in the system.

Since inventory stocks in a pull system are fixed at pre-planned levels, there is a limit on the maximum level of system inventory. The total amount of inventory in the system never exceeds this predefined limit. However, there is no limit on the maximum level of inventory in a push system.

From the planning aspect, Bonney described the differences between push and pull systems as follows. "The emphasis of push systems is on planning, i.e. looking ahead to determine what should happen, whereas the emphasis of the pull systems is on pre-planning, e.g. production starts with pre-planned levels of stock and demand is smoothed" (Bonney 1999).

In a pull system, a stage is not allowed to produce without being driven by the MOS requirements of the current period whereas, in a push system, a stage is allowed to produce based on the future MOS requirements. For example, if there exists no MOS requirement in current period, a pull system becomes idle while some stages of a push system may not be idle and indeed may produce some items based on the predictions of the future MOS requirements.

It is clear that in some environmental settings a push system may outperform a pull system while in some other environmental settings a pull system may outperform a push system. In some circumstances both systems may behave the same. It is the objective of this study to investigate the performance differences of push and pull strategies under different environmental settings.

Measurement of Control Strategy

For a simulation scenario, if push strategy is used, the CS variable is assigned to 0. The CS variable is assigned to 1 if pull strategy is employed.

Inventory Buffer Level

Conceptual Definition

Inventory buffer level is the amount of safety stock required in the system.

Operational Definition

In this study, it is the target level of each inventory stock in a supply network. For each inventory stock, if the inventory level goes below the target level, the stock will be replenished to keep the target level. In a supply network, each business entity consists of two inventory stocks, one for before-processed items and another for after-processed items. Inventory buffer level is calculated from:

$$BBL_{ik} = \alpha * avgDS_{ik}$$

$$ABL_{ik} = \alpha * avgDP_{ik}$$

where;

BBL_i = level of before-processed inventory stock of item k at entity i (items)

ABL_i = level of after-processed inventory stock of item k at entity i (items)

α = safety factor (%)

$avgDS_i$ = average demand of item k at entity i during shipment lead time of item k from upstream entity to entity i (items)

$avgDP_i$ = average demand of item k at entity i during production lead time of item k at entity i (items)

The description of this variable is summarized below:

Variable name: Inventory Buffer Level (BL)

Categorical variable BL

= 0: Low; α = 25%

= 1: Medium; α = 50%

= 2: High; α = 100%

Measurement

There are three levels for this variable: 25% (Low), 50% (Medium), and 100% (High) of average demand during lead-time. The low setting is the same setting specified in Krajewski et al. (1987). In their study, a panel of production and inventory managers established low and high settings for various environmental factors. The panel considered the settings to encompass a variety of manufacturing environments in the United States. The Medium setting is the high setting specified in Krajewski et al 1987. This study set the high setting higher than the high setting specified in Krajewski et al

1987. Pull supply network requires high level of inventory buffer to perform well. 50% of average demand during lead-time may be not sufficient for pull supply network. Therefore, this study used 100% of average demand during lead-time as the high setting to represent high buffer condition for both push and pull supply networks.

Forecast Error

Conceptual Definition

It is demand forecast error, the difference between the actual demand and demand forecast for a given period (Finch and Luebbe 1995).

Operational Definition

In this study, the Forecast Error variable is measured as the standard deviation of the normally distributed error function with a mean of 0, δ_ε (Krajewski et al. 1987; Ritzman and King 1993; Kadipasaoglu and Sridharan 1995). A mean of 0 implies that forecast bias is not considered in this study. It should be noted that unlike inventory buffer level and control strategy that are part of supply network configurations and can be easily altered, forecast error is an environmental condition that cannot be manipulated easily.

The description of this variable is summarized below:

Variable name: Forecast Error (FE)

Categorical variable FE

= 0: Low; δ_ε = 11% of weekly demand average

= 1: Medium; δ_ε = 33% of weekly demand average

= 2: High; δ_ε = 55% of weekly demand average

Measurement

There are three levels for this variable: Low ($\delta_\varepsilon = 11\%$), medium ($\delta_\varepsilon = 33\%$), and high ($\delta_\varepsilon = 55\%$). Krajewski et al. (1987) and Ritzman and King (1993) set δ_ε to be 0%, 5.5% and 11% of weekly demand average for low, medium and high settings respectively. Since there were a large amount of inventories in the medium and high settings of Inventory Buffer Level, this study had to set forecast error higher than the other studies. Otherwise, in these two settings, the large amount of inventory buffers would absorb all the effects of forecast error.

Performance Measures

System Performance

Conceptual Definition

System Performance is operational performance of a system. Conceptually, it has many dimensions.

Operational Definition

In this study, it is global operational performance of a supply network measured in terms of throughput, total inventory and customer service level. Values of these dependent variables are collected from the simulations.

Throughput (TH)

Throughput is a continuous variable. It is defined as the average output of a supply network per week (Hopp and Spearman 1996). Note throughput is the rate of product per week that is produced not the rate of product per week that is sold.

Total Inventory (INV)

Total Inventory is average total inventory in a supply network. It is a continuous variable and measured in physical volume (Sarker and Fitzsimmons 1989). The following formulas are applied to calculate it:

$$INV = \sum_{i=1}^{N} (NINV_i) + \frac{BTINV + ETINV}{2}$$

$$NINV_i = \frac{BINV_i + EINV_i}{2}$$

where;

INV = Average total inventory in a supply network during a time period (units)

$NINV_i$ = Average inventory of entity i during a time period (units)

$BINV_i$ = Inventory level of entity i at the beginning of period (units)

$EINV_i$ = Inventory level of entity i at the end of period (units)

BTINV = In-transit inventory in a supply network at the beginning of period (units)

ETINV = In-transit inventory in a supply network at the end of period (units)

N = Number of business entities in a supply network

Customer Service Level (SL)

Customer Service Level is a continuous variable. In this study, demand fill rate is used to measure customer service level. Demand fill rate is the proportion of customer demand at the retailers that is immediately satisfied from the inventory. It has been commonly used for measuring customer service level (Krajewski et al. 1987; Sridharan and LaForge 1989; Zhao and Lee 1993; Kadipasaoglu and Sridharan 1995). Figure 22 summarizes the independent and dependent variables in this research.

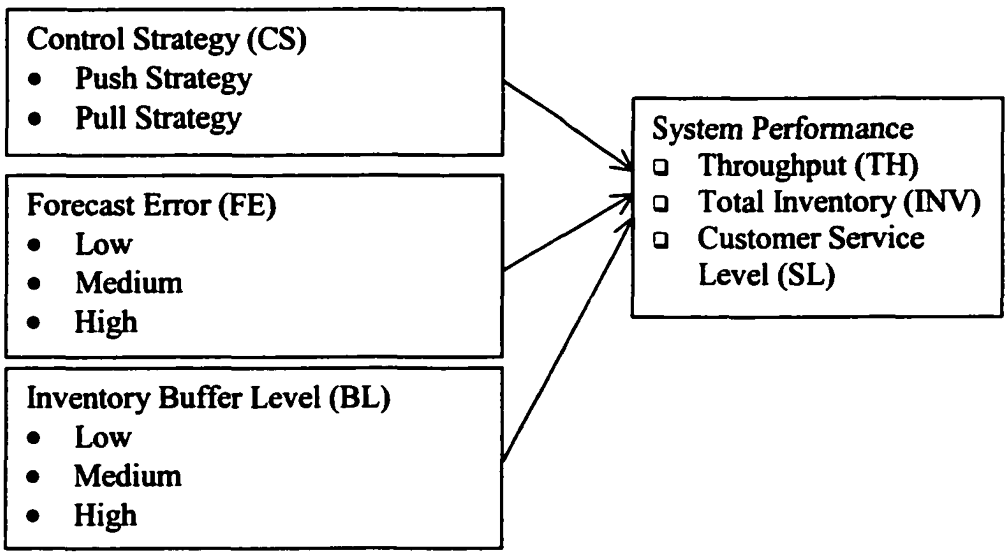


FIGURE 22

Research Model with Independent and Dependent Variables

Assumptions

The following assumptions are applied in this study.

- No alternative routings.
- No pre-emption of jobs once work is begun.
- Constant processing times and shipment times as shown in bill of materials.
- No back orders at retailers. Demands that cannot be satisfied are lost.
- No starvation of raw materials at suppliers (first stages of a supply network).
- Suppliers have infinite capacity available.

- No partial shipment.
- Processing of partial production orders is allowed.
- All weekly demands have the same due dates which are at the beginning of the week.
- All orders are issued at the beginning of the week.
- No overtime. Any orders or parts of orders in excess of the available capacity will be processed in the following week if there will be sufficient capacity for processing them.
- Earliest-Due-Date (EDD) rule is applied to schedule the orders. If some orders are tied, First-Come-First-Serve (FCFS) rule is applied.
- Lot-For-Lot (LFL) lot-sizing rule is applied for every item.

Fixed Parameters

Figure 23 shows the structure of the supply network used in the simulation. This supply network structure is adapted from Lin and Shaw (1998). It represents an apparel industry supply network. The supply network consists of 6 stages including supplier, fiber producers, textile producers, apparel manufacturer, distributors and retailers. The simulation involves one final product or product group called product F01. The Bill of Materials (BOM) for product F01 is illustrated in Figure 24. As shown in the BOM, the products at Tike apparel manufacturer, distributors, and retailers have different names. However, they are identical, which are the final product F01. Other important parameters are listed below:

- Weekly Demand: At each retailer, the weekly demand of product F01 is uniformly distributed between 45-75 units. The average weekly demand is 60 units. The uniform distribution is widely used in the literature to represent the distribution of demand (Krajewski et al. 1987, Lea 1998).

- Number of final products: 1 type of final product or product group.
- Utilization: Average utilization at each production facility except suppliers is 80%.
- Capacity (time): 40 work hours per week. There are 50 weeks in a year.
- Capacity (units/week): The capacity for product *j* at production facility *i* except suppliers is derived from:

  Capacity for product *j* at facility *i*

  = (Average weekly demand of product *j* at facility *i*) / (%utilization)

  For example, the capacity for product F01-Tike at Tike manufacturer

  = (60+60+60+60)/(0.8)

  = 300 units per week
- Processing time: The processing time for product *j* at production facility *i* except suppliers is derived from:

  Processing time (minutes) for product *j* at facility *i*

  = (40*60)/(capacity for product *j* at facility *i*)

  For example, the processing time for product F01-Tike at Tike manufacturer

  = (40*60) / 300

  = 8 minutes
- Replanning period: 1 week.
- The forecast window of MOS is 12 weeks.

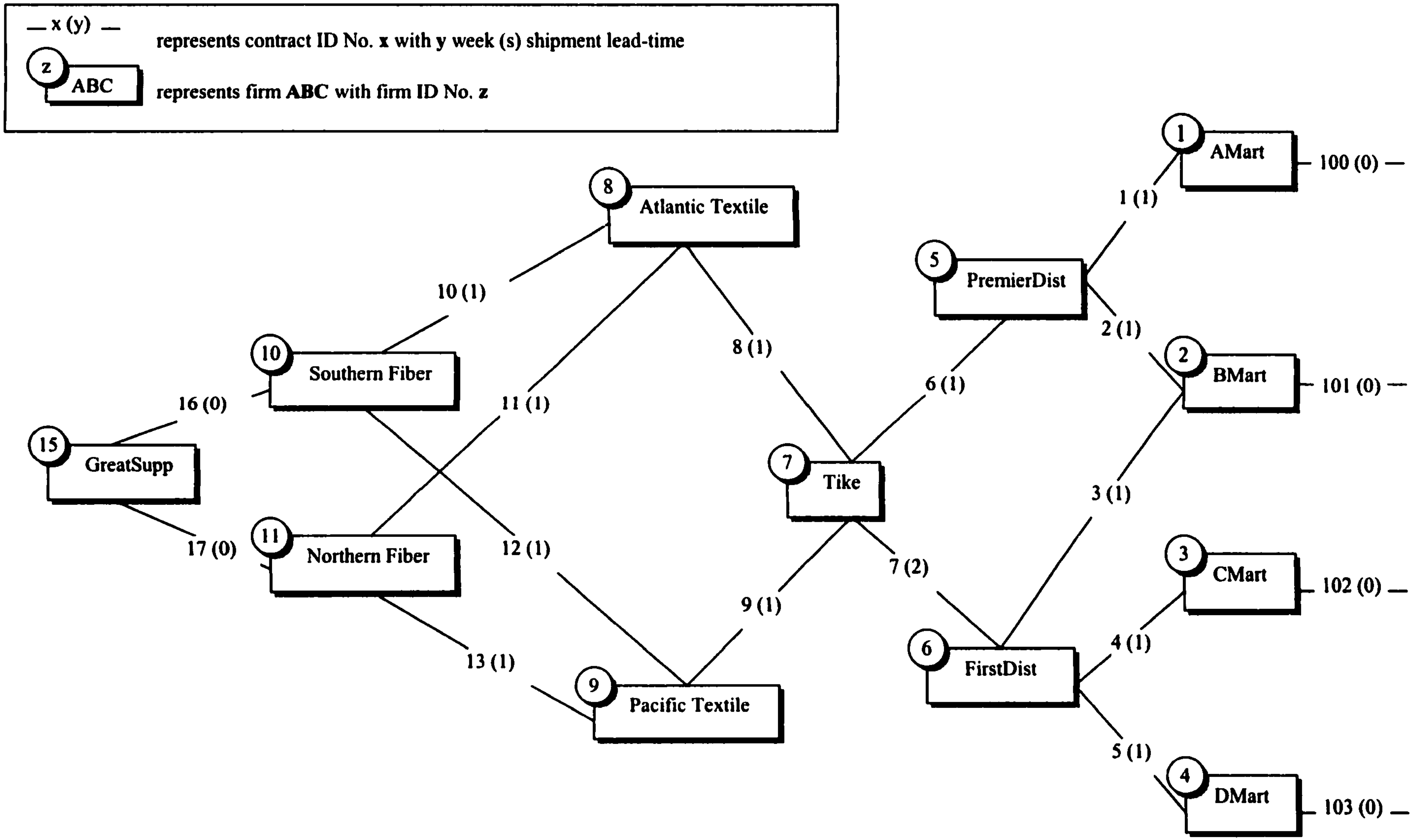


FIGURE 23

Supply Network Structure (adapted from Lin and Shaw 1998)

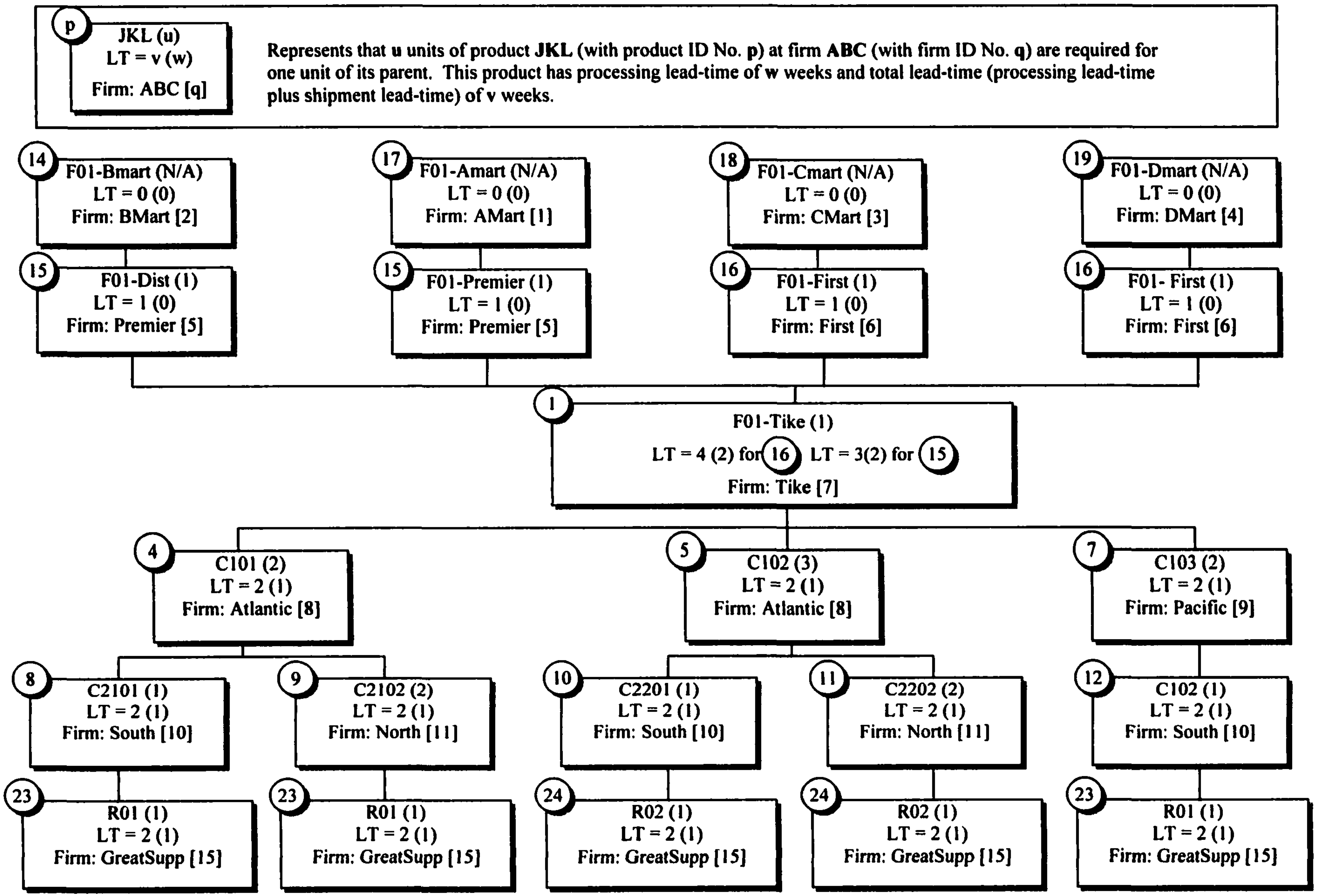


FIGURE 24

Bill of Materials for Product F01

CHAPTER 5

RESULTS

This chapter summarizes the results of the experiment described in Chapter 4. The data collected from the computer simulation were analyzed using SAS (version 8). Multivariate Analysis Of Variance (MANOVA) was used to test the hypotheses. The steps in performing MANOVA were adapted from Hatcher and Stepanski (1994). Multivariate F's generated by MANOVA were used to test the effects of independent variables and their interactions on all of the dependent variables simultaneously. Follow-up tests were performed to interpret each significant effect found in the MANOVA. These follow-up tests included Univariate Analysis Of Variance (ANOVA), simple effect tests and Student-Newman-Keuls (SNK) tests. For each effect found significant in the MANOVA, the results of the Univariate ANOVAs were first reviewed to identify the specific dependent variables on which the effect was found significant. Then, simple effect tests and/or SNK tests were conducted to interpret the impact of the effect on each of the dependent variables identified by the univariate ANOVAs. 0.05 level of significance was applied for all the tests performed in this study.

The first section illustrates descriptive statistics and bivariate correlations among the dependent variables. The second section presents the MANOVA results as well as the outcomes of hypothesis testing. The last section interprets the results of the MANOVA by using the results of the follow–up tests.

Descriptive Statistics and Bivariate Correlations among Dependent Variables

From the simulation, 180 data points were collected. These data points came from 18 experimental combinations (2*3*3 factorial design) with 10 replications for each combination. Table V shows means, standard deviations and correlation coefficients of the dependent variables. As expected, all bivariate correlations among the dependent variables were high and significant with $p < 0.0001$. This implies a supply network having high throughput and a high level of total inventory is likely to have a high service level. The high correlations among the dependent variables supported the appropriate use of MANOVA over multiple univariate ANOVAs. MANOVA considers these correlations when calculating the test statistics. However, univariate tests ignore these correlations (Harris 1993).

TABLE V

Means, Standard Deviations, and Correlation Coefficients
of the Dependent Variables

	Means	SD	1	2
1. Total Inventory (Inv)	26802.0000	8822.0000		
2. Throughput (TH)	198.4153	45.9798	0.6681***	
3. Service Level (SL)	0.8447	0.1612	0.6637***	0.8642***

Note: $n = 180$
***$p < 0.0001$

Hypothesis Testing

Assumptions Underlying MANOVA and ANOVA

The following paragraphs discuss two important assumptions underlying MANOVA and ANOVA, normal distributions and homogeneity of variance.

Normal Distributions

For ANOVA, the observations in each cell should be drawn from a normally distributed population. For MANOVA, in each cell, the observations on various dependent variables should follow a multivariate normal distribution (Stevens 1986; Hatcher and Stepanski 1994). Multivariate normal distribution is different from the assumption of normality on a single dependent variable in ANOVA. In addition to the normality of each of the dependent variables separately, two other properties of a multivariate normal distribution are: 1) any linear combination of the dependent variables will be normally distributed and 2) all subsets of the set of dependent variables will have a multivariate normal distribution (Stevens 1986, p. 205). Fortunately, for both MANOVA and ANOVA, the F statistic is robust with respect to type I error against non-normality (Stevens 1986; Hatcher and Stepanski 1994). Therefore, violating this assumption only has a slight effect on the critical values.

Homogeneity of Variance

For ANOVA, the population variances of various cells should be equal. For MANOVA, the covariance matrices for the dependent variables in each cell should be equal. ANOVA is robust against heterogeneous variances if the numbers of subjects in each cell are equal or approximately equal (Stevens 1986; Hatcher and Stepanski 1994). In this study, the numbers of subjects in each cell were equal.

The MANOVA assumption of equal covariance matrices is unlikely to be satisfied in practice. Nevertheless, the MANOVA is robust with respect to type I error against typical violations of this assumption as long as the numbers of subjects in each cell are equal. On the other hand, the power of the test (1 – type II error) trends to be diminished when the assumption of equal covariance matrices is violated, even for equal cell sizes (Stevens 1986; Hatcher and Stepanski 1994).

MANOVA Results

With MANOVA, a single test can assess the effect of an independent variable or an interaction on all of the dependent variables. Table VI summarizes the results of the MANOVA tests. The relevant results for each hypothesis are discussed below.

TABLE VI

MANOVA Results

Effect tested	Wilks' Lambda	F Value	DF	p-value
CS	0.09947650	482.81	(3,160)	<.0001**
FE	0.87300708	3.75	(6, 320)	0.0013**
BL	0.24084297	55.34	(6, 320)	<.0001**
CS* FE	0.91584883	2.40	(6, 320)	0.0280**
CS* BL	0.46287374	25.06	(6, 320)	<.0001**
FE * BL	0.87587796	1.81	(12, 423.61)	0.0439**
CS* FE* BL	0.89130673	1.57	(12, 423.61)	0.0976

DF = Degree of Freedom
** $p < 0.05$

H1 null: In a MTS environment, there is no difference between push and pull supply networks when they are compared simultaneously on total inventory, throughput, and customer service level.

$CS_i = 0$ where $i = 0,1$

The MANOVA results in Table VI indicated that there was a significant multivariate effect for the type of control strategies (Wilk's Lambda = 0.0995, $F\ (3, 160) = 482.81$, $p < 0.0001$). Hypothesis 1 was rejected. The push supply network and the pull supply network exhibited differences when they were compared simultaneously on all three of the criterions. Small values of Wilk's Lambda (closer to 0) suggest a relatively strong relationship between the independent variable and the multiple dependent variables (Hatcher and Stepanski, 1994). Wilk's Lambda of 0.0995 indicated that there was a very strong relationship between CS and the multiple dependent variables.

Table VII shows the results of the canonical analysis for CS. There was one canonical variate, CAN1. CAN1 was found significant ($F\ (3, 160) = 482.81$, $p < 0.0001$). Canonical correlation (r_c) indicates the correlation between an independent variable and a canonical variate while canonical loading (CL) describes the correlation between a canonical variate and a dependent variable. 90.05% (squared canonical correlation) of the variance in CS was accounted for by CAN1. Inv, TH, and SL roughly had the same size of effects on CAN1 (CL for Inv = 0.7539, CL for TH = 0.8066, and CL for SL = 0.8686). Inv, TH, and SL accounted for 56.84% (squared CL), 65.06%, and 75.45% of the variance in CAN1 respectively.

TABLE VII

Canonical Analysis for CS

	r_c	Test of H_0: r_cs in Current Row and All that Follow = 0			CL within Canonical Structure		
		F Value	DF	p-value	Inv	TH	SL
CAN1	0.9490	482.81	(3, 160)	$< 0.0001^{**}$	0.7539	0.8066	0.8686

Note: r_cs = Canonical correlations
CL = Canonical Loading
$^{**}p < 0.05$

The redundancy coefficient describes the direct relationship between an independent variable and a dependent variable. Table VIII displays redundancy coefficients between CS and the dependent variables. The output of MANOVA analysis from SAS did not include the redundancy coefficients. The redundancy coefficients in Table VIII were derived from the following formulas.

Redundancy coefficient between CS and Inv

$$= r_c^2 * CL^2$$

$$= (0.9490)^2 * (0.7539)^2$$

$$= 0.5119$$

Redundancy coefficient between CS and TH

$$= r_c^2 * CL^2$$

$$= (0.9490)^2 * (0.8066)^2$$

$$= 0.5859$$

Redundancy coefficient between CS and SL

$= r_c^{2} * CL^2$

$= (0.9490)^2 * (0.8686)^2$

$= 0.6795$

Redundancy coefficient between CS and the combination of the dependent variables

$= r_c^{2} *$ Mean of Eigen Value

$$= (0.9490)^2 * \frac{((0.7539)^2 + (0.8066)^2 + (0.8686)^2)}{3}$$

$= 0.5924$

Thus, CS accounted for 59.24% of the variance in the combination of the dependent variables. CS had about the same size of effect on each of the performance measures (51.19% of the variance in Inv, 58.59% of the variance in TH, and 67.95% of the variance in SL). It significantly affected all three of the criterions.

TABLE VIII

Redundancy coefficients between CS and Dependent Variables

Dependent Variables	Redundancy Coefficients
Inv	0.5119
TH	0.5859
SL	0.6795
Combination of Dependent Variables	0.5924

H2 null: In a MTS environment, at different levels of forecast error, there exists the same effect of control strategies when compared simultaneously on total inventory, throughput, and customer service level.

$CS_i * FE_j = 0$ where $i = 0,1$ and $j = 0,1,2$

The MANOVA results in Table VI indicated that there was a significant multivariate effect for the interaction of CS with FE (Wilk's Lambda = 0.9158, F (6, 320) = 2.40, p = 0.0280). Hypothesis 2 was rejected. At different levels of forecast error, the effects of control strategies were different when compared simultaneously on all three of the criterions. Wilk's Lambda of 0.9158, which was not close to 0, indicated that there was a weak relationship between CS*FE and the multiple dependent variables.

Table IX shows the results of the canonical analysis for CS*FE. There were two canonical variates, CAN1 and CAN2. CAN1 was found significant (F (6, 320) = 2.40, p = 0.0280) but CAN2 was not significant (F (2, 161) = 0.58, p = 0.5615). 7.76% (squared canonical correlation) of the variance in CS*FE was accounted for by CAN1. SL and TH had bigger effects on CAN1 than Inv did (CL for Inv = 0.4667, CL for TH = 0.7771, and CL for SL = 0.8037). Inv, TH, and SL accounted for 21.78% (squared CL), 60.39%, and 64.59% of the variance in CAN1 respectively.

TABLE IX

Canonical Analysis for CS*FE

		Test of H_0: r_cs in Current Row and All that Follow = 0			CL within Canonical Structure		
	r_c	F Value	DF	p-value	Inv	TH	SL
CAN1	0.2785	2.40	(6, 320)	0.0280**	0.4667	0.7771	0.8037
CAN2	0.0845	0.58	(2, 161)	0.5615	0.7530	0.1448	-0.5938

Note: r_cs = Canonical Correlations
CL = Canonical Loading
** $p < 0.05$

Table X displays redundancy coefficients between CS*FE and the dependent variables. CS*FE had bigger effects on TH and SL than on Inv (1.69% of the variance in Inv, 4.68% of the variance in TH, and 5.01% of the variance in SL). It accounted for 3.79% of the variance in the combination of the dependent variables. Although CS*FE significantly affected all three of the criterions, it had only small effects on them.

TABLE X

Redundancy coefficients between CS*FE and Dependent Variables

Dependent Variables	Redundancy Coefficients
Inv	0.0169
TH	0.0468
SL	0.0501
Combination of Dependent Variables	0.0379

H3 null: In a MTS environment, at different levels of inventory buffer, there exists the same effect of control strategies when compared simultaneously on total inventory, throughput, and customer service level.

$CS_i * BL_k = 0$ where $i = 0,1$ and $k = 0,1,2$

The MANOVA results in Table VI indicated that there was a significant multivariate effect for the interaction of CS with BL (Wilk's Lambda = 0.4629, $\underline{F}$ (6, 320) = 25.06, $\underline{p} < 0.0001$). Hypothesis 3 was rejected. At different levels of inventory buffer, the effects of control strategies were different when compared simultaneously on all three of the criterions. Wilk's Lambda of 0.4629 indicated that there was a moderate relationship between CS*BL and the multiple dependent variables.

Table XI shows the results of the canonical analysis for CS*BL. There were two canonical variates, CAN1 and CAN2. CAN1 was found significant (F (6, 320) = 25.06, p < 0.0001) but CAN2 was not significant (F (2, 161) = 0.03, p = 0.9695). 53.70% (squared canonical correlation) of the variance in CS*BL was accounted for by CAN1. Among the dependent variables, Inv had the biggest effect on CAN1 (CL for Inv = 0.7984, CL for TH = -0.3874, and CL for SL = -0.5488). Inv, TH, and SL accounted for 63.74% (squared CL), 15.01%, and 30.12% of the variance in CAN1 respectively.

TABLE XI

Canonical Analysis for CS*BL

		Test of H_0: r_cs in Current Row and All that Follow = 0			CL within Canonical Structure		
	r_c	F Value	DF	p-value	Inv	TH	SL
CAN1	0.7328	25.06	(6, 320)	<0.0001**	0.7984	-0.3874	-0.5488
CAN2	0.0196	0.03	(2, 161)	0.9695	0.3727	0.8339	-0.0309

Note: r_cs = Canonical Correlations
CL = Canonical Loading
** $p < 0.05$

Table XII displays redundancy coefficients between CS*BL and the dependent variables. Comparing its effect on each of the dependent variables, CS*BL had the biggest effect on Inv (34.23% of the variance in Inv, 8.06% of the variance in TH, and 16.17% of the variance in SL). The biggest effect on Inv might be attributed to the BL term in CS*BL interaction. In a supply network, the level of inventory buffer had direct impact on the total inventory. CS*BL accounted for 19.49% of the variance in the combination of the dependent variables. It significantly affected all three of the criterions with moderate effects on them.

TABLE XII

Redundancy coefficients between CS*BL and Dependent Variables

Dependent Variables	Redundancy Coefficients
Inv	0.3423
TH	0.0806
SL	0.1617
Combination of Dependent Variables	0.1949

H4 null: In a MTS environment, at different levels of forecast error, there exists the same effect of inventory buffer levels when compared simultaneously on total inventory, throughput, and customer service level.

$FE_j * BL_k = 0$ where $j = 0,1,2$ and $k = 0,1,2$

The MANOVA results in Table VI indicated that there was a significant multivariate effect for the interaction of FE with BL (Wilk's Lambda = 0.8759, $\underline{F}$ (12, 423.61) = 1.81, $\underline{p}$ = 0.0439). Hypothesis 4 was rejected. At different levels of forecast error, the effects of inventory buffer levels were different when compared simultaneously on all three of the criterions. Wilk's Lambda of 0.8759 indicated that there was a weak relationship between FE*BL and the multiple dependent variables.

Table XIII shows the results of the canonical analysis for FE*BL. There were three canonical variates, CAN1, CAN2 and CAN3. CAN1 was found significant ($\underline{F}$ (12, 423.61) = 1.81, $\underline{p}$ = 0.0439) but CAN2 and CAN3 were not significant ($\underline{F}$ (6, 322) = 1.00, $\underline{p}$ = 0.4276 for CAN2 and $\underline{F}$ (2, 162) = 0.75, $\underline{p}$ = 0.4720 for CAN3). 9.13% (squared canonical correlation) of the variance in FE*BL was accounted for by CAN1. Among the dependent variables, SL had the biggest effect on CAN1 (CL for Inv = -0.3049, CL for TH = -0.2642, and CL for SL = 0.6868). Inv, TH, and SL accounted for 9.30% (squared CL), 6.98%, and 47.17% of the variance in CAN1 respectively.

TABLE XIII

Canonical Analysis for FE*BL

		Test of H_0: r_cs in Current Row and All that Follow = 0			CL within Canonical Structure		
	r_c	F Value	DF	p-value	Inv	TH	SL
CAN1	0.3021	1.81	(12, 423.61)	0.0439**	-0.3049	-0.2642	0.6868
CAN2	0.1648	1.00	(6,322)	0.4276	0.9121	0.3835	0.3597
CAN3	0.0960	0.75	(2,162)	0.4720	-0.2742	0.8850	0.6316

Note: r_cs = Canonical Correlations
CL = Canonical Loading
** $p < 0.05$

Table XIV displays redundancy coefficients between FE*BL and the dependent variables. Comparing its effect on each of the dependent variables, FE*BL had the biggest effect on SL (0.85% of the variance in Inv, 0.64% of the variance in TH, and 4.30% of the variance in SL). FE*BL accounted for 1.93% of the variance in the combination of the dependent variables. Although FE*BL significantly affected all three of the criterions, it had only small effects on them.

TABLE XIV

Redundancy coefficients between FE*BL and Dependent Variables

Dependent Variables	Redundancy Coefficients
Inv	0.0085
TH	0.0064
SL	0.0430
Combination of Dependent Variables	0.0193

H5 null: In a MTS environment, at different levels of forecast error, there exists the same effect of the interaction between control strategy and inventory buffer level when compared simultaneously on total inventory, throughput, and customer service level.

$CS_i * FE_j * BL_k = 0$ where $i = 0,1$, $j = 0,1,2$ and $k = 0,1,2$

The MANOVA results in Table VI indicated that there was no significant multivariate effect for the 3-way interaction of CS*FE*BL (Wilk's Lambda = 0.8913, F (12, 423.61) = 1.57, $p = 0.0976$). MANOVA analysis failed to reject Hypothesis 5. At different levels of forecast error, there exists the same effect of the interaction between control strategy and inventory buffer level when compared simultaneously on all three of the criterions. Since the 3-way interaction of CS*FE*BL was not significant, no further analysis or interpretation were conducted for it.

Although this study did not hypothesize the multivariate effects of FE and BL, it is useful to discuss these effects. The MANOVA results pertinent to these effects are discussed below.

FE effect: The MANOVA results in Table VI indicated that there was a significant multivariate effect for FE (Wilk's Lambda = 0.8730, F (6, 320) = 3.75, p =

0.0013). Different levels of forecast error exhibited differences when they were compared simultaneously on all three of the criterions. Wilk's Lambda of 0.8730 indicated that there was a weak relationship between FE and the multiple dependent variables.

Table XV shows the results of the canonical analysis for FE. There were two canonical variates, CAN1 and CAN2. CAN1 was found significant (F (6, 320) = 3.75, p = 0.0013) but CAN2 was not significant (F (2, 161) = 0.08, p = 0.9203). 12.61% (squared canonical correlation) of the variance in FE was accounted for by CAN1. Inv, TH, and SL roughly had the same size of effects on CAN1 (CL for Inv = -0.6539, CL for TH = 0.4940, and CL for SL = 0.7276). Inv, TH, and SL accounted for 42.76% (squared CL), 24.40%, and 52.94% of the variance in CAN1 respectively.

TABLE XV

Canonical Analysis for FE

		Test of H_0: r_cs in Current Row and All that Follow = 0			CL within Canonical Structure		
	r_c	F Value	DF	p-value	Inv	TH	SL
CAN1	0.3551	3.75	(6, 320)	0.0013**	-0.6539	0.4940	0.7276
CAN2	0.0321	0.08	(2, 161)	0.9203	0.4001	0.8222	-0.0458

Note: r_cs = Canonical Correlations
CL = Canonical Loading
** $p < 0.05$

Table XVI displays redundancy coefficients between FE and the dependent variables. FE had about the same size of effect on each of the performance measures (5.39% of the variance in Inv, 3.08% of the variance in TH, and 6.68% of the variance in

SL). It accounted for 5.05% of the variance in the combination of the dependent variables. Although FE significantly affected all three of the criterions, it had only slight effects on them.

TABLE XVI

Redundancy coefficients between FE and Dependent Variables

Dependent Variables	Redundancy Coefficients
Inv	0.0539
TH	0.0308
SL	0.0668
Combination of Dependent Variables	0.0505

BL effect: The MANOVA results in Table VI indicated that there was a significant multivariate effect for BL (Wilk's Lambda = 0.2408, $\underline{F}$ (6, 320) = 55.34, $\underline{p}$ < 0.0001). Different levels of inventory buffer exhibited differences when they were compared simultaneously on all three of the criterions. Wilk's Lambda of 0.2408 indicated that there was a strong relationship between BL and the multiple dependent variables.

Table XVII shows the results of the canonical analysis for BL. There were two canonical variates, CAN1 and CAN2. CAN1 was found significant ($\underline{F}$ (6, 320) = 55.34, $\underline{p}$ < 0.0001) but CAN2 was not significant ($\underline{F}$ (2, 161) = 1.78, $\underline{p}$ = 0.1726). 75.38% (squared canonical correlation) of the variance in BL was accounted for by CAN1. Among the dependent variables, Inv had the biggest effect on CAN1 (CL for Inv = 0.8315, CL for TH = 0.3389, and CL for SL = 0.4955). Inv, TH, and SL accounted for 69.14% (squared CL), 11.49%, and 24.55% of the variance in CAN1 respectively.

TABLE XVII

Canonical Analysis for BL

	r_c	Test of H_0: r_cs in Current Row and All that Follow = 0			CL within Canonical Structure		
		F Value	DF	p-value	Inv	TH	SL
CAN1	0.8682	55.34	(6, 320)	< 0.0001**	0.8315	0.3389	0.4955
CAN2	0.1469	1.78	(2, 161)	0.1726	-0.5094	-0.2135	0.6819

Note: r_cs = Canonical Correlations
CL = Canonical Loading
** $p < 0.05$

Table XVIII displays redundancy coefficients between BL and the dependent variables. Comparing its effect on each of the dependent variables, BL had the biggest effect on Inv (52.12% of the variance in Inv, 8.66% of the variance in TH, and 18.51% of the variance in SL). This was because in a supply network, the level of inventory buffer had direct impact on the total inventory. BL accounted for 26.43% of the variance in the combination of the dependent variables. It significantly affected all three of the criterions with the strongest effect on Inv.

TABLE XVIII

Redundancy coefficients between BL and Dependent Variables

Dependent Variables	Redundancy Coefficients
Inv	0.5212
TH	0.0866
SL	0.1851
Combination of Dependent Variables	0.2643

Interpretation of the MANOVA Results

According to the MANOVA results shown in Table VI, all effects except the three-way interaction effect were found significant. Follow-up tests were needed to further interpret each significant effect. Typically, we do not interpret the main effect of an independent variable when that independent variable involves in a significant interaction. Therefore, further interpretation focused on three significant interactions, CS*FE, CS*BL, and FE*BL. Univariate ANOVAs were carried out to test the effects of these interactions on each of the dependent variables. Following each univariate ANOVA, simple effect testing was performed to interpret each of these interactions found significant in the univariate ANOVA.

Hatcher and Stepanski (1994) gave the definition of the simple effect that "When there is a simple effect for independent variable A at a given level of independent variable B, it means that there is a significant relationship between independent variable A and the dependent variable at that level of independent variable B". To test the simple effects for variable A at each level of variable B, the sample data were divided into subsets according to the different levels of variable B. The simple effect for variable A at a particular level of variable B was tested by performing a one-way ANOVA of variable A and the dependent variable using the subset containing only subjects in that level of variable B (Hatcher and Stepanski 1994).

The following discussions interpret the effects of CS*FE, CS*BL, and FE*BL on each of the dependent variables.

Total Inventory (Inv)

Table XIX displays the univariate ANOVA results for Inv criterion. The highest level interaction found significant was the three-way interaction of CS*FE*BL (F (4, 162) = 2.55, p = 0.0410). However, since the three-way interaction was found nonsignificant in the MANOVA, its interpretation was not continued. Table XIX also provides the R^2 value for each effect. R^2 for a given effect or eta-square represents the unique variance shared between that effect and the dependent variable (Moore 1999). SAS outputs did not include the values of eta-square. The values of eta-square shown in Table XIX were calculated from the following formula (Moore 1999):

$$R^2 \text{ for a given effect (eta-square)} = \frac{\text{SSbetween for effect}}{\text{SStotal}}$$

As shown in Table XIX, CS and BL had strong relationships with Inv (R^2 for CS = 0.5600, R^2 for BL = 0.2311). FE and CS*BL only accounted for a small percent of the variance in Inv.

TABLE XIX

Univariate ANOVA Results for Inv Criterion

Effect Tested	Dependent Variable: Inv			
	F Value	DF	p-value	R^2
CS	833.49	(1,162)	<.0001**	0.5600
FE	5.01	(2,162)	0.0077**	0.0067
BL	171.99	(2,162)	<.0001**	0.2311
CS* FE	1.81	(2,162)	0.1663	0.0024
CS* BL	59.87	(2,162)	<.0001**	0.0804
FE * BL	1.35	(4,162)	0.2549	0.0036
CS* FE* BL	2.55	(4,162)	0.0410**	0.0069

** $p < 0.05$

CS*FE

The univariate F statistic of CS*FE was not significant (F (2, 162) = 1.81, p = 0.1663). Thus its interpretation was not continued even though its multivariate F statistic was significant.

CS*BL

The univariate F statistic of CS*BL was significant (F (2, 162) = 59.87, p < 0.0001). Its multivariate F statistic was also significant. Hence, simple effect tests were performed to interpret its effect.

Simple Effect Testing for BL at Different Levels of CS

The effect of a two-way interaction can be better understood by plotting the means for each level of both variables involving in the interaction. Figure 25 demonstrates the effect of CS*BL on Inv.

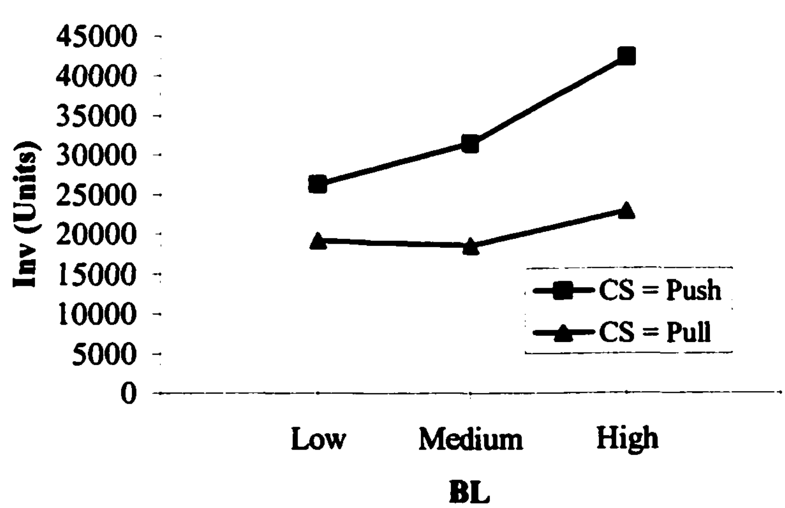


FIGURE 25

Effect of CS*BL on Inv

As illustrated in Figure 25, under all three settings of BL, push strategy resulted in higher total inventory than pull strategy. In this criterion, pull strategy outperformed push strategy. Also, CS moderated the effect of BL on Inv. BL had a stronger effect on Inv in a push supply network, compared to a pull supply network. The reason is that inventory buffers in a push supply network are only used to protect against demand variability and forecast errors. However, in addition to using inventory buffers against demand variability and forecast errors, a pull supply network needs them to make the pull mechanisms work. The requirements are satisfied by using inventory buffers from fixed stocks, and then the productions are triggered to replenish the stocks. A pull supply network operates this way to avoid reacting to the predictions of future MOS requirements. A pull supply network consumes more inventory than does a push supply network.

Although the figure shows that at each level of CS, BL does affect Inv, we have to test whether these effects for BL are significant. Simple effect testing was performed. At each level of CS, a one-way ANOVA of BL as independent variable and Inv as dependent variable was conducted. F statistic for testing simple effect was not the one provided with one-way ANOVA. Instead, it was derived from the following formula (Hatcher and Stepanski, 1994):

$$F = \frac{\text{MS simple effect}}{\text{Within–groups MS}}.$$

MS simple effect is the mean square of simple effect from one-way ANOVA. Within-groups MS is the mean square-error from two-way ANOVA of BL and CS as independent variables and Inv as dependent variable. For example, the F statistic for testing the simple effect of BL at CS = 0 was calculated as below:

$$F_{(2,\,174)} = \frac{2003747859}{10287325} = 194.78.$$

According to the F statistic table, at $p = 0.05$ and 2, 174 degrees of freedom, the critical value of F is 3. The calculated F was 194.78, which was larger than this critical F. Hence there was a simple effect for BL at CS = 0 (push strategy), $F\ (2, 174) = 194.78$, $p < 0.05$. Table XX displays the results of the simple effect testing for BL on Inv at different levels of CS.

For each simple effect for BL found significant, SNK test was performed to determine the significant differences between each level of BL. Table XXI shows the results of the SNK tests for BL at different levels of CS.

TABLE XX

Results of Simple Effect Testing for BL on Inv at Different Levels of CS

CS	F Value	DF	p-value
Push	194.78	(2, 174)	< 0.05**
Pull	16.17	(2, 174)	< 0.05**

** Statistically significant at 0.05 level

TABLE XXI

Results of SNK Tests for BL on Inv at Different Levels of CS

CS	BL	Mean (N = 30)	SNK Grouping
Push	Low	26331.5	C
	Medium	31483.4	B
	High	42341.3	A
Pull	Low	19126.0	B
	Medium	18609.0	B
	High	22922.0	A

As shown in Tables XX and XXI, there was a significant simple effect for BL at CS = 0 (F (2, 174) = 194.78, $p < 0.05$). The SNK test showed that in the push supply network, the high inventory buffer condition resulted in significantly higher total inventory levels than did the medium inventory buffer condition, which in turns, resulted in significantly higher total inventory levels than did the low inventory buffer condition. Also, there was a significant simple effect for BL at CS = 1 (F (2, 174) = 16.17, $p < 0.05$). The SNK test showed that in the pull supply network, the high inventory buffer condition resulted in significantly higher total inventory levels than did the low and medium inventory buffer conditions. There was no significant difference between the low and medium levels of inventory buffer.

FE*BL

The univariate F statistic of FE*BL was not significant (F (4, 162) = 1.35, p = 0.2549). Thus its interpretation was not continued even though its multivariate F statistic was significant.

Main Effect of FE

Among the two-way interactions, only CS*BL was found significant on Inv in both the MANOVA and univariate ANOVA. Since FE did not involve in this interaction and it was found significant in both the MANOVA and univariate ANOVA, its main effect should be discussed. FE was found significant in the univariate ANOVA with F (2, 162) = 5.01 and p = 0.0077. It only had a weak relationship with Inv (R^2 = 0.0067). SNK test was performed to see which levels of FE were significantly different from which. Table XXII displays the results of the SNK test for FE main effect. The results showed that there was no significant difference between the low and medium forecast error groups. However, the high forecast error group resulted in significantly higher total inventory levels than did the low and medium forecast error groups.

TABLE XXII

Results of SNK Test for FE Main Effect

FE	Mean (N = 60)	SNK Grouping
Low	26018.9	B
Medium	26626.8	B
High	27760.8	A

Throughput (TH)

Table XXIII displays the univariate ANOVA results for TH Criterion. CS and BL had the strong relationships with TH (R^2 for CS = 0.5237, R^2 for BL = 0.1012). CS*BL and CS*FE only accounted for a small percent of the variance in TH (R^2 for CS*BL = 0.0500, R^2 for CS*FE = 0.0146). CS*BL had a bigger effect on TH than CS*FE did.

TABLE XXIII

Univariate ANOVA Results for TH Criterion

Effect Tested	Dependent Variable: TH			
	F Value	DF	p-value	R^2
CS	295.64	(1,162)	<.0001**	0.5237
FE	2.91	(2,162)	0.0574	0.0103
BL	28.58	(2,162)	<.0001**	0.1012
CS* FE	4.13	(2,162)	0.0179**	0.0146
CS* BL	14.11	(2,162)	<.0001**	0.0500
FE * BL	0.75	(4,162)	0.5623	0.0053
CS* FE* BL	1.11	(4,162)	0.3555	0.0078

** $p < 0.05$

CS*FE

The univariate F statistic of CS*FE was significant (F (2, 162) = 4.13, p = 0.0179). Its multivariate F statistic was also significant. Hence, simple effect tests were performed to interpret its effect.

Simple Effect Testing for FE at Different Levels of CS

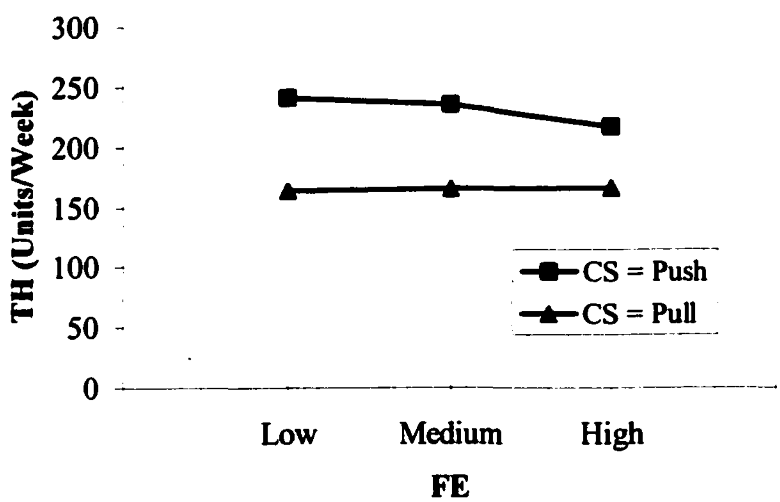


FIGURE 26

Effect of CS*FE on TH

Figure 26 demonstrates the effect of CS*FE on TH. Under all three settings of FE, push strategy resulted in higher throughput than pull strategy. In this criterion, push strategy outperformed pull strategy. Also, CS moderated the effect of FE on TH. FE had a stronger effect on TH in a push supply network, compared to a pull supply network. This indicates that a push supply network is more sensitive to forecast errors than a pull supply network. A pull supply network reacts to the current MOS requirements partly derived from the demand forecast of the current period. On the other hand, the push supply network reacts not only to the MOS requirements of the current period but also to future MOS requirements involving the forecasts of several periods in the future.

Simple effect testing was performed for FE at different levels of CS. Table XXIV displays the results of the simple effect testing. The results indicated that there was a significant simple effect for FE at CS = 0 (F (2, 174) = 4.75, $p < 0.05$). The simple effect for FE at CS = 1 was nonsignificant (F (2, 174) = 0.06, $p > 0.05$). SNK test was performed for the significant simple effect. Table XXV shows the results of the SNK test for FE at CS = 0. The SNK test showed that in the push supply network, the low forecast error condition resulted in significantly higher throughput than did the medium forecast error condition, which in turn, resulted in significantly higher throughput than did the high forecast error condition.

TABLE XXIV

Results of Simple Effect Testing for FE on TH at Different Levels of CS

CS	F Value	DF	p-value
Push	4.75	(2, 174)	< 0.05**
Pull	0.06	(2, 174)	> 0.05

** Statistically significant at 0.05 level

TABLE XXV

Results of SNK Test for FE on TH at CS =0

CS	FE	Mean (N = 30)	SNK Grouping
Push	Low	241.447	A
	Medium	235.761	B
	High	217.586	C

CS*BL

The univariate F statistic of CS*BL was significant (F (2, 162) = 14.11, $p <$ 0.0001). Its multivariate F statistic was also significant. Hence, simple effect tests were performed to interpret its effect.

Simple Effect Testing for BL at Different Levels of CS

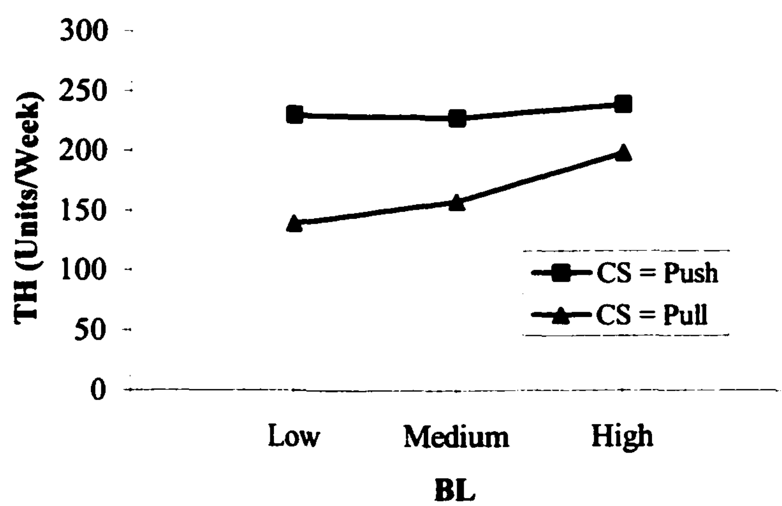


FIGURE 27

Effect of CS*BL on TH

Figure 27 demonstrates the effect of CS*BL on TH. Under all three settings of BL, push strategy resulted in higher throughput than pull strategy. In this criterion, push strategy outperformed pull strategy. Also, CS moderated the effect of BL on TH. BL had a stronger effect on TH in a pull supply network, compared to a push supply network. This indicates that a pull supply network is more sensitive to levels of inventory buffer than a push supply network. A pull supply network reacts to the current requirements. It can react this way because the requirements are satisfied by using inventory buffers from fixed stocks, and then the productions are triggered to replenish the stocks. The fixed stocks should always have sufficient inventory buffers for filling the immediate requirements. Therefore, the level of inventory buffer is vital to the performance of the pull mechanisms. On the other hand, in the push supply network, inventory buffers are used only to protect against demand variability and forecast errors. They are not required to make the push mechanisms work.

Simple effect testing was performed for BL at different levels of CS. Table XXVI displays the results of the simple effect testing. The results indicated that there was a significant simple effect for BL at CS = 1 (F (2, 174) = 38.86, $p < 0.05$). The simple effect for BL at CS = 0 was nonsignificant (F (2, 174) = 1.62, $p > 0.05$). SNK test was performed for the significant simple effect. Table XXVII shows the results of the SNK test for BL at CS = 1. The SNK test showed that in the pull supply network, the high inventory buffer condition resulted in significantly higher throughput than did the medium inventory buffer condition, which in turns, resulted in significantly higher throughput than did the low inventory buffer condition.

TABLE XXVI

Results of Simple Effect Testing for BL on TH at Different Levels of CS

CS	F Value	DF	p-value
Push	1.62	(2, 174)	> 0.05
Pull	38.86	(2, 174)	< 0.05 **

** Statistically significant at 0.05 level

TABLE XXVII

Results of SNK Test for BL on TH at CS =1

CS	BL	Mean (N = 30)	SNK Grouping
Pull	Low	139.342	C
	Medium	157.856	B
	High	198.500	A

FE*BL

The univariate F statistic of FE*BL was not significant (F (4, 162) = 0.75, p = 0.5623). Thus its interpretation was not continued even though its multivariate F statistic was significant.

Customer Service Level (SL)

Table XXVIII displays the univariate ANOVA results for SL Criterion. CS and BL had the strong relationships with SL (R^2 for CS = 0.5950, R^2 for BL = 0.1331). FE, CS*BL and CS*FE only accounted for a small percent of the variance in SL. CS*BL had a bigger effect on SL than CS*FE did (R^2 for CE*BL = 0.0610, R^2 for CS*FE = 0.0099).

TABLE XXVIII

Univariate ANOVA Results for SL Criterion

Effect Tested	Dependent Variable: SL			
	F Value	DF	p-value	R^2
CS	551.80	(1,162)	<.0001**	0.5950
FE	6.19	(2,162)	0.0026**	0.0133
BL	61.74	(2,162)	<.0001**	0.1331
CS* FE	4.60	(2,162)	0.0113**	0.0099
CS* BL	28.29	(2,162)	<.0001**	0.0610
FE * BL	2.22	(4,162)	0.0695	0.0096
CS* FE* BL	0.78	(4,162)	0.5392	0.0034

** $p < 0.05$

CS*FE

The univariate F statistic of CS*FE was significant (F (2, 162) = 4.60, p = 0.0113). Its multivariate F statistic was also significant. Hence, simple effect tests were performed to interpret its effect.

Simple Effect Testing for FE at Different Levels of CS

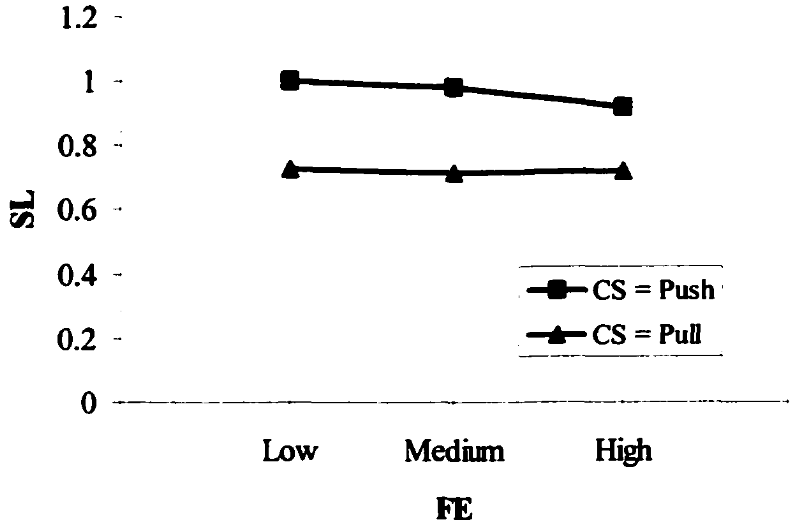


FIGURE 28

Effect of CS*FE on SL

Figure 28 demonstrates the effect of CS*FE on SL. Under all three settings of FE, push strategy resulted in higher service level than pull strategy. In this criterion, push strategy outperformed pull strategy. Also, CS moderated the effect of FE on SL. FE had a stronger effect on SL in a push supply network, compared to a pull supply network. The same rationale used to describe the effect of CS*FE on TH is applied for describing the effect of CS*FE on SL.

Simple effect testing was performed for FE at different levels of CS. Table XXIX displays the results of the simple effect testing. The results indicated that there was a significant simple effect for FE at CS = 0 (F (2, 174) = 5.17, $p < 0.05$). The simple effect for FE at CS = 1 was nonsignificant (F (2, 174) = 0.13, $p > 0.05$). SNK test was performed for the significant simple effect. Table XXX shows the results of the SNK test for FE at CS = 0. The results showed that in the push supply network, there was no significant difference between the low and medium forecast error groups. However, the high forecast error group resulted in significantly lower service levels than did the low and medium forecast error groups.

TABLE XXIX

Results of Simple Effect Testing for FE on SL at Different Levels of CS

CS	F Value	DF	p-value
Push	5.17	(2, 174)	< 0.05**
Pull	0.13	(2, 174)	> 0.05

** Statistically significant at 0.05 level

TABLE XXX

Results of SNK Test for FE on SL at CS =0

CS	FE	Mean (N = 30)	SNK Grouping
Push	Low	0.999863	A
	Medium	0.985350	A
	High	0.921043	B

CS*BL

The univariate F statistic of CS*BL was significant (F (2, 162) = 28.29, $p <$ 0.0001). Its multivariate F statistic was also significant. Hence, simple effect tests were performed to interpret its effect.

Simple Effect Testing for BL at Different Levels of CS

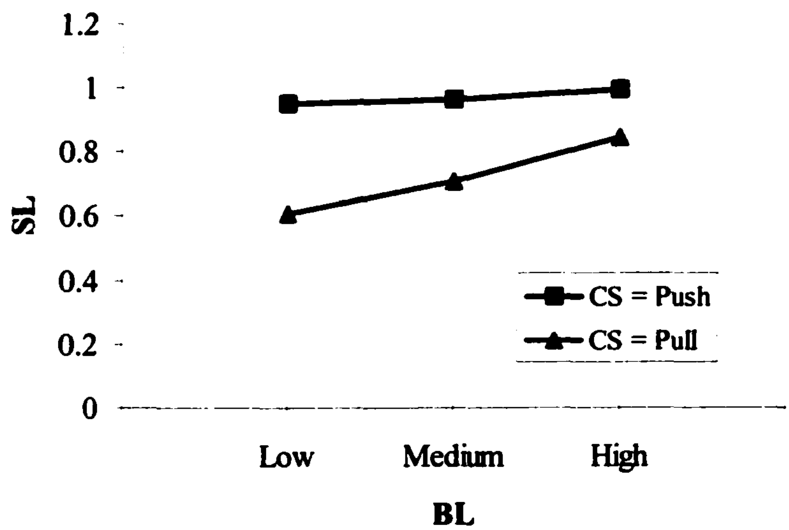


FIGURE 29

Effect of CS*BL on SL

Figure 29 demonstrates the effect of CS*BL on SL. Under all three settings of BL, push strategy resulted in higher service level than pull strategy. In this criterion, push strategy outperformed pull strategy. Also, CS moderated the effect of BL on SL. BL had a stronger effect on SL in a pull supply network, compared to a push supply network. The same rationale used to describe the effect of CS*BL on TH is applied for describing the effect of CS*BL on SL.

Simple effect testing was performed for BL at different levels of CS. Table XXXI displays the results of the simple effect testing. The results indicated that there was a significant simple effect for BL at CS = 1 (F (2, 174) = 77.10, $p < 0.05$). The simple effect for BL at CS = 0 was nonsignificant (F (2, 174) = 2.99, $p > 0.05$). SNK test was performed for the significant simple effect. Table XXXII shows the results of the SNK test for BL at CS = 1. The SNK test showed that in the pull supply network, the high inventory buffer condition resulted in significantly higher service levels than did the medium inventory buffer condition, which in turns, resulted in significantly higher service levels than did the low inventory buffer condition.

TABLE XXXI

Results of Simple Effect Testing for BL on SL at Different Levels of CS

CS	F Value	DF	p-value
Push	2.99	(2, 174)	> 0.05
Pull	77.10	(2, 174)	$< 0.05^{**}$

** Statistically significant at 0.05 level

TABLE XXXII

Results of SNK Test for BL on SL at CS =1

CS	BL	Mean (N = 30)	SNK Grouping
Pull	Low	0.60762	C
	Medium	0.70723	B
	High	0.84727	A

FE*BL

The univariate F statistic of FE*BL was not significant ($\underline{F}$ (4, 162) = 2.22, $\underline{p}$ = 0.0695). Thus its interpretation was not continued even though its multivariate F statistic was significant.

Interpretations of the interactions from another perspective

There are two perspectives on a two-way interaction. For an interaction between variable A and B, one perspective is to interpret the simple effects for variable A at different levels of variable B. Another perspective is to interpret the simple effects for variable B at different levels of variable A (Hatcher and Stepanski 1994). Although interpreting the two-way interaction effect from one of these two perspectives is adequate, in many cases, viewing the interaction from two different perspectives provides different useful information about the interaction effect. Above discussions interpreted the significant interactions from the perspective of simple effects for FE or BL at different levels of CS. The interpretations of the significant interactions from the other perspective are provided below.

Table XXXIII summarizes the results from the tests of simple effects for CS on each of the dependent variables at different levels of FE or BL. The results revealed that all of the simple effects for CS were significant. Table XXXIV shows the means of each criterion observed in push and pull supply networks at each level of FE or BL. Since all of the simple effects for CS were significant and there were only two groups of CS, it was clear that there existed significant difference between each group of CS for all conditions shown in Table XXXIV. For all conditions, push strategy resulted in higher means than pull strategy. Push strategy outperformed pull strategy in terms of throughput and customer service level while pull strategy outperformed push strategy in term of total inventory. These findings are consistent with the interpretations from the other perspective presented in the previous discussions.

TABLE XXXIII

Results from the Tests of Simple Effects for CS on Each Dependent Variable at Different Levels of FE or BL

Dependent Variable	Interaction		F Value	DF	p-value
Inv	CS*BL	BL = 0	75.71	(1, 174)	< 0.05
		BL = 1	241.67	(1, 174)	< 0.05
		BL = 2	549.88	(1, 174)	< 0.05
TH	CS*FE	FE = 0	92.39	(1, 174)	< 0.05
		FE = 1	74.88	(1, 174)	< 0.05
		FE = 2	40.28	(1, 174)	< 0.05
TH	CS*BL	BL = 0	172.21	(1, 174)	< 0.05
		BL = 1	100.87	(1, 174)	< 0.05
		BL = 2	34.06	(1, 174)	< 0.05
SL	CS*FE	FE = 0	108.36	(1, 174)	< 0.05
		FE = 1	106.98	(1, 174)	< 0.05
		FE = 2	60.39	(1, 174)	< 0.05
SL	CS*BL	BL = 0	311.92	(1, 174)	< 0.05
		BL = 1	170.98	(1, 174)	< 0.05
		BL = 2	58.37	(1, 174)	< 0.05

TABLE XXXIV

Means of Each Criterion observed from Push and Pull Supply Networks at Each Level of FE or BL

Criterion	Interaction	FE or BL	CS	Mean (N = 30)	Grouping
Inv	CS*BL	BL = 0	Push	26332	A
			Pull	19126	B
Inv	CS*BL	BL = 1	Push	31483.4	A
			Pull	18609.4	B
Inv	CS*BL	BL = 2	Push	42341.3	A
			Pull	22921.7	B
TH	CS*FE	FE = 0	Push	241.447	A
			Pull	163.692	B
TH	CS*FE	FE = 1	Push	235.761	A
			Pull	165.758	B
TH	CS*FE	FE = 2	Push	217.586	A
			Pull	166.247	B
TH	CS*BL	BL = 0	Push	229.428	A
			Pull	139.342	B
TH	CS*BL	BL = 1	Push	226.803	A
			Pull	157.856	B
TH	CS*BL	BL = 2	Push	238.564	A
			Pull	198.500	B
SL	CS*FE	FE = 0	Push	0.99986	A
			Pull	0.72830	B
SL	CS*FE	FE = 1	Push	0.98535	A
			Pull	0.71552	B
SL	CS*FE	FE = 2	Push	0.92104	A
			Pull	0.71831	B
SL	CS*BL	BL = 0	Push	0.95007	A
			Pull	0.60762	B
SL	CS*BL	BL = 1	Push	0.96077	A
			Pull	0.70723	B
SL	CS*BL	BL = 2	Push	0.99542	A
			Pull	0.84727	B

CHAPTER 6

CONCLUSION

The primary purpose of this research was to explore the impact of "push" and "pull" OPC strategies on supply network performance (in terms of total inventory, throughput, and customer service level) under different settings of inventory buffer level and forecast error in MTS environment. A realistic OPC software system for MTS supply networks was developed and implemented. This software provided a foundation for the simulations used to investigate the performance differences of push and pull strategies.

The results indicated that control strategy, inventory buffer level, and forecast error all significantly affected each of the performance measures. Among the independent variables and their interactions, control strategy and inventory buffer level had the largest effects on supply network performance. At each combination of different conditions of inventory buffer level and forecast error, push strategy outperformed pull strategy in terms of throughput and customer service level while pull strategy outperformed push strategy in term of total inventory.

This chapter concludes the research with a summary of research findings, research contributions, implications for practice, limitations of the current study, and directions for the future research.

Summary of Research Findings

Considering all performance measures simultaneously, all null hypotheses were rejected except hypothesis 5. The effect of the three-way interaction among control strategy, inventory buffer level, and forecast error was found nonsignificant. All of the two-way interactions were found significant. Control strategy, inventory buffer level, and forecast error did have significant impact on supply network performance.

Control strategy and inventory buffer level had larger effects on supply network performance than did forecast error and two-way interactions. Control strategy and inventory buffer level explained about 59% and 27% of the variance in the combination of the dependent variables. Forecast error only explained 5% of the variance in the combination of the dependent variables. This effect may be so small because forecast error was dominated by the effect of inventory buffer level. Both medium and high conditions of inventory buffer level were set to have large amount of buffer inventory, 50% and 100% of average demand during lead-time. A large amount of buffer inventory alleviated the effect of forecast error.

Considering each of the performance measures separately, control strategy, inventory buffer level, and forecast error all significantly affected each of the performance measures. Control strategy and inventory buffer level had the largest effects on every performance measure. At each combination of different conditions of inventory buffer level and forecast error, push strategy outperformed pull strategy in terms of throughput and customer service level while pull strategy outperformed push strategy in terms of total inventory. According to the results of this study, the theory of planning and control strategy proposed in Chapter 2 is refined as follows.

> Under high supply network utilization, a push supply network results in higher inventory, throughput, and service level than a pull supply network when they are compared under the same conditions of inventory buffer level and forecast error.

The crucial findings are summarized below for each performance measure.

Total Inventory

When push and pull supply networks were compared under the same conditions, the pull supply network resulted in lower total inventory than the push supply network. A pull supply network consumes more from the inventory buffers because it consumes them as part of its replenishment mechanism. It satisfies immediate needs from the inventory in the fixed stocks then produces later to replenish the stocks. A push supply network uses inventory buffers only for protecting against demand variability and forecast errors.

The push supply network had the lowest total inventory level when inventory buffer level was set to low condition regardless of the conditions of forecast error.

Throughput and Customer Service Level

Similar results were found for both throughput and customer service level. The push supply network had higher throughput and customer service levels than the pull supply network when they were compared under the same conditions. The interpretations of the two way interactions of control strategy with forecast error and inventory buffer level indicated that, in terms of throughput and customer service level, push was more sensitive to forecast error but less sensitive to inventory buffer level than pull.

Push was more sensitive to forecast error than pull. While forecast error had significant impact on throughput and customer service level of the push supply network, it did not significantly affect those of the pull supply network. High setting of forecast error decreased the throughput and customer service level of the push supply network. This was because a pull supply network only reacted to the demand forecasts of the current period. On the other hand, the push supply network reacted not only to the demand forecasts of the current period but also to the demand forecasts of several periods in the future.

Pull was more sensitive to inventory buffer level than push. For the pull supply network, the best throughputs and customer service levels were found under all conditions with high setting of inventory buffer level. High level of buffer inventory was critical to the high performances of the pull supply network in terms of throughput and customer service level. The pull supply network needed to set the level of inventory buffers at each stage very high in order to have sufficient inventory buffers for satisfying immediate needs. However, inventory buffer level did not affect throughput and customer service level of the push supply network. In the push supply network, the buffer inventory was used only to protect against demand variability and forecast errors. It was not required to make the push mechanisms work.

Setting the inventory buffer level higher improves throughput and customer service level of pull supply networks. However, it only benefits push supply networks if the forecast errors are high. This means that, under low and medium conditions of forecast error, we can decrease inventory buffer level in a push supply network without any impact on throughput and customer service level. Nevertheless, the low setting of inventory buffer level in the push supply network causes more total inventory than does the high setting of inventory buffer level in the pull supply network, as confirmed by a t-test reported in Table XXXV.

TABLE XXXV

Comparison of Total Inventory under Low Setting of Inventory Buffer Level in Push Supply Network and High Setting of Inventory Buffer Level in Pull Supply Network

Control Strategy	Inventory Buffer Level	Mean	Pr > |t|
Push	Low	26331.5	<0.0001
Pull	High	22921.7	

No prior studies have investigated the performances of push and pull strategies for a supply network. However, mixed results among comparative studies of push and pull strategies in factories suggest caution about generalizing the results of this study. In term of total inventory, some studies found pull systems outperformed push systems (Lee 1989; Sarker and Fitzsimmons 1989; Spearman, Woodruff and Hopp 1990; Spearman and Zazanis 1992; Hopp and Spearman 1996) while others found push systems outperformed pull systems (Bonney et al. 1999; Grosfeld-Nir et al. 2000). In term of throughput, Lee (1989) indicated that pull systems surpassed push systems while Bonney et al (1999) as well as Grosfeld-Nir et al. (2000) found that push systems were better than pull systems. I have not known of a study that has compared the performance differences between push and pull systems in term of customer service level. The mixed results among these studies were partly attributed to the assumptions made by these studies regarding to the system environments in which the studied systems operated. Also, although these studied systems were referred to push and pull to classify the type of system, their details about rules of operation for push and pull were different among the studies. Therefore, the conclusions and implications from this study must be applied with caution about environmental conditions as well as details about how push and pull supply networks were defined and operated in this study.

Research Contributions

This research contributes to operations management in three ways: First, this research provides a better understanding of the relationship between OPC strategies and supply network performance in a MTS environment. It develops a theory of control strategy. This theory describes the impact of control strategies on system performance. Two independent variables (inventory buffer level and forecast error) are added to the theory in order to explain a more complex relationship between control strategies and system performance. The refined theory could serve as a useful guide for future research and could increase the body of knowledge in operations management literature.

Second, to operations managers, the insights from this study will serve as guidelines for selecting an appropriate control strategy to coordinate operations in a MTS supply network. The knowledge from this study can help managers decide which strategy to adopt (Sarker and Fitzsimmons 1989; Taylor 2000). Also, it will reduce the cost and the amount of time the managers require in selecting a proper control strategy for a particular supply network (Taylor 2000).

Third, for practitioners, this study designs and implements an object-oriented OPC system for supply networks in a MTS environment. Practitioners can utilize the developed OPC system to facilitate the coordination of planning and control activities of a supply network. Coordinating planning and control activities is expected to improve the global performance of a supply network (Lee and Billington 1992; Lambert and Cooper 2000; Simchi-Levi et al. 2000). Moreover, the practitioners will be able to explore different control strategies by replacing existing planning module in the OPC system (such as a push-based planning module) with the alternative one (such as a pull-based planning module).

Implications for Practice

The results from this study may assist practitioners in making decision about which OPC strategy to adopt to meet current and future needs of a supply network. A supply network should adopt a push strategy if its primary objectives are to maximize throughput and customer service level. In contrast, if its key objective is to reduce overall inventory cost, a pull strategy should be adopted. When using a pull strategy, a supply network should establish high levels of inventory buffers. A push supply network should operate with low levels of inventory buffers unless there exists a high level of forecast error.

One advantage of the pull strategy is that it is insensitive to the forecast error. In the situations where high levels of forecast error exist, a pull strategy tends to be more appropriate than a push strategy. Throughput and customer service level of a pull supply network could be improved by setting the levels of inventory buffers higher. As we keep setting the inventory buffer level higher (even higher than the high setting used in this study), it is expected that the throughput and customer service level of a pull supply network will increase and eventually become equivalent to those of a push supply network.

It is possible for a pull supply network to meet high throughput and customer service level with a low level of inventory buffers by reducing the sizes of transfer batches between each stage. Using a low level of inventory buffers decreases total inventory of a supply network. However, reducing the sizes of transfer batches creates more shipments, which in turn increase transportation costs. It is also limited by the minimum truckload for transferring products to next stage.

Whether using push or pull strategy, the OPC system developed in this study synchronizes planning activities of a supply network. It also provides visibility of data throughout a supply network. Independent demands are used only at the retailers while dependent demands based on the independent demands at the retailers are applied at other stages. All of these should help to lessen the bullwhip effect in a supply network. Bullwhip effect is a phenomenon that the demand order variabilities are amplified as they move up the supply network (Lee et al. 1997).

Limitations of the Current Study

Since this research focused on inventory and demand forecast aspects of supply network planning, it paid a little attention to capacity planning. Capacity planning should be performed to check the feasibility of the MOS and DOP. The MOS and DOP need to be regenerated if the capacity constraints are violated. The simulation conducted in this study did not check the feasibility of the generated MOS and DOP. Instead, any orders or parts of orders in excess of the available capacity were processed in the following periods when there was sufficient capacity for processing them. However, ignoring capacity planning should not affect the results from this study because the average utilization rate of 80% was set at each production facility. Capacity planning was less crucial in this setting. This utilization rate decreased the occurrences of insufficient capacity and made capacity a less important constraint.

Another concern is both forecast error and inventory buffer level were set at some specific settings. Forecast error was set at 11%, 33%, and 55% of weekly demand and inventory buffer level was set at 25%, 50%, and 100% of average demand during lead-time. Other settings of forecast error and inventory buffer level were not considered in this research.

The third limitation is the target levels of inventory buffer stocks at each stage were fixed throughout the simulation. In practice, from time to time a pull system may adjust these target levels based on forecast information. The effects of adjusting these target levels were not addressed in this study.

Although the performance measures used in this study are related to supply network profit, they are not the measures of profit. Their impacts on profit were not explored in this research. It is not clear which performance measures have greater impacts on profit than the other performance measures. An analysis of the effects of the performance measures used in this research on supply network profit would be helpful in relating the results of this study to the profitability of a supply network, the most vital performance measure in practice.

This study concentrated more on planning and less on control. In the simulation, replanning was performed only at the beginning of each planning period to reflect the changes occurring during last planning period. The regenerated plans were not adjusted during the planning period.

Directions for Future Research

Future research is needed to further explain the impact of OPC strategies on supply network performance. This type of research may investigate other types of OPC strategies such as a hybrid strategy (a mix of push and pull strategies). In addition, it may examine the interaction effects between OPC strategies and other variables such as variability of processing and shipment times, utilization rate, and structures of supply networks.

One crucial difference of push and pull strategies is the extent of forecast information used. A further investigation is needed to examine the effect of the extent of forecast information used on the relationship between control strategies and supply network performance. In this research, the push strategy utilized demand forecasts of several weeks into the future while the pull strategy only utilized demand forecasts of the current week. It would be interesting to see what will happen if the push strategy uses less forecast information and the pull strategy uses more forecast information.

For the pull strategy, more research is needed to explore different policies for setting the appropriate target levels of the fixed stocks at each stage. Additionally, it would be valuable to investigate advantages and disadvantages of adjusting the target levels of the fixed stocks more frequently according to forecast revisions.

It would be interesting to conduct a similar study for an OPC system having a capacity planning module. Developing this module would require an algorithm for checking the feasibility of generated plans and a protocol for the coordination between each supply network member to realize that algorithm. Also helpful would be an algorithm for adjusting the plans according to the results from the capacity module.

Several optimization engines should be added into OPC system. Further research should be conducted to develop optimization modules to determine optimal process batch size, transfer batch size, replanning frequency, etc.

The last area of future research is to develop new incentive and performance measure policies for a highly coordinated supply network. Lee et al. (1997) pointed out three challenges for supply network members in counteracting the bullwhip effect: 1) integrating new information systems, 2) defining new organizational relationships, and 3) implementing new incentive and measurement systems. This research addressed first two challenges by developing an integrated planning and control system as well as suggesting a formation of supply network in which supply network members closely coordinate with each other under the supervision of a supply network coordinator. The last challenge needs to be addressed in future research.

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